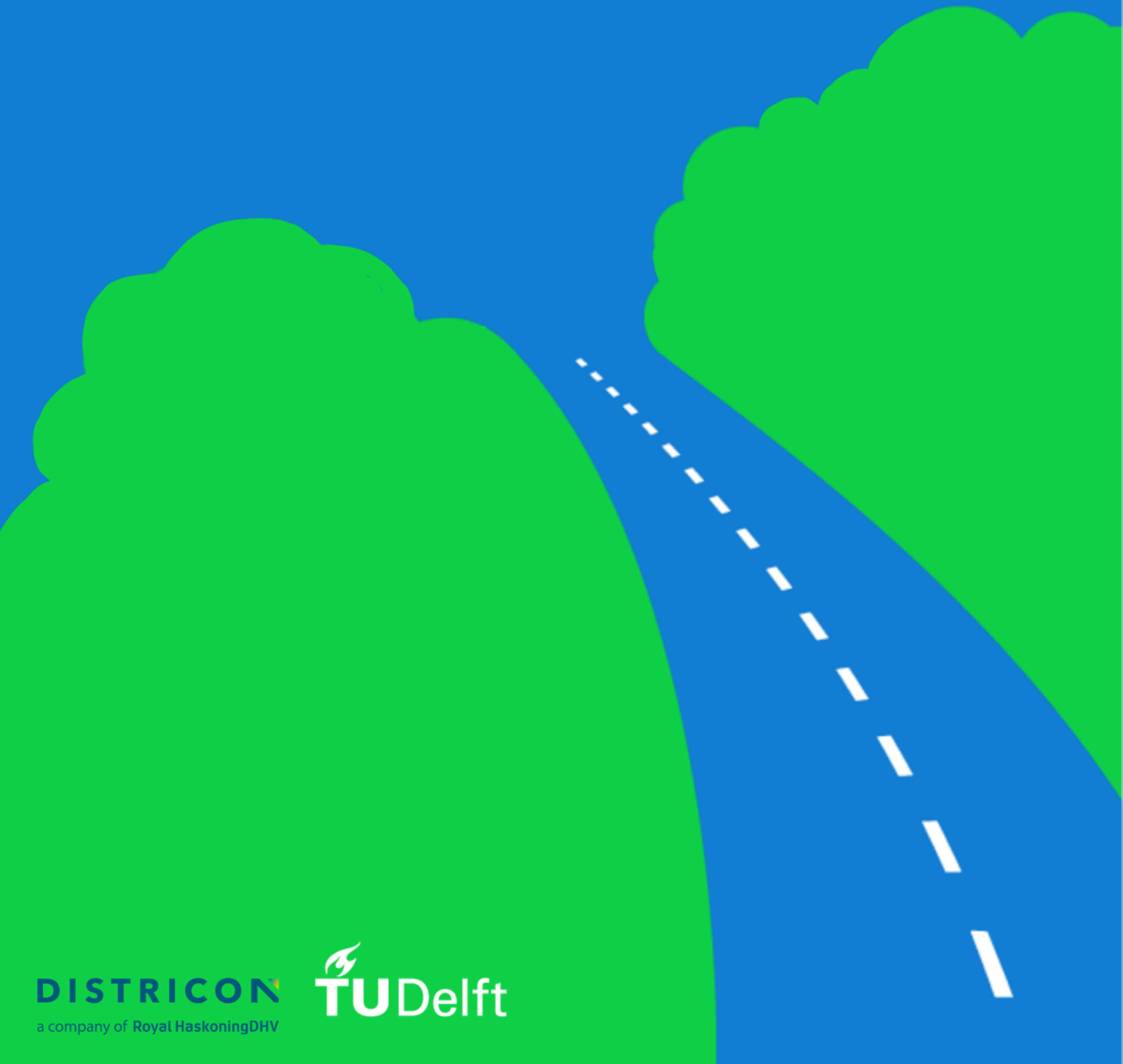
The road towards a more transparent and accurate carbon footprint of freight transportation

Developing a tool for assessing the possible uncertainties underlying the carbon footprint of a shipment

R.H.H Siepman



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The road towards a more transparent and accurate carbon footprint of freight transportation

Developing a tool for assessing the possible uncertainties underlying the carbon footprint of a shipment

by

R.H.H. Siepman

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Preface

This report is written in fulfillment of the Master of Science degree in Transport, Infrastructure, and Logistics. With the completion of this report, my time as a student at TU Delft also comes to an end - a place that has offered me many opportunities and knowledge, as well as joy and lifelong friendships.

The master's thesis before you, titled "The road towards a more transparent and accurate carbon footprint of freight transportation," aims to provide a clear insight into the current state of carbon footprint calculations in the transportation sector, with a special focus on potential uncertainties that may arise in these calculations. This is achieved through empirical data collection via field research and interviews, evaluating different methods for calculating the carbon footprint and examining the possible effects of the uncertainties on the final carbon footprint value. I hope this thesis will serve as a springboard for further discussion and research and elevate the importance of potential uncertainties in carbon footprint calculations on the agendas of policymakers and stakeholders in the transportation industry. Addressing the challenges and uncertainties surrounding carbon footprint calculations is a crucial step toward making well-informed sustainable choices.

Defining the subject of this thesis and shaping the research was a challenge. I wanted to explore a topic that related to sustainability and its implications throughout the supply chain - a topic I knew little about but was eager to learn. Initially, I considered a wide range of potential topics, ultimately choosing the main research objective of "Designing a tool to assess the uncertainties within a carbon footprint of freight transportation." Shortly after, I became involved in a project with Districon, which allowed me to conduct field research. The project focused on mapping the carbon footprint of freight transportation to a construction site, where I could immediately see potential uncertainties arising in practice. The challenge was to further define the scope of my research during this practical experience, maintain a scientific approach, and simultaneously consider the ultimate design. Although the process was sometimes challenging, it was also very educational and valuable, and I am pleased with the result.

This outcome would not have been possible without my insightful conversations with my thesis supervisors, Marcel Ludema and Arjan van Binsbergen, who helped me remain critical and were always available for guidance. I want to express my gratitude for the feedback sessions and enjoyable discussions. Additionally, I would like to extend my gratitude to Lóri Tavasszy for the enthusiastic discussions and feedback throughout the research process.

I also want to express my appreciation to the Sustainable Logistics team from Districon, for the enjoyable time. The team meetings were a rich source of new insights into the logistics sector and its sustainability efforts - a topic I was excited to learn more about. In particular, I want to thank Raymond for the weekly coffee brainstorming sessions and Linde and Maarten for allowing me to observe and assist with the project and always being available for my questions.

Finally but not least, my friends and family have supported me through this journey a lot. I want to thank my parents for their continuous support throughout my research; It was comforting to be able to return home occasionally, to study, and to find a distraction when needed. I want to thank Teun for his ongoing patience, encouragement, and motivating words while sprinting toward deadlines. And, of course, my friends and housemates who provided much-needed laughter and distraction and were always willing to brainstorm with me.

All in all, these last few months have sometimes been challenging but, overall, an incredibly educational experience. I hope you enjoy reading this thesis!

Renée Siepman
Rotterdam, May 2023

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Summary

Situation and objective
Freight transport plays a critical role in our globalized world and contributes significantly to greenhouse gas emissions. Therefore, measuring and reporting carbon footprints in this sector has become essential for regulatory compliance and purposes such as corporate sustainability reporting, informed decision-making, winning tenders, and enhancing competitiveness. Various stakeholders are involved in this process, including shippers, carriers, logistics service providers, freight forwarders, policymakers, and consignees. All these parties have an interest in either calculating their carbon footprint or requesting one from others. Despite its importance, measuring and reporting carbon footprints in the freight transport sector pose significant challenges. One of the main issues lies in the data availability required to calculate accurate carbon footprints. This can lead to uncertainty and a potential deviation of the carbon footprint from its actual value. Current software programs offer no indication of this potential uncertainty, which is why carbon footprints are often presented without any reference to the underlying uncertainty. These uncertainties can lead to incorrect decisions, credibility issues, and difficulties in demonstrating significant change. Hence, a comprehensive understanding of these uncertainties and their implications is essential, further driving the need for research. Consequently, the primary aim of this study is to:

“Design of a ’tool’ to assess the uncertainty of a transport carbon footprint measurement “

Given that several software tools for calculating a carbon footprint already exist, the focus should not be on developing a new model. Instead, the emphasis should be on identifying existing uncertainties, understanding their origins, evaluating whether they can be prevented, and exploring how they can be quantified. After numerous brainstorming sessions, it was concluded that the tool should be designed as a guidance framework. This guidance framework assists in identifying possible sources of underlying uncertainties and provides suggestions for quantifying these uncertainties, allowing to make a range of values around a carbon footprint representable.

With this framework, the causes of uncertainties become apparent, enabling clients or decision-makers to ask questions about how the presented carbon footprints were established and what uncertainties may underpin them. Additionally, it can help establish data requirements that a carbon footprint must satisfy. A consulting firm can utilize this framework as a communication tool in the outcomes of carbon footprint analyses, and the consequences of potential uncertainties can be discussed. A software developer can implement this framework to incorporate uncertainties in existing software programs. A transport company can use this framework to make their carbon footprint more accurate and be aware of the impact of their data quality on the calculated carbon footprint. Most crucially, it can make various stakeholders aware that the carbon footprint is not necessarily an absolute figure.

Design methodology
To achieve the design and fulfill the research objective, this research employs the triple diamond method, consisting of research, tool design, and testing and evaluation phases. *Research Phase*: This phase involved studying definitions, regulations, and factors influencing carbon footprints, as well as exploring the concept of ’uncertainty.’ It utilized Walker’s uncertainty matrix as a theoretical framework. Potential sources of uncertainty were with this framework identified by analyzing protocols and literature, conducting three expert interviews, and undertaking field research in collaboration with Districon to calculate the carbon footprint of freight transport to a construction site. The insights and understanding collected from the research phase, particularly regarding uncertainty, laid the foundation for the subsequent tool design phase. *Tool Design Phase*: Utilizing the knowledge gained in the research phase, requirements are established to incorporate uncertainties into carbon footprint calculations. The tool was iteratively developed to address uncertainties in carbon footprint calculations. The development process emphasized identifying, prioritizing, and quantifying uncertainties, resulting in a tool that provides ”a guidance framework to identify and deal with uncertainties in a carbon footprint analysis

of freight transport at a trip level." The design process resulted in a conceptual design. *Testing and Evaluation Phase*: The tool's effectiveness was tested using three randomly selected trips from the field research. Thereby its usefulness in the field research project is also evaluated. Semi-structured interviews with sustainability and carbon footprinting experts were conducted to validate the research findings and tool, providing valuable feedback and potential improvement suggestions.

Findings and result

This study has resulted in a guidance framework that can help identify the possible causes of underlying uncertainties and provide recommendations to quantify these uncertainties accurately, specifically on a trip level. The term "trip level" refers to emissions being calculated in detail rather than aggregated, which aligns with the approach used in the field research (a project to calculate the carbon footprint of freight transport to a construction site). This approach was chosen because multiple stakeholders ordered goods to the construction site, implying numerous transport companies. An aggregated level would require data on fuel consumption and transport activity on a monthly or yearly basis to allocate emissions to the construction site, which would be very time-consuming. Therefore, instead, data was collected regarding the trips to and from the construction site to calculate the emissions from transportation to the construction site.

Essential data to calculate a carbon footprint includes energy consumption and transport activity. Energy consumption can be converted to a carbon footprint using emission factors per energy type (CO_2e /l or kWh). Transport activity data (origin, destination, and payloads in tons of all shipments delivered) allows for the allocation of emissions across shipments. When data on fuel consumption or transport activity is missing, calculations or assumptions must be made for an approximation. This introduces uncertainties, establishing that uncertainty and data situations are interdependent.

Based on these findings, the guidance framework is built upon various data situations. Existing literature and protocols have highlighted the influence of various data situations on the calculation of a carbon footprint. While the literature initially outlined four main situations, variations were observed during the field research, identifying seven distinct data scenarios. These are based on how carbon footprints are calculated, using available information on energy consumption and transport activity data. Each data situation has its fundamental uncertainties that are always present and context-dependent uncertainties. The fundamental uncertainties include variation in emission factors [F1]; for example, diesel and petrol emission factor differences between the two databases are 3 to 4% giving uncertainty in the conversion of energy to emissions, a default average energy consumption[F2]; an average energy consumption based on industry averages has a margin of +- 16.5%, a modeled energy consumption +-12.5% giving uncertainty in the conversion of energy to emissions, assumptions for other loads or destinations on the route; uncertainty margin depends on the available information and number of stops on the route, but can lead to significant differences in the allocation of emissions[F3], and default emission intensity factors [F4]; varying the underlying assumptions about energy consumption and average payload by 12.5% and 15% results in an emission intensity factor with a -32% and +51% range giving uncertainty in the conversion of ton-kilometers to emissions.

Seven data situations were identified, shown below, with the fundamental uncertainties that apply:

- Data situation 1 [F1]: The carbon footprint of a shipment can be calculated based on the known energy consumption of the trip and known transport activity on that trip.
- Data situation 2 [F1]: The carbon footprint of a shipment can be calculated based on emission intensity (CO_2e/ton-km) or energy intensity factor (l or kWh/ton-km) known and calculated by the transport company, multiplied by the distance and payload of the shipment.
- Data situation 3 [F1]: The carbon footprint of a shipment can be calculated with the average energy consumption of the vehicle in km/l or km/kWh and the transport activity of the trip.
- Data situation 4 [F1, F2]: The carbon footprint of a shipment can be calculated with a default average energy consumption in km/l or km/kWh and the transport activity of the trip.
- Data situation 5 [F1, F3]: The carbon footprint of a shipment can be calculated based on the average energy consumption of the vehicle in km/l or km/kWh, but not all data on transport activity is known, and assumptions must be made.
- Data situation 6 [F1, F2, F3]: The carbon footprint of a shipment can be calculated with a default average energy consumption, and not all data on transport activity is known, and assumptions must be made.

- Data situation 7 [F4]: The carbon footprint of a shipment must be calculated with default emission intensity factors, as there's no better approximation due to missing data on transport activity and energy consumption.

As discussed, in addition to fundamental uncertainties, other factors can also create uncertainty around the carbon footprint. For instance, when average energy consumption is based on the number of liters divided by the actual driven distance, and only the planned distance is available for a route, the planned distance must be converted using a factor to switch to the actual driven distance, or vice versa. This is not a fundamental uncertainty that always occurs in the data situation but is a possible variation in these data situations and is thus context-dependent. The causes of the greatest uncertainties in this study are the use of default emission intensity factors [F4], the use of default average energy consumption [F2], the use of assumptions for other loads or destinations on the route [F3], unknown energy type that is used because this influences the selection of the emission factor, applying a standard conversion factor to convert another load unit to weight, misinterpretation of origin and destination when the distance is needed for calculating energy consumption, and when default emission intensity factors are used additional uncertainty can arise if the vehicle type and/or shipment type is unknown/unclear because this influences the selection of the factor. The guidance framework assists in identifying all (there are more than stated above) potential uncertainties depending on the data situation. Furthermore depending on the nature of each uncertainty, it is determined whether the uncertainty is best quantified using probability density functions (PDFs) and Monte Carlo simulations or scenario analyses.

The final conceptual design of this study is a guidance framework which includes the following steps to identify and deal with different potential causes of uncertainties: **Step 1**: Define data situation and identify which fundamental uncertainties are in this data situation. **Step 2**: Identify potential causes of uncertainties due to definition uncertainties. Ensure that stakeholders sharing information align on these definitions to prevent uncertainty caused by ambiguity. **Step 3**: Identify additional uncertainties that apply when the information is delivered, and the carbon footprint needs to be calculated. **Step 4**: When the need is to quantify the uncertainty around the carbon footprint, follow the suggested approach that is determined by the nature of the uncertainty. If uncertainty is caused by stochastic nature, the guidance recommends using PDFs and Monte Carlo simulations for a more realistic representation of potential uncertainty. By determining a confidence interval, the tool provides insights into the range of possible outcomes, rather than presenting a best-worst case scenario. If uncertainty is caused by assumptions made to fill in missing information, the guidance recommends scenario analysis to understand the implications of these assumptions on the carbon footprint calculation. If Monte Carlo simulations cannot be performed, alternative approaches such as input scenarios can be used. These scenarios can be based on the suggested uniform or triangular distributions (PDFs), which require two or three scenarios (best, worst, and assumption scenarios).

Besides the framework systematically addressing and displaying potential uncertainties for each of the seven identified data situations, it also provides impact scores to assist users in comprehending the importance of every source of uncertainty. By presenting the impact scale of uncertainties, the tool enables users to prioritize actions for mitigating these uncertainties more effectively, allowing a more targeted approach to addressing significant uncertainties and improving the accuracy of carbon footprint calculations.

Verification and validation
Verification of the tool's effectiveness and compliance with requirements was achieved through a series of tests, which included the examination of substituting probability density functions with scenarios. The verification process showed that most requirements were met, with two only partially met due to unavailable data and the new ISO standard;; however, the tool can incorporate future standards.

The tool was also validated and tested within the field research project, it helped with examining data situations and the underlying uncertainties. The tool enhanced transparency in the advisory and provided guidance for reducing uncertainties proactively in future data requests. However, visually presenting uncertainties using Monte Carlo simulations or scenario analyses was time-consuming and required manual work. Integration with existing software programs would streamline this process.

The tool and insights of this research were further validated with expert interviews. The expert feedback largely concurred with the identified uncertainties while highlighting additional uncertainties

and aspects for future consideration. There was a common agreement that uncertainty depends on information availability and found it logical to link these uncertainties to the data situations. A critical point was the level of detail in the data situations, which currently makes the tool suitable for trip-level analysis but necessitates adjustments for aggregate-level use (which will be needed in the new ISO standard). Nevertheless, experts acknowledged that the insights on uncertainties could still be applicable at the aggregate level. Experts recognized the research findings and proposed framework potential in raising awareness and providing an overview of the topic. Some suggested its use in contracts or data improvement efforts, while others saw potential contributions to industry harmonization. Experts emphasized that the growing awareness of upcoming regulations and increased client interest in transportation carbon footprints might incentivize companies to address uncertainties and improve data accuracy. Companies have begun incorporating CO_2 measurement and reduction plans into their contracts and increasingly demand a certain quality of data and calculation methods. However, many companies are not yet advanced in this area, and the focus on carrier-specific emission intensity factors remains in its early stages.

Reflection on tool and the new ISO
The field research led to a highly detailed level of investigation of the carbon footprint, as the routes to and from the construction site had to be modeled as accurately as possible. However, the new ISO standard for calculating emissions, based on the GLEC Framework, calculates the emissions and allocates them from a more aggregated approach. This means calculating the emission intensity factor per Transport Operating Category (TOC). This means that the total energy consumption of this category should be divided by the transport activity from this category and multiplied by an emission factor. To calculate the emissions per client, this emission intensity factor is multiplied by the client's transport activity to allocate the emissions. Consequently, there are fewer and different data situations than in this research, as noted by experts during validation. While the research developed a guidance framework at the trip level, the guidance frameworks for data situations 2 and 7 can be directly applied at aggregated levels. This is because data situation 2 specifically addresses the potential uncertainties introduced by the application of calculated emission intensity factors. Moreover, in situations where data on transport activity and energy consumption are unavailable, the GLEC framework (and the new ISO) recommend the use of default emission intensity factors. This aligns with data situation 7, which mandates the utilization of a default emission intensity factor when primary data is lacking. Furthermore, it is also important to identify the uncertainties that can play a role in calculating an emission intensity factor. If the total energy consumption is unknown, it still needs to be modeled. The same uncertainties apply when this is done at the trip level; this is similar to data situation 4 where the energy consumption of the trip must be modeled to calculate the total emissions. Another cause of uncertainty that might occur and will be a challenge is knowing which energy type is used in a year. If this is not properly monitored, it can cause problems in allocating the number of liters with the relevant emission factor. Another potential cause is also uncertainty is when assumptions must be made if part of the transport activity is unknown and an estimated average payload must be used. Another cause of uncertainty that might occur is the uncertainty due to the use of conversion factors to convert payload from other units to tonnages; inconsistent application of conversion factors can lead to significant uncertainty.

Recommendations improvement tool
The following recommendations are made to enhance the tool. First, as the tool currently focuses on road freight transport, expanding its scope to include other transport modes could increase its applicability. Second, while the research examined the uncertainties and their potential effects, establishing a reliable probability density function proved challenging due to limited data and prior research. Therefore, it is advised to further explore this topic and refine the tool for integration with software applications. Third, additional testing with potential users, is recommended to validate the tool's effectiveness. Forth, to maintain relevance, the tool should be updated to comply with the new ISO standard that emphasizes aggregated-level calculations, ensuring alignment with current industry standards and requirements. Lastly, the tool is primarily useful for recognizing and communicating uncertainties in practice. However, determining the bandwidth around a carbon footprint using this tool may be challenging to make this feature more useful more research is needed to investigate how these findings can be applied in the current software tools for calculating the carbon footprint.

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List of Definitions

CF Carbon Footprint

GHG Green House Gasses

WTW Well-to-Wheel

WTT Well-to-Tank

TTW Tank-to-Wheel

ISO International Standard Organisation

EN European Norm

LCA Life Cycle Analysis

ADD Actual Driven Distance

SFD Shortest Feasible Distance

PD Planned Distance

GCD Great Circle Distance

GLEC Global Logistics Emissions Council

PDF Probability Density Function

EIF Emission Intensity Factor

CPI Carbon Performance Index

FC Fuel Consumption

EF Emission Factor

I

Thesis introduction

This part of the research is the **Introduction**, which consists of two components: 'Introduction' and 'Methodology'. The **Introduction part** delves into various subjects: problem statement, scientific and societal contributions, as well as the design scope and context. Initially, it provides a comprehensive exploration of the problem statement, including its scientific and societal implications. This is followed by an examination of the general scope of the study and the specific context and purpose of the tool being designed. The **Methodological part** of the introduction phase focuses on the design methodology, The Triple Diamond, that is used for this research.

1
Introduction

The world around us is continuously changing, and day by day, we learn more about how we affect the environment and how the environment affects us. One of the most significant problems the world is currently facing is climate change. The Intergovernmental Panel on Climate Change (IPCC) reports that depending on the trajectory of greenhouse gas (GHG) emissions, the average global temperature could increase by 3-6 degrees Celsius by 2100 (Pachauri et al., 2014). However, there is criticism surrounding the IPCC's work, including concerns over potential political influence, biases, and uncertainties in climate models (Curry, 2017). Nonetheless, there is a general consensus that urgent action is needed to mitigate the effects of climate change. This remains an important topic in both societal and political discussions. In response to the climate change challenge, the Paris Agreement is made which aims to limit the global temperature increase to well below 2 degrees Celsius above pre-industrial levels, with an aspirational goal of limiting the increase to 1.5 degrees Celsius (UN, 2015). To achieve this target, there must be no net emissions of GHGs by the end of the century. As a result, increasing attention is being paid to reducing GHG emissions. GHGs include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), fluorinated gases: hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3). To account for the different impacts of these gases, the Global Warming Potential (GWP) concept is used, which measures the warming effect of each gas relative to CO_2 over a specified time horizon (EEA, 2021). For example, one kg of CO_2 equivalents is equivalent to the effect of one kg of CO_2 emission but the emission of 1 kg of nitrous oxide (N_2O) equals 265 kg of CO_2 equivalents, and the emission of 1 kg of methane (CH_4) is equal to 28 kg CO_2 equivalents. The GWPs of fluorinated gases vary greatly and levels can be substantial. For instance, 1 kg of sulphur hexafluoride (SF_6) is equal to 23 thousand kg of CO_2 equivalents (World Resources Institute, 2016).

To better understand and quantify our impact on the environment, various indicators have been developed, including Life Cycle Analysis (LCA) which assesses the environmental impacts associated with all stages of a product's life (Bhatia et al., 2011). One specific indicator within LCA is the carbon footprint, which measures the total GHG emissions, expressed as CO_2 equivalents, resulting from human activities, including the production, transportation, and consumption of goods and services (Wiedmann & Minx, 2008). This metric incorporates the previous mentioned global warming potential (GWP) of the different green house gases. In recent years, there has been a growing trend among companies to map their Scope 1, Scope 2, and Scope 3 emissions in a carbon footprint, which are emissions generated through various activities involved in producing a product or service (Radonjič & Tompa, 2018). Scope 1 refers to a company's direct emissions, Scope 2 to indirect emissions caused by the company itself, and Scope 3 to emissions created by the activities of supply chain partners (Patchell, 2018). These emissions are categorized into different areas, including transportation of goods. Accurate mapping of these emissions has become increasingly important due to the new Corporate Sustainability Reporting Directive, a European Union proposal. This directive requires companies that meet at least two of the following three requirements: 40 million euros in net sales, 20 million euros on its balance sheet, or 250 or more employees to measure and report their GHG data, including Scope 1, 2, and 3 emissions, in accordance with the GHG Protocol, starting in 2024 (European Union, 2022).

This study will focus specifically on the carbon footprint of freight transport, a crucial aspect of the transportation sector's emissions. The transportation sector, heavily reliant on fossil fuels, accounted for 37% of CO_2 emissions from end-use sectors in 2021 (IEA, 2021). Additionally, it is important to note that the transportation sector also generates significant emissions of nitrogen (N_2) and particulate matter (PM), which contribute to air pollution, acid rain, and eutrophication (Van Fan et al., 2018). However, this study specifically focuses on the carbon footprint, due to the urgency of addressing climate change and the growing interest among companies and governments in reducing GHG emissions to meet the goals of international agreements such as the Paris Agreement (UN, 2015). Freight transport represents a significant portion of these emissions, contributing approximately 42% of total transport emissions (ITF, 2021). Road freight, in particular, has a decisive impact on transport decarbonization, as it is responsible for 65% of all freight emissions (ITF, 2021). While this study acknowledges the significance of N_2 and PM emissions, their detailed analysis is beyond the scope of this research.

Given the importance of reducing freight transport GHG emissions, it is crucial for companies to accurately measure and monitor their carbon footprint, including those of their suppliers. However, even companies with their own transportation services find it challenging to map their carbon footprint, let alone that of their suppliers (Piecyk & McKinnon, 2010). To address this issue, various instruments, methods, and guidelines have been developed for measuring the carbon footprint of transportation within supply chains, such as the GLEC Framework developed by the Smart Freight Center (SFC, 2020) and the GHG protocol (Patchell, 2018). Despite the availability of these tools and methods, a significant challenge remains in addressing the uncertainties introduced by the assumptions made during carbon footprint calculations. While these assumptions are necessary to initiate the calculation process, they inevitably lead to variations in the final carbon footprint, raising questions about the accuracy and reliability of these measurements. This study aims to explore these uncertainties in-depth and provide insights into the potential implications for freight transport emissions management.

1.1. Problem statement

Carbon footprint calculations serve various purposes, such as complying with EU ETS regulations, meeting the Corporate Sustainability Reporting Directive (CSRD) requirements, gaining a competitive edge, fulfilling customer requirements, and providing insights for sustainable decision-making (European Union, 2022; Choi et al., 2021; Bayne et al., 2022; Lister, 2018; Radonjič & Tompa, 2018; Wiche et al., 2022). However, accurately measuring and reporting the carbon footprint of freight transport remains challenging, particularly regarding the uncertainties introduced during the calculation process.

Companies thus have different motives for measuring and reporting their carbon footprints. Nevertheless, there is a lack of insight into the extent to which data quality affects the carbon footprint (Lister, 2018). This can be problematic for decision-making regarding sustainability policies (Radonjič & Tompa, 2018) and for determining the price of a carbon footprint when it becomes relevant in the future (Wiche et al., 2022).

Several guidelines and frameworks have been developed to measure the carbon footprint of freight transport, and software tools have been created based on these guidelines. Some of these software tools assign a quality label to the carbon footprint, such as "gold," "silver," or "bronze," which indicates the data quality of the input variables. However, they do not provide transparency about the variations and uncertainties underlying the carbon footprint. Understanding these uncertainties is crucial for improving carbon footprint analyses and developing a reliable methodology for comparison. Furthermore, it can be problematic when a carbon footprint is determined for shipments or attributed to shippers without addressing the uncertainty. This can lead to a distorted view of the actual environmental impact of freight transport and undermine the credibility of carbon footprint measurements. Additionally, high uncertainty can complicate efforts to demonstrate significant change.

Moreover, there is currently limited insight into the extent of the uncertainties surrounding freight transport carbon footprints and the implications of these uncertainties for businesses and policymakers. While some studies have investigated uncertainties in Life Cycle Analysis (LCA), research specifically focusing on the uncertainties in freight transport carbon footprint measurements is scarce. Given the importance of carbon footprint calculations in the freight transport sector and the potential consequences of poorly understood uncertainties, there is a clear need for a tool that can assess the uncertainties associated with freight transport carbon footprints. Therefore, the main thesis objective is:

"Design of a 'tool' to assess the uncertainty of a transport carbon footprint measurement"

1.2. Scientific contribution

This project holds scientific value because it adapts an existing methodology for measuring a transport's carbon footprint to make the variation and uncertainties around a footprint visible. This will create a novel methodology that may be used in various situations, allowing for comparison of different footprint measurements. Adjustments to the currently existing methodology will be based on background and empirical research.

The existing literature, such as Bell & Spinler (2022); Rigot-Muller et al. (2013); Carsten & Nadine (2019) highlights the importance of considering various factors that can influence the accuracy and variability of carbon footprint measurements. However, these studies do not explicitly focus on quantifying and addressing uncertainties in carbon footprint calculations. As a result, there is a research gap regarding the extent of uncertainties surrounding freight transport carbon footprints and their implications for businesses and policymakers.

To the best of our knowledge, there is a lack of empirical research on this subject in the current literature. By making a comparison between current theory and how a carbon footprint measurement is accomplished in practice, this project can lead to improvements in the accuracy of measurements and a better understanding of the uncertainties involved. This could be used for the carbon footprint transportation in the whole supply chain, or for the transportation between a supplier and buying company.

By addressing the uncertainties in carbon footprint measurements, this project contributes to the scientific literature on sustainable freight transport and carbon foot-printing.

1.3. Societal contribution

Value of research for actors

This research can be of interest to multiple actors, as multiple actors have interests and are involved in the logistics process of transportation (Alacam & Sencer, 2021). Thereby a lot of those actors - eventually - can have the obligation to publish their Scope 1, 2 and 3 emissions. For example, the shipper is the company where the shipment's product comes from. The carrier or logistic service provider (LSP), is the actor transporting the goods. These goods are then delivered to the consignee. Then sometimes, there is also a freight forwarder, an individual or company that links shippers and carriers. Besides that, it is also possible that carriers are organized in-house or that carriers win tenders to transport products for a certain period of time. There are several incentives for the shipper, carrier, consignee and LSP to map the carbon footprint of freight. The most important incentives are customer pressure, government pressure, intrinsic motivation and competitive advantage that can be gained (bron). The key performance indicators (KPIs) for the carbon footprint of these actors are different (Davydenko et al., 2019). The carbon footprint KPI for carriers and LSPs is expressed in grams of CO_2 equivalents created per kilometer of transporting a tonne; in other words, grams of CO_2e/tonne-km. This also indicates how efficiently cargo is handled in terms of sustainability. For shippers, consignees, and freight forwarders another KPI of the carbon footprint is important. Knowing how many grams of CO_2 equivalents were emitted while transporting their goods is more important to these actors, in short, the gram CO_2e/tonne. This gives insight into the business's environmental performance, including network selection and contracted carriers. For all these companies, a lower carbon footprint can contribute to a better reputation and provide a competitive advantage when they perform better or provide more insight than their competitors. However, there are uncertainties that come into play when making a carbon footprint due to data accuracy and data availability, understanding these uncertainties can therefore add something for these companies in three ways. First, it can improve the accuracy and credibility of carbon footprint estimates, which can inform decision-making for transportation and logistics companies, policymakers, and consumers. Second, it can help to identify and prioritize areas where there is significant uncertainty, and guide further research to reduce that uncertainty. Third, it can also help to identify opportunities for carbon reduction and mitigation, and to evaluate the effectiveness of different strategies to reduce the carbon footprint of freight.

In addition to the freight transport sector, this tool's ability to assess uncertainties can also contribute to transparency in various processes across different sectors and stakeholders, for example in the construction industry, where understanding and managing carbon footprints is becoming increasingly important. By providing a clearer picture of the carbon footprint values and the uncertainties associated with them, the tool aims to stimulate a more informed dialogue among stakeholders and encourage them to take necessary actions to mitigate their carbon footprint. This increased awareness and understanding will ultimately contribute to a more sustainable and environmentally conscious society.

Examples how this thesis will contribute in different situations

The social relevance of this research is that it takes a critical look at existing methodologies that would allow projects and companies to be compared more reliably. Getting an understanding of the variation in the carbon footprint of the transportation of goods can be very valuable because it allows them to make better policy choices. There are several situations in which this research can make social contributions. These situations will be described further below.

First, it can add value to companies looking to make their fleets more sustainable. For example, a company wants to make its goods transport more sustainable and has to make a trade-off between allocating money to make transport in the Netherlands and Belgium more sustainable. When the carbon footprint is low in Belgium and high in the Netherlands, it seems like a logical choice to invest mainly in the transportation of goods in the Netherlands. However, if the variation is visible around the carbon footprint of the Netherlands and turns out to be really small in comparison to the variation around the carbon footprint of Belgium the choice suddenly becomes a lot more complex. To give a better idea of this, figure 1.1 shows what this would look like; option 2 will then be the carbon footprint of Belgium and option 1 that of the Netherlands. Belgium's average is lower but has greater variation. The high variation of the CF of Belgium could lead to a underestimation. If this is not considered, wrong policy decisions can be made.

Second, it can also add value when an organization has carriers and wants to evaluate the sustainability of the transportation of their goods and reward sustainable transportation. For example, a company has four carriers who all transport 25% of the goods and these carriers would all like to transport more than that 25%. The company wants to become more sustainable in the coming years and make conscious choices. As a result, they want to know the carbon footprint of their freight transportation and based on this, reallocate their transportation as an incentive for the carriers to join the company's sustainability strategy. The carbon footprint of these companies depends heavily on the data the carriers have on their transport movements. When this data is incomplete and many assumptions have to be made, the uncertainty surrounding the carbon footprint increases. When this is not captured it is difficult to compare the transport companies. If this is made clear, the company can make more conscious choices and thereby also encourage the companies to improve their data quality in the future. When the carbon footprint has little uncertainty it also becomes clearer how they can better organize their transport. The more uncertainty there is, the more difficult it is to determine where the bottlenecks to becoming more sustainable lie.

Thirdly, it can support efforts by transportation companies to increase the sustainability of their operations. More and more companies are choosing more environmentally friendly transportation options as a result of the sustainability trend. A transportation company's position in the market may benefit if they take advantage of this. A transportation company can outperform their competition by being transparent about their carbon footprint. For instance, until they are aware of their own carbon footprint, a transportation company cannot claim that they have neutralized their carbon footprint. Additionally, because this information is in high demand, transportation companies can attract more clients the moment they can tell their customers what the emissions share of moving their products through the chain is. A carrier can project more assurance when they acknowledge the degree of uncertainty surrounding

their carbon footprint. This also encourages them to keep better track of freight data and makes sure that when people do the math, they won't be caught off guard if the result isn't exactly right.
Fourth, this can also add value for project situations. Typically, a client and contractor are involved in project settings. Contractors are selected in accordance with the client's conditions. These conditions increasingly incorporate sustainability-related requirements. For instance, contractors are asked to submit their carbon footprint's pre- and post-calculations. Through their pre-calculation, the client is able to offer them the contract, and through their post-calculation, the client evaluates their performance. Understanding the uncertainty surrounding the carbon footprint is helpful for pre- and post-calculation. This can be important for both the contractor and client. For a client, it makes it easier to compare contractors in a fairer way in the pre-calculation and it can help the client to evaluate the post-calculation carbon footprint. For the contractor, it helps to gain trust from the client when they are transparent about the uncertainty surrounding their carbon footprint in the before and after calculation.

By considering the stochastic nature of the values involved, including their expectations and variances, a more formal and standardized approach can be taken towards assessing the key performance indicators (KPIs) associated with carbon footprints. By making the variation around a KPI visible, a company can, for instance, decide to invest resources in improving the accuracy of the data used to calculate the carbon footprint in a given region, leading to a more informed assessment. Similarly, in the context of tenders for transportation of goods, the second KPI can be utilized to better assess outsourcing options. This approach also enables companies to gain more insight into how they can monitor the quality of their transport flow data, which is relevant for both transport companies whose data quality affects their scope 1 emissions and for companies that outsource transport. By identifying the input variables that have the most impact on the accuracy of carbon footprint measurements, quality requirements that suppliers must meet can be effectively managed.

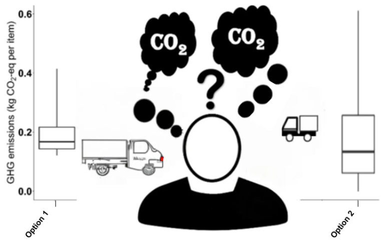


Figure 1.1: CF with variation, image edited from Shahmohammadi et al. (2020)

1.4. Design scope and context

In this section, we discuss the design scope and context of the tool, which aims to address uncertainties in the carbon footprint of freight transport. The section is divided into three subsections.Section 1.4.1 highlights the need for quantifying negative external effects and the focus on the carbon footprint in this research, Section 1.4.2 addresses various situations where a carbon footprint is calculated and the role of uncertainty in decision-making, Section 1.4.3 explains the tool's objective as a guidance framework to identify and deal with uncertainties, filling the gap in existing carbon footprint calculation tools.

1.4.1. General scope

In today's world, quantifying negative external effects is becoming increasingly important due to consumer and customer pressure, regulations, and intrinsic values. The freight transport sector brings numerous negative external effects, such as particulate matter, nitrogen oxides, black carbon, and greenhouse gases. Particulate matter can cause health effects, nitrogen oxides are causing health effects and environmental effects, and greenhouse gases mainly contribute to global warming. To limit these negative external effects, regulations are being developed, partly based on obligations to comply with new regulations, such as the application of particulate filters on vehicles. Moreover, measuring these effects is becoming increasingly important for winning tenders or attracting customers. Measurements and calculations of negative external effects can be achieved in various ways, depending on measuring instruments or data availability. When assumptions are made, or values with underlying uncertainties are used, this affects the final answer, which is often not presented. This can lead to companies being rejected based on this figure or making incorrect investments. Therefore, it is crucial to understand these figures better.

A globally recognized indicator of environmental impact is the carbon footprint. In this study, the scope focuses on determining the carbon footprint of freight transport. This choice was made in collaboration with the company for which this graduation research is partly conducted, Districon, a consulting firm in the logistics world. Districon is currently working on numerous projects related to carbon footprinting in logistics. Understanding the extent to which assumptions or the use of default numbers influence the final carbon footprint can help them advise companies and understand the impact of specific choices made in the calculation process. Therefore the study focuses on the uncertainty that may underlie the carbon footprint, leaving the impact of particulate matter/nitrogen outside the scope. However, these environmental impacts are also becoming increasingly important to measure, especially in the construction sector, where nitrogen, for example, is a critical issue. The method to design a tool that can map the uncertainty of the carbon footprint of freight transport can thus be a basis for extending this to particulate matter and nitrogen in follow-up research.

During the research, the scope was further refined as an opportunity arose to observe a project that aimed to map the carbon footprint of freight transport to and from a construction site. This allowed for a deeper understanding and practical experience in a real-world context, enhancing the quality and applicability of the research findings. This opportunity enabled the acquisition of practical experience through field research. These trips focused on road transport, and the carbon footprint was mapped at a detailed trip level. This approach aimed to document each freight movement in order to calculate a comprehensive carbon footprint. Consequently, the research and scope of the design were specifically focused on mapping uncertainties surrounding the carbon footprint of road transport at the trip level. However, it is important to note that uncertainties at this detailed level may also play a role at more aggregated levels or within other transport groups. The process of narrowing down the scope of the design can be seen visually in Figure 1.2.

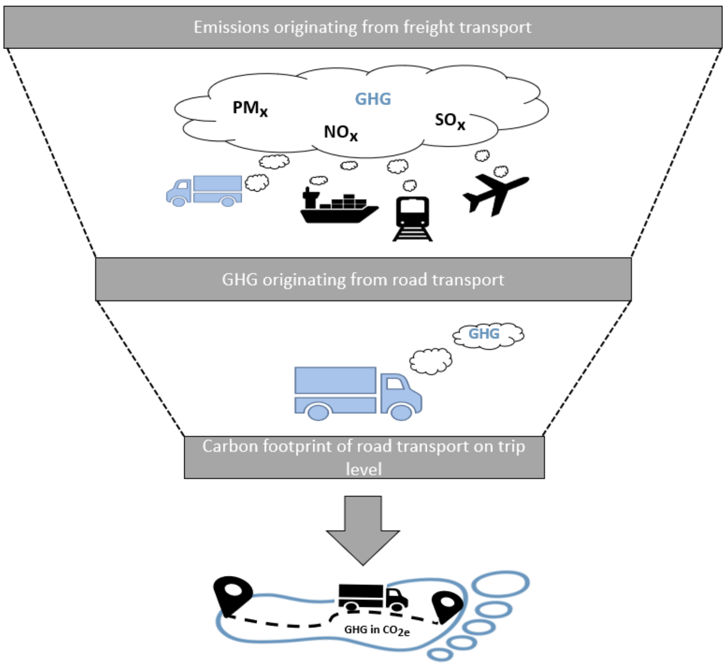


Figure 1.2: General scope

1.4.2. Context of Tool

The context of the tool is briefly discussed here. First, the essential question to answer when creating a carbon footprint is why it is made. This can be a requirement of a client and a criterion during a tender process. Within this, the total carbon footprint of freight movements to and from a construction site or a distribution center may be requested, or the emission intensity factor (CO_2e/ton-km) of a transport company may be required to win a tender to transport a company's goods. In a tender process, there are also two phases: the prior communication of the carbon footprint and the monitoring and subsequent proof of this. The prior communication of a carbon footprint carries risks and is based on assumptions, leading to uncertainties. Reporting after monitoring can also contain assumptions due to incomplete data. It may also be that a company needs to know the emissions from its transport as part of the totalarbon footprint for CSRD regulations or communication to stakeholders, or when a company is mapping its scope 3 emissions, the carbon footprint of outsourced freight transport is needed to have a view of the emissions caused by the company outside its operations when producing a product. The risk of uncertainties in this context is that assumptions could result in a lower carbon footprint, meaning investments in more sustainable solutions may not be reflected in the coming years. In short, there are many situations in which a carbon footprint must be created, and uncertainty can play a role. To make these calculations, companies can use software tools, hire consulting firms to perform the analysis (which also use software programs or their tools), or make their calculations according to existing frameworks and regulations. Once this carbon footprint is created, it is communicated, and decisions are made based on this figure. However, it is questionable whether some decisions are justified or even wise to make if there is significant variation around the figure. The tool can play a role in this context.

1.4.3. Purpose of Tool

The problem statement and rationale for the design objective have already been explained in the previous Section. Here, the purpose of the tool within the context discussed above will be briefly discussed. Currently, when calculating a carbon footprint using various software programs, there is no indication of potential uncertainty around the final figure of the freight transport carbon footprint. While it is known that different accuracy levels exist for a carbon footprint, depending on the type of information used to calculate it, it raises questions about what these accuracy levels truly mean. The tool designed in this study should fill this gap. The following objective was established at the beginning of the research:

"Design of a *'tool'* to assess the uncertainty of a transport carbon footprint measurement"

Since several tools are already available for calculating a carbon footprint, the focus should not be on the development of a new tool. Instead, the emphasis should be on determining the existing uncertainties, understanding how they arise, evaluating whether they are preventable, and exploring how they can be quantified. Through brainstorming sessions, it was eventually decided that the design of the tool should be a guidance framework:

'tool' = a guidance framework to identify and deal with uncertainties

With the help of this framework, the causes of uncertainties become clear, helping clients or potential customers ask the right questions about how the carbon footprint was established and what uncertainties may underlie it. Additionally, it can help set data requirements that a carbon footprint must meet. A consulting firm can also use this framework as a communication tool in the outcomes of carbon footprint analyses, and the consequences of potential uncertainties can be discussed. A software developer can use this framework to implement uncertainties in existing software programs. A transport company can also use this framework to make their carbon footprint more accurate and be aware of the impact of their data quality on the calculated carbon footprint. Most importantly, it can make various stakeholders aware that the carbon footprint is not an absolute figure, even when all data is available; for example, there is still an error in the emission factor used for the calculation. This emission factor even changes annually due to updates. In Figure 1.3 below, a brief overview of the tool is shown:

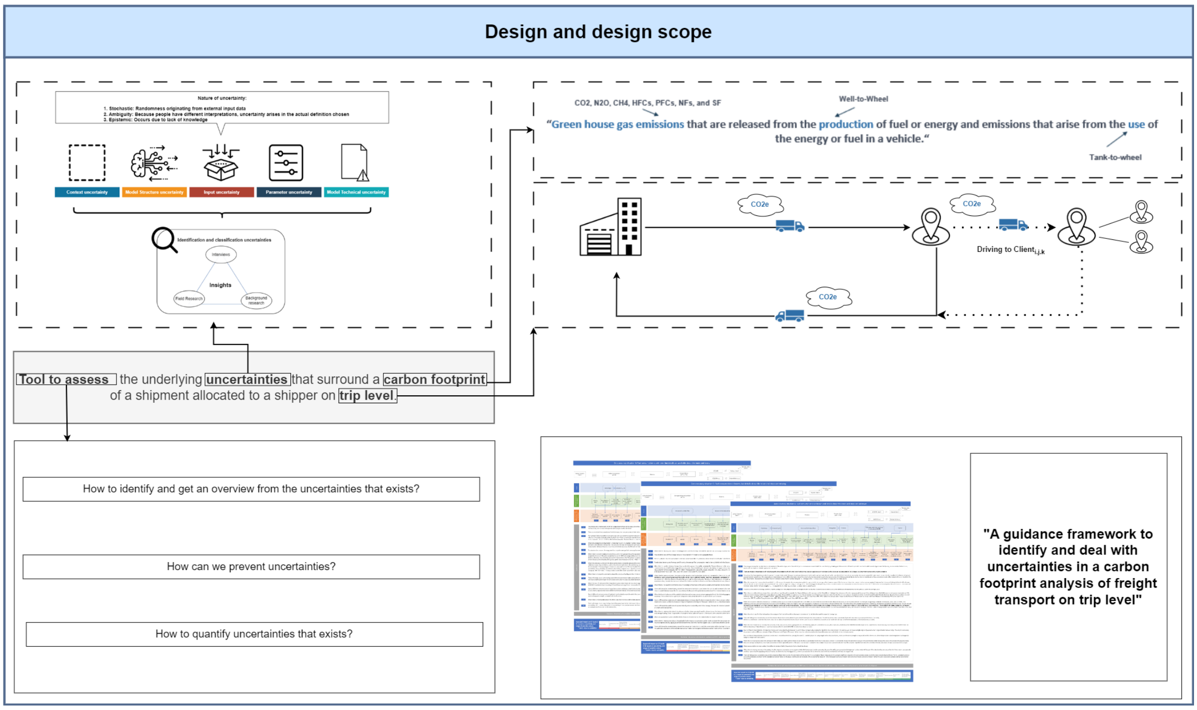


Figure 1.3: Design scope tool

1.5. Report outline

The present chapter provides an introduction to the thesis project. Chapter 2 discusses the methodology used in this thesis, elaborating on the different phases and data collection techniques. Chapters 3 and 4 present background studies on carbon footprint and uncertainties. Chapter 5 delves into the insights of the uncertainties in a carbon footprint measurement. In Chapter 6, requirements and functionalities for the design are developed based on the insights from the previous chapters. Chapter 7 focuses on the input for the design, including the different data situations, uncertainties margins, and prioritization of uncertainties. Chapter 8 details the development of the design and the output of the design process, Chapter 9 presents the verification of the prototype using a case study, and Chapter 10 presents the validation of the findings from the research with experts. Chapter 11 offers a discussion of the results and the limitations of the thesis project. Chapter 12 provides conclusions and recommendations. The appendices contain additional information and deepening analyses presented in the main text of this thesis report.

2
Methodology

2.1. Thesis methodology

To achieve the main objective of this thesis, which is to design a tool to assess the uncertainty of a carbon footprint, a design method called the triple diamond is being used. This method is a modified version of the double diamond designed by the Design Council (Design Council, 2019) . The triple diamond method adds an extra phase to the two phases that are defined in the double diamond method. The purpose of this extra phase (diamond) is that the 'tool' is also tested and evaluated after the 'tool' has been designed. It is then even possible to create an iteration to the previously defined phases. The phases that are defined are 'the research phase', 'a design of tool phase' and a 'test and deliver phase'. In these phases, research questions are also answered to arrive at requirements of a design and to make choices to finally arrive at the design objective. In this thesis the most focus will lay on the 'research phase', this is because in this phase their is a need to dive deep into the scientific literature about uncertainties and the possibilities to measure it, to eventually apply it to the design of the 'tool'. In this way, the preliminary research is prevented from becoming superficial and the application of the findings counts more in the research than the looks of the 'tool'. Therefore, the result will revolve more around the application than the design of the 'tool'. The design methodology is visualized in Figure 2.2. The elaboration of each phase is further discusses in Section 2.2 . Section 2.3 provides further information on the data collection process.

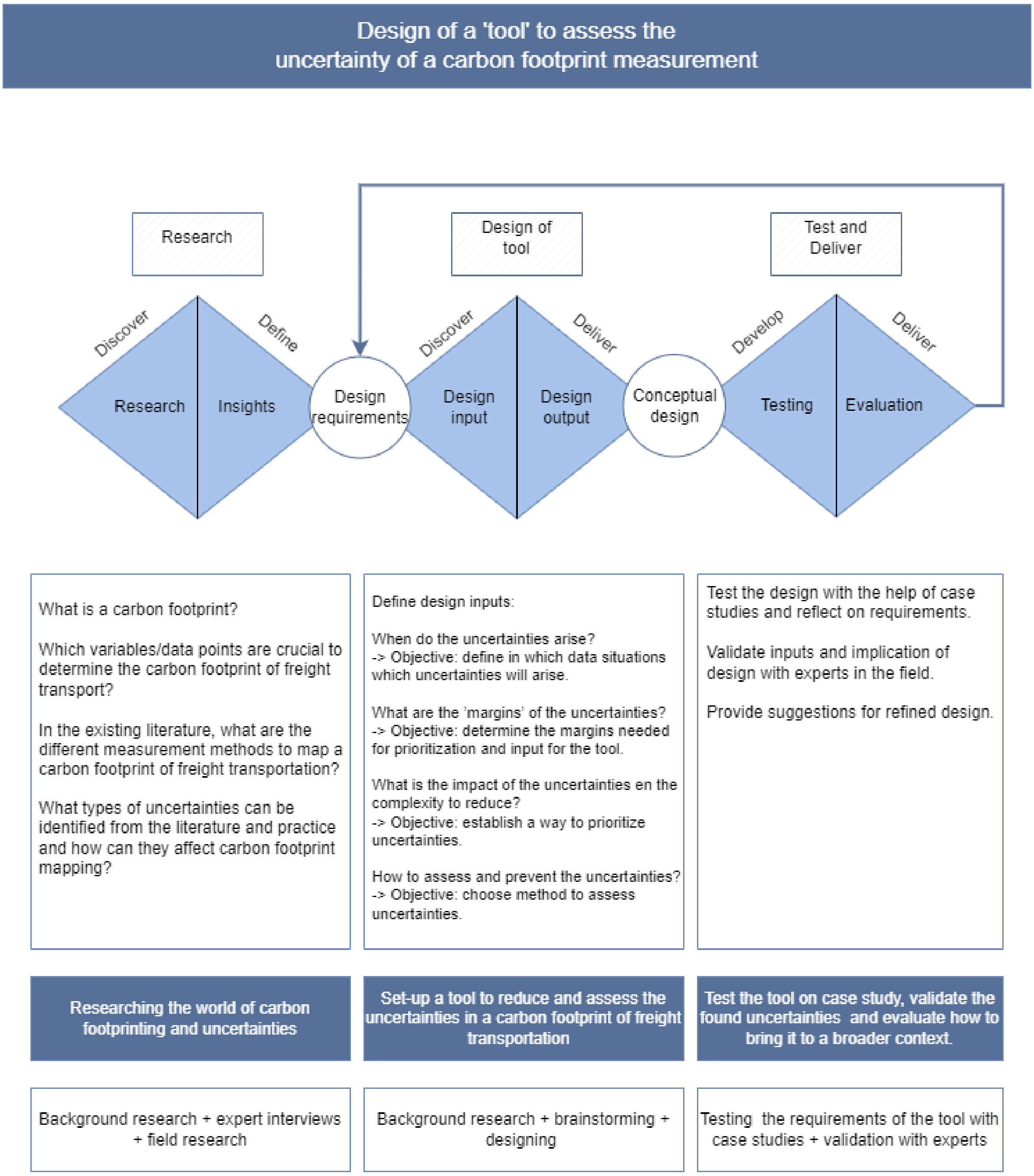


Figure 2.1: Research methodology: Triple diamond

2.2. Elaboration on phases

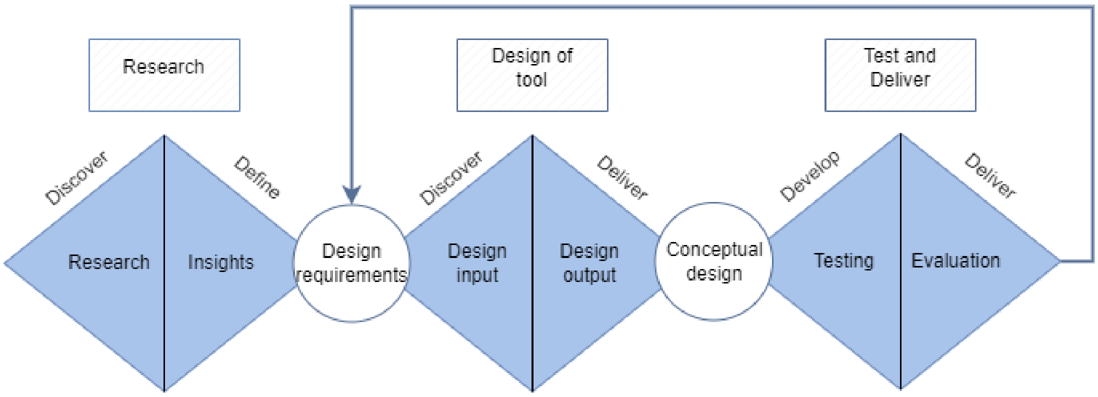


Figure 2.2: Triple diamond phases

2.2.1. Research phase

The first diamond is called the research phase. In this diamond the scope is determined and all relevant background research is done. First it is important to look at the definitions of a carbon footprint and the regulations/standards that are set to calculate a carbon footprint. This will help in determining the definition of a carbon footprint that will be used in this research. When this scope is defined an overview has to be created of the factors that are needed to construct a carbon footprint of freight transport. To figure this out, background research is needed to find out which factors, according to the literature, affect the carbon footprint of freight transport, as well as a review of how the carbon footprint is currently calculated within existing methods. After that the next step is to dive into the literature of uncertainties and explore which kind of uncertainties occur in literature, which will provide a theoretical framework. With the help of this theoretical framework, the background study on the carbon footprint of freight transportation, expert interviews and field research a translation from theory to practice is made.

Through interviews and observations, insights are gained into how the uncertainties actually occur in practice. These interviews will be based on how the different uncertainties found in literature affect the previously identified factors that determine a carbon footprint. Field research is used to investigate how uncertainties emerge in practice. The field research is done by observing a project in which Districon carries out a carbon-footprint measurement for freight movements to and from a construction site. During this field research, it becomes clear which uncertainties influence the output. Using the insights, the end of the first diamond is reached. By the end of the first diamond the design requirements will be established.

Data collection:

- Background research via Scopus and Google Scholar
- Semi-structured interviews with experts

2.2.2. Design of tool

The second diamond is called the design phase, where the tool's design is established. It begins by defining the requirements and constraints for the design, using literature, the researchers' knowledge, and insights gathered from conversations with consultants from Districon to determine the needs. After the constraints are established, functionalities are defined. The functionalities describe the tool's required features, while the constraints set the tool's framework. Once this is set up, the tool's foundation must be determined. This means deciding precisely what the tool should be. Through brainstorming, which was an iterative process, it was determined that the tool should be an approach to identify, assess, and address uncertainties. This way, the tool becomes suitable for multiple stakeholders, meeting a requirement and also aligning with what the researcher/designer felt was needed in practice during the investigation.

Using a design approach, the inputs for the tool were then established, along with the steps that preceded them. These steps were defined in this research as ’input for design’ to ultimately bundle and create an ’output.’ Since the research and insight phase showed that uncertainties depend on a data situation, the input for the design first needed to be framed around the different situations and methods for calculating a carbon footprint. Based on this, the uncertainties were classified. Next, the magnitude of the uncertainties had to be investigated, i.e., what is the margin created in an input variable due to uncertainty. Once this was determined, the uncertainties could be prioritized, which was done using an analogy of the ’risk priority number,’ with the uncertainties classified as ’data uncertainty reduction priority.’ This provided a foundation for the influence each uncertainty could have on the final value and an overview of which uncertainties were difficult to reduce.

The last step for the input of the design was to determine how to address and assess uncertainty. The uncertainties were categorized in three ways: preventing through effective communication, dealing with the ’lack of knowledge’ of uncertainty by making assumptions and sketching scenarios of possible values, and finally, outlining uncertainty using probability density functions due to the variability surrounding the uncertainty. The steps in the design input were ultimately translated into the ’conceptual design phase’ as seven ’one-pagers’ with a step-by-step guidance plan for each data situation.

Data collection:

- Background research via Scopus and Google Scholar
- Brainstorming
- Analyzing data and uncertainties

2.2.3. Test and deliver phase

The third diamond is the test and evaluation phase, in which the conceptual design is verified and validated. The first part of this phase involves testing the ’tool’ or conceptual design. Testing is done using data from the field research. Due to limited time, three random trips were selected from the field research, and the uncertainty was determined and mapped using the conceptual model. This tests whether the conceptual model works and meets the requirements. Additionally, it is explained how the tool was used in the field research for the final report of the study conducted by Districon. This also provides another way of checking whether the design meets the requirements or which ones it does not meet.

The next step is to determine if the tool is ’valid.’ To do this, semi-structured interviews were conducted with experts in the field of sustainability and carbon footprinting in the transport sector. They were asked whether they agreed with the findings on which the tool is based, how the tool could work in practice, and some context questions to gain more insight into the world of carbon footprinting from their perspective.

With the help of verification and validation, feedback can be provided on the conceptual design and how it can be improved. This is represented by the feedback loop in Figure 2.2. This reflects how the design and design requirements can be improved, these are described as recommendations in the conclusion of this research.

Data collection:

- Simulation with case study
- Expert validation with semi-structured interviews

2.3. Elaboration data collection

2.3.1. Desk/background research

Desk research is the ”collection of secondary data from internal sources, the internet, libraries, trade associations, government agencies, and published reports” (Hague, 2006). Desk research and doing a literature review have some parallels. Desk research, follows the same techniques as a literature review, but the materials are examined as part of the primary research. The technique has certain drawbacks, including the fact that some of the material will come from grey literature, where it might be difficult to determine the publication’s quality (Byrne, 2017). To examine protocols, for instance, this study will need to consult gray literature. This is one of the explanations for choosing a background study approach over a literature review.

2.3.2. Semi-structured interviews

Using several semi-structured interviews with experts discuss what is expected of a ’tool’ that measures the carbon footprint in transportation, which current frameworks they currently think are the best, which are the most widely used and what improvement possibilities there are. The potential uncertainties that might arise when calculating the footprint are also covered in these interviews. By doing this it might becomes clear what the bigger and smaller bottlenecks are by asking questions about the various potential causes of uncertainties in a carbon footprint measurement. Experts in the field of calculating the carbon footprint of transportation are therefore contacted for semi-structured face-to-face interviews. These experts will be from Districon, and, if possible also from BigMile, Connekt and Topsector Logistiek. Face-to-face semi-structured interviews should be conducted for a number of reasons. The first advantage of semi-structured interviewing is that it promotes mutual cooperation between the interviewer and the participant (Galletta, 2013). This enables the interviewer to immediately base follow-up questions on the participants’ answers (Kallio et al., 2016). Thereby, experience has proven that in-person interviews frequently adhere to the major elements of the talk, which might leave important information out. This gives the capacity to pick up on nonverbal clues and emotions. However, because the interview is semi-structured, analyzing the data and taking notes takes time. Last but not least, it limits the size of the interviewable sample. The goal is to conduct at least five interviews to ensure significance (Dworkin, 2012).

2.3.3. Field research

Field research is a qualitative research method that involves collecting data through direct observation and interaction with people or objects in their natural settings. The researcher immerses themselves in the field site for an extended period, often living among the people or objects being studied. Field research is being conducted by observing and participating in a project carried out by Districon to determine the carbon footprint of freight transport. This approach enables the gathering of detailed information on potential uncertainties, as well as the identification of effective measures to mitigate them. Through close observation of the project’s process and active participation, the research can gain unique insights into the complexities and challenges of assessing and reducing the carbon footprint of freight transport.

2.3.4. Testing with case study

Using the data from a case study, the conceptual model is tested and suggestions for improvement are proposed. The data comes from the field research: a project to measure the footprint of transportation to and from the construction site. Using this data, the ’tool’ will be tested to see if it can identify the uncertainties and how these uncertainties have an influence on the output.

II

Research and Insights

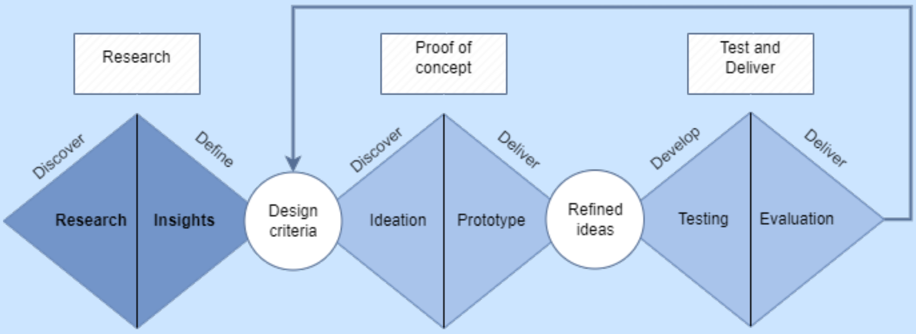


Figure 2.3: Research and Insights

This part of the research is the **Research phase**, which consists of two parts: 'Research' and 'Insights'. The **research part** delves into two topics: carbon footprint and uncertainty. First, it provides a comprehensive background study on carbon footprint, including definitions and standards for carbon footprint measurement of freight. This is followed by examining the factors affecting the carbon footprint of freight transport. The second topic of the research phase is a background study on uncertainties, discussing definitions, the difference between variability and uncertainty, classification of uncertainties, and methods to assess uncertainty. This exploration provides a theoretical framework for uncertainties. With the help of the theoretical framework, expert interviews, and field research, a translation from theory to practice is made. The **insights part** of the research phase focuses on identifying how uncertainties occur in practice. Interviews are conducted to understand how the different uncertainties found in literature affect the factors that determine a carbon footprint. Field research, such as observing a project in which Districon carries out a carbon-footprint measurement for freight movements to and from a construction site, helps to investigate how uncertainties emerge in practice and which uncertainties influence the output.

3
Background study carbon footprint

This chapter involves examining the background of the carbon footprint of freight. First, the literature is reviewed to see which factors influence the carbon footprint of freight transport. Then the underlying methodology of approaches and tools for calculating a carbon footprint is examined. This information comes from established protocols. After this, the criticisms of this method from the literature are discussed, and alternative methodologies used in the literature are considered. Furthermore, the data and parameters used for the method are also examined separately to understand how the model's inputs might influence the outcome.

Research questions to be answered in this chapter:

- RQ1 *What is a carbon footprint?*
- RQ2 *Which variables/data points are crucial to determine the carbon footprint of freight transport?*
- RQ3 *In the existing literature, what are the different measurement methods to map a carbon footprint of freight transportation?*

3.1. Definitions of carbon footprint

The earth's atmosphere consists of a mixture of gases. This mixture is composed of approximately 78% N_2, 21% O_2, and other gases, of which 0.04% is CO_2 Dhaka & Kumar (2023). In 2019, it was found that 76% of all greenhouse gases in the atmosphere were CO_2 (Yoro & Daramola, 2020), which implies that the remaining GHGs account for approximately 0.01%. These greenhouse gases have an impact on global warming. To counteract global warming, the Paris Agreement was established to reduce the amount of GHGs in the atmosphere (UN, 2015).

The carbon footprint (CF) has the purpose of being a guide for these emission reductions and verification. To eventually meet the climate goals set that were set in Paris. International standardization of the carbon footprint is therefore considered necessary. Typically, the carbon footprint is measured in mass units (kilograms) of CO_2 equivalent resulting from Global Warming Potential (GWP) (Matuštík & Kočí, 2021). One kg of CO_2 equivalents is equivalent to the effect of one kg of CO_2 emission but the emission of 1 kg of nitrous oxide (N_2O) equals 265 kg of CO_2 equivalents, and the emission of 1 kg of methane (CH_4) is equal to 28 kg CO_2 equivalents. The GWPs of fluorinated gases vary greatly and levels can be substantial. For instance, 1 kg of sulphur hexafluoride (SF_6) is equal to 23 thousand kg of CO_2 equivalents (World Resources Institute, 2016). To calculate the CO_2 equivalents of a certain amount of GHG, the emissions of that gas (e.g., in tons) are multiplied by its GWP. For instance, if an activity emits 10 tons of methane, the CO_2 equivalent is calculated as follows: 10 tons CH4 * 28 (GWP of CH_4) = 280 tons CO_2.

What this CO_2 equivalent represents varies widely between studies. This is visible in the literature surrounding this topic, where different definitions are used for a carbon footprint. There are disagreements regarding the selection of gases and the order in which they should be included in calculations of carbon footprints. This is such a problem that there are also entire studies on the definition of a carbon footprint. In order to compare studies, and in fact compare carbon footprints, it is important that each study has a concrete definition of what is defined by a carbon footprint.

Carbon footprint's primary strength is certainly its intelligence and ability to communicate with a wide audience (Alvarez et al., 2016). Since it examines the cause of one of the most pressing environmental issues of our time, climate change, CF has gained widespread popularity and helped to increase public awareness over the past several decades. However, there are obvious risks associated with its frequent use as the sole indicator of environmental performance. For instance, a GWP does not intent to represent the impact of GHG emissions on temperature, which may be misleading. In addition, limitations and methodological choices are rarely communicated alongside the results, particularly in the media and grey literature. Given the abundance of methodological approaches to carbon footprint, greater transparency would undoubtedly be advantageous (Matuštík & Kočí, 2021).

Pandey et al. (2011) discusses the fact that carbon footprints are indeed calculated in different ways. The paper shows that Wiedmann & Minx (2008) defined carbon footprint as "a measure of the exclusive total amount of carbon dioxide emissions that is directly and indirectly caused by an activity or is accumulated over the life stages of a product". But an increasing number of new studies advocate including the other green house gases in the calculation of a carbon footprint. While this paints a more complete picture, it also brings difficulties regarding the standard definition of "carbon footprint". Namely: which green house gases do you include and which not?

Wright et al. (2011) noted that some definitions of a carbon footprint in papers include 'all' GHGs, which they see as too vague because the impact of many GHGs on the global climate is still debatable. Thereby one cannot be sure what to include and what to exclude. Other definitions use legislatively controlled GHGs, like the seven Kyoto gases (CO_2, CH_4, N_2O, hydrofluo-rocarbons (HFCs), perfluorocarbons (PFCs), NF_3 and SF_6). This clearly establishes a boundary, reducing misinterpretation, but it relies on accurate data for all cases to allow comparability, which isn't always the case. Matuštík & Kočí (2021) discusses thereby that some studies only account carbonaceous gases (CO_2,CH_4, CO) for estimating a carbon footprint. Furthermore the paper of Wright et al. (2011) concludes with the recommendation of the following definition for a carbon footprint: "A measure of the total amount of CO_2 and CH_4 emissions of a defined population, system or activity, considering all relevant sources, sinks and storage within the spatial and temporal boundary of the population, system or activity of interest. Calculated as CO_2e using the relevant 100-year global warming (GWP100)". The reasoning behind this exclusion is that CO_2 and CH_4 are by far the most significant greenhouse gases. In addition, accurate measurements of other GHGs are not always available; consequently, comparability cannot be guaranteed. So it seems to that there is a trade-off between including additional GHGs for a more complete picture and the accuracy of the resulting carbon footprint.

In the context of freight transport, the carbon footprint is generally related to the emissions associated with the movement of goods over a specific distance or during a particular time period (Piecyk & McKinnon, 2010). It can also be defined based on the emissions generated by a particular mode of transport, such as road, rail, sea, or air transport (Du et al., 2019). Furthermore, the carbon footprint of a product refers to the total emissions generated throughout its life cycle, from the extraction of raw materials to production, transportation, use, and disposal (Laurent et al., 2012). Thus, the carbon footprint can be considered in different dimensions and aspects, depending on the specific scope and objectives of a study. It is crucial to clearly define the boundaries and elements of the carbon footprint in each study to ensure comparability and facilitate a common understanding of the environmental impacts associated with freight transport and the uncertainties that arise.

3.2. Standards of a carbon footprint measurement of freight

There are different standards that help with carbon footprint calculations, namely: ISO-14067, ISO 14064-1, and the Accounting and Reporting Standard of the GHG protocol. The differences between these standards are that the aim of calculation within ISO 14064-1 and the Accounting and Reporting

Standard focuses on the corporate carbon footprints, while the aim of ISO-14067 centers more on the carbon footprint of products and services (Funk et al., 2011). Although these standards mention the carbon footprint of goods and services, they do not explicitly address transport. Therefore, their regulations regarding the carbon footprint of transport are vague and lack clarity (Ehrler & Seidel, 2014). Which is why the European Committee for Standardisation applied a more detailed standard for the carbon footprint of transport, called: EN 16258.

Within this standard, three different stages are defined. The first stage is the Well-to-Wheel approach (WTW); this stage can be divided into two other stages, namely the Well-to-Tank (WTT) and Tank-to-Wheel (TTW) stage. WTT refers to emissions in the activity's pre-chain, such as fuel extraction and production. TTW refers to the direct emissions from an activity, such as fuel consumption. WTW equals TTW plus WTT; the combined emissions from the pre-chain and direct emissions (Gialos et al., 2022). In figure 3.1, an overview of these standards is visible. Several initiatives build on EN 16258 and add additional and strengthened methods - frameworks - for specific areas, such as the GLEC guidelines, Clean Cargo Workgroup's guidelines for estimating emissions and COFRET's recommendations for allocating road transport activities. These frameworks are collections of methods and guidelines where users can choose standards and data levels, which will result in differences of carbon footprints. These differences can cause emissions and intensity reporting inconsistencies. Which is why many CO_2 reduction programs designate not only the frameworks they use but also add their own specifications, such as emission intensity factors, how transport distance is calculated for allocation, and (primary) data requirements (Topsector Logistiek, n.d.).

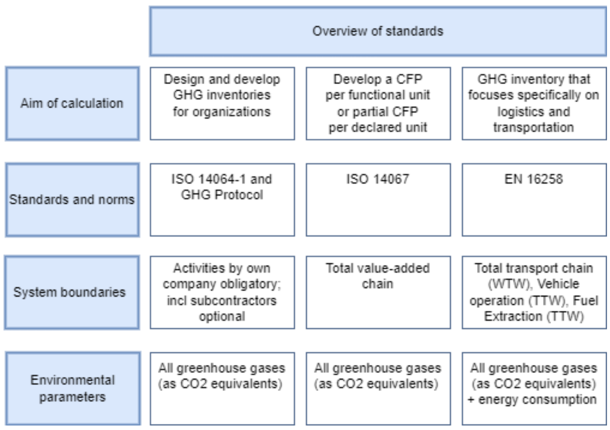


Figure 3.1: Standards of a carbon footprint measurement

The most widely used standard for calculating emissions is the reporting standard of the GHG Protocol. This is because most regulations also require companies to report their emissions according to the identified scopes in this protocol: scope 1 (direct emissions), scope 2 (indirect emissions), and scope 3 (third-party emissions) emissions. The European Commission adopted a proposal for a directive on sustainability reporting on 21 April 2021: the Corporate Sustainability Reporting Directive (CSRD). This proposal foresees that from 2024 or 2025, a larger group of companies will be required to report on their sustainability policies and their performance therein (Topsector Logistiek, 2022). It will become mandatory to map the greenhouse gas emissions on scope 1, scope 2, and where relevant scope 3 (Ecochain Technologies, 2022). The standards of EN16258 and the GHG protocol can also be combined to calculate emissions from transportation. For example, the transport of own goods by the reporting company falls under scope1 and the emissions of transport can be calculated with the Tank-to-Wheel principle. The fuel and energy emissions that are caused by producing the fuel for this transport will fall into a separate category in scope 3, for which the Well-to-Tank method can be used. If the transport is arranged by a third party, this falls entirely within scope 3 and can be calculated using the Wheel-to-Tank principle.

3.3. Purpose of Carbon Footprinting in Freight Transportation

The adoption of carbon footprint measurement standards such as the GHG Protocol and EN 16258 has contributed to the growing relevance of carbon footprinting in freight transportation. Various incentives encourage stakeholders, including shippers, carriers, logistics service providers (LSPs), and consignees, to assess and mitigate CO_2 emissions. Factors such as consumer demand for sustainable products (Zhi et al., 2019), governmental regulations and global protocols (Seuring & Müller, 2008), and the potential for cost savings and enhanced brand reputation have elevated the importance of carbon footprinting in freight transportation. Government policies often require larger organizations to disclose their carbon footprints, while smaller entities may face less rigorous mandates. Emission reporting standards also differ across countries (Drake, 2018). To remain competitive in the market, companies are encouraged to measure and reduce their carbon footprint, especially if their rivals already publish such information (Okhmatovskiy & David, 2012).

The implementation of measurement standards, such as EN 16258 and the GHG Protocol, as discussed in the previous section, has shaped the way stakeholders in freight transportation report their emissions. It has also influenced the development of industry-specific guidelines, including the GLEC Framework, Clean Cargo Workgroup's guidelines, and COFRET's recommendations. These evolving frameworks further underscore the significance of carbon footprinting in freight transportation.

Supply chain stakeholders are prompted to reveal their carbon footprints to purchasing organizations due to buyer pressure, as well as the potential benefits of transparency and collaboration. However, barriers such as lack of understanding, time constraints, cost, and fear of negative repercussions upon disclosure hinder some suppliers from mapping their carbon footprints (Bayne et al., 2022). Since freight transportation is a critical component of the supply chain, its organization can take various forms, including in-house transportation, outsourcing to LSPs, or acquiring companies with their own transportation capabilities (Jazairy, 2020). This leads to diverse responsibilities among stakeholders and impacts carbon footprinting practices.

The relevance of carbon footprinting in freight transportation extends to a broad range of stakeholders, including shippers, carriers, consignees, LSPs, and freight forwarders. These parties participate in the logistics process and may be required to report their Scope 1, 2, and 3 emissions (Alacam & Sencer, 2021) in accordance with the adopted standards. Appropriate Key Performance Indicators (KPIs) related to carbon footprinting differ among stakeholders (Davydenko et al., 2019). Carriers and LSPs focus on KPIs measured in grams of CO_2 equivalents per tonne-kilometer (CO_2e/tonne-km), which reflect the sustainability efficiency of cargo handling. On the other hand, shippers, consignees, and freight forwarders prioritize KPIs based on grams of CO_2 equivalents per tonne (CO_2e/tonne) or CO_2e per shipment to evaluate their businesses' environmental performance, including aspects like network selection and carrier contracts. A critical component of carbon footprinting in freight transportation is the fair allocation of emissions among stakeholders. Proper allocation ensures accurate representation of each party's contribution to overall emissions, enabling more informed decision-making and targeted emission reduction strategies.

3.4. Difference between LCA and WTW analysis

Life Cycle Assessment (LCA) and Well-to-Wheel (WTW) analyses have different scopes (European Union, 2022). LCA is a method that examines the entire life cycle of a product or service and measures its impact on the environment throughout the entire life cycle of the product (Weidema, 2022). When assessing the carbon footprint of freight, LCA involves calculating the emissions that are released during the production of the truck, the fuel used to power the truck, the production of the goods being transported, the transport itself, and the waste disposal at the end of the truck's life cycle. WTW analysis, on the other hand, focuses on the emissions that are released during the extraction, production, transportation, and use of the fuel that is used to power a vehicle. In a way, WTW can be considered as the LCA for fuel (Osorio-Tejada et al., 2022). When assessing the carbon footprint of freight, WTW analysis involves calculating the emissions that are released during the production of the fuel that the truck uses, as well as the emissions that are released during the transportation of the fuel to the gas stations and the use of the fuel by the truck.

The choice between LCA and WTW analysis for policy decisions depends on the government's focus (Moro & Helmers, 2017). If the government is focused on reducing the CO_2 emissions throughout the entire life cycle of the freight, LCA can be useful. On the other hand, if the government is focused on reducing the CO_2 emissions directly related to the transport of goods, WTW analysis can be useful. Policy decisions based on WTW analysis can lead to a shift towards cleaner fuels or reducing transport distances. The advantage of LCA is that it provides a broader perspective on the impact of freight transport on the environment and allows for consideration of the entire life cycle of the product. The advantage of WTW analysis is that it focuses on the emissions directly related to the transport of goods and is therefore more targeted at reducing these emissions.

As the discussion around vehicle emissions evolves, the emissions from the production of batteries and drivetrains in Battery Electric Vehicles (BEVs) have become a topic of interest. These emissions are higher than in Internal Combustion Engine (ICE) vehicles. However, the benefit of recycling offsets a significant portion of the lithium battery's impact (Van Mierlo et al., 2017). This has led to an increasing use of LCA analysis in discussions about vehicle emissions. When comparing different types of vehicles, such as BEVs and ICEs, it may be helpful to limit the LCA analysis to the vehicle itself, excluding the infrastructure, as seen in the research of Van Mierlo et al. (2017). Additionally, one of the benefits of LCA is that it can include other substances besides the carbon footprint, such as air quality emissions (NO2 and PM) that can be harmful to humans and the environment.

For a freight company and shippers, understanding the carbon footprint of their operations is valuable so that it can be better managed (Grant et al., 2017). The total LCA analysis may be less relevant in this context, as it is more complex to perform and understand. However, it is important to consider the production of vehicles when purchasing new vehicles or transportation equipment and to be aware of the 'real' environmental benefits they can provide (Van Mierlo et al., 2017).

Despite the advantages of LCA, this research focuses on the WTW method because it serves as the foundation for estimating the carbon footprint of freight transportation. Currently, transport companies and shippers estimate the carbon footprint of their operations using the EN16258 standard, along with software tools and guidance based on this principle as discussed in the previous section. The primary objective of this research is to uncover the uncertainties that arise around this carbon footprint estimation. However, this section on LCA and WTW analyses has been included to create more awareness of the emissions that surround the carbon footprint of the WTW analysis, emphasizing the importance of considering both direct and indirect emissions when evaluating the environmental impact of freight transport. By focusing on the WTW method, this study aims to contribute valuable insights into the complexities and uncertainties of carbon footprint estimation in freight transportation, while also reminding stakeholders not to overlook the other aspects of emissions that may arise throughout the entire life cycle of the freight transport process. This comprehensive approach ensures a more informed understanding of the true environmental impact of freight transportation and supports better decision-making for sustainable transport solutions.

3.5. Scope research: carbon footprint of freight transportation

Conclusion definition of a carbon footprint for in this thesis

In the above sections, the carbon footprint of freight transport was further examined. First, the literature regarding the definition of a carbon footprint was reviewed. This resulted in a number of interpretations, including solely CO_2 emissions; CO, CO_2, and CH_4 emissions and the seven GHG defined by the Kyoto protocol expressed in CO_2 equivalents. Next, the various standards that exist in the field of calculating a carbon footprint were examined, also for specifically the carbon footprint of freight. Based on these standards, it became apparent that the definition of GHG emissions expressed in CO_2 equivalents was used here. Based on this fact and the ultimate purpose for which a carbon footprint is calculated (against global warming due to GHG), the following definition was selected: the number of GHGs emitted, based on the seven Kyoto gases (CO_2, CH_4, N_2O, hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and styrene (SF_6), NF_3, expressed in CO_2 equivalents. Here the mentioned disadvantage of (Wiedmann & Minx, 2008) should be kept in mind, CO_2 is often easier to calculate/convert than the other GHG so it is questionable how accurate the conversions are.

The defintion of a **Cabon Footprint:** *"The number of GHGs emitted, based on the seven Kyoto gases (CO_2, CH_4, N_2O, HFCs, PFCs, NF_3 and SF_6, expressed in CO_2 equivalents"*

Conclusion scope of a carbon footprint for in this thesis

As discussed in section 3.2 and 3.4, there are several standards to calculate the carbon footprint of freight transport. These methods all have a different scope. So there are different perspectives on the carbon footprint of freight. It can be viewed through a Life Cycle Analysis, which includes everything that a means of transport emits in terms of emissions. Within the Life Cycle Analysis different system boundaries can be chosen. For example, one may include the use of road infrastructure while the other does not. For this study it was decided to choose the system boundaries that correspond to the EN 16258 standard, which is currently the only standard expressing how a carbon footprint of freight transport should be calculated. An advantage of this EN16258 standard is that it can easily be applied for the Green House Gas (GHG) protocol for a company's scope 1, 2 and 3 analysis. Namely, the output of the EN16258 are the carbon footprint emissions from transporting products and emissions associated with the production of the energy used by the vehicles. The output can be used for the GHG category: upstream/downstream transportation and for the GHG category: fuel -and energy-related activities. The scope of the carbon footprint of freight transportation for this research has therefore focused on the following system boundaries: Emissions that fall within the system boundaries are those released from the production of fuel or energy (WTT) and those from the use of the energy or fuel in the vehicle (TTW). The system boundaries are shown schematically in Figure 3.2 and 3.3.

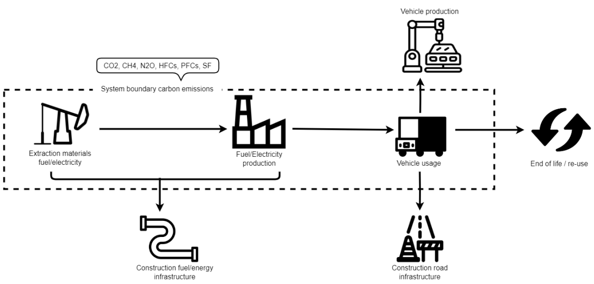


Figure 3.2: System boundaries

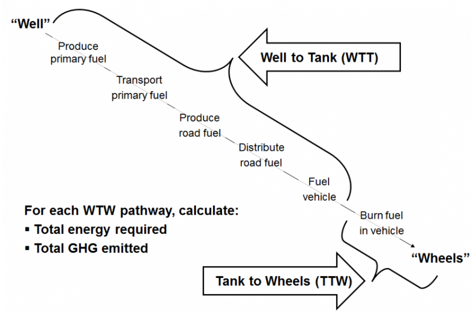


Figure 3.3: WTT and TTW overview obtained from commission (2016)

3.6. Emergence of freight transport carbon emissions

According to the previous chapter, GHG emissions are comprised of six gases: CO_2, N_2O, CH_4, HFCs, PFCs, and SF_6. CO_2 is the most significant greenhouse gas produced by transportation. This is due to the fact that CO_2 accounts for 95% of transportation emissions, weighted by global warming potential. CO_2 emissions caused by (freight) transportation are proportional to the amount of fuel consumed. However, for electric vehicles, the relation between CO_2 emissions and energy consumption is more complex, as it depends on the source of electricity.

Emissions from petroleum-based fuels

This is because petroleum-based fuels, such as diesel and gasoline, contain a substantial amount of carbon. When these carbon-containing fuels are burned, an almost complete conversion of carbon to carbon dioxide occurs (Gallivan et al., 2008). This is not the case when analyzing N_2O (nitrogen oxide) and CH_4 (carbon monoxide) emissions (methane). The amount of CH_4 and N_2O released during combustion is dependent on a number of complex combustion dynamics factors (Lipman & Delucchi, 2002). It's therefore important to note that the amount of N_2O and CH_4 emitted depends not solely on fuel consumption, but also on other variables, this is because both gases are created by insufficient catalytic activity. The function of the three-way catalyst is to reduce air pollutants, but if it is not at temperature N_2O are produced, CH_4 can be found in the exhaust due to inefficient combustion. This phenomenon occurs during the "warm-up period." When the engine is operating at low speeds and needs to start up, this situation will occur Rodriguez & Dornoff (2019). Therefore, this happens more frequently when the traffic intensity is high, such as during congestion or in urban areas with numerous traffic lights. In addition, the catalytic converter becomes less efficient as it ages and as less maintenance is performed on it. In contrast, high speed and heavy weight may lead to a shorter warm-up period Popa et al. (2014). (Wallington et al., 2008). The effective fuel efficiency of a vehicle, which is the actual use of fuel for its intended purpose, also varies due to factors such as traffic intensity, engine age, maintenance, and weight. In addition to the GHG emissions produced by driving a vehicle, the production and transportation of petroleum-based fuels also generate GHG emissions. These are the greenhouse gas emissions associated with the definition of well-to-tank. These GHG can be reduced if they are produced and transported in a sustainable manner.

Emissions from bio-based fuels

Biofuels offer a potential solution to compensating carbon dioxide emissions because they can achieve net neutrality in CO_2 emissions. This is due to their ability to absorb carbon dioxide during their growth phase and release it during combustion, effectively compensating for the CO_2 emitted while driving (Wallington et al., 2008). There are various types of biofuels, such as biodiesel, second-generation biofuel (such as hydrotreated vegetable oil (HVO)), biomethanol, third-generation biofuel (Kularathne et al., 2019; Valeika et al., 2023). The sustainability of each biofuel type, heavily depends on the amount of CO_2 absorbed by its feedstocks and the production process itself, which encompasses the transportation of raw materials and the production of the fuel (Ahmed & Sarkar, 2018). Compared to other biofuels, HVO generally has a lower carbon intensity and can achieve higher greenhouse gas (GHG) emission reductions due to its efficient production process and feedstock flexibility. In addition, HVO100 (no blend but 100% biofuel) can be used as a drop-in fuel in diesel engines without requiring any engine modifications, which enhances its compatibility with existing infrastructure thereby HVO100 reduces 90% of the CO_2 emissions compared to diesel (Valeika et al., 2023).

When these factors are managed sustainably, biofuels can significantly compensate for a vehicle's CO_2 emissions and achieving net zero. However, it is crucial to consider other greenhouse gases, like methane (CH_4) and nitrous oxide (N_2O), when assessing the overall carbon footprint of biofuels. Biofuel combustion can release methane, and the amount emitted is contingent upon the fuel's composition (CE Delft, 2021). Furthermore, when comparing biodiesel blends and regular diesel, there is no significant difference in N_2O emissions if an oxidation catalyst is present (Kuiper et al., 2012). Therefore, the net combustion of biofuel may not reach zero emissions as quickly due to the presence of CH_4 and N_2O. In conclusion, biofuels, can contribute to reducing CO_2 emissions and provide a more sustainable alternative to fossil fuels. However, it is essential to address the various factors influencing their sustainability, such as feedstock CO_2 absorption, production processes, and the release of other greenhouse gases during combustion.

Emissions from electricity

Electric vehicles can indirectly contribute to greenhouse gas emissions, as the emissions are dependent on the type of energy used to generate the electricity that is then stored in the vehicle. Electricity can be derived from fossil fuels, nuclear energy, and renewable energy sources (wind, biomass, solar and hydropower) (Athanasopoulou et al., 2018). The amount of energy then consumed by the vehicle is influenced by factors such as charging efficiency, weather, driver's behavior, and road conditions, which also apply to vehicles with internal combustion engines. However, electric vehicles can additionally recover energy through regenerative braking. Because electric vehicles emit no exhaust emissions, they have no direct impact on air quality. Consequently, the GHG impact of energy consumption is dependent on the type of energy used to charge the vehicle. According to World Nuclear Association (2011), lignite (coal) is the most polluting energy source, while hydroelectric and wind energy are the least polluting.

Emissions from air-conditioning and cooling mechanisms

In addition to these factors that affect fuel/energy efficiency and consumption, the use of electricity or fuel for cooling and heating also impacts energy and fuel consumption. Specifically the use of air-conditioning or cooling mechanisms (for specific goods transport), can result in another type of GHG emissions that can be caused by the transportation of freight. These are HFC emissions and can be emitted from the use of certain cooling systems in vehicles, these arise by leakages or from repair of an air condition system or cooling mechanisms.

The above text explained how energy or fuel consumption affects Tank to Wheel and Wheel to Tank emissions. To clearly display these relationships discussed above, a causal diagram was prepared. This diagram shows causal relationships, a ”plus sign” represents a positive relationship and a ”minus sign” represents a negative relationship. This representation is shown in Figure 3.4 and Table 3.1 shows the relationships and the derived sources. Fuel and energy consumption is again influenced by many factors. To give a more complete picture, these factors will be discussed under the heading of **Fuel/Electricity consumption** discussed. Following this, the diagram below is further expanded to include these factors. This figure is visible in Figure 3.5.

