Electric trucks: wishful thinking or the real deal?

The potential of electric tractor-trailers as a means of CO$_2$$_{eq}$ reduction in the Netherlands by 2030

Mathilde Huismans
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The potential of electric tractor-trailers as a means of \( \text{CO}_2,_{\text{eq}} \) reduction in the Netherlands by 2030

by

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Executive summary

Title: Electric tractor-trailers: wishful thinking or the real deal?
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Research objective
The Netherlands faces the challenge to reduce its transport CO$_2$eq emissions in 2030 by 40% compared to levels of 1990. Taking into account the fleet growth a reduction of 80% will be needed in 2030 when no mitigation steps are taken. While battery-electric vehicles (BEVs) are becoming increasingly commercially available and economically feasible in the operation of city logistics, for long haul transport the main routes for zero-emission transport remain hydrogen and hybrid technology. However, more and more fully electric heavy duty vehicles (HDVs) are becoming available to long haul fleet owners, and adding to this regulations on air quality in cities are becoming more strict giving strong incentives for zero-emission vehicles. These recent developments lead us to investigate the feasibility of BEVs for long haul transport. The research goal of this thesis is to evaluate the operability and feasibility of battery-electric tractor-trailers in the Netherlands by looking at the emission reduction potential and the economic feasibility. There was chosen for the tractor-trailer as this vehicle is most commonly used in the long-haul sector.

Methodology
The emission reduction was determined by extending and validating the Multilevel Energy Optimization (MEO) model of TNO with an electric option. The MEO-model is currently a conventional vehicle model and used to calculate the impact of combined efficiency measures. To get a better understanding of the tractor-trailer sector in the Netherlands a characterization of the sector was made. Furthermore to fully comprehend the emission reduction potential, literature on the additional (Life-Cycle) emissions were evaluated for the conventional and electric vehicles. The developed model, the characterization and life cycle emissions were then used to determine the emission reduction potential in the Netherlands on a national and fleet level. In the last phase a Total Cost of Ownership (TCO) analysis was done to get insight in the viability of this possible solution.

Modeling of an electric tractor-trailer
A simplified vehicle model was developed using linear correlations between incidental power demand and energy usage at four different stages: 1) propulsion, 2) propulsion during braking, 3) regenerative braking, and 4) maximum regenerative power (figure 1a). In the model the efficiencies of: charging and discharging of the battery, the generating and motoring modes of the electric motor, transmission losses and the charging station were included. Validation of the model was done in two ways: signal validation of the Willans Line (figure 1b) and validation using monitoring data of 180 recorded trips of two rigid electric truck in full operation. The model had a median error of 0.06 - 0.2% ± 0.79 kWh/km over all recorded trips. Where the mean of these trips was 0.99 kWh/km.

Characterization of the tractor-trailer sector
From literature study and public available data 4 different typical profiles for tractor-trailers were found. These were: 1) Long-haul mission to Germany, 2) Long-haul mission to Belgium, 3) Regional Mission of nutritional goods, 4) Drayage mission. Also an average mission profile for the Dutch tractor-trailer sector was analyzed.
Additional emissions
The total additional CO$_{2}$,eq emissions can be determined by taking the production and maintenance emissions, which adds up to: 44,950 kg CO$_{2}$,eq for a conventional tractor-trailer. For electric vehicles the battery emissions were found to be 266.6 kg CO$_{2}$,eq/kWh and the sum of the vehicle production, maintenance and charger amount to 39,000 kg CO$_{2}$,eq.

Emission reduction estimation
Three scenarios on a national and fleet level were considered: 1) Business As Usual (BAU), 2) Moderate implementation, and 3) Progressive implementation. These scenarios took into account: the survival rate, a decrease in fuel usage for conventional and electric vehicles, the increase in fleet size, an increase in sustainable energy technologies usage in the Dutch energy mix and a technology adoption curve. It was found that implementation of electric tractor trailers would lead to a reduction of 5.5% (moderate) or 21.3% (progressive) of the Dutch tractor-trailers CO$_{2}$,eq emissions compared to the business as usual scenario (figure 2). On a fleet level it was seen that for the profiles on average a reduction of 35% can be expected. In the profiles were the average velocity is lower a larger reduction can be expected.
TCO analysis
The TCO analysis was depended on 6 direct factors identified from literature. These direct factors were: vehicle costs, battery technology, charging infrastructure, maintenance costs, fuel price and the discount rate. For all mission profiles it was calculated that currently (2018) there is no economic feasibility. However in the near-future the sectors that drive less kilometers and have a smaller battery, the regional distribution and drayage missions, do show to have a lower TCO. In this TCO is has to be noted that the electric vehicle (EV) adaption rate has not been taken into account. Which gives uncertainties in the maintenance and charging infrastructure prices.

Uncertainties in these results
The outcome of this thesis could be improved by combining a time and temperature dependent battery model with the mission profiles. In this way for each mission profile it becomes clearer how long a specific battery will last. Furthermore these mission profiles could become more realistic by taking interviews with companies dealing with long-haul transport. Lastly, the Life-Cycle emissions (additional emissions) did not take into the End-of-Life phase for both vehicles, as not much research is available on this subject.

Conclusion
From a technical point of view this thesis showed that electric tractor-trailers are the real deal considering their emission reduction potential. Although electric tractor-trailers have a battery that has a large share in the total emissions, these are canceled out by the increased efficiency in energy consumption. Furthermore the electric tractor-trailer hold the advantage that in combination with sustainable energy technology it can make a signification impact by either providing more storage capacity to the net or by providing the market with cheaper batteries that have reached their End of Life. A slightly less bright picture is drawn when looking at the costs, although the fuel costs are lower, the electric tractor-trailer does have a large uncertainty in the costs for the charging infrastructure and the maintenance costs.

Recommendations
The main barrier that came forward in this thesis was the TCO gap which was in the advantage of the conventional tractor-trailer. This barrier can be taken away by policy that lowers the financial risk for transportation companies to step into electric tractor-trailers. Furthermore as this thesis only researched the impact of the electric tractor-trailers. It is recommended that other options are also evaluated in a similar manner, and focus on the CO\textsubscript{2eq} reduction potential, and the energy efficiency potential to make a comparisons more equal.
Firstly, I would like to express my sincere gratitude to everyone that offered their support, inputs, criticism and most of all their encouragement throughout the course of this project. Specifically, I would like to thank Veerle Heijne and Jan Anne Annema, who supervised me for the entire duration of the project. The door was always open and their feedback was on-point and helped me greatly throughout my thesis. I would also like to thank Gillis Hommen, Daniel Escobar Valdivies and Gertjan Koonneef of TNO Helmond for their ideas and critical review on the technical side. Equally of importance was the broad-scope of the thesis and for this I got a lot of help from Stephan van Zyl, Rene van Gijswijk and Emiel van Eijk of TNO Den Haag. Of course I would also like to thank my parents, sister and friends for their support during my study.
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Introduction

While battery-electric vehicles (BEVs) are becoming increasingly commercially available, for long haul transport the main routes for zero-emission (ZE) transport remain hydrogen and hybrid technology. For a long time the general viewpoint was that batteries for typical Heavy Duty Vehicle (HDV) ranges were too heavy and expensive, \[1, 2\]. Shell CEO Ben van Beurden stated these concerns during the Elsevier Economy-lecture: 'Transporters who want to move a heavy freight electrically over a large distance are currently faced with the choice: do I transport my cargo, or do I transport the batteries? Because both are still not workable' \[3\]. However, more and more truck manufacturers are launching electric versions of their trucks. And it seems that also for long-haul HDVs the time for electrification has come. The impact this will have on the GHG emissions from long haul transport is yet unknown. This Master thesis will elaborate on the electric tractor-trailer as a measure to reduce the emissions from the freight sector, and will introduce a simple model to calculate the emissions during usage. This first chapter will present the problem statement and scientific relevance of this research. Furthermore the research questions and scope are presented.

1.1. Problem statement

1.1.1. Introduction to the transportation sector, emissions and goals

These days we live in a world where CO\(_2\) emissions and other exhaust fumes from engines are to be minimized. In the UN Paris Agreement of 2015 the Netherlands agreed to lower its emissions in 2030 by at least 40% in comparison to 1990 levels. As a result policymakers enforced many initiatives to decarbonize the energy system. Despite effort REN21\[4\] notes that there exists a sector disconnect between policies and renewable energies in the transportation sector, as currently most emphasis is on the share in renewables in the power sector. In the transportation sector HDVs contribute disproportionally to global greenhouse gas (GHG) emissions, having a share of 40% among all vehicles in total emissions globally while one tenth of the total vehicle fleet consists of HDVs \[5\]. Figure 1.1 shows the result of research into the type of ride (mission profile) and the contribution to the total CO\(_2\) emissions. It can be seen in figure 1.1, that especially long haul missions with a tractor-trailers combination have a high contribution \[6\]. As calculated by TNO using the Multi-level Energy Optimization-model (MEO-model), it is expected that targets set for 2030 will not be met using currently available emission reduction techniques\[2\] for internal combustion engine vehicles (ICEV) (figure 1.2). If all conventional reduction techniques currently available for HDV are adapted this will lead to a reduction of 31% in comparison to the emissions of 2015 (and around 15% compared to 1990). Zero emissions techniques are therefore necessary and hold the advantage that other emissions like NO\(_x\), NH\(_3\), etc are also decreased.

\[1\] Renewable Energy Network for the 21st century
\[2\] With which is meant bio-fuels, more efficient engines/hybrid versions, improvements of aerodynamics or payload reduction
1. Introduction

The figures and numbers above show that action is required to mitigate the impacts of global warming. A relatively new solution for the freight transportation sector is the electric truck, and as shown in appendix A around 40 vehicle-models are available today. Whereas for electric passenger vehicles the reduction potential is calculated to a great extent (e.g. [9], [10]), for these type of trucks the potential is yet unknown. Considering the many mitigation options available, the quantification of this potential is needed. Society and industry have to understand the effectiveness of certain measures to allocate the right funds to promising R&D projects or implement legislation that makes sense. Until now no in-depth papers are available that describe the possible impact of the electric long-haul HDV. Nearly all studies that include electric HDVs in their scope try to assess either the costs, climate impact or viability of zero emission vehicles, e.g. [11], [12] and [13]. Nonetheless, these studies do not evaluate in-depth the actual energy usage and related emissions of these vehicles. Some predict how much CO₂ emissions can be avoided but these predictions are often based on generic numbers and are focused on a broad scale. In contrasts, other studies go in-depth by modeling EVs or components in a very specific manner (for instance [14]). However these models can only be used to assess that specific vehicle or component and can take a long time to run. Which makes these models not suitable to predict emissions for implementation on a broad scale.

Existing Vehicle Simulation Tools

Existing simplistic vehicles models that can evaluate emissions by vehicles, only evaluate Well-to-Wheel (WTW) emissions of conventional vehicles. Some well known models are: the Emission Rate ³, the

³Emission Rate: models the HDV emissions of California using a Emission Rate (g/mile) and miles per day[15]
GEM-model\textsuperscript{4}, the VECTO-model\textsuperscript{5} and the previously mentioned MEO-model. TNO has developed the MEO-model in parallel to the VECTO-model. The model was developed as it is much faster, it can be used to apply different combinations of energy saving measures to each vehicle and it models not only vehicles: also other transportation tools can be chosen (such as trains, vessels and passenger cars).

The impact of electric alternatives
Modeling an electric tractor-trailer is significantly different compared to a conventional version. Firstly since numerous components such as the battery, and electric-motor (EM) will replace the gearbox and internal combustion engine (ICE). Secondly, the freight sector is an energy intensive industry that can have many different fleet-types, where velocity, payload and energy demand may vary widely. This may result in differences in total energy used between freight sectors. And lastly, major emissions from e.g. the production of the battery are not included by only modeling the WTW emissions during the usage phase. Previous research on electric cars already stated that emissions from production and electricity use can make a real difference in the total impact they have on the environment\textsuperscript{16}. Rapporteur on Environmental Mobility of the EU Parliament underlined this during the opening of the European Sustainable Energy Week 2018: 'Considering how far we can go with mobility I’m interested in vehicles that emit less and less, I’m interested in ultimately the Life-Cycle, when we speak about emissions. I’m saying this because at this moment we are more focused on the tail-pipe emissions\textsuperscript{17}.

1.1.3. Feasibility of electric tractor-trailers in the Netherlands
Besides estimating the reduction potential a cost estimation for new innovation is crucial to determine the effectiveness of a technology\textsuperscript{18}. Similarly to the reduction potential for electric HDVs the estimated costs and benefits are hardly addressed in a scientific way. Which doesn’t stop electric tractor-trailer manufactures to claim a reduction in costs compared to conventional vehicles. However economic studies like\textsuperscript{12} indicate that electric trucks will not become commercially profitable until 2023-31, and a share of 5% in the European market is predicted.

1.1.4. Conclusion
From previous writing we now define three knowledge gaps: 1) the reduction in emissions by using electric HDVs is never calculated in-depth, since current literature only addresses this type of vehicle in a very general or too specific way, and governmental tools do not incorporate electric HDVs, 2) the emissions besides the WTW emissions are not taken into account using vehicle simulation tools, which gives a large error considering the contribution in CO\textsubscript{2}\textsubscript{eq} emissions from batteries, and 3) the studies mentioned are all related to the situation in the US or the EU. Currently there is no study which covers the (economic) viability of electric HDVs in the Netherlands.

1.2. Scope and boundaries
As many studies already gave a broad understanding of the European/World potential this thesis will therefore solely focus on the Dutch vehicle fleet. Furthermore another boundary is the type of vehicle that is evaluated. The term HDV comprises many types of vehicles but during this thesis only tractor-trailers, a much used type of vehicle, in long-haul transport are considered. Buses are also HDVs but their (electrical) usage and energy consumption have been discussed in other research and are therefore not included in the scope. Lastly, there will be looked at CO\textsubscript{2}\textsubscript{eq} emissions so the contribution to the GHG emissions can be assessed. Emissions like: NO\textsubscript{x} or Particulate Matter will not be considered.

1.3. Research objectives and questions
Based on the knowledge gaps the main objective of this thesis is formulated in twofold: first of all the objective is to estimate the emission reduction potential of implementing electric tractor-trailer in the Netherlands. Furthermore the goal is to gain insight in the feasibility of the implementation from a business perspective in the Netherlands, thereby combining two types of research normally done on transportation: the emission reduction estimation and the viability research. The first objective

\textsuperscript{4}GEM: the Greenhouse Gas Emission Model, developed by the EPA to calculate the GHG from middle and heavy duty
\textsuperscript{5}VECTO: Vehicle Energy Consumption Calculation Tool developed in the EU, similar to GEM as it is used for CO\textsubscript{2} certification purposes
will have the larger share in this research as it is too soon to evaluate electric tractor-trailers in-depth economically. Therefore the following two main research question with accompanying sub-research questions are proposed:

- **Main research question 1:** How much can the use of fully electric tractor-trailers in the Netherlands contribute to reaching the Paris Agreement emission goals by 2030?

  1. How can the energy that is required for an electric tractor-trailer be modeled based on speed, battery size, weight and auxiliaries?
  2. What are possible mission profiles for an electric tractor-trailer combination, taking into account different charging profiles and distance ranges, and how does it compare to the typical use?
  3. What are roughly the CO$_{2_{eq}}$ emissions aside from the WTW emissions of a typical future electric tractor-trailer combination? And how does this compare to other freight vehicles?
  4. How many long-haul vehicles can enter the market yearly till 2030?
  5. How much Life-Cycle emissions are avoided by implementing the electric tractor-trailer in the Dutch fleet for different implementation scenarios by 2030?

- **Main research question 2:** What is the potential Total Cost of Ownership (TCO) of electric tractor-trailers in 2030 compared to the TCO of the ‘classic’ diesel tractor-trailer

### 1.4. Relevance for different fields

#### 1.4.1. Contribution to scientific literature

This thesis will add to current scientific literature by taking existing literature of regular electric vehicles (EV) and expanding this knowledge to include electric long-haul vehicles on a national level. In this way more detailed estimations on emissions and energy usage from the long-haul sector can be expected. Additionally the modeling outcomes of this thesis will also be validated with real-life data, which can serve future scientific research as a base to several assumptions about the overall energy consumption. Lastly, this research will also supply more knowledge to the EV research area as the freight sector has very different driving, energy and cost patterns than the EV passenger sector.

#### 1.4.2. Societal relevance

There are a number of reasons why this research is relevant for society. Firstly lower emissions from the transportation sector will lower the total GHG emissions and therefore lower the risk of human induced climate change. Furthermore electrification of all sectors will lead to a more efficient society and brings the realization of a smart grid closer (also section 1.4.3). And lastly, due to the many available options for emission reduction a clear and transparent analysis of these options is needed. This is needed for governments that seek scientifically sound advice for making strategic choices for innovations that need to be promoted and for designing appropriate and effective policy measures. Additionally the industry needs to make strategic choices for R&D and product development and wants to be able to invest in innovations that effectively contribute to the reduction goals and at the same time create a profitable business case. A good example is the case of first generation bio-fuels. As these days policy makers are careful implementing policy on transport due to the uncertainties in sustainability that became apparent when the share in first generation bio-fuels grew$^6[19]$.

#### 1.4.3. Relation to the Sustainable Energy Technology field

Currently the largest investments in renewable energy in the transport sector are in liquid bio-fuels (first and second generation). In 2016, they provided around 4% of world road transport fuels. Also bio-gas is growing substantially in the energy mix of the European Union. Usage of EV is also growing, but this goes slowly.

By any means the implementation of EVs will be essential for the energy transition towards more (electrical) sustainable energy technologies. EVs are often regarded as stakeholders in the electricity system. As stakeholders they demand electricity but can also provide services to the electricity system.

$^6$First generation bio-fuels have the disadvantage that they compete with food crops which can increase food prices.
1.4. Relevance for different fields

Their demand for electricity leads to an environmental impact, which is depended on the characteristics of the electricity system (the energy mix, the consumption levels and charging possibilities). The ‘greener’ the energy mix of the future the more impact EVs will make.

The services EVs can provide to the electricity system can be comprehended by: 1) the V2G concept and 2) second-life batteries. The V2G concept stands for: Vehicle-to-Grid and was introduced by [20]. It is seen as a solution in the problem of storing intermittent sustainable energy during the day in EVs. In either decentralized micro-grids or on a larger scale this can lead to an increase in energy efficiency. An already existing example is the EDI PowerDrive 8000 tractor-trailer which has a the power export option (EDI Power2E™), the capability to export a range of power directly from the vehicle for use in disaster recovery, tool operation, or deliver directly to the grid [21].

Additionally the battery of an EV that loses part of its capacity can be used as a storage device for various sustainable energy technologies such as: solar panels on buildings and small scale wind turbines. As this service will become larger both markets (the Sustainable Energy Technology and EV) will greatly benefit from each other by providing cheaper and more efficient battery technology.

The implementation of electric HDVs will be the next step to take for the mobility sector and the success or failure can have a great impact on which road the energy transition will take. Whether the V2G concept can be applied directly on electric HDVs is not clear yet and also the second life of batteries will have to be further developed. This thesis can contribute to these questions as it will give more ideas on the future tractor-trailer sector.
Methodology

This thesis used various methods to answer the research questions posed in the introduction. This chapter shall evaluate on the steps were taken and for what reason.

2.1. Method overview

As mentioned in the introduction the goal of this thesis is two-fold, namely: 1) estimate the emission reduction potential of implementing electric tractor-trailer in the Netherlands and 2) gain insight in the feasibility of the implementation from a business perspective in the Netherlands. During this thesis different steps can be differentiated. Firstly the MEO model as mentioned in section 1.1.2 was extended with an electric option using Python, and validated using real-life data. Secondly a literature study into the different sectors that use tractor-trailers was preformed, this led to different missions profiles that characterize the tractor-trailer sector. By analyzing these closely on their energy usage as calculated by the developed model and driving patterns the battery capacity of their future electric version could be estimated. The third step involved an assessment of the additional emissions resulting from the usage of a conventional and electric tractor-trailers. The information of all these steps was combined in step 4 where market trends for 2030 were analyzed and the total future emissions of the Netherlands and for each fleet type was estimated. These steps were all taken to obtain results for the first goal. In the last part a TCO analysis of the conventional and electric tractor-trailer was done to get more insight in the economical feasibility in 2030. All these steps are also illustrated in figure 2.1. The next two sections will go deeper into the methods: 2.2 will evaluate step 1 to 4 and, 2.3 will evaluate step 5.