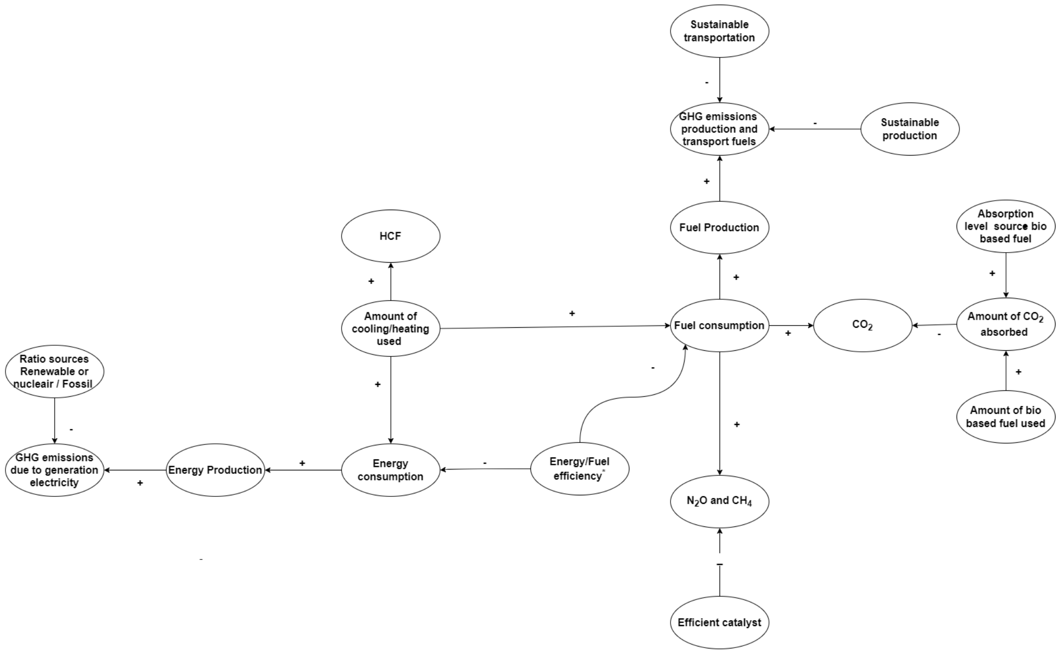


Figure 3.4: Causal diagram causes GHG basic

Table 3.1: Factors that influence the WTT and TTW emissions

Causal relationships of factors	Relation in diagram?	Source
Fuel consumption ->CO_2	+	Gallivan et al. (2008)
Fuel consumption ->Fuel production	+	Ahmed & Sarkar (2018); Gallivan et al. (2008)
Fuel production ->GHG emissions production and transportation fuels	+	Ahmed & Sarkar (2018)
Sustainable transportation fuels ->GHG emissions production and transportation fuels	-	Ahmed & Sarkar (2018)
Sustainable production fuels ->GHG emissions production and transportation fuels	-	Ahmed & Sarkar (2018)
Amount of CO_2 absorbed ->CO_2 in air	-	Wallington et al. (2008); Kularathne et al. (2019)
Amount of bio based fuel used ->Amount of CO_2 absorbed	+	Wallington et al. (2008); Kularathne et al. (2019)
Absorption level of bio based fuel ->Amount of CO_2 absorbed	+	Wallington et al. (2008); Kularathne et al. (2019)
Fuel consumption ->N_2O and CH_4	+	Lipman & Delucchi (2002); Rodriguez & Dornoff (2019)
Efficient catalyst ->N_2O and CH_4	-	Lipman & Delucchi (2002); Rodriguez & Dornoff (2019); Popa et al. (2014)
Energy/Fuel efficiency ->Energy consumption	-	Athanasopoulou et al. (2018)
Energy/Fuel efficiency ->Fuel consumption	-	Gallivan et al. (2008)
Amount of cooling/heating used ->HCF	+	Wallington et al. (2008)
Amount of cooling/heating used ->Fuel consumption	+	Wallington et al. (2008)
Amount of cooling/heating used ->Energy consumption	+	Wallington et al. (2008)
Charging efficiency ->Energy consumption	-	Athanasopoulou et al. (2018)
Energy consumption ->Energy production	+	Athanasopoulou et al. (2018) World Nuclear Association (2011); Athanasopoulou et al. (2018)
Energy production ->GHG emissions due to generation electricity	+	Athanasopoulou et al. (2018) World Nuclear Association (2011); Athanasopoulou et al. (2018)
Ratio sources renewable or nucleair / fossil ->GHG emissions due to generation electricity	-	World Nuclear Association (2011)

Fuel/Electricity consumption

Numerous studies have examined the impact of variables on fuel and energy consumption. Alwakiel (2011), Bigazzi & Bertini (2009), Demir et al. (2014), Piecyk & McKinnon (2010), Waidyathilaka et al. (2018), Li & Yu (2017), Sagaama et al. (2020) and Schmied & Knörr (2012) discovered several factors in the literature through their research. These factors can primarily be divided into five categories: Environmental factors, Factors driving behaviour, Road characteristics, Vehicle characteristics and Operational factors. These categories will be explained individually. *Environmental factors* that influence the fuel and energy efficiency are: extreme weather, humidity, the surface and altitude. The fuel/energy efficiency will be lower when there are extreme weather conditions (such as high winds, high temperatures, and black ice), when driving at high altitude, when the surrounding environment is very humid, when driving on a road with a steep angle. For the factors altitude, humidity, and road gradient, a distinction must be made between their effect on electricity efficiency and fuel efficiency. As far as is known, there is no direct effect of humidity and altitude on the energy efficiency of an electric vehicle, although this effect does exist for fuel efficiency in a vehicle. In addition, an increasing road gradient can have an impact on the efficiency of both electricity and fuel use, and the reverse relationship also applies. Furthermore, it is important to note that when driving downhill, electricity can be generated through braking when driving downhill in an electric vehicle, and this additional effect is also reflected in the causal diagram.

Driving behaviour factors influence the fuel efficiency due to idling and aggressive driving. Idling causes the car to waste energy without resulting in movement, aggressive driving results in 'hard breaking' and 'hard accelerating' this ensures that more energy is required to accelerate and decelerate than when going in a smooth flow. However, for electric vehicles, braking can provide electricity generation. This connection is considered separately because aggressive driving can also have a negative effect on an electric vehicle's battery, as continuous rapid acceleration reduces efficiency.

Road characteristics have also an influence on the fuel efficiency, these factors are: traffic flow, speed and the surface. Driving on a higher speed requires more energy. A rough surface will lead to more resistance from the road and therefore it requires more energy to drive on a rough surface. A high traffic intensity means that there more any vehicles on the road in a given period. This is often caused by, for example, congestion, traffic lights and intersections. This results in frequent stopping and starting of the engine or battery, which reduces fuel/energy efficiency (despite regenerative braking).

Vehicle characteristics that influence the fuel efficiency are: the weight, the size, age, maintenance and the rolling resistance of the tires.Thereby for ICE (internal combustion engine) vehicles, the engine is also a crucial factor that impacts fuel efficiency, while for EVs (electric vehicle), the battery and electric motor play a significant role in energy efficiency. A heavier vehicle needs more fuel/energy per kilometer to move forward than a lighter vehicle and therefore has a lower fuel/energy efficiency. The vehicle's load capacity and its size also play a role in fuel/energy efficiency. A larger vehicle catches more wind, requiring more energy to move forward. Additionally, the vehicle's size or load capacity is often related to its power, which can affect the vehicle's weight and engine size. These factors, in turn, can impact fuel efficiency. Age and mileage also impact the energy and fuel efficiency of a vehicle. As a vehicle ages, its parts function less efficiently. This can be partially fixed with maintenance, which enables the insertion of new parts or the correction of malfunctions. Therefore, the maintenance condition influences the fuel/energy efficiency positively. In addition, a lower rolling resistance of the tires can ensure a more efficient movement of the vehicle.

Operational factors directly influence fuel consumption and indirectly affect fuel/energy efficiency. These operational factors include payload, number of stops, loading and unloading, detours, empty trips, and the number of kilometers driven. The payload affects the vehicle's total weight and fuel/energy efficiency and is limited by the maximum weight and volume the vehicle can carry. Moreover, the vehicle's inherent weight and power also impact its fuel consumption, regardless of whether it is loaded or empty. The number of stops influences the number of kilometers driven, more kilometers are traveled when delivering to multiple locations than when making one shipment. In addition, it affects the number of freight and shipment loading and unloading times. When this is performed, the engine is frequently still running, which can affect a vehicle's idling time. The number of kilometers driven is influenced by the distance between the origin and destination. A detour, such as refueling, charging, or driving the wrong way to an address, also impacts the total distance traveled. The distance a vehicle travels when it has no freight (empty) also has an impact on its mileage. The number of kilometers driven has a direct relationship with a vehicle's fuel and energy consumption; the more kilometers driven, the more fuel/energy is required. Additionally, the type of transport also has an influence, where shared transport (Less than Truckload) is characterized by more stops, lower payload, and less empty running compared to dedicated transport. For dedicated transport, the payload is often higher (Full Truck Load), there is only one stop, and there is more empty running.

This section examines a variety of factors that influence vehicle-related greenhouse gas emissions. Earlier in this section, a causal diagram was constructed to represent the relationships between energy consumption and the resulting emissions. This causal diagram can be seen in Figure 3.4 and provides a basic overview of these relationships. However, to obtain a more comprehensive understanding of how emissions originate from driving a vehicle, it is necessary to examine the factors that influence fuel/energy consumption. As fuel/energy consumption is dependent on numerous factors, the relationships are further explored under the heading above '**Fuel/Electricity Consumption**'. To present a more complete picture, the diagram in Figure 3.4 is expanded to include these factors, which can be seen in Figure 3.5.In a causal Diagram, a plus sign indicates a positive relationship, whereas a minus sign indicates a negative relationship. An illustration of a positive correlation is the increase in the impact of road characteristics, due to for example the number of hills. An increase in the impact of road conditions will give an higher impact of driving conditions. When driving conditions have a greater impact, driving becomes less efficient, which is a negative relationship.

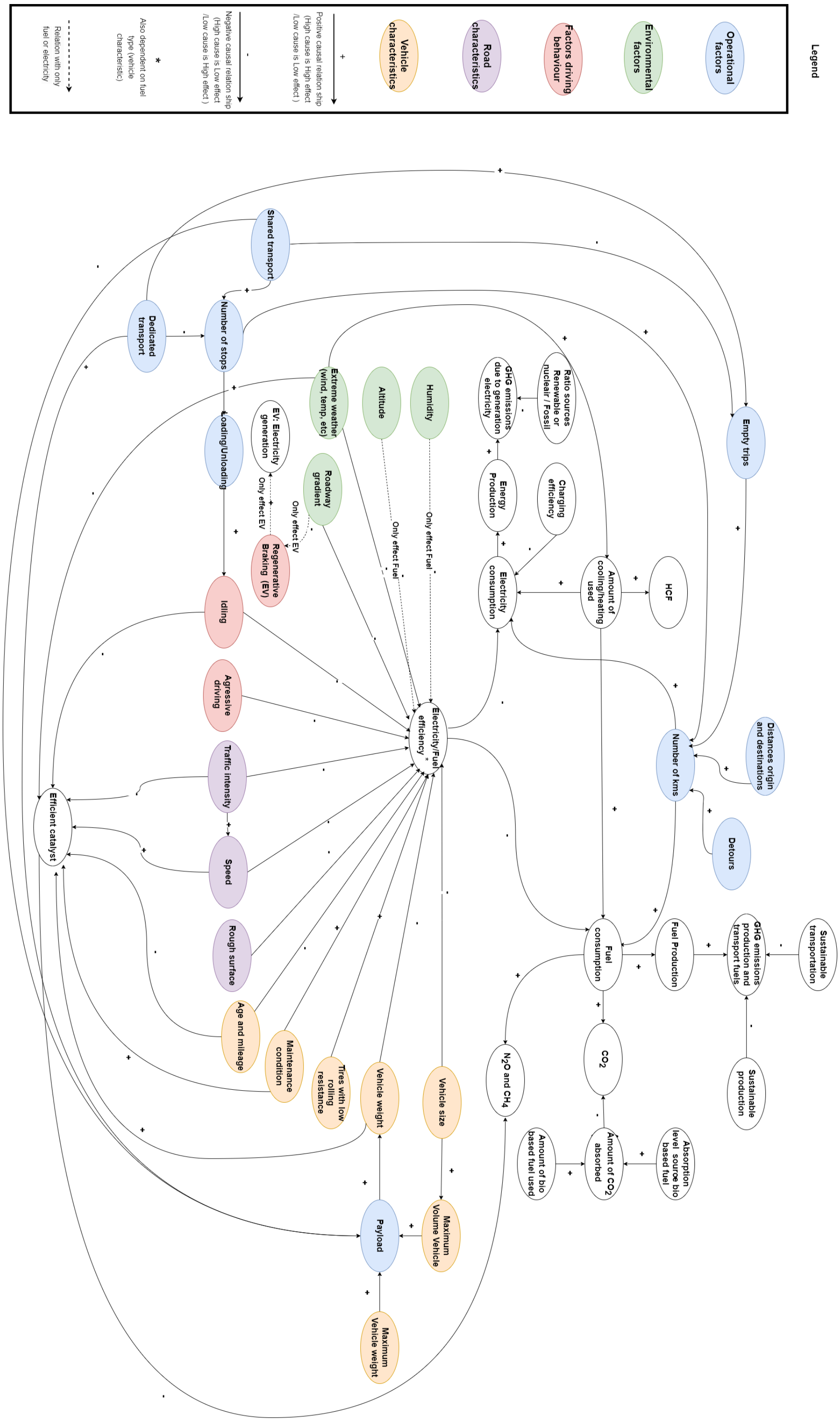


Figure 3.5: Causal diagram causes GHG

Table 3.2: Factors that influence the energy efficiency

Categories	Causal relationships of factors	Relation in diagram?	Source
Environmental factors	Roadway gradient ->Energy/Fuel consumption	-	Demir et al. (2014); Bigazzi & Bertini (2009)
	Roadway gradient ->Regenerative Braking (EV)	-	Sagaama et al. (2020); Li & Yu (2017)
	Humidity ->Energy/Fuel consumption	-	Demir et al. (2014); Bigazzi & Bertini (2009)
	Extreme weather ->Energy/Fuel consumption	-	Demir et al. (2014); Bigazzi & Bertini (2009)
	Extreme weather ->Amount of cooling/heating used	+	Wallington et al. (2008)
	Extreme weather ->Efficient catalyst	-	Rodriguez & Dornoff (2019); Popa et al. (2014)
	Altitude ->Energy/Fuel consumption	-	Demir et al. (2014),
Driving behaviour	Idling ->Energy/Fuel consumption	-	Demir et al. (2014); Alwakiel (2011)
	Idling ->Efficient catalyst	-	Rodriguez & Dornoff (2019); Popa et al. (2014)
	Aggressive driving ->Energy/Fuel consumption	-	, Bigazzi & Bertini (2009),
	Regenerative Braking (EV) ->EV: Electricity generation	+	Sagaama et al. (2020); Li & Yu (2017)
Road characteristics	Traffic intensity ->Energy/Fuel consumption	-	Demir et al. (2014); Bigazzi & Bertini (2009)
	Traffic intensity ->Efficient catalyst	-	Rodriguez & Dornoff (2019); Popa et al. (2014)
	Speed ->Energy/Fuel consumption	-	Demir et al. (2014); Bigazzi & Bertini (2009); Piecyk & McKinnon (2010); Alwakiel (2011)
	Speed ->Efficient catalyst	+	Rodriguez & Dornoff (2019); Popa et al. (2014)
	Rough surface ->Energy/Fuel consumption	-	Demir et al. (2014); Bigazzi & Bertini (2009)
Vehicle characteristics	Age and mileage ->Energy/Fuel consumption	-	Demir et al. (2014)
	Age and mileage ->Efficient catalyst	-	Popa et al. (2014)
	Maintenance condition ->Energy/Fuel consumption	+	Demir et al. (2014)
	Maintenance condition ->Efficient catalyst	+	Popa et al. (2014)
	Tires with low rolling resistance ->Energy/Fuel consumption	+	Demir et al. (2014)
	Vehicle weight ->Energy/Fuel consumption	-	Waidyathilaka et al. (2018); Demir et al. (2014); Piecyk & McKinnon (2010)
	Vehicle weight ->Efficient catalyst	+	Popa et al. (2014); Rodriguez & Dornoff (2019)
	Vehicle size ->Energy/Fuel consumption	-	Demir et al. (2014)
	Vehicle size ->Maximum volume vehicle	+	Demir et al. (2014); Piecyk & McKinnon (2010); Alwakiel (2011)
	Maximum vehicle weight ->Payload	+	Piecyk & McKinnon (2010)
Operational factors	Payload ->Vehicle weight	+	Pichery (2014); Waidyathilaka et al. (2018)
	Loading/Unloading ->Idling	+	Demir et al. (2014)
	Number of stops ->Loading/Unloading	+	Waidyathilaka et al. (2018)
	Number of stops ->Number of kms	+	Piecyk & McKinnon (2010)
	Distance origin and destinations ->Number of kms	+	Piecyk & McKinnon (2010); Demir et al. (2014); Alwakiel (2011)
	Detours ->Number of kms	+	Piecyk & McKinnon (2010); Waidyathilaka et al. (2018)
	Empty trips ->Number of kms	+	Piecyk & McKinnon (2010); Demir et al. (2014)
	Number of kms ->Energy consumption	+	Piecyk & McKinnon (2010)
	Number of kms ->Fuel consumption	+	Piecyk & McKinnon (2010)
	Dedicated transport ->Number of stops	-	Schmied et al. (2012)
	Shared transport + >Number of stops	+	Schmied et al. (2012)
	Dedicated transport + >empty trips	-	Schmied et al. (2012)
	Shared transport ->empty trips	+	Schmied et al. (2012)
	Dedicated transport + >payload	+	Schmied et al. (2012)
	Shared transport ->payload	-	Schmied et al. (2012)

3.7. Method to calculate the carbon footprint of freight

The preceding section discussed the variables that affect greenhouse gas emissions from freight transportation. The carbon footprint is determined by these greenhouse gases. Numerous methods and standards have been developed to map a shipment's carbon footprint. These methods are based on available data, emission factors, and the distribution of emissions when multiple shipments are present. As discussed in section 3.2, there is one officially accepted methodology called the EN16258. In this section the approach of EN16258 will be discussed, the critical views of this method, and other methods to calculate the carbon footprint.

3.7.1. The EN16258 approach

The description of this subsection is based on the methodology descrbed by Schmied & Knörr (2012) The starting point of the standard is to use fuel or energy consumption (henceforth called energy consumption) to calculate emissions. Energy consumption is converted into CO_2 equivalents using a corresponding emission factor of the respective energy source. This includes the emissions of CH_4, N_2O and CO_2. Energy consumption can be calculated based on two methods. The first method is called the consumption-based method and the other is called the distance-based method. The appropriate method is chosen by the amount of information available. Within the distance-based and consumption-based methods, there are different methods based on the detailed level of the information. Under distance is the most specific level of detail when the energy consumption is known per round trip, followed by the average energy consumption using a specific route or specific vehicle and finally, the average energy consumption of the whole fleet (of comparable vehicles). The second method is the 'distance-based' method, in which energy consumption is calculated based on default factors from databases. This energy consumption can be calculated in more detail using more information about the round trip. When information on load utilization and empty trips is available, a different method is used than when it is not. There are also different allocation methods by which the energy consumption is distributed in a "fair way" when there are multiple shipments on a round-trip. This method makes it irrelevant whether a shipment is loaded first or last, or whether the routing system plans clockwise or counterclockwise. An overview of these allocation methods is visible in Figure 3.6. Finally, the standard also says something about refrigeration systems; HCFs can escape into the air when they leak. The standard recommends adding these emissions at the end by calculating how much to refill and dividing this amount using the allocation method, and then multiplying this by the relevant emission factor. A detailed description of the standard can be found in Appendix C.

Allocation unit	Standard trip	Round-trip (delivery/collection trip)
Ton-kilometer (default)	– Ton: shipment weight – Kilometers: real travelled distance	– Ton: shipment weight – Kilometers: great circle distance or shortest feasible distance
Volume-kilometer	– Volume: pallet, parcel, TEU, etc – Kilometers: real travelled distance	– Volume: pallet, parcel, TEU, etc – Kilometers: great circle distance or shortest feasible distance
Ton	Shipment weight	Shipment weight
Volume	Cubic meter, palette, TEU, etc	Cubic meter, palette, TEU, etc
Kilometer	Distance travelled, great circle distance, or shortest feasible distance	Great circle distance or shortest feasible distance

Figure 3.6: Allocation units named in EN-16258 obtained from Kellner (2022)

3.7.2. Discussions around the EN16258 standard

EN-16258 must be accepted by the standardization institutes of 33 European nations. Several studies, however, have shown that the current version of EN-16258 has gaps and ambiguities that leave room for interpretation in a number of areas (Kellner, 2022). This makes it hard to compare how well different supply chains treat the environment and makes it harder to find the best ways to do things (Davydenko et al. (2014); Auvinen et al. (2014); Lewis et al. (2016)). The standard uses multiple allocation options and recommends ton-km as an allocation. For the distance, the standard recommends using the greatest circle distance (GCD) or shortest travel distances (STD) for the allocation for distribution trips. The actual driven distance (ADD) can be used for other types of trips. Several papers advocate using only the GCD or STD in the allocation method because it causes less bias than actual driven distances

(Davydenko et al. (2014); Lewis et al. (2016); Kirschstein et al. (2022)). Furthermore Davydenko et al. (2019) researched the various distances that can be used for allocations and found that GCD has the most support to use for allocation. Lewis et al. (2016) suggests that allocation using weight or ton-km is not always easy and can lead to non-optimal allocation. Kellner & Schneiderbauer (2019) examined the optimal allocation unit according to EN16258 in their analysis and simulation of road shipments. They considered primarily weight, volume, and distance. Consequently, the most precise allocation unit is distance (GCD). However, distance does not affect operator effectiveness. CO_2 per tonne-kilometer assesses the effectiveness of a carrier's network in terms of carbon emissions (Davydenko et al., 2019). In addition, the tonne-kilometer technique encourages operators to increase their efficiency and allows them to compare their performance to those of previous years directly. In addition, Wild (2021) discusses that other researches studied multidimensional capacity allocation techniques (Davydenko et al., 2014), revenue-driven allocation (Davydenko et al., 2019), and game-theoretic allocation methodologies (Naber et al., 2015). However, the ton-kilometer method has apparent benefits in terms of simplicity at the end (Wild, 2021). Ehrler & Seidel (2014) discusses also the problem of data sources and data accessibility is one of the essential concerns that must be addressed in each subsequent step toward a worldwide standard. On the one hand, the amount of detail may vary, resulting in the possibility of diverse outcomes for equivalent transport activities. Another critical issue discussed in the literature is the definition of Vehicle Operating System, this definition in the EN16258 is very broad which creates ambiguity. The VOS is the scope determination of the carbon footprint. This can be defined as, for example: the entire activity of a carrier's fleet during a year. All round trips between two specific locations per quarter. Or a single leg in a pickup and/or delivery trip (Ehrler & Seidel, 2014; Wild, 2021). A couple of these problems are also addressed in the COFRET project of the EU, they made recommendations based on ambiguities and problems that arise from the EN16258 methodology. After this, many tools and methods were devised that built on this, such as BigMile, GLEC and Objectif CO_2 (Davydenko et al., 2019).

3.7.3. Other methodologies and tools

In the literature, there are different ways to calculate energy use and emissions. Demir et al. (2014) discusses different methods of measuring energy consumption at different levels of accuracy (Kirschstein et al., 2022). Demir et al. (2014) distinguishes between the microscopic and macroscopic methods of determining energy consumption. The microscopic models give a more accurate estimate of how much energy a vehicle uses and how much pollution it puts out. The output of macroscopic models is the emission factor for a specific vehicle and driving mode, which is figured out by taking the average of the values over a certain driving cycle. The paper says that macro models are useful when there is not enough information about traffic flow and operational factors. Nunes et al. (2017) distinguishes top-down and bottom-up approaches to calculating emissions in addition to micro and macro models. The bottom-up approach is based on detailed vehicle specifications, whereas the top-down approach is based on aggregated global data such as fuel quantities, sales, fuel type, and corresponding emission factors. The bottom-up method is more accurate, but there are challenges. Due to the use of average input parameters, such as engine load factors, time spent in operating modes, fuel consumption rate, and emission factors, which are dependent on the size, age, fuel type, and market conditions, create uncertainty in the anticipated emissions.

Currently, the tools that are used in practice are macroscopic and bottom-up aproaches. The reason for using macro scopic model is due to its simplicity. Wild (2021) made an overview of the most relevant types of methods. These are visible in Figure3.7.

Standards & Methods	Legal basis	GeographicScope	Modes of Transport	Trans-shipping	Remarks
EN16258	Official	Europe	All	–	
SmartWay	Program	North America	All	–	
CE Delft	Research	Global	Partly	–	
GHG Protocols	Method	Global	–	–	Several specific areas
ISO	NGO	Global	–	–	
GLEC	Framework	Global	All	–	Based and further developed on existing methods
EcoTransIT	Commercial	Global	All	–	Based on EN16258, GLEC
BigMile	Commercial	Global	All	✓	
IMO	Official	Global	SEA	–	United Nation
CCWG	Initiative	Global	SEA	–	
ICAO	Official	Global	AIR	–	
IATA	Association	Global	AIR	–	
Green Logistics	Research	Europe	–	✓	
Green Efforts	Research	Europe	–	✓	
Green Freight Europe/ Asia	Program				
ITEC	Initiative	Europe	–	✓	ECOHubs
CarbonCare	Commercial	Global	All	✓	

Figure 3.7: Standards and Methods obtained from Wild (2021)

3.7.4. Data accuracy of input variables

As described earlier, data quality and accuracy is a challenge when calculating a carbon footprint. To determine the accuracy of a carbon footprint, both Objectif CO_2 and BigMile have created data levels within which footprints can be compared. Davydenko et al. (2019) describes these data levels as follows:

1. Individual journeys for which both transport activity and fuel (energy) use are known;
2. A collection of journeys by a single or multiple vehicles over a specified time (week, month, year) for which both transport activity and fuel (energy) use are known.
3. A journey or a collection of journeys by a single or many vehicles during a certain time, when transport activity is known but fuel (energy) consumption is unknown;
4. A journey or collection of journeys by a single or many vehicles during a certain time period, when transport activity can only be approximated and fuel (energy) consumption is unknown.

Some intermediate degrees of data resolution are feasible, for instance when fuel use is only partially known or when transport activity is approximated. Currently it has yet to be discovered how great the variation of the footprint is over the different levels. In section 3.9 this will be further discussed.

3.8. Ideal scenario carbon footprint estimation

The best case scenario for estimating a carbon footprint is when all necessary information is available, including the type of trip, fuel consumption, allocation strategy, stop data, distance, weight of loads, and CO_2 emission factors (Schmied & Knörr, 2012; Nunes et al., 2017). Trip type refers to the fact that a trip can be a shared or a single trip. A shared trip is one that travels to more than one location, whereas a single trip only transports the load to one location before returning to the original location or to the next loading location. In Figure 3.14 a flow chart is visible from the steps of calculating a carbon footprint in the best case scenario. What is meant by this best case scenario is that all information is available for the most simple calculation. In this simplest calculation, the fewest assumptions have to be made, so this calculation should give the most accurate carbon footprint. Nevertheless, this calculation can be calculated in different ways due to the choices that have to be made for the scope, the allocation method and the data base to be used for the emission factors. In the text below the figure is further described.

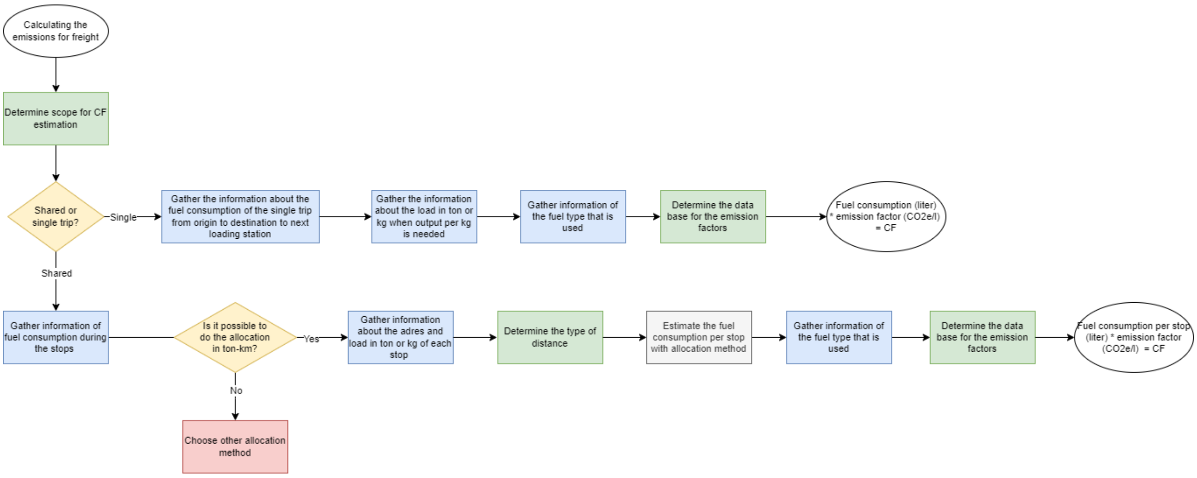


Figure 3.8: flow chart ideal scenario CF calculation

For a shared trip, it is best to have information on the fuel that is used between each stop and throughout the entire journey. The distribution of fuel consumption among the number of stops is then calculated using an allocation method. In ideal circumstances, the number of ton-km is calculated for each stop and should be used in this allocation method. The weight and distance of each shipment must be known for this. Different methods can be used to calculate the distances between the stops; these methods are already illustrated and explained in Figure 3.7. Additionally, it is essential to know the weight of the loads between each stop. Additionally, knowing a shipment's weight is also crucial for a single trip when calculating, for instance, the carbon footprint per unit.

In addition, for shared and single trips it is also important to know the type of vehicle and/or fuel used. Using this data, the most accurate calculation can be made in terms of converting fuel consumption to CO_2 equivalents. There are multiple options for emission factors, just as there are for the various allocation methods and distance calculation methods. The well-to-wheel (WTW), well-to-tank (WTT), or tank-to-wheel (TTW) methods can be used to estimate emissions. The method that is chosen depends on the definition of the carbon footprint measurement's scope, as well-to-tank emission factors take both emissions from fuel production and use into account. Additionally, the data source from which the emission factor is derived must be chosen. Finally, with the help of the chosen emission factor, the number of liters of fuel or number of kWh can be converted to the number of CO_2 equivalents. As a result, the total carbon footprint of a shipment is calculated.

3.9. Data and parameters for a carbon footprint estimation

Section 3.8 describes how a carbon footprint is calculated under ideal conditions. In the ideal conditions, there is precise data of each trip. This section further explains the extent to which data quality can affect the accuracy of the carbon footprint. First, the relationship between data quality, model quality and outcome is discussed. It then discusses how Lean and Green, a European program for the transportation sector with the goal of reducing CO_2, assesses data quality when it comes to calculating a carbon footprint.

3.9.1. Relationship between data quality, model quality and outcome

When a model is used to estimate an outcome because direct measurement is not possible, two things are particularly decisive in making a reasonable estimate. The first is model quality. Model quality represents the extent to which a model represents the actual world and its relationships. In addition, data quality is also important. Data quality is defined as the suitability of data for its intended use (Klobas, 1995). In the context of carbon footprints, the input data is used to quantify the carbon footprint of a shipment as precisely as feasible. The evaluation of the suitability and quality of data is seen as multidimensional (Pipino et al., 2002), whereas completeness and accuracy are two essential dimensions. Incomplete data is imperfect, particularly when at least one characteristic must be substituted by surrogate measures (Wederhake et al., 2022). In the context of the carbon footprint of freight a surrogate estimate is for example the amount of CO_2e emitted per ton-km for a particular vehicle type. In addition to any other data quality problem, inaccurate (quantitative) or mislabeled (qualitative) data can also contribute to imperfect data. In general, imperfect input data cannot provide more accurate conclusions than perfect input data for any deterministic approach without the model having a systematic inaccuracy, often known as bias (Schwarz & Köckler, 2011). The data quality also influences the model quality, because the completeness and accuracy determine which calculations need to be performed to arrive at the carbon footprint. These relationship are showed in Figure 3.9.

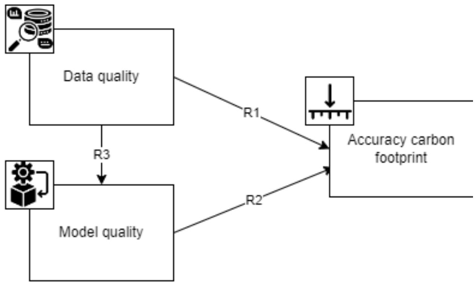


Figure 3.9: Influence data quality

3.9.2. Lean and green data quality indicators

The European program Lean and Green focuses on sustainable and carbon footprint determination of freight transportation. This program has developed indicators to compare carbon footprints based on data quality Logistiek (2021). Shipment data and fuel consumption data are distinguished. Quality levels for fuel consumption are described as bronze, silver, gold, and gold plus, with gold plus being the most accurate data. These levels are differentiated by the aggregation level of the data and the source of the data. Bronze fuel data means that the source of the data is an estimate, regardless of the aggregation level and is therefore considered the least accurate. The silver level is characterized by an average fuel consumption (e.g., l/km) calculated over a year or a month for several vehicles in a fleet or an annual average for a specific vehicle. Gold data means that fuel consumption has been measured for a specific vehicle over a month or a week. Finally, there is also the gold plus category, which means that fuel consumption is known for each trip for a specific vehicle.

For shipment data, the levels are also described as bronze, silver, gold, and gold plus, with gold plus being the most accurate data. Bronze shipment data means that the source of the data is an estimate, regardless of the aggregation level, and an estimate on a yearly or monthly basis remains an estimate and is therefore considered the least accurate. Silver shipment data means that the source of the data is a measurement of the transport volume aggregated over a year, a month, or a week across different license plates, or the transport volume over a year per license plate. Gold shipment data means that the volume per month or week is known per license plate. Gold plus shipment data means that the volume per trip is known per license plate. The ultimate quality of the carbon footprint is determined by the lowest data level. In total, there are 72 possible combinations of data, with 50% resulting in a carbon footprint with bronze data quality, 41.2% resulting in a carbon footprint with silver data quality, and 12.5% resulting in a carbon footprint with gold data quality. This is shown in Table 3.4.

A few things are noteworthy about the choice of categorization of 'data quality':

- The same level of data quality is assumed between the average on a yearly basis of a fleet compared to the average on a yearly basis of a specific vehicle. However, a difference in the level of data quality is made on a monthly basis.
- Shipment data quality is evaluated based on volume, but this also depends on the level of detail known about the locations of these shipments and the distances of the shipments. This is further explained under the heading **Shipment Data and Allocation**.
- The use of aggregation levels can impact the final outcome. When the data is used at the trip level, emissions are allocated accordingly, meaning that they vary from day to day. This can have

the disadvantage of revealing sensitive information to customers and competitors, resulting in the possibility of calculating fuel consumption and the associated costs. However, a high aggregation level where only data from multiple vehicles over a longer period is known does not help optimize greenhouse gases. The high aggregation level only provides insight into how efficient a carrier or logistics service provider is with regard to the entire network when looking at the number of emissions per tonne-km, but not about detailed insights into the GHG emissions generated by specific shipments (Lewis et al., 2016).

Table 3.3: Data quality indicators

	Fuel data	Estimated numbers	Estimated numbers	Average total	Average total	Average per license plate	Measured per license plate	Measured per license plate	Measured per license plate
Shipment data	Aggregation	*Year*	*Month*	*Year*	*Month*	*Year*	*Month*	*Week*	*Trip*
Estimated	*Year*	B,B	B,B	B,S	B,S	B,S	B,G	B,G	B, G+
Estimated	*Month*	B,B	B,B	B,S	B,S	B,S	B,G	B,G	B, G+
Measured total	*Year*	S,B	S,B	S,S	S,S	S,S	S,G	S,G	S,G+
Measured total	*Month*	S,B	S,B	S,S	S,S	S,S	S,G	S,G	S,G+
Measured total	*Week*	S,B	S,B	S,S	S,S	S,S	S,G	S,G	S,G+
Measured per licence plate	*Year*	S,B	S,B	S,S	S,S	S,S	S,G	S,G	S,G+
Measured per licence plate	*Month*	G,B	G,B	G,S	G,S	G,S	G,G	G,G	G,G+
Measured per licence plate	*Week*	G,B	G,B	G,S	G,S	G,S	G,G	G,G	G,G+
Measured	*Trip*	G+,B	G+,B	G+,S	G+,S	G+,S	G+,G	G+,G	G+,G+

Gold +	Gold	Silver	Bronze

Fuel data

Fuel consumption can be measured in several ways. First, the best situation is when the data per shipment is as accurate as possible. When the latest innovations in board computer systems is used, it is possible to keep track of the actual fuel consumption for each trip (Iacob et al., 2013). When this option is possible, the resulting data is most accurate. Another option is to read the fuel consumption through the fuel gauge, but since this is difficult to read in many cars, this is not very convenient and accurate.

Secondly, diversions or estimates can also be made to arrive at the fuel consumption of a shipment. For example, a fuel card is often used to find out how many liters a vehicle has used. It is possible to estimate a vehicle's fuel consumption by keeping track of this information. Data on a fuel card is frequently aggregated because it is frequently based on multiple trips. It also happens that companies do not track this per vehicle but only track the fuel consumption of their total fleet. The accuracy of the fuel consumption data from a fuel card is therefore based on two things: the period for which the data is available and whether the data is for a single vehicle or a fleet. The disadvantage of approximating fuel consumption based on fuel payment cards is that the data does not reflect the fluctuations in fuel consumption between refueling trips (or between the aggregation levels) (Ayyildiz et al., 2017).

Then the third and last option is to calculate the amount of fuel used based on a prefix/default factor. This is the least preferred option because the fuel consumption depends on several things, such as: the type of road, the traffic density, the payload, driving behaviour, etc. When a default factor is used, the influences of these factors cannot be seen. However, there are still different levels for using default factors. For example, there are ways to take into account as many factors as possible when estimating fuel consumption. Several models have been created for this purpose (Demir et al., 2014). Thereby, interpolating the fuel consumption of an empty and fully loaded truck is a widely used strategy in research and practise (Guajardo, 2018). This formula (3.1) calculates fuel consumption by multiplying the vehicle's fuel consumption per kilometer and by the distance traveled. The fuel consumption per kilometer is derived from the fuel consumption of a vehicle over 100 kilometers. This is interpolated from the specific fuel consumption of a vehicle when driving at full truckload (FC_{full}) and when empty (FC_{empty}) and the load factor (payload p / maximum payload C) over the transport route. In this approach, a linear relationship between payload and (extra) fuel consumption is assumed. FC_{empty} and FC_{full} data can be extracted from different databases (Kellner, 2022).

$$Fuel\ consumption = \left(FC_{\text{empty}} + \left(FC_{\text{full}} - FC_{\text{empty}}\right) * \frac{p}{C}\right)/100 * distance \tag{3.1}$$

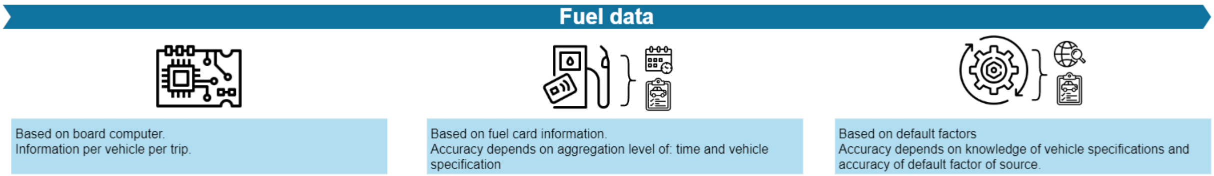


Figure 3.10: fuel data

Shipment data and allocation

In addition to fuel data, load data is also crucial to know. This is important for the allocation of emissions; this principle was discussed earlier in section 3.7.2 but will be repeated briefly. The allocation principle is about dividing the amount of energy used in a trip or period according to the load. This can be distributed in several ways, called the allocation method. The choice of allocation method is determined by: the available data, the limiting cargo unit, or the billable cargo unit. Examples include allocating fuel based on ton-km, cubic meters, distance, or pallets. Many studies have been done on the ideal allocation method, but to date, the ideal allocation method has not been determined. In short, load data is needed to allocate the energy used for customer shipments (loads). The allocation method commonly recommended is the number of tons distributed over the great-circle distance from the origin to the load's destination (Wild, 2021). To achieve the allocation for this, several pieces of information are necessary: the origin of the loads, the destination of the loads, and the weight of the loads.

Furthermore, depending on the level of detail of the fuel data, more data is required; when the fuel consumption in l/km is known or default factors are used, the trip's distance is also required. There has also been research on which distance is best used for this, the research of Davydenko et al. (2021) shows that the actual driven distance clearly comes out best to use when fuel consumption data is not available. The data that needs to be available also depends on the type of shipment, when the fuel consumption of a dedicated trip is known (the trip goes only to one customer), it does not need to be distributed to other shipments and the fuel consumption of that trip can be allocated to the respective customer. This is also dependent on the fuel data.

Freight data can also be accurate through a detailed description on the freight documents. This includes the address of the origin, the adress of the destination, details about the type of transportation (bulk, pallets, for example), and the quantity expressed in freight units. It is also possible that this information is only available on an aggregated level or that the information of an entire trip is only known and not per stop. The three dimensions on which the accuracy of the data depends is whether the data (quantity, origin, destination) are available by stop, by license plate and the period. When data is missing, estimates of the quantity transported must be made based on turnover, for example.

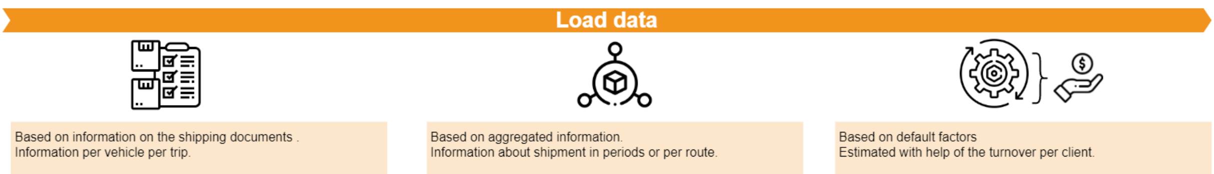


Figure 3.11: payload data

3.9.3. Emission factors

Freight emission factors can vary based on the type of vehicle, fuel, and cargo being transported. There are various types of emission factors and, additionally, diverse databases from which these factors are derived. Depending on the scope, either WTW, TTW, or WTT emission factors are applied. The preferred method for calculating the total greenhouse gas emissions is to multiply the amount of fuel and/or electricity used by the various modes of transportation (in units like liters, kg, or kWh) by the emission factors from the relevant category (fuels, vehicles, electricity) (Rijkswaterstaat, 2022). Since these calculations are based on actual fuel consumption, they are the most accurate. In the absence of fuel consumption data, emissions can be estimated using the estimated emission factors for each freight transport category. The level of detail varies between databases. Some databases assume average loading, average road conditions, etc., while others have different emission factors for each vehicle and circumstance. There are different databases from which emission factors can be extracted. For example, there are European, North American, and Canadian values for fuel emission factors. There are also national emission factor values within Europe, such as those of France and the Netherlands. A graph shows how far apart these emission factors are using various data sources. Figure 3.12 shows diesel emission factors and Figure 3.13 gasoline emission factors. The European and North American emission factors came from the Smart Freight Centre's GLEC Framework (SFC, 2020), the Netherlands' factors from the CO_2emissiefactoren website that used the CE Delft database (Rijkswaterstaat, 2022), Australia's emissions factors came from the report of the Department of Climate Change, and the emission factors of France are obtained from a guideline of the Ministry for an Ecological and Solidarity Transport (for an ecological & solidary Transition, 2019). Each source discussed variables from WTW, TTW, and WTT and calculated CO_2 equivalent from N_2O, CH_4, and CO_2 emissions. Both graphs show also the factor averages to compare values. For example, it can be seen that the Australian WTT deviates a lot and this is also reflected in the WTW value.

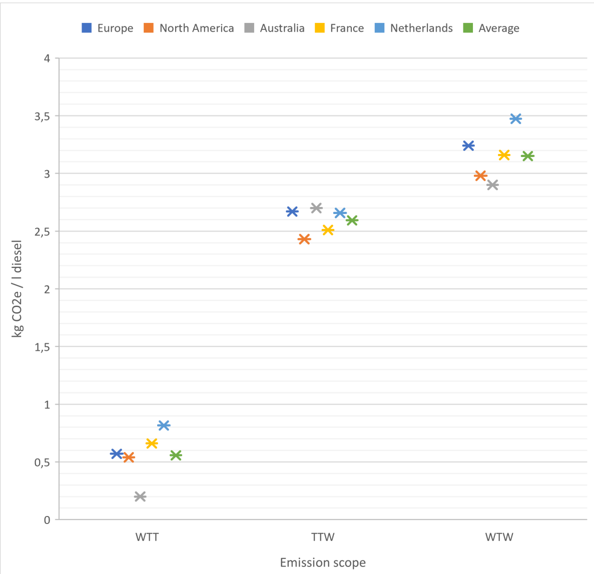


Figure 3.12: Differences CO_2 e emission factors diesel

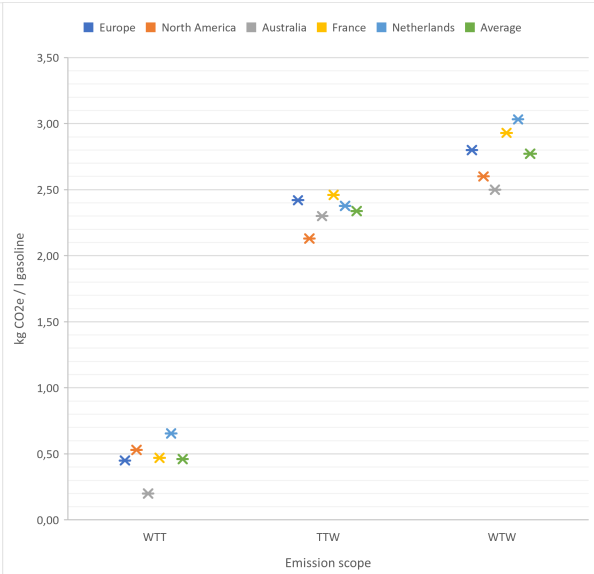


Figure 3.13: Differences CO_2e emission factors gasoline

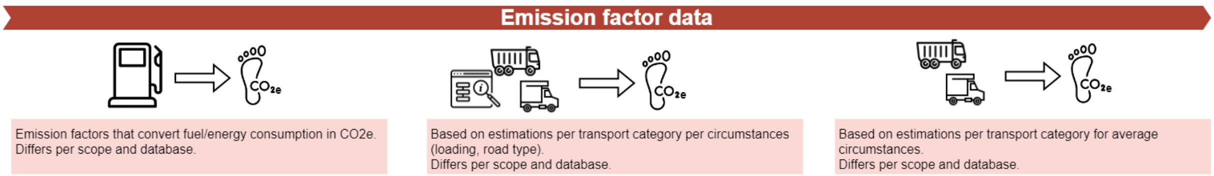


Figure 3.14: fuel data

3.10. The new ISO 14083 standard

During the writing of this thesis, it was learned that a new ISO standard will be published in March 2023. This ISO standard will attempt to address the criticism of EN16258 and further harmonise the carbon footprint of freight. To take this somewhat into account, this section reflects on the knowledge gained in this chapter and how ISO standard is expected to change this.

The basis of the new ISO standard will correspond to the GLEC framework (Gould, 2023). A general recommendation of the GLEC framework and the future ISO 14083 standard is to aggregate TOC activities over a year to smooth out the effects of seasonality related to climate and demand; in justified cases, aggregation over time may be smaller to a lower level of time aggregation and may be reduced to individual trips (Davydenko et al., 2022). TOC implies a specific uniform transport category, a group of transport activities with similar characteristics. The points below reflect how the new standard would modify the above sections:

- This methodology is somewhat similar to the consumption-based method already discussed in the EN16258 method. However, the preferred method is based on fleet averages, with the condition that this should be an average of the comparable modes of transportation instead of measured per trip or license plate. This method is already described in section 6.2.1. and Appendix C.
- The method proposed corresponds to the aggregation level 2 discussed in section 6.2.4., the preferred level is yearly.
- This means the 'ideal scenario carbon footprint estimation' explained in section 6.3. most likely change. A new diagram has been made to illustrate what the new 'ideal' calculation should look like, this is shown in Figure 3.15. This uses the great circle distance, as the most recent literature recommends this as an allocation method. However, it is not sure whether this will be used in the new ISO standard; if not it can be replaced by another distance method (GCD would then become PD; planned distance, for instance).
- In addition, the question is whether the Lean and Green quality indicators should be kept the same. That depends on what the ultimate goal of the indicator is. For example, if the goal is to have insight into fuel consumption per chauffeur, it is essential to have data available per trip. The better these kinds of details are available, the more a transport company can make decisions at a detailed level. When a transport company has to report emissions from shipments to the shipper, the question is whether this detail is necessary and fair. Should specific influences be explicitly charged to a customer, or should they be spread across customers? When working with the principle of the GLEC framework, specific influences should be spread out. This may mean that Bronze data estimates can remain key figure-based. The silver quality indicator should focus then on derived fuel consumption or aggregated data across multiple vehicles. Gold would then mean a specific measurement per license plate. The separation of quality between trip, week, month and year aggregation levels should remain the same within this as GLEC looks at an annual basis This is visible in Table 3.4.

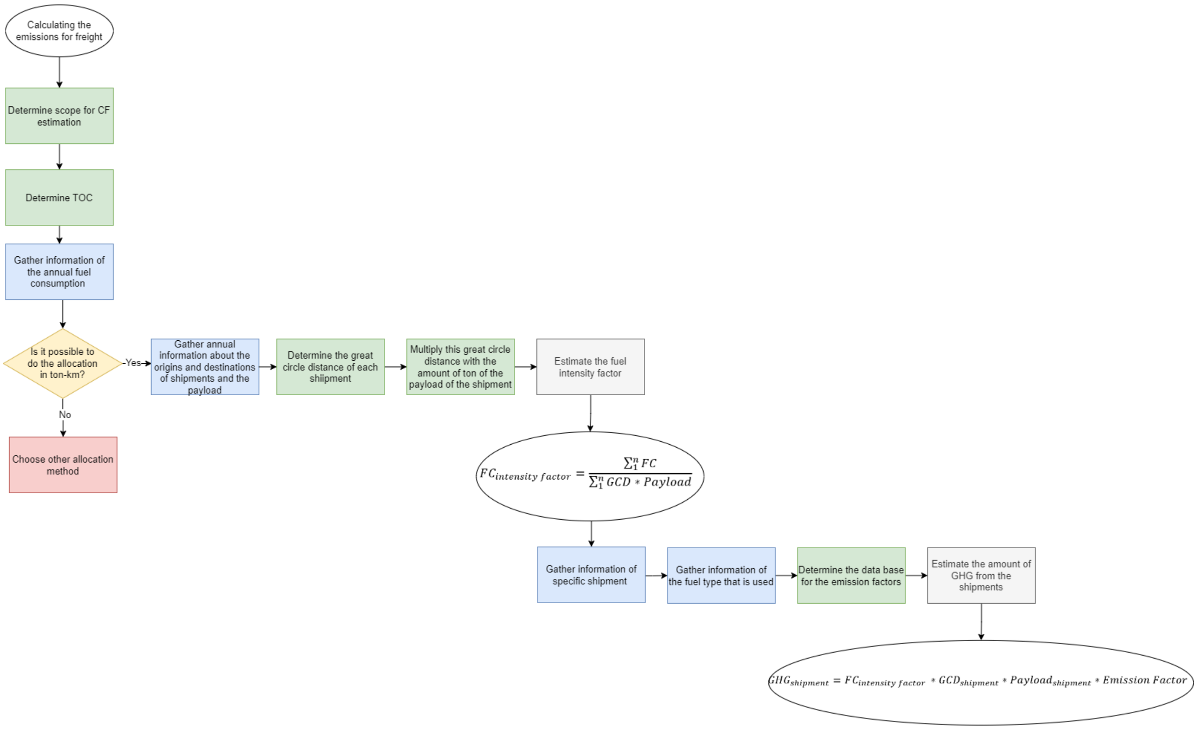


Figure 3.15: Ideal CF estimation GLEC

Table 3.4: Data quality indicators new

	Fuel data	Estimated numbers	Estimated numbers	Average total	Average total	Average per license plate	Measured per license plate	Measured per license plate	Measured per license plate
Shipment data	Aggregation	*Year*	*Month*	*Year*	*Month*	*Year*	*Month*	*Week*	*Trip*
Estimated	*Year*	B,B	B,B	B,S	B,S	B,S	B,G	B,G	B, G+
Estimated	*Month*	B,B	B,B	B,S	B,S	B,S	B,G	B,G	B, G+
Measured total	*Year*	S,B	S,B	S,S	S,S	S,S	S,G	S,G	S,G+
Measured total	*Month*	S,B	S,B	S,S	S,S	S,S	S,G	S,G	S,G+
Measured total	*Week*	S,B	S,B	S,S	S,S	S,S	S,G	S,G	S,G+
Measured per licence plate	*Year*	G,B	G,B	G,S	G,S	G,G	G,G	G,G	G,G+
Measured per licence plate	*Month*	G,B	G,B	G,S	G,S	G,G	G,G	G,G	G,G+
Measured per licence plate	*Week*	G,B	G,B	G,S	G,S	G,G	G,G	G,G	G,G+
Measured	*Trip*	G+,B	G+,B	G+,S	G+,S	G+,G	G+,G	G+,G	G+,G+

Gold +	Gold	Silver	Bronze

3.11. Conclusion carbon footprint

A carbon footprint is a measure that encapsulates the total greenhouse gas (GHG) emissions associated with a particular activity, product, or system, quantified in CO2 equivalents. There's a level of disagreement in the literature on which GHGs to consider in the calculation. Some studies include all GHGs, others focus on legislated GHGs such as the seven Kyoto gases (CO2, CH4, N2O, HFCs, PFCs, SF6 and NF3), or solely carbonaceous gases (CO2, CH4, CO). Consequently, it becomes crucial to explicitly define the boundaries and scope of the carbon footprint for each study to ensure comparability, transparency, and better understanding of associated environmental impacts. The European standard EN 16258 is specifically designed for calculating the carbon footprint of freight transportation, providing a robust methodology for computing and declaring the energy consumption and greenhouse gas emissions associated with transport services. The scope of this standard includes GHG emissions from the production, distribution, and usage of fuel or energy in a vehicle.

The determination of the carbon footprint of freight transport relies on the EN16258 standard, which presents two different calculation approaches: consumption-based and distance-based. The consumption-based approach involves primary data and focuses on total energy consumption to obtain emission figures, which are then allocated to shipments or customers using a transport activity-based allocation factor. The distance-based method uses default data and calculates total consumption using an average factor, which is then allocated based on customer or shipment data. Key inputs for these calculations are energy consumption for a trip and associated transport activity (like load, origin, and destination of each shipment).

Existing literature presents various measurement methods for mapping a carbon footprint of freight transportation. At the beginning of this thesis, the EN16258 was the prevailing standard. However, numerous software tools and updated methods have since been developed based on this standard, such as the GLEC Framework. The GLEC Framework advocates for distributing emissions on an annual basis and distinguishes between primary and secondary/default data. If data is missing, fuel consumption can be modeled; if transport activity is unknown, an average load factor can be used; and if both are unknown, default emission intensity factors can be employed. Towards the end of this research, a new ISO standard was published, which largely adopts the GLEC Framework's method. The primary difference between the ISO standard and EN16258 lies in the aggregation level and the decision to allocate emissions based on ton-kilometers. The ISO standard determines the distance using either the Great Circle Distance or the Shortest Feasible Distance, with possible exceptions. This more detailed conclusion provides an overview of the research and insights phase, emphasizing the importance of understanding and addressing the carbon footprint of freight transportation.

4

Background study uncertainties

In this chapter, we examine the meaning of uncertainty in the literature and the types of uncertainty that occur. Ultimately, a definition or framework will be selected to define uncertainties for the purpose of this chapter. The following question must be addressed in this chapter.

Research questions to be answered in this chapter:

- RQ4 *What is uncertainty and what types of uncertainties currently exists in literature?*

4.1. Definitions of the concept 'Uncertainty'

According to Klir & Yuan (1996) uncertainty occurs when there is not enough knowledge about something to describe the current situation or predict what might happen. Multiple logical statements are true about the world in many different forms. These statements are needed to capture knowledge and to use the knowledge to apply it to different concepts. However, sometimes a statement is only true in a certain context and not in the totality of the logical universe. Klir & Yuan (1996) shows that the concepts of information and uncertainty are strongly connected. The most important aspect about this connection is that uncertainty in any problem-solving situation is caused by a lack of information. The information about the situation's model may be missing, vague, contradictory, or otherwise flawed. In general, the lack of these different kinds of information can lead to different kinds of uncertainty. Due to the fact that while modeling and calculating something, assumptions are made and a portion of reality is quantified, different types of models contain varying degrees of uncertainty. Consequently, it is crucial to be aware of this when these models are utilized in decision-making. The above papers argued that uncertainty follows from a lack of information. However, this is contradicted in the paper of Walker et al. (2003). He discusses that uncertainty is not just simply the absence of knowledge. They discuss that even in a situation with a lot of knowledge, uncertainty can still exist. Thereby he argues that new information can also increase the uncertainty. Because previously unknown or underestimated uncertainties in complicated processes may suddenly be revealed by new information. In such manner, more information reveals that our understanding is more limited or that processes are more complex than previously believed. In addition, the paper distinguishes between uncertainty arising from variability and uncertainty arising from a lack of knowledge. Tonin et al. (2016) also examines many viewpoints on what uncertainty means. Uncertainty is defined simply as the description of the margin of doubt built into every measurement. This definition states that in addition to the measurement's result, it is also required to describe the interval's width and the degree of certainty that can be placed on the "actual value" contained within it (the confidence interval). Furthermore, Sigel et al. (2010) states that uncertainty lies between certainty and lack of knowledge. They argue that a person will not make statements on a topic about which they have no knowledge of. However, when a person has only partial knowledge of a subject, he or she may make a statement; this knowledge gap is the result of uncertainty. They describe this as the confidence degree about if a person can trust his or her knowledge. Nilsson et al. (2007) makes a distinction between precision, accuracy and mistakes within uncertainty. A lack of precision will lead to a measurement error, a lack of correctness will lead to a systematic error (i.e. a bias) and mistakes lead to incorrect measurements.

From the reviewed papers, it can be deduced that uncertainty generally arises when a number deviates from its actual value. However, it is challenging to draw a definite conclusion regarding the concept of uncertainty. This is because the literature discusses numerous types of uncertainties and causes. Additionally, a distinction is made between uncertainties resulting from variability and lack of knowledge. This will be examined in the following sections for a more profound understanding.

4.2. The difference between 'Variability' and 'Uncertainty'

One important distinction that has been made in the literature on uncertainty is the difference between variability and uncertainty. Uncertainty and variability are two terms that are frequently used interchangeably, but a look at their definitions in the literature reveals that they differ in a certain way. Tonin et al. (2016) discusses that uncertainty is imperfect knowledge of a true value of a particularly quantity. Whereas variability is a variation within a measured value. The reduction of uncertainty is possible by collecting additional data, while this is not the case for variability (Nilsson et al., 2007). A practical example to indicate the difference between variability and uncertainty is for example that a dice has an outcome of 1, 2, 3, 4, 5 or 6, this is the variability of the outcome. Uncertainty, however, is which outcome the dice lands on (Abrahamson, 2007). Variability can therefore contribute to uncertainty, within certain limits of outcomes since you know that the outcome can be no more than 6 and no less than 1. Begg et al. (2014) states that the key idea of the relationship between variability and uncertainty is as follows: the probabilities we select to describe uncertainty can be informed by variability.

4.3. Uncertainties in the context of a carbon footprint

Background research reveals that uncertainties in carbon footprint measurements have mainly been investigated in the context of life cycle analyses (LCAs). Quality assurance is important for reducing uncertainties, Weidema & Wesnæs (1996) developed a pedigree matrix with five quality indicators to assess the data quality of a life cycle inventory. The two main sources of uncertainty are basic uncertainty related to measurement errors and normal fluctuations, and additional uncertainty due to poor data quality. Hong et al. (2016) discussed three types of uncertainty sources in LCA-related studies: scenario uncertainty, parameter uncertainty, and model uncertainty.He et al. (2018) used the definition of uncertainty from the standard PAS-2050:2011 and classified it into two types: technical uncertainty arising from incomplete modeling, poor data quality, and other evaluation flaws, and natural variability that is accounted for in a product's average or representative carbon footprint. A brief description of these uncertainties is given in Table 4.1.

Table 4.1: Uncertainty types in the context of carbon foot-printing calculations

<table>
<tr><th>Uncertainty</th><th>Description</th><th>Context</th><th>Source</th></tr>
<tr><td>Basic uncertainty</td><td>Related to all sampled data
(typically measurement errors and
normal fluctuations)</td><td rowspan="2">LCA</td><td rowspan="2">Weidema & Wesnæs (1996)</td></tr>
<tr><td>Additional uncertainty</td><td>Due to poor data quality</td></tr>
<tr><td>Scenario uncertainty</td><td>Due to normative choices, different choices
may generate different outcomes</td><td rowspan="3">LCA</td><td rowspan="3">Hong et al. (2016)
Huijbregts et al. (2003)</td></tr>
<tr><td>Parameter uncertainty</td><td>Due to imprecise measurements,
(expert) estimates, and assumptions.</td></tr>
<tr><td>Model uncertainty</td><td>Due to assumptions and simplifications that
affect the model's real-world validity</td></tr>
<tr><td>Technical uncertainty</td><td>Due to incomplete modeling, poor data quality,
ineffective sampling, wrong assumptions,
and other evaluation flaws</td><td rowspan="2">PLC</td><td rowspan="2">He et al. (2018)
British Standards Institute (2011)</td></tr>
<tr><td>Natural variability</td><td>Due to variability in a product's average or
representative carbon footprint</td></tr>
</table>

4.4. Classification of uncertainties

As described in section 4.1 and 4.3 there are various ways to characterize uncertainty, and therefore, different types of ”uncertainties” emerge in the literature. Uncertainties that have been identified include those arising from missing data, flaws, vague descriptions, assumptions, measurement errors, systematic errors, uncertainties due to poor data quality and uncertainties due to normative choices. Many different papers and literature studies have attempted to define these different uncertainties within a framework. One such framework is the uncertainty matrix developed by Walker. Walker designed a tool for identifying and classifying uncertainties in a model-based decision support context. With the help of various experts, three dimensions were established to characterize uncertainty: the level of uncertainty, the location of uncertainty, and the nature of the cause of uncertainty. For this research, it was decided to build on this framework. The rationale for this decision is as follows:

- The uncertainty types discussed in the previous section, which deals specifically with the uncertainties in a carbon footprint calculation, overlap with the classification of Walker’s uncertainty matrix. With the help of the matrix, it is possible to represent them more comprehensively. A synthesis between them is thus possible. This is discussed more fully in subsection 4.4.
- The Walker uncertainty matrix allows for the identification of uncertainties at different stages of modeling because it distinguishes between different locations where uncertainty can arise. When examining a carbon footprint calculation for freight, models or methodologies are used to map a carbon footprint, and uncertainty may arise at different stages of using these models.
- Because the uncertainty is also described in terms of the cause of uncertainty and the level of uncertainty, it provides a clear and concise way to communicate uncertainties to stakeholders, such as policymakers, investors, or the general public. This can help to build trust and credibility in the carbon footprint calculation and the conclusions drawn from it.

This section will further explore the application of the uncertainty framework to determine how the classification of uncertainty is determined for this thesis research.

Tscheikner-Gratl et al. (2017) describes three dimensions of uncertainty that where found in the papers of Walker et al. (2003), Refsgaard et al. (2007) and Van der Keur et al. (2008). These dimensions are: the location or source of uncertainty, the nature of uncertainty and the level of uncertainty. Within those dimensions there are different types of uncertainties defined. Despite the previously mentioned papers use the same dimensions, it appears that the definitions of uncertainties overlap and even sometimes use different terminologies. To create clarity, Tscheikner-Gratl et al. (2017) has developed a decision tree to determine the types of uncertainty based on the decision tree of (Warmink et al., 2010). A combination of both decision trees is eventually chosen to be used for the definitions in this research. This decision tree is visible in Figure 4.1.

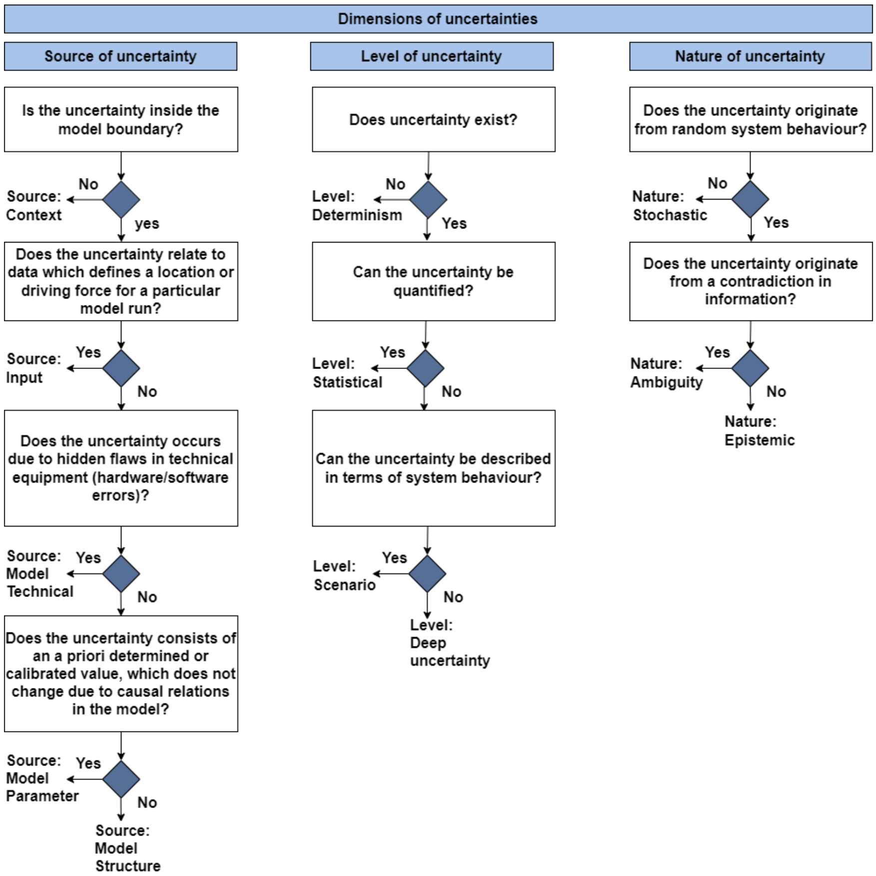


Figure 4.1: Uncertainty decision tree, obtained from Tscheikner-Gratl et al. (2017) and Warmink et al. (2010)

When looking at the decision tree it can be concluded that there are actually five sources of uncertainty, these sources can have four levels of uncertainty. The lowest level of uncertainty is determinism and the highest level will be deep uncertainty. Three potential causes underlie these uncertainties; stochastic, ambiguity and epistemic natures. Ambiguity represents the different views that people may have looked at a model or variable. Because people have their own interpretations, uncertainty arises in the actual definition chosen. Epistemic nature occurs due to lack of knowledge, for example: limited and inaccurate data, measurement error and incomplete knowledge. Measurement error is interpreted as the definition used by Longley et al. (2015): a measurement error occurs due to the fact that different researchers or observers will generate unique data. Because each instrument has different classifications and objectives, the instrument used by the observer also affects the information gathered. Stochastic nature is the randomness originating from external input data, functions, parameters, and model structures. The stochastic nature could be explained by variability, that is discussed in Section 4.2.

To make the concepts clearer, figure 4.2 has been created in which these three dimensions are represented. These figure forms the basis of the classifications of uncertainties in this research. The levels are listed below the types and nature of uncertainties. Where 'determinism' means that there is no uncertainty, 'statistical' means that possible outcomes are known and the probabilities of these outcomes can be described statistically, 'scenario' means that probabilities can be described as 'statistical means' but possible outcomes have to be estimated, 'deep uncertainty' means that not all probabilities of the outcomes are known and the outcomes cannot all be estimated. These levels are also described by (Daniel & Daniel, 2018), however the names are different; 'determinism' is called deterministic certainty where an action will lead to a unique consequence, 'statistical' is called probabilistic certainty where an action will lead to a set of known probabilities of occurrence, 'scenario' is called stable uncertainty where there is a lower degree of knowledge of the relationship of an action and its consequence and 'deep uncertainty' is called 'unstable uncertainty'.

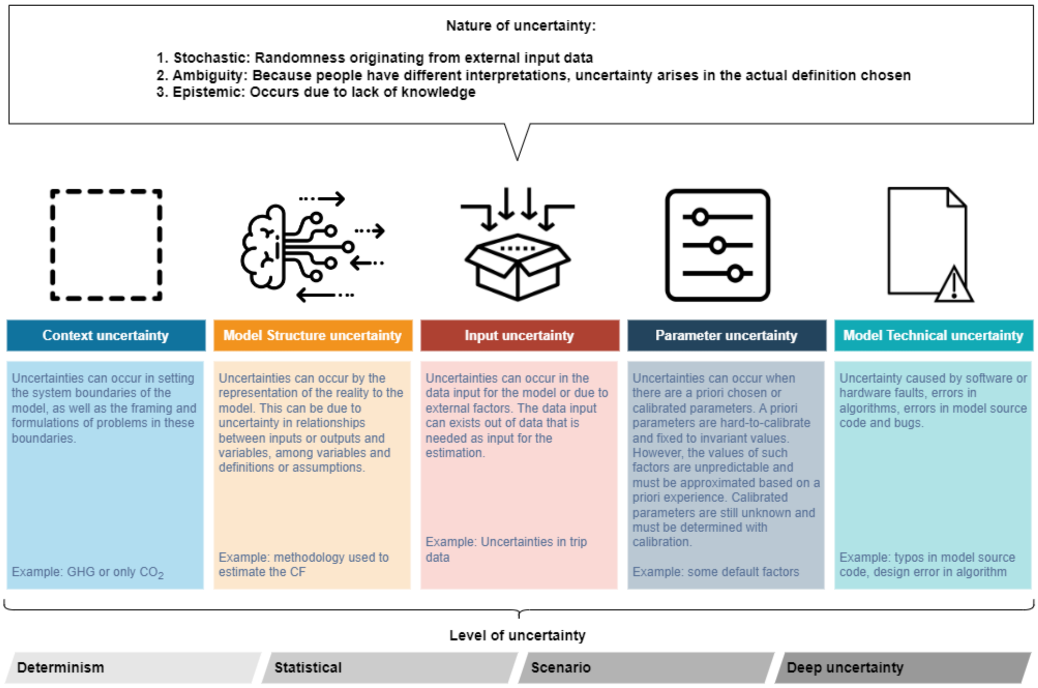


Figure 4.2: Classification framework uncertainties

Synthesis for classification framework and uncertainties within a Carbon Footprint measurement

Because different terms are used for the classifications in the previous section and the uncertainties within a carbon footprint calculation it is important to see if a synthesis is possible. The description of parameter uncertainty in the LCA studies seems to be divisible into input uncertainty and parameter uncertainty shown in Figure 4.2. The definition of scenario uncertainty seems to correspond to context uncertainty. Thereby, model uncertainty seems to correspond to model structure uncertainty.

4.5. Uncertainty analysis

Uncertainty analyses are conducted to identify and assess the impact of uncertainties. These analyses of uncertainty are conducted in numerous domains. For instance, it is used in the analysis of chemical processes, environmental concerns, and economic developments. Despite the fact that these uncertainty analyses are applied in various fields, the ”main steps” of this analysis are essentially the same. The steps of the uncertainty analysis used in Warmink et al. (2010), Committee et al. (2018) and Traple et al. (2014) are combined into the five steps below.

1. Specification of measurand.
2. Identify and classify uncertainties.
3. Importance assessment.
4. Quantification of sources uncertainty.
5. Propagation of sources of uncertainty.
6. Communication of analysis.

The first step involves elucidating the measurement process. It is necessary to describe the process and the steps required to achieve the desired outcome. Consequently, it is essential that it is evident which inputs lead to which outcomes and what the relationship between variables is. In essence, this step defines the variables being measured and establishes the connection between the input quantities and the final result. Step two must be carried out after this. This is the process of identifying uncertainties. This step generates a list of potential sources of uncertainty. Van der Keur et al. (2008) stated that uncertainty identification is a qualitative process involving expert opinion, literature review, brainstorming sessions, group discussions, and stakeholder interviews. However, numerous methods for identifying uncertainties have also been identified in other publications. The Delphi Method is a technique for gathering the information and opinions of a group of experts on a specific topic (Melander, 2018); for an uncertainty analysis, the topic will be the possible measurement uncertainties. Once the uncertainties have been identified, they can be categorized into various categories. These types are elaborated in Section 4.4. Step three involves identifying the most significant uncertainties. This can be accomplished, for instance, through sensitivity analysis or expert interviews. Based on this, the most significant uncertainties can be prioritized. The fourth step involves quantification of uncertainties. In this case, estimates must be made regarding the various sources of uncertainty. Collecting data, performing calculations, or using statistical methods may be necessary steps in this process. The fifth step is to examine how uncertainties affect the final output; there are several methods for this. The sixth step is communicating the results of the analysis.

4.6. Methods to assess uncertainty

4.6.1. Uncertainty analysis

Uncertainty analysis consists of the quantification and propagation of uncertainties. Quantification involves determining the uncertainties of the input factors. Propagation involves looking at how all these factors affect the model's outcome. The Intergovernmental Panel on Climate Change (IPCC) is an organization that makes scientific assessments on climate change and writes reports on it. They also describe how to deal with uncertainties in emission inventories. They describe two methods for propagation, monte carlo simulation, and simple error propagation. These output of these methods is typically a range of possible values for the estimated emissions or removals, along with an indication of the likelihood or confidence associated with those values.

For monte carlo simulation, the uncertainties of input factors must be defined as probability distributions. Uncertainty quantification may be conducted in a variety of methods, computing the uncertainty distribution based on empirical data, expert judgement to generate estimates, or by characterizing the data using quality indicators (Weidema & Wesnæs, 1996). There are five distribution functions that are commonly used; the normal, lognormal, uniform distribution, triangular and fractal distributions. The (Frey et al., 2006) describes in which situations a particular distribution can be chosen. The normal distribution can be chosen when the range of uncertainties is narrow; the lognormal distribution can be chosen when there is non-negative uncertainty and when the uncertainty is larger. The uniform distribution can be chosen when the uncertainty is physically bounded between a lower and upper bound (or by expert judgment). The triangular distribution can be chosen when there is an upper bound, a lower bound, and a preferred value. When there is an empirical distribution in which the relative probabilities of different ranges of values for a variable are calculated, a fractal distribution can be used. When the parameters are specified by a probability distribution, the computation of the output factor is performed several times, with a random parameter value from the probability distribution being used each time. The results of a Monte Carlo (MC) simulation consist of a number of potential outcomes of the computation, so providing a representation of the likelihood of distinct possibilities based on the uncertainty and fluctuation of the input data (Röös et al., 2010). This involves the expected values and standard deviations of the model outputs based on the probability distributions of the inputs and parameters (Kroese et al., 2007).The challenges of this method are that finding probability distributions that characterize the input data can be time-consuming and difficult. Available data rarely occur in the quantities and form needed, to do classical statistical analysis. As a result, expert judgment is often required to determine probability distributions and their parameters. Besides that, correlations between parameters must also be taken into consideration while doing MC simulations, since failure to do so might lead to an overestimation of uncertainty in the final findings (Bojaca & Schrevens, 2010).

Simple error propagation requires estimates of the mean and standard deviation of each input, as well as the equation through which all inputs are combined (Frey et al., 2006). If estimates are derived from models, the uncertainty associated with the activity data and model parameters must be entered, and expert judgement or error propagation calculations may be necessary to separate the uncertainty estimate (Marland et al., 2014). The approach assumes that the relative ranges of uncertainty in the emission and activity factors are the same in the base year and in year t, and that the standard deviation divided by the mean value is theoretically less than 0.3 (Frey et al., 2006). Once the uncertainties in the categories have been determined, they can be combined to provide uncertainty estimates for the entire inventory in any year and the uncertainty in the overall inventory trend over time.

4.6.2. Scenario analysis

Scenario analysis is usually used to determine how future events affect a result. These future events are uncertainties. By looking at how they affect the outcome, it is possible to get a grip on possible outcomes in the future. Frequently, a theoretical best-case scenario and worst-case scenario are used to determine the range of possible outcomes (Balaman, 2019). In addition, Röös & Nylinder (2013) discusses that scenario analysis can be used not only for future situations but also as a kind of sensitivity analysis for model assumptions. Examples mentioned are allocation methods, system boundaries, allocation methods, and data choices. Scenario analysis can be used to test how these choices affect the result.

4.6.3. Sensitivity analysis

Sensitivity Analysis (SA) is a technique that measures the effect of uncertainty on one or more input variables on output variables (Pichery, 2014). There are several methods to perform a sensitivity analysis. The first method is the one-at-a-time sensitivity analysis, which is conceptually the simplest method. A sensitivity ranking may be achieved rapidly by changing each parameter by a fixed percentage while holding the others constant and measuring the change in model output (Hamby, 1994). This type of analysis is called 'local sensitivity analysis'. The most significant disadvantage of sensitivity analysis is that system variables are often interrelated, thus modifying one of the elements would likely influence the others. Assigning an optimistic or pessimistic value to the parameter also relies on the subjective interpretation of the decision maker, which may negatively impact the objectivity and, therefore, the precision and dependability of the study (Balaman, 2019). To make this 'simple' analysis more power full, the parameters can be evaluated by the standard deviation around the mean value (Hamby, 1994). Factorial design is another type of one-at-a-time analysis (Hamby (1994), Hunter et al. (1978)). Within this method a number of samples of each parameter are combined with each other. Factorial sensitivity analysis is a global sensitivity analysis since it entails systematically altering all input parameters throughout a range of values, as opposed to merely examining the output's sensitivity to a single parameter or set of parameters. By analysing the impact of all possible combinations of input parameters, factorial sensitivity analysis provides a comprehensive evaluation of the model's sensitivity and can aid in the identification of the most significant input parameters and their interactions. The sensitivity index is another method to calculate the sensitivity. Hoffman & Miller (1983) advocate varying each parameter by its maximum and minimum allowable values and then observing the effect on the model's output in relative terms. The remaining variables remain unchanged. Using actual minimum and maximum values for input parameters as opposed to arbitrary percentage values provides a more accurate depiction of the model's sensitivity. This is also known as uncertainty importance analysis (Röös & Nylinder, 2013).

4.6.4. Choosing the right method to quantify uncertainty

In this section, three different methods for evaluating uncertainties have been discussed, each with their own advantages, disadvantages, and intended purposes. Maier et al. (2021) has published a paper that discusses the relationship between these methods and identifies which method is best suited for different situations. The suitability is determined according to two characteristics: the desired outcome and whether uncertainties occur in the input of the model or not. This paper focuses primarily on scenario analysis from the perspective of representing possible future scenarios. However, as discussed in section 4.6.2, scenario analysis can also be used for other purposes, namely it also can be used as a kind of sensitivity analysis for model assumptions.

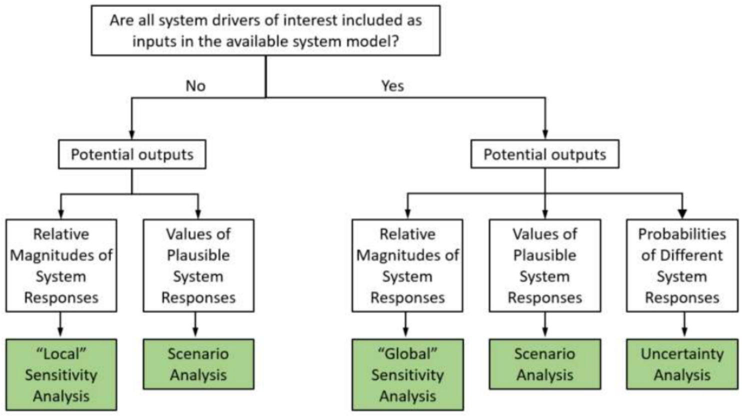


Figure 4.3: Guidance framework suitability of methods Maier et al. (2021)

4.7. Conclusion uncertainties

This research aims to design a tool to determine the uncertainty of a carbon footprint measurement of freight transportation. The previous chapter determined the scope of the carbon footprint of freight transport. This chapter looked at the different types of uncertainties in the literature. It also looked at how a general uncertainty analysis is performed. The steps for this analysis can be of great importance in this research because these steps can help design the tool. The first step is to identify the uncertainties that arise in a carbon footprint of freight. Using the theoretical framework presented in Figure 4.2, uncertainties can be investigated in a structured manner. During the identification phase, attention will be focused on the five locations where uncertainty can arise. Additionally, it is now known that the cause of uncertainty can be attributed to ambiguity, which represents the different views that people may have when looking at a model or variable, epistemic uncertainty, which occurs due to lack of knowledge such as limited and inaccurate data, measurement error and incomplete knowledge, and stochastic uncertainty, which arises from the randomness originating from external input data, functions, parameters, and model structures. By employing these two dimensions, the uncertainties of freight transport can be identified through reflection on the background research on the carbon footprint of freight transport, observing a project that measures carbon footprint to gain practical knowledge and insight into the complexity of the subject that may not be known in the literature. Additionally, interviews are conducted to uncover other uncertainties. The next steps involve determining the most significant uncertainties and attempting to quantify their effects to provide a tool that clarifies not only the carbon footprint, but also the uncertainty.

5 Insights of the uncertainties in a Carbon Footprint measurement

The previous chapters were part of the research phase. This means that all relevant background research has been done. First, the term ”carbon footprint” is researched and how this scope is defined in this research. Then the topic of uncertainty was examined, a framework was chosen that determines how this research defines uncertainties. This chapter represents the insight phase, meaning that insights are created based on the information gathered. The insights provide insight into the uncertainties that arise in a carbon footprint measurement. The uncertainties have been identified based on the framework drawn up in chapter 4. Various data inputs were used for this: interviews, field research, and literature.

Research questions to be answered in this chapter:

- RQ5 *What types of uncertainties can be identified from the literature and practice and how can they affect carbon footprint mapping?*

5.1. Method to identify uncertainties

Identification of uncertainties in the carbon footprint of freight transport involves a structured approach that incorporates several research methods. The theoretical framework that is discussed in the previous chapter outlines the five locations and causes of uncertainties and is a significant input for this approach and enables a targeted search for potential uncertainties in the various components of the carbon footprint calculation. To identify uncertainties in the carbon footprint of freight transport, a reflection of the background research is done. Subsequently, interviews are conducted with experts in carbon footprinting of freight transport. During the interviews, the most significant uncertainties and challenges in the carbon footprint of freight transport are identified. Furthermore, field research is conducted to measure and analyze the carbon footprint of freight transport in practice. By combining these various research methods, a comprehensive understanding of the complexity of the subject is obtained, and the most significant uncertainties in the carbon footprint of freight transport are identified. The approach is visible in Figure 5.1.

Interviews: the first input consists of three interviews with experts in the field of carbon footprint measurements of freight. The interviews are available in Appendix A. Semi-structured interviews were conducted. This means that a few questions were the same for each respondent, but follow-up questions were created based on each respondent's responses in order to get to the heart of the answer. In addition, the responses were compared to determine which uncertainties were named multiple times and which uncertainties were not mentioned as frequently.

Field research: The second data input is knowledge gained from field research, which includes participating in a project of Districon to calculate the carbon footprint of freight transport to a construction site. During the field research, insights were gained through site visits, interviews with co-makers (subcontractors), review of provided data, and project-related meetings. This is elaborated upon in Appendix

D. Field research is an important methodology in studying and understanding real-world phenomena. In the context of carbon footprinting, it can provide valuable insights into the actual operations and practices of the transport and logistics industry. This is particularly important because the accuracy of carbon footprint calculations relies heavily on the quality of the data used, and field research can help to verify and validate the data collected through other sources.

Background study: the third data input is the discussed literature from the Research phase. To identify uncertainties in the carbon footprint of freight transport, this background research is conducted initially. This background study examines relevant studies, reports, and norms related to the carbon footprint of freight transport. The results of the background research served also as an input for this phase. Uncertainties can be identified by examining the literature on freight transport emissions and then examining the theory, its critiques, and its applications.

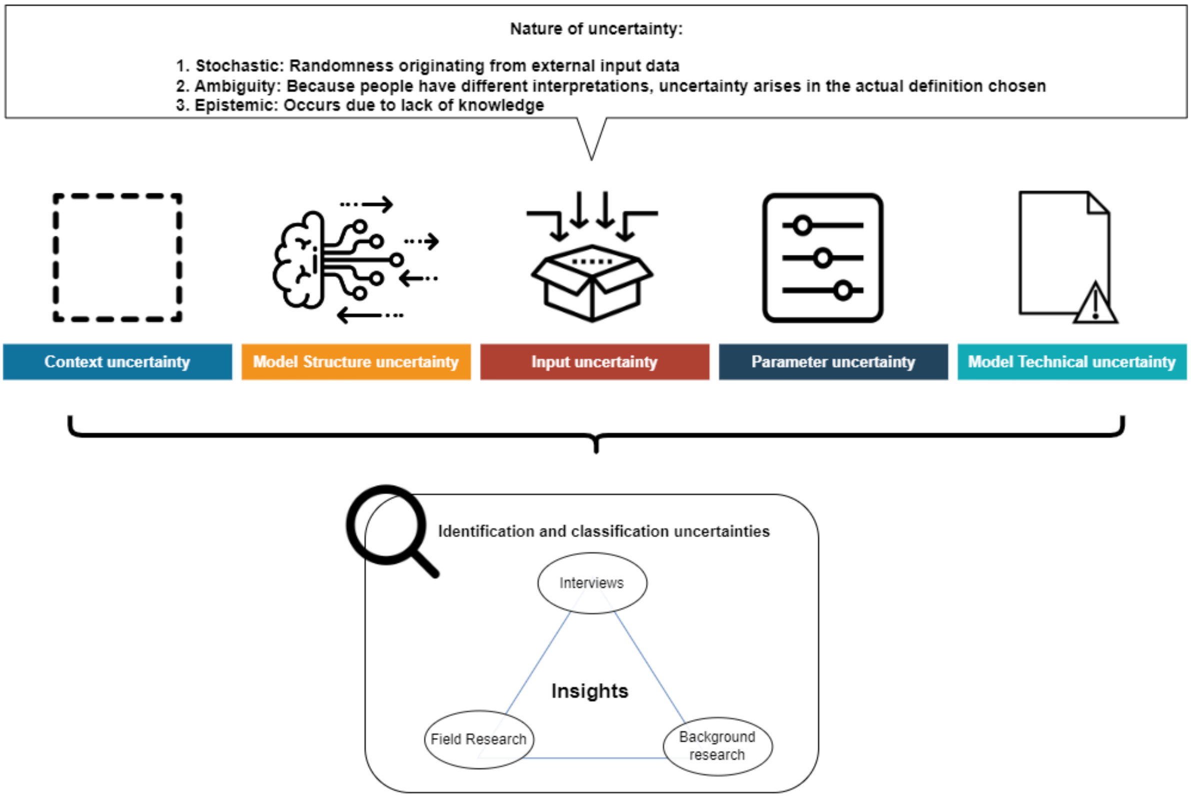
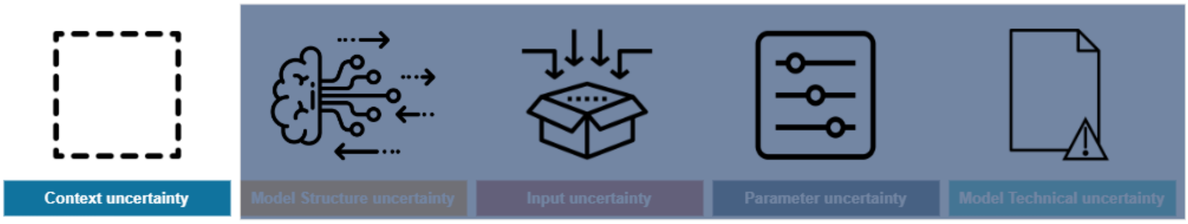


Figure 5.1: Approach to identify uncertainties



5.2. Uncertainties found in the Context

The first location where potential uncertainties arise is the scope of the context. This stage involves determining exactly what will be measured. When the context is unclear, the first uncertainties can arise; these uncertainties can then spill over into data collection and even the incorrect application of a calculation method. To identify potential uncertainties in this phase of the project, factors influencing the context and scope determination of a carbon footprint measurement were examined, as well as how this works in practice. These findings are summarized in Table Y, which further classifies the uncertainties. In addition to the location where the uncertainty occurs, the nature of the uncertainty is assigned and the level of uncertainty is appropriated. Using a 'level of uncertainty' approach to classify uncertainty on a scale ranging from 'complete certainty' to 'total lack of knowledge'. The 'nature of uncertainty' distinguishes whether uncertainty arises mainly from inherent variability within a system or from a lack of knowledge or ambiguity.

Definition of carbon footprint - Data input: *Literature and interviews*
The scope of the context starts with the definition of the carbon footprint. It is already indicated from the literature (Matuštík & Kočí (2021); Pandey et al. (2011); Wiedmann & Minx (2008); Wright et al. (2011)) that this definition is not always clear, as discussed in chapter 3. This was confirmed in the interviews conducted with experts: "Carbon footprint for me is CO2, we are also working on nitrogen emissions and PM10 and PM 2.5 but I don't see that as carbon footprint" - Expert BigMile, "If I had to define it, I would say, it is about all greenhouse gas emissions. From either a company, a product or a service." "With NOX, Black metal and hydrogen, it is often still under discussion whether or not to include these in the Carbon Footprint" - Expert CEDelft, "A carbon footprint is the creation of an emissions profile of certain business processes. In a literal sense, it is the number of CO_2 equivalents emitted." - Expert Districon. From these quotes, it can be seen that two experts give the same kind of answer, and one only discusses CO_2. The expert of CE Delft additionally names three other emissions that are often under discussion. *Consequences of this uncertainty:* incomplete data may be requested when it is unclear what is being investigated. An example is HCFs, a substance that falls under 'green house gases' but not CO_2. When refrigerated transport is used, a separate calculation is needed for the number of CO_2 equivalents to be included in the carbon footprint if the scope is to cover all green house gases.

Boundary freight movements - Data input: *Literature, interviews and field research*
In addition, it is essential to be clear about exactly what one wants to map. The carbon footprint of freight can be enormously broad, so it must be clearly stated what is to be mapped in the chain. This could include transshipment and storage, international freight, all modes of transport or just one. Districon's expert also outlines this importance: "The carbon footprint depends on how broadly you draw the scope. So is it only about the transport a company performs alone or is it also about the transport a company causes. And is it about the emissions from also producing the vehicle or just the activity?". In addition, in the current theory (EN16258), the scope of the calculation is called the Vehicle Operating System (VOS). However, it is unclear how it should be described; this point is also criticized in the literature because this can result in ambiguity (Ehrler & Seidel, 2014; Wild, 2021). This results in a possible cause for uncertainty. When the scope is unclear, the wrong thing can be calculated, and the wrong information requested. This uncertainty was also reflected in practice during the field study.

This uncertainty occurred at several points in the project. It first became apparent when cross-validation was observed on the construction site. Cross-validation was used to see if the data provided by the co-makers matched what was seen in practice. During cross-validation, truck drivers were asked what the origin of the shipment was and whether this was the endpoint of the shipment. However, the ”origin” seemed not well defined beforehand. During cross-validation, truck drivers were asked about the shipment’s origin and whether this was the final destination. In practise, some truck drivers provided the shipping document’s address, which did not always indicate the shipment’s origin, while others provided the shipment’s intended pickup location. However when truck drivers were asked, ”Where are you coming from?” other answers emerged. After some questioning of drivers, it was found that there were mainly six options in terms of transportation movements to the construction site. These options are shown in Figure 5.2. This prompted the following discussion: what is considered as ”freight movement to and from the construction site? And what do we see as ’origin and ’destination?”. Since the goal is to calculate the carbon footprint of freight transport to and from a construction site, it would be incomplete when the movement from the holding place of the truck to the supplier is not included since this is already part of the movement to the construction site. When requesting data from the co-makers, it was also found that the definition of origins, destinations, and stops could be unclear in the beginning. For example, CO-maker X said in an interview, ”The scope and purpose of the carbon footprint must be clear from the beginning; otherwise, we are comparing apples to oranges. So do you include or exclude the drive to the distribution center?”. *Consequences of this uncertainty:* These findings show that when the project’s scope is not clearly defined beforehand, there is ambiguity regarding the boundaries of freight movements. This can cause confusion regarding whether ”origin” refers to the origin of the freight movement or the shipment’s origin. If it is not specified in the data request, a different type of carbon footprint may be calculated. This creates uncertainty regarding the actual number and whether or not the numbers can be compared.

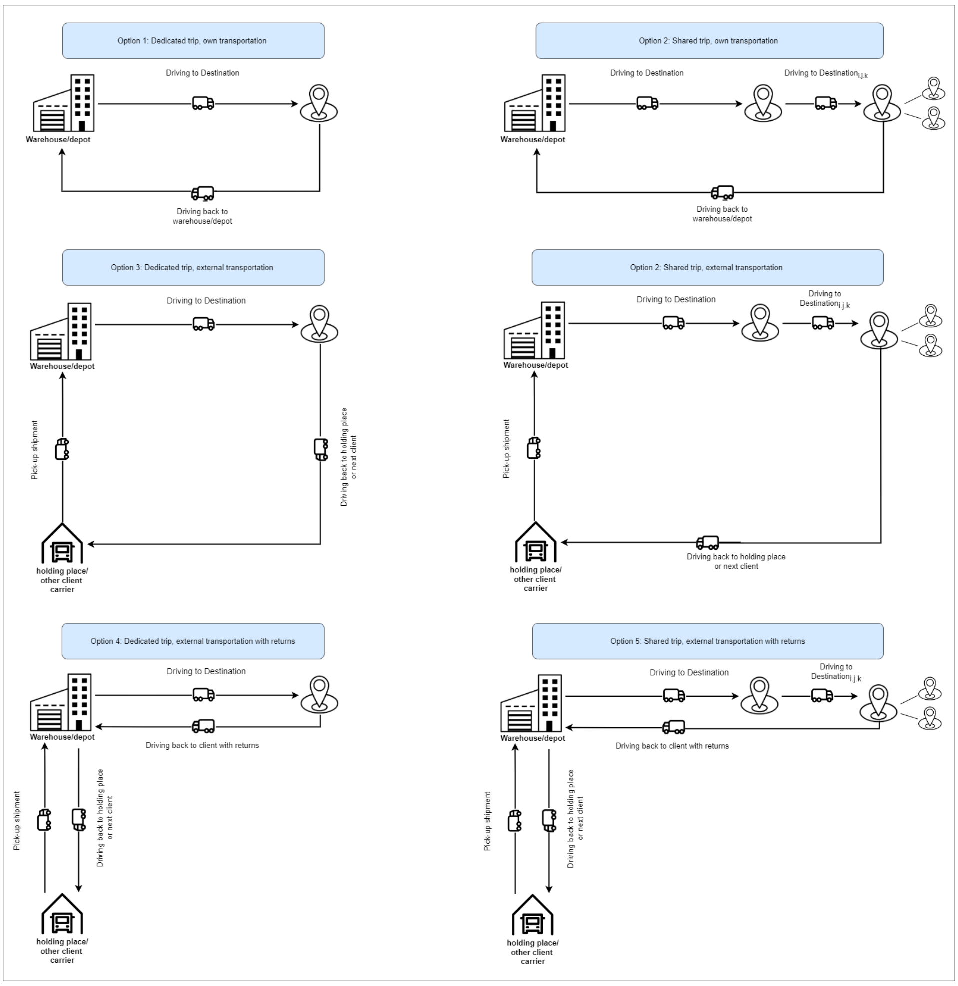
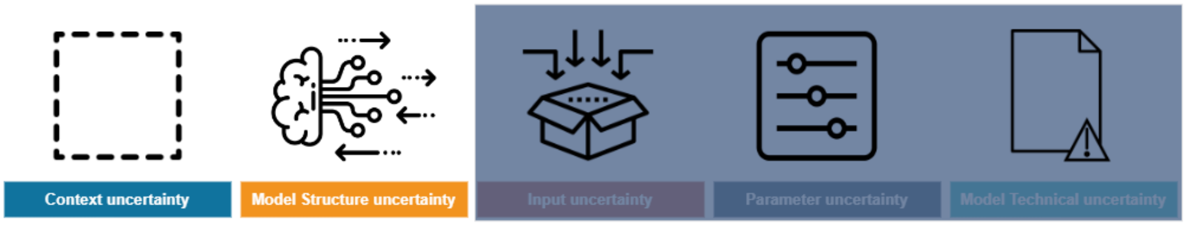


Figure 5.2: Possible routes to building site

Table 5.1: Context uncertainty, classification

Context			
Cause of uncertainty	**Explanation**	**Nature**	**Level**
Definition of carbon footprint	There are different interpretations of a 'carbon footprint', other interpretations can lead to another scope and leads to including or excluding emissions in the measurement.	Ambiguity	Scenario
Boundary carbon footprint of transportation	There are different system boundaries that can be defined for a carbon footprint of freight, for example: taking all the transport elements in the chain or only between two segments. Or including empty trips or not. When these boundaries are not clear, different interpretations can arise.	Ambiguity	Scenario



5.3. Uncertainties found in the Model Structure

The second potential source ('location') of uncertainty that will be discussed is uncertainty within the model's structure. Uncertainties in the model structure can occur by the representation of the reality to the model. This can be due to uncertainty in relationships between inputs or outputs and variables, among variables and definitions or assumptions. The calculation methods behind most tools/models to map a carbon footprint of freight transport are based on the EN16258 method. Although more and more tools also base themselves on the GLEC Framework because the future ISO sees this as the basis. To identify uncertainties arising from assumptions of reality, the interrelationships between factors in the calculation method were examined to determine which relationships were excluded.

Linear relationship CH_4 and N_2O with fuel consumption - Data input: *Literature and protocol*
It was found in the literature that the relationship between nitrous oxide (N_2O) and methane (CH_4) is not linear with fuel consumption (Lipman & Delucchi, 2002; Rodriguez & Dornoff, 2019). As the effect from the catalyst is not incorporated in the carbon footprint calculation, due to the linear effect of energy consumption and emission factor, this means that the amount of CH_4 and N_2O might be underestimated.

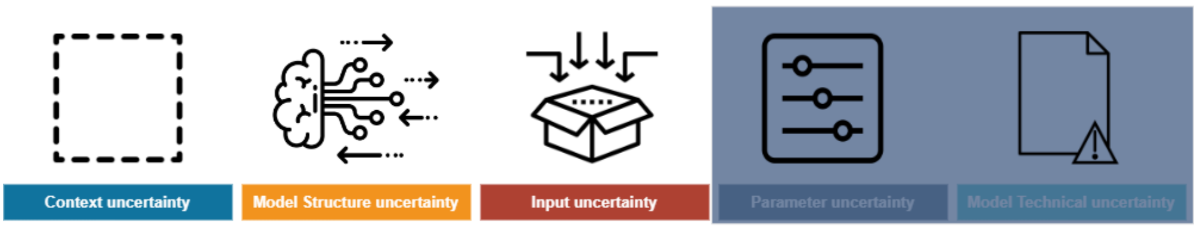
Different allocation methods - Data input: *Literature, protocol and interviews*
Moreover, there is uncertainty in the allocation method. Multiple allocation methods have been tested (Davydenko et al., 2014; Lewis et al., 2016; Kirschstein et al., 2022; Wild, 2021). In reality, when a truck drives a certain route, emissions are generated, and the sequence of stops determines the amount of fuel consumed to reach a particular customer. To prevent, for example, the direction of the route from affecting the emissions of a shipment to a customer, an allocation method is used to distribute the emissions of the entire route as fairly as possible. This means that the allocation method does not affect the total emissions, but only the distribution of emissions among customers. The uncertainty arises from the fact that there are different ways to apply the allocation method. Currently (according to the EN16258 standard), an allocation method must be chosen that represents the 'limiting factor' of the cargo in combination with the distance. There is much discussion about the limiting factor of a shipment, as it can have different meanings and can be misapplied. Therefore, recent studies recommend using the ton-km allocation method, where the distance used represents the great-circle distance. When there is no such standard or regulation in place, uncertainty can persist due to differences in interpretation and the definition of the limiting factor. Therefore, it is important to document the allocation

method used and any assumptions made, and to quantify the uncertainty associated with the allocation method. This is also confirmed in an interview with the expert from CE Delft: "if you're talking about services, then it's very important to allocate in a certain way. There are still many possibilities to allocate in different ways. One tool does it based on great-circle distance, while other parties do it based on the shortest feasible distance, and these kinds of things do lead to significant differences. In addition, there is often a discussion about whether to combine these distances with the load in tons, based on volume, or based on packages.". In essence, allocation methods are essential for assigning emissions fairly to each customer in a freight transport route. The choice of allocation method can significantly impact the distribution of emissions among customers, though the total emissions remain unchanged. It is crucial to understand that the varying interpretations and definitions of the limiting factor contribute to the uncertainty in allocation methods. By clearly documenting the chosen method, its assumptions, and the associated uncertainty, transparency and comparability between different studies and assessments can be promoted. Ultimately, a widely accepted and standardized allocation method, such as the ton-km method with great-circle distance, which is favored by the future ISO standard, could help reduce this uncertainty and improve the consistency of emissions reporting in the freight transport sector. However, it is important to note that even this future ISO standard may have exceptions, which underscores the need for continuous improvement and refinement of allocation methods in the industry.

Assumptions and different approaches in calculating emissions - Data input: *Literature, protocol and interviews*
The carbon footprint calculations are based on the amount of data and information available. When data is missing there are options to reconstruct the data as best as possible to make an accurate estimation. Due to these certain assumptions, certain factors cannot be included 100%. This creates uncertainty because the chosen model or method mimics part of reality, and cannot include everything.

Table 5.2: Model structure uncertainty, classification

Model structure			
Cause of uncertainty	**Explanation**	**Nature**	**Level**
Different allocation methods	There are multiple options to allocate emissions, the method that is used has a big influence on the carbon footprint of a shipment of the customer. In literature, multiple methods are discussed (see Subsection 3.7.2). The EN16258 standard recommends ton-km with GCD, STD, or ADD depending on the trip type, the new ISO standard recommends allocation by the ton-great circle distance or ton-shortest feasible distances. However, there are some exceptions to replace ton with another unit.	Ambiguity	Scenario
Lineair approach calculating emissions	In literature, it was found that the emissions N_2O and CH_4 have not exactly a linear relationship with energy use as CO_2. This is a simplification of the model.	Epistemic	Scenario
Assumptions and different approaches in calculating emissions	Based on the amount of information available on energy consumption and transport activities, other approaches exist to calculate the carbon footprint of a shipment.	Epistemic	Scenario



5.4. Uncertainties found in the Input

The third potential source ('location') of uncertainty that will be discussed is uncertainty within the model's input data. There may be uncertainties in the data used as input for the model or due to external factors. The data input can consist of information that is necessary for estimating the results. Multiple inputs are needed to create a carbon footprint of freight transportation. Depending on the availability and detail level of information, certain inputs are required. All data inputs required are discussed below. These inputs can have multiple types of uncertainties.

Energy type - Data input: *Field research*
To calculate the carbon footprint based on kWh or number of liters of fuel requires knowledge of the energy type. Using this information, the appropriate emission factor is selected to arrive at CO_2 equivalents. In practice, several uncertainties for this have been found: the fuel type is unknown or the fuel type has not been made specific. When the *fuel type is unknown* but the license plate type is known, the fuel type can be looked up on sites such as 'rdw kentekencheck'. However, one then ends up with the second type of uncertainty: these types of websites do not distinguish between, for example, HVO-100 or B7 diesel. These emission factors are quite different, so the effect of this uncertainty can be large (Rijkswaterstaat, 2022). This also applies to electricity. There are differences in the emission factors for "unknown" power, green power, gray power or biomass. So details of the energy type are also important when electric cars are used. For electric energy, an additional unknown is the 'energy mix', i.e., the mix of fossil, bio, renewable, and nuclear fuels. The uncertainty is further increased by the international nature of the electricity market. Gray energy refers to all electricity generated from non-renewable sources, such as fossil fuels, nuclear energy, and others. The emission factor is determined by this energy mix. Emission factors for "unknown" power are influenced by the total energy mix.

Distance - Data input: *Field research and background research*
When the amount of fuel in liters or kWh consumed by a vehicle during a trip is unknown, an estimation is often performed using the average fuel consumption per kilometer or ton kilometer and therefore the distance of the trip is needed. However, uncertainty can arise in the definition of distance or due to the absence of data. These are discussed separately, along with their effects. There are five *different meanings of distance*: the first is great-circle distance, the second is planned distance, the third is shortest feasible distance, the fourth is actual driven distance, and the fifth is network distance. This uncertainty was clearly visible in the field research, as it was observed that companies saw the planned distance as the actual driven distance, but also constructed routes themselves using Google Maps and reported these as the actual driven routes. This was discovered by critically examining the provided data and asking specific questions about the distance. Thereby uncertainty can arise when these distances are assumed to be equal. For example, if the average fuel consumption is calculated using the number of liters and the total planned distance, and then multiplied by the number of kilometers actually driven, an incorrect calculation is made. In addition, it is questionable whether the carbon footprint can be compared when different distances are used. When calculating emissions for an entire route, it is most realistic to use the actual driven distance, as it includes detours. When *distance is unknown*, an estimation must also be made, for which Google Maps can be used, which requires input of address data. If shortest feasible distance is interpreted as shortest time to drive from A to B then this approach is a form of the shortest feasible. However, when shortest feasible distance is seen as shortest distance in kilometers this approximation is not representative with the shortest feasible distance (Davydenko et al., 2021). So the question is whether reconstructing routes in Google Maps falls within the 'range' of five defined distances, or whether this actually involves another type of distance. Another aspect that should be considered is the concept of 'consolidation distance', which refers to the shared transportation of goods with different origins and destinations. In this case, the goods are transported together, resulting in a relatively longer distance due to detours. However, this disadvantage can be partly or entirely offset by the fact that separate trips do not need to be made (e.g., no empty positioning trips are required). This is often dependent on the **Shipment type** and will be discussed further in that piece.

Amount of energy - Data input: *Interviews*
The amount of energy transmitted per trip or used to calculate average energy consumption per km/ton-km/unit-km can also contain uncertainty depending on the measurement method. The total amount of energy can be measured using the latest on-board computers; here, energy consumption is accurately tracked through in-car systems, or it is measured using data on fuel cards. The uncertainty lies in the use of data from fuel cards. If the average energy consumption for the month of January is calculated and the number of liters used that were refueled in January then it is possible that some of this energy is used in February; these kilometers are then not included in the calculation. This results in a measurement uncertainty. This uncertainty was discovered during an interview with an expert: "When reading data from a fuel card, it may happen that if you refuel on the 31st, the number of liters is recorded in a

month in which you did not actually consume those liters. This overlap decreases when you look at a higher level of detail".

Average fuel consumption "delivered" - Data input: *Background research*
The perfect information would be if the fuel consumption of the trip is available. When this information is not available, averages are used. One of the uncertainties of provided averages is the uncertainty about how it was calculated. This has already been briefly discussed in **Amount of energy**, but it also applies to the denominator it is divided by. Namely, it is divided by great circle distance, actual driven distance, or planned distance. One uncertainty is that the average fuel consumption per ton kilometer (CPI) is provided, but the method used to calculate this is unknown. Interpretation of the CPI may vary, which might lead to uncertainty in its use, particularly with respect to differing definitions of payload and distance. This is discussed under the headings **Payload** and **Distance**. Additionally, uncertainty in the representatives of the CPI arises due to its use of an average value, which may not accurately reflect specific delivery scenarios due to differences in route characteristics, driving behavior, environmental influences, and vehicle characteristics. Similarly, the average fuel consumption per vehicle-km may also be affected by payload, but this effect is dampened by averaging over multiple deliveries. In situations where the average fuel consumption is unknown, default factors based on industry averages for specific vehicle types can be utilized. However, this method introduces its own level of uncertainty, as it involves the selection of an industry average for a specific vehicle type, which is discussed in detail under the section labeled **Vehicle type**. Thereby this average does not account for route characteristics, driving behavior, environmental influences, payload, and vehicle characteristics of the carrier. A more specific estimation of fuel consumption can be achieved by modeling the fuel consumption using established models that incorporate standard values, such as payload, to calculate the fuel consumption. The Lean and Green program and the BigMile tool differentiate between levels of aggregation and the accuracy of data. The more aggregated the data, the less accurate the figure is, which means that the actual situation is less accurately reflected. This also applies to whether the data is available at the vehicle level or the fleet level. The less representative the average is for the situation, the more uncertainty this creates. To illustrate visually what the use of averages means for the actual situation, Appendix D shows which factors are obscured by the use of averages and default factors.

Discussion point of the use of average fuel consumption and aggregation level:
A dilemma and point of discussion herein is whether variation in the carbon footprint, due to for example, bad driving behaviour, seasonal variations or a high road gradient on one trip should be passed on to the specific customer(s) of that trip. The GLEC framework advocates that with aggregating the emissions of one year and allocate these emission will even out 'seasonal variations' and outlying values (SFC, 2020). However, one might argue that for example a factor as driving behavior is generally not attributable to a particular customer, road gradient and customer location can be location and customer-specific. For example, customers located in busy areas, such as city centers, might cause more emissions due to increased congestion, while those on the outskirts of a city might contribute less. These insights or options to differentiate are limited when emissions are calculated and allocated on annual basis. This is also still a point of discussion in the literature, this was also discussed in section 3.10 and 3.9.1 because it is a fact that a lower level of aggregation does allow for more detailed insights.

Vehicle type - Data input: *Field research and interviews*
The type of vehicle used to transport goods is important to know when there is no average fuel consumption available from the transporter or shipper. In such cases, an estimate needs to be made regarding the fuel consumption of a vehicle. Alternatively, a default emission factor may be selected based on the type of vehicle. Uncertainty arises in the classification of vehicles into specific categories. Misclassification of a vehicle leads to the selection of an incorrect energy consumption or emission factor. During the field research and site visits, it was observed that there are many different types of trucks and delivery vans coming to the construction site. One truck, for example, has a grab arm, while another does not. As a result, the classification of such vehicles was found to be quite difficult. In addition, trucks with different weights have different average fuel consumption, which further adds to uncertainties in defining the same vehicle class. This was also confirmed in an interview with an expert, who stated that "For example, when talking about smaller trucks, you already notice that the

definition of that truck becomes difficult".

Shipment type - Data input: *Background research*
Another source of uncertainty arises when the *shipment type is unknown*, meaning it is unclear whether the type of goods being transported falls into the 'bulk', 'average', or 'volume' goods category. Moreover, there is *room for interpretation*, which may lead to the incorrect selection of goods type. This uncertainty affects the choice of emission intensity factors. The type of goods determines assumptions about the amount of empty running of the vehicle and its occupancy, as discussed in Subsection 3.9. Schmied & Knörr (2012) provides an example that a characteristic of heavy bulk transport is that the weight of the transport is often a limiting factor, resulting in trips being nearly 100% loaded in terms of maximum weight capacity. However, these trips are almost always dedicated (not shared) and have a high percentage of empty trip kilometers. This differs from volume and general goods, where the limiting factor is often not weight but volume, with a weight-related occupancy rate of around 30 to 40%. However, these trips are often shared, and the proportion of empty trip kilometers is lower. Therefore, when it is unknown or incorrectly determined which category a shipment falls into, this can have a significant impact on the emission intensity factor.

Amount of trips - Data input: *Field research*
Another source of uncertainty that was observed is the number of trips that were made. During the field research, it was found several times that some trips that were made were not reported, this is a reporting omission. This was verified with delivery notes that were provided at the construction site and the reported data. This results in an unrealistic picture of the total emissions because a part of it is not taken into account.

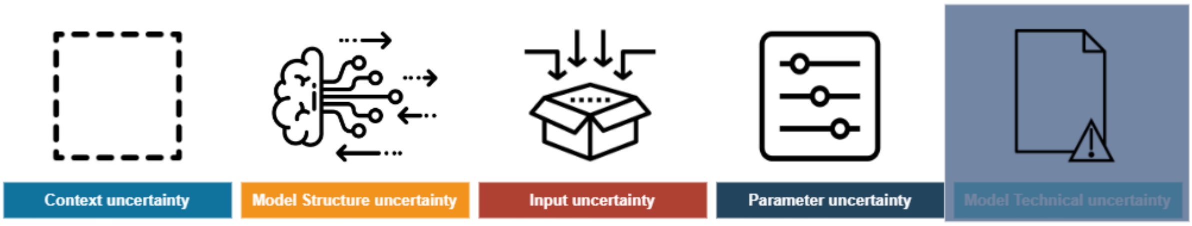
Origin, stops and destinations - Data input: *Field research, background research and interviews*
The origin, stops, and destinations are important for various reasons in calculating the carbon footprint. For instance, in the absence of distance, these data are required to reconstruct the route to calculate the total emissions of the route. Furthermore, these data are important in calculating the allocation based on the great-circle distance. Additionally, misinterpretation of these definitions may result in incorrect data regarding the distance and stops. Also, the data may be incomplete, which can lead to uncertainties. The causes of these uncertainties and their consequences will be discussed one by one, all of these are experienced during field research. *Misinterpretation of definitions* can result in missing parts of the route. This uncertainty is discussed in the context section. The scope of the calculation may not be well understood by the person providing the route data. For example, when the total energy consumption is needed to calculate the total emissions based on the average energy consumption and distance based on the origin of the truck to the final destination of the route of the truck (Guajardo, 2018). When the origin is interpreted as the origin of the cargo, a different address may be provided than when asked where the truck comes from. It may be the case that the truck comes from a base or another customer and has to pick up the cargo and deliver it to, for example the construction site. However, this distance is still caused by the cargo. The same applies to the interpretation of stops on a route and the destination. The person providing the data may understand that stops should only be reported until the delivery destination and not beyond (leaving empty trip information missing). If these definitions are not interpreted correctly and the cargo is a shared cargo, this can lead to a lot of uncertainty about the actual route taken and, therefore, the distribution of emissions. *The level of detail* of the origin, stops, and destination. When an address is provided, the shortest feasible distance and the great-circle distance can be accurately calculated, but this accuracy decreases as fewer details are known (for example, if only the place name of the stopover is provided). This is also mentioned by an expert in a interview: "Furthermore, there are uncertainties in the definition of origin and destination. So what we often see or like to have is that there are postcodes, which we can then view with our Geo code to see where they are located and what the intermediate distances are, but not all companies have that information, especially shippers. Then they only know that a shipment went from New York to Rotterdam. But Rotterdam is very large and so is New York, so that is also quite uncertain". Lastly, there is also the possibility that *no data is available* about intermediate stops or the base of the truck. This results in assumptions that need to be made, which can lead to significant uncertainty.

Payload - Data input: *Interviews and Background research*

The payload is an important input when the KPI CO_2-equivalents/ton or CO_2-equivalents/ton-km is requested. Thereby payload can be expressed in different units, such as ton, m3, m2, load meters, pallets etc. This can also introduce uncertainty. This is particularly important because goods are heterogeneous, and the choice of reference unit can make a significant difference in calculations. This uncertainty is also dependent on the **conversion factors**. When the payload needs to be converted to tons for an emission intensity or fuel intensity figure (expressed in units/ton-km). Additionally this is a crucial element in case of a shared trip, where emissions need to be allocated based on ton-km. Thirdly, it is essential for estimating fuel consumption, where payload is an input. Uncertainty can arise in the payload when it is *interpreted differently*, for example, when the load carriers (the weight of a pallet or container) are included. This was specifically observed in an interview with the expert from CE-Delft: "However, sometimes there is discussion about the calculation of weights in transportation. We always calculate based on the content of the container, for example, and we base the emissions per ton-kilometer on that. So, we only consider the weight of the cargo that is actually inside the containers as the effective load. While some others also take the weight of the container into account and consider the container itself as a type of commodity". Moreover, uncertainty can also arise when the *payload is unknown* and is estimated using an average payload.

Table 5.3: Data input uncertainty, classification

Input				
Data input	**Cause of uncertainty**	**Explanation**	**Nature**	**Level**
Average energy consumption/unit-km during a certain time	Average value, the more aggregated the less detail about a certain situation or trip is known.	Specific route characteristics, driving behaviour, environmental influences and when multiple vehicles are used; also the vehicle characteristics are less reflected in the output.	Stochastic	Statistical
	Unknown how average energy consumption/unit-km is calculated	When it is unknown how the average energy consumption/unit-km is calculated, there is a possibility that wrong calculations are made.	Epistemic	Deep uncertainty
Average energy consumption/km during a certain time	Average value, the more aggregated the less detail about a certain situation or trip is known.	Specific route characteristics, loading characteristics, driving behaviour, environmental influences and when multiple vehicles are used; also the vehicle characteristics are less reflected in the output.	Stochastic	Statistical
	Unknown how average energy consumption/km is calculated	When it is unknown how the average energy consumption/km is calculated, there is a possibility that wrong calculations are made.	Epistemic	Deep uncertainty
Amount of energy	Measurement error amount of energy	When the fuel consumption is based on data from fuel cards, there exists a measurement error, when someone tanked on the 31st of the month, the data is included in the past month but is used in the next month.	Epistemic	Statistical
Default energy consumption/km	Approximation of fuel consumption	No specific route characteristics, driving behaviour, environmental influences and vehicle characteristics of trip reflected in the output. Due to approximation effect of load included (default factors fuel consumption empty, full and capacity).	Stochastic	Statistical
	Industry average	No specific route characteristics, loading characteristics, driving behaviour, environmental influences and vehicle characteristics of trip reflected in the output.	Stochastic	Statistical
Energy type	Specifications or the energy type is unknown	It might be the case that, for example, the fuel type is defined as ”diesel” while there are multiple types of diesel.	Epistemic	Scenario
Origin, stops and destination shipment	Different interpretations of origin	Often the destination of a shipment is known, the origin of the transport of a shipment can have ambiguity when this is not defined clearly.	Ambiguity	Deep uncertainty
	Aggregated level ’origin’ and ’destinations’ due to lack of knowledge or privacy reason	It might be that organizations only know the origin as ’city’ and have no specifications at the ’postal code’ level.	Epistemic	Statistical
	Information stops are unknown, or only a part is known.	When only a part of the trip data is known or the trip data is unknown, assumptions have to be made.	Epistemic	Deep uncertainty
Payload	Multiple definitions of ”weight” payload	When average fuel consumption is defined as per tonne-km, there could be different interpretations of tonne (packaging included or not).	Ambiguity	Deep uncertainty
	Information payloads are unknown, or only a part is known.	When only a part of the payload is known or the payload is unknown, assumptions have to be made.	Epistemic	Scenario
Shipment type	Different interpretations of shipment type	When the shipment type is interpreted differently, the wrong emission intensity factor can be applied.	Ambiguity	Deep uncertainty
	Shipment type unknown	When the shipment type is unknown, there is a range of possible emission intensity factors that can be applied.	Epistemic	Scenario
Distance	Multiple definitions of distance	Uncertainty can arise when these distances are assumed to be equal. For example, if the average fuel consumption is calculated using the number of liters and the total planned distance, and then multiplied by the number of kilometers actually driven, an incorrect calculation is made. In addition, it is questionable whether the carbon footprint can be compared when different distances are used.	Ambiguity	Scenario
	Distance unknown	When the distance is unknown, an estimation must also be made, for which Google Maps can be used, which requires input of address data. When done in this way, the shortest feasible distance is calculated. This means that there is a deviation from the real driven distance.	Epistemic	Statistical
Vehicle type	Different interpretations of vehicle types	There are multiple ways and interpretations to describe a vehicle type. Due to this, the input for fuel consumption estimation can be wrong or the wrong emission factor will be applied.	Ambiguity	Scenario
	Vehicle type unknown	When the vehicle type is unknown, there will be a broad range of possible vehicle types. Due to this, the input for fuel consumption estimation can be wrong or the wrong emission factor will be applied.	Epistemic	Scenario
Amount of trips	The amount of trips is unknown or only a part of the trips is known.	When only a part of the total trips is known or the trip data is unknown, assumptions have to be made, for example based on the total demand and capacity of a vehicle. This brings uncertainty in the amount of trips as input data.	Epistemic	Deep uncertainty



5.5. Uncertainties found in the Parameters

The fourth potential source ('location') of uncertainty that will be discussed is uncertainty within the model's parameters. Uncertainties can occur within a priori chosen or calibrated parameters. In the calculation of a carbon footprint, two types of parameters are commonly used: a priori defined parameters and calibrated parameters. A priori defined parameters are based on theoretical considerations or previous experiences, and are often used when empirical data is lacking or incomplete. In contrast, calibrated parameters are based on empirical data or measurements, and are adjusted to better reflect the actual conditions.

Measurement error conversion factors - Data input: *Literature and interview*
Conversion factors are typically calibrated based on empirical data or measurements. Conversion factors are used to convert other types of 'payload' to weight, to allocate the emissions according to the weight (and distance), to use the default emission intensity factors or to calculate the CPI (kg CO_2e/ton-km) or KPI (kg CO_2e/ton) when companies do not know the weight of their units, which is quite common according to the expert of BigMile. These standard conversion factors, are not without uncertainties. Measurement errors and variations in measurement conditions or methodologies can lead to uncertainties in conversion factors. This is confirmed by an expert from Districon, she/he discusses the use of standard conversion factors within models or tools for for example convert a 'pallet' to an amount of 'tonne': "It differs significantly what is on a pallet, how much the pallet actually weighs in tons. For example, a pallet with beer and a pallet with cushions weigh something completely different.".

Measurement error emission factors - Data input: *Literature and interview*
Emission factors are important parameters used in carbon footprint calculations, which may be either a priori defined or calibrated. This is confirmed by an expert from CE Delft in an interview: "the emission factors actually come from a test, these tests are partially based on tests on the road and partially in a test environment". Emission factors are used to convert activities or amounts of energy into emissions. A priori defined emission factors are based on theoretical considerations, while calibrated emission factors are based on empirical data or measurements. Measurement errors and variations in measurement conditions or methodologies can lead to uncertainties in emission factors. For example, emission factors based on laboratory measurements of tailpipe emissions or on-road measurements of real-world driving conditions may contain errors or variations in measurement conditions. Furthermore, the choice of database used to obtain these factors can also introduce uncertainty. Different databases may contain different sets of emission factors, which may vary depending on the data and methods used to generate them. This means that the accuracy of the final results obtained from the use of these factors depends on the reliability and accuracy of the database used.

Default emission intensity factors - Data input: *Literature and interview*
In carbon footprint calculations, emission intensity factors are typically used as a last resort when more direct measurement methods or modelling based on fuel consumption (and the corresponding emission factors) are not feasible. These factors can be a priori defined or calibrated based on actual measurements, with calibration typically requiring additional testing and modelling to make the factors more specific to a given situation, such as vehicle type, road type, and load factor. Notably, the accuracy of emission intensity factors is impacted by the variability and uncertainty of the data used for calibration. Uncertainty arises when using emission intensity factors due to several reasons, such as data quality and availability, methodological differences and variability in real-world conditions. Thereby it is important to notice that these emission intensity factors take account for load utilization and empty trips made by the vehicle, linking the energy consumption calculation to the allocation step and resulting in a

single-step calculation process. Utilizing these specific values also implies that the allocation variable remains constant (Schmied & Knörr, 2012). Using predetermined values and assumptions for payload and empty journeys may lead to uncertainty in the results, as these assumptions may not accurately reflect the real situation. The expert from CE Delft explained the following uncertainty that exists with using default emission intensity factors: "The default intensity factors are actually what Stream provides. And those are numbers that indicate how much is emitted per ton-kilometer. There is very little primary data in this calculation. When you talk about those ton-km key figures, however there is consensus on how to calculate them. So, we are not the only ones making these calculations; for example, EcoTransit also does this too. But behind these calculations, there are a lot of assumptions that can lead to differences." Consequently, despite the fact that emission intensity factors can be a useful tool for estimating carbon footprints in certain circumstances, it is crucial to recognize their limitations and strive to use more accurate and precise methods whenever possible to obtain reliable carbon footprint estimates.

Different databases for emission (intensity) factors - Data input: *Background research and interview*
During the investigation of emission factors and examination of various databases, it becomes apparent that emission factors (Kg CO_2e/unit) can differ, as discussed in Subsection 3.9.3. This may be due to varying test conditions in laboratories or on-road testing in different countries. These on-road tests take into account factors that can vary by country (such as temperature, elevation differences, road gradient). However, there are also emission factors published by the GLEC Framework, which specify European emission factors; these, however, deviate from Dutch emission factors. Consequently, differences in the carbon footprint can arise from using different databases, creating uncertainty regarding the correct value and how to compare results. This is also the case for emission intensity factors (kg CO_2e/ton-km), as mentioned by the expert from CE Delft, both Stream and EcoTransit serve as sources (and there are many more), each providing a database containing potential emission intensity factors.

Table 5.4: Parameter uncertainty, classification

Parameter uncertainty			
Cause of uncertainty	**Explanation**	**Nature**	**Level**
Measurement error emission factor TTW	Due to multiple measurements of the tank-to-wheel emission factors, there will be a measurement error.	Epistemic	Statistical
Measurement error emission factor WTT	Due to multiple measurements of the well-to-tank emission factors, there will be a measurement error.	Epistemic	Statistical
Different emission (intensity) factor databases	Due to different databases, there are multiple emission factors that can be used for specific situations.	Ambiguity	Statistical
Default emission intensity factors	The default emission intensity factors are the amount of CO_2-equivalent per ton-km. This is a general factor which can deviate from reality.	Epistemic	Statistical
Conversion factor	When the payload is measured in different metrics than the preferred allocation method, a conversion factor is needed. This factor may have measurement errors.	Epistemic	Statistical

5.6. Conclusion insight phase

The aim of the chapter was to identify and categorize uncertainties related to the carbon footprint of freight transportation. Through interviews, literature review, and field research, uncertainties were identified for each "location" and categorized based on the nature in which they can arise, such as differing interpretations, lack-of-knowledge, or stochasticity. The location 'model technical uncertainty' was excluded from consideration because codes of software tools were not looked into in this study. The field study revealed that the main challenge in assessing carbon footprint is the time-consuming and complex process of data collection. Most potential causes of uncertainty were found in data input, which depends on the available information regarding energy consumption and transport activity. If either of these components is partially or completely missing, alternative calculations must be made to arrive at a reasonable estimate, leading to more uncertainties.

The chapter further classified uncertainties based on the level of uncertainty they bring. Stochastic uncertainties arise when the cause of uncertainty can be expressed as a variable with a probabilistic distribution. Scenario uncertainties arise when it is not possible to assign a probability distribution to a value due to uncertainty, but there are possible scenarios that can be performed to assess the impact of assumptions caused by the uncertainty. Finally, deep uncertainty refers to cases where it is difficult to make assumptions or generate probability distributions due to the complexity or novelty of the situation. When all the correct information is available, a precise estimation of emissions can be made using known energy consumption data, and emissions can then be allocated to clients. This process provides clients with an understanding of their carbon footprint per shipment. However, the field study and interviews revealed that obtaining accurate information is often not feasible in practice, leading to a significant source of uncertainty.

This situation raises the question of whether the carbon footprint can be considered an absolute value and how to address the inherent uncertainties. To tackle this issue, a tool is needed that provides insight into when and where uncertainties arise, helps identify preventable uncertainties, and offers guidance on how to reduce and manage uncertainties when they occur. This tool will enable a more accurate and reliable assessment of the carbon footprint of freight transportation.

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III

Design input and output

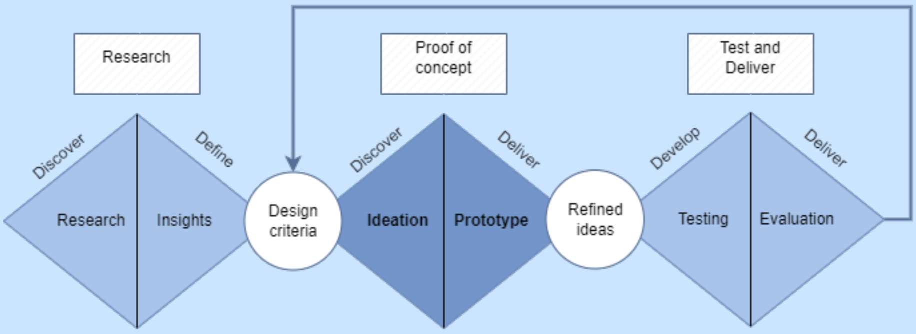

Figure 5.3: Research and Insights

The **Design phase** is focused on creating a tool to identify, assess, and address uncertainties in carbon footprint calculations. This phase starts with defining requirements, constraints, and functionalities based on literature, researchers' knowledge, and insights from conversations with consultants. The design input part involves framing data situations, classifying uncertainties, investigating their magnitude, and prioritizing them. Additionally, it covers addressing and assessing uncertainties through effective communication, making assumptions, sketching scenarios, and using probability density functions. The design output includes the development of a step-by-step guidance framework for each data situation, resulting in a tool suitable for various stakeholders.

6 Requirements and functionalities

This study was established based on a problem statement. This problem statement represents a research gap that was discovered through a literature review and has also garnered interest from Districon. The research objective derived from the problem statement is as follows:

”Design of a ’tool’ to assess the uncertainty of a transport carbon footprint measurement”

Subsequently, during the research phase, the background of carbon footprint calculations was examined, and the topic of uncertainty was investigated. Using the theoretical framework that was developed, uncertainties were identified. The final conclusion of the previous chapter highlighted certain needs that the tool must fulfill, namely: a tool is needed that provides insight into when and where uncertainties arise, helps identify preventable uncertainties, and offers guidance on how to reduce and manage uncertainties when they occur. These needs are further elaborated in this chapter, and the functionalities for the tool are described.

6.1. Design requirements

The engineering design process commences with a design problem expressed as a need (i.e., initial requirements) that must be fulfilled by creating a physical product or system Brace & Cheutet (2012). A need identified in the literature, as well as being an area of interest for gaining deeper insights at Districon, is the influence of uncertainties on the carbon footprint. Identifying requirements is the initial step in designing a model or tool.
According to Bahill et al. (2017), conducting interviews is likely the most common method for gathering requirements. By participating in a project at Districon and conducting several interviews with experts in the field of transport carbon footprint measurements, uncertainties were discovered. Additionally, during conversations and interviews with consultants at Districon (D1, D2, D3), requirements for the design were established. Although not directly asked for, these requirements were derived based on the observed information, needs, and the absence of an overview of uncertainties and their influences that were mentioned.

Based on findings in these interviews, conversations, in the literature, and requirements formulated by the researcher, the requirements in Table 6.1 were formulated. During the discussed field research in the previous section, it was discussed what requirements are needed to determine whether they should be ”essential” or ”nice-to-have” for developing a tool to assess the uncertainty of transport carbon footprint measurements. Finally, based on this, the essential requirements were determined in Table Y, which forms the definitive list of requirements.

Table 6.1: Requirements of tool

”Design of a ’tool’ to assess the uncertainty of a transport carbon footprint measurement”			
#	**Requirement**	**Reference**	**Need-to-have/Nice-to-have**
Uncertainty prevention, identification and quantification			
1	The basis of the tool are the identified uncertainties from previous Chapter 4.4.	R. Siepman	Need-to-have
2	The tool should provide guidance on how to gather accurate and reliable data to minimize uncertainty from the start.	D1, D2*	Need-to-have
3	The tool must provide an approach for identifying and quantifying uncertainty in transport carbon footprint measurements.	D1, D2*	Need-to-have
4	The tool provides insights into the different data ’quality’ levels.	Subsection 3.7.4	Need-to-have
5	The tool must provide guidance on how to prioritize efforts to reduce uncertainty based on their impact on the overall measurement.	D1, D2*	Need-to-have
6	*The tool could allow users to select different probability distributions or specify their own distributions for sources of uncertainty.*	Section 4.6	*Nice-to-have*
7	The tool should include a set of best practices for handling various types of uncertainties, such as data gaps, assumptions, and modeling limitations.	Section 4.4	Need-to-have
8	*The tool should provide a clear method for modelling uncertainties through the analysis, such as incorporating uncertainty ranges or Monte Carlo simulations.*	Section 4.6	Nice-to-have
Usability and compatibility			
9	The tool must be user-friendly and easy to understand.	D1, D2*	Need-to-have
10	The tool must be adaptable to and compatible with various and up-to-date carbon footprint measurement methodologies.	R. Siepman	Need-to-have
11	The tool must be designed to facilitate collaboration between different stakeholders.	R. Siepman	Need-to-have
12	*The tool could allow users to vary input parameters (e.g., distance, fuel consumption, etc.) to explore how they affect the final carbon footprint measurement.*	*D1, D2**	*Nice-to-have*
13	*The tool could offer visualization options that display the impact of uncertainties on the final carbon footprint measurement, emphasizing the range or interval of possible values.*	*D2*	*Nice-to-have*
14	The tool should state clear definitions of all subjects.	D1*	Need-to-have
15	*The tool can be used for different KPI’s.*	*D3*	*Nice-to-have*
Communication and decision-making			
16	*The tool could be designed to support scenario analysis to explore different what-if scenarios and their impact on the carbon footprint measurement.*	*Section 4.6*	*Nice-to-have*
17	The tool should provide guidance on how to communicate uncertainty in a clear and effective way to different stakeholders.	R. Siepman	Need-to-have
18	The tool should support decision-making by providing guidance on the best strategies for reducing uncertainty.	D1, D2*	Need-to-have
19	*The tool should be able to account for uncertainty related to the use of different accounting frameworks (e.g., Scope 1, Scope 2, Scope 3).*	*R. Siepman*	*Need-to-have*
Additional Requirements			
20	Is based on information from traceable sources.	D1, D2*	Need-to-have
21	The tool functions as a widely applicable methodology to gain initial insight into the uncertainties of factors that influence the carbon footprint.	D3*	Need-to-have

**conversations and interviews with consultants at Districon (D1, D2, D3)*

Firstly, based on the previous analysis, the tool should incorporate all the identified uncertainties [1]. Additionally, it is required that the tool helps in limiting uncertainties prior to a carbon footprint analysis to minimize uncertainty as much as possible at the outset [1]. The tool should also serve as an aid for identifying uncertainties and provide a way to quantify them in the output [2]. This entails knowing which uncertainties have the greatest impact so that this information can be communicated to stakeholders, both when requesting information and when presenting the results [4]. Furthermore, the tool should assist with best practices to address various types of uncertainties [7].

Since different calculation methods exist and the quality of a carbon footprint is determined based on these methods, the tool should provide insight into what this quality entails [5]. Currently, Districon uses a tool (software program) to determine the carbon footprint of freight transport, which already calculates the end figure, making the development of a new model less relevant. However, to clearly demonstrate the effect of uncertainties, it is necessary to use analyses (scenario and uncertainty analyses) to show the impact of uncertainties, as discussed in the background research. Therefore, the tool can be used as an add-on for implementing uncertainty spreads in existing tools. A model for quantification is considered a nice-to-have [6, 12, 13, 16], but showing how to handle uncertainty and providing examples of deviations is essential for interpreting uncertainties, making it a must-have to offer possibilities and examples [2, 7]. Thereby it is important that the tool is easy to understand or have an extensive explanation.

Additionally, the tool should be easy to understand [9] and comply with the methodology of the software program currently used by Districon to enable integration [10]. Clarifying the concepts used in the tool is also important for proper usage [14]. Another nice-to-have is that the method or tool can display the uncertainty around a KPI or indicate how the uncertainty might change [15]. The tool should also support effective communication of uncertainties to different stakeholders in two ways. One is by emphasizing the importance of accurate data when requesting information [11]. The second way is to clarify for stakeholders how uncertainties affect outcomes, so that they can take them into account when making strategies [17, 18].

A need-to-have is that the tool represents uncertainties that may arise in scope 1, 2, or 3 analyses [19]. The last two requirements are that the tool should be based on information from traceable sources[20], and that the tool serves as a method for Districon and other stakeholders to be aware of and gain insight into the uncertainty surrounding the final outcome of a carbon footprint measurement [21].

After establishing the requirements, a list of ’need-to-haves’, or constraints to which the tool must adhere, has been created. These are shown in Table 6.2. The design must fall within these boundaries, making it important to consider them when creating a conceptual model that defines the content of the tool.

Table 6.2: Need-to-haves design

"Design of a 'tool' to assess the uncertainty of a transport carbon footprint measurement"	
#	**Final requirements**
	Uncertainty prevention, identification and quantification
1	The basis of the tool are the identified uncertainties from in the insight phase.
2	The tool should provide guidance on how to gather accurate and reliable data to minimize uncertainty from the start.
3	The tool must provide a framework for identifying and quantifying uncertainty in transport carbon footprint measurements.
4	The tool provides insights into the different data 'quality' levels.
5	The tool must provide guidance on how to prioritize efforts to reduce uncertainty based on their impact on the overall measurement.
6	The tool should include a set of best practices for handling various types of uncertainties, such as data gaps, assumptions, and modeling limitations.
7	The tool should provide a clear method for modelling uncertainties.
	Usability and compatibility
8	The tool must be easy to understand or have a comprehensive explanation.
9	The tool must be adaptable to and compatible with various and up-to-date carbon footprint measurement methodologies.
10	The tool must be designed to facilitate collaboration between different stakeholders.
11	The tool should state clear definitions of all subjects.
	Communication and decision-making
12	The tool should provide guidance on how to communicate uncertainty in a clear and effective way to different stakeholders.
13	The tool should support decision-making by providing guidance on the best strategies for reducing uncertainty.
14	The should be able to account for uncertainty related to the use of different accounting frameworks (e.g., Scope 1, Scope 2, Scope 3).
	Additional Requirement
15	Is based on information from traceable sources.
16	The tool functions as a widely applicable methodology to gain initial insight into the uncertainties of factors that influence the carbon footprint.

6.2. Design Functionalities

In the previous section, the requirements and constraints were determined. These constraints define the boundaries of the tool being designed to assess uncertainties in a carbon footprint analysis. To ensure the design meets the requirements, certain functionalities are needed in the tool to satisfy these prerequisites. The functionalities serve as input for the design of the tool, as they determine what the tool must be capable of, in addition to the constraints within which it must operate. Based on the requirements, the following functionalities have been established.

1. Creates awareness of the uncertainies around a carbon footprint of a shipment
2. Helps with identifying possible uncertainties that can arise
3. Gives insights on how to prevent uncertainties
4. Gives insights in how to reduce uncertainties
5. Gives insights in which uncertainties have the biggest impact
6. Provides an assessment method of dealing with uncertainties
7. Provides examples how to implement the assessment methods
8. Is usefull for multiple stakeholders

6.3. Defining 'a tool' and design process

The process of designing a tool is an iterative one, which involves continuous refinement through brainstorming sessions and also conversations with Districon. As the process has progressed, the term "tool" has become more clearly defined and refined in its meaning. Guided by the constraints and functionalities, the design aims to clarify guidance framework for preventing, identifying, and quantifying uncertainties. To develop this approach, inputs for the tool were conceived to ultimately produce an output: 'guidance framework to identifying and dealing with uncertainties in a carbon footprint analysis of freight transport'. Throughout the input stage of the design, questions must be answered to reach the end of a step. An overview of the development can be seen in Figure 6.1.

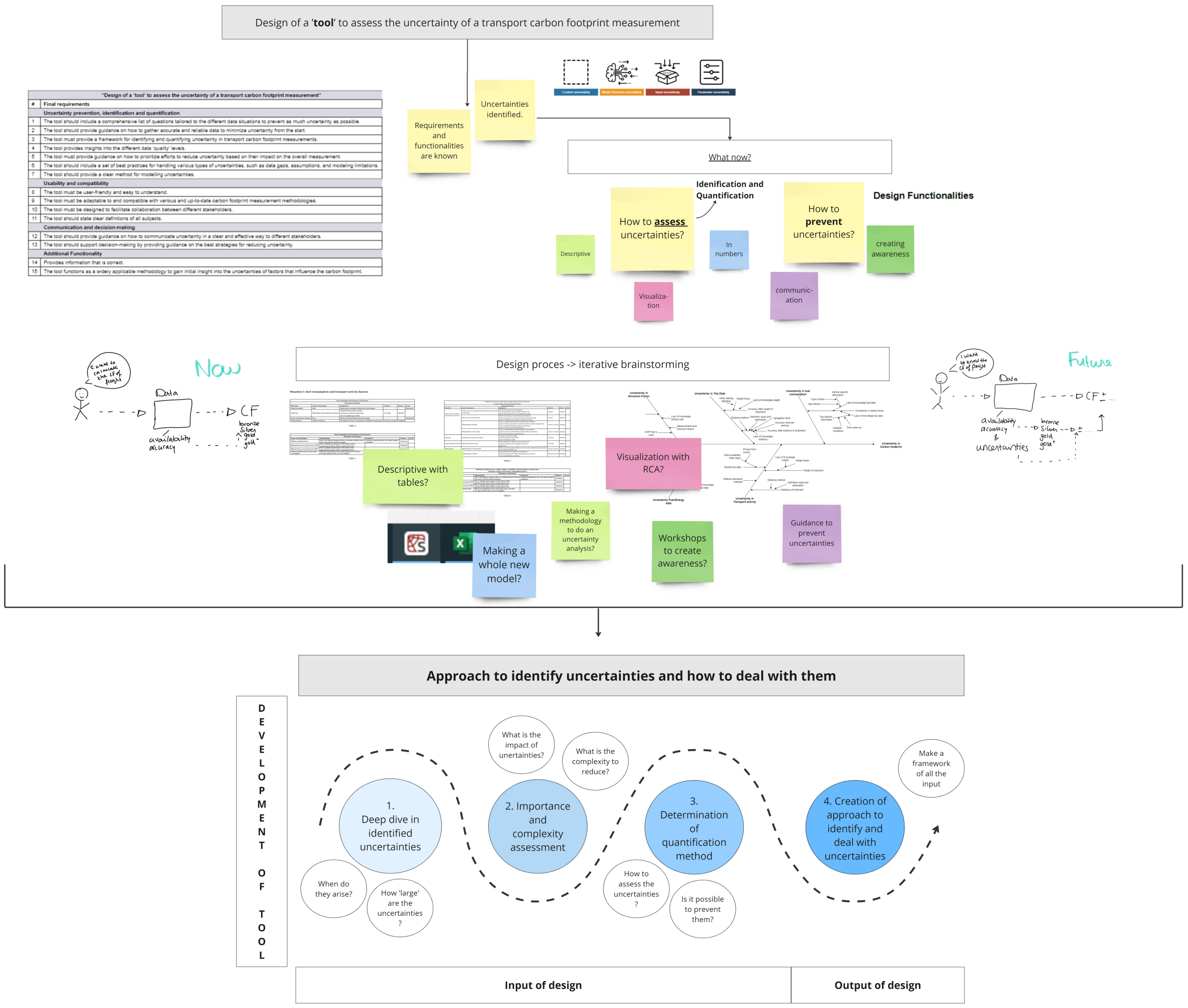

Figure 6.1: Design process

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7

Input for design

During the initial phases of this thesis research, the concept of uncertainty and various methods for determining the carbon footprint of freight transportation were investigated. This examination aimed to provide a comprehensive understanding of the factors contributing to the overall carbon footprint and the uncertainties associated with these factors. As a result, several potential uncertainties were identified. In this chapter, we will delve deeper into the different inputs necessary for the design of a tool, as illustrated in Figure 7.1, that can effectively assess the uncertainties surrounding the carbon footprint of freight transportation. These inputs will serve as the foundation for the development of a robust and reliable tool. To establish this, the following research questions need to be answered:

Research questions to be answered in this chapter:

- RQ6 *When do the uncertainties arise?*
- RQ7 *What are the 'margins' of the uncertainties?*
- RQ8 *What is the impact of the uncertainties en the complexity to reduce?*
- RQ9 *How to assess and prevent the uncertainties?*

In Section 7.1, the first question is addressed by defining data situations and identifying the uncertainties that may arise in each situation. In Section 7.2, the second question is answered by investigating the possible range around an input variable that can result from uncertainty. The third question is addressed in Section 7.3 by prioritizing uncertainties based on complexity and potential impact. Finally, the fourth question is answered in Section 7.4.

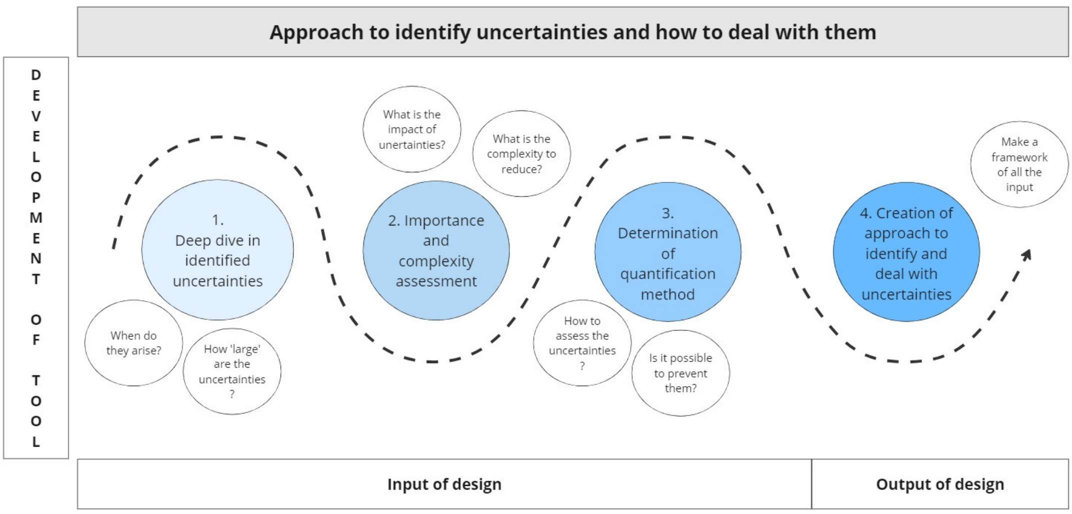

Figure 7.1: Design process

7.1. Data situations and accuracy levels

In order to effectively interpret the identified uncertainties from Chapter 5, a distinction is needed between various calculations that can be performed to arrive at the final carbon footprint of a shipment of freight transport. These calculations are actually dependent on two main categories: transport activity data and energy consumption data. When one of these two is unknown or partially known, estimates must be made or modeled. This is the main reason why the calculation changes. Thus, depending on the data accuracy, the carbon footprint is calculated with the help of different input variables and parameters. In the background research (Subsection3.7.4), a distinction was made between data situations according to data aggregation levels. These included the following four levels. However during the field research, these data levels were partially observed, and others also emerged. Therefore the data situations are re-described as follows:

1. Energy consumption is known and details are available about the current route and stops.
2. Average energy consumption is known at the tonne-kilometer level and details are available about the current route and stops.
3. Average energy consumption is known at the liter/kilometer level and details are available about the current route and stops.
4. Energy consumption is unknown, but details are available about the route and stops.
5. Energy consumption is known, but details about the route and stops are (partly) missing.
6. Energy consumption is unknown and details about the route and stops are partly unknown.
7. Energy consumption is unknown and details about the route and stops are unknown: use of default emission intensity factors.

In order to see in which data situation the carbon footprint calculation should be performed, a decision tree has been drawn up showing when which data situation applies. This decision tree is shown below in Figure 7.2.

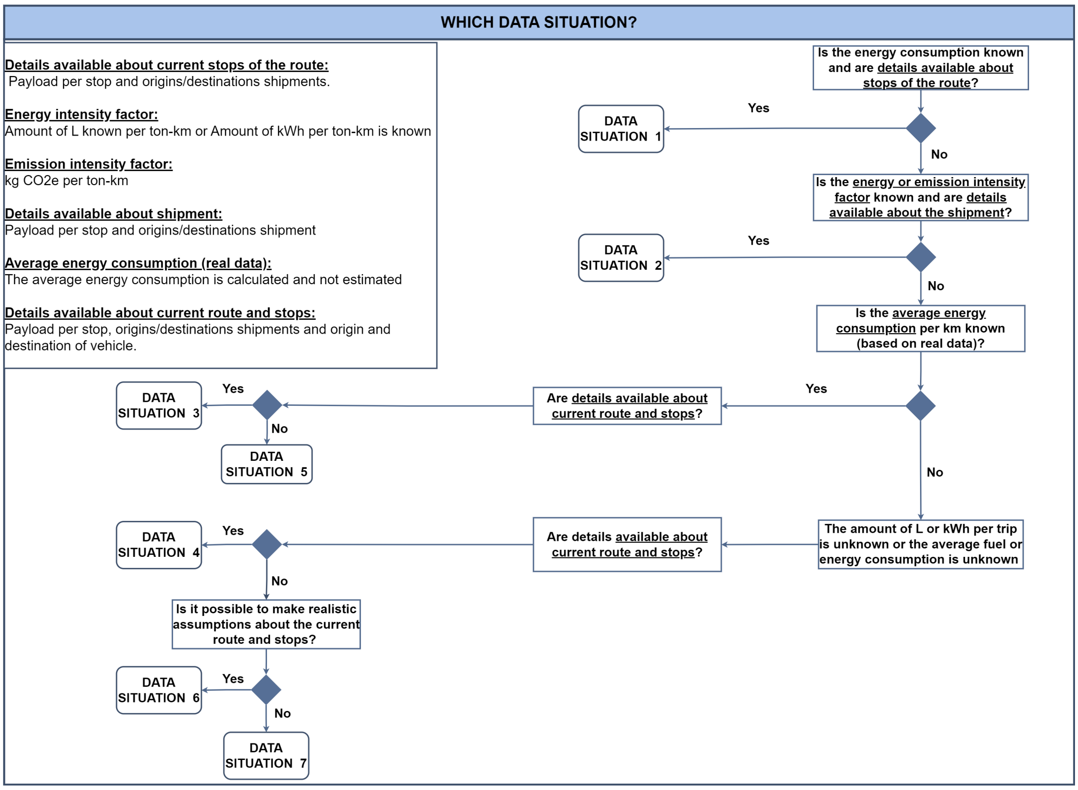

Figure 7.2: Decision tree data situation

Based on these data situations, uncertainties can subsequently be divided. Interestingly, the uncertainties in the context and model structure remain the same. However, what emerges is that in lower data accuracy situations, more information is needed to obtain the best possible picture or standard numbers are needed to make a good estimate; of transport activity or energy consumption. As a result, the input data and the parameters used change. This also changes the potential uncertainties. Therefore, a table is created with an overview of the uncertainties in each situation. This overview is visible in Table 7.1. In general the lower the level, the more assumptions or approximations need to be made, and the more uncertainties that can arise. It is noteworthy that the number of causes for uncertainty increases up to data situation six. After that, there are fewer underlying causes for data situation seven; however, it is essential to recognize that the total uncertainty underlying a carbon footprint in this situation might be higher due to, for example, the uncertainty underlying the emission intensity factor being greater than that of only an emission factor. Nevertheless, the possible causes of uncertainties provide a clear understanding of how less information affects the number of assumptions and potential misinterpretations of requested data to approximate the carbon footprint.

Table 7.1: Possible uncertainty causes per situation

Potential uncertainty causes that can arise per situation	**Situation 1**	**Situation 2**	**Situation 3**	**Situation 4**	**Situation 5**	**Situation 6**	**Situation 7**
Uncertainty in unknown: Energy Type	X	X	X	X	X	X	X
Uncertainty in Emission Factors	X	X	X	X	X	X	
Uncertainty when Conversion Factor needs to be applied	X	X	X	X	X	X	X
Uncertainty in definition: Payload	X	X	X	X	X	X	X
Uncertainty due to variability of Average Value		X	X		X		
Uncertainty about Calculation		X	X				
Uncertainty in definition: Distance		X	X	X	X	X	X
Uncertainty due to other distance type than used for average			X	X	X	X	X
Uncertainty due to unknown distance		X	X	X	X	X	X
Uncertainty in specification level: address Origin, Stops, and Destinations on GCD	X	X	X	X	X	X	
Uncertainty in specification level: address Origin, Stops, and Destinations on Unknown Distance			X	X	X	X	X
Uncertainty in definitions: address Origin, Stops, and Destinations on GCD	X		X	X	X	X	
Uncertainty in definitions: address Origin, Stops, and Destinations on Unknown Distance			X	X	X	X	
Uncertainty due to variability of Default Value				X		X	
Uncertainty due to variability of Average Modeled Value				X		X	
Uncertainty in definition: Vehicle				X		X	X
Uncertainty in unknown: Vehicle Type				X		X	X
Uncertainty in definition: Shipment Type							X
Uncertainty in unknown: Shipment Type							X
Uncertainty in emission intensity factors							X
Uncertainty in unknown: Payload other Stops Assumption average value payload with vehicle capacity					X	X	
Uncertainty in unknown: adres other Stops Assumption trip is Dedicated, replace Allocation Factor with * 2					X	X	
Uncertainty in unknown: Amount of Trips Assumption Total Demand/Capacity Vehicle						X	

The potential uncertainty causes in Table 7.1 all are dependent on the input and parameters within the data situation; this means that these causes are not always present. However, there are **fundamental uncertainties** that always occur, due to the standard variability in the parameters used within the calculation or the standard assumptions that need to be made in the data situations. These fundamental uncertainties are: **uncertainty in emission factors, default energy consumption uncertainty, assumptions for other loads or destinations on the route, and default emission intensity factors**. The emission factor uncertainty applies to every data situation since it is needed to convert energy to

CO_2e, default energy consumption applies to the data situation where the fuel consumption is calculated with the help of industry average numbers or modeled average energy consumption (situations 4 and 6). The uncertainty that occurs with making assumptions on the load or other addresses of the trip due to missing information have an influence on the data situation where transport activity is partly missing (data situation 5 and 6). The last fundamental uncertainty only applies when a default emission intensity factor is used due to missing information on fuel consumption and transport activity; this applies to data situation 7. In Figure **??** is an overview visible of how these causes potentially affect the output.

7.2. Margin uncertainties

In this section, the possible range or margin of uncertainty surrounding input variables in the carbon footprint calculation is investigated. By exploring these margins, the consequences of uncertainties and how they might affect the accuracy and reliability of the carbon footprint estimation can be understood. Per input variables the margins are discussed.

7.2.1. Margin fuel consumption

Uncertainty due to calculation

Uncertainty can arise in the reported average provided by or calculated by the carrier due to the lack of knowledge on how the average was calculated or interpreted. However, it should be noted that the uncertainty regarding the reported average cannot be controlled unless there is an understanding of how the calculation was performed. Furthermore, it is challenging to attach a margin to this uncertainty because there are multiple underlying causes and different consequences subjected to this uncertainty. These are discussed below.

The ambiguity surrounding how the calculation was performed can result in incorrect application of the average, leading to definition uncertainties in terms of the distance (km) and/or payload (ton) used in the calculation. For instance, inconsistencies may arise when the average fuel consumption is calculated using actual distance and applied to planned distance to determine fuel consumption for a shipment or trip, leading to uncertainty. Moreover, the calculation of the average may be subject to variability. For example, when the average fuel consumption per kilometer is calculated using 'fuel card data' and the 'shipment database'. The amount of fuel used is then divided by the total distance driven. However, the number of kilometers driven on a tank of fuel differs from the actual fuel consumption, as a portion of the fuel is carried over from the previous month, and/or a portion of the fuel is not consumed until the following month. Nonetheless, this data is still divided by the distance (or tonne-kilometers) for this specific month. As demonstrated in Appendix F Figure F.3, using more aggregated data leads to reduced deviation. Monthly deviations may be significant (up to 20%) but eventually converge to 0% over a longer period of time. This is because the fuel or energy left over in one month in some cars is partially offset by filling up less energy/fuel in those cars the upcoming month, and thus balanced out over a longer period of time. Furthermore, uncertainty can arise when the average has been calculated incorrectly, such as when multiplying the total number of tonnes and total number of kilometers together instead of performing the calculation per shipment when calculating tonne-kilometers.

Uncertainty due to variability of average value

Fuel or energy consumption is crucial to know when calculating the carbon footprint of freight transport. If fuel consumption is known at the level of individual trips, there is little uncertainty about consumption for the specific situation. However, if an average is used based on aggregated data, there is uncertainty in the form of variability. This variability is influenced by external factors, including environmental, operational, driving behavior, road characteristics, or vehicle-specific factors, which were discussed in Section 3.6. The GLEC Framework recommends this aggregated approach to even out seasonal variations and outlying values (SFC, 2020). Therefore, the method suggests taking the fuel consumption per vehicle (class) over a year and dividing it by the number of ton-kilometers traveled by each shipment. Another way to do this is to take the average fuel consumption and model the quantity of fuel consumed for a given trip, and then multiply this number with the allocation factor. The final approach is to take an industry average fuel consumption (i.e., guessed fuel consumption) or to model fuel consumption per kilometer.

Providing a numerical estimate of the variability caused by the aforementioned factors for each approach is currently unattainable. Nevertheless, it is crucial and relevant to consider the difference in accuracy of energy consumption per approach. To differentiate the accuracy of energy consumption per trip for each method, a visual analysis has been performed to investigate the presence and impact of the previously mentioned factors on the average. Assessing this for each approach reveals how representative the calculated average is of the actual average, with a visual representation found in Appendix D.

From this, it is evident that with an industry-level average, it remains uncertain how the factors (environmental, operational, driving behavior, road characteristics, or vehicle-specific factors) are represented. These averages might assume an opportunistically ideal driving situation, leading to a deviation from the true average. When modeling the average, considering additional factors like road type and load factor can help approach the true average more closely.

For the actual average per kilometer or per ton-kilometer, historical data is used as the basis, which means that both approaches could yield the same result. However, variability due to the factors persists, but is spread across the number of customers/shipments, as suggested by the GLEC Framework. The difference lies in the calculation of the carbon footprint at the shipment level, which can be immediately allocated and calculated with the average per ton-km, while using the average per kilometer requires reconstructing the entire route to arrive at the same number. The fuel consumption variability remains the same, but reconstructing the route and then allocating it may introduce more uncertainty due to the additional steps involved. These uncertainties are discussed under other headings in this section.

The variability of average values is not seen as uncertainty according to the GLEC framework; however, uncertainty can arise if the values are based on a whole fleet rather than a vehicle class. The differences between these vehicles can be significant, as shown in table 7.2.1. These numbers are calculated with the help of the number of the Stream report from CE Delft (CE Delft, 2020), more details of this calculation are visible in Appendix F. Besides the approaches based on historical data there are also approaches that use default factors (average fuel consumption per km) to calculate energy consumption. It is important to understand the inherent limitations of the default factors and the potential improvements that can be achieved by using more accurate, historical data to inform decision-making and reduce uncertainty in carbon footprint calculations. As a result, it has been decided to provide only uncertainty margins for the default energy consumption factors. This is because the uncertainty of variability is intentionally spread across the customers in the GLEC framework, while the default factors have more uncertainty associated with them since they are not based on historical data. Therefore, an uncertainty margin will be determined for the default factors, emphasizing the distinction between these factors and the other approaches based on historical data.

Uncertainty due to variability of Default Value
Uncertainty due to Average Modeled Value

As discussed above, the default factors account for a considerable degree of variability of external factors, as the average might not accurately represent the true average under specific circumstances of the transportation company. Various sources suggest that these numbers are often opportunistic, particularly when considering average fuel consumption derived from laboratory tests. This discrepancy has led to the term ”fuel consumption gap.” The article by (Pavlovic et al., 2020) shows that actual fuel consumption in on-road tests is, for example, 30% higher than the officially declared consumption. Since it is difficult to determine whether an average value is based on on-road or laboratory tests, it has been decided to determine the uncertainty in a different way. The focus has been placed on factors that transportation companies can influence to change their energy consumption. These factors are the average load factor and the driving behavior of their drivers. These factors can create differences between transportation companies, while influences from factors like weather conditions remain the same across companies. Therefore, to determine the uncertainty margin, the impact of these two factors has been chosen in order to establish a margin.

The average payload factor is determined by the percentage of loaded kilometers from an entire trip multiplied by the average payload of that loaded trip multiplied by the total capacity of the vehicle. Several papers have researched the influence of driving behavior on a vehicle's energy consumption. Demir et al. (2014) discussed that the impact on fuel consumption can be quite significant, reaching up to 25% (between the best and worst driver). Therefore the uncertainty margin on the average fuel consumption will be +-12.5%. The influence of the number of empty kilometers and the average loading rate is more challenging to find, as it depends on the type of goods in the truck. Therefore, for now, the assumption is made that the empty kilometers of an average situation can differ by approximately 15%, and the average loading rate can also vary by around 15%. When this is calculated in a standard formula to model fuel consumption, it appears that the influence of these uncertainties has a maximum of approximately 4% on fuel consumption. This can be seen in Appendix F, Figure F.4. The uncertainty margin of the default fuel consumption per vehicle type is considered to be approximately 16.5%. When the average loading and the percentage of loaded kilometers are known, this uncertainty is no longer present, and the uncertainty margin is approximately 12.5%. It should be clearly stated that this is an assumption of uncertainty to see what effect it might have on the carbon footprint. For good margins of uncertainty on an industry average, more research needs to be done.

Uncertainty due vehicle type definition
Uncertainty due to unknown vehicle type

In addition, uncertainty may be even greater if the vehicle type used is not clear or even unknown, as the differences between these vehicles can be significant, as shown in Table 7.2.1 and 3.6. In this Table the average energy consumption per vehicle kilometer is visible. These numbers are calculated based on the average energy consumption per road type and the ratio of these road types in the Netherlands, this calculation is shown in Appendix F in F.1 and F.2.

7.2.2. Margins distances

Uncertainty due to other definition distances
Different definitions of distance can arise, leading to ambiguity. This ambiguity can subsequently impact the accuracy of calculations involving these values. One uncertainty that may emerge is the potential discrepancy when the amount of energy per kilometer or per ton-kilometer is multiplied by a distance different from the one used to calculate the average. It is crucial to know which type of distance was used to calculate the average so that the appropriate distance can be selected for calculating the energy consumption and carbon footprint of a shipment or trip. For this type of uncertainty, it is often challenging to determine an uncertainty margin, as it is difficult to estimate how people report distance. Therefore, it is essential to prevent this uncertainty by asking the right questions and clarifying the definition of distance being used. If it becomes evident that there is a different interpretation of distance, strategies can be considered to address this uncertainty. This uncertainty then transforms into either *Uncertainty due to other distance type than used for average* or *Uncertainty due to unknown distance* for which an uncertainty margin can be assigned.

Uncertainty due to other distance type than used for average energy consumption
There are several ways to calculate distances, including planned distance (PD), shortest feasible distance (SFD), actual driven distance (ADD) and great circle distance (GCD). Distance is used in two ways for emission calculations: 1) it is employed to determine the total energy consumption using an average energy consumption per kilometer, or 2) it is utilized for the allocation of emissions to customers in combination with the payload. However, since there are various possibilities for reporting distance, it is crucial to consistently apply the same distance throughout the calculation.

The ISO being developed during the writing of this report primarily recommends two types of distance: the shortest feasible distance and the great circle distance (GCD). However, this applies to the calculation of the CPI (CO_2e/ton-km) for a transportation company and how it should be implemented and for the allocation of emissions (2). The advantage of the shortest feasible distance and great circle distance is that they can always be replicated. So, when a shipper receives the emissions or liters per ton-km from their carrier and knows that the distance is expressed in great circle distance, they can calculate their emissions using the weight of the shipment's multiplied with the great circle distance that they can calculate based on the origin and destination of the shipment. It is important that the distance that is used for the CPI is multiplied by the same sort of distance to calculate the emissions. For example, if the CPI is calculated using the shortest feasible distance and the emissions for a client need to be calculated with this CPI, it is important not to multiply it with the great circle distance.

However, if the carrier does not know this but knows the energy consumption per liter, and no CPI then the total fuel consumption needs to be calculated before allocating the emissions with help of the total distance and the average energy consumption (l/km or kWh/km) (1). This is often calculated based on planned or actual driven distance. Field research has shown that many shippers know the planned distance, but carriers calculate energy consumption based on actual driven distances. When this is the case (or vice versa), planned distances can be converted to actual driven distances. The GLEC framework applies an increasing margin of 5% to convert a planned distance to an actual driven distance (and vice versa). In addition, an additional 25% is allocated when there is a significant detour due to road works or avoidance of toll roads which was not accounted for in the planned distance. The actual driven distance is often also required to use the default emission intensity factors, as these are established with the actual driven distance. It can also occur that the distance is unknown and needs to be reconstructed, as encountered in the field research. This only causes uncertainty when using default factors or when energy consumption is modeled using averages. This is discussed under the heading *Uncertainty due to unknown distance*.

Uncertainty due to unknown distance

From field research, it was found that few shippers were able to obtain the actual distance, and some co-makers knew the planned kilometers while others did not, which required distances to be calculated using Google Maps. The difference between these types of distances is particularly important when calculating fuel consumption based on an average, which was the case for almost all co-makers. As discussed above the GLEC framework applies an increasing margin of 5% to convert a planned distance (PD) to an actual driven distance (ADD). In addition, an additional 25% is allocated when there is a large detour due to road works or avoidance of toll roads if this is not taken into account in the planned software distance. Furthermore, there is also a discrepancy between the reconstructed route by tools such as Google Maps and the actual driven distance. This can be interpreted as the Shortest Feasible Distance from to points in terms of time. The difference between planned distance and shortest feasible distance with for example Google Maps is that Google Maps is not taking into account the real operating conditions, such as the physical restrictions of a vehicle (e.g. weight and height), road type, topography, congestion or construction (SFC, 2020). Therefore when a route is reconstructed with another tool than the planning software of a company is using, it is stated in this research that the margin should be bigger than of 5%. To investigate this figure, two actual driven distances were compared with the data obtained from Google Maps. It should be noted that this is a small sample size for comparison purposes, but it does provide an indication of how this figure compares to the situation being simulated. The routes and distances are visible in Figure 7.4 and 7.5. The results of the comparison can be seen in Table 7.4. It demonstrates that when the best (shortest "distance" option) was selected in Google Maps, there was a difference of -19%. Conversely, when the worst (longest "distance" option) was selected, the difference from the actual driven distance ranged between -14% and -15%. The problem is that there is no knowledge about the reason of this distance and that there is no comparison with the planned distance. Therefore, for now, a margin of +10% is used between the Google Maps distance and the actual driven distance. In addition, an additional 20% is allocated when there is a large detour due to road works or avoidance of toll roads which is not taken into account in the planned software distance, however this probability is a lot smaller.

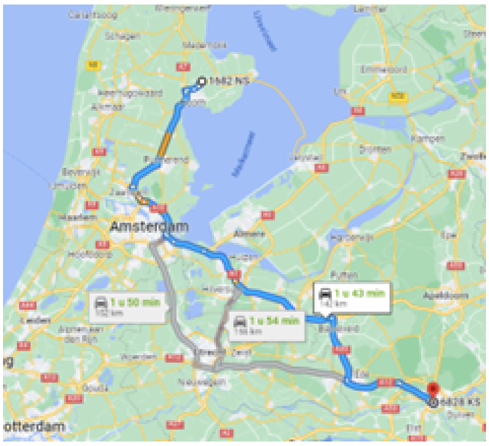

Figure 7.4: Route options google maps Co-maker 1, ADD = 176 km

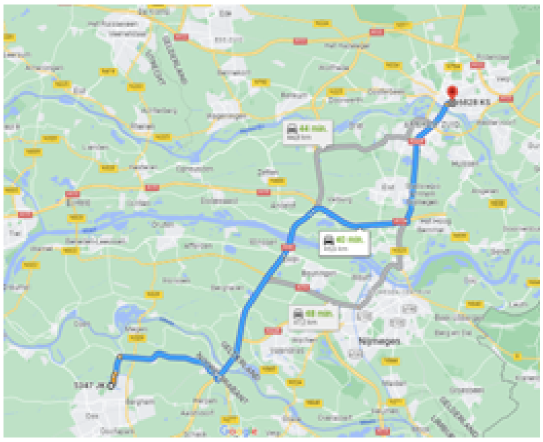

Figure 7.5: Route options google maps Co-maker 2, ADD = 55,6 km

Table 7.4: Difference ADD and Google Maps

	Boordcomputer	**Google maps**		**Difference**	
Data points	ADD	Best case	Worst case	Best case	Worst case
Co-maker 1	176	142	152	19%	14%
Co-maker 2	55.6	44.8	47.2	19%	15%

7.2.3. Margin address origin, stops and destination

Uncertainty due to specification level

Customer addresses are essential for two purposes: emission allocation and when the route distance is unknown (and an average distance is assumed), necessitating the reconstruction of the route to calculate fuel consumption. When data on each address is known for multiple stops, the great circle distance can be accurately calculated to distribute emissions. Due to privacy concerns, the addresses of other customers are often not shared or requested, but the postal code at the PC6 level is provided; this is a postal code with six characters. For allocation, the Great Circle Distance (GCD) is calculated at the PC6 level. When data is not available at the PC6 level, it may be available at the PC4 level; this is a postal code with four characters. One reason for this less detailed data may be stricter privacy concerns for other customers. However, this may result in a difference in the great circle distance. When searching for statistics on average distances within the PC4 and PC6 level, no 'free' database could be found. To provide a margin of uncertainty, the largest PC4 and PC6 postcodes in the Netherlands were examined, based on the data from Esri Nederland (2023a,b). Subsequently, the maximum straight-line distance of this area was calculated, meaning the distance was measured from one extreme point to the other extreme point. Afterward, the deviation from the central point was examined. This provided an indication of the maximum distance difference for the straight-line distance when addresses at the PC4 or PC6 level are provided, and the midpoint of PC4 or PC6 is taken as the basis. From the midpoint at the PC4 level, this is 9.26 kilometers, and at the PC6 level, 5.33 km; from the outer edges, this distance should be multiplied by two. For comparison, these postcodes are quite extreme; for example, the city of 'Amsterdam' has an approximate straight-line distance of 11 km from the midpoint when viewed on Google Maps. In addition, as discussed above, the actual driven distance is important for estimating fuel consumption when the total fuel consumption is unknown. To estimate the uncertainty of this, the outer boundaries of these postcode areas were examined, and the distance between them was determined using Google Maps; thus, the Shortest Feasible Distance (SFD) based on time was considered. The distance from the center of the area was also examined. In this way, it is also possible to get an idea of the maximum possible distance difference that a PC4 and PC6 level can provide to the Shortest Feasible Distance. From the midpoint at the PC4 level, this is 16.3 kilometers and from the outer edges 27.2 km. From the midpoint at the PC6 level, this is 7.3 kilometres; from the outer edges this is 21.8 km. How these distances look and how they were calculated can be seen for PC4 in Figure 7.6, and for PC6 in Figure 7.7. When this must be converted to Actual Driven Distance

(ADD), an additional uncertainty margin is introduced. It is essential to emphasize that the estimate of the maximum difference of the Shortest Feasible Distance is not only dependent on the size of the area, as it is also strongly dependent on the types of roads, bodies of water, or natural areas that can influence the distance between two points. This can also be seen in the example of the PC6 area, as a significant detour must be taken to travel from one extreme point to the other because the extreme point is difficult to reach. Therefore, it is challenging to say whether this distance truly represents the maximum spread of the PC4 and PC6 level; in other areas, this may be much worse.

The uncertainty margin is difficult to estimate in percentages because it depends on the distance from the location of the origin or locations of previous stops. Moreover, it is expected that the uncertainty of origin, destinations, and intermediate stops will have a greater impact on the uncertainty margin of reconstructing a route than on the great circle distance for allocating emissions. It is crucial to mention that the distances discussed here may change over time due to new postal codes or the division of postal code areas.

Figure 7.6: Maximum distance within PC4 level (First picture GCD, Second and third SFD), postal code 8251

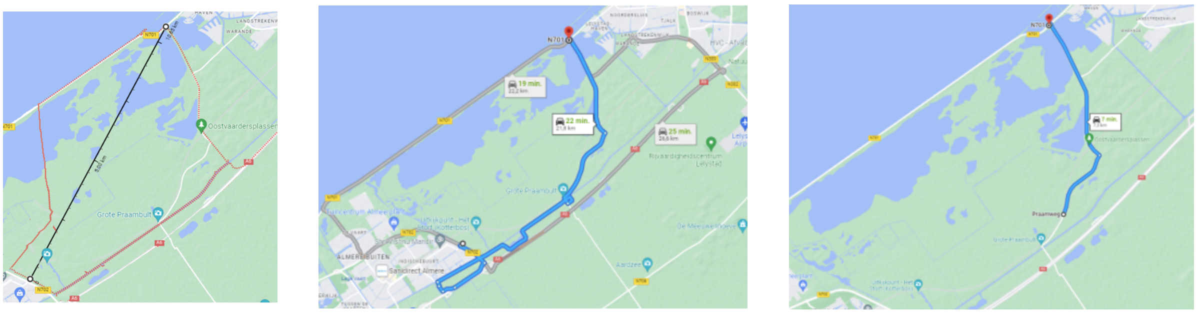

Figure 7.7: Maximum distance within PC6 level (First picture GCD, Second and third SFD), postal code 8218 PZ

Uncertainty due to other definition origin, destination, or stops

An inaccurate interpretation of origin, destination, or stops may lead to uncertainties. Determining a general margin for such uncertainties is complex, but the effect can be illustrated using an example. Field research revealed that these uncertainties mainly arise from a misinterpretation of the scope of the carbon footprint. In mapping transport movements to and from a construction site, for instance, different interpretations of origin, intermediate stops, and destination may emerge. The origin may be viewed as the base location of the truck that picks up the load, the loading site, or the preceding destination of the truck. The destination may be interpreted as the destination of the load, the next stop, or the base location of the truck. Thereby stops can be interpreted differently, for example when a client asks the carrier for data information about the other stops on the trip it can be interpreted as all the stops on the trip, or only the part before of after the stop of the client.

A contributing factor to this issue is the necessity to comprehend the distinctions between a round trip with multiple stops, a round trip with a single stop (dedicated trips), and a truck journeying to an alternate location to collect a subsequent load for delivery to a different customer.Developing a comprehensive understanding of the order transportation network is crucial for asking the appropriate questions when collecting data. This ensures that accurate and relevant information is gathered, which is essential for conducting a thorough analysis, as evidenced by field research. By posing well-informed questions, researchers and stakeholders can avoid misinterpretations and reduce uncertainties, ultimately leading to more reliable and valid conclusions.

Additionally, the importance of other data depends on the amount of available information (the data situation), causing the interpretation of origin, destination, and stops to vary across different data situations, which can create considerable confusion. For example, if the number of liters of diesel or the amount of kWh consumed by a truck over a specific period or trip is known, fuel consumption is directly allocated to the number of customers. If this information is not available, fuel consumption must be modeled and subsequently distributed. When modeling fuel consumption, it is crucial to incorporate empty kilometers, as they are already included in the total energy consumption. Therefore, it is essential to account for the empty kilometers to the pick-up location and the empty kilometers back to obtain an accurate representation of the actual fuel consumption. Subsequently, the fuel consumption must be distributed from the loading location. In essence, there are then two types of 'origin' and 'destination': origin and destination from the perspective of the vehicle, and origin and destination from the perspective of the shipment. The latter is significant in every situation, while the former is relevant only when fuel consumption needs to be modeled. The greatest likelihood of misinterpretation occurs therefore when fuel data is unknown. Inaccurate modeling (due to wrong interpretation of origin and destination) can significantly impact total fuel consumption, as illustrated in Appendix F, Figure F.5. Thereby a different interpretation of the origin and destination can also have an influence on the allocation factor, for example when their is an extra stop where the truck picks up an extra loading; this creates a new 'origin' which can be confusing. The effect of this kind of misinterpretations can be quite significant as shown in F, Figure F.6. A wrong interpretation could potentially lead to a difference of 50% in the GCD.

7.2.4. Margins payload

There are several definitions of payload in the context of transportation, including load meters, carts, volume (m3), pallets, or weight in tons or kilograms. Generally, the payload is combined with the distance traveled to allocate the carbon footprint. In addition, the payload is also used to express the carbon efficiency of transport, namely: CO_2equivalent/payload. It is expected that the future standard will be based on a distribution based on weight and distance, with the weight expressed in tons. However, when converting other cargo units to tons, measurement errors can occur if general factors with large deviations are used.

Payload can be defined in various ways, such as in terms of load meters, carts, volume (m^3), pallets, or weight in tons or kilograms. Typically, payload is combined with distance to calculate the CO_2footprint. Additionally, payload is used to express the CO_2efficiency of transportation, namely in CO_2equivalents per distance-payload unit. The GLEC Framework utilizes weight in tons as payload, as this is consistently applied throughout the supply chain. The forthcoming ISO standard is expected to incorporate not only weight as payload but also other load types, such as volume, load meters, and pallets (Topsector Logistiek, n.d.). The payload unit is important to know for two reasons; the carbon efficiency of transport is typically expressed in CO_2equivalent per ton-kilometer, and it is common for the total emissions of a transport company or a specific route to be allocated to customers based on the payload and the distance to the customer.

Uncertainty due to conversion factor weight

Since the notation of payload can vary and a vehicle may contain multiple types of payload, it is necessary to convert the different freight types into a common unit. Currently, standard conversion factors are available to convert various load types into weight, which are utilized in different software packages. It is also possible to convert pallets into roll containers, as outlined in the guidelines provided by Topsector Logistiek (2021a). Each conversion factor introduces uncertainty, as the factors are based on a situation that may not always be the case. To investigate the spread of this uncertainty, two sources are used: the factors discussed in the Topsector Logistiek guidelines and the output of a project conducted by Districon in this area. Topsector Logistiek guidelines contain standard conversion factors for a shipment with a single type of load carrier and a conversion factor for a type of load carrier as an example for a shipment with multiple types of load carriers. The danger of using conversion factors is that they can be applied incorrectly. For example, when a truck is loaded with pallets and roll containers, and the emissions are distributed based on a common denominator, the number of pallets should be converted to roll containers (or vice versa), not the number of pallets to weight and then the number of roll containers to weight. Otherwise, a large difference may arise in emissions attributed to customers. If the load is to be distributed based on weight or the KPI CO_2e/ton is to be calculated, the number of pallets should first be converted to roll containers (or vice versa) and then converted to weight. This effect is visible in appendix F in Figure A. This will create a difference of 14% in the weight of a shipment.

The conversion factor used to convert the weight or volume of goods always deviates from the actual value. Davydenko et al. (2019) has noted that converting volume to weight can entail a significant margin of error, as the density of goods can vary greatly, even within the same commodity group. However, consistent application of conversion factors can reduce this margin of error by canceling out the errors. This may occur when a carrier transports different types of goods, when the weight of one type of goods is underestimated and the weight of another type is overestimated. If this is not the case, a systematic error may arise, causing the CO_2e emissions per transported unit (CPI) to be higher or lower than the actual value. As the CPI is considered a measure of efficiency, this can create a distorted picture. It is important to note that the total emissions of the carrier remain the same, but the weight can affect the efficiency measure and the distribution of emissions to customers. An example of a systematic error emerged in a study by Districon, where the weight of a load meter at a company was measured. It was found that the load meter equated to 0.5 tons instead of the 1.3 tons applied when converting load meters to tons in a software package. This will create a difference of 60% in the weight of a shipment. As a result, the CPI (Carbon Performance Indicator) may be higher in reality than when the software program's conversion factor is applied. It is difficult to give an uncertainty margin to the conversion factor as it really depends on the type of good that is transported, but due to the knowledge of this result the uncertainty margin is now set at +-60%, it should be noted that there is need for future research on this.