2.2. The CO\(_{2,eq}\) emissions by electric tractor-trailers

For the quantification of the CO\(_{2,eq}\) reduction by electric tractor-trailers a combination of methods are used. Figure 2.1 shows how the final estimation can be made using the output of three methods. Using the model from section 2.2.1, the data from section 2.2.2, and results from the Life Cycle Assessment (LCA) as described in section 2.2.3, the total CO\(_{2,eq}\) avoided emissions can be estimated for different scenarios in the future.

2.2.1. Step 1: Quantitative modeling and validating the energy usage of an electric truck

As described in section 1.1.2 the MEO model is a vehicle simulation tools which models the CO\(_{2,eq}\) emissions of a car during driving. In this thesis the MEO-model was extended to also include electric tractor-trailers. The extended model is based on the so-called Willans Line, which represents the relationship between fuel energy input and engine output. The workings of the model and the Willans line will be discussed in chapter 3.
2. Methodology

Part 1: Model development

[22] described in a conference paper a simplified version of model development process, shown in figure 2.2. The modeling process starts with the determination of the system, which in this case the electric HDV fleet. By analyzing electric HDVs on a vehicle level and constructing mathematical equations to describe their \( \text{CO}_2 \text{eq} \) emissions a conceptual model could be constructed. [23] already described how the Willans Line can be adjusted to include a hybridization of the vehicle. This literature
does not include the modeling of a battery unfortunately. Using this literature and expertise of TNO an extension of the MEO model was programmed in Python, which is the computerized model. The MEO model was chosen as this model is created by TNO and relevant to the Dutch situation. Furthermore it is flexible, simple and fast, also it has less parameters making it more universal applicable. A downside of the MEO-model however is that it is not used by many parties in comparison to VECTO.

Part 2: Validation of the model
As figure 2.2 illustrates each modeling step requires a validation. The conceptual model validation was done by using the real-life data and compared the signals from a data-base with the mathematical lines. The computerized model verification was done within the computerized model as the MEO-model already checks that all energy flows going in the vehicle are equal to the energy flows leaving the vehicle (energy-balance). The Operational validation makes sure that the model’s output behavior has sufficient accuracy for the model’s intended purpose. In this thesis real-life data from two electric rigid trucks was used to do the operational validation. Using measured data from the real system to validate the simulation model is defined as Event Validity [22].

2.2.2. Step 2: Characterization of the tractor-trailer fleet and sectors in the Netherlands by mission profiles
Once the electric tractor-trailer could be modeled using a specific driving profile (the mission profile) as input, the behavior of trucks in the Netherlands was evaluated. The behavior of the trucks for each sector can be comprehended by a frequency of several mission profiles. A mission profile is the change in velocity, mass and slope of a vehicle during a certain mission, going from A to B. The importance of the mission profile can be noted in figure 1.1, where different types of road segments researched. These road segments (urban, rural and motorway) each have their own distinct velocity profile and corresponding energy usage.

From literature the tractor-trailer fleet was characterized on 3 aspects namely: 1) national HDV fleet composition, 2) typical distances, and 3) typical payload and volume capacity. These aspects resulted in 4 typical mission profiles that represent the tractor-trailer sector in the Netherlands. A mission profile can be generated using the Mission Profile Generator (MPG) created by TNO. This tool generates the most likely velocity profile using a Markov Chain algorithm, given the following inputs: 1) GPS coordinates, speed limits and altitudes, 2) type of vehicle and payload specification and 3) monitoring data for all circumstances and vehicle types.

2.2.3. Step 3: Life-Cycle analysis on additional CO₂ emissions
Similarly to other studies on electric vehicles a life-cycle assessment will have to be performed to obtain the full picture. Due to time restrictions this analysis was done fairly roughly. The Well-to-Wheel emissions were already be calculated using the MEO-model with extension, so only the rough production costs had to be analyzed. This was done using the data from EcoInvent database [24], in combination with scientific literature such as [25], [16], and [26]. Most literature sources are related to passenger EVs and battery related CO₂, emissions, and are quite diverse in their outcome. When contradicting values were found a comparison was made by spreading the data and assessing the quality, according to the SAP-scheme of [27]. The SAP-scheme stands for: Spread, Assessment and Pedigree and is used to examine the uncertainty and variability in LCA studies.

2.2.4. Step 4: Predicting for different scenarios the future share of electric tractor-trailers and corresponding reduction
The last step combined the model results for the different missions profiles and the road segments with the Life Cycle emissions to obtain a typical energy usage per year on two levels: 1) national level, and 2) fleet level. This was done as it is unknown how big each fleet is but data is available on the total distance driven by tractor-trailers. The scenarios that are considered are: the Business as Usual, a moderate uptake of electric tractor-trailers and a progressive uptake.

2.3. Economic viability of electric tractor-trailers
Once the model for electric tractor-trailers was validated, the model will be used to answer the more societal relevant question posed (main research question 2).
2.3.1. Step 5: Total Cost of Ownership estimation

Although many truck manufacturers already have prototypes of electric tractor-trailers the exact costs are hard to predict, and currently only a limited amount of in-depth studies on the costs of electric HDV are available. To overcome this knowledge gap there was made use of the work of [18] on the TCO of EVs. [18] analyzed the conceptual framework of influencing factors to the TCO, and how these factors can be calculated or derived (seen in figure 2.3). The TCO that was made in this study is less extensive since many direct and indirect factors remain unknown or uncertain.

Figure 2.3: The simplified conceptual framework of influencing factors to the TCO, figure adapted from [18]
3 The MEO-model extension

This chapter explains the extension that is developed for the MEO-model in detail. The extension is mainly based on literature and expert views. In Appendix B the original MEO model is described in detail. This detailed explanation is done for two reasons, first of all there is currently no literature available that describes the model thoroughly, and secondly the extension that will be made to the model will only be understandable if one knows the preceding formulas that are used in the model. In the second part of this chapter the initial parameters for the model are determined. Once the extension is set-up it will be validated by using data of two electric trucks. This is done in chapter 4.

3.1. Proposed new model using Willans Lines

The MEO-model is a vehicle simulation tool that has been used in many studies of TNO to determine the emissions for specific CO₂ reduction measures, such as [7] and [28]. The model is mainly used to calculate the effect of combined efficiency measures, which is shown in figure 3.1. This is done as efficiency measures cannot simply be added together. Component improvement (e.g. a more efficient engine), pay load changes or aerodynamic drag will have different contributions when applied at once or in certain combinations. The basis of the model is the Willans Line, which is explained in section 3.1 and appendix B.

![Figure 3.1: Overview of the input and output of the MEO-model and where the extension that will be developed is placed in this scheme (green box), the energy efficiency measures combined in one vehicle will change either power train parameters or the vehicle parameters.](image)

During this section the functioning of an electric truck is evaluated and a first model is set-up to obtain the relationship between the power of the motor and the fuel usage, in this case the power of the battery. The relationship between the power demanded by the motor of the vehicle and the energy provided by the fuel is also referred to as the Willans Line. The concept of the Willans Line is given in figure 3.2, where a generic energy converter is shown to convert the available input energy into output flow and effort variables.
We see that the Willans Line model relates the energy that is theoretically available for conversion, to the useful energy that is actually present at the output of the energy converter. The name Willans Line is derived from the fact that the above relationship has the appearance of a straight line. However this model of energy conversion efficiency is not completely linear, because the parameters are represented as functions of the output flow variable [23]. Nevertheless on a large scale validation through vehicle measurements have indicated that with increasing power demand the fuel consumption increases linear [28]. For the electric tractor-trailer we can distinguish 4 different stages of the New Willans Lines (also shown in figure 3.3).

1. Mode 1: Propulsion
2. Mode 2: Regeneration + discharging, where auxiliary power consumption is higher than the regenerated energy
3. Mode 3: Regeneration + charging, where auxiliary power consumption is lower than the amount of regenerated energy
4. Mode 4: Regeneration, where the regenerated power is limited by the generator/inverter combination

In the following subsections the different stages are studied in more detail and their Willans-equivalents are determined for both the perspective of the battery and the charger. Both perspectives are given as this used in chapter 4 where only the battery measurements are available. In Appendix C the implementation in Python script is given.

Mode 1: Propulsion
For the propulsion mode the main interest goes out to the power that is extracted from the battery. Similar to Appendix B we first calculate the power which is needed from the wheels after transmission...
3.1. Proposed new model using Willans Lines

(a) Mode 1: electricity from the battery flows towards the auxiliaries, and EM

(b) Mode 2: the EM is now functioning as a generator, but the power from the auxiliaries is higher than the power provided by the wheels. Electricity flows from the wheels, through the generator, to the battery and finally to the auxiliaries

losses are applied, and therefore get the indicative power needed for the wheels.

\[ P_{\text{ind., wheels}} = \frac{P_{\text{fraction}}}{\eta_{EM}} \]

(3.1)

By following the energy from the battery to the wheels during this stage as in figure 3.4a, the power of the battery and charger will be equal to equation below. Where the \( \eta_{EM} \) is the electric motor efficiency (determined in section 3.2.3), \( P_{\text{Aux}} \) the power needed for the auxiliaries and assumed to be constant, \( \eta_{\text{discharge}} \) and \( \eta_{\text{charge}} \) the battery discharging and charging efficiency (section 3.2.1) and \( \eta_{\text{charger}} \) the efficiency of the charger (section 3.2.5).

\[ P_{\text{battery, out}} = \frac{P_{\text{ind., wheels}} \cdot 1/\eta_{EM} + P_{\text{Aux}}}{\eta_{\text{discharge}}} \]

\[ P_{\text{charger}} = \frac{P_{\text{ind., wheels}} \cdot 1/\eta_{EM} + P_{\text{Aux}}}{\eta_{\text{discharge}} \cdot \eta_{\text{charge}} \cdot \eta_{\text{charger}}} \]

(3.2)

Before the other Willans lines can be set up, the relationship between the maximum torque and maximum motor power has to be incorporated in \( P_{\text{braking}} \). This relationship, as described in subsection 3.2.4, should also be included into the model, to eliminate values that cannot be possible. This can be done by translating the base speed of the electric motor (\( \omega_b \) measured in rad/s) to the corresponding speed of the vehicle (m/s) by using the ratio between the gears (i). Knowing the maximum motor power we can check whether the instantaneous speed will lead to motor power limitation:

\[ \omega_m = \frac{\nu_{\text{vehicle}}}{r} \]

\[ T_{\text{max}} = \frac{P_{\text{motor, max}}}{\omega_b} \]

(3.3)

\[ P_{\text{motor}} = -T_{\text{max}} \cdot i \cdot \omega_m \]

If, during braking, the above calculated \( P_{\text{motor}} \) is found to be higher than the calculated \( P_{\text{braking}} \) as in section B.2 (since we are in the negative window of the \( P_{\text{wheels}} \)), this value of \( P_{\text{braking}} \) is set to \( P_{\text{motor}} \).

Mode 2: Propulsion in auxiliary range

During this stage the auxiliary power consumption is higher than the amount of regenerated energy. Again we follow the energy flow from the battery to the wheels and auxiliaries (figure 3.4b). Which gives us the formulas below. In these formulas is \( \eta_{\text{gen}} \) the generating efficiency of the motor (determined
(a) Mode 3: the battery can store energy because the generated power is higher than the power needed for the auxiliaries. Electricity flows from the generator to the battery.

(b) Mode 4: the electricity still flows the same manner as in figure 3.5a but now amount is limited by the generator capacity in section 3.2.3).

\[ P_{\text{battery, out}} = \frac{P_{\text{braking}} \cdot \eta_{TM} \cdot \eta_{gen} + P_{\text{Aux}}}{\eta_{\text{discharge}}} \]

\[ P_{\text{charger}} = \frac{P_{\text{braking}} \cdot \eta_{TM} \cdot \eta_{gen} + P_{\text{Aux}}}{\eta_{\text{discharge}} \cdot \eta_{\text{charge}} \cdot \eta_{\text{charger}}} \]  

(3.4)

Mode 3: Regeneration
During this stage the motor is regenerating energy and can store energy in the battery. Using figure 3.5a the following formulas are obtained:

\[ P_{\text{battery out}} = (P_{\text{braking}} \cdot \eta_{TM} \cdot \eta_{gen} + P_{\text{Aux}}) \cdot \eta_{\text{charge}} \]

\[ P_{\text{charger}} = \frac{P_{\text{braking}} \cdot \eta_{TM} \cdot \eta_{gen} + P_{\text{Aux}}}{\eta_{\text{charge}}} \]  

(3.5)

Mode 4: Regeneration with limitation by maximum power
In the last stage the regenerated power is limited by the generator/inverter combination.

\[ P_{\text{battery, out}} = -P_{\text{Generator, MAX}} \cdot \eta_{\text{charge}} \]

\[ P_{\text{charger}} = -P_{\text{Generator, MAX}} \cdot \eta_{\text{charge}} \cdot \eta_{\text{charger}} \]  

(3.6)

Power loss in an EV
Similar as section B.3 the losses of the vehicle are explicit mentioned. The total loss are summarized as follows:

\[ P_{\text{loss}} = P_{\text{lossTM}} + P_{\text{lossHeat}} + P_{\text{lossBattery}} + P_{\text{lossBraking}} + P_{\text{lossCharger}} \]  

(3.7)

How these equations are handled exactly in the model is explained in appendix C.
3.2. Initial parameters determination

Now the model is explained in mathematical terms this section will go more in-depth on the behaviour of the mentioned components. Table 3.1 shows the initial assumptions for the components efficiency. How these assumptions were made is explained in the rest of this chapter. Firstly in subsection 3.2.1 general characteristics of batteries are elaborated. Then in section 3.2.2 the model of the battery is extensively evaluated. Followed by section 3.2.4 which explains the important aspects of electric motors such as the possibility of regenerative braking. The last component evaluated is the charger of the truck in section 3.2.5.

Table 3.1: Initial efficiency assumptions

<table>
<thead>
<tr>
<th>Efficiency (η)</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>η_charger</td>
<td>0.96</td>
</tr>
<tr>
<td>η_discharge</td>
<td>0.99</td>
</tr>
<tr>
<td>η_charge</td>
<td>0.99</td>
</tr>
<tr>
<td>η_EM</td>
<td>0.92</td>
</tr>
<tr>
<td>η_GEN</td>
<td>0.91</td>
</tr>
<tr>
<td>η_FD</td>
<td>0.98</td>
</tr>
<tr>
<td>P_EM,max</td>
<td>250</td>
</tr>
<tr>
<td>P_GEN,max</td>
<td>250</td>
</tr>
<tr>
<td>P_aux</td>
<td>1</td>
</tr>
</tbody>
</table>

3.2.1. Battery characteristics

Batteries that are used in EVs need to be safe and have preferably a high energy density while still being light and small. Considering the figure below Li-ion and Li-ion polymer can be considered as two good options for this. As the higher the gravimetric energy density (x-axis), the lighter the battery can be, and comparably the higher the volumetric energy density (y-axis), the smaller the battery can be. Furthermore they are an already established technology in comparison with Zn/Air batteries. Zn/Air batteries are promising as they are expected to be much cheaper and durable than Lithium-ion batteries. However until now no electric vehicle is using this type of technology.

![Figure 3.6: The energy density of different electrolytes compared on a weight and volumetric basis, figure reproduced from [29]](image)

There exist multiple Li-ion and Li-ion Polymer batteries. The most promising according to [30] for EVs are:

- Lithium Nickel Cobalt Aluminium (NCA)
- Lithium Nickel Manganese Cobalt (NMC)
- Lithium Manganese oxide-NCA blend (LMO-NCA or LMO-b)
Lithium Iron Phosphate (LFP)

[31] notes that mostly, material LiXMA\textsubscript{2} (which includes LiCoO\textsubscript{2}, LiNiO\textsubscript{2}, LiMnO\textsubscript{2} and LiFePO\textsubscript{4}) is used at the positive electrode and graphite at the negative electrode. According to [30] NCA is today the most used type of Li-ion battery in EVs, being the furthest in commercial development for EV technology. However the other types show great potential too [32]. [33] indicated that the majority of EV manufactures is expected to use LFP due to its safety and low environmental impacts in comparison with other NCA-types. This is also indicated in the several comparisons between the different types (figure 3.7), only the Lithium Titanate (LTO) has a high score for safety but its costs are higher.

![Figure 3.7: A simple comparison between the six lithium-ion battery types. Scores from the original table are translated as follows: 1 = Low, 2 = Moderate, 3 = High, except for the costs column these are backwards (High = 1 and Low = 3). Table adapted from [34]](image)

In the following sections the influence of the State of Charge (SOC), temperature and the cycling and aging on the batteries are explained.

**State of Charge (SOC):** The voltage across the battery that it can deliver is influenced by the SOC, this is seen in figure 3.8a. As the battery is discharging, the voltage it produces decreases, and therefore the efficiency decreases as well. The slope of the change in voltage over SOC differs per type of battery (figure 3.8b), we see that in lead-acid the voltage drops almost linearly. To keep the average power constant, the current must therefore be increased. NiMH and lithium-ion-LFP on the other hand have nearly constant voltage, which does not depend as much on the SOC. Furthermore the value of the voltage that a battery can deliver is of importance, as higher cell-voltages in lithium-ion increase the energy density. On the other hand, low cell voltage in in NiMH requires many cells to build up a high-voltage system.

**Temperature:** In figure 3.9a it can be seen that also the temperature can alter the efficiency: the higher temperature the more capacity the battery can deliver. This is due to several reasons: 1) the internal resistance increases, 2) the polarization effect at the interface between the electrolyte and electrodes get greater at lower temperature as the diffusivity of Lithium ions increases [37]. For electric vehicles this means that on a cold day the battery might preform up to 25% worse, as can also be seen in figure 3.9b, it shows that the EV available range is substantially reduced as temperature decreases. It also shows that there is an optimum in this relationship, if the battery gets too hot the efficiency decreases again. A well functioning Battery Management System (BMS) can optimize the temperature of the battery so it doesn’t become too hot.
3.2. Initial parameters determination

(a) Voltage versus SOC of a Nanophosphate Li-ion cell, figure adapted from [35]

(b) Discharge voltage curves for different types, figure reproduced from [36]

Figure 3.8: Delivered or applied voltage to a battery compared with the SOC of the battery

(a) Discharge curves at various temperatures of a Nanophosphate Li-ion cell, figure adapted from [38]

(b) Data from 7,375 different individual trips of one major commercial passenger EV in the United States figure reproduced from [39]

Figure 3.9: Temperature effecting the battery performance

Cycles and aging: As the battery ages the capacity it delivers decreases while the internal resistance increases. This aging is among others, influenced by the temperature. Furthermore the Depth of Discharge (DOD) and the cycling frequency [40] all have an effect. The cycle life graph in figure 3.10a shows how the capacity of the cell decreases with respect to the number of full DOD cycles that it delivers. For example, at 25°C, the cell can deliver over 5,000 full DOD cycles before its capacity decrease to 80% of its original Beginning of Life (BOL) capacity. An electric truck which is discharged and charged twice a day will make around 5,800 cycles in an 8 year life time, which implies a capacity reduction of almost 25%. This number is quit significant as the total capacity available is 80% (most Li-ion batteries have a maximum DOD of 20%). Also when the battery isn’t discharged or charged it still looses capacity. As described by [38] a cell can lose 6% or 11% of its capacity in 2 years when stored at respectively 25°C or 35°C (figure 3.10b). A 10% decrease in BOL capacity can be expected at ambient temperatures after 8 years.

The combination of these different reductions in capacity are hard to sum all together. For instance as [41] noted, tests with extremely fast discharging and charging cycles are prone to error, as they don’t take into account the parasitic reactions in the electrolyte, and the mechanical degradation that occur over time. Also the above described experimentation only uses full DOD cycles, which means that it discharges completely, in reality this will never happen.
End of Life: The common definition for battery end-of-life is when 70–80% of original energy capacity remains. After this threshold the battery is considered to be not usable anymore for EVs [31]. With a threshold of 80% one battery will not be enough to survive the common assumed lifetime of a tractor-trailer (8 years). At a minimum the tractor-trailer can use a battery intensively (2 cycles per day) for 4 years before the End of Life threshold is reached (total cycles: 3,000, gives a 12% decrease in BOL and 4 years of calendar aging will give 8% decrease in BOL). If one assumes the discharge and charging rate is 1C and an ambient temperature, an increase of on the assumptions could decrease the possible cycles.

3.2.2. Battery modeling

In order to get a model for the battery several sources are used. In figure 3.11 three different equivalent models of a Li-ion battery are shown. The IR (internal resistance) model is a very simplistic equivalent circuit. The other two models have more dynamic components in them as time constants are incorporated. As we are interested in the average functioning of the battery for the model to be made, we will assume the most simple model and take the time constants as an average.