If the CPI is based solely on converted load meters, the CPI may be higher than the actual value when the 0.5 factor is applied. However, when calculating the carbon footprint of a shipment for a customer, no deviation from the actual situation should occur as long as the number of load meters is consistently converted to tons using the same factor as in the CPI. If a different conversion factor is suddenly used, a significant deviation may arise. When the CPI is calculated based on both actual tons and converted load meters, the CPI provides a more realistic representation of the true efficiency of the shipments because part of the weights has not been converted to tons. However, since the systematic error introduced by the higher conversion factor is mitigated by the actual number of tons, it means that when calculating a customer's emissions based on distance and the amount of tons, the uncertainty still exists and will result in a deviation from the actual value. An example can be found in appendix F Figure F.8, demonstrating a reconstruction of a random situation where the carbon footprint of a shipment is calculated based on the actual conversion factor and the standard conversion factor, in a situation where the CPI is calculated on shipments reported in load meters and in a situation where it is based partly on load meters and partly on the number of tons.

In summary, if all "payload units" are in load meters and are converted to tons using a standard conversion factor, the CPI may have a large deviation if there is a significant difference between the actual and used conversion factors. If the emissions of a shipment are then calculated based on the CPI and the same conversion factor, the total CO_2equivalent emissions of a shipment may remain the same. However, when some shipments are reported in load meters and some in tons, only part of the shipments needs to be converted to tonnages. This makes the CPI more representative, but the total emissions of a shipment will still contain a deviation because the shipments reported in tonnages are multiplied by a CPI that is partly based on converted load units. Additionally, it is crucial to realize that this situation also affects the distribution of emissions when no CPI is available. In a situation without an available CPI, the CO_2emissions of a shipment are determined by dividing the total CO_2emissions of a round trip among customers based on their 'payload' and 'distance', with no role for historical data. When one customer receives shipments in load meters (Customer A) and another customer (Customer B) in actual tonnages, an overestimation of Customer A's weight may result in Customer B being allocated fewer emissions, and the efficiency of Customer B's shipment may be higher than if calculated using a correct conversion factor. In conclusion, it is essential to use accurate conversion factors to obtain a more realistic view of the actual efficiency and emissions of shipments. The main issue is the difference between the actual and used conversion factors, leading to deviations in the calculated CPI and emissions.

Uncertainty due to other definition of payload

Defining weight for the purpose of allocation can be ambiguous. Some may include the weight of the pallet or container, while others may use chargeable weight or include packaging material. To ensure consistency, the EN16258 and GLEC Framework recommend using the weight of the payload plus packaging material, excluding any additional packaging and handling equipment used by the carrier. Incorrect calculations, such as including the weight of the carrier's pallet, can have an impact on the attributed emissions if the pallet's weight is close to that of the contents. To investigate the impact of these uncertainties, calculations were conducted in Excel and are presented in Appendix F in Figure F.7. For example, if the payload of the shipment on a pallet weighs only 1.2 kg more than the pallet itself (25 kg (Topsector Logistiek, 2021b)), the emissions attributed to a customer will be 75% higher if the pallet is included in the weight than if it is not. However, when the shipment weighs 7.2 times more than the pallet, this difference is only 10%, and when the shipment weighs 20 times more than the pallet, the difference is only 2%. In the latter situation, the weight used for calculation should be 500 kg, but a wrong interpretation could result in 525 kg (5% more), which can cause a 2% difference in the total attributed emissions. A commonly used conversion factor from a filled pallet to weight is 700 kg for a euro pallet (Topsector Logistiek, 2021b), this will mean a deviation in the definition of payload (with or without a pallet) of only 3.6%, and the ultimate effect on the amount of CO_2equivalent attributed will be only 1%. The uncertainty spread of the weight definition is therefore dependent on the weight of the payload on the pallet (or roll container, crate, etc.). Based on the expectation that the weight of the payload of the client is generally much higher than the pallet weight of the carrier, it can be assumed that the uncertainty margin will be low. However, to account for situations where this assumption does not hold, the uncertainty margin can be estimated as the weight of the pallet/crate/roll container (from the carrier) divided by the weight of the shipment (chargeable weight of the client plus packaging) and multiplied by 100%.

7.2.5. Margins due to unknown trip details

Trip data is crucial for calculating the carbon footprint of a shipment, as it enables the distribution of emissions or estimation of fuel consumption. This input data is important when the fuel consumption for a trip is known or needs to be modeled. In the case of using a CPI, this uncertainty is embedded in the calculation of the CPI and not in its use. Examples of reasons why this data may be unknown include some carriers not storing the data, storing it for a shorter term, feeling no incentive to share it, or simply not wanting or being able to share it. During the field research, it was found that a few variations of unknown trip data exist: it is unknown how many trips have been or will be made because it is not recorded or data is not stored, some addresses of the trips are known or only the address of a shipper is known, some loads are unknown or only the load of the shipper is known. To address this, assumptions can be made or an emission intensity factor can be used. This section discusses the implications of these assumptions on the outcome of the carbon footprint of a shipment.

Uncertainty due to unknown other addresses

When a shipment is transported in shared freight, and the transport company cannot provide a carbon performance indicator (CPI) or is unable or unwilling to calculate it, the distribution of emissions from the trip must be calculated using trip data. Not only is the fuel consumption of that trip required, but also the origin, destination, and load of all other stops. When the addresses of the other stops are unknown, there are two options: using emission intensity factors (1), or assuming the trip was round-trip and only stopped at the destination of the respective shipment (2). The second assumption was mainly used in the field study and results in a higher carbon footprint than the emission intensity factor. This is because the emission intensity factor partially includes the allocation factor, leading to an assumption about the number of empty kilometers and the average loading rate of a vehicle. This means that the emission intensity factor partly includes the allocation factor in the factor, thereby making an assumption about the number of empty kilometers and the average loading rate of a vehicle. This is why there is considerable uncertainty surrounding this factor, which will be discussed under heading 7.2.7. The assumption of a round trip (1) can be chosen if one wants to show a worst-case scenario. It can be said with high certainty that the actual emissions are lower when calculating with the assumption of considering a shared trip as a round trip.

This is not always the case with emission intensity factors (2). At least two situations were identified during the writing of this research where the emission intensity factor could yield a lower carbon footprint than the actual carbon footprint. The first situation is when the underlying assumptions of the emission intensity factor are better than the actual performance of the transport company. This means that the emission intensity factor assumes a higher loading rate and a lower share of empty kilometers than is actually the case. In general, it is assumed that this is not the case; for example, the GLEC framework states the following: ”Transitioning from the average CO_2e/tonne-km factor for the road sector provided by the Greenhouse Gas Protocol to the GLEC Framework’s value for a 40-tonne truck would lead to a decrease in reported emissions. Transitioning from the GLEC Framework’s factor for a 40-tonne truck to a factor provided by a carrier with a low-emission vehicle fleet would further decrease the reported value of emissions. (SFC, 2020).”. However, field research showed that this is not always the case. An example is a transport company with a loading percentage of 37% and a percentage of 33% empty running during a trip. When comparing the assumptions of empty running and loading percentage for this type of vehicle and type of shipment underlying the GLEC Framework and the emission intensity factors from CO2emissiefactoren.nl (which uses STREAM figures), it turns out that both factors have more positive assumptions. CO2emissiefactoren assumes an emission intensity factor based on a loading percentage of 52% and an empty running factor of 25%. And the emission intensity factors of the GLEC Framework assume a loading percentage of 60% and an empty running factor of 17%. This means that this company performs worse than the assumptions of the emission intensity factor on the discussed trip. However, because this is a random trip, nothing can be said about the representativeness of this trip compared to the other trips of the transport company, but it does show that if this is a representative trip, the underlying assumptions of the emission factor are better than reality. This can have a significant impact on the carbon footprint of the shipment, as discussed in Section 7.2.7. Another situation when assumption (2) can be used is when the load is not aggregated, as it appears that emission intensity factors can give a misleading picture at the ”individual shipment” level. The only source found that specifically addresses this is a protocol by Topsector Logistiek (2021c), which states the following: ”In STREAM studies, or the GLEC standard, the emission intensity numbers are provided. They may only be applied to large aggregated streams of cargo, and not to individual trips. This can go wrong for individual trips.”. Furthermore, CE Delft (2020) mentions the following: ”When STREAM numbers are calculated for a delivery via distribution transport, it is important to realize that ton-kilometers based on the shortest distance between origin and destination underestimate the actual ton-kilometers and thus also the emissions, which are calculated on this basis. This is because a distribution trip, by definition, involves additional mileage to combine the various delivery addresses.”

To examine the influence of this second situation, a case from the field study was used. In this case, the transport company had all the information: it was a shared round trip, where the total amount of fuel consumed during the trip was known, as were the addresses of the stops and origin, and the loading in tons at each stop. One of the stops was the construction site of the field study. Using this information, the carbon footprint of the shipment to the construction site was calculated; since all the information was available, this outcome is highly accurate. Next, the analysis examines what happens when there are no addresses, and either the round trip assumption is made or emission intensity factors are used. Since the actual driven distance to the construction site was also provided, the emission intensity factor was used based on this distance to avoid the problem mentioned by CE Delft (2020). Upon carrying out the different calculations, it was found that the emissions estimated with the round trip assumption, as opposed to a shared trip, were roughly 2.7 times greater than the actual emissions assigned to the shipment. Using an emission intensity factor along with the amount of cargo and driven kilometers results in emissions that are 3.1 times lower than the actual case. This shows that these emission intensity factors can indeed give a wrong picture, even an undeservedly favorable one. The calculations for this can be found in Appendix F Figure F.12. The boundary for when an emission intensity factor can be applied is therefore unclear. The question is whether the statement of Topsector Logistiek (2021c) is correct because the sum of loads times the distance and the emission intensity factor yield exactly the same result as if this were calculated separately for each trip.

It is difficult to attach an uncertainty margin to this uncertainty, as it greatly depends on the type of trip and the number of actual stops. However, it can be said that assuming a round trip for the shared trip ensures that the emissions allocated to the shipment can be significantly lower in reality.

Uncertainty unknown trip input payloads
It may also occur that it is known that a trip is a shared trip, the carrier provides the postal codes of other stops, but does not provide the payload of the other stops. This can have a significant impact on the distribution of emissions. The allocation is divided based on the payload (often in tons) multiplied by the distance (often Great Circle Distance or GCD). The allocation factor is essentially the share of a customer relative to all other customers, and this share is determined by the payload multiplied by the distance. When the location of the stops is clear, an assumption can be made about the distribution of the payload. For example, the payload can be distributed proportionally based on the vehicle's loading capacity and the load delivered to a shipper. To map the uncertainty of this assumption, a best and worst-case scenario can be developed. The best-case scenario for the shipper is when another customer with the largest GCD receives almost all of the remaining load. The worst-case scenario for a customer is when a customer with the shortest distance receives almost all of the load. In the worst-case scenario, the shipper's share is the largest compared to the other customers, and in the best-case scenario, the share is the smallest compared to the other customers. The difference between the best-case and worst-case scenarios can be quite significant if the differences in distance are large. In Appendix F, Figure F.11 presents an example situation, showing that the worst and best cases differ considerably (in the worst-case, the amount of CO_2 attributed to the shipper is four times that of the best-case). Additionally, an extra uncertainty may arise if the vehicle's capacity is unknown, which can also lead to new worst and best-case scenarios. A larger vehicle capacity will generally ensure that the loads of other customers are higher than a smaller capacity, which may be 'advantageous' for the shipper in this case.

Uncertainty due to unknown amount of trips

This situation mainly occurs when trips are not properly tracked or when predictions for the future need to be made. Future predictions can be made using the average per ton-kilometer (the CPI) of a transporter. In doing so, a clear distinction must be made between the types of goods and types of freight movements in order to make an accurate prediction of the freight. If this CPI is not available, an emission intensity factor can be used, which takes into account empty kilometers and the allocation of emissions based on the type of truck and the type of goods. The uncertainties associated with this approach are discussed under the Section 7.2.7. The choice for emission intensity factors is particularly common when dealing with aggregated loads of known types of goods. If this is not the case, the assumption can be made to consider the delivery as a round trip, in which the number of trips is calculated by dividing the total demand by the capacity of the vehicle. The emissions of the trips can then be calculated based on this. The main uncertainty associated with this is that a truck is often not 100% loaded, causing the number of trips to deviate. This is also dependent on the type of goods, for example, a volume good may be maximally loaded at a weight capacity of 30%. The capacity should therefore be requested based on the capacity of the type of goods, for example, "the maximum number of dormer windows that can be carried is X/the maximum weight at the maximum number of dormer windows is X". In addition, the type of vehicle must also be known; otherwise, this introduces additional uncertainty. The uncertainty margin associated with the 100% loading is equal to the uncertainty discussed in Section 7.2.1, and is now not ±15% but -30% as it cannot exceed the maximum capacity, and the ±15% is based on an average and the deviation from it. A consideration to choose this method compared to the emission intensity factor is when the number of liters per kilometer is known, so the fuel consumption is based on historical figures, or when it is clear, for example, that the trips are a round trip with no shared transport present. However, when it is not possible to determine the capacity dependent on the number of goods, the calculation can quickly become unreliable, which is a reason to work with emission intensity factors. An example of this can be seen in Table 7.5.

Table 7.5: Number of trips based on capacity

	Amount	**Unit**
Weight of one dormer	839	kg/dormer
Demand	20	dormers
Total weight	16780	kg
Maximum weight with maximum amount of ’dormers’	3859.4	kg
Capacity truck	12642	kg
	Demand/capacity	**Nr of trips**
# trips based on specific capacity	3.2756387	**4**
# trips based on vehicle capacity	1.3273216	**2**

7.2.6. Margins energy type

In the Netherlands, there are several types of fuel available for vehicles (ANWB, n.d.). Gasoline is available in Euro 95 E10, which contains a maximum of 10% bio-ethanol, and Superplus 98 E5, which contains a maximum of 5% bio-ethanol. Premium gasoline with special additives is also available, such as V-Power, Ultimate, Synergy Supreme+, and Excellium, typically with an octane rating of 98 or higher and always with a maximum of 5% (and sometimes none) bio-ethanol. LPG is moderately available, with approximately 1000 LPG stations across the country. CNG (Compressed Natural Gas) is available at around 180 stations, and H2 (Hydrogen) is available at approximately 15 public stations. LNG (Liquefied Natural Gas) is available at approximately 25 stations, but these are not public and are meant for special LNG trucks. Diesel is widely available in B7, which contains a maximum of 7% biofuel and meets the EN590 standard. Premium diesel is also available, containing special additives and a maximum of 7% biofuel. B100 is a limited availability diesel made from 100% biofuel (HVO100) that is primarily used for commercial vehicles such as trucks and buses. E85 (bio-ethanol) is a biofuel blend of 15% gasoline and 85% bio-ethanol, available at only about 15 stations in the Netherlands, and is intended only for specific flex-fuel vehicles. There are about 100,000 charging points for electric vehicles throughout the country, and almost 3,400 fast-charging points that can recharge an electric car in about half an hour. Currently, diesel dominates as the primary fuel for transportation vehicles. Last year Association (2022) published that in 2021, diesel remained the most popular choice for new medium and heavy commercial vehicles sold in the European Union. Diesel vehicles hold a market share of 95.8%, while electrically-charged vehicles account for only 0.5% of new truck sales across the region. Alternative-fuel vehicles (e.g. natural gas, LPG, biofuels, and ethanol) make up a total of 3.6% of the market. Therefore, there is currently a high likelihood that the energy type for a truck or van is diesel. Table 7.6 presents the differences in emission factors between different fuel types, using data published on the website ”CO2emissiefactoren.nl.” As shown, the differences between fuel types are significant. For example, the largest difference in emission factors per liter is between Diesel and HVO-100, with a difference of 89%. When the fuel type is unknown, this can lead to a large spread of uncertainty. However, this ultimately does not have a major impact, as the likelihood of a vehicle using HVO-100 as a fuel is small. This is because HVO-100 falls under alternative fuels, which only have a market share of 0.5%. The tank-to-wheel fators for biodiesel/HVO are so low because these emissions are offset by the CO2 previously absorbed by the feedstocks used to make the fuel (Jhang et al., 2020); it is to be expected that there are uncertainties behind this as well.

Table 7.6: Emission factors per energy type, obtained from: Rijkswaterstaat (2023)

Category	Unit	Kg CO_2/unit (WTW)	Kg CO_2/unit (TTW)	Kg CO_2/unit (WTT)
Gasoline (E10)	liter	2.821	2.176	0.645
Gasoline (E5)	liter	2.884	2.233	0.651
Diesel (B7)	liter	3.256	2.468	0.787
Biodiesel (HVO100)	liter	0.347	0.032	0.314
Biodiesel (FAME)	liter	0.437	0.031	0.406
LPG	liter	1.802	1.635	0.167
CNG (natural gas)	kg	2.608	2.255	0.353
Bio-CNG (green gas)	kg	1.024	0.112	0.912
LNG	kg	3.651	2.945	0.706
Hydrogen grey	kg	12.516	0	12.516
Hydrogen green	kg	1.14	0	1.140

7.2.7. Margins emission factors

Emission factors for freight are often presented as Tank-to-Wheel (TTW), Wheel-to-Tank (WTT), and Well-to-Wheel (WTW) emission factors. Each of these factors contains an uncertainty margin as they are based on experiments and measurements. Additionally, it is easier to measure Tank-to-Wheel emissions than Well-to-Tank emissions. Therefore, Tank-to-Wheel emissions are expected to be more accurate than Well-to-Wheel emissions. However, in order to calculate the carbon footprint of freight transport, Well-to-Wheel emission factors are currently used, which are a combination of Well-to-Tank and Tank-to-Wheel emission factors. Well-to-Tank emission factors dominate for vehicles that run on more sustainable alternatives, while Tank-to-Wheel emission factors play a larger role in the final Well-to-Tank emission factors for less sustainable alternatives.

When searching for the variation of emission factors, for example, from the GLEC Framework or CO2emissiefactoren.nl, the uncertainty margin for the emission factors is not available. But, it is still expected that this uncertainty is greater for Well-to-Tank emission factors than for Tank-to-Wheel emission factors because the former are more difficult to measure. A certain level of uncertainty can be attributed to the differences between various databases of emission factors, as discussed briefly in Subsection 3.9.3. To illustrate these differences, a comparison was made between the European emission factors for the diesel B7 blend and gasoline E10 blend from the GLEC Framework SFC (2020) and the Dutch emission factors from CO2emissiefactoren.nl Rijkswaterstaat (2023). These were calculated by dividing the emission factor of conventional diesel by 100 and dividing the emission factor of biodiesel by 100. Both factors were then multiplied by the ratio in the B7 blend (93% diesel and 7% biodiesel). The same was done for gasoline and bioethanol following the guidelines provided. The Well-to-Tank emissions showed the most notable differences between these factors, as expected due to the greater uncertainty associated with this factor. However, since this factor represents a smaller component of the Well-to-Wheel emission factor compared to the Tank-to-Wheel emission factor, the overall effect is mitigated. Ultimately, there is a difference of 3.9% for gasoline (E10) and 3.4% for diesel (B7) between the Dutch and European emission factors. When multiplied by the number of liters (or kWh for electricity), this leads to an increase of 3.9% in the carbon footprint of a gasoline vehicle (and 3.4% for diesel) when using the Dutch emission factors instead of the GLEC emission factors. The difference becomes even larger for blends with a higher proportion of biodiesel or bioethanol.

Table 7.7: Intensity factor per vehicle type based on input numbers from Rijkswaterstaat (2023) and SFC (2020)

	kg CO_2e/l gasoline E10			kg CO_2e/l diesel B7		
	WTT	*TTW*	*WTW*	*WTT*	*TTW*	*WTW*
Europe (GLEC)	0.529	2.178	2.707	0.665	2.483	3.148
Netherlands (CO2emissiefactoren)	0.645	2.176	2.821	0.787	2.468	3.256
Difference EU/NL (%)	21.9 %	-0.1 %	3.9 %	18.4 %	-0.6 %	3.4 %

7.2.8. Margins emission intensity factors

Uncertainty emission intensity factor

The emission intensity factors (the number of CO_2equivalents emitted per tonne-km) consist of two components. The first is the energy consumption per vehicle type, which carries the same uncertainty as the default energy consumption discussed under the heading ”margin fuel consumption.” In addition, for this factor, values for load use and empty trips must also be included so that the ”allocation” factor is already incorporated in this factor. Therefore, the emission intensity factor also includes assumptions for the allocation factor, making the uncertainty of this factor greater than default fuel consumption values.

To obtain the emission intensity value, the default consumption factor is calculated based on the energy use of an empty vehicle, a fully loaded vehicle, and the average load factor, and then divided by the average load factor. Dividing by the average load factor represents therefore the allocation factor. The average load is based on the capacity of the vehicle, the average load percentage of loaded trips, and the percentage of vehicle kilometers with load compared to the total number of kilometers. The average load percentage of loaded trips and the percentage of vehicle kilometers with load depend on the type of goods being transported. Bulk goods, for example, have the characteristic of almost 100% load factor (looked at the maximum weight capacity) but a high proportion of empty trips. While for volume products, the maximum load in tons is lower, but the number of empty kilometers will be also lower. The average load also affects the average fuel consumption as discussed earlier in Section 7.2.1, which was +-4% . This means that the uncertainty of the load factor and loaded kilometers (+/- 15% on the load factor and +/- 15% on the percentage of loaded kilometers) has an additional influence on the emission intensity factor compared to the average energy consumption per kilometer.

To assign an uncertainty range to the emission intensity factor, the uncertainties of driving behavior (+-12.5%), average load percentage of loaded trips (+-15%), and average percentage of loaded kilometers (+-15%) are combined to find a minimum and maximum deviation. This is shown in Appendix F Figure F.10. The value will range from -31% to +51% due to the uncertainty associated with the above margins. Because these factors are interdependent, it is strongly recommended to further research this uncertainty margin.

Uncertainty definition/unknown shipment type
Uncertainty definition/unknown vehicle type
Uncertainty definition/unknown energy type

The uncertainty can increase significantly when there is an incorrect interpretation of the vehicle type, energy type (discussed in Section 7.2.6), and/or goods, or when this information is unknown. For instance, the impact of uncertainty regarding the vehicle type on the emission intensity factor can be observed in Table 7.8. Similarly, Table 7.9 demonstrates how the minimum and maximum deviations from the average differ across various vehicle classes. Moreover, the availability of multiple databases for obtaining emission intensity factors can also contribute to uncertainty. These variations in databases are likely due to differing assumptions about the load factor percentage and empty running.

To illustrate this point, consider an example where the vehicle type is unknown or misinterpreted, causing an inaccurate calculation of the carbon footprint for a freight shipment. In such a case, using an incorrect vehicle type could lead to an overestimation or underestimation of the emissions. Furthermore, when comparing data from different databases, discrepancies become evident, as illustrated in Table 7.10. The uncertainty arising from different databases is, to a large extent, already incorporated into the uncertainty of the emission intensity factor. As mentioned earlier, this is primarily due to the underlying assumptions, such as the load factor percentage and empty running, which can vary between databases.

Additionally, the interpretation and knowledge of the shipment type are crucial, as the underlying assumptions of the factors are based on these aspects. Misinterpreting the shipment type can lead to an inaccurate representation of the emissions. In GLEC and emission intensity factors from CE Delft (co2emissiefactoren.nl), a distinction is made, for example, between medium-heavy, light, and heavy transport. However, one must be careful that the definitions of heavy, light, and medium refer to the load-carrying capacity of a vehicle. For instance, a dormer window might sound heavy or medium-heavy, but the maximum capacity for dormer windows is mainly determined by the volume, not by the weight of the material. In comparison to the maximum loading, the shipment is considered 'light'. An example of the differences this can cause is shown in Table 7.11.

Table 7.8: Difference emission intensity factor per vehicle class cluster based on input numbers from Rijkswaterstaat (2023) and CE Delft (2020)

Goods type	**Vehicle type and weight**	**Kg CO_2-eq per ton-km (WTW)**	**In/decrease WTW factor preceding vehicle class**
Bulk and piece goods; average weight	Van (>2 ton)	1.326	
	Truck (<10 ton)	0.363	-73%
	Truck (10-20 ton)	0.256	-29%
	Truck (>20 ton with trailer)	0.105	-59%
	Heavy tractor + trailer	0.088	-16%
	LZV	0.085	-3%
Containers	Truck (>20 ton)	0.212	
	Truck (>20 ton with trailer)	0.122	-42%
	Heavy tractor + trailer	0.121	-1%
	LZV	0.109	-10%

Table 7.9: Difference emission intensity factor per vehicle class cluster based on input numbers from Rijkswaterstaat (2023) and CE Delft (2020)

			Kg CO_2-eq per unit (WTW)		
Vehicle characteristics	**Shipment type**	**Unit**	*Average*	*Min*	*Max*
Truck up to 20 ton + trailer	Average/mixed	ton-km	0.3095	0.256 (-17%)	0.363 (+17%)
Truck over 20 ton	Average/mixed	ton-km	0.0927	0.085 (-8%)	0.105 (+13%)

Table 7.10: Difference databases emission intensity factors SFC (2020) and CE Delft (2020)

Vehicle characteristics	**Shipment type**	**Fuel**	**Load Factor**	**% loaded kms**	**Kg CO_2-eq per ton-km (WTW)**	**Source**
Truck (10-20 ton)	Average/mixed	Diesel	52%	75%	0.256	CO2emissiefactoren.nl
Truck (12-20 ton)	Average/mixed	Diesel. 5% biodiesel blend	60%	83%	0.15	GLEC
		% Difference	15%	11%	-41%	

Table 7.11: Emission intensity factors with different shipment types based on numbers from CE Delft (2020)

Truck GVW >20 with trailer:				
Road type	**Load capacity (ton)**	**WTW-emissies (g CO_2-eq/tkm)**	**Shipment type**	**Difference**
Average	28	136.9	average	-
Average	28	152.2	light	+11% (relative to average)
Average	28	105.2	heavy	-23% (relative to average)

7.2.9. Overview uncertainty margins

Based on the previous subsection, an overview of the margins of uncertainty that are approximately expected has been made. These are visible in 7.8. The margins are from 0-10%, 0-40% and 0 until more than 40% difference caused within the variable to which it relates. Some margins are difficult to determine as they are very context dependent and therefore these uncertainties are based on a worst case scenario. When more information is available, these uncertainties can be reduced. This is for example the case for the assumptions made to fill in route data. In addition, the uncertainty margin of energy type can also be smaller if, for example, it can be said with 80 percent certainty that it is diesel and with 20 percent certainty that it is HVO100. This makes the uncertainty margin smaller again. The argumentation of these margins is visible in Appendix G in Tables G.4.

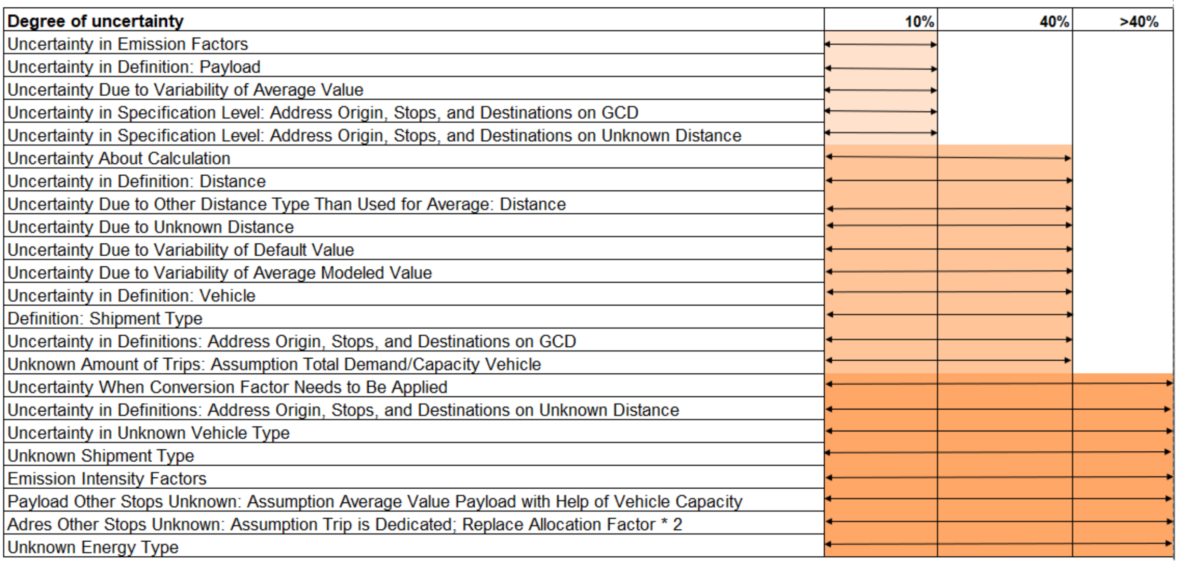

Figure 7.8: Expected margin per cause

7.3. Prioritisation uncertainties

In this section, uncertainties are prioritized based on their complexity and potential impact on the carbon footprint estimation. By ranking the uncertainties, guidance on which areas require further attention and resources to minimize their effects on the overall carbon footprint calculation can be provided.

7.3.1. Methods to prioritize uncertainties

Prioritization is one of the aims of this investigation, as it can help identify the most significant uncertainties. Prioritizing uncertainties can be accomplished through a sensitivity analysis, of which different types have been discussed (factorial, one-factor, etc.), or through a focus group with experts in the field. A third method for assigning priority to a value involves the use of priority numbers, which are frequently employed in safety science through ”Risk Priority Numbers” (RPN). This approach has the benefit of combining multiple factors to determine a priority. In risk analysis, for instance, the probability of a risk occurrence is combined with the severity of the risk and the probability of detection; levels are then assigned to these factors, and scores are assigned. A RPN is established through multiplication, which aids in determining which risk demands a higher priority (Lo & Liou, 2018). This method has the advantages of being easily understandable, repeatable, and accommodating both qualitative and quantitative values. As this study is concerned with uncertainty, this method cannot be adopted directly; however, an analogy can be drawn.

Since the input data of a carbon footprint calculation (of a shipment) has a reasonably straightforward calculation with proportional relationships, a simple sensitivity analysis does not provide sufficient information about the influence of uncertainties. However, when coupled with the degree of uncertainty prevailing in a variable, it does conveys more information. Unfortunately the degree of uncertainty is not always convertible to a quantitative margin, for example, when it involves uncertainty associated with the misapplication of a calculation. The effect of this uncertainty can then be calculated through a relatively simple sensitivity analysis, but the magnitude of the uncertainty is not revealed. Another option is to evaluate uncertainties with experts, but due to time constraints and the possibility of replicating the study, this approach was not pursued. The advantage of the ’risk priority number’ from the FMEA method is that it provides a means to link both qualitative and quantitative values (Xiao et al., 2011). To better assess these uncertainties and their impacts, a new concept called the Data Uncertainty Reduction Priority (DURP) number is proposed. The DURP number builds on the ’risk priority number’ from the FMEA method and enables the analysis of uncertainties by incorporating the effect, degree of uncertainty, and the complexity of uncertainty reduction. This factor immediately assigns urgency to improving estimates. Moreover, the impact of the degree of uncertainty and the degree of effect on the carbon footprint can be compared with the complexity to determine the ’low-hanging fruit.’ The details of the DURP number and its application will be discussed in the following subsection.

7.3.2. The Data Uncertainty Reduction Priority Number

First, it is essential to realize that the DURP is examined per data situation, as the data situation determines how the carbon footprint is calculated, depending on the lack of information in variables of fuel consumption or transport activity. Uncertainties that may arise are identified per data situation, these data situations are already explained in Section 7.1. Per factor a score is assigned to each uncertainty to eventually arrive at the Data Uncertainty Reduction Priority Number (DURP). The higher this number, the higher the urgency of this uncertainty. The first factor is represented as ’Effect on the magnitude of the carbon footprint’, the second factor is ’The degree of uncertainty’, and the third factor is ’The complexity of reducing uncertainty’. The scores are assigned based on a Likert scale of 1 to 3, comprising an ordinal level of ’low’, ’medium’, and ’high’. Using the same scale for each factor of the uncertainty prioritisation ensures that the evaluation of each factor is conducted consistently and comparably. The scales are explained per factor.

Effect on Carbon Footprint Magnitude

The effect on the magnitude of the carbon footprint refers to the extent to which uncertainty can influence the final value. This is examined using elasticity, which represents relative impact on the final value when the variable affected by uncertainty changes. For example, an elasticity of 1 occurs when a 10% change in the variable leads to a 10% change in the carbon footprint. An elasticity greater than 1 implies that the uncertainty affects multiple variables, resulting in a combined impact greater than 10%. The effect of magnitude is often 1, thus it has been decided to classify 0.5 to 1 as ’medium’, less than 0.5 as ’low’, and greater than 1 as ’high’. The scores are visible in Table G.1.

Table 7.12: Scores effect on Carbon Footprint Magnitude

Score	Description	Elasticity
1	Low: The uncertainty has a small effect on the carbon footprint and will not have a significant impact on the calculation.	<0.5
2	Medium: The uncertainty has a moderate effect on the carbon footprint.	0.5-1
3	High: The uncertainty has a very large effect on the carbon footprint because it can have an extra effect on other uncertainties.	>1

Degree of Uncertainty

The degree of uncertainty is expressed both qualitatively and quantitatively. This means that the uncertainty margins from the previous section can be converted to scores. However, not all uncertainties can be expressed in margins, so the expected degree of dispersion based on the other effects of uncertainties must be used. A score of less than 10% between the minimum and maximum values is considered ’low’, which also includes the accepted variability of fuel consumption based on historical data, as this is considered low uncertainty by the GLEC Framework, among others. A spread of 10 to 40 percent between the minimum and maximum values is considered ’medium’, and more than 40 percent is considered ’high’. The scores are visible in Table G.3.

Table 7.13: Scores expected degree of uncertainty

Score	Description	Uncertainty margin
1	Low: There is some uncertainty, but this uncertainty is assumed to be low.	<0.10
2	Medium: There is some uncertainty due to variability, ambiguity or lack of data.	0.10-0.4
3	High: There is significant uncertainty due to ambiguity or a lack of important data that is difficult to obtain.	>0.4

Complexity of Uncertainty Reduction
In addition to managing uncertainty and recognizing its existence, it is also crucial to reduce uncertainty. Therefore, one of the categories for prioritizing uncertainties is the complexity of uncertainty reduction, to which specific scores must be assigned. Since the scores for 'degree of uncertainty' and 'impact on carbon footprint of a shipment' are scaled on a score of 1 to 3, the same must be done for the 'complexity of uncertainty reduction' category. Furthermore, it is not possible to make this scale quantifiable, and it must therefore be a qualitative scale. Literature emphasizes that uncertainty can be reduced in various ways, with the following three being most common: data collection, communication with stakeholders, and quantification of uncertainties (Erkoyuncu et al., 2013; Dankers & Kundzewicz, 2020) . Based on this, the scales are further divided. Communication with a stakeholder to reduce ambiguity is considered 'low', gathering more data to make better estimates is considered 'medium', and conducting further research on the uncertainty surrounding the value due to its unknown nature receives a 'high' score. The scores are visible in Table G.5.

Table 7.14: Scores complexity of uncertainty reduction

Score	Description
1	Low: Communication with a stakeholder to reduce ambiguity.
2	Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
3	High: Reducing the uncertainty is very complex and requires significant effort and resources, \ such as additional research to get insights into the uncertainty that surrounds a value.

By multiplying the scores of the three factors, the Data Uncertainty Reduction Priority Number (DURP) for each uncertainty can be calculated. These DURPs can then be used to determine which uncertainties have the highest priority to address. By comparing the effects of the degree of uncertainty and the impact on the carbon footprint with the complexity of reduction, one can identify the 'low-hanging fruit', i.e., which uncertainties can be relatively easily reduced with a significant impact on the uncertainty of the carbon footprint. Applying this method to the uncertainties identified in this study allows prioritizing and addressing the most important uncertainties. This enables researchers and policymakers to focus their efforts on areas where the greatest improvements are possible and the most benefit can be achieved.

7.3.3. Results prioritization

The scores have been assigned to uncertainties for each data situation, with the rationale provided in Appendix G in Tables G.6, G.4, and G.2. Eventually, three uncertainties showed changes in scores (uncertainty regarding the conversion factor, payload definition, and specification level of origin and destination on the Great Circle Distance). Moreover, it may vary per data situation which uncertainties may occur. In this section, the results for all uncertainties are discussed and visualized in a single graph and table, indicating in which data situation each uncertainty does or does not occur. To see the prioritization per data situation, refer to the graphs in Appendix G (Figures G.1 to G.7). The information remains the same as discussed in this section, but it allows for a more specific examination of the data situation.

The result of prioritizing all identified data and parameter uncertainties is shown in Figure 7.9. Uncertainties 3a/3b, 4a/4b, and 10a/10b change in impact per data situation. The prioritization of uncertainties is depicted in two ways. First, the DURP score illustrates which uncertainties not only have a significant effect but are also the most challenging to reduce. These are color-coded and displayed to the right of the graph, the more 'red' the number is, the higher the priority based on the DURP score. To the left, a graph is displayed, with the impact on the carbon footprint plotted on the Y-axis. The uncertainty's impact on a shipment's carbon footprint is determined by multiplying the uncertainty's sensitivity score on the carbon footprint (Effect on Carbon Footprint Magnitude) by the score of the possible spread of this uncertainty (Degree of Uncertainty). The complexity of reduction is then shown on the X-axis. By plotting the uncertainties on this grid and displaying them in this way next to the DURP score, it becomes clear where the relatively easy solutions to reducing significant uncertainties may lie. These uncertainties have previously been described as 'low-hanging fruit'.

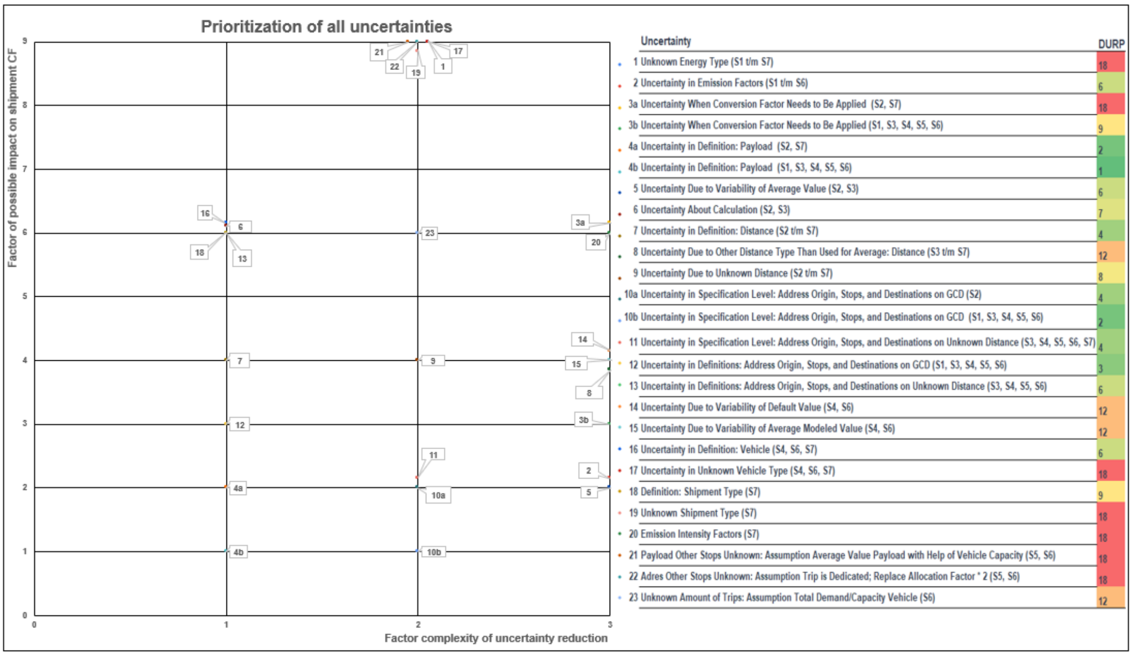

Figure 7.9: Prioritization results

Findings

The findings that become apparent when plotting the graph above (Figure 7.9) are primarily that, at a glance, it is evident which uncertainties have a relatively high impact but also a relatively low complexity to reduce. These mainly include uncertainties in the definition of vehicle type, shipment type, uncertainty of the calculation of the supplied value, and definition uncertainty about the origin and destination on the unknown distance. These uncertainties should be avoided as much as possible through good communication, which can reduce many potential uncertainties in the carbon footprint. These uncertainties can affect both the total emissions calculated and the distribution of emissions across customers. Additionally, it is immediately apparent that there are five uncertainties with the highest impact scores. Three of the five uncertainties are characterized by influencing the choice of a default average fuel consumption, the emission factor, or an emission intensity factor. When these data points are missing, this can have significant effects on the outcome of both the total carbon footprint and the carbon footprint of a shipment. The complexity is considered 'medium,' and with more data (e.g., by requesting a vehicle's license plate), information can be obtained to reduce these uncertainties. The other two uncertainties concern assumptions made in the trip data, which primarily relate to the distribution of emissions across customers; the impact on the carbon footprint of a shipment is also significant. Additionally, the assumption of the number of trips carries some uncertainty, although it is somewhat smaller since certain conditions attached to this assumption can limit the uncertainty (such as the known capacity for a specific type of good and that it is a dedicated roundtrip). Furthermore, it is apparent that the uncertainty of the emission intensity factor is high, and the uncertainty of a conversion factor, with these uncertainties having high complexity for reduction and requiring more research to be mapped. The uncertainties with the least impact appear to be the payload definition, specification levels of origin and destination on the GCD, and the unknown distance, the uncertainty in emission factors, and the variability of the average fuel consumption value. However, it should be noted that there are conditions attached to these uncertainties, and they may change in the future. As mentioned earlier in the previous subsection, the impact of the specification level depends on the total Great Circle Distance. If the GCD is 10 kilometers and the city of Amsterdam is specified as 'destination' instead of a postal code on PC6 level, this can have a significant impact, while if the GCD is 100 kilometers, it is much less. The same applies to emission factors; for diesel and gasoline, the differences between the two databases (GLEC and CO2emissiefactoren.nl) are not very significant. However, for more sustainable fuels, it is expected that the difference will be more significant and increasingly important in the future. The remaining uncertainties have a moderate impact. Notably, parameter factors or uncertainties around averages are the most challenging to minimize. This is because these uncertainties are often associated with variability, meaning some uncertainty will always persist. When looking at the DURP, six uncertainties have the highest priority: the uncertainty when a conversion factor should be applied, the uncertainty if the vehicle type is unknown, the uncertainty in energy type, unknown shipment type, uncertainty around emission intensity factors, and assumptions about the distribution of emissions by dividing the remaining payload across other stops or considering a shared trip as a single trip. It is crucial to realize that these uncertainties do not occur in every situation. Interestingly, these uncertainties primarily occur in data situations 6 and 7, and an unknown energy type in every situation can cause significant uncertainty. These uncertainties should be prioritized for addressing, as they have the highest uncertainty due to the complexity of reduction and influence on the final figure. Uncertainties with medium DURP scores (6 to 12) also require attention but may be of lower priority compared to the highest DURP scores. Uncertainties with low DURP scores (1 to 4) have the least impact on data uncertainty reduction and may be considered lower priority. These findings are valuable input for the following section, where it is discussed how to quantify and address the uncertainties.

7.4. Assessment of uncertainties

In this final section, methods and strategies for assessing and preventing the uncertainties are discussed. Reflecting on the literature of uncertainties in Chapter 4, various methodologies have been proposed for the assessment and evaluation of uncertainties. The previous Section 7.3 primarily focused on ranking uncertainties according to their potential minimum and maximum spread and their sensitivity to the carbon footprint of a shipment. Consequently, this analysis highlights the uncertainties that are expected to have the most significant impact. This section elaborates on a potential approach for addressing these uncertainties, providing a comprehensive understanding of the uncertainties surrounding the final carbon footprint.

In the classification of uncertainties, discussed in Chapter 5, each uncertainty is assigned a 'level': 'stochastic', 'scenario', or 'deep uncertainties'. This study opts to assess and quantify 'stochastic uncertainties' using probability density functions, which, through Monte Carlo simulation, can offer a clear understanding of the degree of uncertainty. This approach is selected because a probability distribution can most effectively represent uncertainty. The other level, 'scenario uncertainties', primarily pertains to uncertainties where assumptions must be made due to the absence of data; to demonstrate the influence of these assumptions, multiple scenarios can be run. The final level, 'deep uncertainties', often involves ambiguity. While it is challenging to base scenarios on different interpretations, the primary aim is to avoid these uncertainties as much as possible. In addition to investing energy and time in obtaining as much complete information as possible, ensuring the accuracy of the information and avoiding interpretation errors is crucial. Proper communication of the correct concepts beforehand can be an effective method for preventing uncertainties. Thereby in terms of complexity this is seen in previous section as least complex. Therefore, the decision has been made not to quantify these uncertainties but to develop a feature in the 'tool' design at a later stage to mitigate them.

7.4.1. Uncertainties to assess with probability density functions

The probability density functions employed are chosen from uniform and triangular distributions, as they are most commonly based on 'expert judgments', while other distributions, such as normal, log-normal, or empirical, are based on datasets (which were not found or available during the writing of this thesis). Additionally, these distributions are created based on assumptions derived from findings in the preceding section 7.3. It is essential to recognize that these assumptions are subject to change and that further research is required to refine them. However, for the time being, these numbers have been assigned to the distributions to provide preliminary insight into the potential impact of uncertainty on the output. In Table 7.15 these uncertainties are visible with further explanation about the type of probability density function that is chosen with the assigned values.

Table 7.15: Uncertainties to assess with probability density functions

Uncertainties	**Explanation**
Uncertainty in Emission Factors	Level of uncertainty is described as stochastic, a method to deal with this uncertainty is to make a probability density function. Because there is little information about the uncertainty/variation underlying the emission factor a probability density function is made based on the different values in data bases. We assume that these are both a same probability, therefore the PDF will be uniform: Uniform (Value data base 1, Value data base 2)
Uncertainty when Conversion Factor needs to be applied	Level of uncertainty is described as stochastic, a method to deal with this uncertainty is to make a probability density function. Because there is little information about the uncertainty/variation underlying the standard conversion factor a probability density function is made based on the assumptions made in this research. This is +- 60 % for the conversion factor. Because there is a clear max and minimum value, the PDF will be triangular. FC = Triangular(min: Conversion Factor -60%, mode: Conversion Factor, max: Conversion Factor +60%)
Uncertainty due to other distance type than used for average	Level of uncertainty is described as stochastic, a method to deal with this uncertainty is to make a probability density function. Because there is little information about the uncertainty/variation underlying the distance a probability density function is made based on the percentage that needs to be applied to convert different distances. This is +5% for Planned Distance to Actual Driven Distance and +10% from Constructed Shortest Feasible Distance with Google Maps (CSFD) to Actual driven distance. Thereby a distinction has to be made when a detour is made which will include a percentage of +30%. The probability of a detour is less likely to happen and a therefore a maximum value, thereby the minimum value of the distance will be the Planned Distance or Shortest feasible distance. Because there is a clear max and minimum value, the PDF will be triangular.
Uncertainty due to unknown distance	When the distance is not known, the distance could be reconstructed with Google Maps. Level of uncertainty is described as stochastic, a method to deal with this uncertainty is to make a probability density function. Because there is little information about the uncertainty/variation underlying the distance a probability density function is made based on the assumptions in this research and a percentage that needs to be applied to account for detours. This is +10% from Shortest Feasible Distance to Actual driven distance. Thereby a distinction has to be made when a detour is made which will include a percentage of +30%. The probability of a detour is less likely to happen and therefore a maximum value, thereby the minimum value of the distance will be the Shortest feasible distance. Because there is a clear max and minimum value, the PDF will be triangular. PDF Constructed distance to ADD = Triangular(min: CSFD, mode: CSFD +10%, max: CSFD +30%)
Uncertainty due to variability of Default Value	Level of uncertainty is described as stochastic, a method to deal with this uncertainty is to make a probability density function. Because there is little information about the uncertainty/variation underlying the fuel consumption a probability density function is made based on the assumptions made in this research. This is +- 16.5% for the fuel consumption. Because there is a clear max and minimum value, the PDF will be triangular. FC = Triangular(min: FC Value -16.5%, mode: FC value, max: FC Value +16.5%)
Uncertainty due to variability of Average Modeled Value	Level of uncertainty is described as stochastic, a method to deal with this uncertainty is to make a probability density function. Because there is little information about the uncertainty/variation underlying the fuel consumption a probability density function is made based on the assumptions made in this research. This is +- 12.5% for the modeled fuel consumption. Because there is a clear max and minimum value, the PDF will be triangular. FC = Triangular(min: FC Value -12.5%, mode: FC value, max: FC Value +12.5%)
Uncertainty in emission intensity factors	Level of uncertainty is described as stochastic, a method to deal with this uncertainty is to make a probability density function. Because there is little information about the uncertainty/variation underlying the distance a probability density function is made based on the assumptions made in this research. This is - 31.5% and +51% for the emission intensity factor. Because there is a clear max and minimum value, the PDF will be triangular. EIF = Triangular(min: Emission intensity value -31.5%, mode: Emission intensity value, max: Emission intensity value +51%)

7.4.2. Uncertainties to assess with scenarios

To determine a possible range of uncertainties based on assumptions, best and worst-case scenarios can be developed. This approach clarifies the upper and lower limits within which the assumption may lie. When it is not feasible to include the assumption, only a best and worst-case scenario can be performed. Furthermore, the best and worst cases can be adapted according to the amount of information available. These uncertainties are not variable in nature; therefore, they must be addressed in this manner, and a probability density function is not applicable. In Table 7.16 these uncertainties are visible with further explanation about the type of scenario's that can be chosen.

Table 7.16: Uncertainties to assess with scenarios

Uncertainties	**Explanation**
Uncertainty in unknown: Energy Type	Level of uncertainty type is described as scenario. The way to deal with this is to show possible scenarios. When it is possible to estimate which energy types is most likely to be used, an scenario for the best-case, worst-case and expected energy type can be calculated to give a bandwidth around the expected energy type with other possible energy types.
Uncertainty in specification level: address Origin, Stops, and Destinations on GCD	Level of uncertainty type is described as scenario. The way to deal with this is to show the best and worst case scenarios. This will give an indication of the bandwidth of the right GCD distance.
Uncertainty in specification level: address Origin, Stops, and Destinations on Unknown Distance	Level of uncertainty type is described as scenario. The way to deal with this is to show the best and worst case scenarios. This will give an indication of the bandwidth of the distance that needs to be reconstructed.
Uncertainty in unknown: Vehicle Type	Level of uncertainty type is described as scenario. The way to deal with this is to show possible scenarios. When it is possible to estimate which vehicle types is most likely used, an scenario for the best-case, worst-case and expected vehicle type can be calculated to give a bandwidth around the expected vehicle type with other possible vehicle types.
Uncertainty in unknown: Shipment Type	Level of uncertainty type is described as scenario. The way to deal with this is to show possible scenarios. When it is possible to estimate which shipment types is most likely transported, an scenario for the best-case, worst-case and expected energy type can be calculated to give a bandwidth around the expected shipment type with other possible shipment types.
Uncertainty in unknown: Payload other Stops Assumption average value payload with vehicle capacity	Level of uncertainty type is described as scenario. The way to deal with this is to show possible scenarios. It is hard to provide expected scenario, therefore it is decided to show the bandwidth in best-case, assumption and worst-case scenario. This will show where the figure based on the assumption will lay in the possible options. The worst case-scenario is when the customer with the smallest GCD has the most load, the best case scenario when the customer with largest GCD has the most load on it.
Uncertainty in unknown: address other Stops Assumption trip is Dedicated, replace Allocation Factor with * 2	Level of uncertainty type is described as scenario. The way to deal with this is to show possible scenarios. It is hard to provide expected scenario, therefore it is decided to show the bandwidth in best-case, and worst-case scenario. Because it is hard to choose a best case for this, it is decided to choose the scenario of using an emission intensity factor because that takes into account the possible empty trips and average loading factor, to provide an example of what a possible option is. The worst case-scenario is when the trip is taken into account as round dedicated trip, the best case scenario will be to take the emission intensity factor and to apply this.
Uncertainty in unknown: Amount of Trips Assumption Total Demand/Capacity Vehicle	Level of uncertainty type is described as scenario. The way to deal with this is to show possible scenarios. A condition for this assumption is that it is used when there is a single round trip (dedicated trip) and the number of full capacity is available based on the goods transported. It is hard to provide ranking to different scenario's, therefore it is decided to show the bandwidth in best-case, and worst-case scenario. The best case scenario will be when the truck is fully loaded and the worst case is when it is 70% loaded.

7.4.3. Uncertainties to be aware of and prevent

Uncertainties rooted in ambiguity should ideally be avoided. When information is scarce or variability or factors arise, it is difficult to address them once they are present, so managing these types of uncertainties is essential. However, the difference with uncertainties that can be introduced is that they do not need to exist if effective communication takes place. As a result, being aware of and preventing these uncertainties is crucial. In Table 7.17 these uncertainties are visible.

Table 7.17: Uncertainties to be aware of and prevent

Uncertainties	**Explanation**
Uncertainty in definition: Payload	Level of uncertainty type is described as deep uncertainty, it is hard to attach scenario's on someones interpretations. Since it is possible to prevent this uncertainty by communicating well and asking the right questions the strategy to deal with this uncertainty is to prevent this uncertainty.
Uncertainty about Calculation	Level of uncertainty type is described as deep uncertainty, it is hard to attach scenario's on someones interpretations. Since it is possible to prevent this uncertainty by communicating well and asking the right questions the strategy to deal with this uncertainty is to prevent this uncertainty.
Uncertainty in definition: Distance	Level of uncertainty type is described as deep uncertainty, it is hard to attach scenario's on someones interpretations. Since it is possible to prevent this uncertainty by communicating well and asking the right questions the strategy to deal with this uncertainty is to prevent this uncertainty.
Uncertainty in definit Origin, Stops, and D on GCD	Level of uncertainty type is described as deep uncertainty, it is hard to attach scenario's on someones interpretations. Since it is possible to prevent this uncertainty by communicating well and asking the right questions the strategy to deal with this uncertainty is to prevent this uncertainty.
Uncertainty in definit Origin, Stops, and D on Unknown Distanc	Level of uncertainty type is described as deep uncertainty, it is hard to attach scenario's on someones interpretations. Since it is possible to prevent this uncertainty by communicating well and asking the right questions the strategy to deal with this uncertainty is to prevent this uncertainty.
Uncertainty in definition: Vehicle	Level of uncertainty type is described as deep uncertainty, it is hard to attach scenario's on someones interpretations. Since it is possible to prevent this uncertainty by communicating well and asking the right questions the strategy to deal with this uncertainty is to prevent this uncertainty.
Uncertainty in definition: Shipment Type	Level of uncertainty type is described as deep uncertainty, it is hard to attach scenario's on someones interpretations. Since it is possible to prevent this uncertainty by communicating well and asking the right questions the strategy to deal with this uncertainty is to prevent this uncertainty.

8

Design output

8.1. Development of design output

”A guidance framework to identify and deal with uncertainties in a carbon footprint analysis of freight transport on a trip level”

Through field research, interviews, and background research, various uncertainties have been identified. These uncertainties depend on the data situation that exists when calculating the carbon footprint of a shipment, as discovered during the data collection process in the field research. To design a tool for assessing uncertainties surrounding a carbon footprint, an guidance framework has been developed to deal with and display potential uncertainties for each data situation. This guidance framework is based on the information gathered in the previous Chapter 7. This approach demonstrates how input data and parameters change per data situation to arrive at a reliable estimate, revealing the potential causes of uncertainty and a strategy for addressing them. Uncertainties with variability attached will always occur and cannot be prevented. These uncertainties are best represented by a probability density function and a Monte Carlo simulation. The advantage of this method is that it allows for determining a confidence interval, providing a more realistic representation of potential uncertainty than, for example, a best-worst-case scenario. A side note is that further research is needed on parameters and distributions, as they are based on assumptions. If a Monte Carlo simulation cannot be integrated into existing tools, an approach could be to use the input of the Monte Carlo simulation as input for scenarios. However, this will be challenging if parameters such as conversion factors for weight and emission factors are built-in and unchangeable. For scenarios, instead of a uniform distribution, the outcome can fall between two numbers; with a triangular distribution, three scenarios are needed, encompassing best, worst, and assumption scenarios. The advantage of this alternative approach is that it can be easily done without making changes to a tool. However, if multiple best-worst case scenarios are present in a single calculation, the spread can become so large that it loses meaning or insight. Uncertainties arising from missing data are associated with both estimates based on additional information and potential assumptions. These cannot be expressed in probability density functions and must be represented using scenario analysis. Finally, uncertainties can arise as a result of incorrect definitions. These should be minimized as much as possible. When requesting data, this must be checked thoroughly, and an extensive explanation should be provided for what is being asked. Since it is often unclear what data situation exists before data collection, an explanation for each data situation can be included, detailing what is expected from the carrier/shipper (from Districon’s perspective) to achieve the most accurate carbon footprint possible. The impact scale of uncertainties on the carbon footprint per data situation is also displayed under the data situation. The tool description is further elaborated in the next Section 8.2 and can be seen on the next pages for the different data situations in Figure 8.1,8.2, 8.3, 8.4, 8.5, 8.6 and 8.7.

8.2. The guidance framework

The final conceptual design of this study is a guidance framework which includes the following steps to identify and deal with different potential causes of uncertainties:

1. Define data situation and identify which fundamental uncertainties (bold in framework) are present in this data situation.

2. Identify potential causes of uncertainties due to definition uncertainties. Ensure that stakeholders sharing information align on these definitions to prevent uncertainty caused by ambiguity.

3. Identify potential causes of uncertainties due to definition uncertainties. Ensure that stakeholders sharing information align on these definitions to prevent uncertainty caused by ambiguity.

4. When the need is to quantify the uncertainty around the carbon footprint, follow the suggested approach that is determined by the nature of the uncertainty. If uncertainty is caused by stochastic nature, the guidance recommends using PDFs and Monte Carlo simulations for a more realistic representation of potential uncertainty. By determining a confidence interval, the tool provides insights into the range of possible outcomes, rather than just presenting a best-worst case scenario. If uncertainty is caused by assumptions made to fill in missing information, the guidance recommends scenario analysis to understand the implications of these assumptions on the carbon footprint calculation. If Monte Carlo simulations cannot be performed, alternative approaches such as input scenarios can be used. These scenarios can be based on uniform or triangular distributions (PDFs), which require two or three scenarios, respectively (best, worst, and assumption scenarios).

Besides the framework systematically addresses and displaying potential uncertainties for each of the seven identified data situations, it includes also impact scores to help users understand the significance of each uncertainty source. By presenting the impact scale of uncertainties, the tool enables users to prioritize actions for mitigating these uncertainties more effectively, allowing a more targeted approach in addressing significant uncertainties and improving the accuracy of carbon footprint calculations.

This framework can assist in understanding the root causes of uncertainties in carbon footprints. It allows users and decision-makers to ask pertinent questions about the data collection, calculation methods, and potential uncertainties that might emerge. Additionally, it can help establish data requirements that a carbon footprint must satisfy and enhance the reliability of a carbon footprint. Consultancies can employ the framework to discuss the outcomes of carbon footprint analyses and the impact of uncertainties. Software developers can incorporate the framework into their software to account for uncertainties in their calculations. Furthermore, transport companies can utilize the framework to enhance the accuracy of their carbon footprint and understand how data quality affects the calculation.

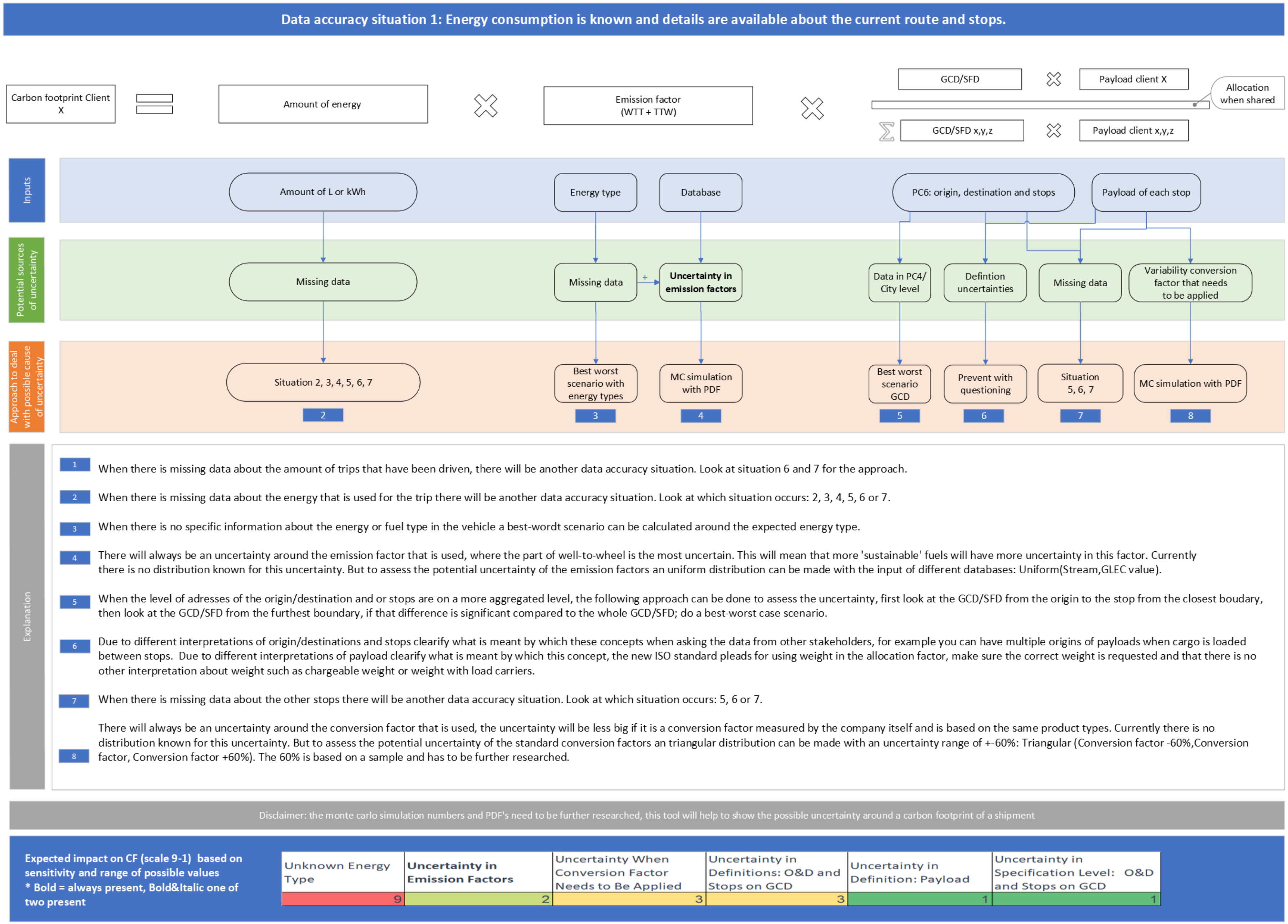

Figure 8.1: Guidance framework Situation 1

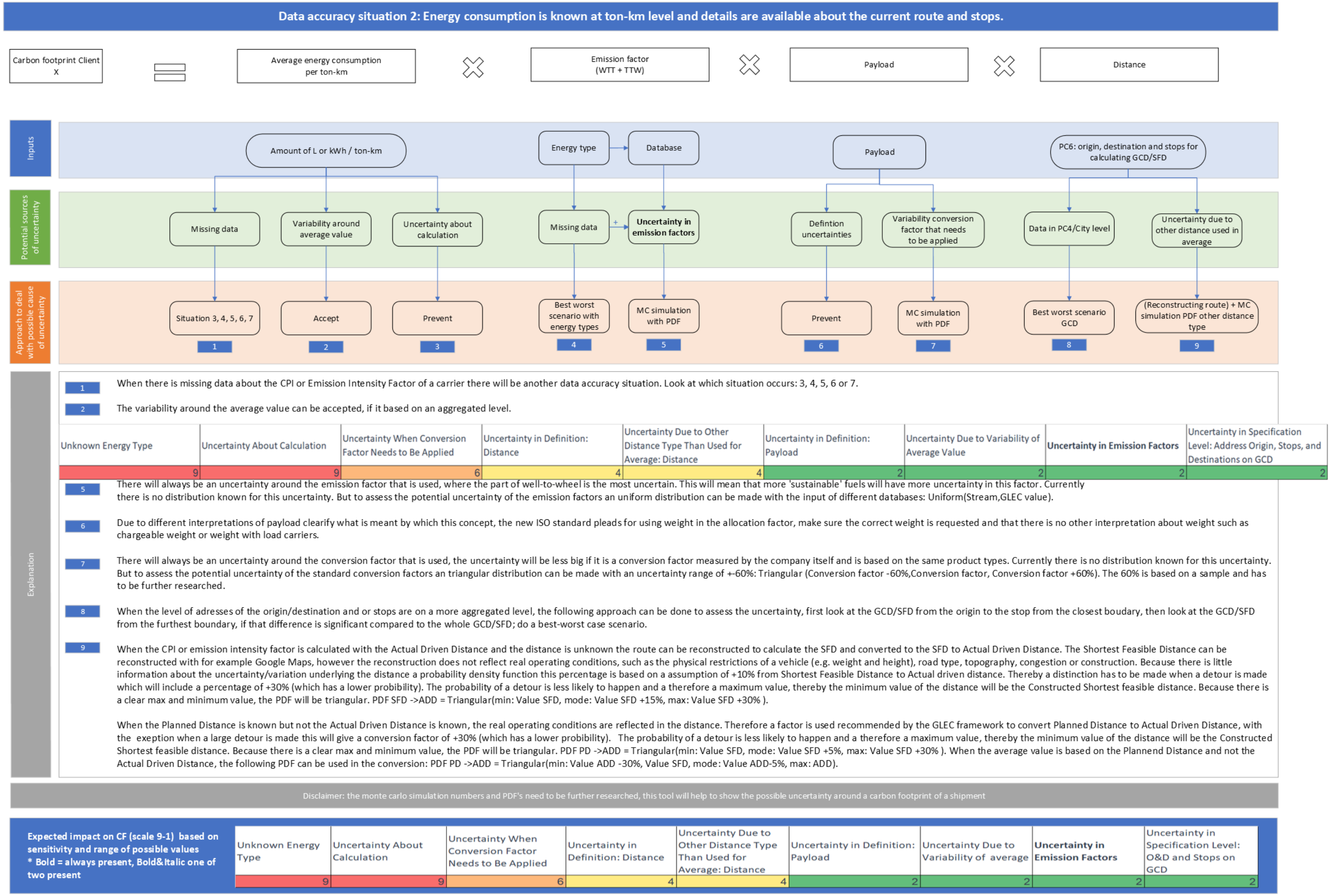

Figure 8.2: Guidance framework Situation 2

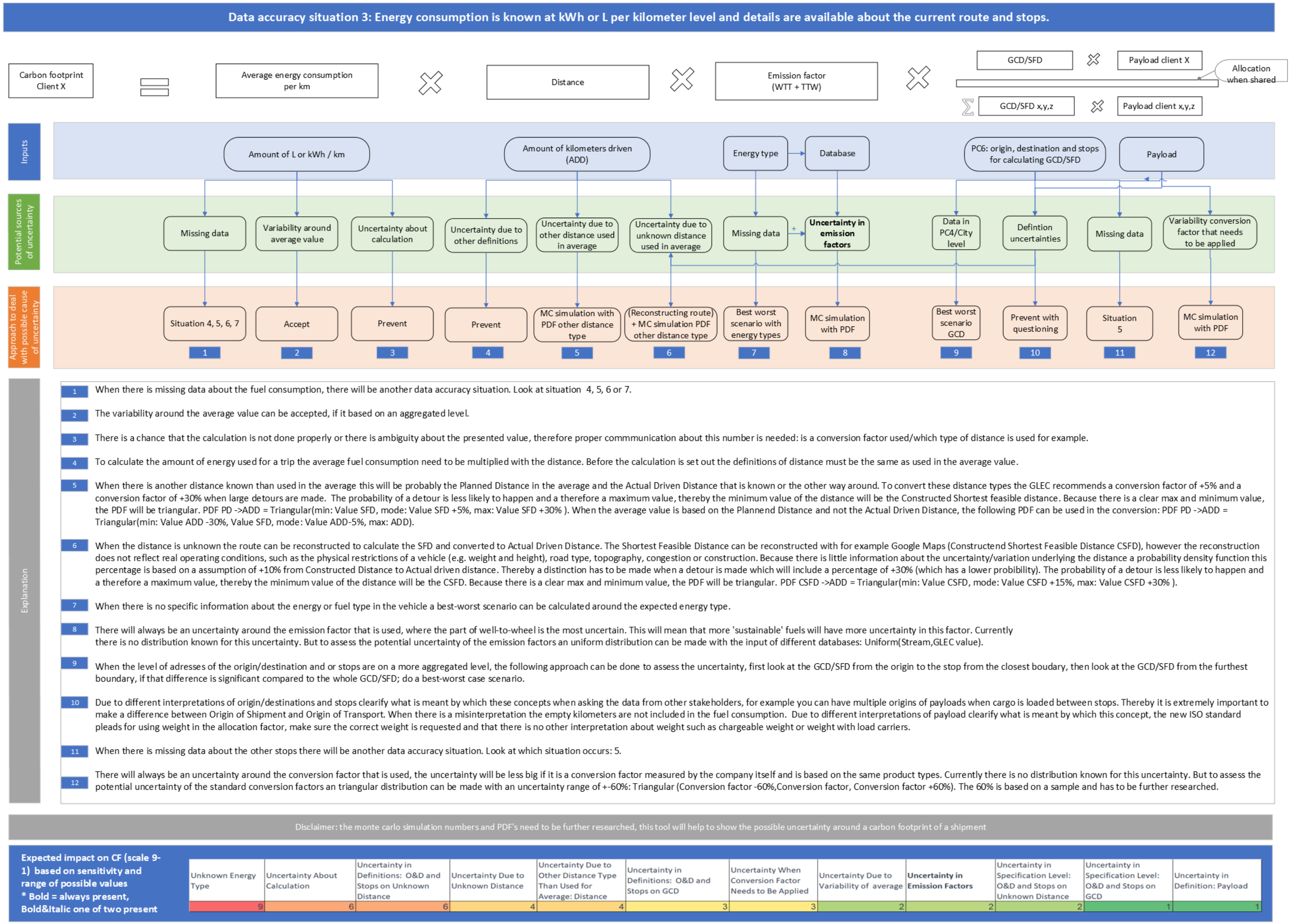

Figure 8.3: Guidance framework Situation 3

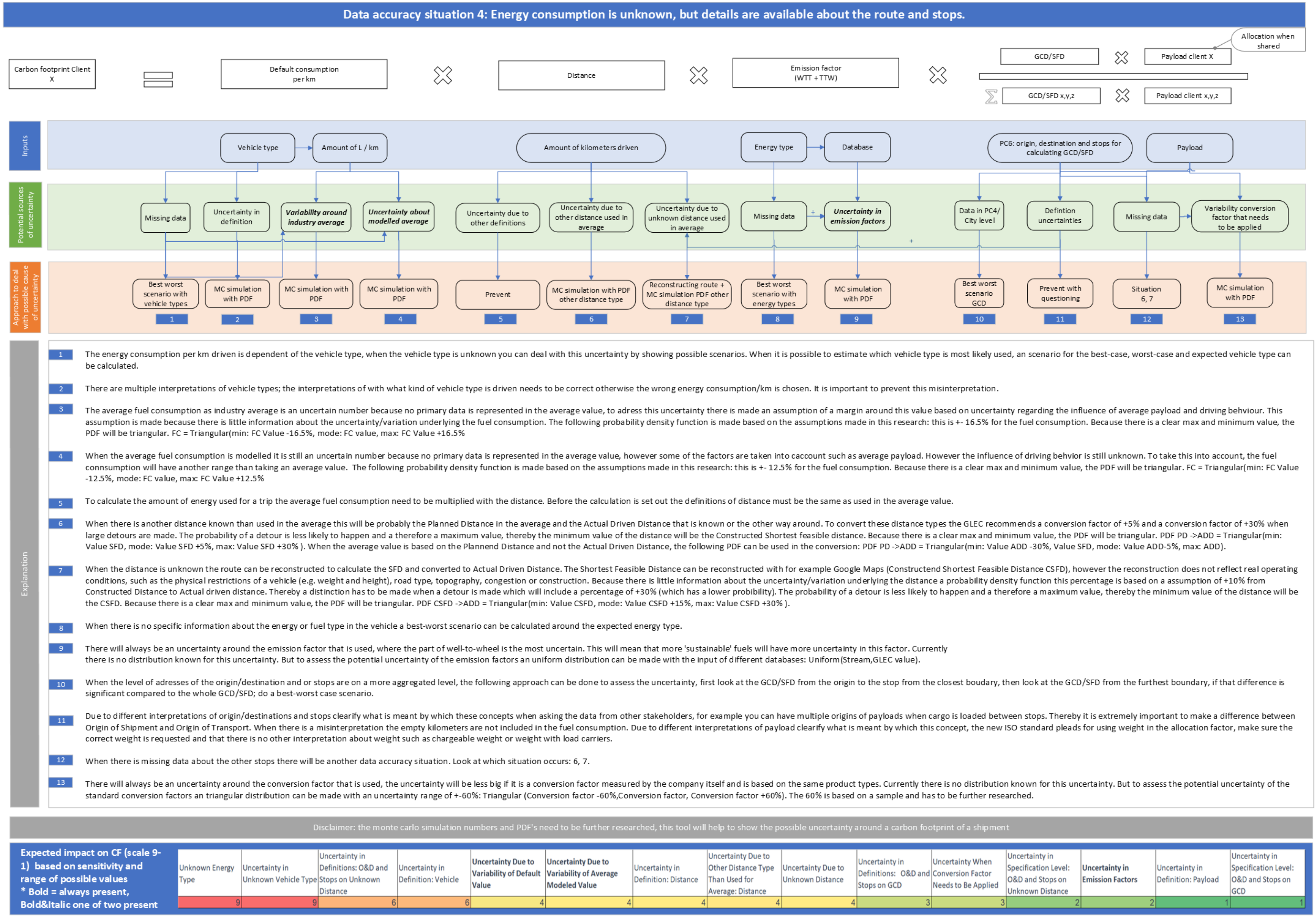

Figure 8.4: Guidance framework Situation 4

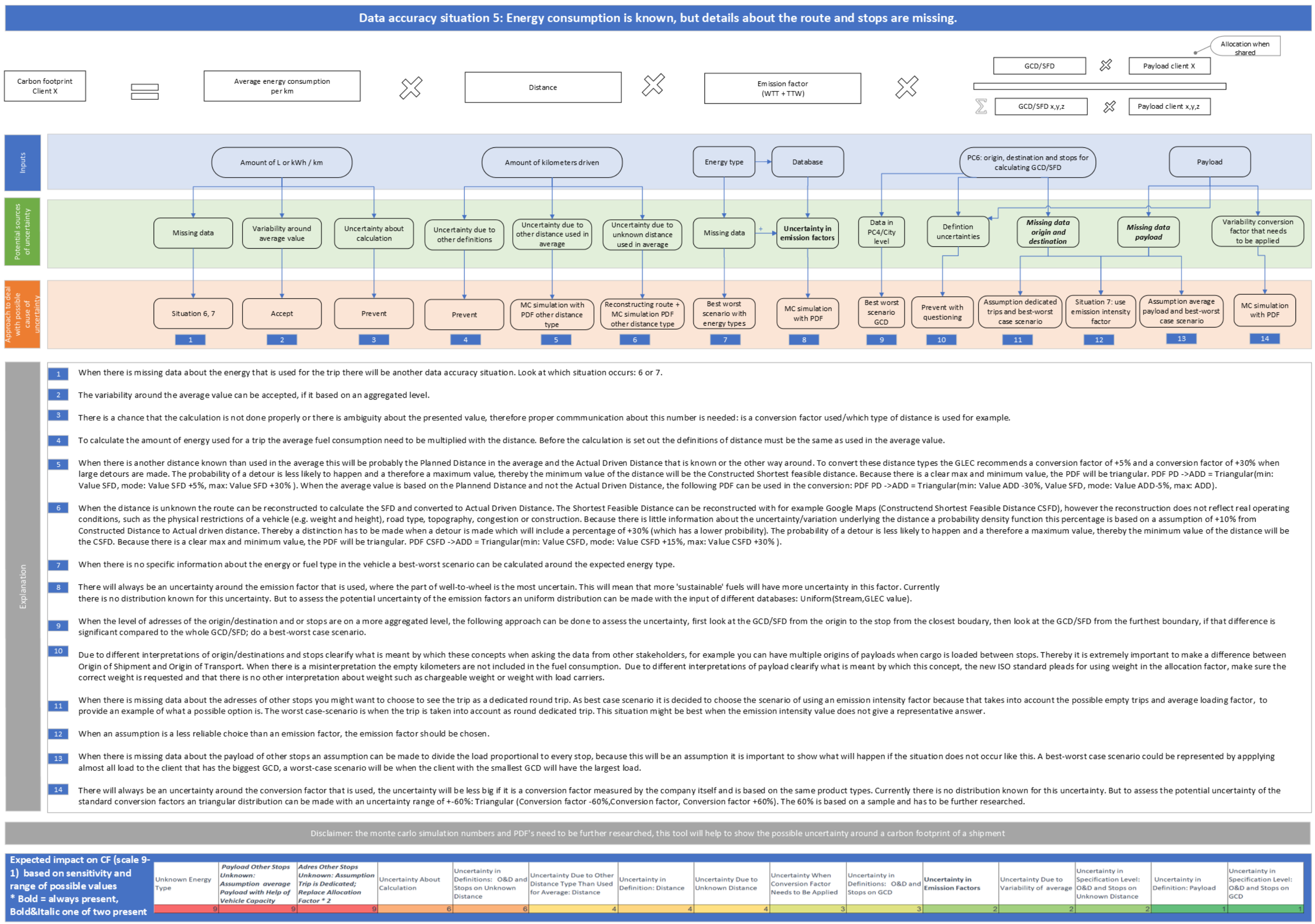

Figure 8.5: Guidance framework Situation 5

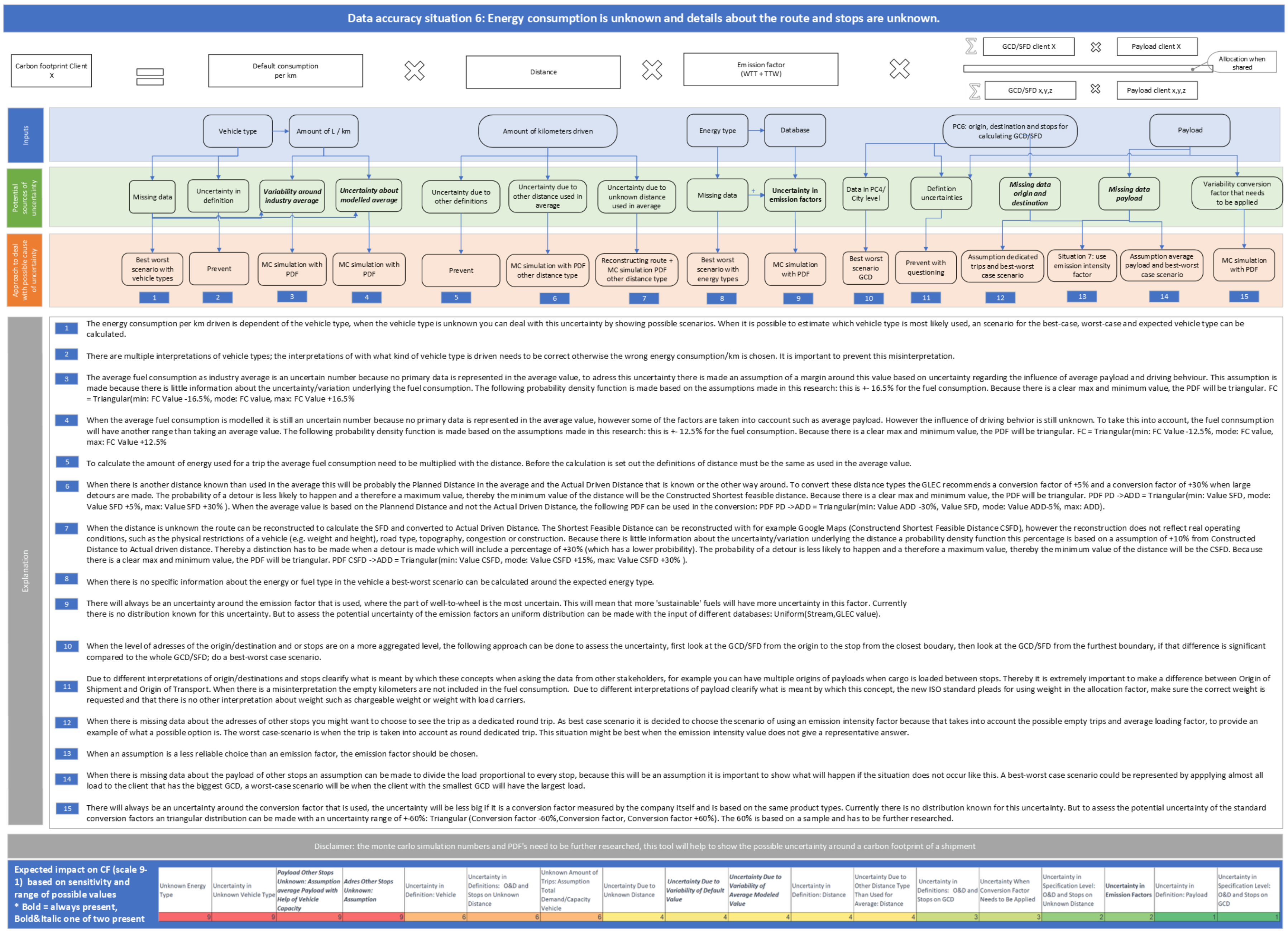

Figure 8.6: Guidance framework Situation 6

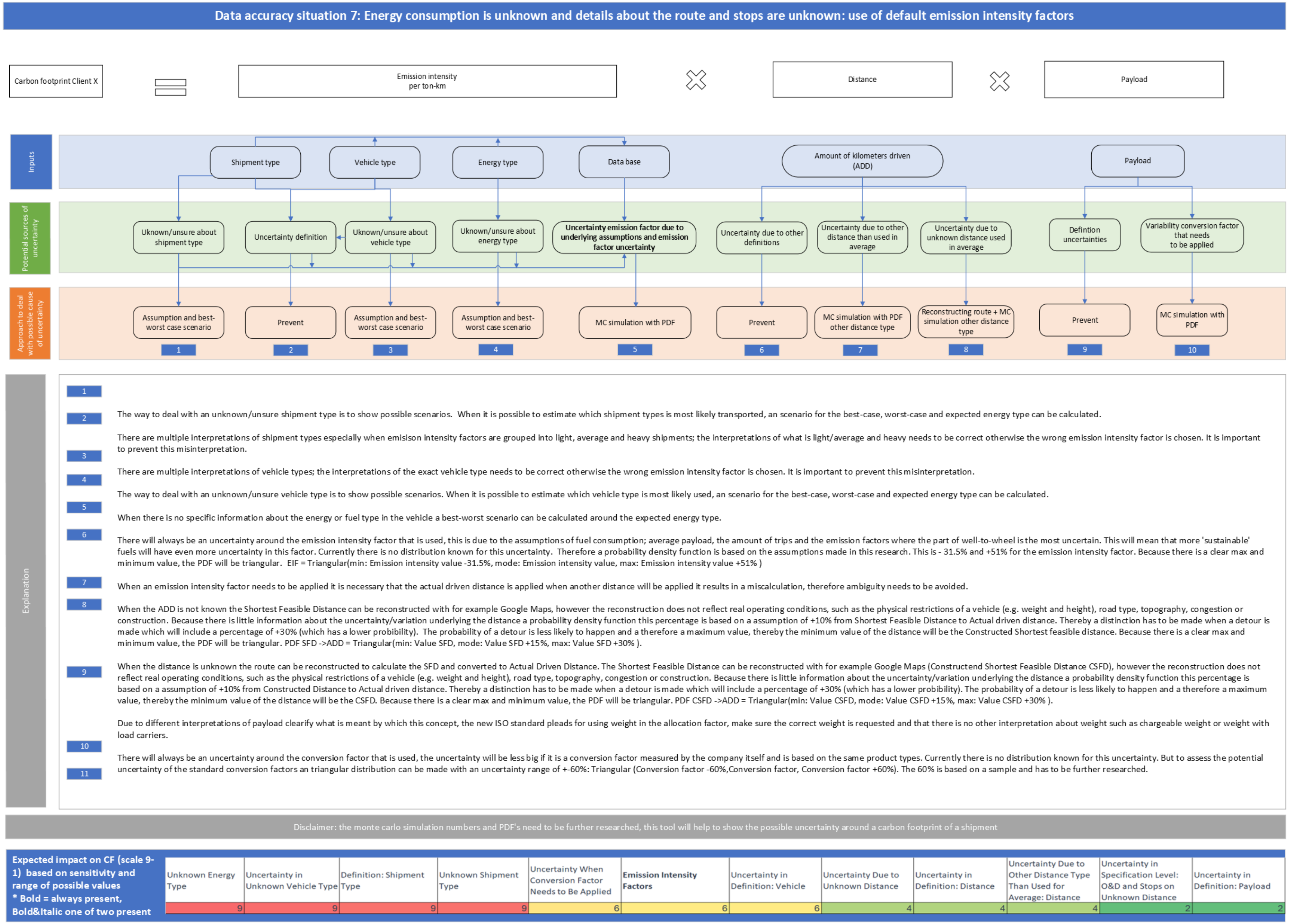

Figure 8.7: Guidance framework Situation 7

IV

Testing and Evaluation

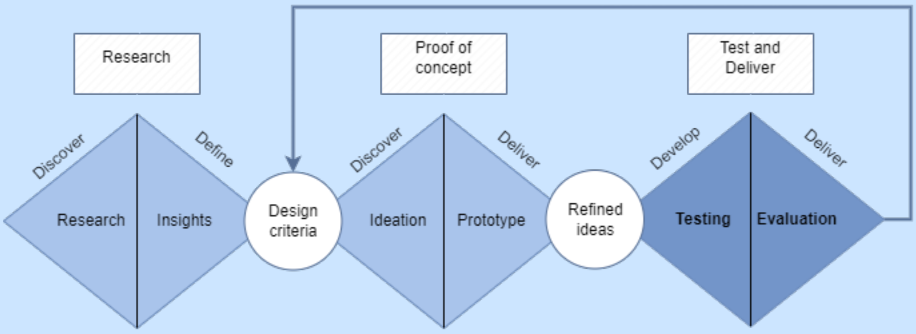

Figure 8.8: Research and Insights

In the **Test and Deliver phase**, the conceptual design is verified and validated to ensure it functions effectively and meets the desired requirements. Initially, the tool is tested using data from field research, where three random trips are selected to determine and map uncertainties using the conceptual design. This process evaluates if the tool works as intended and adheres to the established requirements. Furthermore, the tool's application in the field research for Districon's final report serves as another checkpoint to assess the tool. To validate the tool, semi-structured interviews are conducted with experts in the field of sustainability and carbon footprinting in the transport sector. They provide their opinions on the tool's foundation, practical application, and further insights into the world of carbon footprinting from their perspective. The verification and validation process allows for valuable feedback on the conceptual design and potential improvements. This feedback loop helps refine the design and design requirements, ultimately leading to recommendations for enhancing the tool, as outlined in the research conclusion.

9

Testing: Testing the Tool with Case Studies and verification

9.1. Motivation for the use of Case Studies

To evaluate the effectiveness of the tool and ensure it meets the specified requirements, it is necessary to conduct tests. These tests will also examine the implications of substituting probability density functions with best-worst case scenarios or a combination of best-worst and assumption scenarios. Cases from the Field research have been chosen for this purpose, as data is easily accessible for these instances, and time constraints preclude the selection of additional cases. The tool will be tested on three randomly selected trips from three distinct co-makers to demonstrate the impact of uncertainties on the carbon footprint of a shipment. These co-makers each have a unique data situation. The situations have been modeled in Python, with the code supplied in Appendix I. The following sections will delve into the testing process in detail.

9.1.1. Explanation of carbon footprint measurement for construction site

The company Districon has been asked to calculate the carbon footprint of freight movements to and from a construction site. To do this, the seventeen largest co-makers have been selected according to the 80/20 rule. The transportation can be arranged in several ways: the principal or co-maker handles it in-house, the co-maker/principal orders something from a shipper with their own transport or outsourced transport. By mapping the movements of the freight transport, the emissions can be calculated for the freight movements to and from the construction site.

9.1.2. Data situation case 1

The trip is a shared trip. The **fuel consumption** of the trip is **estimated** by the company itself (not calculated). The cargo is only known for the shipment to the construction site; the **cargo of other shipments is unknown**. In addition, the locations of the other customers are known for the one known trip at city level. The distance of the first trip is a **planned distance**. The assumption is made to distribute the cargo over the remaining stops. The route and information of the stops is visible in Figure 9.1.