The efficiency of the battery is then easy to calculate using the following formulas, and the specifications of known batteries (table 3.2). The voltage of the battery is given by [42] as:

$$v_{batt} = V_{OC} + R_0 i_{batt}$$ \hspace{1cm} (3.8)

For the specifications for the battery-model open-access information of the European Batteries (EB) High Energy (HE) cell is used ([43]). The internal resistance of the cell is slightly higher as compared with the data of the Battery Performance and Cost model (BatPac) developed at Argonne National Laboratory [44]. In this model each cell has a resistance between 0.16-0.84 mΩ, which also includes the terminal resistance of each module. For this thesis there is chosen to go for cell-specific values of a real battery.
Table 3.2: The specifications of the EB HE cell retrieved from [43]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy density cell</td>
<td>145 Wh/kg</td>
</tr>
<tr>
<td>Capacity ($C_{Batt}$)</td>
<td>45 Ah</td>
</tr>
<tr>
<td>Internal resistance at 25°C ($R_0$)</td>
<td>0.93 mΩ</td>
</tr>
<tr>
<td>Nominal voltage ($V_{nom}$)</td>
<td>3.2 V</td>
</tr>
</tbody>
</table>

For the efficiency of the battery this will give:

$$\eta_{Battery} = \frac{v_{Batt} \cdot i_{Batt} - i_{Batt}^2 \cdot R_0}{v_{Batt} \cdot i_{Batt}} = \frac{C_{Batt} \cdot V_{nom} - C_{Batt}^2 \cdot R_0}{C_{Batt} \cdot V_{nom}} = 0.99$$ (3.9)

Using this simplistic circuit gives us a certain error in the internal resistance since the more dynamic components are left out, the less the model is able to capture the charge transfer phenomenon that occurs in a battery. Especially the time and SOC dependent components in the circuit raise errors. As pointed out in section 3.2.1 the effect of the SOC, temperature, cycles and aging of Lithium-ion batteries are important to the available capacity.

### 3.2.3. Electric motor characteristics and model

The functioning of the electric motor will be modeled by two parts, firstly the efficiency of the electric motor ($\eta_{em}$) will determine how much of the mechanical energy can be generated or turned into electricity. Secondly in section 3.2.4 the behaviour of the motor for regenerative braking and the maximum power that can be generated are evaluated.

The efficiency of an electric motor is commonly visualized using an efficiency map, as an (electric) motor does not have a single efficiency value. The efficiency map from PowerPhase 150, is shown figures 3.12a and 3.12b. This particular map includes the speed controller inefficiencies, and so offers a complete representation of the eclectic motor efficiency. The highest efficiency regions are in the central region, located adjacent to the maximum speed/torque line for that motor. Moving away from this peak efficiency point results in lower efficiencies. The lowest efficiency regions lay adjacent to the vertical and horizontal axis.

![Efficiency Maps](attachment:3.12a.png)  
![Efficiency Maps](attachment:3.12b.png)

**Figure 3.12:** The motoring and generating efficiency maps of UQM retrieved from: [45], the dashed line shows the power limitations for continuous operation.

To get an idea of how the power output depends on the speed of the motor we average the efficiencies for different motor speeds, which is shown in figure 3.13. It can be seen that: 1) at very low and high rotations per minute the efficiency drops, 2) the efficiency for the motoring mode is higher than the generating mode and 3) on average we could say that the efficiency of the electric motor is 0.92 ($\eta_{em}$) for motoring mode and 0.91 for generating mode ($\eta_{gen}$).
3.2.4. Regenerative braking and maximum power

For vehicles with an electric motor regenerative brakes can be applied. When the driver steps on the brake pedal of an electric or hybrid vehicle, these types of brakes put the vehicle’s electric motor into reverse mode, causing it to run backwards, and thereby slowing the car’s wheels. While running backwards, the motor also acts as an electric generator, producing electricity that’s then fed into the vehicle’s batteries. The power the motor can generate is the product of the speed of the motor (\(\omega\)) and the torque (T) applied:

\[
P_{\text{motor}} = \omega \, [rad/s] \cdot T \, [Nm]
\]  

(3.10)

The maximum power the motor can generate is depended on either the speed of the motor or on the maximum torque. The speed of the motor is determined by the desired speed of the wheels or during braking the actual speed of the wheels. From this one can see that if the vehicle is driving slow the power output is limited while the applied Torque is maximum, as illustrated in the following figure:

3.2.5. Charger characteristics

The charger is an important component for the energy usage of an electric truck. If we speak of a charger for EVs two different components can be meant, either the on-board charger for fast charging at home or the fast charger which directly charges the battery. During this work only the direct charger will be analyzed as it is unlikely electric trucks will be charged through a socket, also the interest goes out to the use age of electric truck during working hours and therefore overnight charging is left out of the scope. The direct DC charger is sometimes also named a level 3 or fast charger. The two major competing standards for level 3 charging are the SAE combined charging system (CCS) and the Japanese CHAdeMO standard. The third standard is Tesla Motors’ own Supercharger, which is only compatible with their vehicles \([47]\). Comparing two different types of chargers, the 150 kW fast DC charger of Heliox, the Quick Charge Station of EFACEC (50 kW), and the 50kW Delta EV Quick Charger, have an efficiency of respectively 96%, 93% and 94%. As higher charging rates will be needed for tractor-trailers the efficiency of the Heliox is chosen as the initial parameter value.
3.3. Conclusion

In this chapter the first research question was answered. Which was:

**Research question 1.1**

*How can the energy that’s required for an electric tractor-trailer combination be modeled based on speed, battery size, weight and auxiliaries?*

Currently TNO uses the MEO model to determine the energy required for conventional heavy duty vehicles. The basic concept is to model the energy delivered by the fuel to drive a certain mission profile based on the Willans Lines. The Willans Lines are linear lines based on a simple physical model and validated through measured data. This same approach was used to model electric trucks. In this chapter an extension of the MEO model was presented, where the Willans Lines have a negative component. The extension is based on a simple battery and electric motor model. Several uncertainties in the model were explained, for instance the temperature, age and amount of cycles all determine the available capacity. The model that is developed takes into account the efficiencies of: the charger, the battery, the electric motor, the transmission through the system and the auxiliaries. The developed model is simplistic compared to other existing models, however the parameters are relatively easy to determine. The following chapter shall evaluate how well the model can predict the usage during the mission profile. During this chapter it came forward that some energy efficiency parameters cannot be determined using this model, the aging of the battery for instance is time and depended on previous conditions. This has the consequence that the model can only give precise estimations during one mission profile.
Validation MEO extension

Continuing from the model drafted in previous chapter, this chapter will now validate the model. This is done in three ways by conceptual validation, computerized model verification and operational validation. According to the scheme in figure 2.2 from [22]. The conceptual and operational validation will be done by event validation. [22] describes event validation as: “The “events” of occurrences of the simulation model are compared to those of the real system to determine if they are similar.” In this section the real-life events originate from data of two electric trucks. This data is described in section 4.1. Then in section 4.2 the Willans Lines are validated with this data, and readjustments to the model are made to fine-tune the parameters. The computerized model is verified using the internal check in MEO (section 4.3). Then finally the whole MEO-model extension is validated by comparing simulated and real-life missions (section 4.4).

4.1. Description of data

4.1.1. Type and specifications of the vehicles

The event validation is done by using the data of two electric rigid-trucks that have been in use since 2017. This data is confidential so only the aggregated results shall be shown in this thesis. The batteries of the trucks have a size of 180 kWh, the EM can deliver up to 260 kWh and the vehicles itself weighs 12.34 tonnes. When loaded till maximum capacity it weighs 20.5 tonnes. This thesis focuses mainly on tractor-trailers in the Netherlands and not rigid-trucks. But as no data on electric tractor-trailers currently exists the data of these two electric rigid trucks shall be used. Due to the simplicity of the model it is assumed that this data can also applicable for the validation of the model, by adjusting the parameters such as weight, axles etc.

4.1.2. General statistics of the vehicle usage

From the data the following could be deduced about trucks I and II:

1. Average DOD per day: I) 55.47 %, II) 53.64 %

![Figure 4.1: The lowest DOD for each day](image1.png)
2. Average distance driven per day: I) 161.6 km, II) 107.4 km

![Distance graphs for Vehicle 1 and Vehicle 2](image1)

(a) Vehicle 1  
(b) Vehicle 2

Figure 4.2: The total driven km for each day

3. Average distance between charge: I) 47.5 km, II) 42.8 km

4. Average kWh/km: I) 0.919 kWh/km, II) 0.981 kWh/km

![Average kWh/km graphs for Vehicle 1 and Vehicle 2](image2)

(a) Vehicle 1  
(b) Vehicle 2

Figure 4.3: The average kWh/km for each day

5. Average charging events per day: I) 2.5, II) 1.5

6. As was noted in section 3.2.1 the performance of the battery can be influenced by the temperature. This can also be seen in the data. If the available range (80% of the battery capacity divided by the energy usage per km) is shown against the temperature on that day (like figure 3.9b). We see also here that the available range decrease as the temperature decrease, this effect is very small however. Furthermore we cannot indicate an optimum similarly to figure 3.9b, however this can also be due to the limited temperature range in the Netherlands.

![Available range vs Temperature graphs for Vehicle 1 and Vehicle 2](image3)

Figure 4.4: Efficiency data of different trips of two electric trucks in the Netherlands plotted against the minimum, average and maximum temperature of that day. Temperature data was retrieved from the KNMI

4.1.3. Data quality

The data of truck I is of higher quality than the data of truck II. The data of truck II has large gaps between driving moment as compared to truck I. This is due to the website that hosted the database. From the data that is there for truck II, we notice that this truck appears to be used less. And when
it is used less kilometers are driven compared to truck I. The average daily DOD, distance driven and average distance between charging are therefor also less then truck I. The main drawback of the used data is the fact that the payload during each ride is unknown. This will lead to a validation which cannot be without errors, the validation of the model will have to be done by comparing a possible range of outcomes.

4.2. Conceptual Model Validation: Willans Line validation

The validation of the Willans line is done by calculating through the following formulas $P_{Wheels}$ and $P_{Battery}$:

\[ P_{Motor} = \frac{T[Nm] \cdot \omega[RPM] \cdot 2\pi}{1000 \cdot 60} \]

\[ P_{Wheels,propulsion} = \frac{P_{Motor}}{\etaTM} \]

\[ P_{Wheels,regeneration} = \frac{P_{Motor}}{\etaTM} \]

\[ P_{electrodes} = \frac{V \cdot I}{1000} \]

\[ P_{Battery,charging} = P_{electrodes} \cdot \etacharging + P_{Aux}[kW] \]

\[ P_{Battery,discharging} = P_{electrodes} + P_{Aux}[kW] \]

As one can see the definitions for the $P_{Wheels}$ and $P_{Battery}$ are quite elaborate. This is because of several reasons. First of all the $P_{Wheels}$ is calculated through the following two signals: Torque requested $[Nm]$ and the speed of the motor $[RPM]$. The first signal (torque requested) gives rise to several uncertainties, furthermore the combination of these two signals indicates the power the motor needs, but not how much power the wheels need or deliver. Therefore the data is updated by the estimated transmission efficiency ($\etaTM$). Secondly the power delivered to the batteries cannot be deducted straight from the current and voltage signal. This is because inside the battery also losses occur, due to internal resistance and the higher voltage applied when discharging. Therefore the negative values for the battery signal are updated by multiplying them with a factor of 0.99 to compensate for the internal losses. In practice, the internal resistance of a battery is dependent on its size, chemical properties, age, temperature, and the discharge current as we saw in section 3.2.1. When plotting these measurements with the previously defined Willans line the following figure is obtained:

Figure 4.5: All data from truck 1 scattered in one graph, coral line is the modeled Willans Line for validation (assumptions can be found in table 3.1). The colors (blue to red) indicate the density of the data.
Several features can be observed namely: I) the horizontal and vertical lines below the positive Willans line, II) the large cloud of data-points around the Willans Line, and III) the fitting of the Willans Lines. Starting with I), the figure below gives visual representation of which data points are meant:

![Figure 4.6: Selection overview of the data clusters not on the Willans Line](image)

Because it is suspected these points could be related to the speed and acceleration of the vehicle the following figures are also made:

![Figure 4.7a: Speed vs P Wheels](image)

(a) In this figure we see that all the green values are found on the speed limit of the vehicle and all the orange values are found on the maximum of the power provided by the motor

![Figure 4.7b: Acceleration vs P Wheels](image)

(b) In this figure we see that the green values are driving at a constant speed while the orange values show a range between the maximum and minimum of acceleration

From the figures 4.7a and 4.7b we can see that:

- The values with a constant Battery Power: occur when the vehicle is driving at a constant maximum speed of 80 km/hr. This can imply that the signal for the power of the wheels is not always correct, as it is deducted from the pedal position of the driver. When the vehicle already reached its maximum speed it still has to communicate to the engine it wants more energy to keep the
speed constant, however as the motor is already delivering maximum power this will not translate into more power delivery from the battery, hence giving a constant battery power output.

- The values with a constant Wheels Power: occur when the vehicle is asking the maximum power of the motor and the acceleration varies, this implies that this might happen when the vehicle is pulling up and there is a slowness in the reaction of the battery power output.

Secondly, the large cloud of data-points around the modeled Willans Line (II). This cloud can be attributed to several causes, for example:

- An irregular time misalignment in the measured data
- Driving behaviour: braking does not always occur through using the brake, sometimes no brakes are applied but the driver lets the truck coast down. This is especially important for the negative torque values as they are estimated based on the pedal position. This can mean that sometimes power is delivered to the battery but there is no or only a slight power measured at the wheels through the signals.

And lastly, from figure 4.5 it can be noticed that the Willans Lines are not a right fit yet (III). We see that the in the regeneration mode the efficiency of the charging is underestimated (more energy goes back into the battery than expected), while for the propulsion mode the discharge of the battery in overestimated (less energy goes out of the battery). This could be possible as it is also described in some scientific literature such as: [49], where it was found that the charging losses were less than the discharging losses. Also the auxiliaries seem to be higher than expected, as at the origin most of the data is not zero but rather something higher. With this new information new Willans Lines can be plotted resulting in figure 4.8a.

![Efficiency (η)]

<table>
<thead>
<tr>
<th>Efficiency (η)</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>η_charger</td>
<td>0.97</td>
</tr>
<tr>
<td>η_discharge</td>
<td>0.97</td>
</tr>
<tr>
<td>η_charge</td>
<td>0.99</td>
</tr>
<tr>
<td>η EM</td>
<td>0.9</td>
</tr>
<tr>
<td>η_GEN</td>
<td>0.94</td>
</tr>
<tr>
<td>η_FD</td>
<td>0.98</td>
</tr>
<tr>
<td>P_EMMax</td>
<td>260</td>
</tr>
<tr>
<td>P_GENMax</td>
<td>260</td>
</tr>
<tr>
<td>P_aux</td>
<td>7</td>
</tr>
</tbody>
</table>

Figure 4.8: The adjusted Willans Line (right) and the changed efficiencies (left)

4.3. Computerized Model Verification: summation of energies

This section will verify if the computerized model functions according to the equations as thought of in section 3.1. This is done by allocating the losses and summing these. If all calculations are done right these losses should equal the total used electricity. The allocation of the losses is explained in detail in
appendix C. Following two figures are the energy distributions of a conventional and an electric tractor-trailer expressed in percentages. As can be expected the electric energy distribution has a negative element (see also figure B.4), which makes the energy distribution equal to 100%. The figures show that: I) in electric vehicles there is relatively less energy lost to heat, due to the increase efficiency of the motor, II) the losses in the battery and charger are relatively small and lastly III) the regenerative braking recovers around 13% of the energy.

![Figure 4.9: Energy distribution of a conventional tractor-trailer](image)

![Figure 4.10: Energy distribution of an electric tractor-trailer](image)

**4.4. Operational Validation: MEO Model and Extension**

The last step in the validation is to compare the model to the real system, by comparing a random velocity-profile and corresponding actual energy consumption from the data-set. In this section firstly the used signals from the data set will be discussed. Then the Coulomb Counting method is discussed. Lastly the MEO validation is done, firstly for one mission profile, and then for more.
4.4. Operational Validation: MEO Model and Extension

4.4.1. Different signals
The main point of interest during this section is the measured and simulated kWh/km value. Because the data-set is quite extensive and contains many signals it is firstly important to explain the signals that will be compared in detail:

- Energy efficiency [kWh/km] signal (EE-signal): this readily available signal from the data-set is the result of an analysis based on the raw data of the data-set. It gives an overall indication for each day how efficient the truck is. How this signal is measured is unclear but it does vary per second.

- SOC [%] and current [A] signal (CC-signal): to get a better insight in the energy consumption we can also recreate the kWh/km signal by using the SOC signal and the distance driven. To verify the SOC signal the Coulomb Counting method will be used.

4.4.2. Coulomb counting
In this section the Coulomb Counting method is explained, this method is applied to obtain a second, more precise and continuous SOC signal. The Coulomb counting method uses the discharging current, \( I(t) \), and previously estimated SOC values, \( SOC(t-1) \). The SOC is calculated by the following equation:

\[
SOC(t) = SOC(t - 1) + \int_{0}^{t} \frac{I(t)}{C_{battery}} dt \tag{4.3}
\]

Where the symbols mean the following:
- \( SOC(t) \): Battery state-of-charge at time \( t \) [%]
- \( SOC(t-1) \): Battery initial state-of-charge [%]
- \( I(t) \): Charge/discharge current [A]
- \( t \): Time [h]
- \( C_{battery} \): Battery capacity [Ah]

The battery capacity is calculated by estimating the nominal voltage based on the data and then using the following formula:

\[
C_{battery} = \frac{Q[kWh]}{V_{nom}[V]} = \frac{180[kWh]}{615[V]} \tag{4.4}
\]

Doing this for a random trip of half an hour, we obtain the result as in figure 4.11. We can conclude after this that the current signal and SOC-signal give a correct projection of the battery, although by using the Coulomb Counting method more precise values are obtained.

4.4.3. Results
Modeling one mission profile in detail
Firstly one measured trip is simulated and compared to real-life data. This is done so all the assumed parameters can be explained in detail, furthermore the payload can be approximated and the EE-signal and the CC-signal can be compared. The real mission that will be simulated using the Willans Lines and MEO is measured in January, and the speed trajectory is illustrated in figure 4.12. It is most likely that the first trip of the day will be fully loaded, therefore the payload of the trip will be around 4,000 kg.
Figure 4.11: Result of the coulomb counting method, pink line represents the measure current of the battery, the orange stripes are the measured SOC data while the blue line is the calculated SOC by means of the coulomb counting method.

Figure 4.12: The speed [km/hr] of vehicle 1 in January 2018, and the selected mission profile.

In the following figure the two signals as mentioned in the previous section are depicted along with the driven distance during this mission:

Figure 4.13: SOC signals and distance during the mission.

Besides the mission profile the other input-parameters for the MEO model also have to be given:

- the weight of the vehicle empty: 12,340 kg
- the payload of the vehicle is varied from 0 to 8,000 kg
- the electric motor has a power-output of 260 kW
efficiencies and auxiliaries as indicated in table 4.8b

frontal area of 8.74 m²

Table 4.1: The results for the simulation and real-life data

<table>
<thead>
<tr>
<th></th>
<th>kWh/km range</th>
</tr>
</thead>
<tbody>
<tr>
<td>MEO simulation</td>
<td>1.08-1.30</td>
</tr>
<tr>
<td>EE-signal</td>
<td>1.2</td>
</tr>
<tr>
<td>CC-signal</td>
<td>1.08</td>
</tr>
</tbody>
</table>

\[
kWh/km = \frac{ΔC_{battery} [kWh]}{distance [km]} = \frac{ΔSOC \cdot C_{battery}}{distance} = \frac{0.1023 [-] \cdot 180 [kWh]}{16.635 [km]} = 1.082
\] (4.5)

The MEO simulation results are between 1.08-1.30 kWh/km depending on the payload. The EE-signal gives an average of 1.2 kWh/km, while the CC-signal resulted in 1.08 kWh/km (equation 4.5). Both signals show to be within the simulated values. However the difference between the EE-signal and CC-signal is quite large, and furthermore the EE-signal is much higher than the average (table 4.1), this shows that the quality of the database is not always high. Lastly the unknown payload gives an error, in this case if the vehicle is empty the simulated would closely approximate the CC-signal, however if the payload is the assumed 4,000 kg then the simulation overestimates the energy usage. The following section will give a better understanding of these signals and simulated values on a larger scale.

Modeling multiple mission profiles

Using a script to find all mission profiles in four months of real-life data, and the same method as mentioned in previous section the relative difference between the MEO-model with extension and the real-life data can be calculated. The relative difference is expected to be large as the MEO-model does not take into account the temperature, and the payload of the real-life data is unknown. Assumed are payloads of 0.0, 4,500 and 8,000 kg (empty, half-full, full). In total 182 and 166 mission profiles were found by the script during a period of 4 months, for respectively the EE- and CC-signals. The figure below shows velocity change during the four months.