*”–> Data accuracy situation 6: **Fuel consumption** is **unknown** and **details** about the **route and stops** are **unknown**.”*

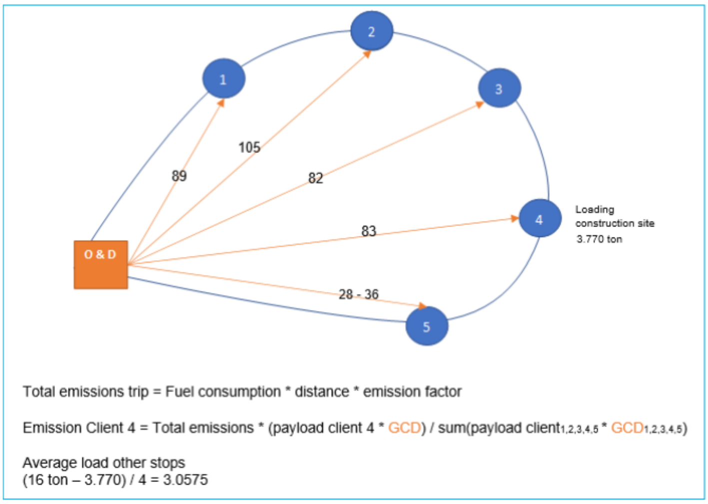

Figure 9.1: Visualization of trip case 1

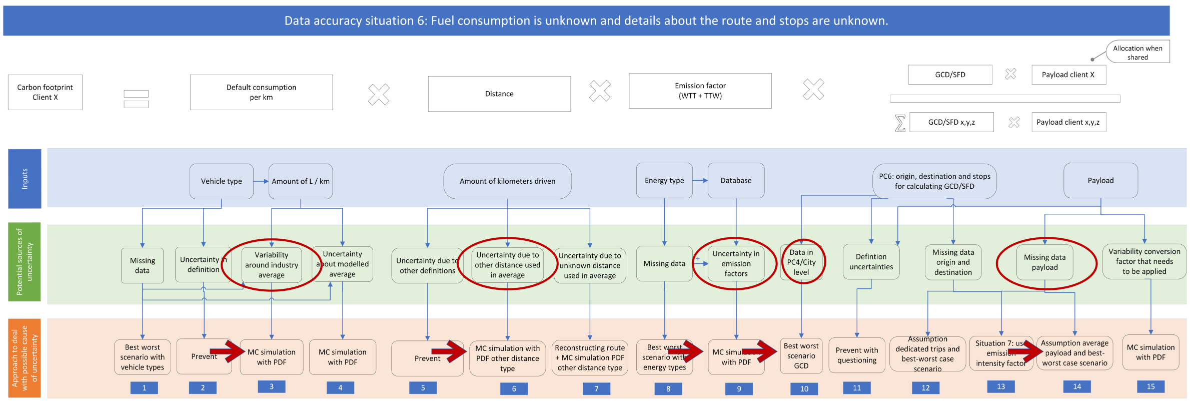

Figure 9.2: Case 1: Situation 6

9.1.3. Inputs case 1:

Figure 9.9 shows the uncertainties involved in calculating the carbon footprint of a shipment to the construction site and how to deal with them. To calculate the carbon footprint with surrounding uncertainties, scenarios and probability density functions (PDFs) that will be simulated are required. The following sections explain the scenarios and PDFs.

Scenario's:

Scenario's average payload:

1. Assumption Scenario 100% loading capacity, load for other stops: $\frac{16\,\text{ton}-3.770\ =3.0575\text{ton}}{4}$
2. Best case scenario for the construction site: when customer 2 has almost all of the load (denominator the largest)
3. Worst case scenario for the construction site: when customer 5 has almost all of the load (denominator the smallest)

Scenario's city level on GCD:

1. The potential difference on the GCD is tested between the different cities. For one client this difference is significant compared to the whole GCD the difference is 8,17 kilometers on the furthest GCD of 36 kilometres.

2. The best case scenario for the construction site will be when the furthest GCD is the true value, the worst scenario will be when the closest GCD is the true value. The assumption will be the midpoint of the city.

Probability density functions: currently based on assumptions made in thesis research:

1. Fuel Consumption (FC) triangular distribution: $\min = 2.1$ km/l, mode: 2.5 km/l, and $\max = 2.9$ km/l

2. Emission Factor (EF) uniform distribution between NL value (3.256) and GLEC value (3.148)

3. Planned Distance (PD) -> Actual Driven Distance with a triangular distribution: $\min = 366$, mode: $366 + 5\%$, max: $366 + 30\%$ (detours)

In Figure 9.3 the PDF's are visualized. The probability density function (PDF) represents the likelihood of specific distance (or fuel consumption or emission factor) values occurring within a triangular (or uniform for emission factor) distribution. The y-axis (f(x)) shows the probability density for each distance (or fuel consumption or emission factor) value (x) on the x-axis. Higher f(x) values indicate a greater likelihood of the corresponding distance (or fuel consumption or emission factor) value (x) occurring. Note that f(x) represents the density around a particular value, not the exact probability of that value occurring.

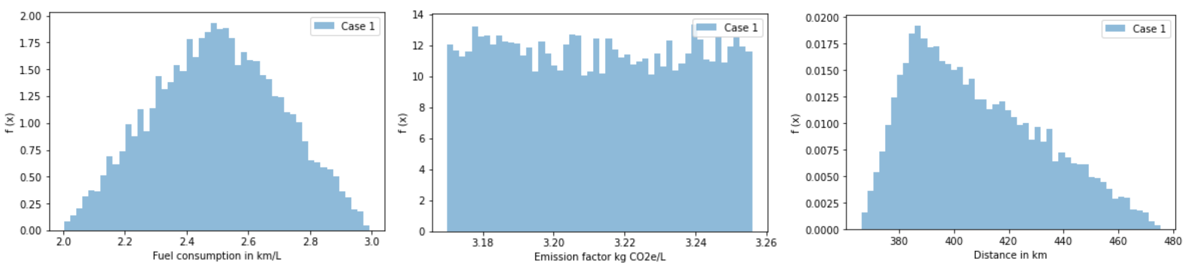

Figure 9.3: Input probability density functions case 1

9.1.4. Results Case 1:

Both the carbon footprint for the entire trip and the portion attributed to the construction site have been calculated. The input of the scenarios and the output of the carbon footprint can be seen in Table 9.1. The output is also plotted in a boxplot for visualization, which is shown in Figure 9.4. The total emissions are influenced by the calculation of total fuel consumption, where the probability density functions primarily have an impact. Next, the emissions attributed to the construction site are presented. These differences are much larger, mainly because the distribution of emissions is influenced by factors such as loading (which is varied in the scenario's). The emissions for the shipment of the construction site will likely fall between the minimum and maximum values of the scenarios. However, the best and worst-case scenarios are relatively unlikely to happen. In contrast, the assumption scenario is likely more representative. Yet, since the actual loads are unknown, this also represents the uncertainty surrounding the allocated emissions for the shipment to the construction site. In the assumption scenario, the carbon footprint of the shipment lies between 117.43 and 143.57 kg CO_2e (within the 95% confidence interval). When other scenarios are also considered, the range can be estimated to be between 117.43 and 244.76 kg CO_2e. The total emissions remain approximately the same in each scenario, with differences arising due to the random numbers drawn in the simulations. It can be stated that this may lie between 472.82 and 583.64 kg CO_2e. Additionally, the case where PDFs cannot be used and Monte Carlo simulations cannot be performed has been tested, requiring the use of scenarios as a replacement. The results of this approach are shown in Table 9.2. In these scenarios, the most favorable, unfavorable, and average situations for the construction site were assumed. As can be seen, the range is now much larger, specifically between 82.26 and 328.48 kg CO_2e. The total emissions also change and have a broader range, namely between 397.30 and 737.72 kg CO_2e.

Table 9.1: Output case 1 with PDF's and scenario's

	Input						Output		
Scenario	**Load Client 1**	**Load Client 2**	**Load Client 3**	**Load Client 4**	**Load Client 5**	**Postal Code Client 5**	**Emissions Client 4 kg CO_2e**	**KPI Client 4 kg CO_2e/ton**	**Total Emissions kg CO_2e**
Assumption	3.0575	3.0575	3.0575	3.77	3.0575	PC Client5 midpoint	130.50 +/- 13.07	34.62 +/- 3.47	528.43 +/- 52.91
Best case	0.001	11.226	0.001	3.77	0.001	PC Client5 furthest	109.37 +/- 11.47	29.01 +/- 3.04	528.23 +/- 55.41
Worst case	0.001	0.001	0.001	3.77	11.226	PC Client5 closest	222.24 +/- 22.52	58.95 +/- 5.97	528.74 +/- 53.59

Table 9.2: Output case 1 with only scenario's

	Input									Output		
Scenario	**Load CL 1 (ton)**	**Load CL 2 (ton)**	**Load CL 3 (ton)**	**Load CL 4 (ton)**	**Load CL 5 (ton)**	**EF (kg/L)**	**FC (km/L)**	**Distance (km)**	**PC CL 5**	**Emissions for CL 4 (kg CO_2e)**	**KPI for CL 4 (kg CO_2e/ton)**	**Total emissions (kg CO_2e)**
Best case	0.001	11.226	0.001	3.77	0.001	3.256	2.9	366	closest	82.26	21.82	397.30
Assumption	30.575	30.575	30.575	3.148	30.575	3.213	2.5	384.3	midpoint	121.98	32.35	493.90
Worst case	0.001	0.001	0.001	3.77	11.226	3.256	2.1	475.8	furthest	329.48	87.39	737.72

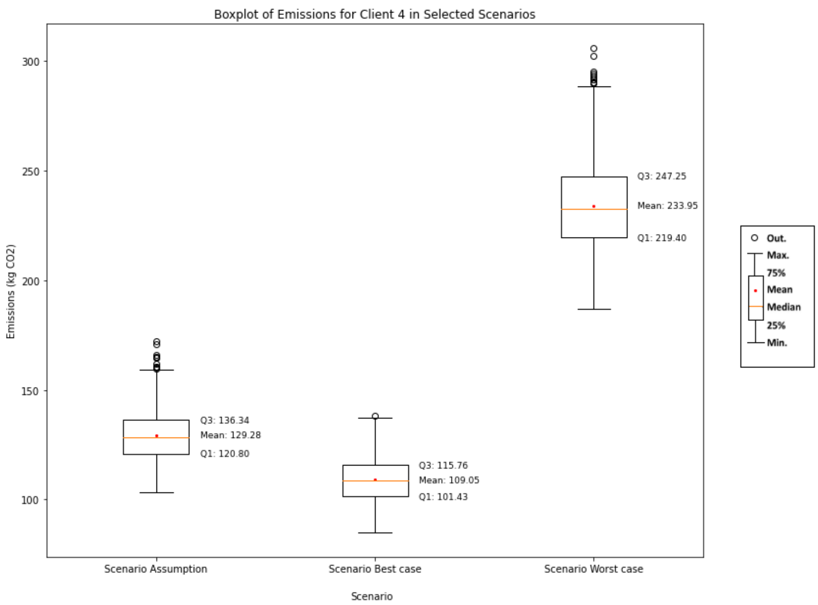

Figure 9.4: Results case 1

9.1.5. Data situation case 2

Data situation description: The trip is a 'shared' trip, the truck is driving a round trip and delivers two shipments in that trip. The truck needs to pick up extra payload from two locations. The **fuel** consumption of the trip is **estimated** by the company itself (not calculated). The **trip** data is known. The cargo is known for the shipment to the construction site and of the other client. The location of the loading point of the other customers shipment and the address of that client are **known on PC4 detail level (instead of preferred PC6 level)**. The distance is unknown and calculated with Google Maps. The route and information of the stops is visible in Figure 9.5.

*"–> Data accuracy situation 4: **Fuel consumption** is **unknown** and **details** about the **route and stops** are **known**."*

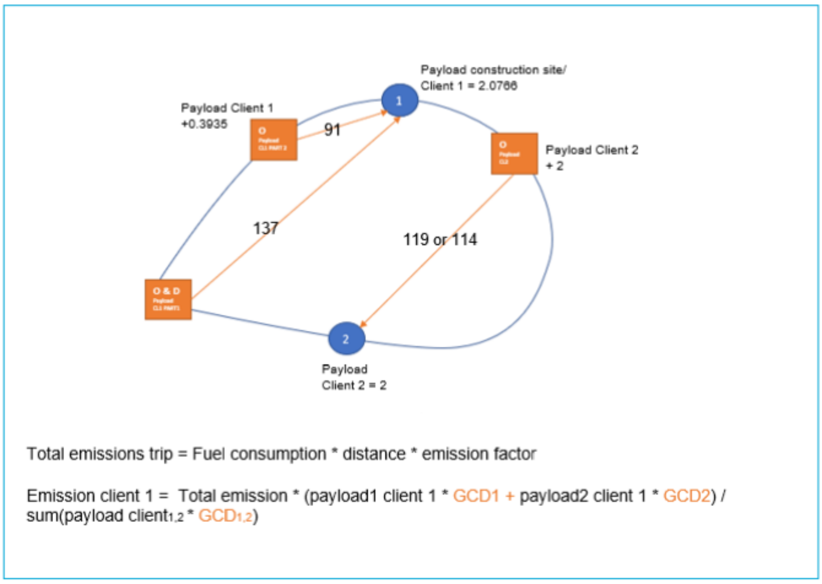

Figure 9.5: Visualization of trip case 2

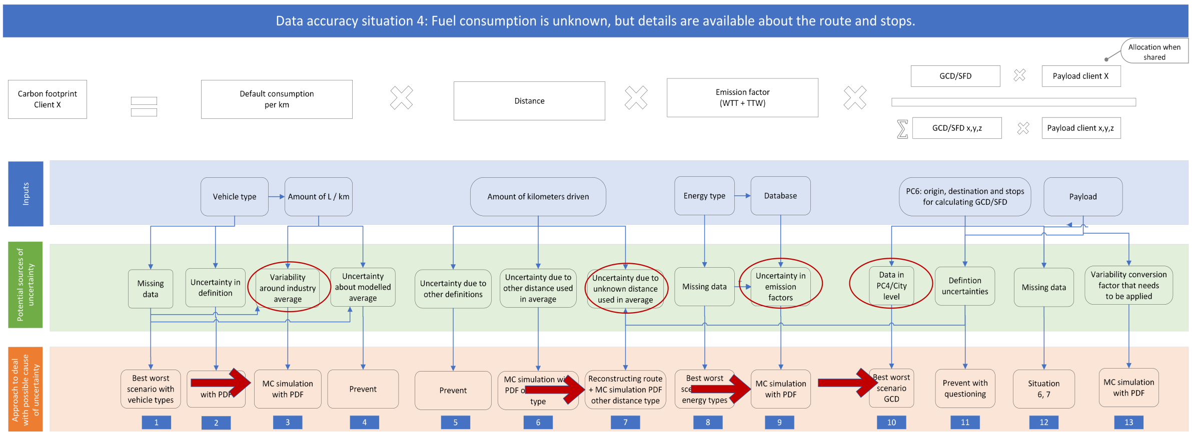

Figure 9.6: Case 2: Situation 4

9.1.6. Inputs case 2:

Figure 9.6 shows the uncertainties involved in calculating the carbon footprint of a shipment to the construction site and how to deal with them. To calculate the carbon footprint with surrounding uncertainties, scenarios and probability density functions (PDFs) that will be simulated are required. The following sections explain the scenarios and PDFs.

Probability density functions: currently based on assumptions made in thesis research:

1. Fuel Consumption (FC) triangular distribution: $\min = 2.5$ km/l, mode: 3.0 km/l, and $\max = 3.5$ km/l
2. Emission Factor (EF) uniform distribution between NL value (3.256) and GLEC value (3.148).
3. Distance triangular distribution: $\min =$ Constructed distance, mode: Constructed distance $+ 15\%$, max: Constructed distance $+ 30\%$ (detours)

In Figure 9.7 the PDF's are visualized. The probability density function (PDF) represents the likelihood of specific distance (or fuel consumption or emission factor) values occurring within a triangular (or uniform for emission factor) distribution. The y-axis (f(x)) shows the probability density for each distance (or fuel consumption or emission factor) value (x) on the x-axis. Higher f(x) values indicate a greater likelihood of the corresponding distance (or fuel consumption or emission factor) value (x) occurring. Note that f(x) represents the density around a particular value, not the exact probability of that value occurring.

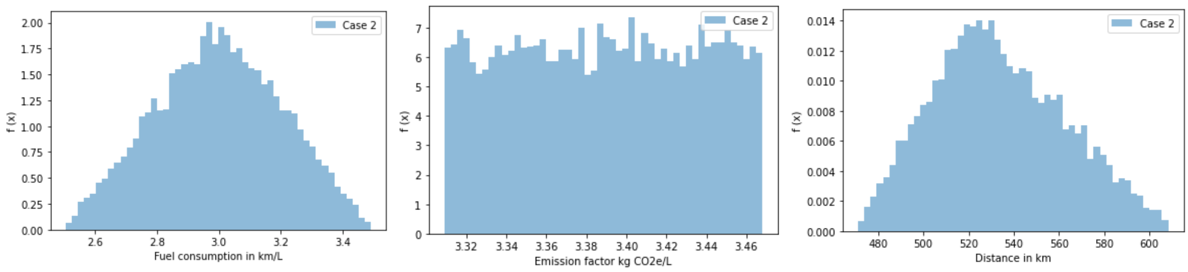

Figure 9.7: Input probability density functions case 2

Scenario's: currently based on assumptions made in thesis research:

1. Best case: when customer 2 has a bigger GCD due to further postal code (denominator the largest)

2. Worst case: when customer 2 has a smaller GCD due to further postal code (denominator the largest)

3. When looking at the difference of the GCD within the PC4 level and the total GCD, this difference will not make a big difference (5 km upon 114 km) in the allocation of the emissions, therefore this scenario is not taken in to account.

9.1.7. Results case 2:

Both the carbon footprint for the entire trip and the portion attributed to the construction site have been calculated. The output of the carbon footprint can be seen in Table 9.3. The output is also plotted in a boxplot for visualization, which is shown in Figure 9.8. The total emissions are influenced by the calculation of total fuel consumption, where the probability density functions primarily have an impact. Next, the emissions attributed to the construction site are presented. This represents the portion assigned to the construction site based on the GCD and the weight in load. Since all the data on this is known, this output is also influenced only by the PDFs. The emissions for the construction site (Client 1) are between the 285.34 en 341.46 kg CO_2e (within the 95% confidence interval). The total emissions may lie between 519.35 en 621.51 kg CO_2e. Additionally, the case where PDFs cannot be used and Monte Carlo simulations cannot be performed has been tested, requiring the use of scenarios as a replacement. The results of this approach are shown in Table 9.4. In these scenarios, the most favorable, unfavorable, and average situations for the total emissions and therefore also for the construction site are taken into account. As can be seen, the range is now much larger, the emissions from the shipment to the construction site will lay between 240.22 and 422.69 kg CO_2e. The total emissions also have a broader range, namely between 437.23 and 769.37 kg CO_2e.

Table 9.3: Output case 2 with PDF's

	Emissions (kg CO_2e)	**KPI (kg CO_2e/ton)**
Client 1	313.40 +/- 28.06	15.092 +/- 13.51
Total	570.43 +/- 51.08	-

Table 9.4: Output case 2 with scenario's instead of PDF's

	Input			Output		
Scenario	**Emission factor ($kg\ CO_2e$ /L)**	**Fuel consumption (km/L)**	**Distance (km)**	**Emissions client 1 ($kg\ CO_2e$)**	**KPI client 1 $kg\ CO_2e$/ton**	**Total emissions ($kg\ CO_2e$)**
Best case	3.148	3.5	470	240.22	11.57	437.23
Assumption	3.213	3.0	520	305.97	14.73	556.92
Worst case	3.256	2.5	611	422.69	20.36	769.37

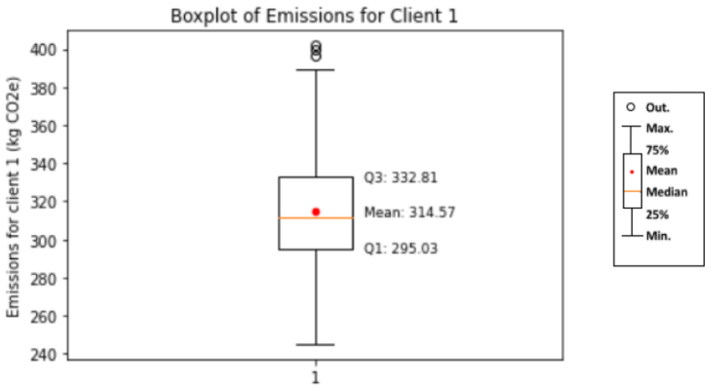

Figure 9.8: Results case 2

9.1.8. Data situation case 3

The co-maker did **not have details of the other stops** on the route even though the trips were shared. Additionally, the **weight and planned distance** from start to delivery point are **known**. The **vehicle type** is described as a box truck with a crane ("bakwagen met autolaadkraan"), which is **not a detailed description**. The **fuel consumption is unknown**. The shipment type is described as neither bulk nor volume goods, indicating an **average load**. This is a situation where an emission intensity factor must be used because no other assumption can be made.

*"–> Data accuracy situation 7: Use of **default emission intensity factors**."*

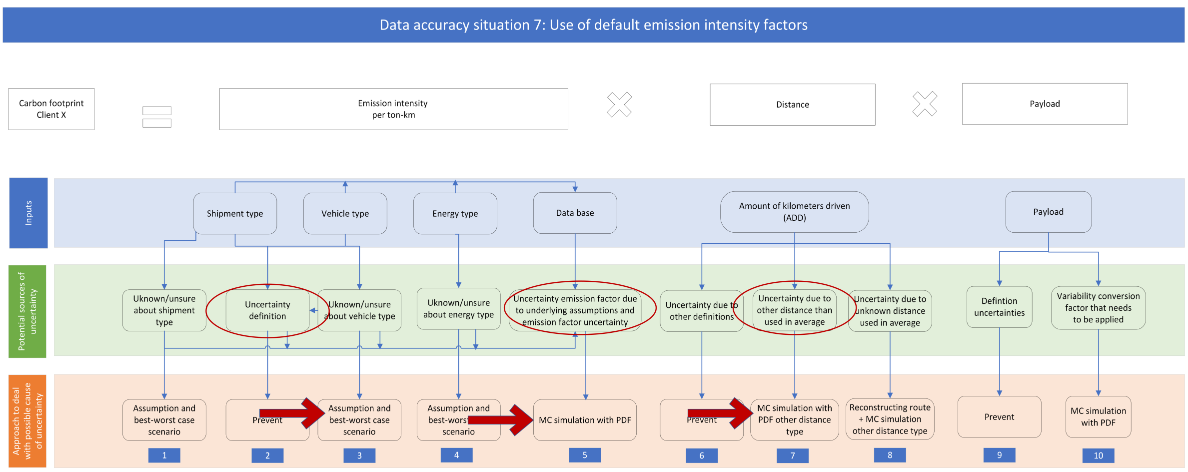

Figure 9.9: Case 3: Situation 7

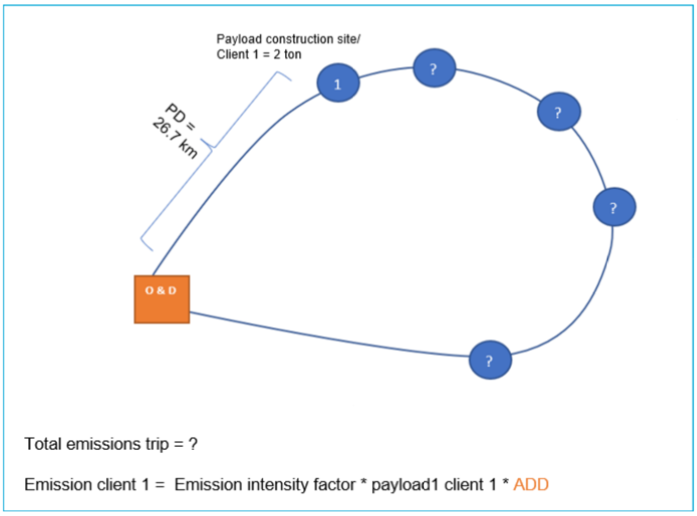

Figure 9.10: Case 3: Situation 7

9.1.9. Inputs case 3:

Figure 9.10 shows the uncertainties involved in calculating the carbon footprint of a shipment to the construction site and how to deal with them. To calculate the carbon footprint with surrounding uncertainties, scenarios and probability density functions (PDFs) that will be simulated are required. The following sections explain the scenarios and PDFs.

Scenarios where vehicle type is uncertain:

1. The vehicle type "bakwagen met autolaadkraan" is not listed as a vehicle type in the emission intensity factors. Therefore, a best-worst case scenario will be chosen for two vehicle types that could potentially represent it. These types are: truck < 10 tons and truck 10-20 tons.
2. The best-case scenario for the construction site would be when the lowest EIF is selected, which is 0.256 per ton-km (truck 10-20 tons), and the worst case for the construction site would be when the highest EIF is selected, which is 0.363 (truck < 10 tons). These numbers come from (CE Delft, 2020).

Probability density functions: currently based on assumptions made in thesis research:

1. Emission Intensity Factor (EIF) triangular distribution: $\min = EIF * 0.685$ kg CO_2e/ton-km, $= EIF$ kg CO_2e/ton-km, and $\max = EIF * 1.51$ kg CO_2e/ton-km
2. Distance triangular distribution: $\min =$ Planned distance, mode: Planned distance $+ 5\%$, max: Planned distance $+ 30\%$ (detours)

In Figure 9.11 the PDF's are visualized. The probability density function (PDF) represents the likelihood of specific distance (or emission intensity factor) values occurring within a triangular distribution. The y-axis (f(x)) shows the probability density for each distance (or emission intensity factor) value (x) on the x-axis. Higher f(x) values indicate a greater likelihood of the corresponding distance (or emission intensity factor) value (x) occurring. Note that f(x) represents the density around a particular value, not the exact probability of that value occurring.

9.1.10. Results case 3:

Because there is no knowledge of the trip data, an estimation of the shipment's emissions can only be made using emission intensity factors. The output of the carbon footprint can be seen in Table 9.5. The output is also plotted in a boxplot for visualization, which is shown in Figure 9.12. The emissions are influenced by the uncertainty of distance and the emission intensity factor, which are mapped using probability density functions. In addition, it is uncertain which vehicle type was used, increasing the uncertainty of the emission intensity factor. This is shown by outlining scenarios of the two types of

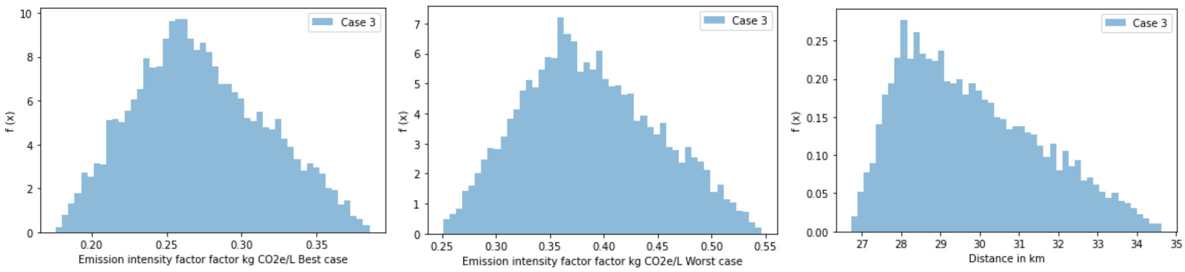

Figure 9.11: Input probability density functions case 3

vehicle types. The vehicle type with the lower emission intensity factor is the best-case scenario, while the worst-case scenario is the vehicle with the higher emission intensity factor. As seen in Table 9.5, the emissions associated with the shipment are between 13.5 and 19.08 kg CO_2e for the best-case scenario and between 19.29 and 27.21 kg CO_2e, resulting in a total spread of 13.5 to 27.21 kg CO_2e. Additionally, the case where PDFs cannot be used and Monte Carlo simulations cannot be performed has been tested, requiring the use of scenarios as a replacement. The results of this approach are shown in Table 9.6. In these scenarios, the most favorable and unfavorable situations for the emissions are taken into account. As can be seen, the range is now much larger; the emissions from the shipment to the construction site will lay between 9.36 and 38.05 kg CO_2e.

Table 9.5: Output case 3 with PDF's

	Input	**Output**
Scenario	**Emission intensity factor (kg/ton-km)**	**Total emissions (kg CO_2e)**
Best case	EIF = 0.256 Triangular Probability Density function min = EIF*0.685, mode= EIF and max = EIF*1.51	16.29 +/- 2.79
Worst case	EIF = 0.363 Triangular Probability Density function min = EIF*0.685, mode = EIF and max = EIF*1.51	23.25 +/- 3.96

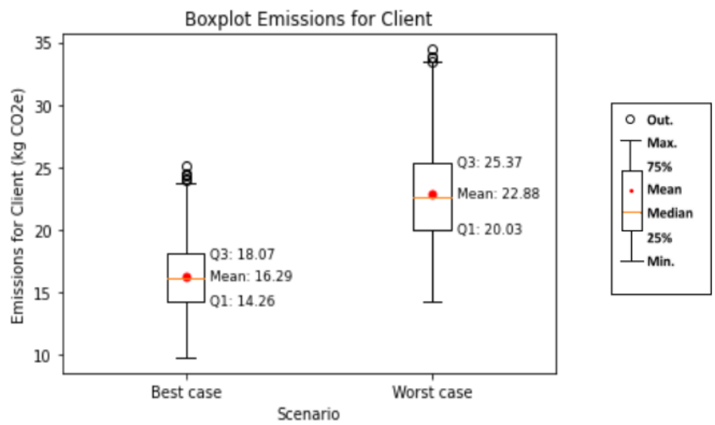

Figure 9.12: Results case 3

9.1.11. Utilization of the tool in field research

During the development of the tool, the field research continued concurrently, enabling the tool's application within the advisory project. The approaches for addressing uncertainties proved challenging to implement in practice due to the need for separate analyses, as described above. The tool was primarily considered useful for providing an overview of potential uncertainties and their implications when

Table 9.6: Output case 3 with scenario's instead of PDF's

	Input			**Output**
Scenario	**Emission intensity factor (kg/ton-km)**	**Distance (km)**	**Load (ton)**	**Total emissions (kg CO_2e)**
Best case	0.17528 (0.256*0.685)	26.7	2	9.36
Worst case	0.54713 (0.363*1.51)	34.71	2	38.05

publishing a carbon footprint. Additionally, the tool helped identify the most significant uncertainties within the project and how to prevent them in the future. This resulted in separate one-pagers being included in the project's advisory documentation. The effects of assumptions made to fill in missing data were represented in the carbon footprint using the tool. Moreover, the tool facilitated reflection on the project and suggestions for improving future data collection and analysis. The advice was divided into two parts: which data uncertainties should be actively addressed, and which conceptual uncertainties should be prevented in the future and how to do so. Therefore, the tool primarily served Districon's advisory process by critically examining data situations, the effects of missing data, and the assumptions made on the carbon footprint. This enhances transparency when communicating with clients and helps to address uncertainties proactively during future data requests. However, visually presenting uncertainties using Monte Carlo simulations or scenario analyses is time-consuming and would be more beneficial if implemented within existing software programs, especially since input at the trip level is currently required.

9.2. Verification through testing with case studies

This section evaluates the extent to which the design meets the requirements based on the tests conducted in the previous section. The discussion will focus on the extent to which the needs and nice-to-haves are fulfilled. The rationale for the evaluation is provided in the following Table 9.7.

Table 9.7: Verification

#	Requirement	Need-to-have/Nice-to-have	Requirement met?	Reasoning
Uncertainty prevention, identification and quantification				
1	The basis of the tool are the identified uncertainties from previous Chapter 5.4.	Need-to-have	Yes	The identified uncertainties are represented in the tool.
2	The tool should provide guidance on how to gather accurate and reliable data to minimize uncertainty from the start.	Need-to-have	Yes	By representing the uncertainties that can be avoided through proper communication, the tool creates awareness about how different interpretations arise. It shows that less data will generate more uncertainty.
3	The tool must provide an approach for identifying and quantifying uncertainty in transport carbon footprint measurements.	Need-to-have	Yes	The diagram gives an overview of the uncertainties per data situation, presenting possible uncertainties and a method to quantify them.
4	The tool provides insights into the different data 'quality' levels.	Need-to-have	Yes	Data situation 1 is considered as Gold, Data situation 2 depends on the level of aggregation, Data situation 3 and 5 are considered as Silver, and other data situations are considered as Bronze.
5	The tool must provide guidance on how to prioritize efforts to reduce uncertainty based on their impact on the overall measurement.	Need-to-have	Yes/Partly	For every data situation, a prioritization of uncertainties is given, providing guidance. However, the prioritization can vary over time, which is why it is only partly helpful with guidance.
6	*The tool could allow users to select different probability distributions or specify their own distributions for sources of uncertainty.*	*Nice-to-have*	*Partly*	The design approach gives guidance and insights on how to implement probability density functions, and the values can be adapted. However, users cannot physically 'select' and 'change' the probability function as they could in a software program or model.
7	The tool should include a set of best practices for handling various types of uncertainties, such as data gaps, assumptions, and modeling limitations.	Need-to-have	Yes	The tool clearly states two different types of uncertainties: uncertainties from parameters and uncertainties from input data. It provides guidance on how to deal with uncertainties arising from assumptions, variability, lack of data, or ambiguity.
8	The tool should provide a clear method for propagating uncertainties through the analysis, such as incorporating uncertainty ranges or Monte Carlo simulations.	Need-to-have	Yes	The approach suggests methods to quantify uncertainties, establish probability density functions, and perform simulations or scenario analysis.
Usability and compatibility				
9	The tool must be easy to understand or have a comprehensive explanation.	Need-to-have	Yes	The tool provides an explanation of every uncertainty and the approach used to address them.
10	The tool must be adaptable to and compatible with various and up-to-date carbon footprint measurement methodologies.	Need-to-have	Partly	The tool was developed before the ISO 14083 standard was published in March 2023. However, based on validation interviews, the tool was reviewed and new insights from the ISO standard were incorporated. It is still compatible but could be more up to date.
11	The tool must be designed to facilitate collaboration between different stakeholders.	Need-to-have	Yes	The tool gives an overview of how and where uncertainties may arise, making it easier to communicate uncertainties among stakeholders.
12	*The tool could allow users to vary input parameters (e.g., distance, fuel consumption, etc.) to explore how they affect the final carbon footprint measurement.*	*Nice-to-have*	*No*	The design approach provides guidance and insights into input parameters. While the values can be adapted, users cannot physically 'select' and 'change' the inputs as they could in a software program or model.
13	*The tool could offer visualization options that display the impact of uncertainties on the final carbon footprint measurement, emphasizing the range or interval of possible values.*	*Nice-to-have*	*No*	The design approach provides guidance and insights into input parameters. When the approach is followed, visualization of the impact of uncertainties is possible, as demonstrated in the testing of the tool. However, the tool itself does not provide visualization options like a dedicated software tool.
14	The tool should state clear definitions of all subjects.	Need-to-have	Partly	The explanation provided in the tool aims to provide further guidance. However, some pre-knowledge is required to fully grasp certain proposed approaches.
15	*The tool can be used for different KPIs.*	*Nice-to-have*	*Partly*	Currently, the approach shows the carbon footprint of a shipment. However, it can be easily adapted by summing up all emissions and dividing by the total amount of tonnes or tonne-kilometers. The same uncertainties will underlie this calculation, making it easier to adapt for different KPIs.
Communication and decision-making				
16	*The tool could be designed to support scenario analysis to explore different what-if scenarios and their impact on the carbon footprint measurement.*	*Nice-to-have*	Yes	The approach suggests methods to quantify uncertainties, including scenario analysis.
17	The tool should provide guidance on how to communicate uncertainty in a clear and effective way to different stakeholders (e.g., investors, regulators, customers).	Need-to-have	Yes	The tool provides an overview of how and where uncertainties may arise and offers a visual representation of possible uncertainties, making it easier to communicate uncertainties to different stakeholders.
18	The tool should support decision-making by providing guidance on the best strategies for reducing uncertainty.	Need-to-have	Yes	By visually representing the calculation and inputs, along with the potential uncertainties and their impacts, the tool provides guidance on how to handle different uncertainties, helping users choose the best strategies to reduce uncertainty.
19	*The tool should be able to account for uncertainty related to the use of different accounting frameworks (e.g., Scope 1, Scope 2, Scope 3).*	*Nice-to-have*	*Yes*	Due to the different data situations, the tool can be viewed from both a shipper's and a carrier's perspective, making it applicable for uncertainties that arise in scope 1 to scope 3 calculations.
Additional Functionality				
20	Is based on information from traceable sources.	Need-to-have	Partly	The probability density functions stated in the tool are based on generic assumptions and require further research, however, they are based as much as possible on traceable sources.
21	The tool functions as a widely applicable methodology to gain initial insight into the uncertainties of factors that influence the carbon footprint.	Need-to-have	Yes	Multiple stakeholders can make use of this approach or tool. It can provide insights for accountants, consultancies involved in carbon footprint analysis, as well as software developers looking to incorporate these insights into their tools.

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10 Validation

10.1. Validation of design

The aim of this validation chapter is to assess the validity of the research findings through expert feedback, focusing on the identified uncertainties, data situations, and the proposed tool. This chapter aims to identify commonalities and differences between the expert opinions by analyzing the feedback. The thesis deliverable is a guidance framework that gives an overview of uncertainties that might exist when calculating the carbon footprint of freight transport. To validate the approach, this chapter seeks feedback from experts to ensure that the identified uncertainties are comprehensive and to understand the practical implications of the research.

10.1.1. Approach of validation

A week before the validation interviews took place, materials were sent out in the form of a slide deck with the information on which feedback is sought. The questions were also shared with the experts beforehand so that he/she would have an idea of what to expect in the validation interview. The interviews were semi-structured, allowing for flexibility in the discussion while maintaining a set of standard questions. Some questions were omitted or explored in more depth depending on the time constraints and the expert's experience. The experts were selected based on their experience in the sustainability field and knowledge of carbon footprinting in transportation. All interviews were conducted through Microsoft Teams and ranged in duration from 45 minutes to 1.5 hours, depending on the expert's availability. In appendix G, the interviews are fully elaborated and visible.

The interview questions focused on the following topics, although some were omitted or explored in more depth as needed:

1. Identified Uncertainties
2. Data Situations
3. Use of tool
4. Context

10.1.2. Experts

Table 10.1 provides an overview of the interviewed experts, their positions/roles, and their experience related to the topic of carbon footprinting in the transport and logistics sector. Each expert represents an organization relevant to the study's focus.
These experts represent the following organizations:

- BigMile is a company that provides a software tool for calculating and reducing the carbon footprint of logistics and supply chains. They help companies gain insights into their emissions and identify opportunities for improvement (BigMile The standard in CO2 footprint calculation for supply chain & mobility, 2023).

- Smart Freight Centre (SFC) / Sustainable Freight Buyers Alliance: The Smart Freight Centre is an organization dedicated to developing and implementing the GLEC Framework, a methodology for calculating and reporting logistics emissions across supply chains. The Sustainable Freight Buyers Alliance is an initiative of the SFC, aiming to promote sustainable practices in the freight and logistics sector (SFC, n.d.)
- The PBL is a Dutch Environmental Assessment Agency that serves as national institution for the strategic evaluation of policies related to environmental, spatial planning, and natural resource management domains (Pbl, 2023).
- TNO: TNO is an independent research organization in the Netherlands that focuses on applied scientific research and innovation across various fields (TNO, n.d.).

Table 10.1: Experts validation

Expert	Position/Role	Experience
Expert 1	Specialist at BigMile	3 years experience in supply chains and carbon footprinting; of which 2 years experience at BigMile with helping companies to use BigMile and developing the platform
Expert 2	Director of the Sustainable Freight Buyers Alliance	10 years experience in the sector of transportation; 2.5 years at Smart Freight Centre
Expert 3	Carbon Footprinting Expert and now working at PBL	15 years experience in transport and logistics carbon footprint analysis
Expert 4	Sustainable Mobility Expert at TNO	13 years experience in sustainable mobility and logistics
Expert 5	Technical Manager at Smart Freight Centre	3 years experience in the field of sustainable freight transport and carbon footprinting and accounting at Smart Freight Centre

10.1.3. Results of validation

Identified uncertainties

Four out of the five experts (Expert 1, 2, 4, and 5) agreed on the identified uncertainties. Expert 1 even stated that "All the uncertainties discussed are recognizable and also occur in my daily work". Furthermore, there were some additional uncertainties discussed and their relevance emphasized.

Expert 1 suggested that in the future, uncertainties related to cross-docking and other modes of transport could be considered. He/She also highlighted that the 'unknown' energy type is becoming increasingly relevant as it becomes more difficult to track the type of fuel mixture used in diesel trucks, with more trucks running on biodiesel, HVO, or mixtures. Expert 2 mentioned that the uncertainty about the allocation factor in the model structure becomes less relevant now that the new ISO has been published. The allocation method is now standardized based on weight and GCD or SFD. He/She explained that this is because weight has an impact on fuel consumption, and other units do not. In some cases, exceptions are allowed, such as in the container industry, where allocation per TEU is permitted. Another sector where distinction can be made is post and parcel deliveries, where the weight is often unknown; in this case, calculation is done per item. It is important to differentiate between chargeable weight and normal weight, as "In contracts, it is often about the space used, and in the CO_2 calculation, it is about weight". When weights are unknown, conversion factors can be used. Additionally, Expert 2 acknowledged the importance of considering the uncertainty of methane and nitrous oxide (CH4 and N2O) emissions, especially methane, which is highly dependent on the fuel source. He/She also pointed out that there is still much debate about emission factors and what should or should not be included in the calculations. Expert 4 agreed with the uncertainties but found the classification challenging due to the interconnected nature of some uncertainties. He/She also mentioned that the uncertainty of default energy consumption depends on many factors and could be further investigated. Expert 5 found the research scope overarching and comprehensive, with all aspects covered in their opinion. Expert 3 disagreed with the terminology, viewing uncertainty as a more mathematical concept and suggesting presenting the overview differently. According to them, there are two fundamental uncertainties: uncertainties in ton-kilometers and uncertainties in fuel consumption/emissions, based on a high-level overview. He/She argue that it might not be crucial to have an overview of each shipment, and knowing the aggregated level could be more important, which would also eliminate certain uncertainties. Additionally, He/She believe that the uncertainty of ton-kms, fuel consumption, and conversion factors are the most important aspects to consider.

Prioritization of uncertainties
Most experts did not have enough time to delve into this beforehand, and explaining the prioritization and its reasoning takes a considerable amount of time. Therefore, the focus was mainly on the logic of prioritization. Expert 1 stated that He/She understood the logic but that the level of complexity for uncertainty highly depends on the perspective from which it is viewed. As an example, he/she mentioned that a carrier has more insight into fuel information, making it easier for them to reduce this uncertainty, while it is more challenging for a shipper. Additionally, the uncertainty of the specification level of origin and destination depends on the length of the GCD up to the city limits, making the impact variable. Expert 2 also understood the approach and found it interesting to present uncertainties in this way but pointed out that people are ultimately looking for an absolute number or percentage. Expert 5 indicated that he/she understood the approach and it seemed logical, but he/she couldn't say if he/she completely agreed with it, as he/she would need more time and information. Due to time constraints, this question was not asked to Expert 3 and 4.

Data situations
All experts agreed that uncertainties indeed depend on the amount of information available and found it logical to link the uncertainties to this. In addition, the experts could relate to the data situations. Expert 5 even said: "I think that you covered all the different situations. I think you have aggregated, dis-aggregated fuel consumption, not fuel consumption and transport activity or no transport activity and everything in between." Only Expert 4 indicated that he/she had insufficient specific knowledge to give a concrete answer.

Moreover, Expert 1, 2, and Expert 3 had some remarks about the outlined data situations. These were as follows: Expert 1 said that he/she had not looked at it at such a detailed level, "in my opinion, there were fewer data situations, but this is a more detailed version of it." Expert 2 stated that he/she did not immediately understand the distinction of the various data situations and how the distinction was made between data situations. After further explanation, it became clear. Expert 3 said that from a highly aggregated level, there are basically two situations: either you have data on fuel consumption, or you have data on transport activity. However, he/she noted that this is at a much more detailed level and a "few steps down" and said that in that sense, looking from that perspective, he/she agreed with the data situations. he/she also mentioned, "the unknown of emissions or fuel consumption is often an uncertainty from the shippers' side, the ton-km side or the transport performance side is often an uncertainty from the carrier or LSP side."

The tool
Most experts stated that the tool is primarily useful for creating awareness and providing an overview of the topic.

Expert 1 saw multiple implications for the tool, stating, "I think this tool is particularly useful for raising awareness. It makes me think, especially about the ranges of uncertainty. It can be useful to indicate the impact of providing less accurate data, for example, if you cannot or do not want to provide certain data, resulting in a range of +/- 20%. This can raise people's awareness of the importance of accurate data, and he/she may reconsider their approach. Providing more insight into this topic is always valuable, as it is often a topic of discussion. For instance, some people suggest using an emission intensity factor instead of collecting more detailed data. This tool can provide clarity on the impact of different approaches. It can also help someone who is responsible for auditing the data to gain a better understanding of the results." Expert 2 mentioned, "Providing insight into uncertainties is always valuable and interesting; however, you often notice that people are interested in an absolute number. This is a start in that sense.". He/she also mentions that people are always looking for ways to use such tools in contracts or to improve their data and to what extent they have influence on it. Expert 3 emphasized that these uncertainties could also be expressed as data requirements: "You mention many practical details that you can call uncertainties. But you could also say: these are simply my data requirements. If you want to know it as accurately as possible, then this is necessary." In addition, expert 3 highlighted that the mathematical aspect of the tool could be interesting for implications. Expert 4 presented a different perspective and raised the question of whether carbon footprint will become less relevant for road transport in the future as more vehicles become electric. He/she suggested that sustainability may be viewed in terms of space or land use instead, and that a similar tool can be created in a similar way using this example. Expert 5 noted that the tool provides a foundation for creating awareness and can aid in working towards harmonization by demonstrating if there is agreement on how something should be calculated.

Context
In order to gain more insights into the potential implications of the tool and the context of carbon footprinting, additional questions were asked. These questions focused on the incentives for companies to share data or obtain more accurate data, the extent to which uncertainties are considered in the procurement process, and the demand for carbon footprint data.

Expert 1 highlighted that people are becoming more aware of upcoming regulations and want to avoid overestimating their carbon footprint, thus aiming to minimize uncertainties. The increasing interest of clients in the carbon footprint of transport services may affect their choice of service providers, making it crucial for companies to address uncertainties to remain competitive. However, smaller companies may lack the necessary resources to do so. Expert 1 also noted that underestimating uncertainties could have negative consequences for a company. As a result, investments might be made that later do not produce the expected returns based on the updated and more accurate data.

Expert 2 explained that there are currently three types of companies interested in this topic: LSPs (Logistics Service Providers), carriers, and shippers. Shippers issue contracts to carriers and LSPs and can calculate their carbon footprint using different methods: default values, modeling, or calculating it afterward based on primary data. Carriers are often small companies without advanced IT systems, while LSPs are usually larger companies with more resources. In terms of incentives, shippers are starting to include CO_2 measurement and reduction plans in their contracts, and he/she increasingly require a certain quality of data and calculation methods. However, many companies are still not very advanced in this regard. Companies do ask for validation of the data provided, but whether he/she truly consider data quality and uncertainties remains uncertain. There is a developing trend in tenders where, in addition to emission measurements and reduction plans, the general CO_2e/ton-km value is also requested from carriers. However, this is still in its early stages. LSPs are becoming more aware of this, and there is a movement towards assurance procedures to ensure that a false reality is not portrayed. However, many people still don’t understand the term ”emission intensity factor” or what else could be done with it.

Expert 3 agreed that carrier-specific emission intensity factors are still in their early stages, adding that implementing these concepts in practice is often challenging due to data availability. The expert believes that incentives largely depend on whether other companies set data requirements, such as when large companies aim to improve their ESG scores and need to meet specific criteria, in turn driving incentives for other companies.

Expert 4 stated that while cost is still the most important factor in the logistics industry, opportunities for savings can be an incentive for sharing data. The expert also pointed out that there is significant room for improvement in data sharing within the transport and logistics sector, which is often due to companies’ inability to share data rather than unwillingness.

Expert 5 suggested that better data availability is likely to emerge when regulations are introduced, for example, by the EU. The expert also noted a growing attempt in sustainable procurement, with emission intensity values potentially becoming part of the tendering process. The expert emphasized the importance of transparency and documentation in the calculation process, as the values calculated can be quite different from the actual emissions emitted. This would allow for potential audits and a clear understanding of the assumptions made.

10.1.4. Conclusions validations

The identified uncertainties and their prioritization were mostly agreed upon by the experts, with some additional uncertainties and aspects highlighted for future consideration. The experts also agreed that uncertainties depend on the amount of information available and found it logical to link them to the data situations. They recognized the tool's potential in creating awareness and providing an overview of the topic. Some experts suggested that the tool could be used in contracts or data improvement efforts, while others believed it could be helpful in working towards harmonization in the industry. The experts highlighted that awareness of upcoming regulations and the increasing interest of clients in the carbon footprint of transport services might incentivize companies to address uncertainties and improve data accuracy. Companies are starting to include CO_2 measurement and reduction plans in their contracts and increasingly require a certain quality of data and calculation methods. However, many companies are still not very advanced in this regard, and the focus on carrier-specific emission intensity factors is still in its early stages. In conclusion, the research findings and the tool developed have the potential to contribute to creating awareness, providing an overview of the topic, and improving data accuracy in the carbon footprinting field. The industry is moving towards increased transparency and better data sharing, driven by upcoming regulations and the growing interest in sustainable procurement. However, there is still room for improvement, and the tool can be further refined and expanded to address additional uncertainties and aspects raised by the experts.

10.2. Reflection on new ISO 14083

During this research, a new ISO was published advocating for the distribution of emissions based on annual data, which enables the calculation of a general emission intensity factor. This factor can then be used to estimate emissions for clients. The ISO also acknowledges that to perform these calculations, companies do not necessarily require the latest on-board computers, as fuel card data and aggregated trip activity data can be utilized instead.

Calculating the emission intensity factor per Transport Operating Category (TOC) involves dividing the total energy consumption of this category by the transport activity from this category, and then multiplying it by an emission factor. To calculate the emissions per client, this emission intensity factor is multiplied by the client's transport activity, allocating the emissions. Experts have noted during validation that there are fewer and different data situations than in this research.

The research has developed a guidance framework at the trip level. However, the guidance frameworks for data situations 2 and 7 can be directly applied at aggregated levels. Data situation 2 specifically addresses potential uncertainties introduced by the application of calculated emission intensity factors. In situations where data on transport activity and energy consumption are unavailable, the GLEC framework (and the new ISO) recommend the use of default emission intensity factors, aligning with data situation 7. This mandates the utilization of a default emission intensity factor when primary data is lacking.

Identifying the uncertainties in calculating an emission intensity factor becomes now, with the new ISO, is also very relevant. If the total energy consumption for calculating this factor is unknown, it needs to be modeled. The same uncertainties apply when this is done at the trip level, similar to data situation 4 where the energy consumption of the trip must be modeled to calculate total emissions. Uncertainties can also arise due to inconsistent application of conversion factors to convert payload from other units to tonnages, not knowing which energy type is used in a year, or when assumptions must be made if part of the transport activity is unknown and an estimated average payload must be used.

This study has investigated (Section7.2.1) what happens with the measurement error that may be inherent in fuel card data. This error diminishes when an average over a longer period is observed. Furthermore, the research has explored what happens when the average load is used in the denominator and multiplied with the total GCD to calculate the emission intensity factor, as currently recommended in the GLEC Framework (and expected in the upcoming ISO) when the calculation for total transport activity is challenging to execute. Notably, significant differences will arise in the emission intensity factor when customers consistently place the same orders and the disparate proportions of loads. Consequently, the emissions attributed can exhibit considerable variations from the real value. This calculation can be found in Appendix F Figure F.13. This is not in-depth researched in this study and, therefore an interesting finding to explore for future research. Furthermore, the uncertainty of the conversion factor is an essential consideration at the aggregated level (as explained in Section 7.2.4). When a load meter is 0.5 tons instead of the conversion factor of 1.3 tons (as applied when converting load meters to tons in a software package), this creates a difference of 60% in the weight of a shipment, potentially causing the emission intensity factor to be higher than when the software program's conversion factor is applied. If the emission intensity factor is based solely on converted load meters, the emission intensity factor may be higher than the actual value when the 0.5 factor is applied. However, when calculating the carbon footprint of a shipment for a customer, no deviation from the actual situation should occur as long as the number of load meters is consistently converted to tons using the same factor as in the emission intensity factor. When a different conversion factor is suddenly used, a significant deviation may arise. If the emission intensity factor is calculated based on both actual tons and converted load meters, the emission intensity factor provides a more realistic representation of the true efficiency of the shipments because part of the weights has not been converted to tons. However, since the systematic error introduced by the higher conversion factor is mitigated by the actual number of tons, when calculating a customer's emissions based on distance and the amount of tons, the uncertainty still exists and will result in a deviation from the actual value. An example can be found in appendix F Figure F.8, demonstrating a reconstruction of a random situation where the carbon footprint of a shipment is calculated based on the actual conversion factor and the standard conversion factor, in a situation where the emission intensity factor is calculated on shipments reported in load meters and in a situation where it is based partly on load meters and partly on the number of tons.

A draft framework, similar to the one developed in this study, has been created to identify uncertainties within the calculations of the emission intensity factor, considering the uncertainties that may also influence emissions at an aggregated level. However, this is a draft version and no further attention is devoted. This Figure is visible in Figure 10.1

Thereby for companies without on-board computers, it becomes challenging to distinguish fuel card data across various services provided by multi-purpose trucks. Maintaining records at the trip level is likely the most effective solution. When all trip-level data is available, it is relatively straightforward to aggregate and allocate emissions across different services on an annual basis. However, when trip-level data is missing and must be collected or summed on an annual basis, distinguishing emissions by service type becomes more complicated.

In conclusion, this reflection highlights the relevance of the study's findings to the new ISO's proposed method for estimating emissions in freight transportation. By considering uncertainties at both detailed and aggregated levels, the research contributes valuable insights that can inform the development and implementation of more accurate and reliable carbon footprint calculations. Future research could further explore the applicability of the developed framework to the ISO's method.

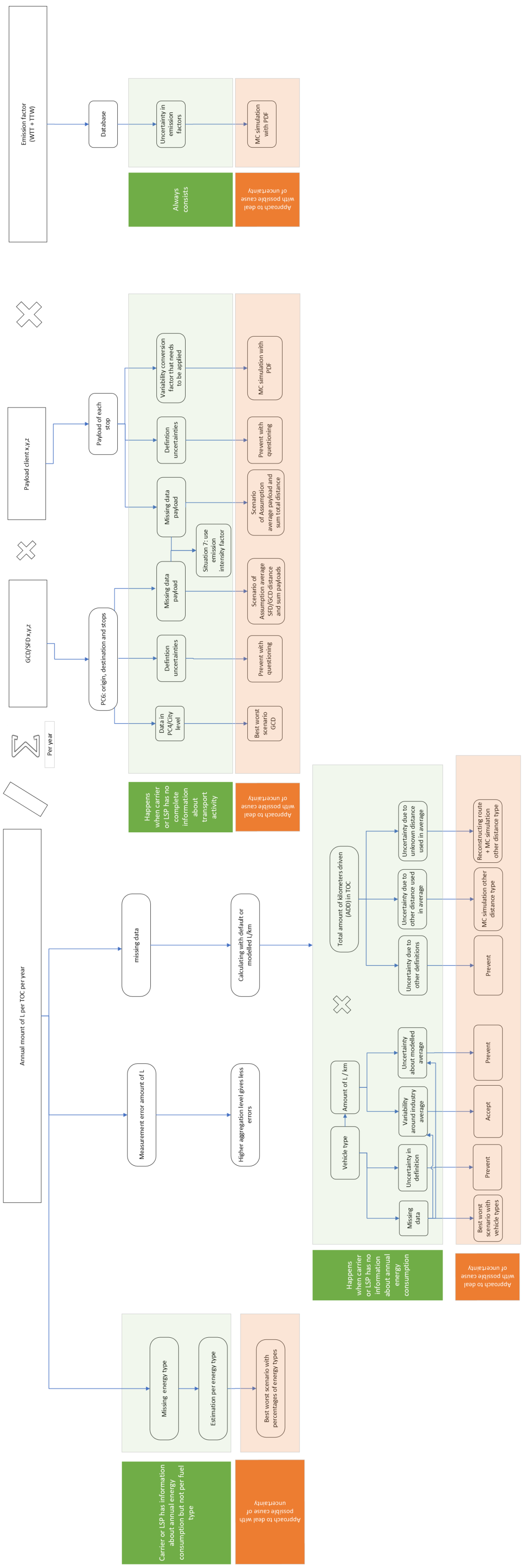

Figure 10.1: Reflection on ISO 14083

V
Discussion and Conclusion

This section of the study is the **Discussion and Conclusion phase**, which is divided into two segments: 'Discussion' and 'Conclusion'. The **Discussion part** delves into several themes: reflection on results, reflection on experts' results, reflection on the new ISO, implications for practice, scientific contributions, and limitations of the study. It begins with a comprehensive review of the results, followed by reflections on experts' results and the implications of the new ISO standard. This part then discusses the practical implications of the findings and the scientific contributions of the study. It concludes with a discussion of the limitations of the study. The second topic in this phase, the **Conclusion part**, provides a summary of the findings, recommendations for future research, and practical suggestions. The conclusion summarizes the main findings of the study, and recommendations for future research are suggested based on these findings. Practical recommendations are also provided, which can be used to inform future practices in this field.

11 Discussion

This chapter reflects on the interpretation and impact of the results, the contributions to the literature, and the practical implications of the research findings. The main limitations of the study are also discussed.

11.1. Reflection on results

This research aimed to develop a tool to assess and map uncertainties surrounding a carbon footprint. The design of the tool is based on interviews, field research, and a literature review. In this section, the results from these components are reflected upon.

The background study conducted in this research can be divided into two parts: an investigation into the carbon footprint and how freight transport emissions are generated, and the methods currently used to map the carbon footprint. The second component focused on the study of uncertainties, investigating the concept of uncertainty and how it arises.

An interesting finding from the carbon footprint research was that there was limited information on uncertainties; the literature and protocols primarily focused on accuracy without further reflecting on the consequences of inaccurate data. In addition, the literature identified a significant shortcoming of EN16258 as the broad definition of the scope of a Vehicle Operating System (VOS) for determining the carbon footprint, leading to ambiguity. Moreover, there has been much criticism and research on the most 'fair' allocation method for distributing emissions. The GLEC Framework attempts to address these criticisms and harmonize the process by standardizing allocation based on ton-kilometers and an aggregation level of one year. This must be done per VOS (now TOC: transport operation category) based on journey/contract type.

An interesting finding in the background research on uncertainties was that there is no general consensus on the concept of 'uncertainty'. Furthermore, it became apparent that uncertainty in LCA studies was a widely researched topic, but not specifically for mapping the carbon footprint of freight transport. In the background study on uncertainty, a theoretical framework was chosen to map uncertainty, namely Walker's uncertainty matrix. This provided a fundamental basis for the research. This uncertainty matrix was used to identify uncertainties in a carbon footprint calculation for freight transport. With the help of the theoretical framework, uncertainties were identified by critically reviewing the carbon footprint background study, conducting interviews, and participating in a project that Districon conducted to map the carbon footprint of freight transport to and from construction sites.

The causes of the uncertainties that emerged were categorized based on where uncertainty can occur. In the context definition, possible causes include the different definitions of carbon footprint and the boundary of the carbon footprint. In the model structure, the uncertainty was seen as arising from the linear relationship between N_2O and CH_4, while the background research showed that this relationship is not 1-to-1. Additionally, in the model structure, it was mentioned that different allocation methods and calculation methods can cause uncertainty depending on the amount of information available. Most causes can be found in the input data. This is because the data needed for a good estimate of the carbon footprint depends on the data available about energy consumption and transport activity. When there is no information about a vehicle's energy consumption or transport activity, an emission intensity factor must be chosen. To select an appropriate emission intensity factor from a table, for example, the vehicle type and shipment type must be known. If there is uncertainty about this, the wrong factor may be chosen, resulting in a significant effect. When the total fuel consumption can be modeled, it is essential to include empty trips in the total emissions, making distance and a good understanding of origin and destination crucial for avoiding uncertainty in the outcome. The potential causes of uncertainty in the parameters are always present when they are applied. These include the conversion factor, emission factors, and default emission intensity factors. However, a conversion factor is only used when another loading unit needs to be converted to tons, and the emission intensity factor is only applied when there is no known data and a reliable estimate cannot be made for transport activity and fuel consumption.

The interviews revealed that there is still much discussion about the concept of carbon footprint in practice. Particularly, Black carbon, NO_X, hydrogen, and PM were mentioned as points of discussion. Additionally, the interviews addressed the scope definition of a carbon footprint and the various existing allocation methods. Furthermore, the experts interviewed identified the default emission intensity factors as the primary source of uncertainty, mainly because they are based on assumptions and not primary data. There are significant differences among databases due to these assumptions. As far as known, the literature has not mapped the uncertainty of these factors or reflected much on them.

Field research showed that requesting data from carriers is a complex and time-consuming process. As the data collection was for a construction site, there were many different stakeholders involved. The client was the construction site, but subcontractors also purchased materials to ship to the site. As a result, many shippers and carriers/LSPs were involved in this project. It appeared that many carriers and transporters had different data situations and no emission intensity factors of their own. Moreover, much effort had to be spent on explaining the requested data and terminology, and many shippers found it challenging to obtain all the necessary data due to the transporters' inability or lack of incentive to share data or because they did not want to share information for privacy reasons. To use the GLEC Framework method to determine the carbon footprint, the information from each transporter and carrier must be available annually. Additionally, each carrier/transporter needs assistance to perform the aggregated calculation, which is very time-consuming. As a result, the field research did not map the carbon footprint at an aggregated level but at the trip level. This means that all transport movements to and from the construction site of the selected subcontractors had to be mapped to calculate a carbon footprint based on that. This was a crucial point for the research scope. Since practical experience was gained by measuring a carbon footprint at the trip level, subsequent steps in the research and design were based on this.

To map the carbon footprint of freight movements to and from a construction site, it was crucial to know the energy consumption per trip, the load brought to the site, and, if the trip involved shared freight, the loading and addresses of the other stops needed to calculate the emissions allocated to the construction site. Based on the background study and practical experience, seven data situations were identified for mapping a construction site's carbon footprint. These are based on how carbon footprints are calculated, using available information on energy consumption and transport activity data. Each data situation has its fundamental uncertainties, that are always present, and situation-dependent uncertainties. The fundamental uncertainties include variation in emission factors (diesel and petrol emission factor difference between two databases are 3 to 4%) (F1), default energy consumption uncertainty (energy consumption based on industry averages has a margin of +- 16.5%, a modeled energy consumption +-12.5%) (F2), assumptions for other loads or destinations on the route (dependent on the number of stops on the route, but can lead to significant differences in the allocation factor) (F3), and default emission intensity factors (varying the underlying assumptions about energy consumption and average payload by 12.5% and 15% results in an emission intensity factor with a -32% and +51% range) (F4).

Seven data situations were identified, shown below with the fundamental uncertainties that and equation that applies:

- Data situation 1(F1 and Eq 11.1): The carbon footprint of a shipment can be calculated based on known energy consumption of the trip and known transport activity on that trip.
- Data situation 2 (F1 and Eq 11.2): The carbon footprint of a shipment can be calculated based on emission intensity (CO_2e/ton-km) or energy intensity factor (l or kWh/ton-km) known and calculated by the transport company, multiplied by the distance and payload of the shipment.
- Data situation 3 (F1 and Eq 11.3): The carbon footprint of a shipment can be calculated with the average energy consumption of the vehicle in km/l or km/kWh and the transport activity of the trip.
- Data situation 4 (F1, F2 and Eq 11.4): The carbon footprint of a shipment can be calculated with a default average energy consumption in km/l or km/kWh and the transport activity of the trip.
- Data situation 5 (F1, F3 and Eq 11.3): The carbon footprint of a shipment can be calculated based on the average energy consumption of the vehicle in km/l or km/kWh, but not all data on transport activity is known, and assumptions must be made.
- Data situation 6 (F1, F2, F3 and Eq 11.4): The carbon footprint of a shipment can be calculated with a default average energy consumption and not all data on transport activity is known, assumptions must be made.
- Data situation 7 (F4 and Eq 11.5): The carbon footprint of a shipment must be calculated with default emission intensity factors, as there's no better approximation due to missing data on transport activity and energy consumption.

$$\text{CF} = \text{Total Energy Consumption of the trip} \times \text{EF} \times \text{Allocation factor} \tag{11.1}$$

$$\text{CF} = \text{Energy Intensity Factor} \times \text{EF} \times \text{Distance shipment} \times \text{Payload shipment} \tag{11.2}$$

$$\text{CF} = \text{Average Energy Consumption per km} \times \text{Distance} \times \text{EF} \times \text{Allocation factor} \tag{11.3}$$

$$\text{CF} = \text{Default Energy Consumption per km} \times \text{Distance} \times \text{EF} \times \text{Allocation factor} \tag{11.4}$$

$$\text{CF} = \text{Default emission intensity factor} \times \text{Distance} \times \text{Payload shipment} \tag{11.5}$$

As discussed, in addition to fundamental uncertainties, other factors can also create uncertainty around the carbon footprint. For instance, when average energy consumption is based on the number of liters divided by the actual driven distance, and only the planned distance is available for a route, the planned distance must be converted using a factor to switch to the actual driven distance, or vice versa. This is not a fundamental uncertainty that always occurs in the data situation but is a possible variation within this data situation and is thus context-dependent.

After categorizing the uncertainties based on the data situation, the potential effects of these uncertainties were examined. Several interesting findings emerged from this analysis. The causes of the greatest uncertainties in this study are the use of default emission intensity factors [F4], the use of default average energy consumption [F2], the use of assumptions for other loads or destinations on the route [F3], unknown energy type that is used because this influences the selection of the emission factor, applying a standard conversion factor to convert another load unit to weight, misinterpretation of origin and destination when the distance is needed for calculating energy consumption, and when default emission intensity factors are used additional uncertainty can arise if the vehicle type and/or shipment type is unknown/unclear because this influences the selection of the factor.

The data situation determines the calculation method for estimating the carbon footprint (Eq 11.1, Eq 11.2, Eq 11.3, Eq 11.4, Eq 11.5), beneath which lie additional potential uncertainties. The research indicates that the computation of a carbon footprint is primarily sensitive to uncertainties. This is particularly risky for data situations where many possible causes of uncertainties can occur or fundamental uncertainties are present. Especially when energy consumption must be extrapolated, assumptions need to be made for the transport activity, or emission intensity factors are required.

In all situations, a significant uncertainty arises when the type of energy used for the trip is unknown, affecting the emission factor used to calculate the total fuel consumption. Assumptions need to be made in this situation.

The use of a conversion factor, for converting other units of payload into tonnages. introduces potential significant uncertainty for situations 2 and 7. In situation 2, if an emission intensity factor is given in CO_2e per ton-km and must be multiplied by the number of ton-km and the payload is not known in tons but in pallets or loading meters, a conversion factor must be used to calculate emissions. If the CO_2e/ton-km value is calculated with the same conversion factor applied to a shipment, this can be accurate. However, if a different conversion factor is applied than the one used in the emission intensity factor or if the emission intensity factor is based on different types of payloads, there is a significant potential uncertainty. The same applies when using a default emission intensity factor and applying a standard conversion factor to arrive at the total kg CO_2e.

For situations where an average fuel consumption or emission intensity factor is provided, possible uncertainties include incorrect calculations, underlying assumptions, or differing interpretations. Clear communication is essential for accurate calculations.

For situations where total fuel consumption must be calculated based on an average amount of liters or kWh per kilometer (situations 3, 4, 5, and 6), a significant influence on uncertainty is the incorrect interpretation of origin and destination. If the route given is from and to a distribution center, but the truck originates from a different location, empty trips are not considered, leading to inaccurate total fuel consumption and CO_2e emissions.

In situations where fuel consumption must be modeled using an industry average l/km value (situations 4 and 6), several factors contribute to uncertainty. Incorrect vehicle identification or interpretation can result in the wrong average being chosen, directly affecting total emissions. Assumptions must be made when this uncertainty arises. Additionally, industry averages may not reflect primary data from the transport company, such as driving behavior and average loading. This uncertainty may be reduced if fuel consumption is modeled and average loading is considered, but driving behavior remains unaccounted for.

For situations where parts of the transport activity are unknown (situations 5 and 6), assumptions made regarding shared trips without complete address or loading information greatly influence emission allocation.

The use of an emission intensity factor (situation 7) introduces several potential causes of uncertainty. The factor is chosen based on vehicle type, shipment type, and energy type, which may be unclear or missing. Assumptions made in this case greatly impact the final factor and emissions. One interesting point to mention is the ambiguity introduced by the terms ”light,” ”heavy,” and ”average” for shipment type. Underlying assumptions in the emission intensity factors are based on the average load factor and fuel consumption of the vehicle type, as well as the emission factors included in the calculation.

An underestimated cause of uncertainty may be the uncertainty underlying emission factors. This research determined the impact by comparing gasoline and diesel emission factors between the GLEC Framework and CO2emissiefactoren.nl. The impact of uncertainty in the Well-to-tank emission factors for renewables and electricity is likely underestimated since other energy types were not compared. Therefore, it is worth mentioning this potential significant uncertainty.

The causes outlined above are expected to have the most significant effects on the uncertainty of a trip's carbon footprint and the allocation of emissions to a shipment. After determining the impact of all uncertainties found for each data situation, a tool was developed to identify potential causes of uncertainties, their effects, and how to deal with them for each data situation. The approach is divided into three possibilities: for assumptions, uncertainties are best represented based on scenarios (often arising from lack of data), and for average values with stochasticity, probability density functions can be created to represent the uncertainty. Ambiguity-related uncertainties should be prevented through communication. The tool was eventually tested on three different trips and proved to be effective. A sidenote regarding the tool is that mapping uncertainty using scenarios and probability density functions can be time-consuming. Probability density functions and Monte Carlo simulations also require software and specific knowledge and skills. Therefore, the tool was also tested to assess the outcome if uncertainty was only mapped using scenarios. It should be noted that the range around the carbon footprint can quickly become large, potentially losing its meaning.

11.2. Reflection results from experts

The experts mostly agreed on the identified uncertainties and their prioritization, with some additional uncertainties and aspects highlighted for future consideration. They also agreed that uncertainties depend on the amount of information available and found it logical to link them to the data situations. The most critical point was the level of detail of the data situations. Here it was also made clear that the tool is now useful for trip level but for use at the aggregate level adjustments are needed. However, experts did reveal that the insights of uncertainties and the uncertainties can work through at the aggregate level.The experts recognized the tool's potential in creating awareness and providing an overview of the topic. Some suggested that the tool could be used in contracts or data improvement efforts, while others believed it could contribute to industry harmonization. The experts emphasized that awareness of upcoming regulations and increasing client interest in the carbon footprint of transport services might incentivize companies to address uncertainties and improve data accuracy. Companies are starting to include CO_2 measurement and reduction plans in their contracts and increasingly require a certain quality of data and calculation methods. However, many companies are still not very advanced in this regard, and the focus on carrier-specific emission intensity factors is still in its early stages. In conclusion, the research findings and the developed tool have the potential to contribute to creating awareness, providing an overview of the topic, and improving data accuracy in the carbon footprinting field. The industry is moving towards increased transparency and better data sharing, driven by upcoming regulations and the growing interest in sustainable procurement. However, there is still room for improvement, and the tool can be further refined and expanded to address additional uncertainties and aspects raised by the experts.

11.3. Reflection results on new ISO

The practical research choices led to a very detailed level of investigation, as the routes to and from the construction site had to be modeled as accurately as possible. However, later in the research, it was learned that the new ISO standard for calculating and allocating emissions would be based on the GLEC Framework. This means that a carbon footprint must be calculated at a more aggregated level. For a particular Transport Operation Category, the total amount of liters or kilowatt-hours is divided by the total transport activity (sum of ton-kilometers based on Great Circle Distance or Shortest Feasible Distance) and multiplied by an emission intensity factor. This number must then be multiplied by the transport activity of a client.

As a result, there are fewer and different data situations. This was also referred to by experts. Therefore, at the end of the research, a translation was made to determine how the findings and the detailed level tool can still be meaningful at an aggregated level. Data situation 7 also applies at an aggregated level; according to the new ISO, a default emission intensity factor must be used in the absence of primary data on transport activity and fuel consumption. In addition, data situation 2 demonstrates how the application of a calculated emission intensity factor can introduce uncertainties. It is also important to identify the uncertainties that can play a role in calculating an emission intensity factor. If the total energy consumption is unknown, it still needs to be modeled, and the same uncertainties apply as when this is done at the trip level. Moreover, there is uncertainty about which energy type is used in a year and whether this has changed; if this is not properly monitored, it can cause problems in the allocation of the number of liters with the applicable emission factor. There is also uncertainty when assumptions must be made if part of the transport activity is unknown, and an estimated average payload must be used. Another cause of uncertainty that remains is the use of conversion factors. Inconsistent application of conversion factors can lead to significant uncertainty.

One of the reasons for advocating an aggregated approach is that seasonal influences are distributed among all clients. Additionally, it is argued that achieving an emission intensity factor is relatively easy when fuel card data is available, and the latest onboard computers are not necessarily required for a good approximation.

My reflection on the above is that there may still be a lot of uncertainty between defining TOCs and using fuel card data. When a fuel card is available per truck, it can still be challenging to distinguish fuel consumption per TOC if a truck is used for multiple purposes, such as shared trips and dedicated trips.

Furthermore, I understand that a general allocation factor (ton-km) was chosen to better compare apples and oranges, but I believe this will cause many problems for LSPs (or carriers) who are unaware of cargo weights and measure payload in different units. If a pallet has a weight of 50 kg and a standard conversion factor for a pallet is 400 kg, and the LSP (or carrier) is unaware of this (or ignores this), a completely wrong impression of the annual emission intensity factor can be created. Additionally, when the client knows the weight and calculates the emission based on this number, there is no consistent calculation, increasing the uncertainty surrounding this figure.

11.4. Implications for practice

In the auditing and tender processes of transportation companies, the tool and insights from this research can be invaluable. It helps set data requirements and understand the uncertainties that may underlie a carbon footprint, ensuring that companies are better informed during the decision-making process. In the future, this will mainly be about the emission intensity factors of transportation companies, something experts say is in its infancy. The findings in this study can help interpret these numbers.

Software companies that currently map carbon footprints can benefit from incorporating the ”dealing with uncertainties” or ”showing uncertainties” aspect of the tool. This will make customers aware of the extent of uncertainty surrounding their carbon footprint due to missing data, leading to more accurate and reliable calculations. When, for instance, a default emission intensity factor is used and the associated uncertainty is displayed (in this study determined to be -31% and +51%), companies may reconsider the interpretation of the carbon footprint. This could also create an incentive for them to provide more accurate data for calculating a carbon footprint.

The study highlights that certain assumptions in carbon footprint calculations can lead to lower emission estimates. Companies should be aware of this potential bias and critically evaluate the assumptions they make. Failing to do so can result in efforts to reduce the carbon footprint not being accurately reflected in the numbers, damaging the company’s credibility.

Lastly, the tool developed in this research serves as a valuable aid for companies to communicate the uncertainties associated with their carbon footprint calculations to stakeholders. By providing a clear overview of the uncertainties and their potential impact, the tool fosters a better understanding of the data and methods used. This increased transparency and trust between companies and their clients, regulators, and other stakeholders is crucial for successful collaboration and decision-making.

11.5. Scientific contributions

The scientific contributions of this thesis are rooted in the in-depth exploration of uncertainties in carbon footprint assessments, a dimension that adds a new layer to the existing body of knowledge. The study emphasizes the crucial role of recognizing and addressing these uncertainties when quantifying the carbon footprint of freight transport at the trip level. This perspective adds a new dimension to the carbon footprinting field, revealing the variation and uncertainties inherent in these calculations and making them more visible and understandable.

In this study, the theoretical framework utilizes Walker’s uncertainty matrix to analyze and categorize uncertainties in carbon footprint assessments. This approach offers a new perspective and showcases the adaptability of the framework in the domain of carbon footprint calculation for freight transport. The adjustment to the existing methodology, informed by both background and empirical research, creates a novel approach that holds potential for widespread application.

In terms of empirical evidence, this research integrates a variety of methodologies, combining interviews, field research, and literature reviews to gather a robust dataset on the sources and impacts of uncertainties in carbon footprint assessments. This empirical approach serves to enrich the existing literature, bridging the gap between theory and practice in the field of carbon footprinting. The practical insights gleaned from this research not only add depth to the academic discourse but also offer valuable guidance for practitioners in the field.

Previous studies, such as Bell & Spinler (2022); Rigot-Muller et al. (2013); Carsten & Nadine (2019), underscore the importance of considering various factors that can influence the accuracy and variability of carbon footprint measurements. However, the specific focus on quantifying and addressing uncertainties in carbon footprint calculations is relatively unexplored in the existing literature. This research aims to fill a notable gap by shedding light on the uncertainties that surround carbon footprints of freight transport. It also highlights the implications of these uncertainties for businesses and policymakers.

11.6. Limitations of the study

While this research provides valuable insights and a practical tool for assessing uncertainties in carbon footprinting of road freight transport, it is important to acknowledge several limitations that could inform future improvements to the tool and guide further research.

Firstly, the study's scope is specific to road freight transport. Consequently, the findings and the tool developed may not be directly applicable to other transportation modes.

Secondly, data availability posed a challenge. The limited data on variations and uncertainties necessitated assumptions about probability density functions, potentially affecting the accuracy of the findings.

Thirdly, the tool developed in this research mainly addresses parameter and data input uncertainties, potentially overlooking other sources of uncertainty. Furthermore, the tool is instrumental in recognizing and communicating uncertainties in practice; the determination of the bandwidth around a carbon footprint using this tool may be challenging and reliant on assumptions.

Furthermore, the tool's testing was limited to case studies for which it was specifically designed. Its effectiveness in real-world scenarios may be constrained since potential users, such as consultants, have not directly employed it. This limitation highlights the need for more comprehensive user testing in future tool development.

In terms of research methodology, the study primarily engaged with shippers rather than carriers during field research. As a result, the creation of a carbon footprint was looked at more from a scope 3 perspective. This approach may have curtailed the range of insights and perspectives gained from the study, and future research could benefit from more diverse stakeholder engagement.

The theoretical underpinning of the tool is also a point to consider. The tool is based on a specific theoretical framework, namely Walker's uncertainty matrix. Exploring alternative frameworks could yield different insights or perspectives on uncertainty, and future research could delve into this potential. Finally, the new ISO standard presents a challenge. The tool developed in this study is designed to assess uncertainties at the trip level, whereas the new ISO standard emphasizes aggregated level calculations. This discrepancy may limit the tool's applicability to the requirements of the new ISO standard, suggesting that future tool development may need to align more closely with emerging standards.

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12 Conclusion

12.1. Conclusion

In order to come to a conclusion of this study and design objective, the findings will be discussed by design phase of the study. At the end of the conclusion, an overall conclusion will be given about the insights of this research.

Design objective

Given the importance of carbon footprint calculations in the freight transport sector and the potential consequences of poorly understood uncertainties, there is a clear need for a tool that can assess the uncertainties associated with freight transport carbon footprints. Therefore, the main thesis objective is:

"Design of a 'tool' to assess the uncertainty of a transport carbon footprint measurement"

Research and Insights Phase

What is a carbon footprint?

Calculating the total greenhouse gas emissions associated with an activity or product is called a carbon footprint. However, there are varying definitions across studies, leading to disagreements on which gases to include. Defining the boundaries and elements of the carbon footprint is crucial for comparability. The EN 16258 standard focuses on the carbon footprint of freight transportation, including emissions from production and distribution of fuel and energy, as well as from vehicle use. This defines also the scope of the carbon footprint of this research: "Green house gas emissions (CO_2, CH_4, N_2O, HFCs, PFCs, SF_6 and NF_3) that are released from the production and distribution (well-to-tank) of fuel or energy and emissions that arise from the use (tank-to-wheel) of the energy or fuel in a vehicle".

Which variables/data points are crucial to determine the carbon footprint of freight transport?

To determine the carbon footprint of freight transport, various calculation methods have been devised, with the EN16258 standard serving as the foundation. This European standard presents two approaches: 1) consumption-based calculations and 2) distance-based calculations. The former relies on primary data, while the latter uses default data. In the consumption-based calculation (1), the total energy consumption is first calculated to obtain the emission figures (total kg CO_2 equivalents), which are then allocated to shipments or customers using an allocation factor based on transport activity. In the distance-based calculation (2), the total consumption is calculated using a default average and subsequently allocated based on customer or shipment data. If transport activity information is unavailable, a default factor representing energy consumption is used. Different calculation methods are used depending on the available data. The critical inputs for the carbon footprint are the energy consumption for a trip and the associated transport activity (e.g., load, origin, and destination of each shipment). Additionally, the system boundary, or scope, of the carbon footprint must be defined, which can encompass the entire activity of a carrier's fleet during a year, all round trips between two specific locations per quarter, or a single leg in a pickup and/or delivery trip.

In the existing literature, what are the different measurement methods to map a carbon footprint of freight transportation?

At the beginning of this thesis, the EN16258 was the prevailing standard for mapping a carbon footprint. Various software tools and updated methods have since been developed based on this standard. An essential method is the GLEC Framework, which advocates for distributing emissions on an annual basis. The energy consumption per system boundary is summed over a year and divided by transport activity to obtain an emission intensity or fuel intensity factor, which can then be multiplied by the transport activity of a corresponding customer or shipment. The GLEC Framework also distinguishes between primary data and secondary/default data. If data is missing, fuel consumption can be modeled. If transport activity is unknown, an average load factor can be used, and if both are unknown, default emission intensity factors can be employed. At the end of this thesis, the new ISO standard was published, which largely adopts the GLEC Framework's method. As far as is known, the main difference between the ISO standard and EN16258 is the aggregation level and the decision to allocate emissions based on ton-kilometers, where kilometers are determined by the Great Circle Distance or the Shortest Feasible Distance, with possible exceptions.

What types of uncertainties can be identified from the literature and practice and how can they affect carbon footprint mapping?
The uncertainty matrix by Walker was employed to map the uncertainties in the carbon footprint of freight transport. This matrix is based on the premise that uncertainty is a complex concept arising from three dimensions: the location, nature, and level of uncertainty. By applying this theoretical framework, uncertainties were identified in various aspects of the carbon footprint calculation, including context determination, model structure, data input, and parameters. To explore these uncertainties, a combination of interviews, literature reviews, and field research was conducted. The field study examined the carbon footprint of freight transport to and from a construction site, as determined by Districon. One of the main challenges identified in the field study was the time-consuming and complex process of data collection, which proved to be more difficult than anticipated.

The uncertainties discovered in this phase were classified based on their nature (differing interpretations, lack of knowledge, or variability), and level (stochastic, scenario, or deep uncertainties). Most potential causes of uncertainty were found in the data input, as the amount of data needed to calculate a carbon footprint depends on the available information related to energy consumption and transport activity (this determines from now on "the data situation"). Thereby the causes of parameter uncertainty were also dependent on this, because it determines the use of an emission factor or emission intensity factor. However, it seemed that the potential causes for uncertainties in the context and model structure of the carbon footprint analysis remain the same. This raised the question of whether the carbon footprint can be considered an absolute value and how to address inherent uncertainties and how this differs per data situation. The causes of potential uncertainties that are independent of the data situation are as follows: **Causes found in the context of a carbon footprint allocated to a client/shipment:** The definition of Carbon Footprint: Different interpretations of a 'carbon footprint' lead to different scopes and the inclusion or exclusion of emissions in the measurement. Boundary Carbon Footprint of Transportation: Different system boundaries can be defined for a carbon footprint of freight. Unclear boundaries can lead to different interpretations. **Causes found in the model structure of a carbon footprint allocated to a client/shipment:** Different Allocation Methods: Multiple options exist for allocating emissions, and the method used has a significant influence on the carbon footprint of a customer's shipment. Linear Approach Calculating Emissions: The emissions N_2O and CH_4 do not have a linear relationship with energy use as CO_2, resulting in a simplification of the model. Assumptions of trip data: When trip details are partially available, assumptions can be made to estimate with available information, leading to uncertainties.

Design Input and Output Phase

Designing a tool to address uncertainties in carbon footprint analysis of freight transport requires multiple rounds of iterative designing and brainstorming sessions. The tool aims to prevent, identify, and quantify uncertainties by working within the constraints and functionalities. Steps include discussing potential causes of uncertainty, assessing their importance and complexity, determining a method to address them, and developing the tool to assess uncertainties in transport carbon footprint measurement.

The first step of the data input phase focused on determining the data situations concerning energy consumption and transport activity, as these factors influence the potential causes of uncertainties. The potential causes for uncertainties were therefore categorized by data situation in Table 12.1. Seven distinct data situations were identified based on the field research. These are based on how carbon footprints are calculated, using available information on energy consumption and transport activity data. Each data situation has its fundamental uncertainties that are always present and context-dependent uncertainties. The fundamental uncertainties include variation in emission factors [F1]; for example, diesel and petrol emission factor differences between the two databases are 3 to 4% giving uncertainty in the conversion of energy to emissions, a default average energy consumption[F2]; an average energy consumption based on industry averages has a margin of +- 16.5%, a modeled energy consumption +-12.5% giving uncertainty in the conversion of energy to emissions, assumptions for other loads or destinations on the route; uncertainty margin depends on the available information and number of stops on the route, but can lead to significant differences in the allocation of emissions[F3], and default emission intensity factors [F4]; varying the underlying assumptions about energy consumption and average payload by 12.5% and 15% results in an emission intensity factor with a -32% and +51% range giving uncertainty in the conversion of ton-kilometers to emissions.

The seven identified data situations are shown below, with the fundamental uncertainties that apply:

- Data situation 1 [F1]: The carbon footprint of a shipment can be calculated based on the known energy consumption of the trip and known transport activity on that trip.
- Data situation 2 [F1]: The carbon footprint of a shipment can be calculated based on emission intensity (CO_2e/ton-km) or energy intensity factor (l or kWh/ton-km) known and calculated by the transport company, multiplied by the distance and payload of the shipment.
- Data situation 3 [F1]: The carbon footprint of a shipment can be calculated with the average energy consumption of the vehicle in km/l or km/kWh and the transport activity of the trip.
- Data situation 4 [F1, F2]: The carbon footprint of a shipment can be calculated with a default average energy consumption in km/l or km/kWh and the transport activity of the trip.
- Data situation 5 [F1, F3]: The carbon footprint of a shipment can be calculated based on the average energy consumption of the vehicle in km/l or km/kWh, but not all data on transport activity is known, and assumptions must be made.
- Data situation 6 [F1, F2, F3]: The carbon footprint of a shipment can be calculated with a default average energy consumption, and not all data on transport activity is known, and assumptions must be made.
- Data situation 7 [F4]: The carbon footprint of a shipment must be calculated with default emission intensity factors, as there's no better approximation due to missing data on transport activity and energy consumption.

As discussed, in addition to fundamental uncertainties, other factors can also create uncertainty around the carbon footprint. For instance, when average energy consumption is based on the number of liters divided by the actual driven distance, and only the planned distance is available for a route, the planned distance must be converted using a factor to switch to the actual driven distance, or vice versa. This is not a fundamental uncertainty that always occurs in the data situation but is a possible variation in these data situations and is thus context-dependent. In Table 12.1 all the possible uncertainty causes are visible per data situation.

Subsequently, the study examined the possible effects of these uncertainties on the carbon footprint and their respective influences. This was determined by: the sensitivity of the output based on the variable that the uncertainty influenced and the spread that the uncertainty would cause. It was discovered that the causes with the highest impact on the carbon footprint primarily occurred in situations 4, 5, 6, and 7. The causes of the greatest uncertainties in this study are the use of default emission intensity factors [F4], the use of default average energy consumption [F2], the use of assumptions for other loads or destinations on the route [F3], unknown energy type that is used because this influences the selection of the emission factor, applying a standard conversion factor to convert another load unit to weight, misinterpretation of origin and destination when the distance is needed for calculating energy consumption, and when default emission intensity factors are used additional uncertainty can arise if the vehicle type and/or shipment type is unknown/unclear because this influences the selection of the factor. Besides the possible effects, the complexity of the uncertainties is also determined. This complexity is divided into three categories: Communication with a stakeholder to reduce ambiguity is considered 'low', gathering more data to make better estimates is considered 'medium', and conducting further research on the uncertainty surrounding the value due to its unknown nature receives a 'high' score.

Table 12.1: Possible uncertainty causes per situation

Potential uncertainty causes that can arise per situation	**Situation 1**	**Situation 2**	**Situation 3**	**Situation 4**	**Situation 5**	**Situation 6**	**Situation 7**
Uncertainty in unknown: Energy Type	X	X	X	X	X	X	X
Uncertainty in Emission Factors	X	X	X	X	X	X	
Uncertainty when Conversion Factor needs to be applied	X	X	X	X	X	X	X
Uncertainty in definition: Payload	X	X	X	X	X	X	X
Uncertainty due to variability of Average Value		X	X		X		
Uncertainty about Calculation		X	X				
Uncertainty in definition: Distance		X	X	X	X	X	X
Uncertainty due to other distance type than used for average			X	X	X	X	X
Uncertainty due to unknown distance		X	X	X	X	X	X
Uncertainty in specification level: address Origin, Stops, and Destinations on GCD	X	X	X	X	X	X	
Uncertainty in specification level: address Origin, Stops, and Destinations on Unknown Distance			X	X	X	X	X
Uncertainty in definitions: address Origin, Stops, and Destinations on GCD	X		X	X	X	X	
Uncertainty in definitions: address Origin, Stops, and Destinations on Unknown Distance			X	X	X	X	
Uncertainty due to variability of Default Value				X		X	
Uncertainty due to variability of Average Modeled Value				X		X	
Uncertainty due to definition: Vehicle				X		X	X
Uncertainty due to unknown: Vehicle Type				X		X	X
Uncertainty due to definition: Shipment Type							X
Uncertainty due to unknown: Shipment Type							X
Uncertainty due to emission intensity factors							X
Uncertainty due to unknown: Payload other Stops Assumption average value payload with vehicle capacity					X	X	
Uncertainty due to unknown: adres other Stops Assumption trip is Dedicated, replace Allocation Factor with * 2					X	X	
Uncertainty due to unknown: Amount of Trips Assumption Total Demand/Capacity Vehicle						X	

Thirdly to address the potential uncertainties, different approaches were employed depending on the level of uncertainty. For stochastic uncertainties, probability density functions and Monte Carlo simulations are suggested to quantify and understand the degree of uncertainty. For scenario uncertainties, multiple scenarios could be run to demonstrate the influence of assumptions. The main goal for deep uncertainties was to avoid them as much as possible through proper communication.

Based on the findings from both phases, a tool was developed to help recognize, prevent, and manage uncertainties for each data situation. This tool provides guidance on identifying and managing uncertainties in freight transportation carbon footprint calculations. By incorporating the various data situations, potential causes of uncertainties, and their effects, the tool allows users to navigate the complex landscape of carbon footprint assessments.