Figure 4.14: The start (green) and stop (red) points as found by the script for four different months, noted can be that in some months more data is available than other months.

For each mission profile the average kWh/km from the real-life database was calculated using the EE- and CC-signal (see also section 4.4.1). These values were compared with the MEO-model outcome for the same mission profile using the following equation, where \( x_{EE} \) is the value from the EE-signal, \( x_{CC} \) the value using the current signal with the Coulomb Counting method and \( x_{MEO} \) the value obtained
In the following figures the results are shown. It can be noted in figure 4.15 and 4.16 that most points center around in the same region, however there are some outliers if we note the Kernel Density Estimation plots on the axis. The figures also show a close-up of the cloud. This figure is supported by the histogram, box-plot seen in figures 4.18 and 4.19 and the statistics. In these figures the outliers are excluded. For normal distributed data 99.7% of all data-points will be within 3 standard deviations from the mean. If only the data between the 0.15% and 99.85% quantiles are assumed 2 outliers are detected. After these outliers were analyzed it showed that these values had an extremely long mission profile (>20 hours). The long length of these missions can be attributed to the used script. Not all mission are correctly recognized. This time duration error affects the MEO model simulations and the cc-calculations (figures 4.15 and 4.16) but not the EE-signal. Based on these findings the outliers were omitted from the data-set.
Figure 4.16: Scatter plot of the MEO predicted values and the values from the real-life database using the Coulomb Counting method

Figure 4.17: Scatter plot of the Energy Efficiency signal of the database and the values obtained by Coulomb Counting
The histograms and statistics table indicate several things:

- **Difference between the EE- and CC-signal**: there are noticeable differences between the EE- and CC-signal. In section 4.4.3 the CC-signal appeared to be more precise, but from the distribution in the scatter diagrams and histograms we see that the EE-data is more centered around one point in comparison with the CC-data (figure 4.17). The CC-signal seems to be affected when the mission profile is too long (extreme outliers were found). Furthermore more data on the EE-signal was available than the CC-signal (16 more points for EE- than CC-signal). Since the spreading of the EE-signal is less, there are less outliers, and more data points are available for the EE-signal, we may say that this signal is of higher quality than the CC-signal.

- **Shape of the histograms**: the shapes for the histograms for all payloads show to be normally distributed with a tail to the right (which means that the MEO-model overestimates the outcome). Also their width is quite equal if the minimum and maximum values are compared. However the higher the payload the more the histogram is shifted to the right, which indicates a larger error for that data-set. This is reasonable as trucks are seldom filled till their maximum capacity. It's more likely that the average payload is between the empty or half-full capacity.

- **Mean, median and quantiles**: the shift to the right for the different payloads is seen in the mean, median and quantiles. The half and empty simulations show to have the smallest error compared to the full simulation. Comparing the EE- and CC-signal we see that the histograms have a similar mean value.

- **Standard deviation**: The standard deviations of the EE-signal are around 35%, while the standard deviation of the cc-signal are within a range of 38-47% and increase as the payloads increase. The median for the payloads are different, the most precise simulations can be attributed to the half and empty simulations. Since the CC-signal is less precise and the empty payload assumption is the most probable the error of the MEO model with extension is said to be: between 0.83 % and 15.32% with a standard deviation of 35.0%. To get an idea of magnitude this equals an error of 0.06 - 0.2 ±0.79 kWh/km, where the mean of the EE signal is 0.99 kWh/km.
4.5. Conclusion

In this chapter the created model was validated using data from two electric trucks. The conceptual model validation showed that the chosen efficiencies (section 3.2) could not precisely predict the energy demand from the battery, and therefore they were slightly adjusted. Additionally several data trends were presented and explained: a constant battery power was observed at maximum speed which was attributed to the pedal signal and furthermore a constant maximum wheel power was found when the vehicle was accelerating. The computerized model verification served as a way to make sure that the model summed everything correctly. This showed to be the case. Lastly the MEO model with extension was validated by Event Validity with real-life mission profiles from the confidential data-base. Two different signals from the data-base were compared with the MEO simulated. The Coulomb-Counting method showed to be less accurate than the standard value in the data-base, due to the missing of part of this data. A difficulty with this simulation is the fact that it is unknown what the payload for each mission is. Therefore 3 simulations were done for each mission profile in the data-base, thereby assuming that the truck was either: empty, half-full or full. The most probable is assumed to be empty or half-full, which also appeared from the results: empty and half-full simulations gave the smallest error. Finalizing the results we could see that: for the most probable case (half-full or empty) the error of the MEO model with extension is said to be: between 0.83 % and 15.32% with a standard deviation of 35.0%. To get an idea of magnitude this equals an error of 0.06 - 0.2 ±0.79 kWh/km, where the mean of the EE signal is 0.99 kWh/km.

4.5.1. Uncertainties

Uncertainties in this model can be attributed to several elements in the model. Firstly as became apparent from the first validation (section 4.2), the efficiency values of the vehicle to model are crucial to determine correctly. The battery, EM and transmission efficiencies were assessed in section 4.2 in an aggregated manner. This aggregated manner, where one only looks at the signals in combination with other signals and not into detail, was needed due to the type of data available and the model specifications. Secondly, the errors found in this validation could also be due to the simplifications made in the previous section on (again) the efficiency of the battery and motor. In reality these efficiencies are depended on a multitude of factors, such as: temperature, driving behavior or road type.

In the end the intended purpose of the model determines the needed accuracy level given by the model. This thesis will only assess a general type of tractor trailer and therefore the efficiencies as chosen and dissected in previous chapter will have to be taken as average efficiencies rather than efficiencies of an existing vehicle. From the histogram we found a large standard deviation, it is expected that this
large standard deviation is a result of the missing in payload information, and that if the payload was known a smaller standard deviation would be found. How large the standard deviation is cannot be said based on the current data.
Characterization of the Dutch tractor-trailer sector by mission profiles

In this chapter possible mission profiles and the usage behavior of regional and long-haul transportation in the Netherlands will be evaluated. Goal is to find in the end several mission profiles which can represent the whole tractor-trailer sector.

5.1. Literature and data on the current HDV sector in the NL

5.1.1. HDV fleet and usage

The transportation of goods by trucks and tractor-trailers is divided between national transportation and international transportation. The following figure depicts the share in distance driven by different types of trucks in the two different sectors. The transportation of goods by Dutch vehicles in the Netherlands (69%) is bigger than the transportation of goods outside the Netherlands (31%). From the figure we see that tractor-trailers make to most kilometers especially outside the Netherlands. Furthermore we see that usage of the lightest truck (>10 tonnes) is small in comparison with the other two weight-classes. As noted by [50] these days heavier vehicles are favored over the lighter vehicles, as the distribution of goods is more often divided between smaller vans for the city-distribution and heavier trucks for the motorway. Figure 5.2 shows for three types of road-types the share in mileage for the four types of vehicles. Again we see a large share of tractor-trailers (semi-trailers), especially for the motorway, and a very small share of the lightest truck. The share between the other two types are more or less equal.

Figure 5.1: Share of kilometers driven in the Netherlands (left) and outside the Netherlands (right) by the following vehicles of the Dutch fleet: semi-trailer (tractor-trailer), trucks with GVW: 0-10, 10-20 and >20 tons. Figures are made based on data from CBS [51]
5. Characterization of the Dutch tractor-trailer sector by mission profiles

### Table 5.1: The average properties of the vehicles

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;10</td>
<td>4669</td>
<td>1082</td>
<td>1.77</td>
<td>121</td>
</tr>
<tr>
<td>10-20</td>
<td>8820</td>
<td>2376</td>
<td>11.11</td>
<td>187</td>
</tr>
<tr>
<td>&gt;20</td>
<td>15583</td>
<td>5489</td>
<td>5.14</td>
<td>281</td>
</tr>
<tr>
<td>&lt;10 yes</td>
<td>6947</td>
<td>3514</td>
<td>0.21</td>
<td>124</td>
</tr>
<tr>
<td>10-20 yes</td>
<td>15605</td>
<td>7107</td>
<td>2.37</td>
<td>252</td>
</tr>
<tr>
<td>&gt;20 yes</td>
<td>18379</td>
<td>13304</td>
<td>7.51</td>
<td>320</td>
</tr>
<tr>
<td>Tractor-trailer yes</td>
<td>15729</td>
<td>11756</td>
<td>71.53</td>
<td>310</td>
</tr>
</tbody>
</table>

### Figure 5.2: The share of mileage for the different vehicle types per road-type for national transportation

#### 5.1.2. Distance

The following numbers all originate from the report of TLN ‘Transport in cijfers 2016’, unless otherwise specified. TLN reports a lower total number of trucks and tractor-trailers in the Netherlands, respectively 63,356 and 70,533. This difference might be due to a slightly different definition (private ownership or company) and the fact that the data of TLN is less recent. These trucks drove a total of 6.5 billion kilometers in 2016. The average distance per type of good transported ranges between 51-104 km as can be seen in the following table in the second column.

### Table 5.2: Average distance (from [52]) and percentage of total payload per good category (from [53])

<table>
<thead>
<tr>
<th>Type of good</th>
<th>National [km]</th>
<th>International [km]</th>
<th>Payload %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural products</td>
<td>84</td>
<td>444</td>
<td>31</td>
</tr>
<tr>
<td>Nutritional products</td>
<td>100</td>
<td>337</td>
<td>61</td>
</tr>
<tr>
<td>Solid fuels</td>
<td>81</td>
<td>254</td>
<td>-</td>
</tr>
<tr>
<td>Crude oil and products</td>
<td>56</td>
<td>327</td>
<td>37</td>
</tr>
<tr>
<td>Ores and metal residues</td>
<td>70</td>
<td>248</td>
<td>66</td>
</tr>
<tr>
<td>Metal products</td>
<td>104</td>
<td>316</td>
<td>75</td>
</tr>
<tr>
<td>Construction materials</td>
<td>53</td>
<td>202</td>
<td>46</td>
</tr>
<tr>
<td>Fertilizers</td>
<td>51</td>
<td>243</td>
<td>33</td>
</tr>
<tr>
<td>Chemical products</td>
<td>65</td>
<td>307</td>
<td>73</td>
</tr>
<tr>
<td>Other</td>
<td>76</td>
<td>332</td>
<td>69</td>
</tr>
</tbody>
</table>

On an international level Germany and Belgium are the most important countries to deliver goods. Around 50% of total mass transported on the road can be attributed to Germany, and around 35% to Belgium. The average distance driven to Germany is 296 km and to Belgium this is 166 km. Also for this sector similar numbers for the average distance per type of good can be found, which are depicted in the right column of table 5.2. A last good indicator for the different types of distances there are
5.2. Characterization of the (electric) HDV sector in the Netherlands

5.2.1. Resulting mission profiles

In the previous sections we found that most of the HDV fleet relies on tractor-trailers and that these mostly drive on the motorway. From section 5.1.1 (table 5.1 and figure 5.2) we saw that tractor-trailers are most important for the international and national transport. For national transport >10 and 10-20
tons are after the tractor-trailer most important. So far the actual weight of the maximum payload that is being transported couldn’t be found, only the average values as depicted in table 5.1 were found.

The most common national missions are divided between the distance classes: 0-49, 50-149 and 150-499 kilometers. It is interesting to see for each category what the implications are for electrification. By assigning one or more mission profiles to each category a characterization of the HDV fleet can be made:

• **0-49 km**: An already promising short distance trip can be found in the **drayage sector**, which was demonstrated by projects around Los Angeles [54]. Translating this to a more abstract mission profile we describe this type of trip as a short frequent mission with a distance around 20 km and a payload of 60%.

• **50-149**: These distances concern regional transportation, this regional transportation can either be city-to-city transportation where lighter goods for residential use are transported or short long-haul transportation where heavier goods are transported for the industry. We shall translate this to two different mission profiles: the **distribution of nutritional products** (distance 100 km and changing payload between 10-30%) and the **long-haul transport to Belgium** as this is one of the most important countries to transport goods to (with a distance of 130 km and a payload of 60%).

• **149-499**: We saw that besides Belgium also Germany is of great importance. And than in particular the close-by provinces. This type of mission profile can be described as a **long-haul mission to Germany** with a distance around 300 km and a payload of 50%.

Using the Mission Profile Generator (MPG) of TNO, the velocity profiles of the above missions can be constructed. The MPG is used for several reasons: 1) no measuring equipment is needed as the MPG constructs these profiles based on a large data-set of already measure trips, 2) the only input is the speed-limits and corresponding distance on the road and, 3) the resulting velocity profiles are realistic and randomized. The missions as illustrated below will be driven multiple times a day. The charging patterns will determine the capacity of the battery. Appendix E gives the routes these missions profiles are based on.

![mission profiles](image)

**Figure 5.4: Overview of the different mission profiles, mission profiles were generated using the MPG**

• The last mission profile will function as the **average usage of a Dutch tractor-trailer**. This is done by finding the energy usage of the road-segments: urban, rural and motorway and weight these according to the average as found in section 5.1.1. TNO already has standardized these profiles and shall also be used in the following steps.

**5.2.2. Resulting energy usage**

With the mission profiles now clear the energy usage per profile is calculated by the developed model. Table 5.4 depicts the usage per mission profile and for the three road-segments. As the interest
also goes out the the energy usage of future tractor-trailers, the increase in energy efficiency must be considered as well. The MEO-model can be used to calculate the maximum saving potential by adding different measures to each other. These measures include: power train, auxiliaries, air drag, transmission, breaking, payload and rolling resistance savings. In Appendix D the measures that are applied in the model are described in detail. Results from MEO show that in 2030 a reduction of 38.0% percent can be expected for the conventional tractor-trailer (table 5.4, column: Conventional 2030). This is slightly less compared to what the ICCT projects. The ICCT projects that compared to the baseline tractor-trailer of 2010, available efficiency technologies can reduce fuel use by 27% in long-haul operation by 2025 (average annual of -3.1%). From 2025-2030 well-known but not yet widely commercialized technologies can achieve a 43% fuel consumption reduction in long-haul operation by 2030 (average annual of -3.6%) [55]. Also the efficiency of an electric tractor-trailer can be assumed to increase, either by road-load reductions or by improvements in the drive-line. Again the MEO model can be used to determine the maximum potential savings, this time the following measures are included: auxiliaries, air drag, transmission, breaking, payload and rolling resistance savings. Results show that in 2030 a reduction of 32% percent can be expected.

Table 5.4: Results from the extended MEO model, all values obtained by the MEO-model and developed extension

<table>
<thead>
<tr>
<th>Profile</th>
<th>Conventional [kWh/km]</th>
<th>Electric [kWh/km]</th>
<th>Conventional 2030 [kWh/km]</th>
<th>Electric 2030 [kWh/km]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motorway</td>
<td>3.37</td>
<td>1.53</td>
<td>2.03</td>
<td>1.01</td>
</tr>
<tr>
<td>Rural</td>
<td>4.45</td>
<td>1.74</td>
<td>3.50</td>
<td>1.55</td>
</tr>
<tr>
<td>Urban</td>
<td>4.92</td>
<td>2.02</td>
<td>3.15</td>
<td>1.28</td>
</tr>
<tr>
<td>Germany</td>
<td>3.76</td>
<td>1.67</td>
<td>2.50</td>
<td>1.17</td>
</tr>
<tr>
<td>Belgium</td>
<td>4.85</td>
<td>2.18</td>
<td>3.31</td>
<td>1.62</td>
</tr>
<tr>
<td>Regional Distribution</td>
<td>4.18</td>
<td>1.59</td>
<td>2.95</td>
<td>1.21</td>
</tr>
<tr>
<td>Drayage</td>
<td>5.02</td>
<td>2.07</td>
<td>3.59</td>
<td>1.55</td>
</tr>
</tbody>
</table>

### 5.2.3. Battery capacity, distance per day and charging pattern

**Battery capacity**

This section shall elaborate on the mission profiles by evaluating the needed battery capacity for different road-types and charging patterns. To get a first impression of the battery capacities that are necessary for the different profiles, the kWh/km usage of the different types (10-20,>20 tons and tractor-trailer) is used. When these values are multiplied with the range the left figure below is obtained. The maximum battery size for truck more than 20 tons is expected to be around 1,300 kWh for a range of 500 km. While for a truck below 10 tons a battery size of 540 kWh is needed. On the right side the increase in weight compared to the empty weight is shown, with an expected maximum of 10% increase in weight. Furthermore is it shown that for urban trips more battery capacity is required than for motorway trips, this is because less acceleration is required. These numbers and figures are just a first estimation what electric trucks will look like. In the left figure existing electric trucks and passenger cars are also plotted for comparison.

![Figure 5.5: The range in km versus the expected required battery capacity and increase in the empty weight. Data is based on the energy usage as calculated by MEO, assuming a available capacity of 80% and a weight of 160 kg/Wh](image-url)
What can be noted is the large difference between Tesla and other electric trucks. This difference in battery size could be the first sign that in the future two types of categories in the electric tractor-trailers sector can be expected to crystallize: 1) a category where electric trucks have battery sizes up to 400 kWh, but with a range of different capacities, and 2) a category that has battery capacities larger than 800 kWh specially designed for long haul multi-day trips.

### Charging patterns

There exist multiple ways of charging the battery of an EV. The rapid charging of a battery is commonly known as overnight charging, while the fast charger is currently used to quickly charge the battery during the day, ultra-fast charging is even more fast and can be used in the future recharging at pit stops. For fast chargers the charge speed drops when the battery is almost fully charged to prevent the battery cells from overheating. Typically at 80-90% SOC the speed drops and charging will slow down further closer to 100% SOC. For the ultra-fast chargers the battery can only be charged up to 70%. The rate of charge or discharge is often expressed in relation to the capacity of the battery. This rate is known as the C-Rate. The maximum charge current a Li-ion can accept is governed by cell design, the goal is to avoid lithium-plating on the anode and to keep the temperature under control. Some cells for example (hybrid Cobalt cells) can be charged above 1C with only moderate stress. It is generally advised not to charge higher than 1C to optimize the life-time of the battery [32].

What does all this mean for a electric HDV charging station?

As we saw in figure 5.5 a battery range between 200 and 1,000 kWh can be expected. A vehicle which charges at a Fastned station, is charged with 400 V and depending on the type of battery different currents. The required current for an electric HDV with a capacity of 200 kWh would then be 500 Ah, to charge in one hour. For a 1,000 kWh battery a current of 2,500 Ah is necessary. Currently the highest charging rate possible in the Netherlands is 350 kW, which implies that for smaller trucks charging within an hour at these stations is already possible. However the bigger the vehicle and the range the higher the charging rate will have to be. For a truck with a battery of 1,000 kWh to be able to charge fully within half an hour 2 MW will be needed. The driver of an electric tractor-trailer is bound to European rules that give a maximum amount of hours per day and per week. These rules combined with the distance and time per mission profile can determine the optimal charging pattern for each fleet. The following is a quick summation of the different rules:

“A truck driver is required by law not to drive more than 9 hours a day. Twice a week this can be prolonged to 10 hours. Furthermore a truck driver needs to take a break of 45 minutes after 4.5 hours of continuous driving. This break can be divided into two breaks: one of 15 minutes and one of 30 minutes. Besides these rules a driver isn’t allowed to drive more than 56 hours a week, and not more than 90 hours per two weeks. Lastly the driver has to be able to sleep for 11 hours each day. Three times a week this can be shortened to 9 hours.”

In figure 5.6 it is indicated which charging rate is suited for what type of mission profile with a certain battery capacity. In this figure we see that for most mission profiles a rate of 350 kW will be sufficient to charge within 45 minutes after the complete mission. For the mission profile to Germany this is different however, this type of vehicle is perhaps better off to take a smaller battery and charge during the obliged stop. From the figure we can now determine which battery capacity would be suited best for each mission: Germany has a battery of 300 kWh which requires the vehicle to charge for at least 45 minutes during the mission, the missions: Belgium, Regional Distribution and Drayage will require battery packs of 360, 217 and 52 kWh. These capacities are an indication of what type of battery each profile will have in the future, they do not represent specific existing trucks or prototypes. Charging infrastructure will have a big influence on the eventual electric tractor-trailers in the end.

### Distance per day

The distance that it can drive a day is then depended on the frequency of the mission. In the table on the next page we see how often a mission can be driven per day taking into account the charging between each mission. Furthermore the total distance driven and the battery capacity are given. Apparent is that the mission to Germany is quite short compared to other missions. This is because there is a pay-off between the fast charging and the battery size. In practice the German mission could be able to drive around 1.5 missions per day.
5.2. Characterization of the (electric) HDV sector in the Netherlands

Figure 5.6: On the x-axis we see 4 times 5 profiles (far, Germany, Belgium, Regional Distribution and Drayage) the number 1 to 4 indicate the number driving moments during one mission, so how often the vehicle can stop, on the z-axis the corresponding battery capacity is given, and on the y-axis the charging rate that will be required to charge that battery capacity in either 15 minutes or 45 minutes. The code to make the figure is found in Appendix G.3

Table 5.5: The specifications of each mission profile, it is estimated that each battery can deliver 3,000 cycles (see also section 3.2.1), and each vehicle has a life time of 8 years.