Design testing, verification, and validation

Verification of the tool's effectiveness and compliance with requirements was achieved through a series of tests, which included the examination of substituting probability density functions with scenarios. The verification process showed that most requirements were met, with two only partially met due to unavailable data and the new ISO standard. The first issue arises from the fact that the probability density functions are based on assumption due to limited data; however, these are based on, where possible, sources. The second is related to the new ISO standard published towards the end of the research. While the tool is not explicitly based on this standard, it is designed at a less aggregated level, revealing potential uncertainties at a detailed level. However, the tool can incorporate future standard, a proposal at the end of this research was made to address this issue. The tool was also validated and tested within the field research project, it helped with examining data situations and the underlying uncertainties. The tool enhanced transparency in the advisory and provided guidance for reducing uncertainties proactively in future data requests. However, visually presenting uncertainties using Monte Carlo simulations or scenario analyses was time-consuming and required manual work. Integration with existing software programs would streamline this process. Validation discussions with experts revealed general agreement on the identified uncertainties and corresponding data situations, although the data situations were at a fairly detailed level. Experts primarily saw the tool as a means to raise awareness, and one expert particularly appreciated the tool's ability to mathematically represent uncertainties.

Overall conclusion of research

The purpose of this research was to elucidate the uncertainties intrinsic to carbon footprint assessments, thereby fostering a more informed dialogue among stakeholders. By providing a clearer understanding of these calculations, the research encourages stakeholders to acknowledge the variability inherent in such assessments when making decisions. This study highlights the impact of uncertainties on carbon footprint. These uncertainties are most significant when default values are used and/or assumptions are made. The case studies exemplified the effect of uncertainties when employing both best and worst-case scenarios. However, utilizing probability density functions rendered the uncertainties more realistic, although they are based on assumptions requiring further examination. Several factors causing uncertainty were identified; the uncertainties that are expected to have the biggest effects are the use of default emission intensity factors, energy consumption values, assumptions for other loads or destinations, unknown energy types, application of standard conversion factors, misinterpretation of origin and destination, and the use of default factors when the vehicle or shipment type is unclear. The identified uncertainties influence the outcome of these calculations and highlight the need for clear communication between data requesters and providers. Mitigating these uncertainties is critical to ensuring the reliability and validity of carbon footprint calculations.

The data situation determines the calculation method for estimating the carbon footprint, beneath which lie additional potential uncertainties. The research indicates that the computation of a carbon footprint is primarily sensitive to uncertainties. This is particularly risky for data situations where many possible causes of uncertainties can occur or fundamental uncertainties are present. Especially when energy consumption must be extrapolated, assumptions need to be made for the transport activity, or emission intensity factors are required. A 10% change in the input variables of distance or average energy consumption due to inherent uncertainties immediately influences the carbon footprint by 10%. Notably, uncertainty always exists in the case of average energy consumption if a standard average not based on primary data is employed. Assumptions in transport activities do not affect the total carbon footprint but do influence the distribution across clients; therefore, an assumption in the total transport activity directly affects this distribution. Additionally, the emission intensity factor is inherently uncertain, as it is based on a default average energy consumption and carries assumptions about transport activity. This uncertainty can further increase when there is a lack of knowledge about the vehicle used and the type of goods transported. It seems relatively easy to make adjustments in these situations and arrive at a lower figure. Hence, caution must be exercised in controlling and interpreting carbon footprint figures.

In addition to mapping uncertainties when they exist, there are also suggestions for reducing these uncertainties. Stemming from the theoretical framework utilized for this study, it was found that uncertainty can arise from three natures: ambiguity, lack of data, and variability. By being aware of the causes, solutions can be proposed. Effective communication about the type of data being requested and supplied can prevent uncertainties due to ambiguity. The uncertainty caused by default factors and assumptions made can only be reduced with more comprehensive information. This requires good data management and a willingness to share data. Moreover, emission factors, calculated average energy consumption, and calculated average conversion factors to weight will always inherently contain some degree of variability. The main issue is to limit the uncertainty around this variability, which can be achieved, in part, through accurate measurements. By implementing these strategies, as many uncertainties as possible can be avoided.

Finally, the results of this research have far-reaching implications, not only within the realm of carbon footprint assessments but also for broader efforts to combat climate change. The road to a more sustainable future is fraught with uncertainties. The capacity to control and minimize these uncertainties largely predicates the effectiveness in tracking progress and steering necessary actions. The journey toward a sustainable future is steeped in uncertainties. The capacity to control and minimize these uncertainties largely predicates the effectiveness in tracking progress and steering necessary actions. Even though there are significant challenges, they can be conquered with careful and deliberate actions. As demonstrated by this research, it is possible to acknowledge, comprehend, and address these complexities, ultimately leading to more transparent and accurate carbon footprint assessments and a more sustainable future.

12.2. Recommendations for future research

In light of the findings and limitations of this study, a number of potential directions for future research emerge that could further enhance our understanding of uncertainties in carbon footprint assessments, and improve the applicability and accuracy of the developed tool. This section outlines several recommended areas for further investigation.

- **Probability density functions:** This research mainly looked at the uncertainties that can arise and their possible effects. During the research, it was discovered how difficult it is to establish a good probability density function based on previous research and available data, which is why assumptions were made for the uncertainty in default average fuel consumption, the conversion of distance, emission intensity factors, conversion factors and emission factors. If one wants to reconstruct this accurately, further research is recommended.
- **Updated tool for the new ISO:** An updated version of the tool that aligns with the new ISO standard should be developed. This new version can build on the concepts established in this research, taking into account any changes or advancements made in the standard, and be better suited for aggregated data as recommended by the ISO.
- **Well-to-tank emission factors:** Investigate potential uncertainties in well-to-tank emission factors, which are crucial for accurately calculating the carbon footprint of freight transport. As the use of renewable fuels and electricity in freight transport increases, understanding and managing uncertainties in well-to-tank emission factors will become even more important.
- **Tender process:** Examine how uncertainties in carbon footprint assessments might influence the choice of LSP or carrier in a tender process. This could help both shippers and transporters better understand the implications of uncertainty in their decision-making processes and improve the overall efficiency and sustainability of the logistics sector.
- **Big data and blockchain:** Explore the potential of big data and blockchain technologies to address data-related uncertainties in carbon footprint assessments. These technologies could improve data sharing, enhance data quality, and reduce the reliance on assumptions, particularly in companies where technology adoption is lagging behind. Further research should also consider the challenges and barriers to implementing such technologies in practice.
- **Other modes of transport:** Investigate whether similar uncertainties occur in other modes of transport (e.g., rail, sea, air) and identify any additional uncertainties that may arise. This research could help expand the scope of the tool developed in this study and contribute to a more comprehensive understanding of uncertainties in carbon footprint assessments across the entire transport sector.
- **Uncertainties within calculations for other emissions:** For future research, it is suggested to extend the scope of this study to include other emissions in the transport sector, such as particulate matter (PM) and Nitrogen Oxides (NO_x). This research has focused on the uncertainties and complexities involved in calculating the carbon footprint, but these challenges are equally relevant when considering other emissions. By applying the methodologies and insights gained from this study, future researchers could investigate the uncertainties in the calculation of PM and (NO_x) emissions. Such a study would provide a broader and more comprehensive understanding of the environmental impacts of the transport sector. Exploring the correlations and possible trade-offs between different types of emissions could also be a valuable area for future research. For instance, efforts to reduce CO2 emissions might inadvertently lead to an increase

in NOx emissions, or vice versa. Understanding these relationships could help policymakers and industry stakeholders make more informed and holistic decisions in their efforts to mitigate the environmental impacts of transport.

12.3. Practical Recommendations

In addition to the research-oriented suggestions, several practical recommendations have been derived from the research findings. These recommendations aim to facilitate more accurate carbon footprint assessments, promote transparency and improve decision-making in the freight transport sector.

- **Preventing ambiguity:** To reduce ambiguity-related uncertainties, stakeholders should clarify data requirements and calculation methods in advance. This includes asking the right questions and providing clear instructions on how to collect and process data, which can help prevent misunderstandings and improve the overall accuracy of carbon footprint assessments.
- **Guidelines for using standard conversion factors for payload:** Practitioners should exercise caution when using standard conversion factors to convert other payload units to weight, as these can significantly impact efficiency calculations. If a standard conversion factor is larger than what the transport normally weighs, the efficiency immediately appears much better. Understanding the limitations of standard conversion factors can help stakeholders make more informed decisions about the data they use in their calculations.
- **Calculating carbon footprints:** Clear guidelines are needed for calculating carbon footprints with assumptions about trip data or when to use emission intensity factors. This will help practitioners navigate the complexities of carbon footprint assessments and ensure that their calculations are as accurate and reliable as possible.
- **Emission intensity factor uncertainty:** Display the uncertainty in emission intensity factors with a bandwidth, since these factors are often based on numerous assumptions. It is important not to treat emission intensity factors as absolute values, especially since some companies may report lower values than those observed in practice. By displaying the uncertainty, stakeholders can better understand the potential variability in these factors and make more informed decisions.
- **Shipment type categories:** Adjust the naming of shipment types for emission intensity factors to categories such as volume goods, heavy goods, or average goods. This can help reduce ambiguity and improve the accuracy of calculations by providing clearer definitions than terms like light, average, and heavy.
- **Data sharing and collaboration:** Shippers and transport companies should include data sharing provisions in their contracts and work together to develop a comprehensive understanding of the emissions associated with their operations. This collaborative approach can help optimize decision-making processes and drive improvements in sustainability and efficiency.
- **Emission intensity calculation on different time scales:** Although the new ISO recommends calculating emission intensity on an annual basis, it may be beneficial to track this metric on a monthly or weekly basis to identify opportunities for improvements in the planning process. By monitoring emission intensity over shorter time frames, shippers and transport companies can be more proactive in implementing changes that can reduce emissions.
- **Training and education:** Provide training and education for transport companies to ensure they can accurately calculate emission intensity factors as recommended by the future ISO standard. Field research and expert interviews revealed that data sharing and record-keeping challenges are often not just a matter of unwillingness but also a lack of ability. Investing in training and education can help address these challenges and improve the overall accuracy of carbon footprint assessments.

VI

Appendices

A

Thesis paper

B
Interviews

B.1. Interview BigMile

1. Wat is volgens jou de definitie van een carbon footprint?

Ik heb niet echt een definities opgezocht, maar wat mij betreft is het de CO2 waar je direct of indirect verantwoordelijk bent. Dus voor een deel je eigen productieactiviteiten of je eigen het transport bijvoorbeeld maar ook wanneer je transport inkoopt bij een ander dan ben je daar ook indirect verantwoordelijk voor. Dus mijn definitie is de CO2 uitstoot waar jij links of rechtsom verantwoordelijk voor bent.

a) Vervolg vraag: En zie je dan ook dat de andere greenhouse gases daarin of zie je het alleen als CO2?

Carbon is voor mij CO2, we zijn ook bezig met stikstof emissies en PM10 en PM 2,5 maar dat zie ik niet als carbon footprint.

2. Wat voor soort bedrijven komen bij jullie aankloppen om een CF te berekenen en wat is hun grootste drijfveer?

Bedrijven komen naar BigMile toe uit eigen initiatief of omdat dit van hun wordt gevraagd. Beide komen voor. De soorten bedrijven lopen ook veel uiteen, het kunnen eigenlijk alle bedrijven zijn die een supply chain hebben en transport inkopen, de shippers dus. Maar we hebben ook veel carriers, dus transporteurs. BigMile is in eerste instantie begonnen voor wegtransport en wegtransporteurs maar we hebben nu hele diverse klanten van FrieslandCampina tot Wolter Koops. FrieslandCampina heeft eigenlijk helemaal geen eigen vloot. Het zijn allemaal gewoon lange termijn tenders die carriers hebben en ze rijden allemaal in opdracht voor FrieslandCampina.

b) Hoe werkt het dan met data delen? De transporteurs hebben hun eigen data, wat ze niet kunnen delen, dat moet eigenlijk zelf proberen aan te vullen. En dan hebben ze dus alleen bijvoorbeeld zending data van A naar B maar dan weet je niet iets over de brandstof verbruik en dat soort dingen.
Qua drijfveer: Eerst was het eigenlijk vooral de early adapters die het echt vanuit hun eigen nou mbo strategie (management by objectives) wilde weten en eigenlijk wilde voorsorteren. En nu zijn het ook heel veel bedrijven die het willen weten omdat bijvoorbeeld een klant vraagt: ik boek In het jaar 2022, 2000 zendingen bij jou, wat is daar de carbon footprint van. En daarnaast ook wetgeving, de CSRD is een grote drijfveer nu. Deze wetgeving wil eigenlijk dat je in 2024 over het vorig jaar dus over die 23 al een CO2 rapportage maakt. De volgende stap is dan CO2 taks. Daardoor zien we ook veel beweging. Je ziet nu bijvoorbeeld dat de zeevaart dit moet gaan betalen en de mensen die dus goederen importeren. Dit is een wetgeving waaruit een bedrijf ook echt verplicht wordt gesteld om iets met carbon footprint in te doen. Dus die die komen ook bij ons.

3. Wat zijn de grootste verschillen tussen de methodes die jullie gebruiken om een CF te berekenen?

Vooral de emissie kengetallen. Allocatie is volgens mij hetzelfde. Er kan wel een kleine methodiek verschil inzitten. Bijvoorbeeld met luchtvracht wordt bij GLEC de landing anders meegerekend dan bij de

NLse emissiefactoren methode. Echter is het grootste verschil de factoren van de brandstoffen. Ook definiëren ze hier en daar ook voertuigtypes anders, bij GLEC heb je iets meer verschillende soorten dan bij NLse emissiefactoren. Maar de allocatie methodes zijn hetzelfde. GLEC gaat uit van het ergste, NL emissiefactoren gebruikt meer gemiddeldes. Bijvoorbeeld als jij aan geeft diesel gaat GLEC uit van de vervuilendste diesel en NLse emissiefactoren gaat dan uit van de gemiddelde diesel blend.

4. Welke data is volgens jou het belangrijkste om de meest accurate CF te maken?

Je hebt eigenlijk twee approaches om het zo te zeggen. Je hebt een Fuel-based approach. Die op basis van je brandstofverbruik de emissies berekend. Daarnaast heb je een transport-activity-based approach en die gebruik je wanneer geen brandstofverbruik beschikbaar is, wanneer dit het geval is gaan wij kijken: zending A naar B dit is de afstand; dit is de storingsfactor die daarbij hoort. Het beste (in bigmile ook aangeduidt met GOLD+) is om het aantal liters van een trip te hebben, dit kan uit een boordcomputer van een vrachtwagen komen bijvoorbeeld. Dan komt daarna qua accuraatheid gold wat inhoudt dat je per vehicle het brandstofverbruik over een periode weet. Daarna heb je zilver en dat is het brandstofverbruik per periode over je hele vloot. Met dat consumptie getal, kun je niet per voertuig verschil in efficiency zien.

a) Vervolg vraag: wanneer je dat gemiddelde verbruik hebt. Hoe reken je daarin de zwaarte van je shipments mee?

Als je bijvoorbeeld het aantal kms van een trip wel weet en hoeveel de zending weegt, maar het brandstofverbruik niet dan gebruik je allocatie om het brandstofverbruik te verdelen. Je doet dan een benadering van het aantal getankte liters. Die benadering is vaak: alle data van de tankpas/kms gereden volgens de boordcomputer.

b) Stel je hebt het aantal l per km berekend over een bepaalde periode van een voertuig, maar dit voertuig rijdt voor meerdere klanten. Hoe bepaal je dan de CF voor één klant? Het kan namelijk zo zijn dat zendingen van bijvoorbeeld bedrijf A of B veel zwaarder zijn.

Het aantal kms per rit gaan we verrekenen met het aantal km/l dat bekend is. Dan krijgen we het aantal liters per rit. Op basis van de afstanden van de individuele zendingen en de gewichten gaan we de CO2 die gecreëerd is door het aantal kms toekennen. Het is volgens de COFRET methode.

5. Wanneer een CF-meting gedaan moet worden, wat zijn volgens jou de grootste barrières op dit moment?

Trip data is er meestal wel, dat is niet het grootste probleem. Die data komt uit TMS systemen. Er wordt gewoon ingepland en er worden al die zending aan gehangen en dan komt er al een afstand uit: de geplande afstand. Ja, soms wordt hij nog overschreven door de daadwerkelijk gereden kilometers met die boordcomputer. Ja, dat zit vaak wel aan elkaar gelinkt, omdat zo'n transportbedrijf het vaak voor hun planning moet weten. De brandstofdata daarentegen is wat lastiger te koppelen, vooral per rit. Voor ieder transport bedrijf is de definitie van een rit alweer anders. Is een rit altijd van standplaats dan een rondje en dan weer naar standplaats of kan die eindigen onderweg en heb je dan weer een nieuwe start. En hoe ga je vervolgens dan die liters die je begin van de week heb getankt, hoe ga je die uitsmeren over al die ritten. Sommige bedrijven kunnen dat omdat ze de consumptie uit de boordcomputer beter. Maar wat we vaak doen, is dat we het brandstofverbruik per periode nemen, dus elk voertuig tankt een aantal keer in de maand. Meestal hebben we gewoon elke tankpas en dan voor iedere maand je die getankte liters ophalen. Dat weet dan administratie vaak wel. Dan ga al die liters in die maand alloceren over al die zendingen verreden door die auto in die maand. Dat is wel een beetje benadering. Het uitstoot getal klopt, want die liters die zijn hetzelfde, alleen de allocatie is iets meer hoog over.

a) Vervolgvraag: en dat doe je dus dan vervolgens met behulp van de tonnages dan weer?

Ja dat klopt.

6. Zijn er weleens misverstanden over bepaalde definities (zoals hoe afstand wordt gemeten of de ladingen/allocatie methodes)?

Origin en Destination definities gaat vaak fout, de definities van Trip/rondrit/enkele rit ook. Daarnaast ook de meet eenheden.

7. Welke assumpties worden er in BigMile gedaan wanneer data niet beschikbaar is?

Brandstofverbruik/energieverbruik: Transport-activity based approach wordt dan gehanteerd. Ladingen onbekend shared trip: Als je de rit data niet hebt dan zit het al in die ton-km factoren van het framework zelf dus ook activity based.

9. Waar ontstaat de meeste onzekerheid tijdens het berekenen van een carbon footprint volgens jou?

Als je het brandstofverbruik niet weet en met standaard ton-km kengetallen moet rekenen. Zijn van goede kwaliteit en goed onderbouwd. Alleen wat we zien dat als je je brandstofverbruik wel meeneemt dan is je uitstoot veel lager dan als je de factoren gebruikt. Daar zit de grootste assumptie in. Een ander ding wat we veel zien is dat bedrijven de gewichten van hun eenheden niet weten. Bijvoorbeeld met iemand In de sierteeltsector zijn we bezig met de CF uitrekenen voor de bloemen. Alleen die weten de gewichten niet van hun van hun eenheden. Dus ja, die die bloemen die komen allemaal in van die metalen karren. Ze weten eigenlijk alleen het aantal karren had getransporteerd wordt en niet niet de kilo's. Dus ja, dat zulke grote onzekerheid, want daar moeten wij een aanname doen. Hoe zwaar zo'n kar is. Daarnaast heb je onzekerheden in oorsprong en bestemming definiëring. Dus wat we vaak zien of graag hebben, is dat dat er postcodes zijn, die postcodes die kunnen wij dan met onze Geo code bekijken waar die liggen en wat de tussenafstanden zijn, maar niet alle bedrijven hebben die informatie en vooral shippers niet. Dan weten ze alleen dat een zending van New York naar Rotterdam is gegaan. Maar Rotterdam is erg groot en New York ook dus dat is ook een aardige onzekerheid.

a) Doorvraag over die case bij BAM: Als trip data ontbreekt zit je eigenlijk al aan de ton-km kengetallen van het framework vast. Als je dit wel weet dan zou je het wel uit kunnen rekenen. Wat dat betreft is het vaak alles of niets. -> activity based manier

Verdere notities:

- Er begint wel veel te verschuiven. Je ziet dat bijvoorbeeld, dat bedrijven in tenders al rekening houden met dat ze die data nodig hebben om de CF uit te kunnen rekenen. Ik denk dat dat wel een hele goede beweging is om een beetje van die activity based maar hier af te komen.
- Data delen is daarnaast ook echt een interessante ontwikkeling. Transporteurs kunnen namelijk ook tegen hun klant zeggen dat ze een vervuilende klant zijn voor hun. Door data te delen komt een dialoog op gang en gaan mensen samenwerken.
- Daarnaast als je meer weet, dan is vaak ook je CO2 ook lager omdat je niet afgestraft wordt met de trip based factoren.

B.2. Interview CE Delft

1. Wat is volgens jou de definitie van een carbon footprint?

Als ik het zou moeten omschrijven, zou ik zeggen, dat het over alle greenhouse gas emissions gaat. Van ofwel een bedrijf, een product of een service.

2. Wat voor soort bedrijven komen bij jullie aankloppen om een CF-calculatie te doen en wat is hun grootste drijfveer?

We doen eigenlijk projecten voor zowel overheden, NGO's en bedrijven. We doen vooral advisering betreft mogelijke maatregelen die genomen zouden kunnen worden om te verduurzamen. En we doen ook af en toe carbon footprint berekeningen voor bedrijven. De bedrijven die vooral bezig zijn met de carbon footprint in kaart te brengen van transport zijn bijvoorbeeld toch wel echt vaak de grote verladers. Deze hebben bijvoorbeeld ook interne doelstellingen om de uitstoot in 2030 met 30

3. Zijn er verschillen in methodes om emissie kengetallen te berekenen of zijn hier strakke richtlijnen voor?

De manier om CO2-emissies te berekenen voor een bedrijf kan eigenlijk op basis van 3 methoden, je hebt dat je het volledig doet op basis van primaire data, dus dan heb je eigenlijk gewoon je brandstofverbruik cijfers. Dan kun je vrij nauwkeurig op basis daarvan de CO2-uitstoot berekenen. Er zit nog wel een conversiefactor tussen die ook nog wel verschillende verschillen heeft. Dan heb je eigenlijk gemodelleerde data en daar gebruik je een stukje primaire data, dus je weet bijvoorbeeld welk voertuig je hebt of je weet hoeveel kilometer gereden zijn dat soort kenmerken, die stop je erin en dan ga je met een paar aannames in je model (emissie per voertuig kilometer of per ton kilometer) je uitstoot berekenen. En daarna heb je nog default factors en dat is eigenlijk wat Stream levert. En dat zijn getallen die weergeven hoeveel per ton kilometer uitgestoten wordt. In deze berekening zit vrij weinig primaire data. Wanneer je het over die ton-km kengetallen hebt, is er wel gewoon consensus over hoe je men dat berekend. Dus, wij zijn niet de enige die die berekeningen maken dit doet bijvoorbeeld EcoTransit ook. Maar achter deze berekeningen zitten wel een hoop aannames waardoor je op verschillen kunt uitkomen.

4. Merk jij dat er weleens misverstanden over bepaalde definities van input data/parameters, zo ja; welke?

Ton-km: Een tonkilometer is gedefinieerd als 1 ton verplaatsen over 1 km, en de emissies van lege kilometers zitten als het ware opgesloten in de emissie kentallen per tonkilometer. Dus als je zegt, ik heb zoveel emissies per tonkilometer ga je ervan uit dat er ook een stukje leeggereden wordt en dat is een vaste aanname die in het cijfer zit. Dit getalletje is gebaseerd op het gemiddelde percentage lege kilometers volgens CBS statistieken. Concreet voorbeeld: *"Ik krijg echt heel vaak de vraag; ik heb leeg transport, maar hoeveel emissie per tonkilometer moet ik dan eigenlijk rekenen. Zoals bijvoorbeeld bij containertransport: dan gaan ze de lege container bijvoorbeeld doorrekenen met met gewicht van de lege container."* Voorbeeld van waar het mis gaat in voertuig definitie: *"Vanuit de topsector logistiek hebben wij hier bijvoorbeeld ook wel eens vragen over gehad. Waarbij ze voor een bestelauto een kengetal hebben gepakt gebaseerd op Stream en die hebben terug gerekend en dan op een niet kloppend getal uitkomen. Bij dit voorbeeld stoppen ze bijvoorbeeld 2 ton goederen In de bestelauto, terwijl een bestelauto eigenlijk nooit meer dan 1 ton aan laadcapaciteit heeft. Dus dan klopt de definitie van het voertuig niet met de manier hoe ze het gebruiken en daar gaan er dan wel dingen vaak fout."*

Echter ontstaat er soms wel discussie over de doorrekening van gewichten in het transport. Wij rekenen altijd met de inhoud van de van de container bijvoorbeeld, en dat daar baseren we de emissies per tonkilometer op. Dus alleen het gewicht wat in de containers zit rekenen we als effectieve lading. Terwijl sommigen dan ook het gewicht van de container meenemen en de container zelf ook als een type goed zien.

a) Vervolg vraag: Zie jij dan bijvoorbeeld een pallet die hoort bij het verpakkingsmateriaal van een zending dat vervoert wordt in een vrachtwagen ook als lading van het gewicht?

Nee, maar daar kun je wel discussies over voeren. Want dat zijn eigenlijk de ladingdragers van hetgeen wat je wil vervoeren. Als je getallen met elkaar wil vergelijken en uiteindelijk weet iemand het voor elkaar te krijgen om met minder ladingdragers te werken. Dan zou je dat eigenlijk moeten terugzien in je emissies per tonkilometer. Op het moment dat je die ladingdragers als gewicht gaat meenemen kan je op een veel lage emissie per tonkilometer uitkomen wanneer je zware ladingsdragers hebt, terwijl je het eigenlijk heel slecht doet. Dus als je de efficiency van je transport zo goed mogelijk tot uiting wil laten komen in je emissie per tonkilometer, dan zou je eigenlijk je ladingdragers niet mee moeten nemen in je emissie kentallen.

b) Vervolg vraag: Stel de klant/verlader wil de emissies van zijn zending weten, moet diegene dan wel bij het gebruiken van de emissiekengetallen per ton-km de verpakkingsmaterialen meerekenen?

Wanneer je de totale CO2 uitstoot moet berekenen dan zitten die verpakkingen er gewoon bij. Alleen als wij de emissiekengetallen per tonkilometer uit Stream gebruiken, dan zeggen we, dan moet je niet het gewicht van je verpakkingsmateriaal meerekenen. Want als je dat doet, dan wordt er een overschatting gemaakt van emissies. Als je onze kentallen gaat gebruiken uit Stream als vereenvoudiging, omdat je alleen maar de tonkilometers weet. Dan zeg ik, je moet de tonkilometers pakken op basis van het gewicht van de goederen. Want zo zijn onze emissie kentallen ook vastgelegd.

5. Wat zijn de belangrijkste aannames die tot verschillen kunnen leiden?

Enerzijds zijn de emissiekengetallen gebaseerd op de emissies per voertuig kilometer maar daar begint al de eerste stap waar onduidelijkheid kan ontstaan. Ik heb bijvoorbeeld wel eens een analyse gedaan op verschillende datasets en je zie je dat er bijvoorbeeld redelijk veel consensus is over wat de emissies per voertuig kilometers zijn van een trekker-oplegger, wat betreft brandstof gebruik. Dat hoor je ook in de markt, dat is ongeveer een op 3 en dat klopt bij iedereen ongeveer wel. Maar als je het bijvoorbeeld hebt over de kleinere vrachtauto's dan merk je dat de definitie van die vrachtauto bijvoorbeeld al moeilijk wordt en dan worden daar emissie per voertuig kilometer bij gehaald. Als je het niet over dezelfde vrachtauto hebt, of dat klopt niet helemaal, dan gaat het wel fout op dat punt. Dus dat is al een best een gevoelig puntje. De definitie van het voertuig en de bijbehorende emissies per voertuig kilometer komen uit modellen (TNO en een universiteit in Griekenland hebben deze data). En wat je dan gaat doen is eigenlijk dat je gaat kijken wat de gemiddelde lading is die ze aan boord hebben om tot de emissies per tonkilometer te komen. De gemiddelde lading heeft ermee te maken met wat het voertuig beladen is en hoeveel procent het voertuig beladen is. Hiervoor moet je ook weten wat de beladingscapaciteit is, en dat zit weer in die definitie van het voertuig. Vervolgens hoeveel lege kilometers worden er gemaakt en die samen maken dus de beladingsgraad van het beladen voertuig maken dan eigenlijk hoeveel lading er gemiddeld genomen in een voertuig zit. Nou dat, dat verschilt natuurlijk ook gewoon heel erg per branche. Als het over zwaarte transport gaat van zand bijvoorbeeld, dan is die beladinggraad best hoog. Maar dan is vaak het aantal lege kilometers ook hoog, want die gaan vaak vol heen en leeg terug. Bij stukgoederen is het vaak dat je veel meer combinatie ritten hebt, dus dan heb je vaak een lagere beladingsgraad. Echter heb je dan wel weer een hoger of een lager aantal lege kilometers. Daarom maken we in stream hier onderscheid in, dit doen we met behulp van data die beschikbaar wordt gemaakt door het CBS.

6. Welke informatie ontbreekt vaak om een accurate carbon footprint te maken? Welke assumpties worden het meeste gemaakt?

Bij kleinere bedrijven merkte ik dat ze vooral hun leveringsdata niet altijd helemaal goed op orde hebben, dus de hoeveelheden goederen die geleverd zijn.

7. De emissiekengetallen van CO2emissifactoren komen van STREAM, voor zover ik heb kunnen zien wordt er onderscheid in weg-type gemaakt, hoe wordt dit onderscheid gemaakt?

Deze getallen zijn niet een factor maar komen daadwerkelijk uit een test, deze testen zijn gebaseerd gedeeltelijk uit testen op de weg en gedeeltelijk in testomgeving. Van andere externe factoren zoals rijgedrag zeggen we niet echt direct wat in Stream. Echter als je kentallen over neemt vanuit stream, denk ik dat je als bedrijf niet echt bezig bent met monitoren dus zou het misschien ook niet een goed idee zijn als mensen zich bijvoorbeeld rijk gaan rekenen met 'zuinig rijdende' chauffeuren. Maar er zijn wel bijvoorbeeld rapporten met programma's die zeggen dat de effecten van zuinig rijden 5 tot 10% kan schelen voor de co2 uitstoot.

8. Hebben jullie marges van deze kengetallen (niet per modaliteit maar 'per sub modaliteit')?

Er zit een bandbreedte op bij wegverkeer en leeg-tot volle voertuigen voor default factors. Echter hebben we daar niet nog een keer een bandbreedte overheen gegooid omdat we per type goederen kijken. En in de emissie per voertuig kilometer zit daarnaast ook een banbreedte maar dan wordt het zo ingewikkeld om tot kentallen te komen die bruikbaar zijn, dat we dat dat we dat niet doen.

9. Zijn er nu methodes die stikstof en fijnstof in kaart kunnen brengen en is het zo dat je daarvoor dezelfde data nodig hebt als met een carbon footprint meting?

Met de emissies per voertuig kilometer of per tonkilometer kun je nu al een inschatting maken van je van je emissies. Echter is het zelfs zo dat een berekening op basis van voertuig-km of tonkilometer nu nauwkeuriger is dan een berekening op basis van het brandstofverbruik. Omdat de emissies van fijnstof en Nox eigenlijk meer gerelateerd aan de plek waar je rijdt, dus het onderscheid tussen stad, buitenweg en snelweg is daarin nog veel belangrijker en dat heeft ook te maken met de temperatuur in de motor, het is daarnaast heel snelheidsafhankelijk en het functioneren van de katalysator van het voertuig speelt ook een rol. Op dit moment kan je daarom beter de berekening doen op basis van voertuig-kilometer.

Verdere notities:

- Het allerbeste wat je kan doen is je brandstof gewoon opvragen of monitoren en daar een emissie factor per liter over heen te doen. Dat is eigenlijk het allerbeste wat je kan reproduceren tenzij je nog bij wijzen van spreken je CO2-emissies aan de aan de aan de uitlaatpijp wil meten, echter zit daar trouwens ook nog een kanttekening bij.

- Het twee naar beste wat je kan doen is op basis van je voertuig kilometers. Aan de emissie per voertuig kilometer zou dan nog mooier zijn als je differentieert naar of die hoe zwaar het voertuig beladen is. Dus daarvoor hebben we ook die bandbreedte in Stream staan. Als je een zwaarbeladen voertuig hebt, dan heb je immers per voertuig kilometer een hogere emissie per voertuig kilometer dan een minder zwaarbeladen voertuig.

- Als laatste kom je op de kengetallen per tonkilometer, want dan heb je nog weer een aanname over de belading van je voertuig. Dan heb je de minste informatie en is het getal het meest onzekere.

- Als je dan kijkt bij fijnstof en NOx emissies dan zou ik zeggen, kijk naar het aantal gram per voertuig kilometer en daarna gram per tonkilometer, want dan maak je weer een aanname over de belading van je voertuig. Bij een normale verbrandingsmotor zonder katalysatoren is het zo dat je bij een hoge verbrandingstemperatuur een hoge NOX uitstoot hebt maar weinig fijnstof uitstoot, want dan wordt je brandstof volledig verbrand. Bij een lage temperatuur gaat het juist andersom, dan heb je meer fijnstof, want dan heb je een wat onvolledige verbranding. Maar krijg je ook geen NOx vorming, want dat is eigenlijk puur de reactie van stikstof met zuurstof In de lucht, die ervoor zorgen dat je bij die hoge temperaturen NOX krijgt.

- GLEC kijkt ook naar Black Metal, voornamelijk bij scheepsvaart komt dit voor. Dat is een zwarte materie en als die op de grond neerslaat, dan absorbeert hij ook zonlicht en creëert daarmee warmte. Als dat in de poolcirkel in de sneeuw neerslaat, dan smelt de ijslaag eerder en dat zijn effecten die nog best groot zijn dus. Bij luchtvaart speelt NOX en waterstof (RF factor) ook nog een grote rol. Bij deze drie stoffen staat het vaak nog onder discussie of je deze nou juist wel of niet in de Carbon Footprint mee moet nemen.

- Dan ook nog een ding over de allocatie van emissies. Als je het hebt over services, dan is het dus heel belangrijk dat je op een bepaalde manier alloceert. Daar bestaan nog best veel mogelijkheden in om het op verschillende manieren te doen. Er zit als onzekerheid in de CO2 emissies van je rondrit, daar zitten al onzekerheden in, als je dat uitrekent op basis van default factoren. Als je het dan ook nog gaat toe delen, dan zijn er ook nog verschillende opties. BigMile doet het op basis van vogel vlucht afstand, andere partijen op basis van shortest feasible distance en dat soort dingen leiden tot wel degelijk grote verschillen. Daarnaast heb je nog vaak discussie of je dit combineert met de lading in tonnen, op basis van volume of op basis van pakketjes.

B.3. Interview Districon

1. Wat is volgens jou de definitie van een carbon footprint?

Een carbon footprint is het opstellen van een uitstoot profiel van bepaalde bedrijfsprocessen. Waarbij Districon zich met name focust op het transport. In letterlijke zin is het het aantal CO2 equivalenten wat uitgestoten wordt. Dan is het afhankelijk hoe breed je de scope trekt. Dus gaat het er alleen om het transport wat een bedrijf alleen verricht of gaat het ook om het transport wat een bedrijf veroorzaakt. En gaat het om de emissies van ook het produceren van het voertuig of alleen om de activiteit.

2. Wat voor soort bedrijven vragen aan Districon om een CF te berekenen en wat is hun grootste drijfveer?

Voornamelijk komen de vragen nu vooral vanuit Connekt. Hiervoor is de grootste reden waarschijnlijk omdat het op dit moment nog niet verplicht is. Wat je nu wel ziet gebeuren is dat veel bedrijven bij Royal Haskoning aankloppen om een scope 1, 2 en soms ook 3 analyse te doen. Hierin wordt transport wel meegenomen maar op een minder detail niveau dan hoe wij het doen. Dat detail niveau wordt waarschijnlijk pas gevraagd als voor de CO2 betaald moet gaan worden. Dan wordt het ook interessant hoe je het gaat doorberekenen naar klanten.

3. Wanneer een CF-meting gedaan moet worden, wat zijn volgens jou de grootste barrières op dit moment?

Op dit moment hangt het vooral af van het type bedrijf waar je contact mee hebt. Wanneer je het in kaart moet brengen voor bedrijven met logistieke dienstverleners is het vaak een stuk ingewikkelder om data op te vragen dan als jet voor een logistiek dienstverlener doet. Het is dus niet perse of er data er wel of niet beschikbaar is, maar of je de data daadwerkelijk kan krijgen. Echter bij kleinere bedrijven, zie je wel vaker dat informatie ontbreekt of niet goed opgeslagen wordt. Dus wat vaak voor komt voor klanten is dat je van de logistieke dienstverlening bijvoorbeeld het aantal ritten krijgt met ladingen en kilometers maar niet de informatie van de andere zendingen. Dit komt bijvoorbeeld doordat de concurrentiegevoelige informatie kan zijn. Wat je wel kan vragen is om de logistieke serviceprovider de CPI (aantal kg CO2e/tonkm) te laten berekenen. Echter verlies je dan een deel van je detail niveau, omdat je dan rekent op basis van de CPI en niet op basis van brandstofverbruik.

4. Welke informatie ontbreekt vaak om een accurate carbon footprint te maken? Welke assumpties worden het meeste gemaakt?

Een grote flaw van BigMile is dat er een standaard conversiefactor is om van pallet naar aantal ton te komen. Echter verschilt het aanzienlijk wat er op de pallet ligt, hoeveel ton de pallet daadwerkelijk weegt. Bijvoorbeeld een pallet met bier en een pallet met kussens wegen totaal iets anders. Het liefst zo je het gewicht per laadeenheid in kunnen voeren. Maar dit kan op dit moment niet.

5. Waar ontstaat de meeste onzekerheid tijdens het berekenen van een carbon footprint volgens jou?

Je hebt eigenlijk verschillende componenten waarin onzekerheid ontstaat bij het berekenen van de carbon footprint van transport. Aan de ene kant is het de vraag wat de uitstoot is geweest aan de hand van het brandstofverbruik. Dan zit de zekerheid hem erin over welke periode je je brandstofverbruik hebt gemeten. Daarnaast is het ook de vraag of een Euro 5 motor bijvoorbeeld meer of minder uitstoot of gelijk is (gelijk is waar we nu vanuit gaan) aan een Euro 6 motor. Dan ligt het er ook aan hoe je je brandstofverbruik bijvoorbeeld aan het meten bent. Ga je heel specifiek kijken wanneer je je tank leeg is en weer vol gooit en dat verdelen over het aantal zendingen. Of kijk je bijvoorbeeld naar je tankpas gegevens. Hierin kunnen overlappingen zijn. Bijvoorbeeld bij het precies bij houden van het bijtanken komt het bijna nooit voor dat je je tank helemaal leegrijdt. Bij gegevens aflezen vanaf een tankpas kan het zo zijn dat als je tank op de 31e dat het aantal liter geregistreerd staat in een maand waarop je het aantal liter “niet oprijdt”. Deze overlap wordt minder als je op een hoger detail niveau gaat kijken. Verder als je kijkt naar het aantal kilometers dat gereden wordt ontstaat er vaak onzekerheid over de afstand. Als je niet het aantal kilometers uit de auto zelf haalt is het eigenlijk een afgeleide vanuit andere gegevens, zoals de geplande afstand. De vraag is eigenlijk ook dat wat uiteindelijk accurater is. Wanneer je op een vrij gedetailleerd niveau kijkt naar informatie die beschikbaar is en op basis hiervan een carbon footprint maakt of op basis van extrapolatie met zuivere jaarlijkse data.

C
EN16258 Standard

This appendix discusses the factors currently required to calculate a carbon footprint in accordance with the EN16258 standard. The source for the methodology of the EN16258 is a guidance published by the European Association for Forwarding, Transport, Logistics and Customs Services (Schmied & Knörr, 2012). Based on this standard, numerous new tools and methods have been developed. The following procedures are followed in order to attribute emissions to a shipment:

1. Determine the total energy consumption for the journey.
2. Using allocation methods, distribute the energy consumption among shipments.
3. Use emission factors to convert energy consumption to CO2 equivalents

In step 1, the energy consumption is calculated. If the trip is a single trip (has to go to 1 delivery point), this means that the energy consumption of the round trip can be multiplied by the emission factor. The calculation for this is written down in step 3. If it is a shared trip, the energy consumption of the whole route is essential. Once this is known, the energy consumption has to be divided over the separate 'legs' (trips to delivery points in a route); how this is done is made clear in step 2. After which, for each leg, the emission can be calculated using the formula in step 3.

C.1. Step 1: Determine the total energy consumption for the journey

The energy consumption and greenhouse gas emissions of transportation services can be determined using either distance-based or consumption-based methods. Using measured energy consumption and energy-specific emission factors, the consumption-based method calculates greenhouse gas emissions. The consumption-based method yields more accurate results than the distance-based method, and is therefore recommended by EN 16258. The standard classifies the consumption-based option into three distinct situations.

Method based on consumption, with specific fuel/energy data
According to existing methods, fuel consumption provides the most accurate estimate of a carbon footprint. This fuel consumption can be calculated in a number of ways. When fuel consumption per shipment is known, the results are the most accurate. This can be monitored by an on-board computer, for example. When this information is known, the fuel consumption can be multiplied by the emission factor.

Method based on consumption, using vehicle/route-specific averages
Typically, it is only possible to obtain average fuel/energy consumption values for the majority of

businesses. Then, these are the average values for a particular vehicle or route (which is driven frequently). Using information on the number of litres refuelled during a given period and shipment details, for instance, the average consumption per tonne-km is calculated. For the further calculation of the energy/fuel consumption for a route, the number of kilometers driven (including empty trip kilometers) and the load characteristics must be known. After calculating the fuel consumption, the emission factor associated with the vehicle's fuel is multiplied by it. Several methods exist for calculating averages.

Method based on consumption, using fleet averages
This method is similar to the vehicle-specific method, except that average fuel consumption per vehicle cannot be determined. The data is now only available at the fleet level, so the average fuel consumption for a fleet is determined. A crucial aspect of this is that it is an average of comparable modes of transportation.

The Distance-based method, default factors
When transport is outsourced, shipment information is often more difficult to obtain. In such situations, the distance-based method is utilized. Then, database values are used to calculate energy consumption. Typically, these values are expressed in terms of litres of fuel or energy in kWh per tonne-kilometer or per vehicle-kilometer by vehicle category. Some databases also distinguish between the "type of roads" on which vehicles traveled (highway vs. urban area), whereas in others this is a weighted average of all roads. There are also correction factors for roads of different types. There are also databases that consider whether a road is flat or hilly. Depending on the level of shipment information available, the distance-based method offers a variety of calculation options.

Quantity and distance are known, but information on loading utilization and empty trips is unavailable.
When the quantity and distance are known, but there are no details on how the load is distributed within the vehicle or how long the vehicle has traveled empty (empty trip data), assumptions must be made to assign the emissions. To further specify this assumption, energy consumption can be calculated by product type. A significant portion of the total number of kilometres driven, for instance, is empty when transporting bulky goods. In addition, when transporting bulk products, weight is frequently the limiting factor, and the maximum load weight is almost always equal to the load. For other types of goods with a high volume, the number of empty kilometers is typically much lower, and the maximum load is determined by the volume. When calculating the energy consumption of a long-distance shipment, using a weighted average of these products can produce a skewed result. Consequently, there are default factors that differentiate the energy consumption per tonne-kilometer by product type. When using these values, it is necessary to know the shipment's weight, the type of product, the distance traveled, the type of vehicle, and the type of fuel utilized. It is important to note that this default factor (consumption per tonnekm) includes a percentage of empty kilometres and percentage for allocation (since the load of any other cargo is unknown). As a result, further allocation of consumption is not necessary. The formula for energy consumption is as follows:

$$\mathrm{EC_i} = \mathrm{W_i} \times \mathrm{ADD_i} \times \mathrm{E_{m,t,r}}$$

where EC_i is the energy consumption for round trip i (in liters, kg or kWh), $\mathrm{W_i}$ is the weight of round trip i (in kg or ton), $\mathrm{ASD_i}$ is the actual driven distance of the round trip i (in km), and $\mathrm{E_{m,t,r}}$ is the default factor for the energy consumption of the specific mode m, that carries product type t (volume, bulk or average good) and drives on a specific road gradient r (hilly, flat) in (l/ ton-km).

Quantity and distance are known information on loading utilization and empty trips is available.
Quantity and distance, loading and empty trips are identified. When the quantity and distance of the

shipment as well as the load utilisation and empty trip data are known, it is possible to make a more accurate estimate of fuel consumption. When the load is included, the default factors could be refined. Several pieces of information are required, including the weight of the load of every stop, the distance between each stop, and the maximum payload at each stop. The default factors are now more closely tied to the payload, making them more accurate. When these default values are used, it is necessary to know the weight of the shipment at each stop, the number of kilometers traveled to each stop, the type of vehicle and the type of fuel used in the vehicle. Using this information, the fuel consumption of a journey can be computed, and the corresponding emission factor can be applied to convert the fuel consumption to CO2e. Using the following formulas, this should be possible:

$$\mathrm{EC_i} = ADD_{\mathrm{i}} \times \mathrm{E_s}/100$$

$$\mathrm{EC_s} = \mathrm{A_m} + \mathrm{B_m} \times \mathrm{W_i}/\mathrm{C_m}$$

where EC_i is the energy consumption for a round trip i (in liters, kg or kWh), $\mathrm{D_i}$ is the actual driven distance of the round trip i (in km), $\mathrm{E_s}$ is the specific calculated energy consumption (in litre/100km), A is a default factor of the consumption of an empty vehicle of specific mode m, B is a default factor of the consumption of a fully loaded vehicle of specific mode m, $\mathrm{W_i}$ is the average load of round trip i and $\mathrm{C_m}$ is the maximum weight of the payload of the vehicle

C.2. Step 2: Allocate the emissions.

When multiple shipments are transported by a single vehicle, it is necessary to assign emissions. In the allocation step, the amount of carbon dioxide associated with a shipment delivered to a specific customer is determined. The standard establishes several essential rules for the allocation of emissions. The distribution of empty trips must be proportional. The same holds true for route order; no marginal allocation is permitted. This will result in earlier shipments having a greater environmental impact than reloaded shipments, for instance. In addition, the allocation method should always be specified, as an alternative method may have a substantial impact on the outcome.

The standard recommends allocating based on the weight of cargo (weight of cargo supports must only be considered if they are a fixed part of the load) and the actual distance driven, resulting in the tonne-km as the allocation parameter. However, the standard also permits the use of other methods of allocation, such as the product of distance, the number of volume, loading metres, the number of pallets, and the number of standard containers, when these are the limiting factors of greatest importance. When distances are unknown, weight or shipment count may also be used as allocation factors. Conversely, only distance can be used when no shipment details are available. With tonne-km allocation, the calculation is as follows:

$$\mathrm{EC_j} = \left(\mathrm{ADD_j} * \mathrm{W_j} / \sum_{j=1}^{k} \mathrm{ADD_{i,j}} * \mathrm{W_{i,j}}\right) \times \mathrm{EC_i}$$

where $\mathrm{EC_j}$ is the allocated energy consumption of leg j from route i, where $\mathrm{GCD_j}$ is the actual driven distance of leg j, $\mathrm{W_j}$ is the weight of the payload of leg j, and $\mathrm{EC_i}$ is the energy consumption of round trip i.

However, the standard distinguishes between multi-destination trips and distribution trips (same start and end point) with regard to the allocation method. The standard recommends, for distribution trips, to first calculate the consumption over the entire trip using the actual distance driven, and then to allocate using direct distances from the start point to the customer location. This ensures that a customer is unaffected by whether shipments are transported clockwise or counterclockwise, or whether an item is loaded at the beginning or end. The standard provides two distance options for this: the great circle distance and the shortest practicable distance. The great circle distance is the shortest distance between two points on the Earth's surface, as measured along the Earth's surface. It is also known as the distance "as the crow flies." On a mode-specific network, the shortest feasible distance is the shortest distance between two locations. The allocation calculation is then performed as follows:

$$\mathrm{EC_j} = \left(\mathrm{GCD_j} * \mathrm{W_j} / \sum_{j=1}^{k} \mathrm{GCD_{i,j}} * \mathrm{W_{i,j}} \right) \times \mathrm{EC_i}$$

where $\mathrm{EC_j}$ is the allocated energy consumption of leg j from route i, where $\mathrm{GCD_j}$ is the great circle distance of leg j, $\mathrm{W_j}$ is the weight of the payload of leg j, and $\mathrm{EC_i}$ is the energy consumption of round trip i.

C.3. Step 3: Convert energy consumption to CO2 equivalents

Different studies have been done to calculate emission factors. In addition, there are several databases from which emission factors can be calculated. Emission factors are factors that can convert consumption per fuel type and type of electricity into CO2 equivalences. The unit of an emission factor is therefore often Kg CO2 equivalence per unit (litre or kWh, for example). This emission factor exists to calculate well-to-wheel, tank-to-wheel and well-to-tank emissions. According to the standard, well-to-tank factors are the way to calculate emissions caused by transport. The emission factors are based on energy consumption per litre (MJ/l). The number of grams of N2O, CO2 and CH4 released per MJ of energy consumption was then determined. Using the Global Warming Potential (GWP), this is then converted to the number of CO2 equivalents per litre. The calculation from energy consumption to the carbon footprint of a shipment is as follows:

$$\mathrm{CF_{wi}} = \mathrm{EC_i} \times \mathrm{EF_w}$$
$$\mathrm{CF_{wj}} = \mathrm{EC_j} \times \mathrm{EF_w}$$

where GHG_{wi} are the Well-to-Wheel GHG emissions (the carbon footprint) for leg j or round trip i (in $\mathrm{KgCO_{2e}}$), $\mathrm{EC_i}$ is the energy consumption for for leg j or round trip i (in liters, kg or kWh), and EF_w is the GHG emission factor for the well-to-wheels stage ($\mathrm{KgCO_{2e}/unit}$).

Cooling mechanisms

The standard does not elaborate on the use of air conditioning or other cooling mechanisms utilized in freight transport. The standard stipulates that all energy consumption must be measured and reported, so it is only suggested that cooling energy be included in the final energy consumption calculation. In addition, the standard mentions something about the coolants that can be used in vehicles; when released, HCFs can enter the atmosphere. These are discharged in the event of leaks and accidents. One way to account for this is to determine the amount of refills of refrigerant that is required in a period of time. This amount should be allocated as energy consumption and then converted to CO2 equivalents using an emission factor.

D

EN16258 Methodology vs Literature

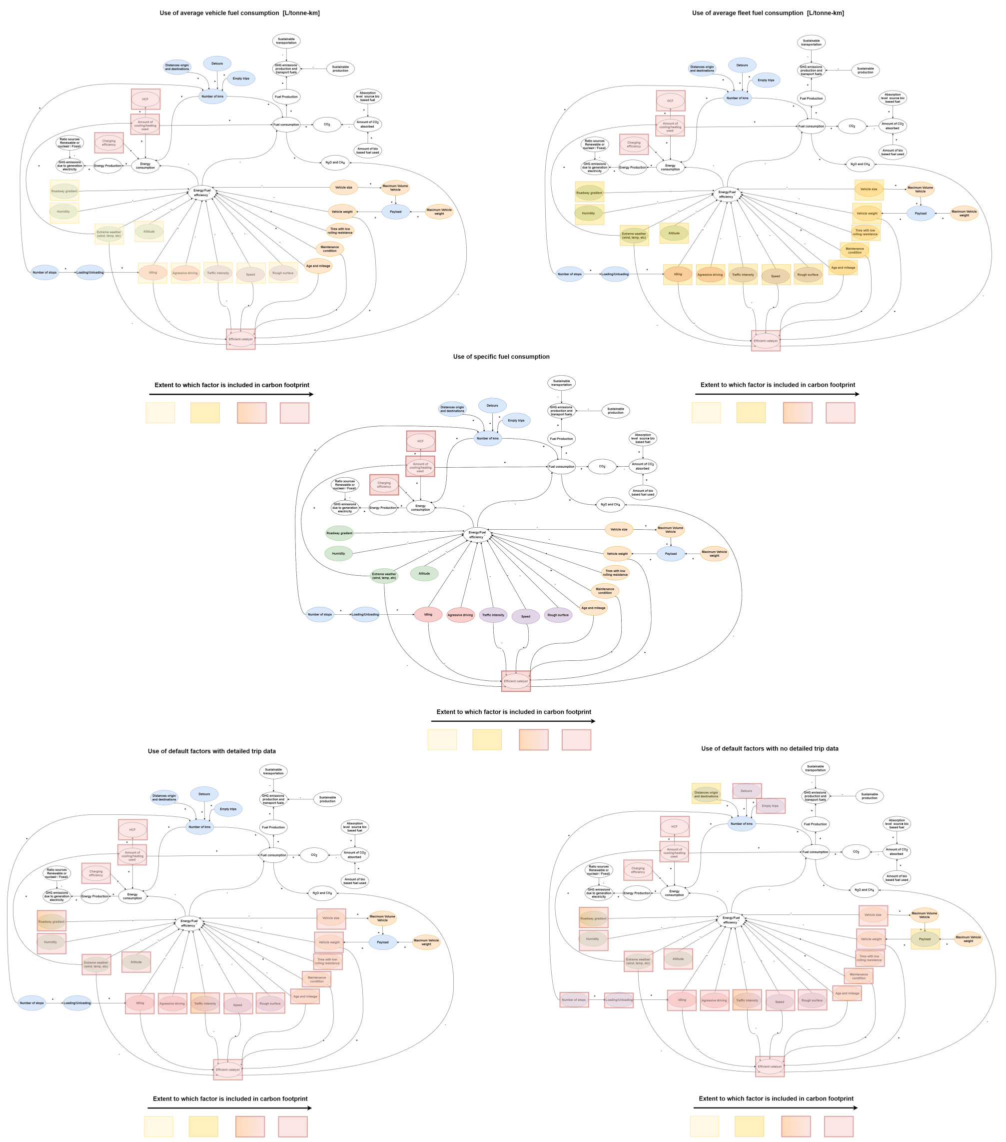


Figure D.1: Influence of assumptions on carbon footprint

Use of specific fuel consumption

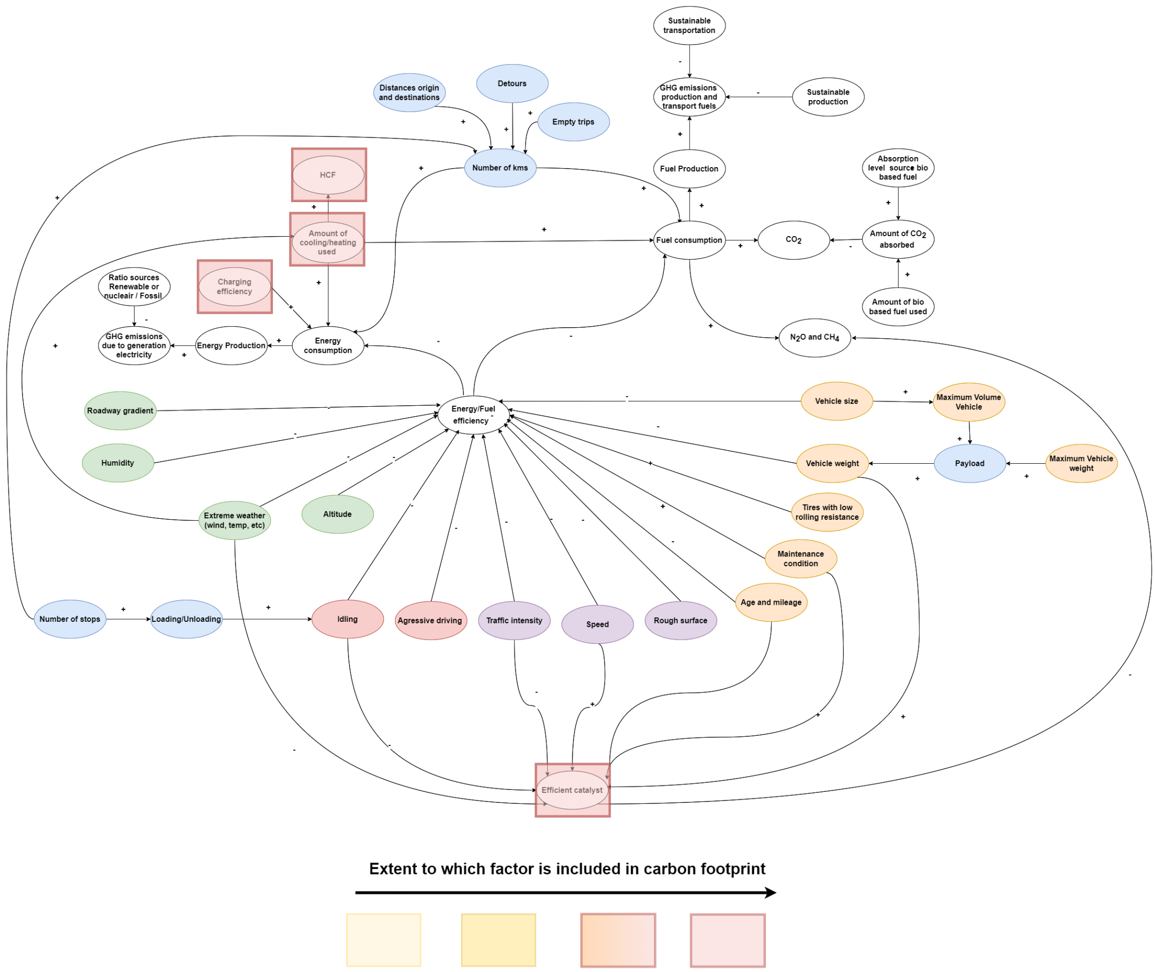


Figure D.2: CF = Specific Energy Consumption Vehicle + Amount of leakage HCF * Emission factor

Use of average vehicle fuel consumption [L/tonne-km]

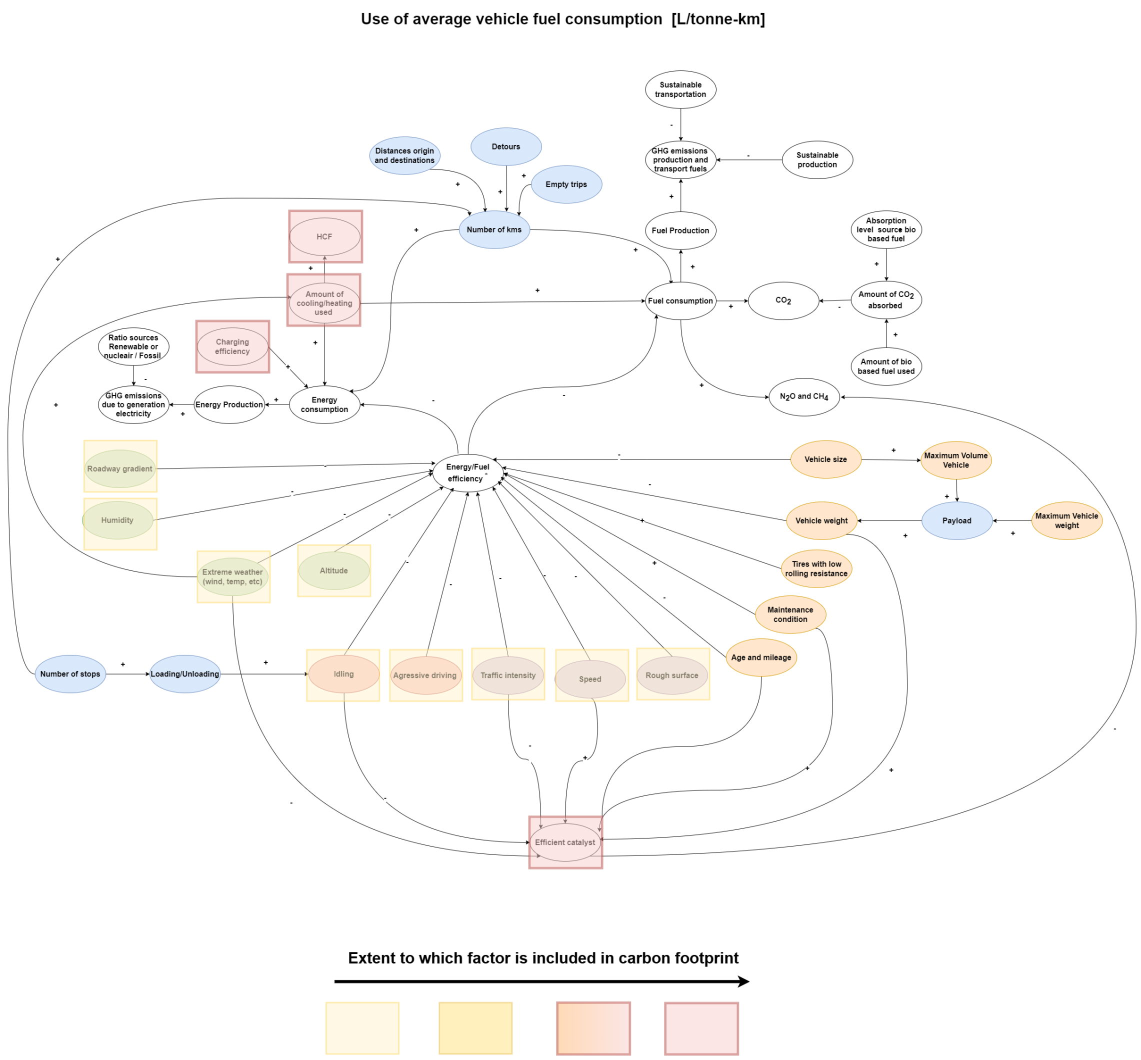


Figure D.3: CF = Average Energy Consumption per tonne-km Vehicle * Distance shipment * Payload shipment * Emission factor + Amount of leakage HCF * Emission factor

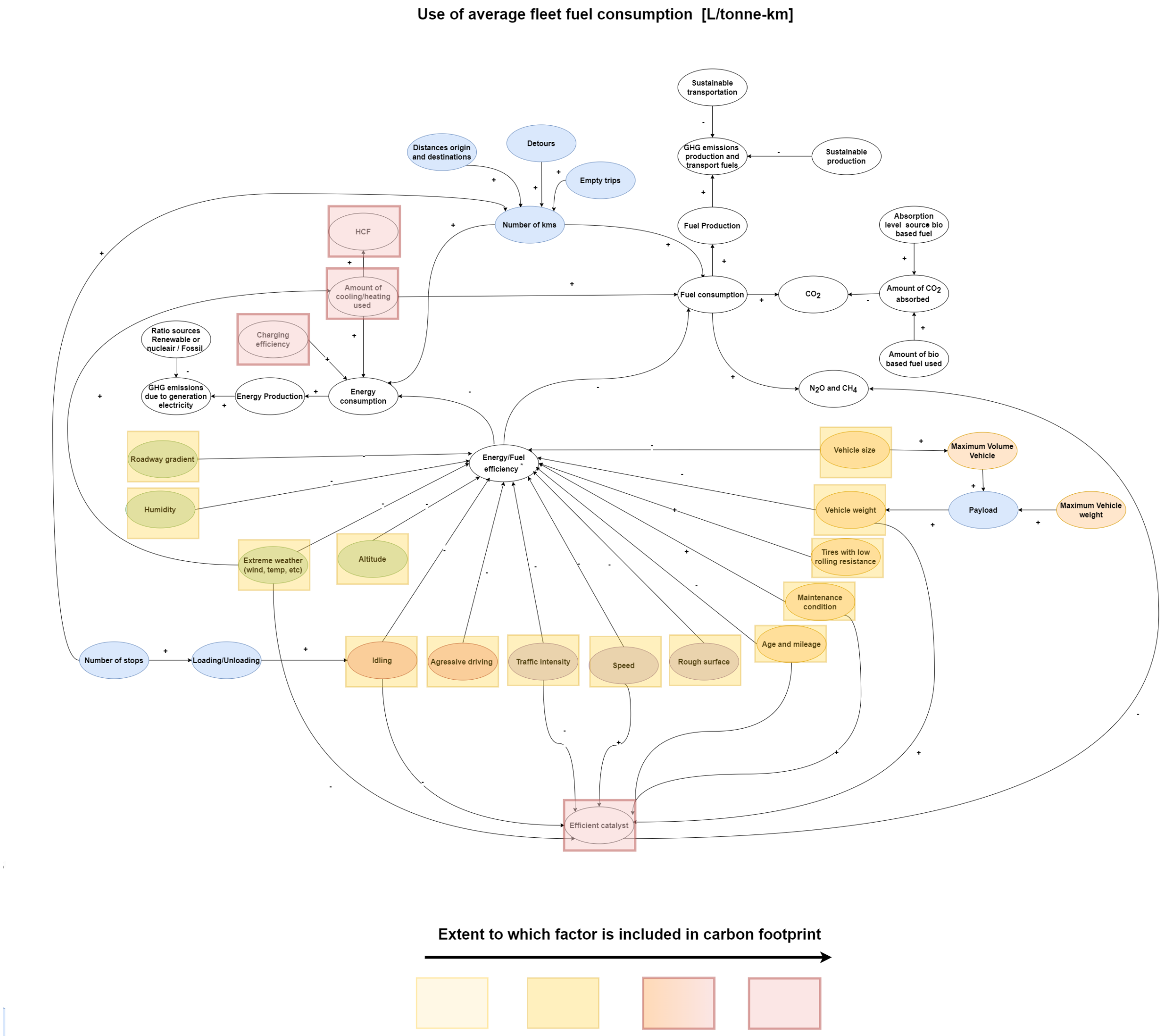


Figure D.4: CF = Average Energy Consumption per tonne-km Fleet * Distance * Payload * Emission factor + Amount of leakage HCF * Emission factor

Use of default factors with detailed trip data

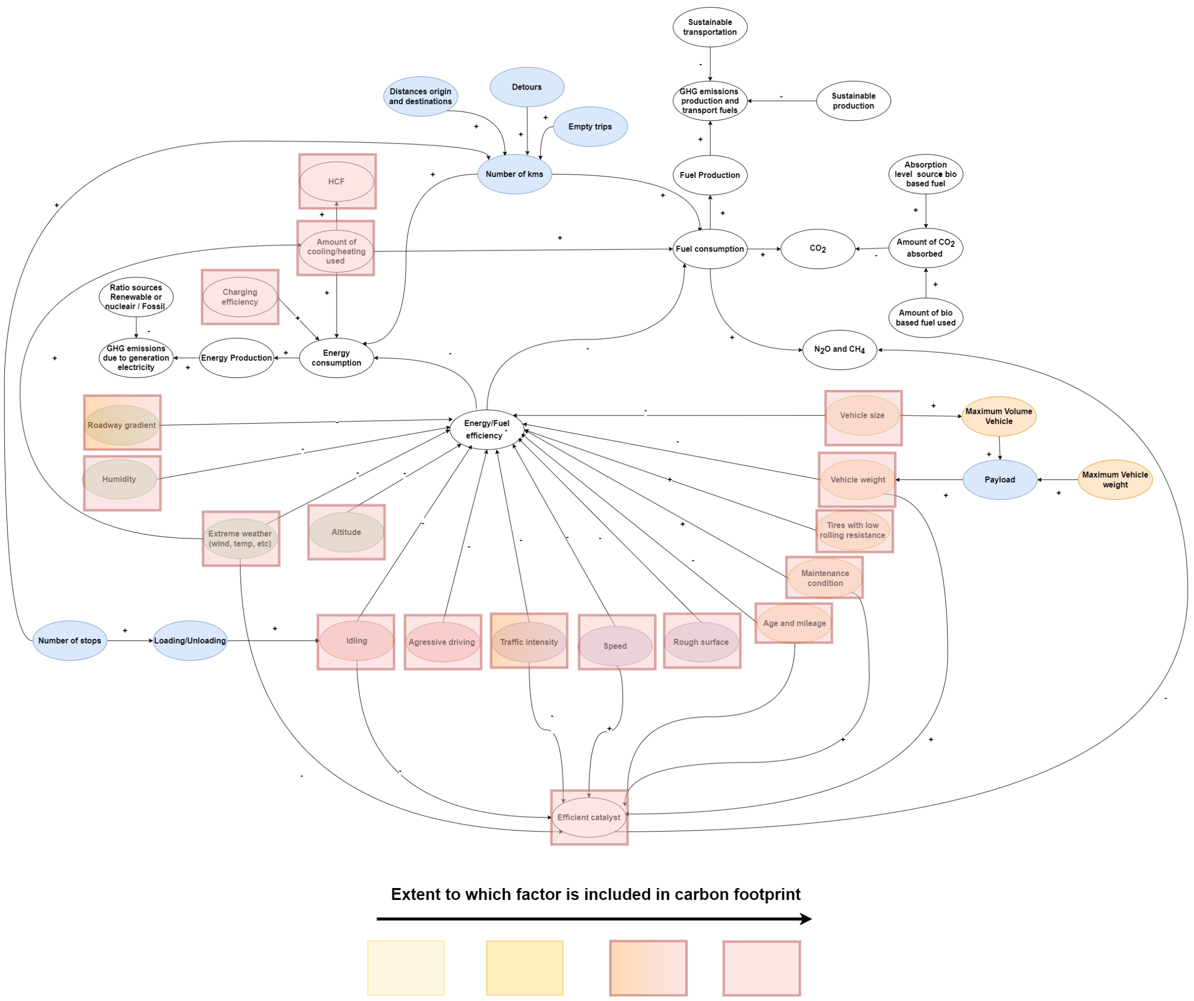


Figure D.5: CF = Default energy consumption (with details about load utilization and empty trips) * Distance * Weight shipment

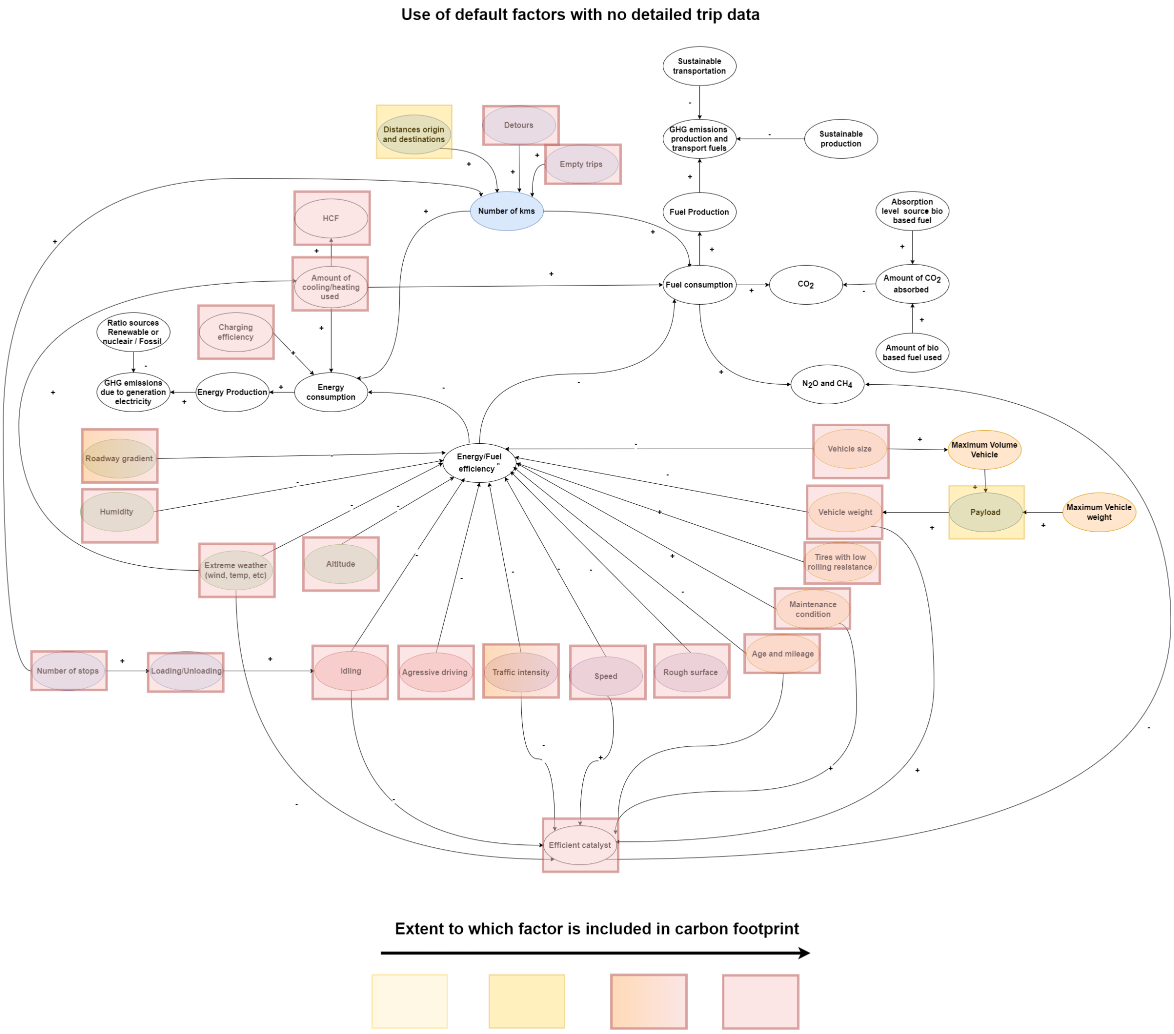


Figure D.6: CF = Default energy consumption (without details about load utilization and empty trips) * Distance * Weight shipment

E

Field research

E.1. Effect of building site logistics on environment

Urban construction relies heavily on logistics because buildings are always built on site. This requires a large number of resources that need to be transported to and from the site at the right time. The supply of materials to a construction site is therefore one of the most important elements in construction operations (Ying et al., 2021). Construction is responsible for 20–35% of overall urban freight traffic in Europe. These transport movements entail a large share of negative environmental externalities. These externalities include air pollution, climate change, congestion, accidents, infrastructure, noise, habitat loss, and well-to-tank expenses. These nuisances spread beyond the building site, as transports to and from the site affect the surrounding environment (Brusselaers et al., 2022). To estimate accurate external costs, accurate data is essential to consider key variables that are generally scarce and spread across the construction chain (Brusselaers et al., 2020). The effect of material transportation on the negative externalities of a construction project is highly dependent on the scope of the construction project.

For instance, there are studies that examine the GHG emissions of a construction project from the Embodied GHG emissions of building materials to the complete construction (cradle-to-site) or even to its utilization and disposal (cradle-to-grave) (Pan et al., 2018). Whereby the Embodied GHG emissions are defined as the GHG emissions related to the energy usage during the manufacturing of building materials (Yan et al., 2010). Besides cradle-to-site and cradle-to-grave, there are other studies that focus solely on the construction phase (transportation, construction and disposal stage). According to the majority of cradle-to-gate and cradle-to-grave studies, the embodied GHG emissions have the largest impact (Wiik et al., 2018), (Yan et al., 2010), (Salah & Romanova, 2021) in the construction of buildings. Although transportation is also discussed, the fraction of transportation-related GHG emissions is almost negligible in comparison to embedded GHG emissions. However, when examining GHG emissions from the supplier to the construction of houses, it indicates that the emissions of transportation of goods are a significant contributor (Wang & Tan, 2012), (Lee et al., 2018), (Jafary Nasab et al., 2020). This shows that transport is a major GHG polluter in the construction phase (from goods supplier to completion of building project). When looking from production of materials to completion of the project, transportation of materials to and from the construction site has a smaller share. A couple of details were interesting to see from these papers. The first thing to notice is that the papers looked from a high-over perspective, used an life cycle analysis and therein many different approaches; for example, transportation of raw materials to the factory is not counted (Yan et al., 2010), or only diesel and one type of truck (undefined) are counted when looking at the emissions (Salah & Romanova, 2021) (Yan et al., 2010), another paper looks at number of vehicles used and not the loading (Lee et al., 2018), thereby all of the papers reviewed above only look at the transportation of material and not the transportation of equipment and in addition, one report includes emissions from employers in the construction phase and another paper does not (Wiik et al., 2018). Another important fact is that the papers discussed the GHG emissions but eventually looked at the CO_2 footprint.

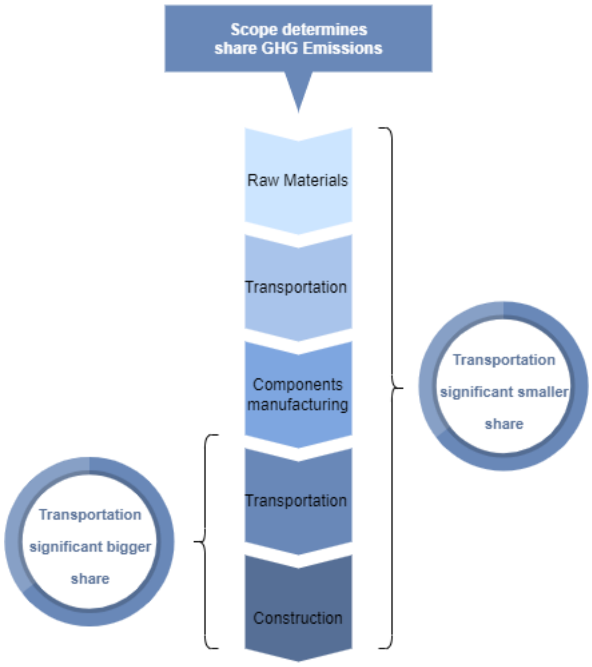


Figure E.1: Relative share GHG emissions from transport depends on scope

E.2. Context project carbon footprint measurement

Districon has to map the transport movements of the largest co-makers for a construction project. In total, there are seventeen co-makers. Therefore, these seventeen co-makers need to give information about the products transported to and from the construction site. This assignment has to deal with many different actors and much information but also missing information. The added value of watching this process is that it allows empirical findings on the barriers and difficulties in mapping the carbon footprint and how this also translates into uncertainties. This section first explains at which stages of a construction project the carbon footprint calculation of freight can be relevant. Next, the scope of Districon's project will be discussed, including the various actors involved. Next, findings from interviews with the co-makers, findings obtained at the construction site, and findings that can be drawn from the data sent by the co-makers will be discussed.

E.3. Carbon footprint in a construction project

Material, equipment, and labor are the three main incoming flows at a construction site. Waste and excavated materials are the two major outgoing flows. The moving objects in these flows make up a site's transportation pattern. The case study deals with emissions from freight transport to and from a construction site. To understand the context of a carbon footprint calculation in this domain, it is important to understand the different phases of a construction project. Further, a carbon footprint calculation can play a role in these different phases of the construction project. This calculation will become clearer and more accurate with each project phase as more information becomes available. This section will therefore discuss for each phase what happens in the phase, how carbon footprinting plays a role, how it can be determined specifically for transportation and what assumptions need to be made to make a calculation. The phases that will be discussed are as follows: the design phase, the pre-construction phase, the procurement phase, the construction phase and the post-construction phase. These phases and the description are based on the Design and Construction Process of (Jackson, 2020).

The design phase

The project team, which consists of architects, engineers, and other experts, creates the project's plans and specifications during the design stage. The design phase also takes into account function and layout in addition to aesthetics. Documents outlining what will be constructed and, in some cases, how it will be constructed are the result of this stage. These are the papers that the contractor is asked to submit in order to receive bids and prices. The pricing is impacted by the caliber of these documents. A significant design element won't be priced by the contractor if it isn't shown in the drawings. Obtaining all required licenses or approvals for the project may also fall under this phase. The competitive bidding phase that follows the design phase allows the builder (contractor) to choose the builder and award the contract based on selection criteria.

A carbon footprint estimate may be requested during the design process to help determine possibilities to minimize the carbon footprint of the project. To analyze the environmental effect of various design alternatives, such as the use of various materials or building processes, the project team may, for instance, perform a carbon footprint calculation to choose the option that is the most sustainable. This carbon footprint contains many assumptions and estimates. When looking specifically at transportation, an estimate must be made of the number of transport movements going to the construction site. The specifications of the transport movements such as the type of fuel used and the ton-miles traveled are difficult to determine at this time. Based on previous projects that have been done, this can be estimated. Estimates can be made for different types of designs.

The pre-construction phase
The project team can move on to the pre-construction phase, which deals with setting up the construction process, after the design phase is finished. This can involve tasks like selecting contractors, planning the timeline for the project, and securing any required permits or approvals. Selecting a contractor to manage the entire project and coordinate the work of any subcontractors is the first step in the hiring process. In the pre-construction phase, the project team will assess the bids and choose a contractor based on a variety of criteria, including the strength of their proposal, their experience and reputation, and the cost of their services. After the contractor is selected, the project team will be extended. The project team will then create a detailed schedule outlining all of the tasks and deadlines that must be met in order to finish the project on time. This is known as a construction schedule. Thereby the project team may require a number of permits or approvals from local, state, or federal agencies to move forward with construction work, depending on the location and nature of the project.

A carbon footprint estimate may be requested as part of the planning process to identify the environmental effect of the project. The project's materials and building techniques may be chosen using this information, which may also be used to find ways to reduce the project's carbon impact. The constructor has been chosen at this point in the project, and a rough building timeline was drawn out. More information about the construction process is now available. The quantity of transportation movements to and from the building site can be estimated based on the tasks that need to be completed. The specifications of the transport movements such as the type of fuel used and the ton-miles traveled are still difficult to determine at this time. However, the constructor has already indicated in the bid for the tender how it wants to select certain subcontractors. He already has more knowledge about where certain subcontractors and materials will come from. Based on the contractor's knowledge, a more accurate estimate can be made about the carbon footprint of transportation.

The procurement phase
The project enters the procurement phase after the end of the pre-construction stage. The project team acquires all necessary materials, equipment, and labor during the procurement phase. This may involve soliciting bids and evaluating proposals from vendors and suppliers, as well as hiring subcontractors to complete particular tasks or phases of the project. Typically, the general contractor hires subcontractors to carry out particular duties or stages of the project, such as electrical, plumbing, or concrete work. To select subcontractors, the contractor will typically issue a request for proposals (RFP) or request for bids (RFB) describing the scope of the work to be performed and the deadline for completion. Subcontractors who are interested in the work will then review the RFP or RFB and submit a bid that includes a comprehensive proposal outlining how they will carry out the work and a cost estimate for the work. After evaluating the bids, the contractor will decide which subcontractor is the most qualified for the job.

A carbon footprint estimate may be requested during the procurement phase as part of the materials and equipment evaluation process. The project's total emissions may be decreased by using this information to choose suppliers and goods with a smaller carbon footprint.

The construction phase
The next phase of the project is construction, during which the project is actually built in accordance with the blueprints and guidelines created during the design phase. Excavation and foundation work, structural work, mechanical engineering and plumbing (MEP) work, finishing, and commissioning are some of the sub-phases that fall under this phase. Before this work can begin, mobilization must occur and staging and layout plans must be developed. Mobilization refers to all of the tasks that must be completed before construction can begin. To ensure the highest productivity and movement efficiency, the site layout plan and staging strategy are required. The paper of (Sezer & Fredriksson, 2021) discusses the transportation and material flows that occur during the construction phase. Excavated materials are the primary source of transportation throughout the first stages of a house-building project, these materials are bulk commodities. Pallets and packages are more often delivered in smaller quantities later in the project, the transit pattern for these goods is influenced by the project's buying strategy.

A carbon footprint estimate may be requested throughout the construction period in order to monitor the project's progress and identify potential for further emission reductions. With the use of this data, it may be possible to pinpoint places where emissions might be decreased, such as by the use of more energy-efficient machinery or the adoption of better waste disposal techniques.

The post-construction phase The project then enters the closing phase, when all outstanding works are finished and ownership of the building is transferred. The project can go into a maintenance phase after the construction stage, during which time the building will be maintained and any required repairs or upgrades will be done.

A carbon footprint estimate may be required during the project's closeout phase in order to evaluate its overall environmental effect. This data may be used to pinpoint locations where emissions may have been decreased, as well as to guide future initiatives and advance sustainability in the building sector.

E.4. Case study

E.4.1. Scope

When looking at the construction project and its emissions, the freight movement to and from the construction site is just a part of the emissions. To clarify the scope, the Delft System Approach (Veeke et al., 2008) is used to explain the boundary of the case study. First, it is necessary to indicate the system boundaries of the project. The system boundaries are gate-to-site (transporting materials from and to the construction site). The sub-system under consideration is transporting materials for the seventeen largest co-makers to the construction site. The largest co-makers were determined based on the financial impact of the construction project. Within this, emissions relevant to the carbon footprint will be considered, and other emissions will be excluded. The emissions of the carbon footprint of the freight transportation of seventeen co-makers can then be defined as the sub-aspects system.

E.4.2. Actors within the system

Within the previous defined sub-aspect system different actors are responsible for the transportation from and towards the building site. First the principal can have its own transportation service that can move materials/equipment from storage or another construction site towards the building site. The other options are to instruct co-makers, suppliers or carriers to transport materials/equipment. The co-maker may transport the materials directly to the construction site using its own vehicles or arrange for a supplier or transportation service to do so (carrier). When the supplier receives the order, it either arranges its own transportation or through a carrier. Figure E.2 shows how all these actors, the connection between those actors is defined as well as the information flows between them. This information is obtained through conversations with Districon about the building site.

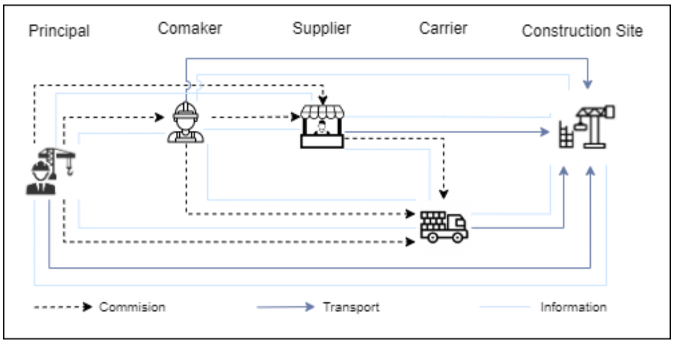


Figure E.2: Actors within sub-aspect system

E.4.3. Project process

Within the previous defined sub-aspect system different actors are responsible for the transportation from and towards the building site. First the principal can have its own transportation service that can move materials/equipment from storage or another construction site towards the building site. The other options are to instruct co-makers, suppliers or carriers to transport materials/equipment. The co-maker may transport the materials directly to the construction site using its own vehicles or arrange for a supplier or transportation service to do so (carrier). When the supplier receives the order, it either arranges its own transportation or through a carrier. Figure E.2 shows how all these actors, the connection between those actors is defined as well as the information flows between them. This information is obtained through conversations with Districon about the building site.

E.4.4. Findings from interviews with co-makers

Several interesting insights were gained from interviews with co-makers. One co-maker, L, with 60% own transport, mentioned that they could not know the actual distances traveled, only the planned distances. Moreover, it was revealed that fuel consumption was determined over a period for the entire fleet, instead of per vehicle, which was deemed too time-consuming. It was emphasized that it is more useful to make agreements about carbon footprint determination beforehand. Co-maker L also pointed out that the transport and construction industries can have conservative tendencies, and that transport can be easily organized when the construction sector allows for it. For instance, he gave the example that every construction site wants to receive materials delivered at 8:00 AM, causing inefficiencies. Additionally, co-maker L mentioned that scope determination at the start of the project was unclear, which is crucial to avoid comparing apples to oranges. The other 40% of transport, done by external transporters, cannot be monitored, and their routes must be calculated manually. Co-maker D confirmed this, stating that the actual distances traveled were difficult to obtain and had to be calculated manually. Data collection was reportedly straightforward, although it emerged that the information sent by the transporters was for shared loads, not individual loads. Co-maker B indicated specific problems with defining shared and direct routes and difficulty in completing the data template. Co-maker B stated that the distance of the routes was the actual distance, but upon further inquiry, this was found to be incorrect. Co-maker B also noted that they do not have a clear understanding of how their transporter calculates fuel consumption. Furthermore, Co-maker B said that they plan for full loads with the transporter, but sometimes smaller loads occur, and the transporter serves other clients, although they have little insight into this. Co-maker B also mentioned that trucks sometimes return empty.

E.4.5. Findings from data

the goal of looking at the data provided by the co-makers was to investigate the uncertainties that arise when asking data from shippers/co-makers to eventually calculate the carbon footprint of freight. The research looked at 11 different co-makers and analyzed their data situation, assumptions made, and external transportation factors. First a quick summary is given, then the situation per Co-maker is discussed.

Overall data Situations: The data situation of each co-maker was unique, with varying levels of information available. Some co-makers had detailed information about their trips, including fuel consumption and distance driven, while others had limited information about their trips. For example, Co-maker A had information on the average fuel consumption and payload of their trips, but the distance was planned instead of the actual driven distance. Co-maker H had all the necessary information, including fuel type, fuel consumption, postal codes of other clients, load of other clients, and driven distances.

Assumptions that have to be made: In some cases, assumptions were made to fill in the gaps of missing information. For example, Co-maker B had limited information about their trips, so they made assumptions about the number of trips, fuel consumption, and distance based on previous trips. Similarly, Co-maker F had limited information about their trips and made assumptions about the payload and fuel consumption based on their experience. The scope of the carbon footprint was assumed to be a round trip between the pickup location and building site for Co-makers A, I, and K.

External Transportation: The external transportation factors also varied between the co-makers. Some co-makers used their own transportation, while others used external carriers. Co-makers B, C, E, F, G, J, and K used external carriers, while Co-makers A, D, H, and I used their own transportation.

Main conclusions The field research showed that there is a significant variation in the data situation, assumptions made, and external transportation factors between the different co-makers. This variation can lead to uncertainty in calculating the carbon footprint of freight. To ensure accuracy, it is important to have as much detailed information as possible about the trips, including fuel consumption, payload, distance driven, and external transportation factors. Additionally, it is important to avoid making assumptions, as they can introduce further uncertainty into the calculations. Finally,the fuel consumption and distance were calculated differently depending on the mode of transportation. The mode of transportation and its associated fuel consumption and distance calculations should be carefully considered when calculating the carbon footprint of freight.