<table>
<thead>
<tr>
<th>Mission</th>
<th>Duration [hr]</th>
<th>Missions per day</th>
<th>Capacity [kWh]</th>
<th>Distance [km]</th>
<th>Cycles</th>
<th>Batteries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>6.2</td>
<td>1</td>
<td>300</td>
<td>308</td>
<td>4,000</td>
<td>2</td>
</tr>
<tr>
<td>Belgium</td>
<td>2.3</td>
<td>3</td>
<td>360</td>
<td>396</td>
<td>6,000</td>
<td>2</td>
</tr>
<tr>
<td>Regional Dist.</td>
<td>4.4</td>
<td>2</td>
<td>217</td>
<td>217</td>
<td>4,000</td>
<td>2</td>
</tr>
<tr>
<td>Drayage</td>
<td>0.5</td>
<td>11</td>
<td>52</td>
<td>253</td>
<td>22,000</td>
<td>8</td>
</tr>
<tr>
<td>Average</td>
<td>-</td>
<td>-</td>
<td>200 kWh</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
</tbody>
</table>
5.3. Conclusion

The chapter tried to answer the second research question which was:

<table>
<thead>
<tr>
<th>Research question 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>What are possible mission profiles for an electric tractor-trailer combination, taking into account different charging profiles and distance ranges, and how does it compare to the typical use?</strong></td>
</tr>
</tbody>
</table>

During this chapter the Dutch HDV fleet was characterized and therefore assessed the typical range and usage of HDVs in the Netherlands. It appeared that most of the HDV fleet relies on tractor-trailers and that these drive mostly on the motorway. From different data-sources 5 different mission profiles could be distilled that represented the largest part of sector tractor-trailer sector. The found mission profiles were missions: to Germany, Belgium, Regional Distribution, Drayage and an average mission profile for the Netherlands. Using the MPG of TNO velocity profiles could be constructed that served as the input for the MEO-model. Energy usage of these profiles show a range of: 3.37 to 5.02 kWh/km for conventional tractor-trailers and for electrical tractor-trailers: 1.53 to 2.18 kWh/km, which is a moderate range. The Germany mission profile and Regional Distribution are the most efficient compared to the Belgium and Drayage mission. Which is partly the result of the speed limits for the chosen mission (as found in Appendix E).

The second part explored future characteristics of the electric fleet of the Netherlands. Firstly the battery capacity and corresponding range were analyzed. Using the results from the MEO-model with extension we saw that on the motorway less battery capacity is needed, while driving the same distance in an urban area more capacity will be needed. Furthermore it was seen that battery capacities between 200-1,200 kWh could be possible with corresponding a range of 100-500 km which would imply share of 2-10% increase of the total weight of the tractor-trailer. Lastly the possible charging patterns were evaluated. It was seen that it is necessary to find the right battery capacity for each type of mission profile, as an optimal balance between charging and the battery capacity is needed. Ultimately the following capacities were chosen for the German, Belgium, Regional Distribution, Drayage mission and Dutch average profiles: 300, 360, 217, 52 and 200 kWh.

5.3.1. Uncertainties

The characterization of a whole vehicle sector will never result in a characterization that comprehends all types of fleet types. There are simply too many possible routes and business models to gaps in 5 mission profiles. The largest uncertainties in this chapter lay in the characterization of the future electric mission profiles. The charging infrastructure of the future is uncertain and difficult to incorporate. This uncertainty directly affects the chosen values for the battery size as well. A last uncertainty in this chapter was the lack of payload data on a national or regional level. The payload affects all the underlying assumption as it directly influence the energy usage of the vehicle.
The additional CO$_{2,eq}$ emissions from tractor trailers

The following chapter presents the results from the CO$_{2,eq}$ assessment on the production and maintenance phases, which are all steps within the Life Cycle Assessment (LCA) of HDVs. During the chapter conventional tractor-trailers are compared with electric versions. Firstly literature on LCA is evaluated, which is followed by the determination of the CO$_{2,eq}$ emissions during the phases.

6.1. Literature on LCAs of tractor trailers and EVs
Numerous articles have been published in the literature that have addressed the life-cycle environmental impact and the costs of HDVs. According to [56] the two primary types of LCA methodologies include process-based LCA and economic-input output LCA (EIO-LCA), or a combination of these two known as hybrid LCA. The main difference between the two is that process-LCA analyses the actual process (an example is the ISO 14040 Standards), while the EIO-LCA uses history of economic transactions to acquire the value added along a supply chain, which in then interpolated on environmental impacts from accompanying data-sets. Most articles focus on analyzing and comparing alternative fuel technologies in passenger vehicles and in light commercial vehicles, [26] already published an extensive list on related literature. For now we will focus on the literature that deals with electric HDVs. Currently there are multiple articles specifically on the LCA of electric HDVs. Namely [26], evaluates electric tractor-trailers based on a hybrid-LCA, [57] performs an EIO-LCA on electric delivery trucks and [58] evaluates EVs by a process-LCA. The different phases they distinguish are: 1) vehicle and battery manufacturing, 2) maintenance and repair, 3) use phase (fuel consumption and production) and 4) the End-of-Life (EOL) phase. In the following sections of this chapter the phases 1 and 2 are are evaluated using data of the EcoInvent database and other literature. The usage phase is calculated with help of the MEO-model and as there is no available data for the EOL of electric tractor-trailers this phase will be left out, similarly to the research of [58] and [57].

6.2. Production phase
6.2.1. Conventional vehicles
The three vehicles that will be compared are: >20, 10-20 and <10 tonnes trucks. Their production costs can be found in the EcoInvent database [24]. For the tractor-trailer no comparable information was found. Table 6.1b lists the total production related CO$_{2,eq}$ emissions. The weights of the lorries range from 16 tot 40 tons, for comparison the weight of an empty tractor-trailer was found to be 15.7 tons in section 5.1.1. Figure 6.1a shows the share of CO$_{2,eq}$ emissions per type of material used during the production phase.
6.2.2. Electric vehicles

Currently there is no reliable data available on the CO$_{2,eq}$ emissions for the production of an electric tractor-trailer. Therefore during this chapter it will be assumed that the production emissions for the electric vehicles will be equal to: 1) the production emissions of conventional vehicles (see paragraph above), 2) charger production related emissions and 3) emissions resulted by the production of the battery.

The charger emissions, can be found in the EcoInvent database as generic number. The CO$_{2,eq}$ kg of a battery is a value which can vary significantly according to literature [59]. Figure 6.2 shows a part of the results from [25] and the overall average value of 216.7 CO$_{2,eq}$ kg/kWh. We can see that three out of five papers are around this average value, the USEPA value is relatively low while Ellingse has a very broad range. [59] noted that the differences between these articles are significant and that most differences result from different assumptions rather than cell chemistry. The paper does not provide a more precise value or estimation but does give normalized values for the CO$_{2,eq}$ kg/kg of battery, which cover a range between 13.5-16 kg CO$_{2,eq}$/kg. On a pack level batteries currently show that the specific energy is between 0.06-0.14 kWh/kg while in the future this could be 2 kWh/kg [60]. By taking the higher range of the normalized values of [59] and the lower range of the specific energy by [60] the emissions per kWh battery are: 266.6 CO$_{2,eq}$ kg/kWh. This leads us to the conclusion that the emissions resulting from the production of an electric tractor trailer can be written as:

\[
CO_{2,eq,prod} = 33,145 + 266.6 \cdot \frac{d}{0.8} \cdot \left(\frac{kWh}{km}\right)_{MEO}
\] (6.1)

Where \(d\) is the required action radius and \(\left(\frac{kWh}{km}\right)_{MEO}\) the usages as calculated by the MEO model. Which results in the needed battery capacity [kWh], with a battery capacity of 80%.
6.3. Maintenance and repair phase

6.3.1. Conventional vehicles

The emissions during the usage phase of a conventional vehicles can be generalized by the amount of fuel used and the energy needed for maintenance of the vehicle. For conventional vehicles maintenance is quite extensive since they have many moving parts and usage will degrade these parts. [24] calculated the maintenance of the 40 and 28 tons lorries to be: 19,114 and 11,901 kg CO$_{2}$,eq during its lifetime (also in table 6.3b). Additionally figure 6.3a shows the share of CO$_{2}$,eq emissions per type of material used during the maintenance phase.

![Figure 6.3a: The share of different materials needed for the maintenance of a 40 metric ton lorry](image)

(b) The results for different sizes of lorries

<table>
<thead>
<tr>
<th>Truck total weight [tons]</th>
<th>CO$_{2}$,eq [kg]</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td>19,114</td>
</tr>
<tr>
<td>28</td>
<td>11,901</td>
</tr>
<tr>
<td>16</td>
<td>Not Available</td>
</tr>
</tbody>
</table>

![Figure 6.3b: The total CO$_{2}$,eq for the maintenance of different sizes of lorries as calculated by [24] according to the IPCC GWP 100a method](image)

6.3.2. Electric vehicles

Electric vehicles require less maintenance and repair compared to conventional vehicles. According to [16] the maintenance costs for an EV is approximately 65–80% of that of an ICEV due to fewer components and moving parts, as well as lower maintenance requirements for electric motors in EVs. Similarly, according to [61] the maintenance emission costs of a BEV could be around 30% lower compared to the ICE vehicles. However these emissions all depend on the usage of the battery and the engine. The maintenance of electric vehicles also requires the possibility of replacing the battery after its life-time, this fact is often overlooked but should also be noted. Therefore the emission resulting from battery replacement will be taken separately from the maintenance emissions. Based
on the previously mentioned sources we assume that the maintenance of an electric tractor trailer will be half of a conventional tractor trailer.

### 6.4. Conclusion

The chapter tried to answer the third research question which was:

<table>
<thead>
<tr>
<th>Research question 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>What are roughly the CO$_{2,eq}$ emissions aside from the WTW emissions of a typical future electric tractor-trailer combination? And how does this compare to other freight vehicles?</em></td>
</tr>
</tbody>
</table>

After literature review and the usage of the EcoInvent database the production and maintenance emissions could be determined. For conventional vehicles more reliable data was available from the EcoInvent database. The total additional CO$_{2,eq}$ emissions can be determined by taking the production and maintenance emissions from EcoInvent for the 28 tonnes trucks, which adds up to: 44,950 kg CO$_{2,eq}$. For electric vehicles the available data is less reliable as currently there are no electric tractor trailers available. Therefore the production phase includes only the production emissions of conventional tractor trailers, the production of the chargers and the production of the battery. Furthermore maintenance costs for electric vehicles are assumed to be less than conventional vehicles according to literature. In this thesis it is assumed that 50% of conventional maintenance costs is applicable to electric tractor trailers. The production and maintenance for an electric tractor trailer can be summed up according to:

\[
CO_{2eq,\text{total}} = 39,000 + 266.6 \cdot \frac{d}{0.8} \cdot \left( \frac{kWh}{km} \right)_{MEO}
\]

Comparing this outcome to [58], the found values for the production emissions are in the same magnitude, values for maintenance and battery emissions are higher however.

#### 6.4.1. Uncertainties

A first uncertainty in this chapter is the fact that one step in the LCA was not considered, namely the End-Of-Life phase was not taken into account. This is because this chapter only does a rough estimate. The End-Of-Life phase is quite elaborate as different scenarios are possible for the vehicle and battery assembly and recycling. It is estimated that the assembly, disposal, and recycling of the electric and conventional vehicle are the same. The main uncertainty is in the energy required to recycle the battery, which can be very location dependent. Secondly, for the data that was available uncertainty should also be considered. [27] already described the SAP-scheme to address these uncertainties where:

- Spread, for data for which more than one value is available;
- Assessment, for data for which an inappropriate value is available;
- Pedigree, for data for which no value is available

In this chapter multiple values for the battery components were found. These values were then shown in a graph (spread) and we saw that an average of these values would be suited. The data for the production of the vehicle and maintenance was not available and falls therefore under the P-part. The found values were from EcoInvent which bases their estimation on a tree of processes.
Quantitative estimation of the total $\text{CO}_2,_{eq}$ emissions

As now the model is validated, typical mission profiles are selected and the additional $\text{CO}_2,_{eq}$ emissions are clear the total emissions from the Netherlands and specific fleets can be calculated and analyzed.

7.1. Future mileage and market entrance

The figure below represents predictions by Plan Bureau Leefomgeving (PBL) of the traffic volume in 2020 and 2030. These projections are based on the expected economic growth, the energy price and demographic growth. For the figure several considerations are taken into account: 1) the Nationale Energieverkenning (NEV) of 2016 states that the traffic volumes of tractor-trailers will be 1% higher in 2030 than predicted in the NEV of 2015 [62], 2) between 2013-2020 and 2020-2030 the NEV 2015 expects a growth of respectively, 14% and 8%, 3) the exact numbers of PBL are not considered as the historic numbers of PBL differ from the numbers of CBS, 4) PBL only considers mileage in the Netherlands whereas CBS makes a distinction between mileage driven by Dutch vehicles in the Netherlands and outside the Netherlands in the figure the growth is assumed to be equal.

(a) The historic and projected mileages of tractor-trailers with uncertainty range, historic data: CBS [63], projections: NEV of 2016 [62]

(b) Survival rate of tractor-trailers to age of vehicle [64]

Figure 7.1: Predicted mileage and survival rate of tractor-trailers
7. Quantitative estimation of the total $\text{CO}_{2\text{eq}}$ emissions

The rate at which tractor-trailers can enter the market is depended on the failure-curve. Figure 7.1b shows the failure-curve of tractor-trailers. The failure-curve is quite steep: after 10 years 75% of the Dutch fleet is replaced by a new tractor-trailer. This fast replacement is attributed to export of tractor-trailers, and results in a relatively young fleet [64].

7.2. Scenarios to consider

In this chapter three different scenarios are analyzed. Firstly the business as usual scenario, where electric trucks will not be introduced in the market. Secondly the moderate market-entrance scenario, where electric trucks are introduced in the market on a moderate level. And thirdly the progressive market-entrance scenario, where a large share of trucks that enter the market are electric.

7.2.1. Business as usual scenario

The business as usual scenario (BAU) will serve as a base comparison with the other two scenarios. As was already seen when the demand in tractor-trailers in the Netherlands is expected to grow and furthermore the ICE tractor-trailers are expected to become more efficient in the future. Results from MEO show that in 2030 a reduction of 38.0% percent can be expected (table 5.4, column: Conventional 2030).

7.2.2. Moderate market-entrance scenario

In the second scenario the electric tractor-trailers are assumed to become commercialized. In order to model this market entrance two more curves will have to be assumed: 1) the technology adaption logistic s-curve, 2) the electric vehicle efficiency increase over time. In many studies on the implementation of EV technology the technology adaption over time is described as an logistic S-curve. This curve is an useful framework describing the substitution of new for old technologies at the industry level [65]. [66] describes the technology s-curve adaption as follows:

\[
P(t) = \frac{S_0}{1 + e^{-k(t-m)}}
\]

\[
k = \frac{\ln 9}{t_s - m}
\]

\[
m = t_g + t_s \frac{2}{2}
\]  

(7.1)

Where $S_0$ is the saturation level, $k$ the scaling parameter, $m$ the midpoint scalar, $t_s$ is the time where 90% of potential market penetration and $t_g$ the time where 10% of the market penetration level is reached. For the moderate scenario $t_g$ and $t_s$ are respectively, 2022 and 2050. With a start year of 2016. Besides the logistic s-curve the efficiency of an electric tractor-trailer can be assumed to increase, either by road-load reductions or by improvements in the drive-line. Results from MEO show that in 2030 a reduction of 32% percent can be expected (results can be found in table 5.4, column Electric 2030).

A last trend to consider is the kg $\text{CO}_{2\text{eq}}$ per kWh as a result of the Dutch energy-mix for electricity. The current government has the goal to increase the share of renewables in the total electricity capacity. This will have significant influence on the kg $\text{CO}_{2\text{eq}}$ per kWh. The NEV of 2017 has made an estimation on the $\text{CO}_{2\text{eq}}$/kWh over time. This estimation includes current policy goals and also economic and social trends [67], figure 7.2 shows this decreasing trend.

7.2.3. Progressive market-entrance scenario

In the progressive market-entrance scenario, certain policy measures will make companies less hesitant to buy an electric tractor-trailer. These measures will lead to a steeper s-curve. The in the adaption curve the $t_g$ and $t_s$ are therefore changed to: 2020 and 2030.
The information in the above three subsections can be comprehended by the following figure of the different curves described.

![Curves](image)

Figure 7.2: The survival rate, decreasing emission factor for electricity, fuel efficiencies of ICE and EVs, the fleet increase and the technology adoption curves

### 7.3. Dutch fleet reduction emission potential

The following assumptions are made to estimate the total emissions of the Dutch fleet for each scenario:

#### 7.3.1. BAU
- The volume traffic (km/year) increases according to the curve given in figure 7.2
- Also the survival rate, and the decrease of fuel rate (increase in efficiency) are given in this figure
- 1 kWh of Diesel equals 0.327 kg CO$_2$ eq
- Conventional vehicles are on average 86.9% on the motorway, 4.8% on an urban road and 8.3% on a rural road, using the data in table 5.4 this leads to an usage of 3.536 kWh/km
- Production and maintenance costs of a conventional vehicle are respectively, 33,215 and 11,901 kg CO$_2$ eq

#### 7.3.2. Moderate and progressive

Additional to the above assumptions the moderate and progressive scenarios have assumptions about the electric vehicles.

- The vehicles that leave the market will be replaced by either electric or conventional vehicles. The share of these electric vehicles is depended on the technology adoption curve (figure 7.2).
- A decrease in the CO$_2$ emission factor [CO$_2$ eq kg/kWh] on electricity is expected and given in figure 7.2
- The EVs have a usage of 1.571 kWh/km based on table 5.4, which decreases similarly the conventional vehicles.
- The EVs will have a battery of 2 times 200 kWh, which gives an action radius of 100-200 km. According to equation 9.1 this will lead to a total of 1,149,414.5 kg additional CO$_2$ eq emissions.
The figures below show the final results. First, figure 7.3a shows that for the moderate and progressive scenarios a reduction of respectively, 5.5% and 21.3% can be expected after an initial increase till the year 2023. This initial increase is due to the shape of the s-curve and the increase of the fleet during this time. Figure 7.4 shows the contribution of the WTW, the production, battery and maintenance related emissions, during the years 2016, 2025 and 2030 for the three different scenarios. It can be seen that battery emissions have a large share in the total for the second and third scenario.

The goal of the Paris Agreement was to reduce 40% emissions by 2030 compared to 1990. In 1990 rigid trucks and tractor-trailers emitted a total of 5,070 ktons, which translates to 3,029 ktons by 2030. The reason why these trucks will be summed is because the share of rigid trucks versus tractor-trailers is shifting. In 1990 rigid trucks had a share of 60% while tractor-trailers had a share of 40% in the total WTW emissions. However in 2012 the share of rigid trucks is 34% and tractor-trailers 66% [52]. Moreover it should be noted that the reduction goal of 2030 cannot be compared to the life cycle emissions directly as the data available for 1990 only compromises the amount of WTW emissions. Therefore they can only be compared to the WTW emissions resulted from the model, figure 7.3b shows the result. We see that the goal still is not reached by implementing electric tractor-trailer but approached it. Compared to 1990 the implementation from the moderate scenario leads to an increase of 22.7%, and implementation from the progressive scenario leads to a reduction of 11%. The BAU scenario would lead to an increase of 35.4% compared to the level of 1990.

(a) Total life cycle emissions in kg CO$_2$eq. In year 2016 production costs are not taken into account.
(b) WTW kg CO$_2$eq emissions with the goal of the Paris Agreement

Figure 7.3: The total life cycle emissions and WTW kg CO$_2$eq over time for the different scenarios (BAU, moderate and progressive), the code to make the figure is found in Appendix G.1

Figure 7.4: Stacked total emissions based on assumption in section 7.3 for all scenarios (above: BAU, center: moderate, below: progressive) for three moments in time (2016, 2025, 2030) the code to make the figure is found in Appendix G.2
7.4. Fleet specific reduction emission potential

Now we’ll dive more into the specific fleets that were found in section 5.2. This is done because the energy usage and battery capacity is more precisely determined. And it will be interesting to see which type of fleets have a higher reduction potential than other types. Before the reduction potential is calculated the parameters: the fleet size and lifetime, are explained in more detail.