Co-maker A: The data situation of Co-maker A seems to be relatively comprehensive. All the trips are dedicated, and the average fuel consumption in [km/l] is known per licence plate. The payload is also known in tonnes. However, the trip data is partly known because the postal codes are from distribution centres and the construction site. This means that the location of the carrier is excluded from the carbon footprint scope. Also the distance is the planned distance and not the actual driven distance.

Co-maker B: Co-maker B also has also a relatively comprehensive data situation, where all the trips are dedicated, and the fuel consumption of the trip is known per licence plate. The payload is known in tonnes, and the trip data is partly known because some trips need to be extrapolated. However, the distance is the planned distance and not the actual driven distance. The assumption is that trips are extrapolated based on demand/truck capacity, average fuel consumption of the other trucks and planned distance.

Co-maker C: Co-maker C's data situation seems less comprehensive than the previous two co-makers. The trips are shared, and the fuel consumption of the trip is an estimated number from the company itself. The payload is only known in tonnes for the shipment of the construction site, and the payload of other shipments is unknown. The trip data is partly known because only half the information is known, and the distance is calculated with Google Maps. The assumption made here is that the second trip is unknown, and therefore the same details as the first trip are used. The load for the clients is calculated based on capacity trucks- shipment construction site / clients-1, and postal codes are unknown, so a random postal code of the reported city is used.

Co-maker D: Co-maker D's data situation seems to have some missing information. Part of the trips are shared, but information about the other clients is not available. The average fuel consumption in [km/l] is known per licence plate, and the payload is known in tonnes for the shipment of the construction site, but the payload of other shipments is unknown. The distances are estimated with Google Maps, and two of the thirteen trips are returns with no details about the return location. The assumption made is that all the trips are dedicated, and distances are calculated with Google Maps.

Co-maker E: Co-maker E's data situation seems to be relatively comprehensive. The trips are shared, however the fuel consumption of the trip is an estimated number based on industry average. The payload is known in tonnes for all the shipments, and the trip data is partly known because some of the locations of the other clients are known as postal codes on PC4 level. The distance is calculated with Google Maps. The assumption made is that fuel consumption is an industry average number, and distances are calculated with Google Maps.

Co-maker F: The data situation for Co-maker F is unclear due to a switch in data systems, which has resulted in a lot of missing information. As a result, they were unable to contact their carrier for more information. They estimated the payload based on personal experience and the fuel type based on two example license plates. The fuel consumption was unknown and therefore assumed to be a default factor. They also lacked information about the distance and were unsure about the origin of the truck. The trips are considered as full truck load round trips. The distance of these round trips was based on Google maps, and the origin and destination of the material were known. In summary, Co-maker F's data situation appears to be incomplete, with a lack of clarity around many key variables.

Co-maker G: Co-maker G's data situation appears to be better than some of the other co-makers. A big difference is that this co-maker knows the actual driven distance to the building site. Furthermore, all trips trips are dedicated. However, they extrapolated the fuel consumption and distance based on one known trip and assumed that these values will remain constant for future trips. They know the payload in tonnes and the fuel type, and two future trips have been extrapolated.

Co-maker H: Co-maker H appears to have the most complete data situation, with all key variables known. They have information on the fuel type, fuel consumption, postal codes of other clients, load of other clients, and driven distances. They have made no assumptions, and all the trips are their own transportation. Thus, they have more accurate and complete data than most of the other co-makers.

Co-maker I: Co-maker I's data situation for material is similar to Co-maker A, with shared trips and unknown carrier origin/destination. They have estimated fuel consumption and assumed planned distance. They know the fuel type and postal codes/loading of shipments, but not where the carrier comes from to pick up the load or where the carrier goes after picking up the co-maker's shipments. Assumptions have to be made about the carbon footprint scope and distance. Overall, their data situation is incomplete, with missing carrier information and lack of clarity around some key variables.

Co-maker J: Co-maker J's data situation is mixed, with some trips considered as own transportation and others using a carrier. They know the load, origin, and destination for all trips but lack information on the fuel consumption and carrier details for the shared trips. Co-maker J has made is own assumptions on the fuel consumption based on experience. The assumptions that have been made are the distances that are derived with google maps, that 8 out of 12 trips are assumed to be dedicated while they are shared and that the fuel consumption is an estimation instead of based on real values and data.

Co-maker K: Co-maker K has a limited data situation, with only one dedicated round trip and the second trip extrapolated using the details from the first. They have estimated fuel consumption using a default factor and assumed planned distance.

In summary, the co-makers have varying data situations, with some having incomplete or unclear information about key variables like fuel consumption, distance, and shared/dedicated status. Co-maker H has the most complete data situation, while Co-maker F has the most incomplete data situation.

E.4.6. Interview project consultant Districon

1. Hoe verliep de data verzameling van het project?

Aan het begin begon het goed, ik zal eerst wat over het project vertellen. We kregen van de opdrachtgever kregen we een bepaalde scope dat hadden we ook in de offerte besproken en dat was een scope van data ophalen wij tien bedrijven, wat uitgebreid is naar zeventien. Het onderwerp waar ik mij specifiek veel mee bezig heb gehouden is het data ophalen bij co-makers en toen ik die lijst van zeventien kreeg, toen ben ik eigenlijk zo snel mogelijk gaan bellen met alle co-makers en dat verliep in het begin heel erg goed. Begin november, heb ik heel veel co-makers kunnen spreken en wilden ze allemaal graag mee werken. Er waren enkele co-makers die niet zo graag wilden meewerken omdat ze te veel moeite vonden. Maar na een tweede gesprek bijvoorbeeld ging dat op zich ook wel prima. Alleen wat je merkte is dat na dat eerste introductiegesprek en hun enthousiaste reacties dat dat de data ophaal proces eigenlijk heel slecht verliep. Het ging heel langzaam, omdat ze heel erg afhankelijk waren van andere afdelingen binnen het bedrijf om de data op te halen, of ze hadden transporteur. Vaak waren er meerdere lagen in de organisatie, waar ze op moesten bouwen en ook op moesten wachten voor de data. Ik denk dat dat daardoor het heel erg lang duurde voordat ik de eerste data binnenkreeg en van sommige co-makers verliep dat wel goed als in ik kreeg goede data door, maar dat is eigenlijk in totaal gezien een minderheid van de groepen en met wie ik heb samengewerkt.

2. Merkte je een groot verschil in de data inzameling als bedrijven zelf hun transport regelden?

De kleinere bedrijven, die ook weinig ritten hebben gedaan, die vonden het ook minder erg om mee te werken en die hebben snel ook de data aan kunnen leveren. Wat je wel merkt is dat die 'minder professioneel' waren, in de data die ze aanleverden dus dan vroeg je bijvoorbeeld dat ze het in Excel moesten aanleveren en dan leverden zij het in een pdf-document in of dat je nog drie keer een terugkoppeling moest geven om ervoor te zorgen dat ze snapten wat data betekende. Bijvoorbeeld de laad plaats, dat je dan niet het adres kreeg, maar gewoon echt de postcode, dat soort dingen, terwijl daar wel gewoon boven stond, postcode van de laadplaats. Waar liep jijzelf het meeste tegenaan in dit proces? Één van de dingen waar wij heel erg tegenaan liepen, is de tijd waarin de data werd aangevraagd. Dus wij hebben dit best wel na afloop van van het project gedaan. Dus de helft van de co-makers die had al veel leveringen gedaan, of die zouden in de aankomende periode de laatste leveringen doen. En er waren er ook een paar bij die al heel lang klaar waren, dus die zagen het niet echt zitten om mee te werken. Daarbij waren er ook een partijen die nog tot het einde van de bouw moesten gaan leveren, dus die snapte ook niet welke data ze moesten aanleveren enzovoort. Ik denk dat als we waren begonnen voordat het bouwproject was begonnen, dat het dan veel makkelijker was gegaan.

3. Wat ik me dan afvraag is hoe kan je dat dan in kaart brengen? Als je misschien niet weet waar de transporteur allemaal langs is gegaan, want voorafgaans zijn die ritten misschien niet duidelijk?

Dit is ook een belangrijk punt. In dat introductiegesprek met de co-makers moet je er echt voor zorgt dat je een netwerk begrijpt. Dus oké, waar komen jullie producten vandaan? Moet er nog ergens gelaad worden. Bijvoorbeeld, staat die vrachtwagen bij een transporteur of bij jullie eigen magazijn. En welke tussenstops maakt het maakt de reis allemaal, etc. Bij veel van de co-makers zag je eigenlijk dat dat wel goed ging, dus dat zij heel erg door hadden hoe hun netwerk in elkaar zat. Maar dat was vooral van de co-makers die ook verantwoordelijk waren voor het hele productieproces van hun producten, die konden dit heel makkelijk inzichtelijk maken. De keten van materialen was daarnaast makkelijker dan dat van materieel. Maar ja, er zijn bijvoorbeeld ook co-makers die alleen inkopen. Deze zijn een soort tussen organisatie, dus die kopen producten in en dan leveren zij het weer aan een bouwplaats onder hun eigen naam en zij staan dan in contract bij de bouwplaats en de bouwplaats bestelt dan bij hun. Maar zij maken zelf niet de producten, dus dan is het veel lastiger om de herkomst van al die producten, en dus het begin van zo'n keten, in kaart te brengen.

4. Dus dan is de scope van distributiecentrum naar bouwplaats gezet?

Als ik het goed bedenk, dan is er van een paar ritten is wel inzichtelijk gemaakt waar het vandaan komt, maar niet van allemaal. Maar je merkt bij het ophalen van data dat er inderdaad een gaten zitten in de volledige rit die gereden is. Wat je vooral ziet is dat of bedrijven wel van die hele rit weten hoeveel kilometer er is gereden, dus het totaal aantal kilometers voor zo'n rit weten ze wel, maar ze kunnen niet ophalen langs welke stop ze het allemaal zijn gegaan. Dus dan zie je ook weer dat, de data voor de volledige rit er wel is, maar niet voor de exacte ladingen per stop bijvoorbeeld.

5. Zit er ook nog verschil in de soort goederen die worden getransporteert bij het ophalen van rit-gegevens?

Ja, wat veel ziet bij materieel is dat het vaak dedicated transport is. Dat gaat bijvoorbeeld om kranen en echt groot materieel. Dat is een uniek transport, zeg maar. Daarvoor heb je ook speciale vrachtwagens nodig die eigenlijk nergens anders voor worden gebruikt. Dan zijn gegevens ook veel makkelijker om het op te halen, want dat gaat gewoon van a naar B. Het enige wat dan wel lastig is met materieel is dat het vaak van een andere bouwplaats komt, dan naar deze specifieke bouwplaats gaat en dan weer naar een andere bouwplaats gaat. Dat kan je best wel makkelijk in kaart brengen, omdat ze dat best wel snel weten, maar ze weten niet de volledige route van die vrachtwagen. Dus aan de ene kant heb je het materieel, dat weet je wel, maar van de vrachtwagen zelf vandaan komt is moeilijk om op te halen; dat weten ze vaak niet, omdat dat zo'n lange rit is.

5 a. Doorvraag: ik weet nog bij een van de gesprekken met de Co-makers dat inderdaad de kraan vanaf Den Haag kwam en naar de bouwplaats werd gereden daarna naar een nieuwe bouwplaats werd gebracht. Tijdens dit vervoer kwamen er ook weer begeleiders meerijden die weer uit andere plaatsen met vervoer komen. Hierbij is denk ik de manier van scopen (wat je meeneemt en wat niet) belangrijk. Hoe zie jij dit?

Ik snap wat je bedoelt. Wij proberen zoveel mogelijk informatie mee te nemen. Dus wij doen dan wel van de standplaats naar de late plaats en dan van de laatste plaats naar bam en dan naar de volgende bouwplaats indien dat beschikbaar is. Zo kan je uiteindelijk dus wel de totale hoeveelheid kilometers verkrijgen. Indien die niet beschikbaar zijn, is belangrijk om die zo ver mogelijk uit te rekenen, want aan die lege kilometers die gereden worden zit alsnog een uitstoot aan verbonden. Ons uitgangspunt is natuurlijk dat we een volledige rit meenemen, de volledige aantal kilometers en brandstofverbruik per rit. Maar indien dit niet beschikbaar is, dan moet je gewoon concessies gaan maken. Hoewel je dit eigenlijk echt niet wilt doen. Zien we gewoon dat, het heel erg lastig is om die volledige rit te krijgen. Dus wat we dan doen is dat we met hun in gesprek gaan en kijken kijken hoe zij die aannames willen maken. Hoe willen zij dat hun uitstoot wordt berekend? Voor hun is het natuurlijk ook belangrijk dat die uitstoot wel representatief is voor een normale rit. Echter vaak zeggen ze gewoon omdat ze er geen zin meer in hebben dat er gewoon maar een schatting gedaan moet worden of het meegenomen moet worden als dedicated rit. Dus we hebben nu volgens mij bij drie of vier co-makers dat het eigenlijk gedeelde ritten zijn, maar dat we dat meenemen als dedicated rit.

6. Is dat ook eigenlijk hetgeen wat het minst beschikbaar is in de data? De andere stops bijvoorbeeld.

In principe wel. Maar bijvoorbeeld het brandstofgebruik is ook bijvoorbeeld bijna altijd niet-volledig beschikbaar, precies voor die rit. Maar dan weten ze wel het gemiddelde brandstofgebruik van die auto, voor een normale rit, dus dan wordt dat gebruikt. Echter zitten daar nog best veel lagen in. Want soms zeggen ze; deze informatie is niet beschikbaar, maar we kunnen bijvoorbeeld wel kengetallen of het brandstofverbruik van een andere rit gebruiken. Maar het probleem bij de rit gegevens is, dus welke postcodes en welke laadplaats ze allemaal langs zijn geweest, als ze het niet hebben, dan hebben ze dat niet. Ja, dat is heel finaal zegmaar, je kan daar verder vrij weinig mee; je kan dan wel aannames gaan maken zoals misschien zijn ze hier niet er langs geweest, maar dat willen de co-maker dus ook weer niet. Dus dan zeggen: als je van nou weet je wat, schrap dat maar, en doe de rit maar gewoon van a naar b en terug naar a.

6 a. Doorvraag: Dus eigenlijk is het grootste probleem wat onzekerheid veroorzaakt dat de availabilty van informatie van andere stops er niet is en hierdoor een aanname gemaakt moet worden, en dat

voor brandstofverbruik geldt dat er bijvoorbeeld meerdere 'lagen' van de accuraatheid mogelijk zijn?

Ja, dat klopt. Wanneer er meer tijd voor het zou zijn en de co-maker het zou willen is het nuttig om de data van van alle ritten op te halen en er een gemiddelde rit uit te pakken. Dan kan je veel representatiever zien hoe die hele rit eruit ziet. Wat betreft brandstofverbruik, als zij het niet hebben, dan kan je ook zelf kijken wat voor vrachtwagen het is en hoeveel deze gemiddeld uitstoot. Maar dit zijn natuurlijk dan een soort schattingen.

6 b. Doorvraag: Legden de co-mmakers ook uit hoe ze op het brancdstofverbruik kwamen? Of leverde ze het zonder uitleg aan?

Dat ligt eraan. Bij sommigen konden zij gewoon zien, per vrachtwagen, dus per kenteken, wat het gemiddelde verbruik was. Dat is dan wel per kenteken en niet per se per rit geweest. Bij een wat kleiner bedrijf, hadden ze echt de informatie van die specifieke rit door de nieuwste boordcomputer in hun vrachtwagen. Verder zijn er ook nog co-makers die kengetallen gebruiken of wat zijzelf denken dat het beste is. Daarmee ga ik ook altijd een discussie van: wil je je eigen gemiddelde gebruiken of wil je dat ik online kijk om te kijken wat dit type vrachtwagen gemiddeld uitstoot?

6 c. Doorvraag: Dus wanneer ze data niet kunnen leveren ontstaat er een gesprek hoe een getal dan tot stand komt?

Klopt, ik bel eigenlijk altijd met ze omdat ik ik merk dat als je mailt, dat ze het vaak niet begrijpen. Dat is ook wel echt een leerproces geweest. Aan het begin dacht je dan bijvoorbeeld bij dat introductiegesprek dat je een keten begreep maar dan ging je later weer met ze in gesprek en over de data die ze hadden aangeleverd en dan klopte ereigenlijk er helemaal niks van. Dus het was belangrijk om vaak te checken of denk stappen klopte. Je ziet dan vaak dan uiteindelijk wel goed gaat, maar dat het wel heel veel tijd kost om dat goed in beeld te krijgen.

7. In hoeverre zit er een verschil in data verzameling van de transporteurs en van co-makers zelf?

Het liefst praat ik zelf met de transporteurs maar het komt ook vooor dat co-makers dat liever zelf doen. Over het algemeen weet de transporteur zelf het beste hoe de informatie eruit ziet, meestal is dan hun data aanlevering zorgvuldiger dan als je kijkt bij de co-makers zelf.

8. Had jij het gevoel dat er problemen waren met definities die werden gevraagd, waren er dingen die mensen niet echt goed begrepen?

Ja, bijvoorbeeld, de gereden kilometers was altijd wel een issue. Dan stond er wel bij van de volledige rit, maar zij zagen dat dan heel vaak, ook als het een gedeelde rit was, gewoon van het laatste punt naar bam. Waar je vaak achter kwam door de route na te construeren. Soms hebben ze gewoon sowieso niet het aantal gereden kilometers opgegeven dan gebruik ik google Maps, wanneer meerdere routes zijn gereden kies ik het gemiddelde. En dan deed ik altijd het gemiddelde van alle drie de routes die werden uitgestippeld. Wat verder verrassend is, is dat als jij zei: vult het in, in een excel hoe weinig co-makers dat deden, omdat ze of geen ervaring hadden met Excel bijvoorbeeld. Een ander punt wat misschien misschien ook nog wel belangrijk is, is dat je ziet dat bij de co-makers die al bezig zijn met uitstoot, veel meer motivatie hebben om hieraan mee te werken dan de traditionele co-makers, die zien het meer als een onbenullig werkje.

9. Waar denk jij dat vooral de meeste onzekerheid bij komt kijken als je een carbon footprint moet bewerkstelligen?

Niveau van datakwaliteit vergelijken van alle co-makers ik vind het zelf heel erg lastig. Bijvoorbeeld dat je een co-maker moet gaan vergelijken die perfecte data heeft opgeleverd met een co-maker waarbij je eigenlijk tien aannames maakt over alle data en tot eigenlijk elke rit geëxtrapoleerd is. Ookal gaat dit project niet om de vergelijking van co-makers ega je toch kijken, hoe kan het zijn dat die en die een hoge uitstoot hebben en die en die zo laag? Daarnaast denk ik omdat je niet in een organisatie zit, dat de data aanvraag echt een moment opname is; of ze je wel of niet begrijpen.

10. Wat ik me bijvoorbeeld ook afvraag, wanneer je bijvoorbeeld bigmile gebruikt dan komen daar data levels uit. Dus goud, zilver en brons. Kan het dat door de aannames die je doet voor een co-maker de gegevens op het level goud komen?

De datakwaliteit die uit BigMile komt is ook niet degene die we gebruiken voor de presentaties van de one-pagers. We zien namelijk in dat zeg maar een aantal aannames voor het onderzoek wat wij hebben gedaan gewoon belangrijker zijn dan andere aannames. Daardoor krijg je gewoon sneller, een een minder goeie datakwaliteit . De datakwaliteit zoals die gepresenteerd wordt op BIGMile is vooral, zeg maar bepaald op basis van de volgende vragen: is dit data van de specifieke rit? Of is het een soort sample? Of is het gewoon maar een schatting? Dus op zich is het wel accuraat maar misschien niet helemaal. Je kan ook bronze data hebben, wat gebaseerd is op een sample voor één variabel terwijl een ander variabele voor dit onderzoek belangrijker is. Dus bijvoorbeeld met die gereden kilometers: het kan zijn dat ik dat zelf moet moet uitrekenen en dan mag je dus niet zeggen dat dat de actual driven distance is maar dan moet je dus kiezen of het een sample of schatting is, en dat is eigenlijk wel iets waar je een beetje op moet letten, of dat of dat dan een hele belangrijke aanname is geweest. Terwijl bij een andere moet je een schatting maken van wat een standplaats is. Dat is veel belangrijker voor de volledige rit.Dus dat is ook wel echt een knelpunt voor ons; hoe gaan we brons, zilver, goud toewijzen aan die verschillende one-pagers.

F

Calculation uncertainty margins

Average fuel consumption per road type and margins

Numbers from Stream 2020: CE Delft

	MJ/km					
	City		Off-road		Highway	
Voertuigtype	*min*	*max*	*min*	*max*	*min*	*max*
Light commercial vehicle < 1.5 ton	2,6	2,8	1,9	2,1	2,5	2
Light commercial vehicle 1.5-2 ton	3,4	3,7	2,6	2,8	3,3	3
Light commercial vehicle 2-2.5 ton	4	4,3	3	3,2	3,9	4
Light commercial vehicle > 2.5 ton	4,8	5	3,6	3,7	4,6	4
Truck < 10 ton	5,5	6,2	3,7	4,2	3,4	3,8
Truck 10-20 ton	10,9	13	7,3	8,7	6,1	7,3
Truck 10-20 ton + trailer	13,3	18,4	8,6	11,9	7,2	10
Truck > 20 ton	15,7	19,4	10,5	12,9	8,6	10,7
Truck > 20 ton + trailer	17,9	26,7	10,8	16,1	8,9	13,2
Tractor-trailer light	15,1	19,6	10,4	13,5	8,5	11,1
Tractor-trailer heavy	21,2	31,4	13,3	19,7	8,9	13,2
Long Combination Vehicle (LCV)	28,6	42,3	18	26,6	12,1	17,8

Average MJ/km per road type calculated and ratio vehicle to road type from Stream

	MJ/km			ratio of vehicle to road type		
Vehicleclass	Stad	Buitenweg	Snelweg	Stad	Buitenweg	Snelweg
Light commercial vehicle < 1.5 ton	2,7	2	2,25	16%	32%	52%
Light commercial vehicle 1.5-2 ton	3,55	2,7	3,15	16%	32%	52%
Light commercial vehicle 2-2.5 ton	4,15	3,1	3,95	16%	32%	52%
Light commercial vehicle > 2.5 ton	4,9	3,65	4,3	16%	32%	52%
Truck < 10 ton	5,85	3,95	3,6	29%	33%	38%
Truck 10-20 ton	11,95	8	6,7	19%	23%	58%
Truck 10-20 ton + trailer	15,85	10,25	8,6	19%	23%	58%
Truck > 20 ton	17,55	11,7	9,65	14%	18%	67%
Truck > 20 ton + trailer	22,3	13,45	11,05	14%	18%	67%
Tractor-trailer light	17,35	11,95	9,8	5%	8%	87%
Tractor-trailer heavy	26,3	16,5	11,05	5%	8%	87%
Long Combination Vehicle (LCV)	35,45	22,3	14,95	5%	8%	87%

Figure F.1: Calculation in Excel part 1, input numbers CE Delft (2020)

Ratio road type * Average MJ/km per road type

Vehicleclass	Average in MJ/km	In/decrease average consumption preceding vehicle class
Light commercial vehicle < 1.5 ton	2,2	0%
Light commercial vehicle 1.5-2 ton	3,1	37%
Light commercial vehicle 2-2.5 ton	3,7	21%
Light commercial vehicle > 2.5 ton	4,2	13%
Truck < 10 ton	4,4	4%
Truck 10-20 ton	8,0	83%
Truck 10-20 ton + trailer	10,4	30%
Truck > 20 ton	11,0	6%
Truck > 20 ton + trailer	12,9	17%
Tractor-trailer light	10,3	-20%
Tractor-trailer heavy	12,2	18%
Long Combination Vehicle (LCV)	16,6	35%
Average	8,3	20%

Cluster vehicle class	Average in MJ/km	Min	Max
Light commercial vehicle	3,3	2,242 (-32%)	4,188 (27%)
Truck till 10-20 ton + trailer	7,6	4,368 (-42%)	10,357 (37%)
Truck > 20 ton	12,6	10,3495 (-18%)	16,563 (31%)

Figure F.2: Calculation in Excel part 2, input numbers CE Delft (2020)

Average fuel consumption based on fuel card data

	FC	Amount of L in a tank begin month A	Distance driven in month A	Amount of L used in month A	Amount of L in tank end of month A	Distance driven in month B	Amount of L used in month B	Amount of L in tank end of month B	Distance driven in month C	Amount of L used in month C	Amount of L in tank end of month C
Truck 1	3,46	495	932	269,4	225,6	725	209,6	16,0	730	211,0	305,0
Truck 2	2,67	410	928	347,6	62,4	858	321,3	241,1	633	237,1	4,0
Truck 3	2,61	38	575	220,6	317,4	1239	475,4	341,9	855	328,1	13,8
Truck 4	2,82	164	666	236,5	427,5	933	331,3	96,1	1179	418,7	177,4
Truck 5	3,23	426	919	284,2	141,8	922	285,2	356,6	1021	315,8	40,8
Truck 6	2,98	307	727	244,0	63,0	1179	395,6	167,4	931	312,4	355,0
Truck 7	2,94	403	648	220,4	182,6	1061	360,9	321,7	1091	371,1	450,7
Truck 8	3,33	87	1104	331,1	255,9	1016	304,7	451,1	1106	331,7	119,4
Truck 9	3,28	81	647	197,4	383,6	1135	346,2	37,4	774	236,1	301,3
Truck 10	3,09	233	733	237,4	495,6	880	285,0	210,6	583	188,8	21,8
Real average	3,04										

	Distance driven in month D	Amount of L used in month D	Amount of L in tank end of month D	Distance driven in month E	Amount of L used in month E	Amount of L in tank end of month E	Distance driven in month F	Amount of L used in month F	Amount of L in tank end of month F
Truck 1	606	175,2	129,8	1083	313,1	316,7	692	200,0	116,7
Truck 2	1164	436,0	68,1	984	368,5	199,5	623	233,3	466,2
Truck 3	1233	473,1	40,7	674	258,6	282,0	1237	474,7	307,4
Truck 4	778	276,3	401,1	791	280,9	120,2	803	285,2	335,0
Truck 5	894	276,5	264,3	711	219,9	44,4	1119	346,1	198,2
Truck 6	1099	368,8	486,2	1118	375,2	111,0	1024	343,6	267,4
Truck 7	946	321,8	128,9	795	270,4	358,5	714	242,8	115,7
Truck 8	1104	331,1	288,3	1228	368,3	419,9	621	186,3	233,7
Truck 9	1127	343,8	457,6	796	242,8	214,8	1186	361,8	353,0
Truck 10	836	270,7	251,1	976	316,1	435,0	947	306,7	128,3

Refueled with full tank: 500L

Start value FC trucks:	Start value Tank month A:	All distances:
Random generated	Random generated	Random generated
from 3,33 to 2,5 km/L	from 0 to 500 L	from 550 to 1250 km

		Month A	Month B	Month C	***3 Months***	Month D	Month E	Month F	***6 Months***
Fuel card	L tanked in month	2500	3000	2500	*8000,0*	4000	3000	3000	*18000*
Database	kms driven in month	7879	9948	8903,0	*26730,0*	9787	9156	8966	*54639*
Average FC	km/L	3,2	3,3	3,6	*3,3*	2,4	3,1	3,0	*3,04*
Deviation	%	*4%*	*9%*	*17%*	***10%***	*-20%*	*0%*	*-2%*	***0%***

Figure F.3: Calculation in Excel, numbers random generated

Default fuel consumption

	Input	Source
Calorific value diesel	36 MJ/L	CO2emissiefactoren.nl
Emission factor diesel	3,309	CO2emissiefactoren.nl

Unit	Empty	Full	Source
MJ/km	10,8	16,1	Stream: Truck > 20 ton + trailer Off-road
L/km	0,3	0,447	MJ/km divided by calorific value diesel
CO2e/km	0,93	1,38	L/km mulitplied with emissionfactor Diesel

Variables	Input	Source
Percentage_loaded_vkm	0,9	GLECAT
Average_Loadfactor_loadedtrip	0,3	GLECAT
EF_empty	0,927	Calculated
Capacity	26	GLECAT
EF_max	1,381916667	Calculated

$$Ton_{gemiddeld(1en2)} = Cap \times \%ton \times \%vkm_{beladen} \quad (4)$$

Calculation to estimate the average load
Source: Stream (CE Delft, 2020)

Ton_gemiddeld	7,02	ton

$$EF_{vkm} = EF_{leeg} + \frac{Ton_{gemiddeld(2)}}{Cap} \times (EF_{max\,vol} - EF_{leeg}) \quad (3)$$

Calculation to estimate energy consumption (in CO2e/km)
Source: Stream (CE Delft, 2020)

Variables	Base	+15%	+15%	+15%	+ 12,5%	+ 12,5% and +15%
Percentage_loaded_vkm	0,90	1,04*	0,90	1,04*	0,90	1,04*
Average_Loadfactor_loadedtrip	0,30	0,30	0,35	0,35	0,30	0,35
EF_empty	0,93	0,93	0,93	0,93	1,04	1,04
Capacity	26,00	26,00	26,00	26,00	26,00	26,00
EF_max	1,38	1,38	1,38	1,38	1,55	1,55
Ton_gemiddeld	7,02	8,11	8,07	9,33	7,02	9,33
% Difference		16%	15%	33%	0%	33%
EF_vkm	1,05	1,07	1,07	1,09	1,18	1,23
% Difference		2%	2%	4%	12,5%	16,8%

* 1,04 is not realistic because 100% is max, but it is to see the effect of 15% increase

Figure F.4: Calculation in Excel, source input data from CE Delft (2020) and Schmied & Knörr (2012)

Effect uncertainty definition origin and destination when modelling fuel consumption

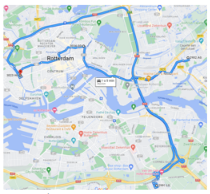
Modelling Energy consumption with different interpretation of origin and destination

Fuel use	3,09	km/L
Fuel type	Diesel B7	
Emission factor	3,256	kg CO2e/L

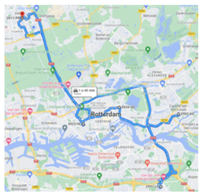
Route X	Postal code	Weight
Location lorry depot	2611 PR	
DC	3023 HL	
Client A	2991 LG	7
Client B	2902 AG	8
Client C	3034 GD	4
DC	3023 HL	
Location lorry depot	2611 PR	

	Distance	kg CO2e
DC round trip	45	47,4
truck round trip	76	80,1

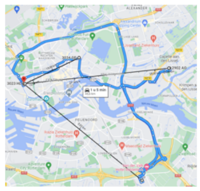
	GCD DC->Client	Weight	Ton-GCD	kg CO2e *DC round trip*	*Truck round trip*	*% Difference*
Client A	9,87	7	69,09	14,8	25,0	69%
Client B	17,07	8	136,56	29,3	49,4	69%
Client C	3,89	4	15,56	3,3	5,6	69%
		Total	221,21			



DC round trip



Truck round trip



Allocation, both situations

Figure F.5: Calculation in Excel, numbers own input

Effect uncertainty definition origin and destination on allocation factor

Modelling allocation factor with different interpretation of origin and destination

Fuel use	3,09	km/L
Fuel type	Diesel B7	
Emission factor	3,256	kg CO2e/L
ADD (considered for example as knov	470	

Route X	Postal code	Weight
Origin payload part 1 client 1	9288 XH	
Origin payload part 2 client 1	9201 HB	
Destination client 1 part 1	6827 AS	1,6831
Destination client 1 part 2	6827 AS	0,3935
Origin payload client 2	4191	
Client 2	7705	2

	Distance		kg CO2e
truck round trip	470		495,2

	GCD DC->Client	% Difference GCD other cases	Weight	Ton-GCD	kg CO2e *Real*
Client 1 part 1	137		1,6831	230,5847	226,4
Client 1 part 2	91	51%	0,3935	35,8085	35,2
Client 2	119	-41%	2	238	233,7
			Total	504,3932	

	GCD DC->Client	Weight	Ton-GCD	kg CO2e *Wrong interpretation origin client 1 and 2*	*% Difference*
Client 1 part 1 and 2	137	2,0766	284,4942	279,3	23%
Client 2	70,5	2	141	138,4	-41%
		Total	425,4942		

	GCD DC->Client	Weight	Ton-GCD	kg CO2e *Wrong interpretation origin client 1*	*% Difference*
Client 1 part 1 and 2	137	2,0766	284,4942	279,3	23%
Client 2	119	2	238	233,7	0%
		Total	522,4942		

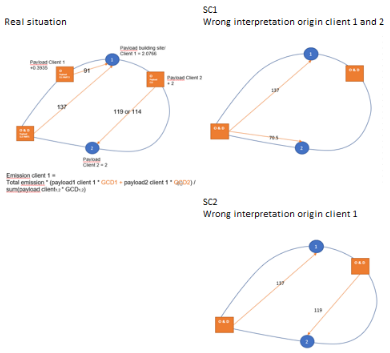


Figure F.6: Calculation in Excel, numbers based on a case in field research

Definition payload

		Kms (GCD)	Weight shipment	Weight pallet(s)	without pallet	with pallet
Locked	**Client 1**	80	0,5	0	40	40
Locked	**Client 2**	80	0,5	0	40	40
Locked	**Client 3**	80	0,5	0	40	40
Varied	**Client 4**	80		0,025		
Locked	**Total CO2e**	530	kg CO2e			

		Kms (GCD)	Weight shipment	Weight pallet(s) (ton)	# ton-km without	# ton-km with	CO2e without	CO2e with	CO2e/ton without	CO2e/ton with	Difference with/without	Uncertainty margin (weight pallet / weight shipment)
Test1	**Client 4**	80	0,01	0,025	0,8	2,8	3,5	11,6	346,4	1155,8	234%	250,0%
Test2	Client 4	80	0,02	0,025	1,6	3,6	6,8	14,6	339,7	729,4	115%	125,0%
Test3	Client 4	80	0,03	0,025	2,4	4,4	10,0	17,5	333,3	583,6	75%	83,3%
Test4	Client 4	80	0,04	0,025	3,2	5,2	13,1	20,3	327,2	508,1	55%	62,5%
Test5	Client 4	80	0,05	0,025	4	6	16,1	23,0	321,2	460,9	43%	50,0%
Test6	Client 4	80	0,06	0,025	4,8	6,8	18,9	25,7	315,5	427,8	36%	41,7%
Test7	Client 4	80	0,07	0,025	5,6	7,6	21,7	28,2	309,9	403,0	30%	35,7%
Test8	Client 4	80	0,08	0,025	6,4	8,4	24,4	30,7	304,6	383,3	26%	31,3%
Test9	Client 4	80	0,09	0,025	7,2	9,2	26,9	33,0	299,4	367,1	23%	27,8%
Test10	Client 4	80	0,1	0,025	8	10	29,4	35,3	294,4	353,3	20%	25,0%
Test11	Client 4	80	0,11	0,025	8,8	10,8	31,9	37,6	289,6	341,4	18%	22,7%
Test12	Client 4	80	0,12	0,025	9,6	11,6	34,2	39,7	284,9	331,0	16%	20,8%
Test13	Client 4	80	0,13	0,025	10,4	12,4	36,5	41,8	280,4	321,6	15%	19,2%
Test14	Client 4	80	0,14	0,025	11,2	13,2	38,6	43,8	276,0	313,1	13%	17,9%
Test15	Client 4	80	0,15	0,025	12	14	40,8	45,8	271,8	305,3	12%	16,7%
Test16	Client 4	80	0,16	0,025	12,8	14,8	42,8	47,7	267,7	298,2	11%	15,6%
Test17	Client 4	80	0,17	0,025	13,6	15,6	44,8	49,6	263,7	291,6	11%	14,7%
Test18	Client 4	80	0,18	0,025	14,4	16,4	46,8	51,4	259,8	285,4	10%	13,9%
Test48	Client 4	80	0,48	0,025	38,4	40,4	86,5	88,8	180,3	184,9	3%	5,2%
Test49	Client 4	80	0,49	0,025	39,2	41,2	87,4	89,6	178,5	182,9	3%	5,1%
Test50	Client 4	80	0,5	0,025	40	42	88,3	90,5	176,7	181,0	2%	5,0%
Test51	Client 4	80	0,51	0,025	40,8	42,8	89,2	91,3	174,9	179,1	2%	4,9%
Test52	Client 4	80	0,52	0,025	41,6	43,6	90,1	92,1	173,2	177,2	2%	4,8%
Test53	Client 4	80	0,53	0,025	42,4	44,4	90,9	92,9	171,5	175,4	2%	4,7%
Test54	Client 4	80	0,54	0,025	43,2	45,2	91,7	93,7	169,9	173,6	2%	4,6%
Test55	Client 4	80	0,55	0,025	44	46	92,5	94,5	168,3	171,8	2%	4,5%
Test56	Client 4	80	0,56	0,025	44,8	46,8	93,3	95,3	166,7	170,1	2%	4,5%
Test57	Client 4	80	0,57	0,025	45,6	47,6	94,1	96,0	165,1	168,4	2%	4,4%
Test58	Client 4	80	0,58	0,025	46,4	48,4	94,9	96,7	163,6	166,8	2%	4,3%
Test59	Client 4	80	0,59	0,025	47,2	49,2	95,6	97,4	162,1	165,2	2%	4,2%
Test60	Client 4	80	0,6	0,025	48	50	96,4	98,1	160,6	163,6	2%	4,2%
Test61	Client 4	80	0,61	0,025	48,8	50,8	97,1	98,8	159,2	162,0	2%	4,1%
Test62	Client 4	80	0,62	0,025	49,6	51,6	97,8	99,5	157,7	160,5	2%	4,0%
Test63	Client 4	80	0,63	0,025	50,4	52,4	98,5	100,2	156,3	159,0	2%	4,0%
Test64	Client 4	80	0,64	0,025	51,2	53,2	99,2	100,8	155,0	157,6	2%	3,9%
Test65	Client 4	80	0,65	0,025	52	54	99,9	101,5	153,6	156,1	2%	3,8%
Test66	Client 4	80	0,66	0,025	52,8	54,8	100,5	102,1	152,3	154,7	2%	3,8%
Test67	Client 4	80	0,67	0,025	53,6	55,6	101,2	102,7	151,0	153,4	2%	3,7%
Test68	Client 4	80	0,68	0,025	54,4	56,4	101,8	103,4	149,7	152,0	2%	3,7%
Test69	Client 4	80	0,69	0,025	55,2	57,2	102,4	104,0	148,5	150,7	1%	3,6%
Test70	Client 4	80	0,7	0,025	56	58	103,1	104,6	147,2	149,4	1%	3,6%

Figure F.7: Calculation in Excel, numbers own input

Error conversion factor payload and CPI

Example 1: different types of payloads

Conversion factor software	1 load meter	1,3
Real situation	1 load meter	0,5
	Difference	-62%

150 L for 6 clients	495	kg CO2e

$$CPI = \frac{\sum CO_{2e}}{\sum_{client} D_{GCD} \cdot P}$$

	GCD	Payload	Payload conversion	ton-GCD conv	Payload Real	ton-GCD
Client 1	80	2 ton	2	160	2	160
Client 2	65	3 load meter	3,9	253,5	1,5	97,5
Client 3	40	4 ton	4	160	4	160
Client 4	30	4 load meter	5,2	156	2	60
Client 5	90	1 load meter	1,3	117	0,5	45
Client 6	10	8 ton	8	80	8	80

CPI conversion f	0,5	CO2e/ton-gcd
CPI real situation	0,8	CO2e/ton-gcd
Difference	54%	

$$CO_{2e_{client-x}} = CPI * D_{GCD_{client-x}} * P_{client-x}$$

Example 1: different types of payloads

Hypothetical situation:

Customer A:
2 laadmeter, GCD 80 km

Customer B:
3 ton, GCD 100 km

				Total CO2e		Total CO2e/ton	
	Payload conversion	Payload real	GCD	Conversion f	Real	Conversion	Real
Customer A	2,6	1	80	111,1	65,7	42,7	65,7
Customer B	3	3	100	160,3	246,5	53,4	82,2

Difference total CO2e conversion f & real	*Customer A*	-41%
	Customer B	54%

When the load of client A is overestimated:
The total emissions of shipment A will be higher than in reality, but the efficiency of the shipment will be better than in reality. The total emissions of shipment B will be lower than in reality and also the efficiency will be better than in the real situation.

Example 2: one type of payload

Conversion factor software	1 load meter	1,3
Real situation	1 load meter	0,5

75 L for 3 clients	247,5	kg CO2e

	GCD	Payload	Payload conversion	ton-GCD conv	Payload Real	ton-GCD
Client 2	65	3 load meter	3,9	253,5	1,5	97,5
Client 4	30	4 load meter	5,2	156	2	60
Client 5	90	1 load meter	1,3	117	0,5	45

CPI conversion f	0,5	CO2e/ton-gcd
CPI real situation	1,2	CO2e/ton-gcd
Difference	160%	

Example 2: same type of payload

Hypothetical situation:

Customer A:
2 laadmeter, GCD 80 km

Customer B:
3 laadmeter, GCD 100 km

				Total CO2e		Total CO2e/ton	
	Payload conversion	Payload real	GCD	Conversion f	Real	Conversion	Real
Customer A	2,6	1	80	97,8	97,8	37,6	97,8
Customer B	3,9	1,5	100	183,3	183,3	47,0	122,2

Difference total CO2e conversion f & real	*Customer A*	0%
	Customer B	0%

When the load of client A and B is overestimated:
The total emissions of shipment A and B will be the same as in reality, but the efficiency of the shipment will be lower than in reality and also the efficiency will be much better than in the real situation.

Figure F.8: Calculation in Excel, random situation: input numbers conversion factor based on measurement

Error conversion factor payload without CPI

Conversion factor software	1 load meter	1,3
Real situation	1 load meter	0,5
	Difference	-62%
	kg CO2e round trip	350

$$CO_{2e_{client-x}} = CO_{2_{total}} \cdot \frac{D_{GCD_{client-x}} \cdot P}{\sum_{client} D_{GCD} \cdot P}$$

Example 1: different types of payloads

Hypothetical situation:

Customer A:
2 laadmeter, GCD 80 km

Customer B:
3 ton, GCD 100 km

					Total CO2e		Total CO2e/ton	
	Payload conversion	Payload real	GCD-payload conversion	GCD-payload real	Conversion f	Real	Conversion f	Real
Customer A	2,6	1	208	80	143,3	73,7	55,1	73,7
Customer B	3	3	300	300	206,7	276,3	68,9	92,1
Total	5,6	4	508	380	350	350		

Difference total CO2e conversion f & real	*Customer A*	-49%
	Customer B	34%

When the load of client A is overestimated:
The total emissions of shipment A will be higher than in reality, but the efficiency of the shipment will be better than in reality. The total emissions of shipment B will be lower than in reality and also the efficiency will be better than in the real situation.

Example 2: same type of payload

Hypothetical situation:

Customer A:
2 laadmeter, GCD 80 km

Customer B:
3 laadmeter, GCD 100 km

					Total CO2e		Total CO2e/ton	
	Payload conversion	Payload real	GCD-payload conversion	GCD-payload real	Conversion f	Real	Conversion f	Real
Customer A	2,6	1	208	80	121,7	121,7	46,8	121,7
Customer B	3,9	1,5	390	150	228,3	228,3	58,5	152,2
Total	6,5	2,5	598	230	350,0	350,0		

Difference total CO2e conversion f & real	*Customer A*	0%
	Customer B	0%

When the load of client A and B is overestimated:
The total emissions of shipment A and B will be the same as in reality, but the efficiency of the shipment will be lower than in reality and also the efficiency will be much better than in the real situation.

Figure F.9: Calculation in Excel, random situation: input numbers conversion factor based on measurement

Margin emission intensity factor

	Input	Source
Calorific value diesel	36 MJ/L	CO2emissiefactoren.nl
Emission factor diesel	3,309	CO2emissiefactoren.nl

Unit	Empty	Full	Source
MJ/km	10,8	16,1	Stream Table 40: Energy use Truck > 20 ton + trailer Off-road
L/km	0,300	0,447	MJ/km divided by calorific value diesel
CO2e/km	0,93	1,38	L/km mulitplied with emissionfactor Diesel

Variables	Input	Source
Percentage_loaded_vkm	0,9	GLECAT Table 10 Volume good lorry 24-40t
Average_Loadfactor_loadedtrip	0,3	GLECAT Table 10
EF_empty	0,927	Calculated
Capacity	26	GLECAT Table 10
EF_max	1,382	Calculated

$$Ton_{gemiddeld(1en2)} = Cap \times \%ton \times \%vkm_{beladen} \quad (4)$$

Calculation to estimate the average load
Source: Stream (CE Delft, 2020)

Ton_gemiddeld	7,02	ton

$$EF_{vkm} = EF_{leeg} + \frac{Ton_{gemiddeld(2)}}{Cap} \times (EF_{max\,vol} - EF_{leeg}) \quad (3)$$

Calculation to estimate energy consumption (in CO2e/km)
Source: Stream (CE Delft, 2020)

EF_vkm	1,0498275	CO2e/km

$$EK_{tkm} = \frac{EF_{vkm}}{Ton_{gemiddeld(1)}} \quad (2)$$

Calculation to estimate energy consumption of one ton shipped over a kilometer (in CO2e/ton-km)
Source: Stream (CE Delft, 2020)

EK_tkm	0,1495481	CO2e/tonkm

Variables	Base	+15%	+15%	-15%	-15%	-15%	+12,5%	-12,5%	-15% and +12,5%	+15% and -12,5%
Percentage_loaded_vkm	0,90	1,04 *	0,90	0,77	0,90	0,77	0,90	0,90	0,77	1,04 *
Average_Loadfactor_loaded trip	0,30	0,30	0,35	0,30	0,26	0,26	0,30	0,30	0,26	0,35
EF_empty	0,93	0,93	0,93	0,93	0,93	0,93	1,04	0,81	1,04	0,81
Capacity	26,00	26,00	26,00	26,00	26,00	26,00	26,00	26,00	26,00	26,00
EF_max	1,38	1,38	1,38	1,38	1,38	1,38	1,55	1,21	1,55	1,21

Ton_gemiddeld	7,02	8,11	8,07	5,97	5,97	5,07	7,02	7,02	5,07	9,33
% Difference		16%	15%	-15%	-15%	-28%	0%	0%	-28%	33%
EF_vkm	1,05	1,07	1,07	1,03	1,03	1,02	1,18	0,92	1,14	0,95
% Difference		2%	2%	-2%	-2%	-3%	13%	-13%	9%	-9%
EK_tkm	0,15	0,13	0,13	0,17	0,17	0,20	0,17	0,13	0,23	0,10
% Difference		-12%	-12%	16%	16%	34%	13%	-13%	51%	-32%

* 1,04 is not realistic because 100% is max, but it is to see the effect of 15% increase

Figure F.10: Calculation in Excel, input numbers from CE Delft (2020) and Schmied & Knörr (2012)

Margin scenario payload unknown

	Payload	GCD	Payload: Assumption; other loads evenly distributed among the stops	Payload: Worst case	Payload: Best case
Client 1	?	20	3,83	1	0,5
Client 2	?	30	3,83	0,5	0,5
Client 3	2	40	2	2	2
Client 4	?	50	3,83	0,5	0,5
Client 5	?	80	3,83	0,5	20
Client 6	?	40	3,83	0,5	0,5
Client 7	?	12	3,83	20	1
		Sum (ton-km)	969,3	440	1762
	Emissions shipper: Client 3		49,5	109,1	27,2

Ton-GCD: Assumption; other loads evenly	Ton-GCD: Worst case	Ton-GCD: Best case
76,7	20,0	10,0
115,0	15,0	15,0
80,0	80,0	80,0
191,7	25,0	25,0
306,7	40,0	1600,0
153,3	20,0	20,0
46,0	240,0	12,0

Vehicle Capacity	25	ton
Total emissions	600	kg CO2e

$$CO_{2e\_shipper3} = CO_{2e\_trip} * \frac{D_{GCD\_s3} * P_{s3}}{\sum_{client} D_{GCD} \cdot P}$$

Known numbers

	CO2e	*% Difference*
Best	27,2	-45%
Assumption	49,5	0
Worst	109,1	120%

Figure F.11: Calculation in Excel, random input numbers

Margin scenario addresses unknown

Margin scenario Emission Intensity factor/CPI and average payload

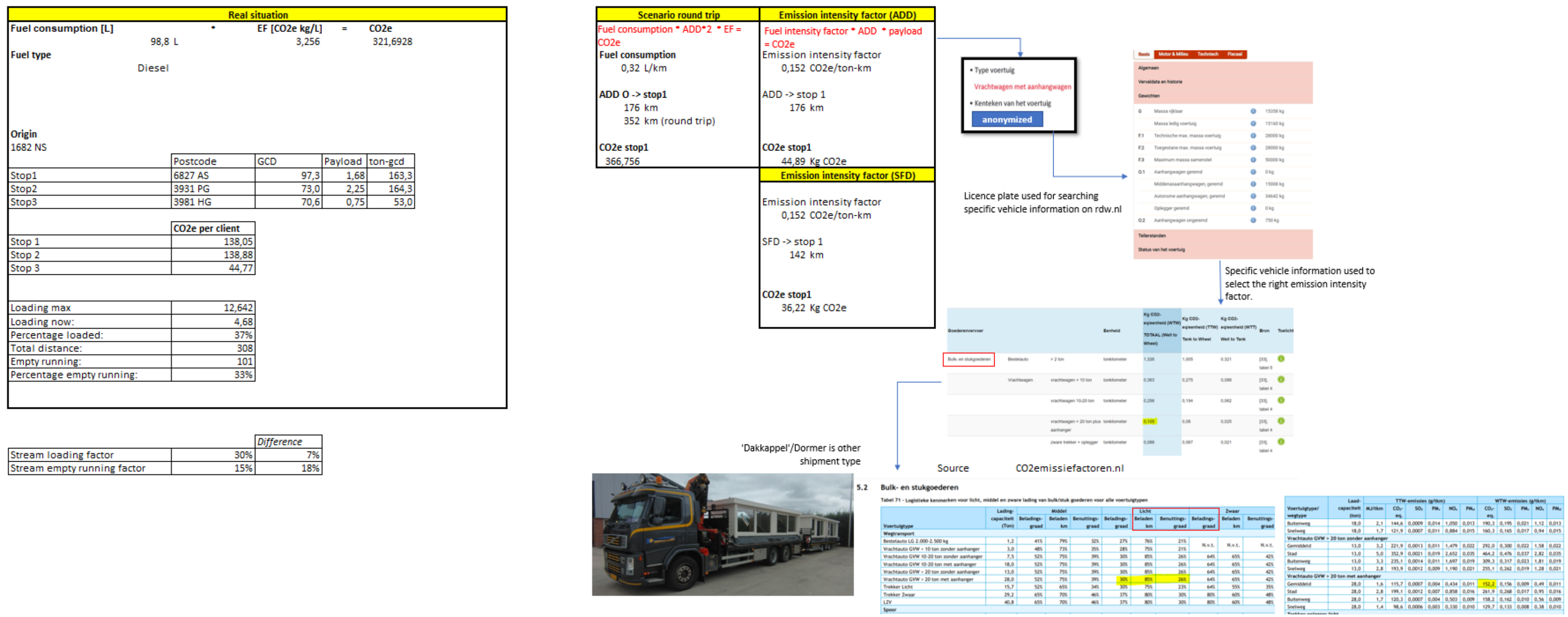


Figure F.12: Calculation in Excel, random input numbers month

	Payload	GCD	Ton-GCD
Client A	5	69	357
Client A	2	69	165
Client A	4	69	301
Client A	7	69	470
Client A	8	69	534
Client A	5	69	328
Client A	8	69	554
Client A	4	69	272
Client A	10	69	695
Client A	9	69	624
Client A	3	69	216
Client A	10	69	698
Client B	0	25	9
Client B	4	25	102
Client B	4	25	105
Client B	10	25	250
Client B	6	25	140
Client B	7	25	182
Client B	5	25	133
Client B	1	25	37
Client B	3	25	83
Client B	5	25	132
Client B	8	25	199
Client C	1	104	152
Client C	3	104	323
Client C	5	104	525
Client C	5	104	556
Client C	6	104	578
Client C	10	104	1084
Client C	5	104	523
Client C	11	104	1178
Client C	7	104	680
Client C	5	104	556
Client C	11	104	1128
Client C	7	104	761
Client D	12	70	818
Client D	6	70	431
Client D	0	70	1
Client D	7	70	470
Client D	3	70	190
Client D	4	70	253
Client D	3	70	232
Client D	0	70	17
Client D	0	70	13
Client D	8	70	587
Client D	6	70	390
Client D	10	70	727
Client D	10	70	702
Client D	4	70	305

Emission Client A		
Average	Real	Difference
2725,17	2637,36	3%

Emission Client B		
Average	Real	Difference
717,30	694,19	3%

Emission Client C		
Average	Real	Difference
4205,52	4070,01	3%

Emission Client C		
Average	Real	Difference
2158,35	2088,80	3%

CO2e	Payload average	Total GCD	Total ton-km with average	Real number of total ton-kms
10000	6	3322	19128,78153	19766
		Emission intensity factor	0,522772451	0,50592698

month

	Payload	GCD	
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client A	5	69	357
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278

Emission Client A		
Average	Real	Difference
2241,44	2023,58	11%

Emission Client B		
Average	Real	Difference
284,45	256,81	11%

Emission Client C		
Average	Real	Difference
6514,16	5881,01	11%

Emission Client C		
Average	Real	Difference
1745,61	1575,95	11%

CO2e	Payload average	Total GCD	Total ton-km with average	Real number of total ton-kms
10000	5	3322	17626,483	21188
		Emission intensity factor	0,5673281	0,471960837

month

	Payload	GCD	
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client A	10	69	691
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client B	2	25	49
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client C	10	104	1038
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278
Client D	4	70	278

Emission Client A		
Average	Real	Difference
4337,66	3292,88	32%

Emission Client B		
Average	Real	Difference
284,45	215,94	32%

Emission Client C		
Average	Real	Difference
6514,16	4945,15	32%

Emission Client C		
Average	Real	Difference
1745,61	1325,16	32%

CO2e	Payload average	Total GCD	Total ton-km with average	Real number of total ton-kms
10000	6	3322	21557,81571	25198
		Emission intensity factor	0,463868888	0,39685684

$$CO_{2e_{client-x}} = D_{GCD_{client-x}} \cdot \frac{CO_{2_{total}}}{\sum_{client}(D_{GCD} \cdot P)}$$

$$CO_{2e_{client-x}} = D_{GCD_{client-x}} \cdot \frac{CO_{2_{total}}}{(\sum_{client} D_{GCD}) \cdot P\_average}$$

This data is random generated,
to simulate the effect of using average payload values
For calculating the emission intensity factor.

It needs to represent a database of orders from clients
in a month. There are three scenarios;
1. Payload is random for every client during the month
2. Payload is standard for clients in a month
3. Payload is standard for clients in a month (big difference

Figure F.13: Calculation in Excel, random input numbers

G

Motivation of scores prioritization

G.0.1. Effect on Carbon Footprint Magnitude

The effect on the magnitude of the carbon footprint refers to the extent to which uncertainty can influence the final value. This is examined using elasticity, which represents relative impact on the final value when the variable affected by uncertainty changes. For example, an elasticity of 1 occurs when a 10% change in the variable leads to a 10% change in the carbon footprint. An elasticity greater than 1 implies that the uncertainty affects multiple variables, resulting in a combined impact greater than 10%. The effect of magnitude is often 1, thus it has been decided to classify 0.5 to 1 as 'medium', less than 0.5 as 'low', and greater than 1 as 'high'. The scores are visible in Table G.1.

Table G.1: Scores effect on Carbon Footprint Magnitude

Score	Description	Elasticity
1	Low: The uncertainty has a small effect on the carbon footprint and will not have a significant impact on the calculation.	<0.5
2	Medium: The uncertainty has a moderate effect on the carbon footprint.	0.5-1
3	High: The uncertainty has a very large effect on the carbon footprint because it can have an extra effect on other uncertainties.	>1

Table G.2: Evaluating uncertainty scores and their impact on carbon footprint magnitude, per situation

	Score 'Effect on CF Magnitude' per Situation							
Uncertainties that can arise per situation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Explanation**
Uncertainty in unknown: Energy Type	3	3	3	3	3	3	3	This uncertainty cannot be increased or decreased by 10%; it is a nominal variable. Thus, a change in energy type can result in an effect of more than 10%.
Uncertainty in Emission Factors	2	2	2	2	2	2		An increase of 10% in the emission factor results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty when Conversion Factor needs to be applied	1	2	1	1	1	1	2	An increase of 10% in the payload of a customer, in different experiments, results in a maximum difference of 5%, the elasticity is assumed less than 0.5. Except in the situation where the payload is multiplied, in which case it is 10% (The elasticity is then assumed to be equal to 1).
Uncertainty in definition: Payload	1	2	1	1	1	1	2	An increase of 10% in the payload of a customer, in different experiments, results in a maximum difference of 5%, the elasticity is assumed less than 0.5. Except in the situation where the payload is multiplied, in which case it is 10% (The elasticity is then assumed to be equal to 1).
Uncertainty due to variability of Average Value		2	2		2			An increase of 10% in the average energy consumption results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty about Calculation		3	3		3			The uncertainty in the calculation of average values (l/km or l/ton-km) affects the uncertainty in other factors. Hence, the elasticity is assumed to be greater than 1.
Uncertainty in definition: Distance		2	2	2	2	2	2	An increase of 10% in the distance results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty due to other distance type than used for average		2	2	2	2	2	2	An increase of 10% in the distance results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty due to unknown distance			2	2	2	2	2	An increase of 10% in the distance results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty in specification level: address Origin, Stops, and Destinations on GCD	1	2	1	1	1	1		An increase of 10% in the GCD of a customer, in different experiments, results in a maximum difference of 5%, the elasticity is assumed less than 0.5. Except in the situation where the GCD is multiplied, in which case it is 10% (The elasticity is then assumed to be equal to 1.).
Uncertainty in specification level: address Origin, Stops, and Destinations on Unknown Distance			2	2	2	2	2	An increase of 10% in the distance results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty in definitions: address Origin, Stops, and Destinations on GCD	1		1	1	1	1		An increase of 10% in the GCD of a customer, in different experiments, results in a maximum difference of 5%, the elasticity is assumed less than 0.5.
Uncertainty in definitions: address Origin, Stops, and Destinations on Unknown Distance			2	2	2	2		An increase of 10% in the distance results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty due to variability of Default Value				2		2		An increase of 10% in the fuel consumption results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty due to variability of Average Modeled Value				2		2		An increase of 10% in the fuel consumption results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty in definition: Vehicle				3		3	3	This uncertainty cannot be increased or decreased by 10%; it is a nominal variable. Thus, a change in vehicle type can result in an effect of more than 10%. Hence, the elasticity is assumed to be greater than 1.
Uncertainty in unknown: Vehicle Type				3		3	3	This uncertainty cannot be increased or decreased by 10%; it is a nominal variable. Thus, a change in vehicle type can result in an effect of more than 10%. Hence, the elasticity is assumed to be greater than 1.
Uncertainty in definition: Shipment Type							3	This uncertainty cannot be increased or decreased by 10%; it is a nominal variable. Thus, a change in vehicle type can result in an effect of more than 10%. Hence, the elasticity is assumed to be greater than 1.
Uncertainty in unknown: Shipment Type							3	This uncertainty cannot be increased or decreased by 10%; it is a nominal variable. Thus, a change in vehicle type can result in an effect of more than 10%. Hence, the elasticity is assumed to be greater than 1.
Uncertainty in emission intensity factors							2	An increase of 10% results in an increase of 10% in the carbon footprint of a shipment. The elasticity is assumed to be equal to 1.
Uncertainty in unknown: Payload other Stops Assumption average value payload with vehicle capacity					3	3		This uncertainty cannot be increased or decreased by 10%, but it affects the distribution of different loads, thus affecting multiple input variables. Hence, the elasticity is assumed to be greater than 1.
Uncertainty in unknown: adres other Stops Assumption trip is Dedicated, replace Allocation Factor with * 2					3	3		This uncertainty cannot be increased or decreased by 10%, but it changes the type of route that is taken, thus affecting multiple input variables. Hence, the elasticity is assumed to be greater than 1.
Uncertainty in unknown: Amount of Trips Assumption Total Demand/Capacity Vehicle						3		This uncertainty cannot be increased or decreased by 10%, but it changes the number of trips, thus affecting multiple input variables. Hence, the elasticity is assumed to be greater than 1.

G.0.2. Degree of Uncertainty

The degree of uncertainty is expressed both qualitatively and quantitatively. This means that the uncertainty margins from the previous section can be converted to scores. However, not all uncertainties can be expressed in margins, so the expected degree of dispersion based on the other effects of uncertainties must be used. A score of less than 10% between the minimum and maximum values is considered ’low’, which also includes the accepted variability of fuel consumption based on historical data, as this is considered low uncertainty by the GLEC Framework, among others. A spread of 10 to 40 percent between the minimum and maximum values is considered ’medium’, and more than 40 percent is considered ’high’. The scores are visible in Table G.3.

Table G.3: Scores expected degree of uncertainty

Score	Description	Uncertainty margin
1	Low: There is some uncertainty, but this uncertainty is assumed to be low.	<0.10
2	Medium: There is some uncertainty due to variability, ambiguity or lack of data.	0.10-0.4
3	High: There is significant uncertainty due to ambiguity or a lack of important data that is difficult to obtain.	>0.4

Table G.4: Evaluating uncertainty scores and their degree of uncertainty, per situation

	Score 'Degree of uncertainty' per Situation							
Uncertainties that can arise per situation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Explanation**
Uncertainty in unknown: Energy Type	3	3	3	3	3	3	3	When the energy type is unknown, this will lead to a lot of different possibilities. The effect of the unknown energy type is a broad range of emission factors, which can lead to an emission factor with more than 40% difference.
Uncertainty in Emission Factors	1	1	1	1	1	1		The uncertainty in the emission factors is assumed to be low, due to the comparison made in this thesis.
Uncertainty when Conversion Factor needs to be applied	3	3	3	3	3	3	3	It should be noted that this uncertainty is based on the assumption of one result and is set at +-60%.
Uncertainty in definition: Payload	1	1	1	1	1	1	1	Based on the expectation that the weight of the client's payload is generally much higher than the carrier's packaging weight, it can be assumed that the uncertainty margin will be low.
Uncertainty due to variability of Average Value		1	1		1			The uncertainty margin is assumed to be low because the uncertainty of the variability is intentionally spread across the customers in the GLEC framework and future ISO norm.
Uncertainty about Calculation		3	2		2			It should be noted that it is not possible to give a 'standard' uncertainty margin on this activity. However, there can be uncertainty in the calculation of the average value of fuel consumption (L/ton-km or L/km). It can be wrongly calculated, there might be uncertainty caused by the aggregation level, or it can lead to uncertainty in applying the wrong distance and/or payload. It is expected that this uncertainty will be higher in the case of the average figure of L/ton-km as it is more difficult to calculate than L/km.
Uncertainty in definition: Distance		2	2	2	2	2	2	When there is uncertainty in the definition, one cannot know which is the best to apply. Therefore the maximum deviation from the different type of distance is taken into account and is expected to be medium.
Uncertainty due to other distance type than used for average		2	2	2	2	2	2	When another distance is used to calculate the average fuel consumption or the emission intensity factor than the known distance, there is an expected deviation. For example, the planned distance is expected to have a deviation from +5%, and with large detours, it can be +30%. The shortest feasible distance is also expected to have a deviation from +5%, and with large detours, it can be +30%. Therefore, the maximum deviation is taken into account and is expected to be medium.
Uncertainty due to unknown distance			2	2	2	2	2	When the distance needs to be reconstructed, it is assumed in this research that the SFD calculated by Google Maps has a deviation of +10%, and when there have been large detours, it can be even +30%. Therefore the margin is expected to be medium.
Uncertainty in specification level: address Origin, Stops, and Destinations on GCD	1	1	1	1	1	1		The expected maximum difference at PC4 or city level is 9-11 km from the center, which is extreme. The expected minimum difference is 0km. It is expected that the deviation from the exact value is not more than 10%. For example, on a GCD of 50km, we expect that in most circumstances, the deviation will be less than 5 km.
Uncertainty in specification level: address Origin, Stops, and Destinations on Unknown Distance			1	1	1	1	1	The expected maximum difference at PC4 level is 16.3 km from the center, which is extreme. The expected minimum difference is 0km. It is expected that the deviation from the exact value is not more than 10%. For example, on an SFD of 50km, we expect that in most circumstances, the deviation will be less than 5 km.
Uncertainty in definitions: address Origin, Stops, and Destinations on GCD	2		2	2	2	2		It should be noted that it is not possible to give a 'standard' uncertainty margin on this activity. However, a wrong interpretation of the origin and destination can lead to a difference in the GCD and therefore in the allocation factor. As proven in an example in this thesis, a wrong interpretation of the origin and destination can lead to a large effect on the GCD. In this example, the difference was even -41% and 50%. It is expected that this difference can be even larger in other situations; therefore, the possible margin is assumed to be high.
Uncertainty in definitions: address Origin, Stops, and Destinations on Unknown Distance			3	3	3	3		It should be noted that it is not possible to give a 'standard' uncertainty margin on this activity. However, as proven in an example in this thesis, a wrong interpretation of the origin and destination can lead to a large effect on the distance. In this example, the difference was even 69%; therefore, the possible margin is assumed to be high.
Uncertainty due to variability of Default Value				2		2		The uncertainty margin is assumed to be medium according to the uncertainty margin given in this thesis report, which is +-16.5%.
Uncertainty due to variability of Average Modeled Value				2		2		The uncertainty margin is assumed to be medium according to the uncertainty margin given in this thesis report, which is +-12.5%.
Uncertainty in definition: Vehicle				2		2	2	The uncertainty margin is assumed to be medium according to the differences in vehicle classes, which are on average below +-40% and more than +-10%.
Uncertainty in unknown: Vehicle Type				3		3	3	The uncertainty margin is high according to the differences between the different vehicle classes, which can run up to far more than 40%.
Uncertainty in definition: Shipment Type							3	The uncertainty margin is assumed to be medium according to the differences in shipment classes, which are on average below +-40% and more than +-10%.
Uncertainty in unknown: Shipment Type							3	The uncertainty margin is high according to the differences between the different shipment classes, which can run up to far more than 40%.
Uncertainty in emission intensity factors							3	The assumptions underlying the emission intensity factor can give an uncertainty range from -31% to +51%; therefore, the margin is assumed to be high.
Uncertainty in unknown: Payload other Stops Assumption average value payload with vehicle capacity					3	3		It should be noted that it is not possible to give a 'standard' uncertainty margin on this activity. However, as proven in an example in this thesis, this assumption can lead to a large effect on the payloads of the other stops. Because many different payload combinations can be possible, the uncertainty is assumed to be high.
Uncertainty in unknown: adres other Stops Assumption trip is Dedicated, replace Allocation Factor with * 2					3	3		It should be noted that it is not possible to give a 'standard' uncertainty margin on this activity. However, as proven in an example in this thesis, this assumption can lead to a large effect on the empty trip distance. In this example, the difference was even 74% higher; therefore, the possible margin is assumed to be high.
Uncertainty in unknown: Amount of Trips Assumption Total Demand/Capacity Vehicle						2		When the vehicle capacity is known at a good detail level and the trips are assumed to be dedicated, the uncertainty margin of the amount of load that is truly transported in the vehicle is expected to have a deviation of -30% from the full truckload based on assumptions made in this thesis.

G.0.3. Complexity of Uncertainty Reduction

In addition to managing uncertainty and recognizing its existence, it is also crucial to reduce uncertainty. Therefore, one of the categories for prioritizing uncertainties is the complexity of uncertainty reduction, to which specific scores must be assigned. Since the scores for 'degree of uncertainty' and 'impact on carbon footprint of a shipment' are scaled on a score of 1 to 3, the same must be done for the 'complexity of uncertainty reduction' category. Furthermore, it is not possible to make this scale quantifiable, and it must therefore be a qualitative scale. Literature emphasizes that uncertainty can be reduced in various ways, with the following three being most common: data collection, communication with stakeholders, and quantification of uncertainties (Erkoyuncu et al., 2013; Dankers & Kundzewicz, 2020) . Based on this, the scales are further divided. Communication with a stakeholder to reduce ambiguity is considered 'low', gathering more data to make better estimates is considered 'medium', and conducting further research on the uncertainty surrounding the value due to its unknown nature receives a 'high' score. The scores are visible in Table G.5.

Table G.5: Scores complexity of uncertainty reduction

Score	Description
1	Low: Communication with a stakeholder to reduce ambiguity.
2	Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
3	High: Reducing the uncertainty is very complex and requires significant effort and resources, \ such as additional research to get insights into the uncertainty that surrounds a value.

Table G.6: Evaluating uncertainty scores and their complexity to reduce the uncertainty, per situation

	Score 'Complexity of uncertainty reduction' per situation							
Uncertainties that can arise per situation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Explanation**
Uncertainty in unknown: Energy Type	2	2	2	2	2	2	2	Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions
Uncertainty in Emission Factors	3	3	3	3	3	3		High: Reducing the uncertainty is very complex and requires significant effort and resources, such as additional research to get insights into the uncertainty that surrounds a value.
Uncertainty when Conversion Factor needs to be applied	3	3	3	3	3	3	3	High: Reducing the uncertainty is very complex and requires significant effort and resources, such as additional research to get insights into the uncertainty that surrounds a value.
Uncertainty in definition: Payload	1	1	1	1	1	1	1	Low: Communication with a stakeholder to reduce ambiguity.
Uncertainty due to variability of Average Value		3	3		3			High: Reducing the uncertainty is very complex and requires significant effort and resources, such as additional research to get insights into the uncertainty that surrounds a value.
Uncertainty about Calculation		1	1		1			Low: Communication with a stakeholder to reduce ambiguity.
Uncertainty in definition: Distance		1	1	1	1	1	1	Low: Communication with a stakeholder to reduce ambiguity.
Uncertainty due to other distance type than used for average		3	3	3	3	3	3	High: Reducing the uncertainty is very complex and requires significant effort and resources, such as additional research to get insights into the uncertainty that surrounds a value.
Uncertainty due to unknown distance			2	2	2	2	2	Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
Uncertainty in specification level: address Origin, Stops, and Destinations on GCD	2	2	2	2	2	2		Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
Uncertainty in specification level: address Origin, Stops, and Destinations on Unknown Distance			2	2	2	2	2	Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
Uncertainty in definitions: address Origin, Stops, and Destinations on GCD	1		1	1	1	1		Low: Communication with a stakeholder to reduce ambiguity.
Uncertainty in definitions: address Origin, Stops, and Destinations on Unknown Distance			1	1	1	1		Low: Communication with a stakeholder to reduce ambiguity.
Uncertainty due to variability of Default Value				3		3		High: Reducing the uncertainty is very complex and requires significant effort and resources, such as additional research to get insights into the uncertainty that surrounds a value.
Uncertainty due to variability of Average Modeled Value				3		3		High: Reducing the uncertainty is very complex and requires significant effort and resources, such as additional research to get insights into the uncertainty that surrounds a value.
Uncertainty in definition: Vehicle				1		1	1	Low: Communication with a stakeholder to reduce ambiguity.
Uncertainty in unknown: Vehicle Type				2		2	2	Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
Uncertainty in definition: Shipment Type							1	Low: Communication with a stakeholder to reduce ambiguity.
Uncertainty in unknown: Shipment Type							2	Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
Uncertainty in emission intensity factors							3	High: Reducing the uncertainty is very complex and requires significant effort and resources, such as additional research to get insights into the uncertainty that surrounds a value.
Uncertainty in unknown: Payload other Stops Assumption average value payload with vehicle capacity					2	2		Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
Uncertainty in unknown: adres other Stops Assumption trip is Dedicated, replace Allocation Factor with * 2					2	2		Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.
Uncertainty in unknown: Amount of Trips Assumption Total Demand/Capacity Vehicle						2		Medium: Gathering more information to make better estimates or doing more analysis for more accurate assumptions.

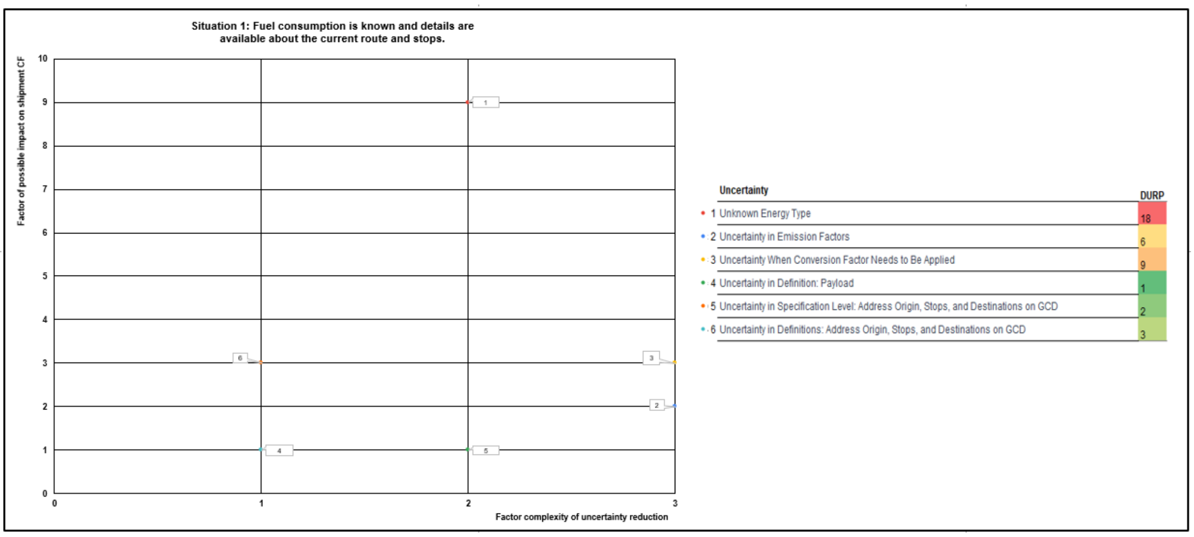


Figure G.1: Prioritization results situation 1

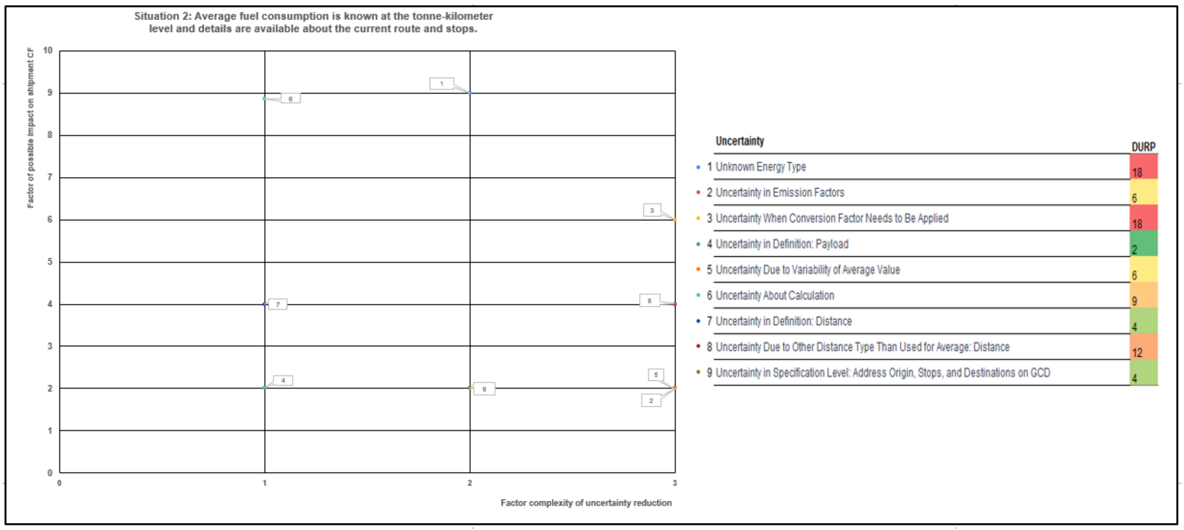


Figure G.2: Prioritization results situation 2

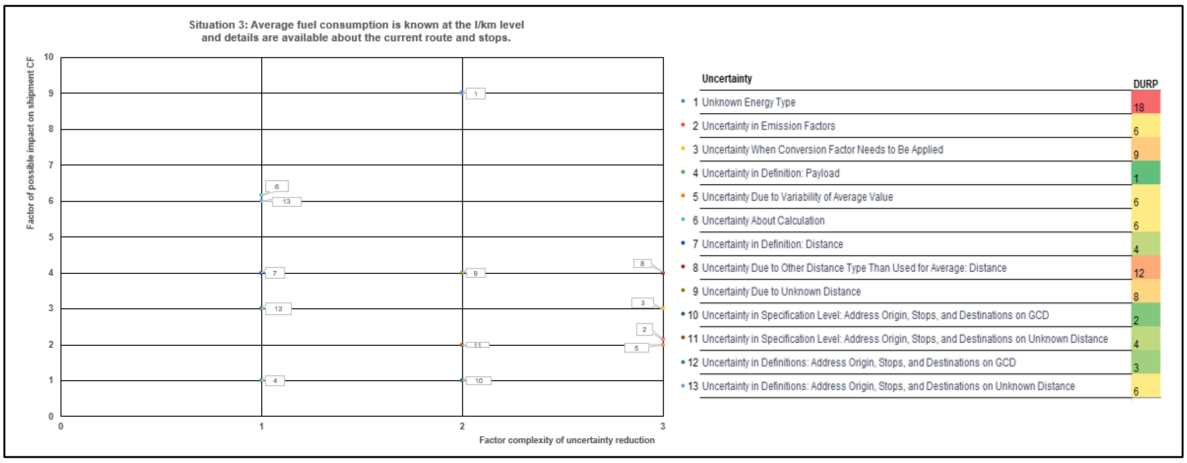


Figure G.3: Prioritization results situation 3

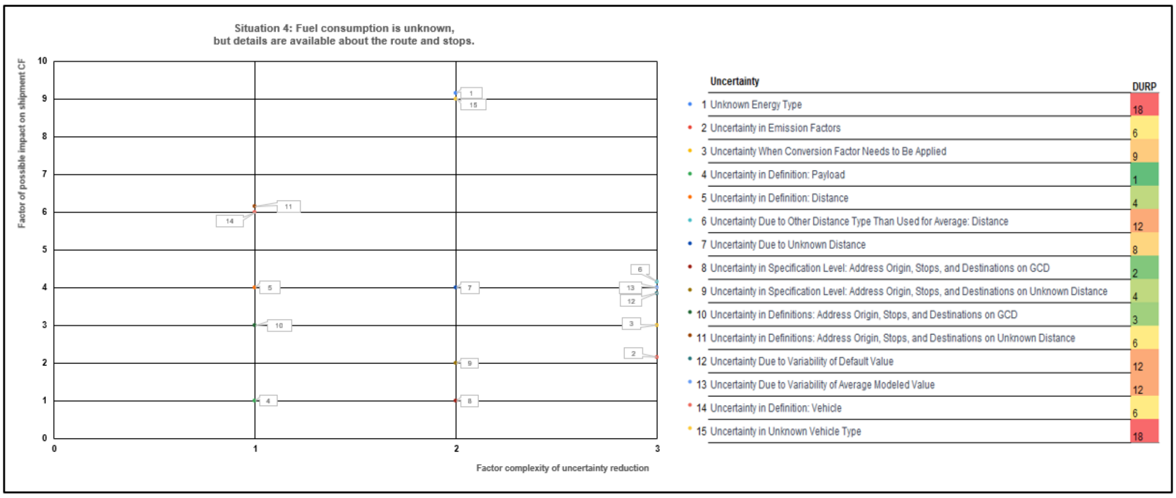
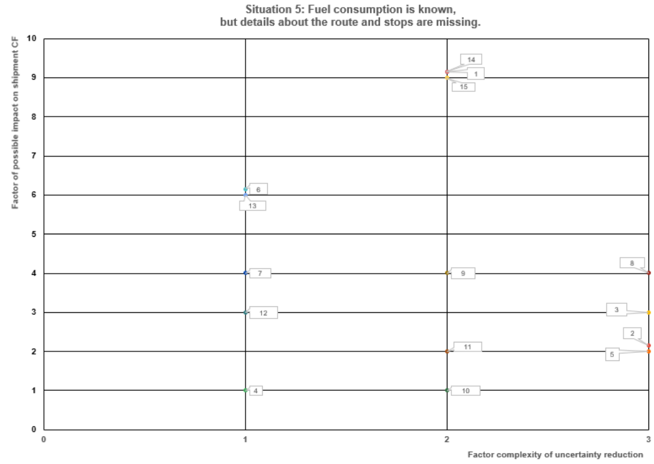
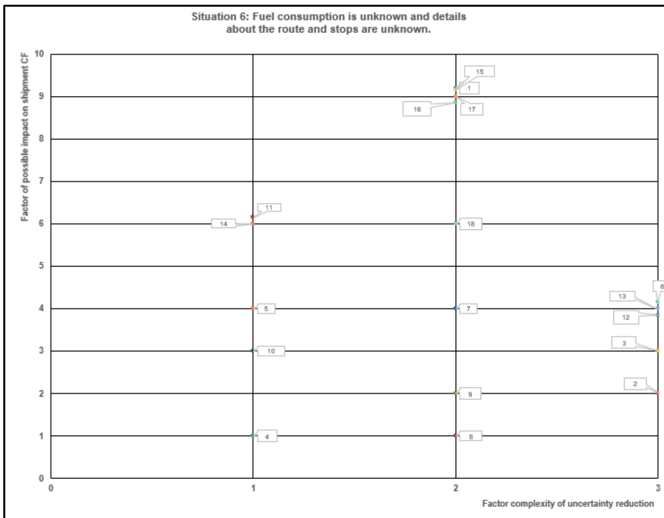


Figure G.4: Prioritization results situation 4



	Uncertainty	DURP
1	Unknown Energy Type	18
2	Uncertainty in Emission Factors	6
3	Uncertainty When Conversion Factor Needs to Be Applied	9
4	Uncertainty in Definition: Payload	1
5	Uncertainty Due to Variability of Average Value	6
6	Uncertainty About Calculation	6
7	Uncertainty in Definition: Distance	4
8	Uncertainty Due to Other Distance Type Than Used for Average: Distance	12
9	Uncertainty Due to Unknown Distance	8
10	Uncertainty in Specification Level: Address Origin, Stops, and Destinations on GCD	2
11	Uncertainty in Specification Level: Address Origin, Stops, and Destinations on Unknown Distance	4
12	Uncertainty in Definitions: Address Origin, Stops, and Destinations on GCD	3
13	Uncertainty in Definitions: Address Origin, Stops, and Destinations on Unknown Distance	6
14	Payload Other Stops Unknown: Assumption Average Value Payload with Help of Vehicle Capacity	18
15	Adres Other Stops Unknown: Assumption Trip is Dedicated; Replace Allocation Factor * 2	18

Figure G.5: Prioritization results situation 5



	Uncertainty	DURP
1	Unknown Energy Type	18
2	Uncertainty in Emission Factors	6
3	Uncertainty When Conversion Factor Needs to Be Applied	9
4	Uncertainty in Definition: Payload	1
5	Uncertainty in Definition: Distance	4
6	Uncertainty Due to Other Distance Type Than Used for Average: Distance	12
7	Uncertainty Due to Unknown Distance	8
8	Uncertainty in Specification Level: Address Origin, Stops, and Destinations on GCD	2
9	Uncertainty in Specification Level: Address Origin, Stops, and Destinations on Unknown Distance	4
10	Uncertainty in Definitions: Address Origin, Stops, and Destinations on GCD	3
11	Uncertainty in Definitions: Address Origin, Stops, and Destinations on Unknown Distance	6
12	Uncertainty Due to Variability of Default Value	12
13	Uncertainty Due to Variability of Average Modeled Value	12
14	Uncertainty in Definition: Vehicle	6
15	Uncertainty in Unknown Vehicle Type	18
16	Payload Other Stops Unknown: Assumption Average Value Payload with Help of Vehicle Capacity	18
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Figure G.6: Prioritization results situation 6

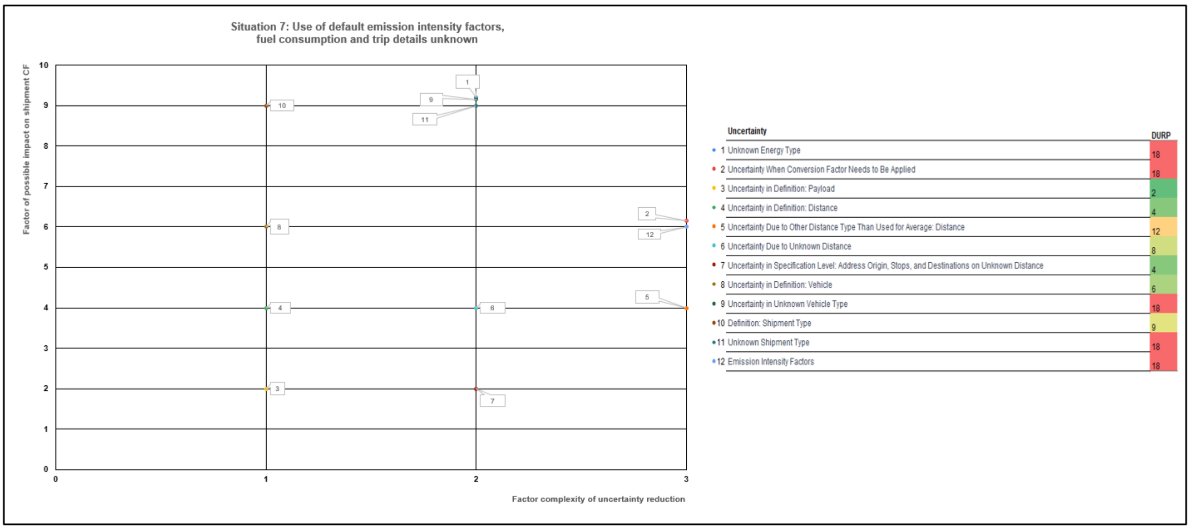

Figure G.7: Prioritization results situation 7

H
Validation

H.1. Purpose of validation

With the help of a validation interview with experts I would like to check the validity of the findings of my research. The purpose of validation is to gain feedback from experts on the identified uncertainties, data situations, and the proposed tool. The feedback will be analyzed to identify common points and differences.

During the meeting, the following questions will be asked to the experts:

Data Situations:
a. Do you find the presentation of uncertainties per data situation logical? Why or why not?
b. Do you agree with the identification of data situations? Are there other data situations that you recommend considering?

Identified Uncertainties:
c. Do you agree with the identified uncertainties? Are there uncertainties missing or identified that are not relevant?
d. Do you agree with the prioritization of uncertainties and their ease of addressing in each data situation?

Tool:
e. What do you think of the approach used in the tool? Are there any improvements that you recommend?
f. Are there other aspects that you think are important to consider when evaluating the uncertainty of transport carbon footprint?
g. Do you think this tool is useful in practice, and if so, how?

Context:
h. What are the incentives for transporters to provide accurate data, according to your expertise? Should there be regulations for this?
i. What is the impact of uncertainties on the acceptance of orders by clients, and are companies paying attention to this?

H.2. Expert from BigMile

Data Situations:
a. Do you find the presentation of uncertainties per data situation logical? Why or why not?
Yes, it is true that in some situations uncertainties do not exist while they do in others.

b. Do you agree with the identification of data situations? Are there other data situations that you recommend considering?
In my opinion, there are fewer data situations, but this is a more detailed version of it. For me, it is either you know all the fuel, or you know this through average consumption and distance, or you do not know at all. The danger with these assumptions that lead to extra situations is that you have to justify everything to an accountant. As BigMile, we do not want to be blamed when an accountant says something is wrong, so we avoid situations with assumptions when providing information to our clients about the use of BigMile.

Identified Uncertainties:
c. Do you agree with the identified uncertainties? Are there uncertainties missing or identified that are not relevant?
All the uncertainties discussed are recognizable and also occur in daily work. Currently, we are trying to guide our customers as well as possible to avoid as many uncertainties as possible. The only addition I have is regarding cross-docking, which we take into account in BigMile, and there are also some uncertainties involved, which may be interesting to consider in the future. In addition, the uncertainty of ”energy type” is now a thing for diesel vehicles. It is generally possible to determine whether diesel, gasoline, or electricity has been used in a truck because vehicle data is known, but a diesel car can now fill multiple fuels, which makes it more difficult to determine. It may also be useful to mention that planned and actual driven distance can be very close in practice.

d. Do you agree with the prioritization of uncertainties and their ease of addressing in each data situation?
I understand what you have done, but the complexity depends heavily on whether you are talking to a shipper or a carrier. Reducing unknown data complexity, for example, is easier for a carrier than for a shipper. In addition, the impact of, for example, specifying the destination or origin depends on the known GCD. This is because over a long distance, it has less impact than a short distance. Furthermore, you often see that a shipper has the destination at the city level and not more specific.

Tool:
e. What do you think of the approach used in the tool? Are there any improvements that you recommend?
Cross-docking and other means of transport, such as road transport, also have uncertainties. I also hope that more cooperation will take place in the future. In your framework, for example, ”prevent” appears a few times, and one way to avoid uncertainties is to collaborate with your carrier to obtain validated fuel data. So basically, to get that data situation as good as possible. I think this will be a solution for many and fortunately, I see more and more examples of this. I think this is also an important aspect to consider.

f. Are there other aspects that you think are important to consider when evaluating the uncertainty of transport carbon footprint?
At GLEC, if, for example, fuel consumption or vehicle type is unknown, it always chooses the worst option in BigMile. However, the best-case scenario is not shown. Nevertheless, the worst-case is an incentive to improve.

g. Do you think this tool is useful in practice, and if so, how?
I think this tool is particularly useful for raising awareness. It makes me think, especially about the ranges of uncertainty. It can be useful to indicate the impact of providing less accurate data, for example, if you cannot or do not want to provide certain data, resulting in a range of +/- 20%. This can raise people’s awareness of the importance of accurate data, and they may reconsider their approach. Perhaps they will need to take extra steps to comply with regulations or meet the expectations of their headquarters. Providing more insight into this topic is always valuable, as it is often a topic of discussion. For instance, some people suggest using an emission intensity factor instead of collecting more detailed data. This tool can provide clarity on the impact of different approaches. It can also help someone who is responsible for auditing the data to gain a better understanding of the results.