7.4.1. Fleet size

The difference with previous section is that in this case the energy usage of the vehicle can be predicted fairly good but the number of vehicle per fleet is an estimation. From [52] it appears that a small fraction (32%) of the companies operating on the market own the most licenses (86%). The companies that have more than 100 licenses have on average 193 licences [62]. During this work it is assumed that it’s more likely that such a large company will be able to make investments and therefor each fleet size is assumed to be 195 vehicles.

7.4.2. Lifetime

The lifetime of each fleet-type is assumed to be the same since all vehicles are used with the same intensity. As mentioned in the first section of the chapter the lifetime is expected to be around 8 years. The lifetime of the battery can differ as it is depended on the number of cycles. Furthermore it is depended on other parameters as mentioned in section 5. For this estimation the lifetime of the batteries are assumed to be 3,000 cycles. For the different fleets this will mean that some require more batteries during its life time. This is indicated in table 5.5. It can be seen that at least 2 batteries are needed for each profile and for the Drayage sector 8 batteries are required.

7.4.3. Reduction potential

The information from preceding subsections can now be used to calculate the reduction potential for the different fleets. The figure below shows the result from these calculations. It appears that for the regional distribution the largest reduction is expected and for the missions to Belgium the least. All of the values are between 34 to 41%. The share in CO$_{2}$eq emissions from the battery production are now better estimated compared to figure 7.4, and we see that for especially the Belgium mission profile this is of importance. Furthermore the long-haul missions (Germany and Belgium) have a lower emission reduction potential. This is due to the combination of a larger contribution of the battery.

![Figure 7.5: The reduction potential per fleet-type, with the following assumptions: 250 working days, life-time of 8 years, battery capacity and usage according to tables 5.4 and 5.5, 3,000 life cycles per battery according to section 3.2.1 and production and maintenance according to chapter 6](image-url)
Table 7.1: The reduction potential per fleet-type, contribution of the battery and the reduction in WTW emissions (also seen in figure 7.5)

<table>
<thead>
<tr>
<th>Mission profile</th>
<th>Total reduction</th>
<th>Share of battery</th>
<th>Reduction in WTW emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>34%</td>
<td>31%</td>
<td>56%</td>
</tr>
<tr>
<td>Belgium</td>
<td>35%</td>
<td>23%</td>
<td>51%</td>
</tr>
<tr>
<td>Regional Distribution</td>
<td>38%</td>
<td>30%</td>
<td>58%</td>
</tr>
<tr>
<td>Drayage</td>
<td>41%</td>
<td>22%</td>
<td>55%</td>
</tr>
</tbody>
</table>

7.5. Conclusion

During this chapter two research questions were answered. Firstly research question 4:

**Research question 4**

How many long-haul vehicles can enter the market yearly till 2030?

The NEV predicted for the years 2013 to 2020 a tractor-trailer fleet growth of 14% and for the years 2020–2030 an increase of 8%. Besides the growth in the fleet, market entrance can also be done by replacing new vehicles. This replacement is based on the failure-curve for tractor-trailers. This curve is quite steep: after 10 years 75% of the tractor-trailers is replaced. The model developed for this chapter took into account both these trends. From this model it resulted that on average 8,824 new tractor-trailers could yearly enter the Dutch market from 2015-2030 (132,364 in total). Which is a 10% of the current fleet. Taking into consideration the technology adaption curve for the moderate scenario a total of 18,831 electric tractor-trailers is calculated. For the optimistic scenario a total of 66,977 electric tractor-trailers.

**Research question 5**

How much Life-Cycle emissions are avoided by implementing the electric tractor-trailer in the Dutch fleet for different implementation scenarios?

Firstly this questions was regarded in a broad perspective. This perspective took into account three scenarios: 1) the BAU, 2) a moderate and 3) a progressive market-entrance scenario. The later two scenarios only differed from each other by the technology adaption s-curve. Other trends that were taken into account were: the survival rate of electric tractor-trailers, the fleet increase, the change in CO$_2$eq/kWh over time and the efficiency increase of the conventional and electric vehicle. From previous chapters a multiple of inputs was used namely: the addition CO$_2$eq emissions of both vehicles ad the extended MEO-model was used to obtain the energy usage per km. Combining all, it shows that by comparing the BAU scenario to the moderate and progressive scenarios a reduction of respectively, 5.5% and 21.3% can be expected after an initial increase till the year 2023. When comparing the WTW emissions a better idea of the absolute reduction since 1990 can be obtained: the moderate implementation leads to an increase of 22.7%, and progressive implementation leads to a reduction of 11%. The BAU scenario would lead to an increase of 35.4% compared to the level of 1990.

Secondly a more in-depth analysis was done to determine the differences between different fleet-types as found in chapter 6. The results showed that reductions potentials of the fleets varied from 34 to 41%. Especially the fleet that require lower speeds and a lower battery capacity (regional distribution and drayage) showed to have a larger saving potential compared to the other profiles. The difference between the fleets were however not that large, the share of the different phases were comparable. Whether this will also be the case for the economic feasibility is discussed in the next chapter.
7.5.1. **Uncertainties**
The diversity between the scenarios (BAU, moderate and progressive) considered in this chapter have to be limited to a certain extent. Therefore the trends that were considered in these scenarios could overlook or generalize the market of tractor-trailers. The most important trend that can cause uncertainty is the implementation rate of electric tractor-trailers. Regarding the implementation rate of passenger EVs the chosen rates are quite high, but necessary to come to conclusions for the chosen goal of this thesis. Not to withstand the fact that policy measures by the Dutch government and EU will contribute greatly to the implementation.
Total Cost of Ownership

The Total Cost of Ownership (TCO) is a framework that helps buyers, producers and investors to estimate all the direct and indirect costs. The TCO helps them to make the decision whether to invest in a product or not, moreover the TCO framework can help to distinguish how costs can be managed. In this chapter literature on the TCO framework will be introduced, and the costs for conventional and electric tractor trailers are summarized and compared.

8.1. Literature on the Total Cost of Ownership

Literature on the TCO of electric vehicles is quite extensive. The TCO of a specific vehicle can be very different when changing for example the time of purchase, the location and the inclusion of certain indirect factors (fiscal polices, profit margin etc.). The thesis of van Velzen [18] already gave an extensive review on the literature related to TCO frameworks. As noted by [18] the TCO can be defined by the following equation:

\[
TCO = OTC + \sum_{n=1}^{N} RC \cdot \frac{1}{(1+i)^n}
\]  

(8.1)

Where \( OTC \) represents the One Time Costs, \( RC \) the Recurring Costs, \( i \) the discount factor and \( N \) the total years of recurring costs. The OTC and RC can be divided between indirect and direct factors that influence the TCO. Based on interviews and literature [18] presents a framework that takes into account the both factors. A simplified version of this framework (figure 2.3) will be used during the rest of this chapter. Besides literature on the TCO of passenger EVs there also exists a small selection of literature on TCOs for electric Medium Duty Vehicles (MDV) and HDV, namely: [26], [57] and [58]. In figure 8.1 the different assumptions as found in this literature are given. Based on the literature in figure 8.1 and [18] equation 8.1 can be rewritten to apply to electric tractor trailers:

\[
TCO = (p_v + p_b + p_{infra}) + \sum_{n=1}^{N} (p_{maint} + p_e + p_{fuel}) \cdot \frac{1}{(1+i)^n}
\]  

(8.2)

Where \( OTC \) consists out of the price of the vehicle technology, \( p_v \), the battery, \( p_b \), and the initial charging infrastructure \( p_{infra} \). This can then be rewritten to include factors that concern the fleet and the market, e.g. the battery capacity \( C_{battery} \):

\[
OTC = p_v + \frac{e_{kWh}}{kWh} \cdot C_{battery} + p_{infra} \cdot n_{chargers}
\]  

(8.3)

The RC includes the costs made during the usage phase namely: the maintenance of the vehicle, \( p_{maint} \), which is depended on the distance driven per year, \( km_y \). The fuel costs are depended on the usage of kWh per km (as calculated by MEO), \( u_{meo} \), and the fuel price. Furthermore fast charging
Costs are reoccurring and rely on the total driven kilometers.

\[ RC = \frac{e_{\text{maint}}}{km} \cdot km_y + \frac{e_{\text{charging}}}{km} \cdot km_y + \frac{e_{\text{fuel}}}{kWh} \cdot u_{\text{meo}} \cdot km_y \]  

8.2. Cost review on 6 crucial direct factors influencing the TCO

This section shall review the mentioned parameters the previous section (formulas 8.2–8.4). These factors were indicated by [18] as the crucial direct factors influencing the TCO of an EV (figure 2.3).

8.2.1. Vehicle costs

The vehicle costs comprises the vehicle technology and the powertrain (so not the battery). [18] estimates these costs by taking into account the current retail price found on auto-websites and convert these into the current production prices. These retail prices were then related to the production costs. For the future production and retail costs [18] assumed that EV technology would be the same price as ICEV technology. In the literature on electric MDVs and HDVs different approaches were applied for each study. [26] and [57] assume that the manufacturing of a conventional truck is equal to manufacturing of an electric version, [58] assumes that the conventional tractor-trailer is the base case in costs, and for electric tractor-trailers additional costs are added to this, lastly TNO doesn’t take into account a base price but rather calculates the difference in TCO for the conventional and electric versions, by comparing the components (for example: the combustion engine, transmission equipment, converter, control units etc.). This results in cheaper vehicle costs for the electric version, however this difference is relatively small (around 2,580 euros) compared to the costs of an average tractor-trailer. Due to this small difference the vehicle costs will be assumed to be the same. The average vehicle price in this research are assumed to be 102,826 euros according to the current costs of an Actros Mercedes [58].
8.2. Cost review on 6 crucial direct factors influencing the TCO

8.2.2. Battery technology

Battery costs are crucial in this TCO as they are expected to have a large share in the final result. It is expected that in the future the performance as well as the costs of the battery will significantly improve. [18] estimated future battery costs by means of a literature study (figure 8.2) and using experience curves with different implementation rates. The average battery price for 2015, 2020 and 2030 were respectively found to be: 383, 300 and 200 €2015/kWh. Battery costs by the available literature (figure 8.1) were within a range of 290 to 600 $2015/kWh (266.47-551.32 €2015/kWh). As the estimation of [18] is more recent than the literature these prices will be assumed. In figure 8.2 the chosen values for each year are shown, where the solid lines are values from [18] and the striped lines the values as used in this TCO analysis. As this TCO will look further than 2030 the values are extrapolated.

![Figure 8.2: BEV battery price development according to high quality studies in euro-2015 (calculations by [18]) in this figure also the prices that are assumed during this TCO](image)

It became apparent from section 3.2.1 that the battery will need to be replaced after several years. This replacement is needed due to calender aging and capacity fade by the cycling of the battery. In section 3.2.1 a minimum of 3,000 cycles was found. It is expected however that the number of cycles will go up as technology advances further. The battery replacement costs will therefore take into account an upward trend for the amount of cycles that batteries are able to withstand without losing crucial capacity. There will be assumed that the battery performance will increase from 3,000 cycles per battery to 5,500 cycles per battery in 2030, and to 6,000 cycles in 2030. This estimation is based on numbers circulating on web-fora [69], [70]. The increase in performance is shown the figure below.

![Figure 8.3: Estimation of increase in performance of batteries over time](image)

8.2.3. Charging costs and infrastructure

The charging equipment is an important factor but which is difficult to assess. There are different scenarios possible for the future of charging infrastructure that will ultimately determine the costs. In this thesis it is assumed that all mission profiles will use fast charging and over-night charging, and that 350 kW fast-charging stations are available. In [71] the mark-up value1 that is added on top of the electricity price for fast-charging is calculated by comparing the EV adaption rate and costs of a charging station. It was found that fast charging infrastructure is hardly profitable with low EV rates.

---

1Mark up value: is the added price by the retailer on top off the cost price to compensate the costs of doing business and create a profit.
differentiated between fixed and variable costs in the resulted mark-up value. The fixed costs of the EV station were found to be 0.045 €/kWh or 0.013 €/kWh for respectively, low and high EV adaptation. Similarly the variable costs are said to amount to 0.041 €/kWh and 0.012 €/kWh. Which resulted in a mark-up percentage of 25% and 9.1% on top of the electricity price. This leads to a total markup value of 8.6 ct/kWh in considering the lowest EV adoption rate. TNO computed the additional fast-charging cost to be 0.14 €/kWh [71] (figure 8.4), which is considerably higher.

A last source that can be used is the current retail price of a 350 kW charger. ABB indicated that their 350 kW is sold for 150,000€. By just taking this rough value and adding 20% overhead costs and combing this with an estimation of how many fast charging stations are needed, the costs per kWh fast charged can be calculated. Table 8.1 gives these calculations. The Belgium and Drayage missions need to use the fast charging station multiple times a day and therefore one charging station is assumed per vehicle. The other two missions can share a station during a time slot of 4 hours. The mark-up value shows to be around 0.08-0.19€/kWh.

Table 8.1: Rough calculation for each mission profile on fast-charging costs based on a fast-charging of 350 kW of ABB, for the German and Regional Distribution mission it is assumed that there is a time slot available of 4 hours to fast charge at one station, the other two mission will need each one fast charging station as they need to charge multiple times a day

<table>
<thead>
<tr>
<th>Mission</th>
<th>km/day</th>
<th>kWh/km</th>
<th>kWh_life</th>
<th>kWh_fast</th>
<th>stations vehicle</th>
<th>€/kWh_fast</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>308</td>
<td>1.67</td>
<td>1.03E+06</td>
<td>50%</td>
<td>0.2</td>
<td>0.08</td>
</tr>
<tr>
<td>Belgium</td>
<td>396</td>
<td>2.18</td>
<td>1.73E+06</td>
<td>66%</td>
<td>1.0</td>
<td>0.16</td>
</tr>
<tr>
<td>Regional</td>
<td>218</td>
<td>1.60</td>
<td>6.97E+05</td>
<td>50%</td>
<td>0.2</td>
<td>0.10</td>
</tr>
<tr>
<td>Distribution</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drayage</td>
<td>253</td>
<td>2.07</td>
<td>1.05E+06</td>
<td>91%</td>
<td>1.0</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Comparing the numbers in this thesis an average of 0.11 €/kWh is used. For overnight charging the costs of an already available 50 kW DC will be used according to [72].

### 8.2.4. Maintenance

As became clear in chapter 6 it is expected that maintenance of an electric tractor-trailer will be less than a conventional tractor-trailer. The studies in figure 8.1 also make this clear, by mostly assuming a reduction of half of the maintenance costs. For most studies it is unclear how these numbers were found and therefore the numbers of TNO will be given, they indicated to be obtained from expert views.

### 8.2.5. Fuel price

TNO assessed the fuel prices prices based on the EU reference scenario of 2015. They are given in the figure below. The diesel and electricity prices are both expected to increase. The electricity price for industry will remain constant after 2025 however. Figure 8.5 shows the extrapolation of these prices beyond 2030. In Appendix F a overview of the historic prices can be found. For this TCO analysis the energy usage as found in chapter 5 shall be used in this chapter.

![Figure 8.4: Electricity and diesel prices for 2015, 2025 and 2030, figure from [8]](image-url)
8.3. Results

Using the numbers as found in the sections above and the formulas at the start of this chapter the TCO of each mission type can be calculated. The TCO results of each mission profile are described below one by one. Overall these results show that only a few TCOs are viable by 2030. These potential sectors are: regional distribution and drayage missions. For long-haul missions the business case is depended on future battery costs and their performance. The energy and maintenance cost savings do not cancel out the increase in TCO due to the battery or the increase in RC by fast charging. The TCO gap is the highest for missions that take longer. Their battery costs and fast-charging costs are higher compared to the shorter missions.

The Germany mission

The TCO of the German mission profile for the different years is illustrated in figure 8.8. The largest contributor to the value of the conventional TCO is the energy usage. For the electric vehicles the OTC is most important. This is due to the high costs of the battery. As time passes several apparent trends can be noticed: 1) firstly due to the battery performance improvement electric tractor trailers bought in 2025 will not need a replacement battery, 2) the energy usage over time becomes smaller, for the EV the decrease is the largest, this is due to a combination between the slower rising electricity prices and the expected efficiency improvements, 3) additionally the OTC for the EV is expected to become smaller as the battery price decreases, this also decreases the uncertainty range. It can be concluded that the TCO gap is quite large but will decreases over time.

The Belgium mission

In the TCO analysis of the Belgium mission we see again that the biggest contributor for the TCO of the ICEV is the energy usage. For the EV the energy usage and the OTC costs are comparable. The
difference in cost for energy usage between the German and Belgium mission can be attributed to the fact that the Belgium mission is less efficient and drives overall more kilometers due to the smaller charging time during the day. Overall this TCO looks really similar to the TCO of the German mission profile.

The Regional Distribution mission
The regional mission has one of the most favorable TCO of all missions. It is expected that battery replacement will not be necessary with the assumed cycle life. This in combination with the fact that less fast charging costs are expected, greatly improves the business case for this mission. This mission shows furthermore the same trends as previous analyzed missions: 1) energy usage for ICEV have a larger share in the TCO than the energy usage costs for the EV, 2) furthermore energy usage costs decrease over time for both vehicles, and 3) the OTC for EV decreases as well. In comparison again with other missions we see that the costs on energy usage are less, this is due to the fact that this mission needs a longer time for the same amount of distance due to long loading and unloading time.

The Drayage mission
In the last mission we see a combination of different trends that we saw before. This results in a TCO gap which is positive for the electric tractor-trailer in 2025 and 2030. Despite that the battery still needs to be replaced. The battery for this mission is very small and used intensively. This leads to a total of 5, 3 and 2 replaced batteries for respectively 2018, 2025 and 2030. The combination of the good performance of these batteries in later years and lower costs results in a very good TCO during all years. However due to the high total batteries that will be replaced the maintenance costs for the drayage mission are expected to be higher compared to other missions. This has not been taken into account during this analysis.

Figure 8.6: TCO results for 2018, 2020 and 2030 as a starting year for the German mission profile, the black vertical line indicates the uncertainty due to the battery price

Figure 8.7: TCO results for 2018, 2020 and 2030 as a starting year for the Belgium mission profile, the black vertical line indicates the uncertainty due to the battery price
8.3. Results

8.3.1. Sensitivity analysis

This section will perform a sensitivity analysis to understand better which parameters affect the total TCO the most. The results are given below.

Typical range

This parameter is indirectly influencing many other parameters, namely: the fuel costs, maintenance and fast charging. During this sensitivity analysis several (simplistic) assumptions are made namely: the battery capacity is proportional to the typical range while the fast charging is inversely proportional. From the resulting figures (8.10 to 8.13) it is seen that the typical range of the mission profile has a large influence. The sensitivity for the conventional TCOs is larger than the electric TCO. What can be attributed to the larger share of fuel costs for the conventional vehicle. A reasonable change in km range is depending on the mission profile: for the German and Drayage mission profile the range is likely to increase, while the other missions have this tendency less. It is estimated that the typical range will change within ±30%.

Fuel price

For this parameter the large influence of the electricity and diesel price is noticeable. If we look at figures 8.10 to 8.13 we see that between the ICEV and EV it can be noted that for the ICEV a change in fuel price has a larger effect on the total TCO. This can be the result of 1) the TCO of the ICEV consists out of less components than the EV, therefore the total TCO is affected more, 2) the fuel costs of the ICEV have a larger share in the total TCO compared to the EV. It was expected that the electricity price will increase slowly, however this prediction can be altered due to changing duty prices or an increase in electricity production costs due to the energy transition. If one looks back at 2006-2017 on average prices tend to change 1-3% compared to the yearly average (Appendix F). A reasonable change in this parameter is therefore ±2-6%.
One Time Costs
The change caused by the OTC is depended on the type of mission profile. For the ICEV the maximum change in TCO varies between: 12-19%, and it has the third highest sensitivity. For the EV changes varies between: 10-16% and has for the German and regional mission the (almost) largest sensitivity. For the ICEV a large change in the parameter is not expected as existing values have been taken, for the EV the OTC can be different. Tesla indicated that the Tesla Semi will costs 150,000 $ which is on the lower side of the estimation in this thesis. A good uncertainty range for the ICEV OTC and EV OTC is therefore respectively 5% and 20%.

Discount rate
The discount rate gives a moderate impact for the conventional and electric vehicle. As mentioned in section 8.2.6 discount rates in literature range from 0 to 10%. If the discount rate parameter changes with 50% we see for all mission profiles similar changes in the TCO. This would lead to a change in 7% (conventional), and 6% (electrical).

Maintenance
In the figures below it seems that the TCO analysis is less sensitive to a change in maintenance costs. A 50% change in maintenance costs result in 8-10% TCO change, for either the ICEV and EV. This is fairly small considering other parameters. However as mentioned in section 8.2.4 the the maintenance costs were based on expert opinions. And contrary to other literature a very small difference for ICEV and EV is assumed, it is therefore possible that the assumption in this chapter is an overestimation, and could be half of the estimated value.

Fast Charging
The effect of charging costs and infrastructure seems to be uncorrelated to the mission profile and has a smaller effect compared to other parameters. For all mission profiles a 50% change in fast charging infrastructure will lead to a change in TCO of around 6%. Similar to the maintenance costs the uncertainty range of this parameter is quite large. It is difficult to asses the costs for an infrastructure that isn't build yet. Therefore the uncertainty range of the fast charging could be 50% or larger.

![Figure 8.10: Sensitivity analysis for the German-TCO factors as described in section 8.2 and the typical range, in this figure it is hard to see but the fuel price and OTC lines are overlapping in the right figure.](image)

![Figure 8.11: Sensitivity analysis for the Belgium-TCO factors as described in section 8.2.](image)
8.3. Results

Figure 8.12: Sensitivity analysis for the regional-TCO factors as described in section 8.2.

Figure 8.13: Sensitivity analysis for the drayage-TCO factors as described in section 8.2.

Conclusion

The above section can be concluded by taking each expected uncertainty range and look up the corresponding change in TCO value. This is done in table 8.2. The typical range, maintenance and fast charging parameters are expected to give the largest uncertainty and change in TCO gap. The other parameters give either similar change in TCO (discount factor, will lead to the same TCO gap) or small TCO changes (fuel price and OTC).

Table 8.2: The final sensitivities based on expected uncertainty range

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Uncertainty range ICEV [%]</th>
<th>Uncertainty range EV [%]</th>
<th>ΔTCO ICEV [%]</th>
<th>ΔTCO EV [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel price</td>
<td>±6.0</td>
<td>±6.0</td>
<td>3.0</td>
<td>1.5</td>
</tr>
<tr>
<td>OTC</td>
<td>±5.0</td>
<td>±20.0</td>
<td>2.0</td>
<td>5.0</td>
</tr>
<tr>
<td>Discount</td>
<td>±50.0</td>
<td>±50.0</td>
<td>7.0</td>
<td>6.0</td>
</tr>
<tr>
<td>Maintenance</td>
<td>±25.0</td>
<td>±50.0</td>
<td>5.0</td>
<td>10.0</td>
</tr>
<tr>
<td>Fast Charging</td>
<td>±50.0</td>
<td>±50.0</td>
<td>0.0</td>
<td>6.0</td>
</tr>
<tr>
<td>Typical range</td>
<td>±30.0</td>
<td>±30.0</td>
<td>22.0</td>
<td>17.0</td>
</tr>
</tbody>
</table>
8.4. Conclusion

This chapter answered the last research question, namely:

<table>
<thead>
<tr>
<th>Research question 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>What could be the future costs savings by using electric engines in tractor-trailer combinations in comparison with regular vehicles?</td>
</tr>
</tbody>
</table>

During this chapter the future costs savings were estimated by means of a Total Cost of Ownership (TCO) analysis for the electrical and a conventional tractor trailer in the years 2018, 2025 and 2030. The thesis of [18] gave a good direction on which factors for EVs can be taken into account as the literature on TCOs for electric HDVs is limited. Combining the framework of [18], the (limited) scientific research and consultancy reports, 6 crucial direct factors that influence the TCO of a tractor trailer were found: the vehicle costs, battery technology, charging costs and infrastructure, maintenance, energy usage and price and the discount rate. TCOs were calculated for each mission as found in chapter 5. Overall these results show that: most TCOs are not viable by 2030. The potential sectors that are viable are the sectors that drive less kilometers and have a smaller battery: which were the regional distribution and drayage missions. For long-haul missions the business case is depended on either the future battery costs and their performance or the charging infrastructure availability. Overall it can be said that the energy and maintenance cost savings measures do not cancel out the increase in TCO resulted by the battery and charging costs.

8.4.1. Uncertainties

The TCO method always implies uncertainties in various domains. From the sensitivity analysis it became clear that the TCO model is the most sensitive towards the parameters: fuel price and OTC. Taking into account that some parameters are harder to predict than others it was seen that the maintenance and charging prices can result in uncertainties up to ±10% TCO change. The parameters: fuel price and OTC were found to have an impact of smaller than 5%, and the typical range and discount rate had comparable TCO changes (17-22% and 6-7%), which would lead to a similar TCO gap. That being said it is important to note that parameters that are mission specific (as determined in chapter 5) also greatly influence the final TCO gap.

Besides the parameters this TCO analysis shows differences with existing literature. For instance, most EV literature takes into account a certain EV adaption rate ([18] and [71]). In this chapter an adaption rate has so far not been taken into account. But it could decrease the uncertainty in the fast charging infrastructure parameter and show what possible pathways there exist. In this thesis a EV adaption rate was not used since it leads to many changes in the direct factors (the battery prices, electricity price are all indirectly depended on the adaption-rate (figure 2.3)).
Conclusion

In the introduction the research goal and questions were posed. This chapter shall use the results from previous chapters to answer the posed questions shortly and give a final conclusion about the obtained results. The sub research questions are now answered one by one and lastly the main research question is answered.

How can the energy that is required for an electric tractor-trailer be modeled based on speed, battery size, weight and auxiliaries?

The energy usage of an electric tractor-trailer during driving can be modeled using Willans Lines with a negative component. The developed model uses linear correlations between incidental power demand and energy usage at four different stages: 1) propulsion phase, 2) propulsion phase during braking, 3) regenerative braking phase, and 4) maximum regenerative power. In the model the efficiencies of: charging and discharging of the battery, the generating and motoring mode of the electric motor, transmission losses and the charging station are included. Although the simplicity of the model limits the accuracy of the result, the model is fast and applicable for many types of tractor trailers.

What are possible mission profiles for an electric tractor-trailer combination, taking into account different charging profiles and distance ranges, and how does it compare to the typical use?

From different data-sources 5 different mission profiles could be distilled that represented the largest part of sector tractor-trailer sector. The found mission profiles were missions: to Germany, to Belgium, Regional Distribution, Drayage and an overall average mission profile for the Netherlands. Energy usage of these profiles show a range of: 3.37 to 5.02 kWh/km for conventional tractor trailers and for electrical tractor trailers: 1.53 to 2.18 kWh/km. The optimal battery capacity for each profile was estimated to be (in the same order): 300, 360, 217, 52 and 200 kWh. The typical usage of a tractor-trailer will therefore be different. Transport companies will have to carefully plan the mission of an electric tractor-trailer to make optimal use of the battery and charging points. Especially companies that will pioneer with electric tractor-trailers will have to deal with a sparse charging infrastructure.

What are roughly the CO$_{2,eq}$ emissions aside from the WTW emissions of a typical future electric tractor-trailer combination? And how does this compare to other freight vehicles?

The total additional CO$_{2,eq}$ emissions can be determined by taking the production and maintenance emissions, which adds up to: 44,950 kg CO$_{2,eq}$. For electric vehicles the additional emission were estimated to be the sum of: production emissions of conventional tractor trailers, the production of the chargers, maintenance emissions and the production of the battery. The maintenance costs for electric vehicles are assumed to be 50 % less than conventional vehicles according to literature. The production and maintenance for an electric tractor-trailer can be summed up as follows:

\[
CO_{2,eq,total} = 39,000 + 266.6 \cdot \frac{d}{0.8} \cdot \left( k\text{Wh/km} \right)_{MEO}
\]

(9.1)

Where \(d\) is the required action radius and \(\left( \frac{k\text{Wh}}{k\text{m}} \right)_{MEO}\) the usages as calculated by the MEO model.

Which results in the needed battery capacity [kWh], with a battery capacity of 80%. As expected the
additional emissions of the electric tractor-trailers are higher than the conventional tractor-trailers. The size of the battery will have a large share in these total additional emissions.

How many long-haul vehicles can enter the market yearly till 2030?
Tractor trailers enter the market either by compensating for the increase in fleet growth or replacing depreciated tractor-trailers. For the years 2013-2020 a tractor-trailer fleet growth of 14% and for the years 2020-2030 an increase of 8% is expected. The replacement curve for tractor-trailers is quite steep: after 10 years 75% of the tractor-trailers is replaced. The model developed for this chapter took into account both these trends. From the developed market model it resulted that on average 8,824 new tractor-trailers could yearly enter the Dutch market from 2015-2030 (132,364 in total).

How much Life-Cycle emissions are avoided by implementing the electric tractor-trailer in the Dutch fleet for different implementation scenarios by 2030?
From a broad perspective (national level) it shows that by comparing the business as usual scenario to the moderate and progressive scenarios a reduction of respectively, 5.5% and 21.3% can be expected after an initial increase till the year 2023. When comparing the WTW emissions a better idea of the absolute reduction of the HDV fleet since 1990 can be obtained: the moderate implementation leads to an increase of 22.7%, and progressive implementation leads to a reduction of 11%. The BAU scenario would lead to an increase of 32% compared to the level of 1990. Considering the different fleets, it showed that reductions potentials of the fleets varied from 34 to 41%. Especially the fleet that requires lower speeds (regional distribution and drayage) showed to have a larger saving potential. All fleets had a comparable reduction potential suggesting that they are either set up too similar and generic or that the mission profile is not as important for the emission reduction potential.

What could be the future costs savings by using electric engines in tractor-trailer combinations in comparison with regular vehicles?
The future costs savings were estimated by means of a Total Cost of Ownership (TCO) for the electrical and a conventional tractor-trailer in the years 2018, 2020 and 2030. TCOs were calculated for each mission as found in chapter 5. Overall these results show that most TCOs for electric tractor-trailers compared to conventional are not viable by 2030. Potential sectors are: regional distribution and drayage missions. For long-haul missions the business case is dependent on the future battery costs and their performance. In this case the energy- and maintenance cost savings do not cancel out the increase in TCO. The TCO method always implies uncertainty in various domains. From the sensitivity analysis it became clear that the developed TCO model is affected mostly by uncertainty in charging infrastructure and maintenance costs. Regarding the small TCO gaps for some mission profiles this could have a significant effect on the outcome.

Main research question: To what extent is a complete fleet of zero-emission tractor-trailers in the Netherlands by 2030 a feasible solution to reach the Paris Agreement emission Goals?
With respect to the conclusions from the sub research questions it may be said that the tractor-trailer can be assumed to be a feasible solution to lower the CO₂,eq emissions drastically by 2030. However it cannot be used to reach the Paris Agreement emission goals completely, for several reasons: 1) the implementation of electric-tractors will have to be unrealistically high, which is unfeasible considering the business case for electric tractor-trailers on the short term and the manufacturing of these vehicles, 2) the battery performances of the tractor-trailer are an uncertainty which have a high contribution in the share of CO₂,eq emissions, 3) the energy mix of the Dutch electricity grid will have to become much greener in comparison with the current energy mix and on top of that 4) tractor-trailers are only a part of the transport sector.

Considering the conservative estimations of the TCO and its uncertainties considering charging infrastructure it is still too early to tell whether electric tractor-trailers will be as profitable as their manufactures are claiming. The sector will need pioneers that are willing to take the first few steps in up-scaling before mass implementation as in the progressive scenario is drawn can happen. Once it will be clear to transportation companies that the risk is relatively small to step in, legislation on CO₂,eq emissions and air quality can give them the last push to go electric. It is therefore expected that electric tractor trailers will have a significant contribution to reach the Paris Agreement goals.
The title of this thesis is: *electric tractor-trailers: the real deal or wishful thinking?* By assessing the results from this thesis we can say that electric tractor-trailers are the real deal considering the $\text{CO}_{2,eq}$ emissions reduction but do need more concrete steps towards a real economic profitable solution.
Discussion

In this last chapter the obtained results and answers will be compared to existing literature to assess their scientific contribution, also recommendations on future research will be given.

10.1. Results of this thesis

Although this research has been done in an extensive way, unavoidably every research project will have improvement points that can result into different conclusions. Not only the methods can be improved, but also certain used data sets were found to have drawbacks.

First of all the developed model could improve greatly by the following:

1. In the validation chapter the payload was clearly missing, if one has this data the large standard deviation could become smaller. Often the payload is not measured in detail but an estimation of three categories: heavy, moderate or light could already have a big influence.

2. Until now only one type of battery and motor was considered. A more extensive list on efficiency differences between types of batteries and electric motors could give more insight in the energy usage among different models.

3. The behavior of the battery is now captured by one efficiency but as was mentioned several times: this efficiency is very time-dependent, where the usage and temperature of the battery can determine to a great extent the efficiency. Using a time-dependent model will improve estimations on the life-time of the battery.

Secondly the characterization of the Dutch tractor-trailer sector was in this research completely based on publicly available data. We saw that for this data mostly the payload was missing and that no clear correlation existed between the driven distance or vehicle type. The current characterization therefore did not lead to essential differences between the mission profiles. There was an indication however that low speed missions tend to be more profitable and reduce more emissions. Which is logical as these mission profile have the tendency to stop and start often. To get more detailed and qualitative information the current method can be augmented by taking interviews of stakeholders in the sector. By combing quantitative and qualitative information in this way more detailed and realistic sub-sectors can be found. Adding to this is the fact that the assumptions for the infrastructure were quite conservative. It was assumed that each tractor-trailer had its own battery and could charge only at 350 kW. However there are different scenarios possible that can alter the outcome, as pointed out by possible charging scenarios could also be: a battery swapping system, overhead catenary wire and inductive charging. Which all decrease the needed capacity and reduce the charging time.

Lastly the TCO analysis has until now only assessed the direct factors. It was pointed out that the adaption rate of passenger and truck EVs have a major effect on these direct factors. The inclusion of different scenarios for this in combination with charging infrastructure scenarios could have improved this method.

Overall, these improvement points will lead to impact mainly the fleet-specific conclusions. As the fleet-type level is on a smaller scale than the Dutch fleet level. Especially when different scenarios
are considered conclusions considering the type of fleet can change. However the conclusions for the Dutch fleet as a total will be less affected, because during the research mostly the conservative scenarios were chosen based on literature and publicly available data.

10.2. Scientific contribution

The scientific contribution can be assessed in two types of research areas: 1) modeling HDV efficiency and 2) research on the impact and energy usage of electric passenger and tractor-trailer vehicles.

In the field of modeling HDV efficiency the results from this thesis contributed by validating a simplistic model for an electric tractor trailer. The model is developed in a way that any electric vehicle can be modeled using several parameters that are fairly easy to determine. And although it is simplistic compared to other literature ([14], [74] or [23]) the validation with real-life data shows that the share in regenerative braking and total energy usage can be simulated reasonably well, while still being fast and applicable to many types of tractor-trailers. Moreover these values are easy to determine and available for most vehicle types.

The second research area is research on EV-technology and its Life-Cycle impacts. Until now the main focus of EV-technology research has been on passenger vehicles. The contributions from this thesis show that for other vehicle sectors the same knowledge gaps exist, but these cannot always be solved by extrapolating directly from passenger EV research. For instance the energy usage of an EV is dependent on the driving style and fleet specific vehicle demands. We saw that regional distribution demands less energy than long-haul transport in absolute numbers, and that their emission reduction potentials are different. Overall a reduction of around 35% on a fleet level was found which is higher in comparison with other literature on passenger EV technology, namely: [10] found a reduction potential of 30% and [9] found a reduction potential in a range of 10-14% per vehicle. This difference is due to different assumptions in energy usage and also assumptions considering the energy mix.

Furthermore existing research on electric tractor-trailers (such as [26]) is taken a step further by differentiating the tractor trailer sector in different types driving profiles and therefore making the reduction potentials more detailed. Also this estimation becomes more detailed by matching the optimal battery capacity (in a realistic way) to the energy usage profile.

10.3. Policy recommendations

Policy has to deal with combinations of measures and different types of technology or innovations. This thesis gave a detailed answer on one type of technology. This upcoming technology seems moderately promising. The reduction potential is fairly good in comparison with conventional CO$_2$eq reduction measures. However the TCO gap is not in favor of the EVs that drive long distances, and are either dependent on a large battery or costly fast charging infrastructure.

As mentioned in the introduction, policy concerning decarbonizing the transportation fleet has had difficulties before with the sustainability of primary bio-fuels. This thesis again showed that the same can happen to the electric tractor-trailers. The tail-pipe emissions are not the only emissions and impact an alternative vehicle has. For the electric tractor-trailer it was seen that the battery emits a large share of the total Life-Cycle emissions. Currently the EU commission is on its way to make legislation that set standards for the total emitted CO$_{2eq}$ kg/tonne-km (or CO$_{2eq}$ kg/km). Legislation is most likely to be beneficial for the implementation of electric tractor-trailers. However there should be found a way to also include additional emissions. One way to do this is by assigning different energy labels to vehicles, as has been done before with houses or appliances.

Lastly, in order to reduce the current (financial) barriers in place for electric tractor-trailer policy can help to overcome these in various areas. As was seen in the TCO analysis there is needed more certainty in fast charging infrastructure. Governments can help by providing a more systemic approach so manufactures and potential EV charging companies can find each other. Also scenarios such as battery swapping or catenary charging will have to be developed by collaborations between governments and vehicle manufacture’s, either by tax exemptions or by organizing stakeholder meetings. Furthermore, currently it is allowed to recycle batteries from vehicles into other machines, and a mandatory contribution to cover the recycle costs is in places (according to the polluter pays principle). However, so far these costs are only determined for batteries with a weight less than 900 kg. A battery of 300 kWh
10.4. Contribution to the Sustainable Energy Technology field

As was mentioned in the introduction this research could shine more light on the contribution of electric tractor-trailers to the Sustainable Energy Technology (SET) field. There can be distinguished 3 roles in which electric tractor-trailer, as a stakeholder, can either contribute or will be affected by the SET field:

- **Service providers:** electric tractor-trailers could provide a better penetration of SET by either supplying the following services: the V2G concept or secondhand batteries for SET such as wind or solar parks. The V2G is mainly attractive as this means a larger flexibility by load management of the grid (also called peak shaving) and ‘free’ costs of storage. If electric tractor-trailers were implemented based on the two assessed scenarios this would mean that by 2030 a total of 3 (moderate) or 11.4 (progressive) GWh of capacity extra available to the grid. In order for the V2G concept to work this capacity must be available in times when a shortage or excess of sustainable energy sources occurs. Looking at the mission profiles the capacity of electric tractor-trailer will only be available to store energy during the day. At night there is no need to peak shave the electricity grid. The flexibility of the storage is therefore not optimal but could certainly been of use. Adding to this is the potential extra storage available after these batteries reached their EOL. It was found that is will happen around 4 years of usage and that a capacity of 80% of the original capacity is left for SET.

- **Energy consumers:** the share of SET in the Dutch energy mix in the future will be crucial to the final reduction potential. In this thesis the slightly optimistic scenario of PBL is assumed, and therefore the reduction potential is quite large. However if in the future the Netherlands has a smaller share of SET in their energy mix this will to a smaller reduction potential. As we can see electric tractor-trailers and SET can lead to a synergy where the CO₂ reductions are greater when used together than the simple sum of either reductions by SET and electric-tractor trailers.

- **Innovation drivers:** from this thesis we saw that battery and charging technology will greatly have to advance, if implementation of electric tractor-trailers becomes a reality. The large scale of the battery compared to passenger EVs will lead to different types of research: how do producers keep batteries in larger pack still as efficient as smaller battery packs (temperature control)? Or how can high power charger be made in a safe way? Besides a foreseen increase in innovation the implementation of electric tractor-trailers will mean a higher EV adaption rate. This rate, as we saw in this thesis, is crucial to the financial feasibility of all EVs.

10.5. Conclusion: future research paths

From the above sections future research paths can now be developed. Looking in a narrow scope the improvements as mentioned in section 10.1 can be used to make more detailed estimations of the reduction potential of electric tractor-trailers. These improvements were: 1) usage of a data base that contains the payload data, 2) use a time depended battery model to estimate the life time, 3) obtain more qualitative data on the tractor-trailer sector, 4) take into account different scenarios for charging infrastructure and the EV adaption rate.

In a broader scope, future research will also have to direct itself towards other alternative vehicles. And specifically to the hybrid or hydrogen tractor-trailers. By comparing all the alternatives in a similar way, more can be said about the best option. This has been done before but never to the extend in detail as done in this thesis. Future research shall then have to take into account the reduction potential in CO₂ emissions and energy.

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1 Assuming a battery pack density of 160 Wh/kg
2 the process of balancing the supply of electricity on the network with the electrical load by adjusting or controlling the load rather than the power station output.
3 Based on the number of total electric vehicles in 2030 (chapter 7) times 200 kWh
Bibliography


Electric Tractor-trailer Overview
Table A.1: Recent ZE commercial or prototype Truck Ventures, the source is a hyperlink and only available in the electronic version, the next pages gives a list of the websites where the information was found.