Context:
h. What are the incentives for transporters to provide accurate data, according to your expertise?

Should there be regulations for this?
Incentives for transporters to provide accurate data include reducing their carbon footprint and improving their sustainability. In addition, people are becoming more aware of the upcoming regulations and want to avoid overestimating their carbon footprint. Thus, they want to minimize uncertainties. Moreover, clients are increasingly interested in the carbon footprint of the transport services they use, and they may require data from smaller transport companies. However, small companies may not have the time, resources, or personnel to focus on this issue.

i. What is the impact of uncertainties on the acceptance of orders by clients, and are companies paying attention to this?
Uncertainties can significantly impact a company's ability to meet their carbon footprint reduction targets. For example, if fuel consumption is estimated to be lower than it actually is, this could hinder progress towards their sustainability goals. The impact of uncertainties may become even more relevant if a CO2 tax is introduced in the future. Companies need to be aware of the potential impact of uncertainties and ensure they take appropriate measures to minimize them. Clients are becoming more interested in the carbon footprint of the transport services they use, and this may affect their decisions about which company to choose. Therefore, companies should pay attention to uncertainties and take steps to address them to remain competitive in the market.

H.3. Expert 1 from Smart Freight Centre, Director:

Data Situations:
a. Do you find the presentation of uncertainties per data situation logical? Why or why not?
Yes, it is logical that certain uncertainties occur in one calculation and not in another.

b. Do you agree with the identification of data situations? Are there other data situations that you recommend considering?
There are also data situations where people do not know what type of fuel was consumed or the distribution of the fuel, which could also be a data situation, right? It might not be immediately clear what a data situation entails.

Identified Uncertainties:
c. Do you agree with the identified uncertainties? Are there uncertainties missing or identified that are not relevant?
Uncertainty of allocation method: the allocation method in the ISO standard is now based on GCD/SFD and weight. In some cases, this is done per item, and in the container industry, it is done per TEU and a conversion factor. The main motivation for this is that weight does indeed have an influence on fuel consumption. At the same time, it is often the case, especially in the maritime and parcel services sector, that it is often full in terms of volume but not weight. As a result, the price calculation is done based on volume, for example, but this does not apply to CO2 allocation. In contracts, it is often about the space used, and in the CO2 calculation, it is about weight. In terms of distance, GCD is currently the best since it is universal and always the same.

Uncertainty about carbon footprint boundary: in terms of boundary, it is important to acknowledge that we always talk about the operational phase of transport. So, we are not talking about the production of a truck in terms of emissions not included in the current system. Not by us, but also not by ISO or in other versions. So, that is something that needs to be acknowledged.

Uncertainty about methane and laughing gas (N2O and CH4): I heard you mention methane, and that is something to consider. Indeed, it can sometimes be a relatively small percentage, but this depends very much on the fuel. And the global warming potential of these greenhouse gases is significantly different and therefore not just a few percent but can have serious effects. And that is actually quite interesting because what has recently emerged is that it also depends very much on where the oil actually comes from and how it is produced, which is often not included in these calculations. Often these calculations are still made on relatively limited datasets, which are then seen as the actual reality.

Emission factor uncertainty: there are now two ways in which emission factors are calculated. There are two calculation methods for this using LCA: consequential and attributional. Both have a valid reason, but we must ensure that the values are used correctly. The ISO standard and the GLEC Framework are also working on harmonizing this. The second thing that comes into play here again are the boundaries, for example with biodiesel, what do you include and not include, such as indirect land use change, induced land use change, or direct land use change, and to what extent is what included. As emissions decrease, these types of discussions and uncertainties become more important.

d. Do you agree with the prioritization of uncertainties and their ease of addressing in each data situation?
It is very interesting to quantify and map the uncertainties in this way, but in the end, people are really looking for an absolute number in a percentage.

Tool:
e. What do you think of the approach used in the tool? Are there any improvements that you recommend?
And secondly, what people always search for is in what way they can use this in contracts or can I use this to improve my data, do I have influence on that? And there is a notion behind that that you will always inherently not know certain things. Especially when talking about future situations, for example: if I switch carriers, will I get a better footprint or not? That is of course a very relevant question. And at the same time, which uncertainty in the data are you addressing? Which ones are important and which are not, and that link would be an interesting one for further research.

f. Are there other aspects that you think are important to consider when evaluating the uncertainty of transport carbon footprint?
It depends on the perspective and with what mindset you want to make a carbon footprint. Because there are different calculation methods, there are also different uncertainties. In addition, it is true that certain uncertainties are now irrelevant or ignored, but will become increasingly important in the future. Just like those TTW emissions.

g. Do you think this tool is useful in practice, and if so, how?
Providing insight into uncertainties is always valuable and interesting, however, you often notice that people are interested in an absolute number. This is a start in that sense.

Context:
h. What are the incentives for transporters to provide accurate data, according to your expertise? Should there be regulations for this?
Currently, there are three types of companies that have an interest in this: LSPs, carriers, and shippers. Ultimately, shippers issue contracts to carriers and LSPs. They can calculate their carbon footprint in different ways: using default values, modeling, or calculating it afterward based on primary data. The interesting thing is that carriers are often relatively small companies and often do not have the IT systems, while logistics service providers are often large companies. The large players in the world also often have the necessary reporting systems available. The question is actually; what are you going to use the data for? That is often the underlying question. For example, what can you do with better data and why would you want to use it? So that's the first question you need to ask before talking about an incentive. Because if you, as a shipper, want to get certain information to make a certain decision, the question is whether better primary data is the right solution? And are we really comparing apples to apples, as there are still significant differences in philosophies and perspectives. That's not to say that we have to acknowledge that there's still a whole world to be won in terms of data quantity and detailed calculations. What we always continue to say by definition is that default data is wrong; it doesn't have to be bad, but by definition, it is not reality. What we are starting to see in terms of incentives is that shippers include in their contracts and ask whether organizations have a plan and whether they

measure their CO2. We also see more and more that companies increasingly say; you also have to provide us with a certain quality and have calculated it in a certain way. So it is getting stricter. This is in development, but at the same time, we also see that the reality today is that many companies are not very advanced in this regard. When asked for data, you do notice that shippers increasingly desire to demonstrate accurate data and that it is validated data.

i. What is the impact of uncertainties on the acceptance of orders by clients, and are companies paying attention to this?
Companies do ask for validation of the data provided, but whether they really look at data quality and uncertainties is the question. You notice that many companies do not really have their affairs in order and may therefore be less aware of this.

j. What do you think are the latest developments in the carbon footprint of shipments?
An important development in this regard is the CSR reporting that is now coming up. At first, it was about a generic annual report, and now it's really about a more detailed level, which requires more data. In addition, this also increasingly plays a role in a company's financial system. So we see companies where this used to fall under a Sustainability team, it now often falls under a financial team. So then you are really talking about accounting and assurance procedures. This makes validation and verification increasingly important. A second development is, but this is still in its infancy, that in tendering or procurement, not only is the plan asked for but also the emissions. And that this is used as a kind of evaluation criterion. The CO2/ton-km factor.

k. And then the question remains how reliable that factor is?
Absolutely, logistics service providers are quite aware of this. This is an important point to ensure that a false reality is not being portrayed. That's why we're now really seeing a movement towards assurance procedures, so the processes regarding verification. But it also turns out that people often don't understand the term 'emission intensity factor' or don't know what else could possibly be done with it. The GLEC Framework is now the basis for the new ISO standard. We are also working on a verification system. So, how can someone be certified against the standard? In addition, there is an opinion about whether the data going into it and the calculation methods are good. We are now really seeing a world unfolding of auditors who will do this.

Other questions/discussion topics during conversation:

l. What is your position, or that of SFC/GLEC, on developments such as labeling of packages or shipments?
We are not in favor of emission labeling systems, and that is actually the essential question: what do you want to use it for? Modeling the shipment of a particular package, for example, is less accurate than how much emissions the package has been responsible for. There is also a significant difference in calculation methods and data input. An emission labeling system sometimes obscures the actual details behind it, and it is not that easy to automatically compare one-to-one between two parties. It can be done, but the question is, what does an emission labeling system add?

About detailed level calculations: In general, it often comes down to what choice you want to make and what information you need for that. In general, an annual report is often requested, and then an average over a year is perfect. And then you don't necessarily need to know that emissions are higher in December because more packages are being sent or even less because it is more efficient. The actual question is, if I, as a shipper, remain flexible, can I lower my CO2 level? That requires certain detailed calculations that are indeed relevant. So the question that always lies behind it is, why do you want this carbon footprint and what do you want to do with it, and what do you need for that?

H.4. Expert carbon footprinting methodology

Data Situations:
a. Do you find the presentation of uncertainties per data situation logical? Why or why not?
This is very detailed. The big picture is just: you have two fundamental uncertainties: you have uncertainties in ton-kilometers and uncertainties in fuel consumption/emissions. This is based on a high-level

overview. What you do is take a few more steps down, and indeed you get new uncertainties. So in that sense, I agree with that.

b. Do you agree with the identification of data situations? Are there other data situations that you recommend considering?
The unknown of emissions or fuel consumption is often an uncertainty from the shippers' side, the ton-km side or the transport performance side is often an uncertainty from the carrier or LSP side.

Identified Uncertainties:
c. Do you agree with the identified uncertainties? Are there uncertainties missing or identified that are not relevant?
I have some difficulty with the terminology. I see uncertainty from two perspectives. You have mathematical uncertainty and perspective. I would rather see these two things separately. I see uncertainty, for example, more as a sample based on which you make an estimate. So more the mathematical term. How people perceive things I see as perception. The question is also how important it is to know the exact emission of a single shipment. It's more about optimizing the whole system. Every day is different and every day a truck can drive differently, but the network has the most influence. So I wonder if information from on-board computers has any added value. The conversion factor is indeed an important uncertainty, as there are many LSPs who, for example, simply pick up pallets but have no idea of the weight on them. If you then calculate with averages, the margin of error is very large.

Follow-up question: it depends on what level you want to monitor, I think, less aggregated data gives a better picture of how you could make different choices?
Then he enters another discussion, the discussion about where and by whom optimization is done? I was initially more in favor of looking at individual trips at an individual level, but eventually concluded that it should be looked at on a more aggregated level. So more from an annual perspective, so that seasonality effects are spread out as well. The choice for an LSP or carrier could ultimately be based on the emission intensity figure of that party.

Follow-up question: I think this is still in its infancy, what do you think?
I agree, I have conducted a few projects in practice and there you see again that things are conceptually well thought out but become complicated in practice, due to data availability, among other things.

~~d. Do you agree with the prioritization of uncertainties and their ease of addressing in each data situation?~~

Tool:
e. What do you think of the approach used in the tool? Are there any improvements that you recommend?
You mention many practical details that you can call uncertainties. But you could also say: these are simply my data requirements. If you want to know it as accurately as possible; then this is necessary. If you don't have that; then we have to estimate the data and that's where the uncertainty lies. I advise you to pay close attention to your terminology in this regard. Is uncertainty also the same as missing data that you actually need? I see uncertainty as something when you make an estimate and there is a margin of error around it. I see uncertainty in ordinary language and mathematical uncertainty. That's why it's very good that you've also looked at these mathematical uncertainties and shown them as well.

f. Are there other aspects that you think are important to consider when evaluating the uncertainty of transport carbon footprint?
At a high level, there are two concrete uncertainties from the shipper's perspective: you need two numbers. You need to know the CO2 emissions and the transport activity. For shippers, the ton-km figures are often known. They know where the goods are picked up and where they are delivered. Unless you have more complex chains. What shippers have little insight into is the CO2. They don't know how efficient their service providers are. So conceptually there are two uncertainties. On the emission side, this is fuel consumption, and on the ton-kilometer side, this is transport performance. By using different approaches, you have ways to reduce these uncertainties. But fundamentally, you

have these two uncertainties, and based on data sources and data collection, you can reduce them. And that can almost never be reduced 100%.

~~g. Do you think this tool is useful in practice, and if so, how?~~

Context:
h. What are the incentives for transporters to provide accurate data, according to your expertise? Should there be regulations for this? The question is always: why do a carbon footprint or why would you want to calculate this? I think that policy often does not work well at the company level but more at the market level. Carbon footprinting is actually at the micro-level. Governments and institutions like the Port of Rotterdam can provide guidance, but the most important reason for having more accurate data is when other companies impose data requirements. So there should be some data requirements. In addition, carbon footprinting goes hand in hand with cost minimization because less fuel is less cost and also better for the environment. This last point is a significant reason for companies to minimize their carbon footprint. Moreover, you have the image interests; large companies try to have or maintain a good image and are therefore working on their ESG scores, and in recent years, this has not been so much about a plan but also about clear quantification. When sustainability can be quantified, you get a higher ESG score.

~~i. What is the impact of uncertainties on the acceptance of orders by clients, and are companies paying attention to this?~~

Other reasons to map carbon footprint:

Larger companies attach more value to their ESG scores because this can also provide certainty and attract investors. The more involved you are with sustainability, the more future-proof you are, and because you are less risky, you can then ask for more from investors.

Other discussion about findings, not clear to what extent assumptions can be used and when standard emission intensity factors:

Fuel consumption: It was a long discussion in ISO, and my position was that you should always give priority to observed data. That's a kind of gold standard. So if you have the number of liters of fuel, you should use that to arrive at the number of CO2 emissions. If you don't have that, you have two ways to do this: 1) applying default emission factors or 2) modeling your fuel consumption. The condition for using modeled data is that what comes out of your model is more accurate than the use of emission factors. You really need an argument that what comes out of your model is better than default emission factors. There are no concrete guidelines for model use.

Trip data and allocation: that trip data is unknown; this often occurs with LSPs and carriers. So the number of ton-kilometers or the transport performance. That is indeed a fundamental uncertainty.

H.5. Expert in Sustainable Mobility at TNO

Data Situations:
~~a. Do you find the presentation of uncertainties per data situation logical? Why or why not?~~

~~b. Do you agree with the identification of data situations? Are there other data situations that you recommend considering?~~

Identified Uncertainties:
c. Do you agree with the identified uncertainties? Are there uncertainties missing or identified that are not relevant?

I do agree with them. There are also uncertainties in the allocation when different components are present in a shipment. It's hard for me to say if I'm missing any uncertainties; however, all parts seem relevant. There's sometimes overlap between these uncertainties, which I think makes it more difficult. They don't all stand entirely on their own. So, the uncertainty in CO2 emissions arises from uncertainties in parameters but also from data input. Regarding if I'm missing something, of course, there are many more factors that can impact energy use beyond the ones already considered, such as weather, driving behavior, and terrain. You mention there is uncertainty around the energy use figure due to these factors, but you could, of course, delve much deeper into this topic. Furthermore, this research mainly assumes that carbon-containing substances are used for driving. When driving electric vehicles, a carbon footprint is no longer really relevant. However, this doesn't mean that electric vehicles (powered by green energy) have no societal impact. That electricity still has to be generated somewhere, and space is needed for infrastructure like wind turbines, solar panels, etc., and space is also scarce. But then again, you're also talking about scope, which is not currently included in the identified uncertainties. Besides, I think it's important to show CO2 emissions per package or per efficiency instead of the total number, as that tells more about choices.

~~d. Do you agree with the prioritization of uncertainties and their ease of addressing in each data situation?~~

Tool:

~~e. What do you think of the approach used in the tool? Are there any improvements that you recommend?~~

f. Are there other aspects that you think are important to consider when evaluating the uncertainty of transport carbon footprint?
In the future, uncertainties related to energy will be much more critical. For example, when only electric vehicles are used, the carbon footprint becomes less relevant. It might be interesting to see how your method could adapt to this.

~~g. Do you think this tool is useful in practice, and if so, how?~~

Context:

h. What are the incentives for transporters to provide accurate data, according to your expertise? Ultimately, cost is the most important factor in the logistics sector, even if a company is actively working to reduce its carbon footprint. Companies will invest in efficient logistics, electric vehicles, and other sustainable solutions if they can provide value to their customers and help them gain a competitive advantage. While green initiatives may have some value, cost remains the primary driver for most logistics companies. Innocent, a drinks company, worked with a logistics company that used electric trucks because it provided good plan-able logistics, and it was cheaper than using diesel trucks. Although customers may request more sustainable options, ultimately, cost is the most important consideration for logistics companies.

I have a lot of colleagues who are looking specifically into that topic. What I know is that there is a world to win in this area because this is currently not happening on a large scale. Therefore, there's a lot of impact in doing just that more because, after all, the idea is that you can get a lot of gains out of it. I think there may be a lack of expertise rather than a lack of willingness to share data. From what I hear, many logistics companies still plan their routes by hand. That is miles away from a platform where data is shared. First, they should try to get their own route planning in order with less interference from personal choices or gut feelings of the individuals who plan them.

i. In your opinion, what are the latest developments regarding the carbon footprint of freight transport?

I cannot say much about carbon footprinting itself, but I can talk about CO2 reduction. There is a lot of movement in the area of CO2 reduction among logistics companies. European legislation is an important driver for reducing CO2 emissions, as vehicle choices of logistics companies are strongly influenced by the CO2 emission standard for newly sold vehicles. Technological improvements and declining costs of electric trucks also contribute to the reduction of CO2 emissions. I think the shift towards electric trucks will accelerate in the coming years, as these vehicles will be more cost-effective than diesel trucks.

Follow-up question: What about the supply of more sustainable fuels such as HVO? HVO 100, a type of biodiesel, is currently more expensive than fossil diesel. While electric trucks may already be cheaper than diesel for some use cases, not everyone has the option of buying a new electric truck and may need to consider using HVO or biodiesel in their existing diesel truck to make their transport more sustainable. However, this will increase the costs, which is not convenient. But there may be opportunities to market the use of more sustainable fuels as a selling point to customers, especially in industries like bus transport where municipalities may be willing to pay more for sustainable fuel usage.

The thing is that biobased fuels, such as HVO, can provide a viable alternative to fossil fuels in reducing greenhouse gas emissions in the short term. However, their potential availability for the road transportation sector may be limited due to their demand in other sectors, such as aviation and shipping. So biobased fuels are a helpful solution, but they are not the most desirable one in the long term, as they still emit harmful pollutants. Instead, renewable energy sources such as hydrogen, fuel cells, and electricity are preferred due to their lower emissions and associated health benefits. However, there are potential challenges to implementing these solutions, such as material shortages and inadequate infrastructure.

i. What is the impact of uncertainties on the acceptance of orders by clients, and are companies paying attention to this?
In this example, we are discussing the tender process for the procurement of fuels for a municipality's vehicle fleet, with the expert having been involved in this project:

In that project, a significant amount of attention was given to striking a balance between preventing uncertainties and feasibility. You cannot ask everything from a transporter; some things are simply not feasible in that sense. So it mainly comes down to how you can set up a tender in such a way that parties can distinguish themselves from each other in a feasible manner. For example, you can look at the average CO2 emissions of HVO (Hydrotreated Vegetable Oil) across an entire chain, or do you instead base it on a worst-case scenario. As a transporter, you can then indicate that you use HVO, and it is up to the municipality to determine a kind of evaluation framework for assessing the value of HVO compared to others. After all, not all HVOs are the same. However, you can't always trace it back to the source, as I mentioned earlier, so you make a choice in the tender about how you value that. The goal is not to be accurate because you never know exactly how much has been emitted; you know that there is a chance that you can achieve at least a certain CO2 reduction. You enable parties to distinguish themselves, and whether you can be sure that the fuels are the actual fuels they promised is then problem number two. The verification is probably done with certificates now. A better way to make biofuels traceable is actually a blockchain system. However, the system that is currently available, as far as I know, could only trace from the moment the fuels are imported, not from the source. It remains very difficult to accurately determine the CO2 emissions of the fuels because there is a lot of noise around emission factors, and it is very difficult to trace the raw material. To determine the source, one would have to go to the plantation where the raw material comes from. This makes the process very complex and difficult to verify.

Further discussion on findings: It is indeed difficult to estimate in general when assumptions should be used and when standard values should be applied. It is always a trade-off: when you allow someone to provide a certain value estimate for somewhere in the chain or the final number of a carbon footprint, you give them an opportunity to distinguish themselves from others at the smallest detail level, but on the other hand, it also increases a lot of uncertainties. If someone else had done exactly the same thing, they might have interpreted it very differently, so there is a trade-off somewhere in relation to having to take your number from a table with standard values.

H.6. Expert 2 Smart Freight Centre

Data Situations:

a. Do you find the presentation of uncertainties per data situation logical? Why or why not?
I also agree wit the data situation, there is sort of a hierarchy of scenarios whereby if you have primary fuel consumption data and all the transport activity data, that is a more complete scenario than if you are, let's say you don't have fuel consumption data and you have transport activity data or some of those are missing.

b. Do you agree with the identification of data situations? Are there other data situations that you recommend considering?
I think that you covered all the different situations. I think you have aggregated, dis aggregated fuel consumption, not fuel consumption and transport activity or no transport activity and everything in between. Thereby you went from the big picture, you know, defining the scope of what we're calculating and I saw you make a reference to empty running and load factor and all these different kind of things that take into consideration the total fuel perspective.Yeah, I think that you covered it, I think that we're quite safe in that regard. Also, making sure that we align when it comes to the distance calculation and saw you make a mention of that. I saw you mention actual distance and shortest feasible distance. That's also something people don't necessarily think about all the time.

Identified Uncertainties:

c. Do you agree with the identified uncertainties? Are there uncertainties missing or identified that are not relevant?
So overall, I think the scope of your research was quite, overarching: so you covered that it is important to set the boundaries right, to make sure that we have a total fuel perspective, the well-to-wheel emission factors, the inclusion of empty trips, and what kind of assumptions that we do when data is missing. So yes I agree with them, and see no other uncertainties at the the moment.

d. Do you agree with the prioritization of uncertainties and their ease of addressing in each data situation?
The approach you have done I understand and seem logical however I can not say if I total agree with them, therefore I need more time and information.

Tool:

e. What do you think of the approach used in the tool? Are there any improvements that you recommend?
It seems that you've done a very comprehensive job, you've thought through it logically, and you're trying to tie the knots. To make sure that when we're doing carbon foot-printing calculations, we agree of what are we calculating.

f. Are there other aspects that you think are important to consider when evaluating the uncertainty of transport carbon footprint?
For other transport modes it is even harder to have primary data. Thereby there is always a kind of ambiguity, and in the new ISO they replace planned distance with Shortest Feasible Distance. So the description of planned distance in the GLEC framework is now Shortest Feasible Distance. So this is not the same as a Google Maps distance. When you're calculating with default emission intensity factors, it's not expected that you would have access to the actual distance traveled. ISO made the choice and said, Shortest feasible distance, What used to be called planned distance in the framework is a more universal distance metric and can be used to calculate transport activity and therefore you multiply it by that. Now, obviously, if you're doing for a fuel based approach whereby you're deriving a fuel consumption. Obviously that fuel consumption will be reflective of the actual distance travelled. But after that you're reallocating it to a transport activity that is calculated using shortest feasible distance. So the 5% adjustment factor is needed when aligning averages with each other and is not always needed. But in the case for road, all you need to make sure is that you're consistent in the distance metric that you use. And when calculating transport activities that is shortest feasible distance.

g. Do you think this tool is useful in practice, and if so, how?
Creating awareness mainly and showing ways to calculate the emissions and which assumptions are underlying there.

Context:

h. What are the incentives for transporters to provide accurate data, according to your expertise?

Should there be regulations for this?
Availability of primary data is not available for all modes. If there's any mode where it tends to exist more than others it is road transportation. But it still makes up a small percentage of how emissions are calculated within logistics. Because just as you said, fuel consumption data is seen as potentially sensitive business information. And to this day, calculating scope three emissions or subcontracted emissions are still done on a voluntary basis. And so there isn't that incentive to necessarily go the extra mile and share fuel consumption data. That's where legislation on a regional level, at least to begin with, maybe on a European level, will incentivize people to share fuel consumption data so that we can have more accurate calculations. But even in the scenario where you have fuel consumption data, sometimes you only have fuel consumption data related to the loaded distance and not the empty distance. And then you have to apply an industry average empty running factor to then account for it. So there's still a little and there's a long way to go.

i. What is the impact of uncertainties on the acceptance of orders by clients, and are companies paying attention to this?
So I know that there is an attempt to do a bit of sustainable procurement. And one of the things that they look at would be maybe an emission intensity value. Um, so I know that's potentially part of the tendering process, but I have limited experience in the practicalities of procurement and what that looks like. So I can't comment too much, but it is a topic that will be increasingly more popular. The Smart Freight Centre has also created a procurement guideline and a procurement questionnaire to help shippers make certain procurement questions when soliciting transport from their carriers or freight forwarders. For uncertainties, I think a lot of times the value that is calculated can be quite different from the actual emissions emitted. So this is something that we need to be aware of. So when you're calculating based on a certain methodology or methods, you need to be transparent about it and document it in your methodology so that it can potentially be audited. Or so we know why you came to that result and what assumptions that you made. In my honest opinion, the the way to get as close to actual emissions as possible is just to move to primary data as close as possible and just to rely on technical technological innovations and also the sharing of this kind of information between different actors along the physical supply chain. I think legislation would be a big push for that because it will level out the playing field. It would take out the risk that only certain companies are volunteering that information rather than others and then create a feeling that there is a logic competition. So if we make it a requirement, then we could get closer to calculating emissions. But at the same time, we want people to calculate emissions even though they're not perfect, because we're just still want to account for them in one way or another.

j. Which uncertainties do you see the most in practice? It's just the absence of primary fuel consumption data. And when it exists, it's specifically on an individual trip level. But then you see a lot of the absence of empty running fuel consumption because people only have it from A to be loaded distance. So. I see a lot of people who are calculating point to point deliveries on an individual trip basis, and they have to refer to an industry average running factor. And if we take it from the framework for a 40 ton articulated truck, that is 17% and that 17% is an expression of empty kilometers over the total vehicle kilometers, and not just the loaded distance. So for me, it's just a complete absence of data when it comes to certain elements. So even when you have primary data, sometimes you have to enrich it. Thereby there is an over representation of, let's say, European data that is used also outside of Europe. It would be good if we multiplied fuel consumption studies or the development of emission intensity factors in different geographies so that we can calculate emissions reflecting the logistics operations in different geographies. That's also something that we can do because the framework is a comprehensive and global framework, but it has its limitations. For example, we simply don't have emission intensity factors for Africa or Latin America or Asia, and therefore we have to rely on European values and make certain uplifts. But it's extremely imperfect. So what would be good is going for primary data. And in the meantime, until we get primary data, maybe develop emission intensive factors locally for different regions. If we're using a transport activity based approach, which is still the main way of calculating emissions.

Discussion I am now aware of the ISO and the recommendations to divide emissions by a highly aggregated level. But I was wondering, what if you know your fuel consumption due to for example fuel cards, but you drive multiple services with a truck, and they have another VOS/TOC. How do you make a distinction between the different services? when you're defining a transport operation category or your VOS, um, you would ideally distinguish between, um, an aggregated fleet average that is specifically for Ftls or one that is specifically for TLS. And so you'd want to match the TOC as closely with the TOC that is representative of the transport service that you solicited. But is there a possibility that you don't know that information that you can't determine between a dedicated and a an LTL when it comes to the fuel consumption? Because I would assume that a carrier would know that.

My answer: Well I think you would only know that when you have a specific board computer that measures the amount of fuel used per trip.

Yeah. So if you have that situation, then think that you're a bit limited. So then what you would do is that for that carrier you would just calculate an average emission intensity based on the total fuel consumption of that month and the total transport activity.

This was something I was thinking about:if you are a carrier with limited data because you don't have a board computer, but you have the transcriptions of your fuel card, so you know how much you tanked in a month. But you have different services that you provide to your clients. How do you distinguish your fuel consumption and allocate it good to the different clients you have by the service you provide?

I don't see that being possible, to be honest. Otherwise you would have to make wild assumptions and it seems that in this scenario you just have the total fuel consumption and the total transport activity and that's it. So you're very limited. I personally don't see a way how you could do things differently, in the future. What I would tell to this carrier is try and separate the fuel consumption associated with a fleet dedicated to different kinds of services: point to point, dedicated collection and delivery rounds. But this would be an example of a primary fuel consumption, but with limited insights into the kind of transport activity associated with it. So it would be just a general.

Python script case studies

I.1. Case 1

I.2. Case 2

I.3. Case 3

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Assessing the possible uncertainties underlying the carbon footprint of a shipment.

The road towards a more transparent and accurate carbon footprint of freight transportation.

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ABSTRACT This paper investigates the uncertainties underlying carbon footprint estimations of freight transportation, with a particular focus on trip-level shipment data. The research aimed to identify and classify possible causes of these uncertainties using Walker's uncertainty matrix, drawing from literature reviews, protocol analyses, field research, and interviews. Findings suggest that the accuracy and transparency of assumptions are crucial when communicating carbon footprint estimations, as emphasized in current literature. This study contributes to the existing knowledge by providing deeper insights into the influence of uncertainty causes on the final estimation. The primary source of these uncertainties can largely be attributed to data accuracy in the calculation of carbon footprints. A structured approach is proposed to examine potential causes of uncertainties and their potential impacts on the final carbon footprint estimation. To demonstrate the effectiveness of this approach, a case study analyzing three freight movements to a building site was conducted. This research offers valuable insights and a systematic method for addressing uncertainties in carbon footprint estimations, ultimately supporting more informed decision-making in the freight transportation sector.

INDEX TERMS Carbon footprint, Walker uncertainty matrix, freight transportation, logistics, EN16258, ISO 14083, data quality, data accuracy.

I. INTRODUCTION

The world faces significant environmental challenges, with climate change being a major concern. Various efforts have been made to address this issue, including the Paris Agreement, which aims to limit global temperature increase to well below 2 degrees Celsius above pre-industrial levels, with an aspirational goal of limiting the increase to 1.5 degrees Celsius [47]. To achieve this target, there must be no net emissions of greenhouse gases (GHGs) by the end of the century. As a result, increasing attention is being paid to reducing GHG emissions, with the transportation sector being a crucial area of focus.

Freight transport represents a significant portion of transportation emissions, contributing approximately 42% of total transport emissions [23]. Road freight, in particular, has a decisive impact on transport decarbonization, as it is responsible for 65% of all freight emissions [23]. Given the importance of reducing freight transport GHG emissions, it is essential for companies to accurately measure and monitor their carbon footprint, including those of their suppliers.

Various instruments, methods, and guidelines have been developed for measuring the carbon footprint of transportation within supply chains, such as the EN16258 [42], the GLEC Framework developed by the Smart Freight Center [43], the recently (03-2023) published ISO14083 [22] and the GHG protocol [34]. These standards aim to ensure consistency and reliability in carbon footprint measurements and reporting for freight transportation. However, addressing the uncertainties stemming from assumptions or default factors used in carbon footprint calculations remains a significant challenge. Although these assumptions are necessary for initiating the calculation process, they inevitably lead to variations in the resulting carbon footprint, raising questions about the accuracy and reliability of these measurements.

This study seeks to delve into these uncertainties and shed light on their implications for managing freight transport emissions. Through empirical research involving field research and interviews, as well as an analysis of current methods, this research aims to provide insight into the uncertainties surrounding freight transport carbon footprints and their consequences for businesses and policymakers.

The scientific contribution of this project is underpinned by existing literature, such as [6, 37, 8], which highlights the importance of taking into account various factors that can impact the accuracy of carbon footprint measurements. However, these studies do not specifically focus on quantifying and addressing uncertainties in carbon footprint calculations.

Furthermore, this research holds the potential to benefit a wide range of stakeholders in the logistics and transportation sector, including shippers, carriers, consignees, and logistics service providers. By elucidating the uncertainties associated with carbon footprint assessments in freight transportation, this study can enhance the precision and reliability of these measurements. Consequently, this can support informed decision-making for transportation and logistics companies, policymakers, and consumers.

By providing a clearer understanding of the carbon footprint values and their associated uncertainties, the study aims to stimulate more informed dialogue among stakeholders when discussing the carbon footprint. This improved understanding can encourage stakeholders to recognize the inherent variability in carbon footprint calculations and make decisions based on a broader perspective, ultimately contributing to a more sustainable and environmentally conscious society.

This paper is structured as follows: Section II reviews relevant literature on uncertainty and carbon footprint measurements. Section III discusses the methodology used to identify and classify uncertainties. Section IV presents the analysis and assessment of the identified uncertainties. Section V presents the results of using the insights in IV to map the uncertainties around the carbon footprint of three cases from field research. Followed by a validation of the study in Section VI and discussion in Section VII. Finally, Section VIII concludes the paper and provides recommendations for future research.

II. LITERATURE REVIEW

A. The concept 'uncertainty'

Uncertainty arises when there is insufficient knowledge about a situation to describe it accurately or predict its outcomes [26]. Some researchers argue that uncertainty results from a lack of information. However, others, such as [49], contend that uncertainty can persist even when ample knowledge is available. In these cases, new information might reveal previously unknown or underestimated uncertainties in complex processes, leading to increased uncertainty. Various definitions of uncertainty have been proposed in the literature. For example, [45] defines uncertainty as the margin of doubt built into every measurement. In contrast, [44] posits that uncertainty lies between certainty and lack of knowledge. According to [32], uncertainty can result from a lack of precision (measurement error), accuracy (systematic error), or mistakes (incorrect measurements).

A critical distinction in the literature on uncertainty is the difference between variability and uncertainty. While variability refers to the variation within a measured value, uncertainty denotes imperfect knowledge of the true value of a particular quantity [45]. Uncertainty can be reduced by collecting additional data, but this is not possible for variability [32]. The relationship between variability and uncertainty is such that the probabilities used to describe uncertainty can be informed by variability [5].

Various frameworks have been developed to classify uncertainties, such as the uncertainty matrix by [49] and the decision tree by [50]. Based on these frameworks, uncertainties can be classified along three dimensions: the location or source of uncertainty, the nature of uncertainty, and the level of uncertainty [46].

Five sources of uncertainty (context, model structure, data input, parameter and model technical) have been identified, each with four levels ranging from determinism (lowest level) to deep uncertainty (highest level). The potential causes underlying these uncertainties include stochastic, ambiguity, and epistemic natures. Ambiguity represents the different interpretations people may have of a model or variable, leading to uncertainty in the actual definition chosen. Epistemic nature occurs due to a lack of knowledge, such as limited and inaccurate data, measurement error, and incomplete knowledge. Stochastic nature refers to the randomness originating from external input data, functions, parameters, and model structures, which could be explained by variability.

Uncertainties in carbon footprint measurements are primarily studied in the context of life cycle analyses (LCAs). Sources of uncertainty in LCA-related studies include scenario uncertainty, parameter uncertainty, and model uncertainty [20]. In PAS-2050:2011, uncertainty is categorized into two types: technical uncertainty, which arises from incomplete modeling, poor data quality, and other evaluation flaws; and natural variability, which is accounted for in a product's average or representative carbon footprint [18].

Assessing uncertainty

Assessing uncertainty is crucial in carbon footprint measurements and life cycle analyses. Various methods have been developed to quantify and address uncertainties, including uncertainty analysis, scenario analysis, and sensitivity analysis:

1) **Uncertainty analysis**: involves quantifying and propagating uncertainties in input factors. The IPCC suggests two methods for propagation: Monte Carlo simulation, which requires defining input uncertainties as probability distributions, and simple error propagation, which uses estimates of the mean and standard deviation for each input [51, 15].
2) **Scenario analysis**: determines how future events or uncertainties affect a result, usually by examining best-case and worst-case scenarios [4]. It can also be employed as a sensitivity analysis for model assumptions, such as allocation methods, system boundaries, and data choices [40].
3) **Sensitivity analysis**: measures the effect of uncertainty in input variables on output variables [35]. Several methods for performing SA exist, such as one-at-a-time sensitivity analysis, factorial design, and sensitivity index [17, 21, 19].

B. Carbon footprint

A carbon footprint is a measure of the total greenhouse gas (GHG) emissions associated with an activity, product, or system, expressed in CO_2 equivalents. The definition of a carbon footprint varies across studies, with disagreements on which GHGs to include in the calculations. Some studies include all GHGs, while others focus on legislated GHGs like the seven Kyoto gases (CO_2, CH_4, N_2O, HFCs, PFCs, SF_6 and NF_3) [54] or only carbonaceous gases (CO_2, CH_4, CO) [31]. It is essential to clearly define the boundaries and elements of the carbon footprint in each study to ensure comparability and facilitate a common understanding of the environmental impacts associated with the subject being studied.

Calculation Methods:

To determine the carbon footprint of freight transport, various calculation methods have been devised, with the EN16258 standard serving as the foundation. This European standard presents two approaches [42]: 1) consumption-based calculations and 2) distance-based calculations. The former relies on primary data, while the latter uses default data. In the consumption-based calculation (1), the total energy consumption is first calculated to obtain the emission figures (total kg CO_2 equivalents), which are then allocated to shipments or customers using an allocation factor based on transport activity. In the distance-based calculation (2), the total consumption is calculated using a default average (l or kWh/km) and subsequently allocated based on customer or shipment data. A default emission intensity factor representing energy consumption per ton-km is used if transport activity information is unavailable. The critical inputs for the carbon footprint are the energy consumption for a trip and the associated transport activity (e.g., load, origin, and destination of each shipment). Additionally, the system boundary, or scope, of the carbon footprint must be defined, which can encompass the entire activity of a carrier's fleet during a year, all round trips between two specific locations per quarter, or a single leg in a pickup and/or delivery trip.

Debates and Discussions:

EN-16258 must be accepted by the standardization institutes of 33 European nations. Several studies, however, have shown that the current version of EN-16258 has gaps and ambiguities that leave room for interpretation in a number of areas [24]. This makes it hard to compare how well different supply chains treat the environment and makes it harder to find the best ways to do things ([12]; [2]; [27]). The main points of critics are the different allocation methods, the problem of data sources and data accessibility, the definition of Vehicle Operating System, this definition in the EN16258 is very broad which creates ambiguity. The VOS is the scope determination of the carbon footprint. This can be defined as, for example: the entire activity of a carrier's fleet during a year. All round trips between two specific locations per quarter. Or a single leg in a pickup and/or delivery trip [14, 53]. The GLEC Framework attempts to address these criticisms and harmonize the process by standardizing allocation based on ton-kilometers and an aggregation level of one year. This must be done per VOS (now TOC: transport operation category) based on journey/contract type. The GLEC Framework will be the basis of the new ISO standard (ISO14083) that was in development to improve the EN16258 standard during this study.

III. PROPOSED METHOD

In this research, a method is proposed to classify and identify uncertainties in carbon footprint calculations for freight transport. This method is based on the theoretical framework derived from Walker's uncertainty matrix and incorporates insights from literature, field research, and interviews to systematically identify uncertainties and assess their effects on carbon footprint calculations.

A. Classification of Uncertainties

The theoretical framework is based on the uncertainty matrix developed by Walker, which provides a comprehensive tool for identifying and classifying uncertainties in a model-based decision support context. The framework consists of three dimensions that characterize uncertainty:

1) **Level of Uncertainty:** This dimension reflects the extent to which the uncertainty is known or quantifiable, ranging from determinism (no uncertainty) to deep uncertainty (unknown probabilities and outcomes).
2) **Location of Uncertainty:** This dimension pertains to the specific aspect of the carbon footprint calculation where the uncertainty arises, such as input data, parameters, model structure, or context.
3) **Nature of the Cause of Uncertainty:** This dimension refers to the underlying cause of the uncertainty, which can be stochastic (randomness), ambiguity (differing interpretations), or epistemic (lack of knowledge).

By applying this theoretical framework to the carbon footprint of freight transport, it is possible to systematically identify and classify uncertainties that may affect the accuracy and reliability of carbon footprint calculations. The theoretical framework is visible in Figure 1.

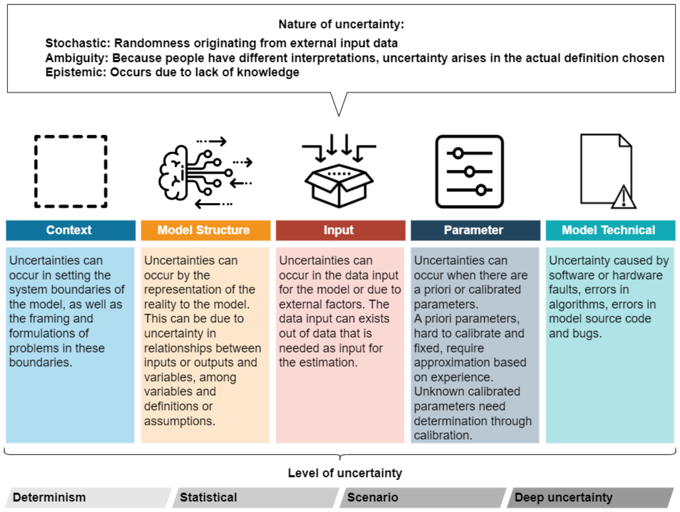

FIGURE 1: Theoretical framework

B. Identification of Uncertainties

To identify uncertainties in the carbon footprint of freight transport, a combination of research methods is employed, including literature review, field research, and interviews with experts. This approach enables a comprehensive understanding of the subject and ensures that the most significant uncertainties are identified.

1) **Background research:** An extensive review of relevant studies in literature, reports, and norms related to the carbon footprint of freight transport helps in identifying potential uncertainties in carbon footprint calculations.
2) **Field Research:** This research incorporates active participation in a project focused on calculating the carbon footprint of freight transport to a construction site. Engaging in this project offers valuable insights into the challenges and uncertainties arising during the carbon footprint calculation process. Field research components, such as site visits, interviews with co-makers (sub contractors), data review, and project-related meetings, facilitate a comprehensive understanding of the actual operations and practices within the transport and logistics industry. This helps verify and validate the data collected through other sources.
3) **Interviews:** Semi-structured interviews with three experts in carbon footprint measurements of freight transport help in identifying the most significant uncertainties and challenges in the field.

C. Assessing the Effects of Uncertainties

The identified uncertainties are further investigated to understand their effects on the variables used in carbon footprint calculations. By assessing the impact of uncertainties on the calculation, the reliability and accuracy of the carbon footprint results can be better understood. This, in turn, can help in improving the carbon footprint calculations and enhance their credibility for stakeholders such as policymakers, investors, and the general public.

In conclusion, the proposed method builds on the theoretical framework of Walker's uncertainty matrix and employs a combination of research methods to systematically identify and classify uncertainties in the carbon footprint of freight transport. By assessing the effects of these uncertainties on carbon footprint calculations, the aim is to enhance the credibility and reliability of carbon footprint measurements in the freight transport sector.

IV. CAUSES OF UNCERTAINTY UNDERLYING THE CARBON FOOTPRINT OF A SHIPMENT

A. Identification of uncertainty causes

As described in Subsection III.B, the theoretical framework that outlines the five locations and causes of uncertainties enables a targeted search for potential uncertainty causes in the various components of the carbon footprint calculation. To identify uncertainties in the carbon footprint of freight transport, a reflection of the background research is done. Subsequently, three interviews are conducted with experts in carbon footprinting of freight transport.The experts interviewed come from a variety of backgrounds. Expert 1 [E1] works at a software company that develops tooling to map the carbon footprint of freight transportation, Expert 2 is from a research and consulting firm that publishes emission intensity factors for freight transportation [E2], and Expert 3 is a consultant who has been involved in several carbon footprint projects [E3]. In this subsection, the list of potential causes of uncertainties that have been identified is presented, organized by 'location'. Accompanying each cause is the source from which the uncertainty was identified. Furthermore, the notations E1/E2/E3 are used to reference expert interviews, while an F indicates field research.

Potential causes of uncertainty arising in the context:

- Definition of Carbon Footprint: Different interpretations of a 'carbon footprint' lead to different scopes and the inclusion or exclusion of emissions in the measurement [E1, E2, E3] [31, 33, 52, 54].
- Boundary Carbon Footprint of Transportation: Different system boundaries can be defined for a carbon footprint of freight. Unclear boundaries can lead to different interpretations [E1][F] [14, 53].

Potential causes of uncertainty arising in the model structure:

- Different Allocation Methods: Multiple options exist for allocating emissions, and the method used has a significant influence on the carbon footprint of a customer's shipment [E2] [12, 27, 25, 53].
- Linear Approach Calculating Emissions: The emissions N2O and CH4 do not have a linear relationship with energy use as CO2, resulting in a simplification of the model [29, 39].

- Assumptions of trip data: When trip details are partially available, assumptions can be made to estimate with available information, leading to uncertainties [F].

Potential causes of uncertainty arising in the data input:

- Energy consumption/unit-km during a certain time (also known as energy intensity factor).
  - Average value: There are many factors that affect fuel consumption [1, 7, 36, 13, 48, 28, 41, 42]. Specific route characteristics, driving behaviour, environmental influences and when multiple vehicles are used; also the vehicle characteristics are less reflected in the output [E3] [3].
  - Unknown how average energy consumption/unit-km is calculated: When it is unknown how the average energy consumption/unit-km is calculated there is a possibility that wrong calculations are made.
- Average energy consumption/km during a certain time
  - Average value: There are many factors that affect fuel consumption [1, 7, 36, 13, 48, 28, 41, 42]. Specific route characteristics, loading characteristics, driving behavior, environmental influences and when multiple vehicles are used; also the vehicle characteristics are less reflected in the output [3].
  - Unknown how average energy consumption/km is calculated: When it is unknown how the average energy consumption/km is calculated there is a possibility that wrong calculations are made.
- Amount of energy
  - Measurement error amount of energy: When the average fuel consumption is based on data from fuel cards there exists a measurement error, when someone tanked on the 31st of the month the data is included in the past month but is used in the next month [E2, E3].
- Default energy consumption/km
  - Approximation of fuel consumption by modelling: There are many factors that affect fuel consumption [1, 7, 36, 13, 48, 28, 41, 42]. No specific route characteristics, driving behavior, environmental influences and vehicle characteristics of trip reflected in the output. Due to approximation effect of load included (default factors fuel consumption empty, full and capacity) [13, 16].
  - Industry average: There are many factors that affect fuel consumption [1, 7, 36, 13, 48, 28, 41, 42]. No specific route characteristics, loading characteristics, driving behaviour, environmental influences and vehicle characteristics of trip reflected in the output.
- Energy type
  - Specifications or the energy type is unknown: It might be the case that for example the fuel type is defined as “(bio-)diesel” while there are multiple types of (bio-)diesel [F].
- Origin, stops and destination
  - Different interpretations of origin: Often the destination of a shipment is known, the origin of the transport of a shipment can have ambiguity when this is not defined clearly [E1] [F] [16].
  - Aggregated level ’origin’ and ’destinations’ due to lack of knowledge or privacy reason: It might be that organizations only know the origin as ’city’ and have no specifications in ’postal code’ level [E2][F].
  - Information stops are unknown, or only a part is known: When only a part of the trip data is known, or the trip data is unknown. Assumptions have to be made [F].
- Distance
  - Multiple definitions of distance: Uncertainty can arise when these distances are assumed to be equal. For example, if the average fuel consumption is calculated using the number of liters and the total planned distance, and then multiplied by the number of kilometers actually driven, an incorrect calculation is made. In addition, it is questionable whether the carbon footprint can be compared when different distances are used [E3] [11] [F].
  - Distance Unknown: When distance is unknown, an estimation must also be made, for which Google Maps can be used, which requires input of address data. When done in this way, the shortest feasible distance is calculated. This means that there is a deviation from the real driven distance [F].
- Payload
  - Multiple definitions of ”weight” payload: There could be different interpretations of tonne (packaging included or not) [E2], [42].
  - Information payloads are unknown, or only a part is known: When only a part of the payload is known, or the payload is unknown. This occurs mainly in smaller companies or when data cannot be shared by carriers to shippers about other customers. Assumptions have to be made for the allocation of emissions [E1, E2, E3] [F].
  - Unknown weights: the payload is measured in units other than weight and the weights of the shipments are unknown. When allocation has to be done by weight this causes uncertainty [E1,E3].
- Shipment type
  - Different interpretation shipment type: When the shipment type is different interpreted the wrong emission intensity factor can be applied [E2].
- Vehicle type
  - Different Interpretations of Vehicle Types: There are multiple ways and interpretations to describe a vehicle type. Due to this, the input for fuel consumption estimation can be wrong, or the wrong emission intensity factor will be applied [E2] [F].

  - Vehicle Type unknown: When the vehicle type is unknown, there will be a broad range of possible vehicle types. Due to this, the input for fuel consumption estimation can be wrong, or the wrong emission intensity factor will be applied [E2] [F].
- Amount of trips
  - The Amount of Trips are Unknown or Only a Part of the Trips is Known: When only a part of the total trips is known or the trip data is unknown, assumptions have to be made, for example, based on the total demand and capacity of a vehicle. This brings uncertainty in the amount of trips as input data [F].

Potential causes of uncertainty arising in the parameters:

- Measurement error emission factor TTW (Tank-to-Wheel): Multiple measurements result in a measurement error [E2] [30].
- Measurement error emission factor WTT (Well-to-Tank): Multiple measurements result in a measurement error [E2] [30].
- Different emission (intensity) factor databases: Different databases can be used to select emission factors such as the data base of the GLEC Framework [43] and dutch emission factors from co2emissiefactoren.nl [38]. The use of different databases leads to multiple emission factors for specific situations and different outcomes.
- Default emission intensity factors: These general factors are very generic and often deviate from reality [E1,E2].
- Conversion factor: The conversion factor needed when the payload is measured in different metrics has measurement errors [E3].

B. Dependency of uncertainty causes from data input and parameter input on data situation

As the field research emphasized trip-level carbon footprints, it influenced subsequent research steps. Field research, interviews, and background research unveiled that the uncertainties from the data input and parameters depend on data availability. Existing literature and protocols have highlighted this influence of various data situations on the calculation of a carbon footprint [10, 14]. While the literature initially outlined four main situations [10], variations were observed during the field research, resulting in the identification of seven distinct data scenarios. These are based on how carbon footprints are calculated, using available information on energy consumption and transport activity data (origin, destination, and payload). Each data situation has its fundamental uncertainties, that are always present, and situation-dependent uncertainties. The fundamental uncertainties include variation in emission factors (diesel and petrol emission factor difference between two databases are 3 to 4%) (F1), default energy consumption uncertainty (energy consumption based on industry averages has a margin of +- 16.5%, a modeled energy consumption +-12.5%) (F2), assumptions for other loads or destinations on the route (dependent on the number of stops on the route, but can lead to significant differences in the allocation factor) (F3), and default emission intensity factors (varying the underlying assumptions about energy consumption and average payload by 12.5% and 15% results in an emission intensity factor with a -32% and +51% range) (F4).

Seven data situations were identified, shown below, with the fundamental uncertainties and equation that applies:

- Data situation 1(F1 and Eq 1): The carbon footprint of a shipment can be calculated based on known energy consumption of the trip and known transport activity on that trip.
- Data situation 2 (F1 and Eq 2): The carbon footprint of a shipment can be calculated based on emission intensity (CO_2e/ton-km) or energy intensity factor (l or kWh/ton-km) known and calculated by the transport company, multiplied by the distance and payload of the shipment.
- Data situation 3 (F1 and Eq 3): The carbon footprint of a shipment can be calculated with the average energy consumption of the vehicle in km/l or km/kWh and the transport activity of the trip.
- Data situation 4 (F1, F2 and Eq 4): The carbon footprint of a shipment can be calculated with a default average energy consumption in km/l or km/kWh and the transport activity of the trip.
- Data situation 5 (F1, F3 and Eq 3): The carbon footprint of a shipment can be calculated based on the average energy consumption of the vehicle in km/l or km/kWh, but not all data on transport activity is known, and assumptions must be made.
- Data situation 6 (F1, F2, F3 and Eq 4): The carbon footprint of a shipment can be calculated with a default average energy consumption and not all data on transport activity is known, assumptions must be made.
- Data situation 7 (F4 and Eq 5): The carbon footprint of a shipment must be calculated with default emission intensity factors, as there's no better approximation due to missing data on transport activity and energy consumption.

$$CF = \text{Total Energy Consumption of the trip} \times \text{EF} \times \text{Allocation factor} \quad (1)$$

$$CF = \text{Energy Intensity Factor} \times \text{EF} \times \text{Distance shipment} \times \text{Payload shipment} \quad (2)$$

$$CF = \text{Average Energy Consumption per km} \times \text{Distance} \times \text{EF} \times \text{Allocation factor} \quad (3)$$

$$CF = \text{Default Energy Consumption per km} \times \text{Distance} \times \text{EF} \times \text{Allocation factor} \quad (4)$$

$$CF = \text{Default emission intensity factor} \times \text{Distance} \times \text{Payload shipment} \quad (5)$$

As discussed fundamental uncertainties are not the only uncertainties that can occur when calculating a carbon footprint. Other causes have been discovered that can create uncertainty around an input variable of the carbon footprint. For example, when an average energy consumption is based on the number of liters divided by the actual driven distance, and only the planned distance is available for a route, the planned distance must be converted using a factor to switch to the actual driven distance, or vice versa. This is not a fundamental uncertainty that always occurs in the data situation but is a possible variation in these data situations. The uncertainties found in Subsection IV.A are subdivided based on when they can occur in the table below 1

TABLE 1: Possible uncertainty causes per situation

Potential uncertainty causes that can arise per situation	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
Uncertainty in unknown: Energy Type	X	X	X	X	X	X	X
Uncertainty in Emission Factors	X	X	X	X	X	X	
Uncertainty when Conversion Factor needs to be applied	X	X	X	X	X	X	X
Uncertainty in definition: Payload	X	X	X	X	X	X	X
Uncertainty due to variability of Average Value		X	X		X		
Uncertainty about Calculation		X	X				
Uncertainty in definition: Distance		X	X	X	X	X	X
Uncertainty due to other distance type than used for average			X	X	X	X	X
Uncertainty due to unknown distance		X	X	X	X	X	X
Uncertainty in specification level: address Origin, Stops, and Destinations on GCD	X	X	X	X	X	X	
Uncertainty in specification level: address Origin, Stops, and Destinations on Unknown Distance			X	X	X	X	X
Uncertainty in definitions: address Origin, Stops, and Destinations on GCD	X		X	X	X	X	
Uncertainty in definitions: address Origin, Stops, and Destinations on Unknown Distance			X	X	X	X	
Uncertainty due to variability of Default Value				X		X	
Uncertainty due to variability of Average Modeled Value				X		X	
Uncertainty due to definition: Vehicle				X		X	X
Uncertainty due to unknown: Vehicle Type				X		X	X
Uncertainty due to definition: Shipment Type							X
Uncertainty due to unknown: Shipment Type							X
Uncertainty due to emission intensity factors							X
Uncertainty due to unknown: Payload other Stops Assumption average value payload with vehicle capacity					X	X	
Uncertainty due to unknown: adres other Stops Assumption trip is Dedicated, replace Allocation Factor with * 2					X	X	
Uncertainty due to unknown: Amount of Trips Assumption Total Demand/Capacity Vehicle						X	

C. Impact of uncertainties on the end figure

Each identified uncertainty affects a data input variable or the parameter used to calculate a carbon footprint. Due to the uncertainty, the input variable changes, resulting in a certain margin. As the carbon footprint calculation formula consists of many multiplications, uncertainties can quickly have a significant impact on the carbon footprint if present. An example of how uncertainty works in the formula can be seen in Figure 2, which illustrates this for the situation where energy consumption must be calculated using default values and the situation where emission intensity factors must be used because no primary data is available. This research also looked at which causes will have the biggest effect, by determining the possible margin that occurs within the input variable due to the cause and the effect on the carbon footprint. The causes of uncertainties that have the biggest effect are: the use of default emission intensity factors (F4), the use of default energy consumption values (F2), the use of assumptions for other loads or destinations on the route (F3), the unknown energy type that is used because this influences the selection of the emission factor, applying a standard conversion factor to convert another load unit to weight, wrong interpretation of origin and destination when the distance is needed to calculate energy consumption, and when default factors are used additional uncertainty can arise if the vehicle type and/or shipment type is unknown or unclear because this influences the selection of the default factor.

D. Assessment of uncertainties

After identifying the uncertainties and examining how they can influence the final result, it is necessary to quantify these uncertainties to properly assess their impact. Several methods are available for this purpose, as discussed in Subsection II.A. In this study, the decision has been made to quantify uncertainties that have underlying causes, such as assumptions or stochastic uncertainty around default values or conversion factors. Uncertainties caused by definitional issues can be prevented through effective communication. In this research, it is recommended to take definitional uncertainties seriously during data collection or calculation of a carbon footprint, and to prevent them as much as possible. To address uncertainties arising from assumptions, it is suggested to use worst-case and best-case scenarios, as well as assumption scenarios, where possible. To address uncertainties arising from stochasticity, the use of probability density functions in combination with Monte Carlo simulations is recommended. This approach offers a more realistic representation of uncertainty. By determining a confidence interval, insights into possible outcome ranges can be provided instead of presenting best-worst-case scenarios. In Section V, the effects of the uncertainties on two cases are demonstrated.

V. CASE STUDY

This study developed a tool (an approach) to support identifying and quantifying the uncertainties described in Section IV. Using the developed approach, this section will test and investigate how uncertainties can impact the final value. Two tests will be discussed based on data from the field research. This involves selecting two random trips from two random co-makers/subcontractors (clients requesting products to be transported to a construction site) to calculate the carbon footprint and assess the underlying uncertainties based on the provided data. Furthermore, the research will examine the effects of substituting probability density functions and Monte Carlo simulations for stochastic uncertainties with best-worst case scenarios, similar to how assumptions are treated. The two random trips have been identified as data situations 4 and 7, presented in Figure 2. By conducting these tests, the study aims to provide a deeper understanding of the consequences of different methods for dealing with uncertainties on the calculated carbon footprints, ultimately shedding light on the most

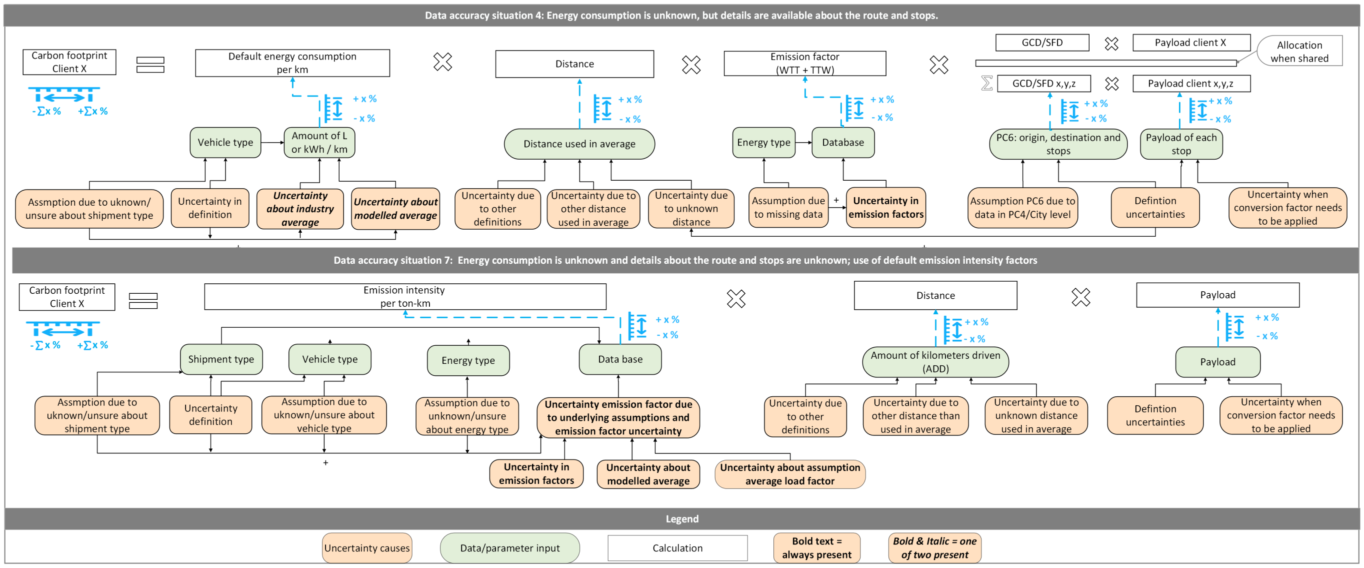

FIGURE 2: Visualization of effects of uncertainty

effective approach for the accurate assessment of carbon emissions from transportation.

A. CASE 1

Data situation description: The trip is a 'shared' trip, the truck is driving a round trip and delivers two shipments in that trip. The truck needs to pick up extra payload from two locations. The **fuel consumption** of the trip is **estimated** by the company itself (not calculated). The **trip data is known**. The cargo is known for the shipment to the construction site and of the other client. The location of the loading point of the other customers shipment and the address of that client are **known on PC4 detail level (instead of preferred PC6 level)**. The distance is unknown and calculated with Google Maps. The route and information of the stops is visible in Figure 3. Thereby data situation 4 applies: the carbon footprint of a shipment can be calculated with a default average energy consumption in km/l or km/kWh and the transport activity of the trip.

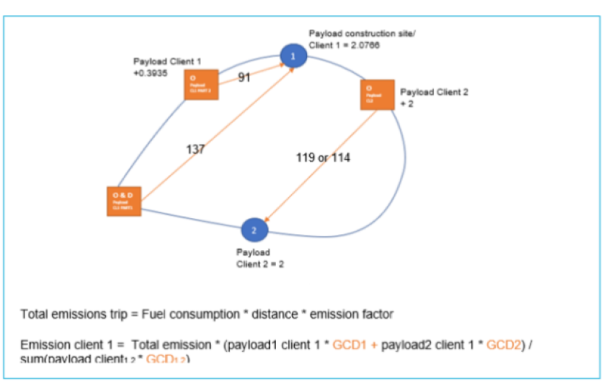

FIGURE 3: Visualization of trip case 1

1) Inputs case 1:

To establish the carbon footprint of the emissions that are allocated to the building site, the total fuel consumption needs to be calculated. The company has no information about the fuel consumption of the trip, has no average fuel consumption based on primary data and had no emission intensity value calculated by the company. This means an average estimated average is provided by the company. Following the approach, this average fuel consumption carries uncertainty because it is not based on primary data and is influenced by many factors that cause variability. To account for this the approach recommends to use a probability density function that takes into account the possible effects of payload and driving behaviour on the average fuel consumption. The second important factor that is needed, is the distance of the trip. This distance is unknown; to make a propper estimation the route is reconstructed with the help of Google Maps. This also causes uncertainty; google maps does not account for the characteristics of the vehicle and decides the route based on the shortest time at a certain time thereby this distance does not take into account any detours caused by driving the wrong way or refueling. To take this uncertainty into account the approach recommends also to take into account the uncertainty with the help of probability density function. When the total fuel consumption is known this need to be converted to CO_2e. Thereby another cause of uncertainty is the uncertainty in emission factors; the approach recommends to use a probability density function that uses the emission factor of the GLEC database (EU value) [43] and CO2emisisonfactor data base (NL value) [38] to account for this uncertainty. After this the emission that is allocated to the building site needs to be calculated. This is done with the Great-Circle-Distance (estimated with the origin and destination of the shipments) and the weight of the shipments. The last source of uncertainty that is found, is the aggregation level of the destination of the stop of the other client. The approach recommends to look at the great-circle-distance difference this will cause, when looking at the difference of the GCD within the PC4 level and the total GCD, this difference will not make a big difference (5 km upon 114 km) in the allocation of the emissions, this will cause a difference of less than 2% and is therefore for now not included. The estimation of the carbon footprint attributed to the construction site is conducted by incorporating probability density functions (PDFs), which are simulated using Monte Carlo methods implemented in Python. The following part of this section explains the constructed PDFs.

Probability density functions: currently based on assumptions made in thesis research:

1) Average fuel Consumption (FC): because there is little information about the uncertainty/variation underlying the fuel consumption, a probability density function is made based on the assumptions made in this study. This is +- 16.5% for the average fuel consumption. Because there is a clear max and minimum value, the PDF will be triangular: $\min = 2.5\,\text{km/l}$, mode: $3.0\,\text{km/l}$, and $\max = 3.5\,\text{km/l}$
2) Because there is little information about the uncertainty/variation underlying the emission factor a probability density function is made based on the different values in data bases. It is assumed that these have the same probability, therefore the PDF will be uniform: Emission Factor (EF) uniform distribution between NL value (3.256) and GLEC value (3.148).
3) Distance: Because there is little information about the uncertainty/variation underlying the distance a probability density function is made based on the assumptions in this research and a percentage that needs to be applied to account for detours. This is +10% from the constructed distance to the actual driven distance (assumption from study based on comparing actual driven distances to Google Maps distances). Thereby a distinction has to be made when a detour is made which will include a percentage of +30% (according to [43]). The probability of a detour is less likely to happen and therefore a maximum value, thereby the minimum value of the distance will be the Shortest feasible distance. Because there is a clear max and minimum value, the PDF will be triangular: $\min =$ Shortest Feasible Distance, mode: distance $+\,10\%$, max: distance $+\,30\%$ (detours)

In Figure 4 the PDF's are visualized. The probability density function (PDF) represents the likelihood of specific distance (or fuel consumption or emission factor) values occurring within a triangular (or uniform for emission factor) distribution. The y-axis (f(x)) shows the probability density for each distance (or fuel consumption or emission factor) value (x) on the x-axis. Higher f(x) values indicate a greater likelihood of the corresponding distance (or fuel consumption or emission factor) value (x) occurring. Note that f(x) represents the density around a particular value, not the exact probability of that value occurring.

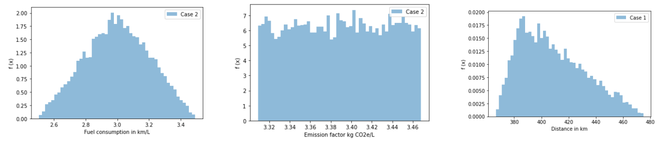

FIGURE 4: Input probability density functions case 1

2) Results case 1:

Both the carbon footprint for the entire trip and the portion attributed to the construction site have been calculated. The output of the carbon footprint can be seen in Table 2. The output is also plotted in a boxplot for visualization, which is shown in Figure 5. The total emissions are influenced by the calculation of total fuel consumption, where the probability density functions primarily have an impact. Next, the emissions attributed to the construction site are presented. This represents the portion assigned to the construction site based on the GCD and the weight in load. Since all the data on this is known, this output is also influenced only by the PDFs. The emissions for the construction site (Client 1) are between the 285.34 en 341.46 kg CO_2e (within the 95% confidence interval). The total emissions may lie between 519.35 en 621.51 kg CO_2e. Additionally, the case where PDFs cannot be used and Monte Carlo simulations cannot be performed has been tested, requiring the use of scenarios as a replacement. The results of this approach are shown in Table 3. In these scenarios, the most favorable, unfavorable, and average situations for the total emissions and therefore also for the construction site are taken into account. As can be seen, the range is now much larger, the emissions from the shipment to the construction site will lay between 240.22 and 422.69 kg CO_2e. The total emissions also have a broader range, namely between 437.23 and 769.37 kg CO_2e.

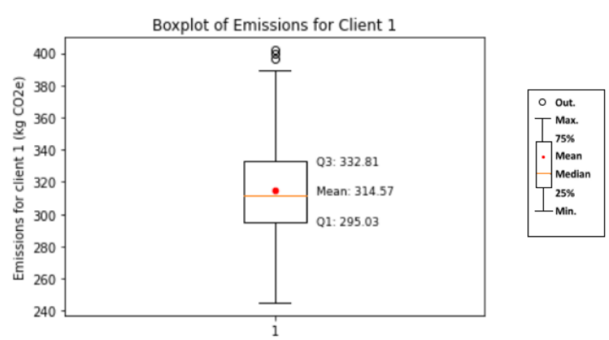

FIGURE 5: Results case 1

TABLE 2: Output case 1 with PDF's

	Emissions (kg CO_2e)	**KPI (kg CO_2e/ton)**
Client 1	313.40 +/- 28.06	150.92 +/- 13.51
Total	570.43 +/- 51.08	-

TABLE 3: Output case 1 with scenario's instead of PDF's

	Input			**Output**		
Scenario	**Emission factor (kg CO_2e /L)**	**Fuel consumption (km/L)**	**Distance (km)**	**Emissions client 1 (kg CO_2e)**	**KPI client 1 kg CO_2e/ton**	**Total emissions (kg CO_2e)**
Best case	3.148	3.5	470	240.22	115.68	437.23
Assumption	3.213	3.0	520	305.97	147.34	556.92
Worst case	3.256	2.5	611	422.69	203.55	769.37

B. CASE 2

The co-maker/subcontractor did **not have details of the other stops** on the route even though the trips were shared. Additionally, the **weight and planned distance** from start to delivery point are **known**. The **vehicle type** is described as a box truck with a crane ("bakwagen met autolaadkraan"), which is **not a detailed description**. The **fuel consumption is unknown**. The shipment type is described as neither bulk nor volume goods, indicating an **average load**. This is a situation where an emission intensity factor must be used because no other assumption can be made. The route and information of the stops is visible in Figure 6. Thereby data situation 7 applies: the carbon footprint of a shipment must be calculated with default emission intensity factors, as there's no better approximation due to missing data on transport activity and energy consumption.

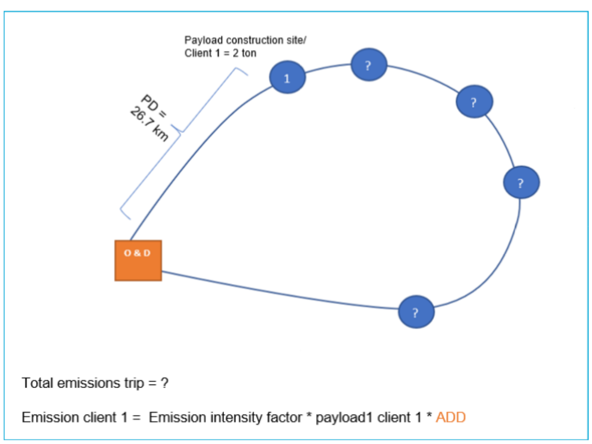

FIGURE 6: Case 2: Situation 7

1) Inputs case 2:

To establish the carbon footprint of the emissions allocated to the building site with no information about the transport activity and energy consumption, a default emission intensity factor should be used. The first step is to select the right factor, which is based on the shipment, vehicle and energy type. The shipment type is 'average', the energy type is 'Diesel' and the vehicle type is described as 'Bakwagen met autokraan (dutch), Box truck with car crane (translation)". Uncertainty arises due to the inadequate specificity in the vehicle type description, preventing the selection of a singular vehicle type. This effect can be quantified through scenario analysis, as suggested by the used approach. Furthermore, the emission intensity factor introduces additional uncertainty, as it relies on a multitude of assumptions originating from variable factors. The assumptions that are made are the energy consumption per km and the average load factor, thereby also the uncertainty of the emission factor applies. To account for this the approach recommends using of a probability density function that takes into account the possible effects of the average payload (based on the ratio of loaded kilometers and average load factor of loaded trip) and the average fuel consumption (modelled based on capacity of vehicle and average load factor). When the emission intensity factor is selected, the emissions are calculated based on the payload of the shipment and the distance to deliver the shipment to the construction site. The weight of the shipment and the planned distance are known. Because the emission intensity factor is based on actual driven distance the planned distance need to be converted to actual driven distance. This is also a cause of uncertainty, the approach recommends to take this uncertainty into account with the help of probability density functions. The estimation of the carbon footprint attributed to the construction site is conducted by incorporating the scenarios and probability density functions (PDFs), which are simulated using Monte Carlo methods implemented in Python. The following part of this section explains the constructed PDFs. The following part of this section explains the scenario's and constructed PDFs.

Scenarios where vehicle type is uncertain:

1) The vehicle type "bakwagen met autolaadkraan" is not listed as a vehicle type in the emission intensity factors. Therefore, a best-worst case scenario will be chosen for two vehicle types that could represent it. These types are truck $<$ 10 tons and truck 10-20 tons.
2) The best-case scenario for the construction site would be when the lowest EIF is selected, which is 0.256 per ton-km (truck 10-20 tons), and the worst case for the construction site would be when the highest EIF is selected, which is 0.363 (truck $<$ 10 tons). These numbers come from [9].

Probability density functions: currently based on assumptions made in thesis research:

1) Emission Intensity Factor (EIF): Because there is little information about the uncertainty/variation underlying the distance a probability density function is made based on the assumptions made in this research: varying the assumptions for load factor by +-15% and modeled

energy consumption with +-12.5% will lead to a variation of - 31.5% and +51% for the emission intensity factor. Because there is a clear max and minimum value, the PDF will be triangular: $\min = EIF \times 0.685$ kg CO_2e/ton-km, mode $= EIF$ kg CO_2e/ton-km, and $\max = EIF \times 1.51$ kg CO_2e/ton-km.

2) Because there is little information about the uncertainty/variation underlying the distance, a probability density function is made based on the percentage that needs to be applied to convert different distances. These are based on the factors provided by the GLEC Framework [43]. This is +5% for Planned Distance to Actual Driven Distance, and thereby, a distinction has to be made when a detour is made, which will include a percentage of +30%. The probability of a detour is less likely to happen, and therefore, a maximum value, thereby the minimum value of the distance, will be the Planned Distance or Shortest feasible distance. Because there is a clear max and minimum value, the PDF will be triangular: $\min =$ Plannend Distance, mode: SFD $+ 5\%$, max: PD $+ 30\%$ (detours)

In Figure 7 the PDF's are visualized. The probability density function (PDF) represents the likelihood of specific distance (or emission intensity factor) values occurring within a triangular distribution. The y-axis (f(x)) shows the probability density for each distance (or emission intensity factor) value (x) on the x-axis. Higher f(x) values indicate a greater likelihood of the corresponding distance (or emission intensity factor) value (x) occurring. Note that f(x) represents the density around a particular value, not the exact probability of that value occurring.

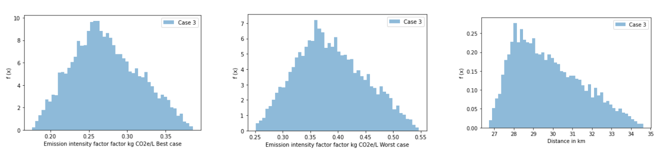

FIGURE 7: Input probability density functions case 2

2) Results case 2:

Because there is no knowledge of the trip data, an estimation of the shipment's emissions can only be made using emission intensity factors. The output of the carbon footprint can be seen in Table 4. The output is also plotted in a boxplot for visualization, which is shown in Figure 8. The emissions are influenced by the uncertainty of distance and the emission intensity factor, which are mapped using probability density functions. In addition, it is uncertain which vehicle type was used, increasing the uncertainty of the emission intensity factor. This is shown by outlining scenarios of the two types of vehicle types. The vehicle type with the lower emission intensity factor is the best-case scenario, while the worst-case scenario is the vehicle with the higher emission intensity factor. As seen in Table 4, the emissions associated with the shipment are between 13.5 and 19.08 kg CO_2e for the best-case scenario and between 19.29 and 27.21 kg CO_2e, resulting in a total spread of 13.5 to 27.21 kg CO_2e. Additionally, the case where PDFs cannot be used and Monte Carlo simulations cannot be performed has been tested, requiring the use of scenarios as a replacement. The results of this approach are shown in Table 5. In these scenarios, the most favorable and unfavorable situations for the emissions are taken into account. As can be seen, the range is now much larger; the emissions from the shipment to the construction site will lay between 9.36 and 38.05 kg CO_2e.

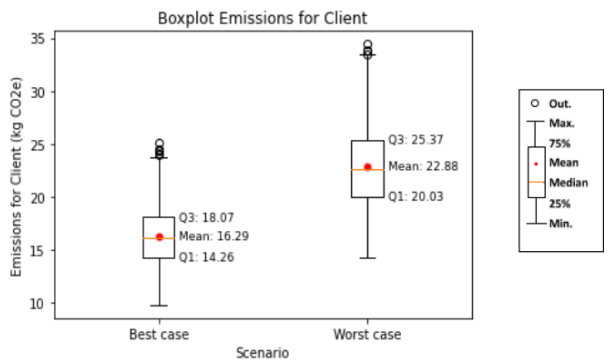

FIGURE 8: Results case 2

TABLE 4: Output case 2 with PDF's

	Input	Output
Scenario	**Emission intensity factor (kg/ton-km)**	**Total emissions (kg CO_2e)**
Best case	EIF = 0.256 Triangular Probability Density function min = EIF*0.685, mode= EIF and max = EIF*1.51	16.29 +/- 2.79
Worst case	EIF = 0.363 Triangular Probability Density function min = EIF*0.685, mode = EIF and max = EIF*1.51	23.25 +/- 3.96

TABLE 5: Output case 2 with scenario's instead of PDF's

	Input			Output
Scenario	**Emission intensity factor (kg/ton-km)**	**Distance (km)**	**Load (ton)**	**Total emissions (kg CO_2e)**
Best case	0.17528 (0.256*0.685)	26.7	2	9.36
Worst case	0.54713 (0.363*1.51)	34.71	2	38.05

VI. VALIDATION RESEARCH

his assessment is achieved through the feedback of five interviewed experts, each providing a unique perspective based on their respective experience ranging from three to fifteen years in areas such as supply chains, carbon footprinting, sustainable freight transport, and sustainable mobility. Their collective knowledge and diversity of expertise served as a comprehensive mechanism for validating the results of the study.

The expert feedback largely concurred with the identified uncertainties while highlighting additional uncertainties and aspects for future consideration. An important point that emerged about the uncertainties underlying emission factors is that one expert said that differences arise because different boundaries are currently used to achieve them using a life-cycle approach. In addition, this uncertainty is greatest for well-to-tank emission factors than tank-to-wheel emission factors. This is something that gave a deeper look into this uncertainty. Furthermore, experts agreed that uncertainty depends on information availability and found it logical to link these uncertainties to data situations. However, a critical point was the level of detail in the data situations, which are based on trip-level analysis but necessitate adjustments for aggregate-level use (which will be needed in the new ISO standard: ISO 14083). Thereby, one expert found the distinction of the data situations not immediately clear. Nevertheless, experts acknowledged that the insights on uncertainties could still be applicable at the aggregate level. Experts emphasized that the growing awareness of upcoming regulations and increased client interest in transportation carbon footprints might incentivize companies to address uncertainties and improve data accuracy. Companies have begun incorporating CO_2 measurement and reduction plans into their contracts and increasingly demand a certain quality of data and calculation methods. However, many companies are not yet advanced in this area, and the focus on carrier-specific emission intensity factors remains in its early stages.

VII. DISCUSSION

This section will reflect on the results, and implications for theory and practice will be mentioned. In addition, the limitations of this research will be discussed.

A. Reflection on the results

Firstly, the results of the case studies revealed that the causes of uncertainty can significantly impact the carbon footprint. This effect is particularly evident when all uncertainties are quantified using best and worst-case scenarios. However, using probability density functions narrows the range, providing a more realistic perspective. The probability distributions used in this research are based on assumptions and require further investigation, but they demonstrate the effect of their application. The two case studies presented here demonstrate the influence of uncertainties on the final outcome, but it is important to note that other causes, beyond those discussed in these studies, also have an impact. The main causes of uncertainty with the greatest impact include the use of default emission intensity factors, default energy consumption values, assumptions for other loads or destinations on the route, unknown energy types that affect the selection of emission factors, the application of standard conversion factors to convert different load units into weight, misinterpretation of origin and destination when calculating energy consumption based on distance, and the additional uncertainty that can arise from using default factors when the vehicle type and/or shipment type is unknown or unclear, as this affects the selection of the default factor. It is crucial to address these causes to minimize uncertainties. Additionally, it is important to prevent definitional uncertainties through effective communication between those requesting data and those providing data to calculate the carbon footprint.

Secondly, the validation process conducted with experts in the field demonstrated a general consensus on the identified uncertainties. This shared understanding of uncertainties highlights the need for further exploration, as they depend heavily on the amount and level of detail of the available information. An important point of discussion among the experts was that this research focused on estimating the carbon footprint at the trip level, while the new ISO Standard recommends considering an aggregated level. The following subsection provides a reflection on the identified uncertainties that will remain relevant at this aggregated level. Furthermore, it is recommended to investigate these aspects further in future research.

B. Reflection findings and ISO 14083

The new ISO standard for calculating emissions, based on the GLEC Framework, calculates and allocates emissions from a more aggregated approach. This means calculating the carbon footprint for a Transport Operation Category by dividing total energy consumption by transport activity and multiplying it by an emission intensity factor (resulting in an emission intensity factor), which is then multiplied by the client's transport activity. Consequently, there are fewer and different data situations, as noted by experts during validation. While the research developed a guidance framework at the trip level, the guidance frameworks for data situations 2 and 7 can be directly applied at aggregated levels. This is because data situation 2 specifically addresses the potential uncertainties introduced by the application of calculated emission intensity factors. Moreover, in situations where data on transport activity and energy consumption are unavailable, the use of default emission intensity factors is recommended by the GLEC framework (and new ISO). This aligns with data situation 7, which mandates the utilization of a default emission intensity factor when primary data is lacking. Furthermore, it is also important to identify the uncertainties that can play a role in calculating an emission intensity factor. If the total energy consumption is unknown, it still needs to be modeled, and the same uncertainties apply when this is done at the trip level; this is similar to data situation 4 where the energy consumption of the trip must be modeled to calculate the total emissions. Another cause of uncertainty that might occur and will be a challenge is the knowledge about which energy type is used in a year. If this is not properly monitored, it can cause problems in the allocation of the number of liters with the relevant emission factor. Another potential cause is also uncertainty is when assumptions must be made if part of the transport activity is unknown and an estimated average payload must be used. Another cause of uncertainty that might occur is the uncertainty due to the use of conversion factors to convert payload from other units to tonnages; inconsistent application of conversion factors can lead to significant uncertainty.

Furthermore, after examining this field, several significant challenges are anticipated in the implementation of the ISO approach, in addition to the aforementioned uncertainties. One compelling rationale for advocating an aggregated approach is the equitable distribution of seasonal influences among all clients. Furthermore, it is argued that achieving an emission intensity factor becomes relatively straightforward with the availability of fuel card data, obviating the necessity for state-of-the-art onboard computers for a reasonably accurate estimation.

A pertinent consideration arises regarding the potential uncertainty associated with defining Transport-Operational Combinations (TOCs), particularly in relation to the utilization of fuel card data. Even with individual fuel cards assigned to each truck, distinguishing fuel consumption per TOC remains challenging when a truck serves multiple purposes, such as shared and dedicated trips, particularly in the absence of onboard computers.

Additionally, the adoption of a general allocation factor (ton-km) to facilitate meaningful comparisons poses significant challenges for Logistics Service Providers (LSPs) or carriers who lack knowledge of cargo weights and employ diverse payload measurement units. For instance, the unawareness or disregard of a standard conversion factor for pallets, where a pallet weighs 50 kg and the standard conversion factor is 400 kg, may result in a grossly inaccurate estimation of the annual emission intensity factor. Furthermore, when clients possess knowledge of the weight and calculate emissions based on their own figures, the lack of consistent calculation methodology further exacerbates the uncertainty surrounding this value.

Furthermore, the notion of Great Circle Distance is not widely known within the context of road transportation communication, and it is imperative for many companies to become acquainted with this concept.

C. Limitations

This research provides insights into carbon footprinting in the freight transport sector, yet it is important to acknowledge its limitations, which may influence the generalizability and applicability of the findings.

First, the study's focus is primarily on freight transport, specifically road transport. Therefore, its results may not directly apply to other types of transport.

Second, the field research primarily involved interactions with shippers, which may have limited the range of insights and perspectives and influenced the identified uncertainties and data situations. Another consequence of this is that the study focused more on estimating the carbon footprint from a Scope 3 perspective.

Third, data availability posed a significant challenge in this research. The limited data regarding variations and uncertainties necessitated certain assumptions about the probability density functions, which may influence the accuracy and reliability of the findings from the case studies.

Fourth, the focus of this research lays more on parameter and data input uncertainties. While the context and model structure uncertainties have also an impact on the uncertainties in carbon footprinting estimates.

Five the research findings are fundamentally shaped by a specific theoretical framework, Walker's uncertainty matrix. Utilization of alternative theoretical frameworks could provide varied insights or perspectives on uncertainty.

Lastly, the research focuses on uncertainties at the trip level, while the new ISO standard emphasizes aggregated level calculations. This discrepancy could limit the applicability of the findings to the requirements of the new ISO standard.

VIII. CONCLUSION AND RECOMMENDATIONS

A. Conclusion

The purpose of this study was to elucidate the uncertainties intrinsic to carbon footprint assessments, thereby fostering a more informed dialogue among stakeholders. By providing a clearer understanding of these calculations, the research encourages stakeholders to acknowledge the variability inherent in such assessments when making decisions.

This study highlights the impact of uncertainties on carbon footprint. Such uncertainties are most significant when default values are used and/or assumptions are made. The case studies exemplified the effect of uncertainties when employing both best and worst-case scenarios. However, utilizing probability density functions rendered the range of uncertainties more realistic, although based on assumptions requiring further examination. Several factors causing uncertainty were identified; the uncertainties that are expected to have the biggest effects are the use of default emission intensity factors, energy consumption values, assumptions for other loads or destinations, unknown energy types, application of standard conversion factors, misinterpretation of origin and destination, and the use of default factors when the vehicle or shipment type is unclear.

In the context of the research objective, these results underscore the complexities associated with carbon footprint assessments. The identified uncertainties not only influence the outcome of these calculations but also highlight the need for clear communication between data requesters and providers. Mitigating these uncertainties is critical to ensuring the reliability and validity of carbon footprint calculations.

The data situation essentially determines the calculation method for estimating the carbon footprint, beneath which lie additional potential uncertainties. The research indicates that the computation of a carbon footprint is primarily sensitive to uncertainties when energy consumption must be extrapolated, assumptions need to be made for the transport activity, or the use of emission intensity factors is required. A 10% change in the input variables of distance or average energy consumption due to inherent uncertainties immediately influences the carbon footprint by 10%. Notably, uncertainty always exists in the case of average energy consumption if a standard average not based on primary data is employed. Assumptions in transport activities do not affect the total carbon footprint but do influence the distribution across clients; therefore, an assumption in the total transport activity directly affects this distribution. Additionally, the emission intensity factor is inherently uncertain, as it is based on a default average energy consumption and carries assumptions about transport activity. This uncertainty can further increase when there is a lack of knowledge about the vehicle used and the type of goods transported. When calculations involve these factors, it is relatively easy to make adjustments and arrive at a lower figure. Hence, caution must be exercised in controlling and interpreting carbon footprint data.

In addition to mapping uncertainties when they exist, there are also suggestions for reducing these uncertainties. Stemming from the theoretical framework utilized for this study, it was found that uncertainty can arise from three natures: ambiguity, lack of data, and variability. By being aware of the causes, solutions can be proposed. Effective communication about the type of data being requested and supplied can prevent uncertainties due to ambiguity. The uncertainty caused by default factors and assumptions made can only be reduced with more comprehensive information. This requires good data management and a willingness to share data. Moreover, emission factors, calculated average energy consumption, and calculated average conversion factors to weight will always inherently contain some degree of variability. The main issue is to limit the uncertainty around this variability, which can be achieved, in part, through accurate measurements. By implementing these strategies, as many uncertainties as possible can be avoided.

The practical implications of this research are significant. The study highlights the necessity for clear communication, a thorough understanding of data requirements, and the importance of being transparent about causes that introduce uncertainty around the carbon footprint. Furthermore, it underscores the importance of awareness of the effects of using standard conversion factors to convert other payload units to tonnages. Thereby it is recommended to standard display the uncertainty associated with emission intensity factors and to give more guidelines to when it is allowed to make assumptions that affect the allocation of emissions or when then emission intensity factors may be used. Enhancing data sharing and collaboration, tracking emission intensity more frequently, and investing in training and education are also integral to minimizing causes of uncertainty and advancing the accuracy of carbon footprint assessments. In conclusion, the practical recommendations will lead to more informed decision-making, greater transparency, and progress towards a more accurate carbon footprint estimation.

Finally, the results of this research have far-reaching implications, not only within the realm of carbon footprint assessments but also for broader efforts to combat climate change. The road to a more sustainable future is fraught with uncertainties. The capacity to control and minimize these uncertainties largely predicates the effectiveness in tracking progress and steering necessary actions. The journey towards a sustainable future is steeped in uncertainties. The capacity to control and minimize these uncertainties largely predicates the effectiveness in tracking progress and steering necessary actions. Although the challenges are significant, they can be overcome with a careful and deliberate approach. As demonstrated by this research, it is possible to acknowledge, comprehend, and address these complexities, ultimately leading to more accurate carbon footprint assessments and a more sustainable future.

B. Recommendations

The study suggests various opportunities for further research. First, there is a need to establish accurate probability density functions based on existing research and data. This is key to improving our understanding of uncertainties in various factors, particularly those associated with fuel consumption and emissions. Second,

the development of an updated methodology is required, one that aligns with the new ISO standard for carbon footprint assessment. This methodology should be capable of accommodating aggregated data and incorporating improvements in the standard.

Thirdly, an interesting direction for future research is the examination of uncertainties in well-to-tank emission factors. This is a crucial area for accurately determining the carbon footprint of freight transport as it converts energy to CO_2 equivalents. This is expected even more relevant in the future as the utilization of renewable fuels and electricity continues to rise and this part of the well-to-wheel emission factor becomes more important.

Fourthly, an analysis of the impact of uncertainties in carbon footprint assessments on the selection of logistics service providers or carriers during the tender process is a promising research direction. This could potentially enhance decision-making, fostering greater efficiency and sustainability in the logistics sector.

Fifthly, many uncertainties arise due to a lack of data, stemming from inadequate data storage systems or difficulties in data retrieval. These issues can be motivators for not sharing data. However, the reluctance may also be linked to concerns about sharing sensitive information. It would be interesting to investigate how to effect change in this area, possibly through the application of new technologies. Additionally, it is important to explore how small to medium-sized enterprises can be better encouraged to manage their data effectively.

Lastly, expanding the investigation of uncertainties into other modes of transport, such as rail, sea, and air, could greatly enhance the scope of the topic. This would contribute to a comprehensive understanding of uncertainties in carbon footprint assessments across the entire transport sector.

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