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B.1. Willans Line

The relationship between the power demanded by the motor of the vehicle and the energy provided by the fuel is referred to as the Willans line. The concept of the Willans Line is given in figure B.1, where a generic energy converter is shown to convert the available input energy into output flow and effort variables.

![Willans Line Diagram]

Figure B.1: The Willans line concept illustrated graphically adapted from [23]

We see that the Willans Line model relates the energy that is theoretically available for conversion, to the useful energy that is actually present at the output of the energy converter. Also written as (from [23]):

\[ W_{out} = e \cdot W_{in} - W_{loss} \]  

(B.1)

Where \( e \) represents the efficiency of the converter, and \( W_{loss} \) represents external losses. The name Willans line is derived from the fact that the above relationship has the appearance of a straight line. However this model of energy conversion efficiency is not completely linear, because the parameters \( e \) and \( W_{loss} \) are represented as functions of the output flow variable [23]. However on a large scale validation through vehicle measurements have indicated that with increasing power demand the fuel consumption increases linear [28].

The CO\(_2\) emission of a vehicle is closely related to the vehicle’s power demand, \( W_{out} \) in equation B.1[28]. Therefore the ratio between the power of the motor and the power of the fuel can be used to determine the total CO\(_2\) emissions. The relationship is equivalent to the Willans line and can be expressed as (from [28]):

\[ CO_2 = \alpha \cdot P_{Wheels} + P_{losses} \]  

(B.2)

Where \( \alpha \) is a measure for the efficiency of the power-train (similar to \( e \) in equation B.1) as well as the carbon content of the fuel, \( P_{Wheels} \) the power demand and \( P_{losses} \) the internal losses in the power-train. The MEO-model evaluates this equation according to the diagram in figure B.2. The following subsections will explain how \( P_{Wheels} \) and \( P_{losses} \) are calculated.
B.2. Power needed for the wheels

The power needed for the vehicle can be calculated according to:

\[
P_{\text{Wheels}} = P_{\text{rrc}} + P_{\text{drag}} + P_{\text{inertia}} + P_{\text{gradient}}
\]

\[
P_{\text{Wheels}} = MC_{rr}Agv\cos(\theta) + \frac{1}{2}\rho C_{d}A v^3 + Ma + Mg\sin(\theta)
\]

(B.3)

Where the parameters mean the following:
- \(C_{rr}\): coefficient of rolling resistance
- \(C_{d}\): drag coefficient
- \(g\): earth’s acceleration
- \(\rho\): air density
- \(A\): frontal area of the vehicle
- \(M\): vehicle mass [empty weight + payload]
- \(\theta\): road gradient
- \(v\): instantaneous velocity
- \(a\): vehicle acceleration

To implement equation B.3 as a model that can take into account different types of measures for emission reduction, the equation needs to be broken down into different functions. Firstly we define the following factors, where the \(k\) is the increase or decrease in percentages.

\[
f_{\text{inertia}} = (1 + k_{\text{inertia}}) \cdot M
\]

\[
f_{\text{rotting}} = (1 + k_{\text{rr}}) \cdot Crr Mg\cos(\theta)
\]

\[
f_{\text{gradient}} = Mg \sin(\theta)
\]

\[
f_{\text{drag}} = (1 + k_{\text{d}}) \cdot \frac{1}{2}\rho C_{d}A
\]

(B.4)

The the power contribution of each element in equation B.3 is then calculated according to:

\[
P_{\text{inertia}} = f_{\text{inertia}} \cdot v \cdot a
\]

\[
P_{\text{rotting}} = f_{\text{rotting}} \cdot v
\]

\[
P_{\text{gradient}} = f_{\text{gradient}} \cdot v
\]

\[
P_{\text{drag}} = f_{\text{drag}} \cdot v^3
\]

(B.5)
B.3. Power loss in a vehicle

To determine the total energy used the losses inside the vehicle will have to be estimated. In the
original model the following formulas are used to determine the losses in a vehicle and thereby the
total needed power for the vehicle to drive.

\[ P_{\text{loss}} = P_{\text{lossTM}} + P_{\text{lossBraking}} + P_{\text{lossHeat}} + P_{\text{lossAux}} \]  

(B.6)

Where \( P_{\text{lossTM}} \) equals the transmission losses, \( P_{\text{lossBraking}} \) losses by braking, \( P_{\text{lossHeat}} \) the loss due
to heat forming in the engine and \( P_{\text{lossAux}} \) the auxiliaries.

The power for the wheels \( P_{\text{Wheels}} \) can be divided in Traction power and Braking power (figure B.2).
Traction \( (P_{\text{Traction}}) \) is equal to the power of the wheels when it’s larger or equal to zero, in other
words the power needed to move the vehicle. While the power needed to brake \( (P_{\text{Braking}}) \) is equal
to the power of the wheels when it becomes negative, this happens when braking or when the slope
increases.

Firstly the power needed to move forward is given by \( P_{\text{powertrain,out}} \) and equal to the traction
power divided by the transmission efficiency. From thereon we can calculate the power loss to the
transmission.

\[ P_{\text{powertrain,out}} = \frac{P_{\text{Traction}}}{\eta_{\text{Tm}}} \]  

(B.7)

Secondly, the power lost to braking is mirrors the power needed to brake. Defined in the above
paragraph:

\[ P_{\text{lossBraking}} = -P_{\text{Braking}} \]  

(B.8)

During generation part of the power which goes in the motor will be transformed into heat, due
to the inefficiency of the motor. The use-full power that is obtained from the motor is also called
the indicative power \( (P_{\text{ind}}) \) and can be calculated by adding the power needed to overcome traction, to
compensate for the internal losses \( (P_{\text{lossint}}) \) and the auxiliaries \( (P_{\text{Aux}}) \). Using the efficiency of the motor
the heatloss is obtained.

\[ P_{\text{ind}} = P_{\text{powertrain,out}} + P_{\text{lossint}} + P_{\text{Aux}} \]  

(B.9)

\[ P_{\text{Engine}} = \frac{P_{\text{ind}}}{\eta_{\text{engine}}} \]

\[ P_{\text{lossHeat}} = P_{\text{Engine}} - P_{\text{ind}} \]

Finally the total energy that has to be provided by the fuel equals:

\[ P_{\text{Fuel}} = P_{\text{Engine}} \]  

(B.10)

The above equations can be made more clear by means of the following figure:

Figure B.4: Visualization of formulas B.6 to B.10
New Willans Line implementation in the MEO model

This appendix will evaluate on how the new Willans Lines are implemented in the MEO-model. Some lines are quite detailed (for example for the allocation of the losses) this is due to the structure of Pandas in Python. In the MEO-model an extra function (eTruck) is made in place of the formulas as described in section 2.2.1. This function is used after the calculations as in \( P_{\text{Wheels}} \). In this function there are six efficiencies: \( \eta_{TM}, \eta_{\text{gen}}, \eta_{EM}, \eta_{\text{charger}}, \eta_{\text{discharge}}, \text{and } \eta_{\text{charger}} \). The total losses are:

\[
P_{\text{Loss}} = P_{\text{LossTM}} + P_{\text{LossHeat}} + P_{\text{LossCharger}} + P_{\text{LossBattery}} + P_{\text{LossBraking}} - P_{\text{Regenerative}}
\]  

(C.1)

And the total consumed energy equals:

\[
P_{\text{Fuel}} = P_{\text{Charger}} + P_{\text{Regen}} + P_{\text{Aux}}
\]  

(C.2)

Firstly the indicative power is calculated. The indicative power is based on the Traction power (\( P_{\text{Traction}} \), the positive side of \( P_{\text{Wheels}} \)) and the internal losses (\( P_{\text{LossInt}} \)) which is based on the idling of the motor:

\[
P_{\text{Ind}} = \frac{P_{\text{Traction}}}{\eta_{TM}} + P_{\text{LossInt}}
\]  

(C.3)

Then the similarly the power needed for the engine, battery and the charger:

\[
P_{\text{Engine}} = \frac{P_{\text{Ind}}}{\eta_{EM}}
\]

\[
P_{\text{LossHeat}} = P_{\text{Engine}} - P_{\text{Ind}}
\]

\[
P_{\text{Battery}} = \frac{P_{\text{Engine}}}{\eta_{\text{discharge}} \cdot \eta_{\text{charge}}}
\]

\[
P_{\text{LossBattery}} = P_{\text{Battery}} - P_{\text{Engine}}
\]

\[
P_{\text{Charger}} = \frac{P_{\text{Battery}}}{\eta_{\text{charger}}}
\]

\[
P_{\text{LossCharger}} = P_{\text{Charger}} - P_{\text{Battery}}
\]

(C.4)

Thirdly, the braking has to be adjusted as described in section 3.2.4. This is done so the regenerative braking can be correctly determined. In the code we select all the values for \( P_{\text{Braking}} \) that exceed the
base speed of the EM, and lower these values to the maximum possible. Then the Willans Lines are implemented by applying the following formulas for different selections:

\[
P_{\text{Regen, mode}2} = \frac{P_{\text{braking}} \cdot \eta_{\text{gen}} \cdot \eta_{\text{TM}}}{\eta_{\text{charge}} \cdot \eta_{\text{discharge}} \cdot \eta_{\text{charger}}} \\
P_{\text{Regen, mode}3} = \frac{P_{\text{braking}} \cdot \eta_{\text{gen}} \cdot \eta_{\text{TM}}}{\eta_{\text{charger}}} \\
P_{\text{Regen, mode}4} = \frac{P_{\text{EM, max}}}{\eta_{\text{charger}} \cdot \eta_{\text{TM}}}
\]

(C.5)

As one can notice the auxiliaries aren’t taken into account yet. We did this for the first two equations in equation-set C.5, by checking which values of \(P_{\text{Regen, mode}3}\) were higher than the \(P_{\text{aux}}\) values. In a similar way we determine the new \(P_{\text{Aux}}\) values:

\[
P_{\text{Aux, mode}1} = \frac{P_{\text{Aux}}}{\eta_{\text{charger}}} \\
P_{\text{Aux, mode}2} = P_{\text{Aux, mode}1} \\
P_{\text{Aux, mode}3} = \frac{P_{\text{Aux}}}{\eta_{\text{charger}}}
\]

(C.6)

By merging the modes of \(P_{\text{Regen}}\) and \(P_{\text{Aux}}\) equation C.2 can be filled in.
Overview of clusters and reduction measures available in MEO

This Appendix is a copy of the appendix as found in [75]. Table D.1 summarizes the total number of reduction measures that are modelled and evaluated in MEO. Reduction measures are clustered according to their main improvement potential and the optimization cluster they fall into.

In the cluster powertrain four improvement potentials are differentiated: engine losses, heat losses, idling losses and braking losses. Engine losses and heat losses primarily affect the efficiency of the motor and therefore dependent on the required power demand. Typical measures are waste heat recovery, engine downsizing and reduced friction. Braking or inertial losses can be a large share of the overall losses. This share can be reduced through mild or full hybridization. In MEO, only parallel hybridization measures are regarded.

Auxiliary losses scale independent of the power demand and include measures like the electrification of auxiliaries and light hybridization. In earlier research, monitoring data of a city distribution truck has shown that up to 25% of the time the truck was idling. Although the stationary fuel consumption is not very high, reducing this amount, through start-stop mechanism or manually, could easily result in a few percent reduced fuel consumption.

Air drag and rolling resistances are the main driving resistances. For both, a few measures are enumerated. The measures respectively affect the air drag coefficient Cw and of the coefficient of rolling resistance Cr. 
Table D.1: Reduction measures that are modelled in MEO

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Improvement potential</th>
<th>Reduction measures</th>
<th>#</th>
</tr>
</thead>
<tbody>
<tr>
<td>Powertrain</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Powertrain</td>
<td>Engine losses</td>
<td>Engine downsizing</td>
<td>ENG1</td>
</tr>
<tr>
<td></td>
<td>Engine losses</td>
<td>Increased peak firing pressure</td>
<td>ENG2</td>
</tr>
<tr>
<td>Powertrain</td>
<td>Friction losses</td>
<td>Friction reduction through mechanic fit</td>
<td>FRIC1</td>
</tr>
<tr>
<td>Powertrain</td>
<td>Friction losses</td>
<td>Friction reduction through lubricants</td>
<td>FRIC2</td>
</tr>
<tr>
<td>Powertrain</td>
<td>Pumping losses</td>
<td>Water pump / variable flow (mech./elec.)</td>
<td>PUMP1</td>
</tr>
<tr>
<td>Powertrain</td>
<td>Pumping losses</td>
<td>Oil pump / variable flow</td>
<td>PUMP2</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Integrated Energy Management (IEM)</td>
<td>OPT1</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Cylinder deactivation</td>
<td>OPT2</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Engine downspeeding</td>
<td>OPT3</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Turbo-compound: Mechanical, Electrical, ORC or thermoelectric generator</td>
<td>WHR1-4</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Hybridization / Light - Start-stop</td>
<td>BRK1</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Hybridization / Full</td>
<td>BRK2</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Increase of transmission efficiency by 1%</td>
<td>TM1</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Decrease in Alpha slope</td>
<td>TM2</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Electrification of the cooling fan</td>
<td>AUX1A</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Controllable air compressor</td>
<td>AUX2</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Electrification of the steering pump</td>
<td>AUX3</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Electrification of the A/C compressor</td>
<td>AUX4</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Electrification of the generator</td>
<td>AUX5</td>
</tr>
<tr>
<td>Control optimization</td>
<td>Control optimization</td>
<td>Improved efficiency of lights</td>
<td>AUX6</td>
</tr>
<tr>
<td>Auxiliaries</td>
<td>Auxiliary losses</td>
<td>Tractor / Top-Spoiler</td>
<td>AERO1</td>
</tr>
<tr>
<td>Auxiliaries</td>
<td>Auxiliary losses</td>
<td>Camera vs. Mirror</td>
<td>AERO2</td>
</tr>
<tr>
<td>Auxiliaries</td>
<td>Auxiliary losses</td>
<td>Side-skirts</td>
<td>AERO3</td>
</tr>
<tr>
<td>Auxiliaries</td>
<td>Auxiliary losses</td>
<td>Aerodynamic Mud Guards</td>
<td>AERO4</td>
</tr>
<tr>
<td>Auxiliaries</td>
<td>Auxiliary losses</td>
<td>Aerodynamic Tails</td>
<td>AERO5</td>
</tr>
<tr>
<td>Auxiliaries</td>
<td>Auxiliary losses</td>
<td>Trailer / Tear Drop</td>
<td>AERO6</td>
</tr>
<tr>
<td>Auxiliaries</td>
<td>Auxiliary losses</td>
<td>Vehicle platooning</td>
<td>AERO7</td>
</tr>
<tr>
<td>Body</td>
<td></td>
<td>Low Rolling Resistance Tyres</td>
<td>RRC1</td>
</tr>
<tr>
<td>Body</td>
<td></td>
<td>Single Wide Tyres</td>
<td>RRC2</td>
</tr>
<tr>
<td>Body</td>
<td></td>
<td>TPMS</td>
<td>RRC3</td>
</tr>
<tr>
<td>Body</td>
<td></td>
<td>Lifting axles</td>
<td>RRC4</td>
</tr>
<tr>
<td>Body</td>
<td></td>
<td>Aluminium chassis weight decrease of 40%</td>
<td>WGT1</td>
</tr>
</tbody>
</table>
Routes of the mission profiles

E.1. Input to obtain the Missions profile to Germany

Figure E.1: The route of an average long haul mission to Germany

Figure E.2: Speed profile and total distance
E.2. Input to obtain the Missions profile to Belgium

![Map showing route of an average long haul mission to Belgium](image)

**Figure E.3:** The route of an average long haul mission to Belgium

![Graph showing speed profile and total distance](image)

**Figure E.4:** Speed profile and total distance
E.3. **Input to obtain the Regional Distribution Missions profile**

![Map of the route of an average regional distribution mission](image1)

*Figure E.5: The route of an average regional distribution mission*

![Graph showing velocity and payload over time](image2)

*Figure E.6: Speed profile and total distance*

E.4. **Output of the Drayage Missions profile**

![Graph showing velocity and distance](image3)

*Figure E.7: Speed profile and total distance*
Fuel prices
Figure F.1: Diesel prices at the tank station during the years 2006-2017, including duty and taxes; average is 1.23 euro/l, the average change per month compared to the average during the whole period is 10.67% (abs) and the average difference per month compared to the yearly average is 3% (abs), figure adapted from [76]

Figure F.2: Electricity prices during the years 2007-2017, non-household prices 5-15 MWh, including duty and taxes; overall average is 0.1952 €/kWh, average change per month compared to the average during the whole period is 4.45% (abs) and the average difference per month compared to the yearly average is 1.31% (abs), figure adapted from [77]
G.1. Code to make total emissions figure

```python
# coding: utf-8

Created on Sat Apr 21 16:38:12 2018
@author: huismansm

import numpy as np
import os
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy

def plotCurve(func, ylabel, xrange, totyears):
x = range(0, totyears, 1)
plt.subplots()
plt.subplot(231)
plt.plot(xrange, func(x))
plt.title(ylabel, fontsize=9)

def plotCurve2(xrange, yrange, ylabel, i, toplot, label, c):
    if toplot == True:
        plt.plot(xrange, yrange, color=c, label=label)
        plt.legend()
    else:
        plt.subplot(2,3,i)
        plt.plot(xrange, yrange, label = label)
        plt.title(ylabel, fontsize=9)

def calculate(rates, scenario):
    failure, eta_ICE, eta_EV, adapt, fleet_growth, e_co2_kwh = rates
    km_y2016 = 6.66E+09
df_km_y = 7.55E+04
    d_co2_kwh = 0.327
    d_co2_kwh = 0.327
    d_co2_per = 216.7
    capacity = 400.0
    meo_e = 1.571938674
    meo_d = 3.535702143
    co2_prod = 47400.
    vehicles = []
    tot_CO2 = []
    bat_CO2 = []
    CO2_prod_E = []
```

99
CO2_prod_D = []
WTW_D_list = []
WTW_E_list = []
maint_D = []
maint_E = []
E_perc = []
D_perc = []
km = []
km_i = []
km_y = 15, 15;
km_iD = [[0 for x in range(w)] for y in range(h)]
km_iE = [[0 for x in range(w)] for y in range(h)]
km.append(km_y2016)
km_iD[0][0] = km_y2016/avg_km_y
km_iE[0][0] = 0
veh = [[0 for x in range(w)] for y in range(h)]
veh[0][0] = km_y2016/avg_km_y
PROD_D = [[0 for x in range(w)] for y in range(h)]
MAINT_D = [[0 for x in range(w)] for y in range(h)]
CO2_BAT = [[0 for x in range(w)] for y in range(h)]

# fleet growth
for i in range(1,15):
    km_yi = km_y2016*(fleet_growth[i])
    km.append(km_yi)
    num_veh_new = (km_y2016*(fleet_growth[i]-fleet_growth[i-1]))/avg_km_y
    km_i[i][i] = num_veh_new
    km_iD[i][i] = num_veh_new * (1-adapt[i])
    km_iE[i][i] = num_veh_new * adapt[i]

    counter = 0

# failure
for i in range(0,15):
    for j in range(0,15):
        if km_i[i][j] != 0:
            new_veh = []
            for k in range(1,counter+1):
                new_veh.append((failure[k-1]-failure[k])*km_i[i-k][j-k])
            km_i[i][j] = failure[k] * km_i[i-k][j-k]
            km_iD[i][j] = failure[k] * km_iD[i-k][j-k]
            km_iE[i][j] = failure[k] * km_iE[i-k][j-k]

            km_i[i][j] = sum(new_veh) + km_i[i][j]
            km_iD[i][j] = km_iD[i][j] + sum(new_veh) * (1-adapt[counter])
            km_iE[i][j] = km_iE[i][j] + sum(new_veh) * adapt[counter]

            PROD_D[i][j] = km_iD[i][j] * co2_prod
            PROD_E[i][j] = km_iE[i][j] * co2_prod
            MAINT_D[i][j] = km_iD[i][j] * co2_maint_D
            MAINT_E[i][j] = km_iE[i][j] * co2_maint_E
            CO2_BAT[i][j] = km_iE[i][j] * co2_per_bat * capacity

            counter = counter +1
break

PROD_D[0][0] = km_iD[0][0]*#co2_prod/10.
PROD_E[0][0] = km_iE[0][0]*#co2_prod/10.
MAINT_D[0][0] = km_iD[0][0]*#co2_maint_D/10.
MAINT_E[0][0] = km_iE[0][0]*#co2_maint_E/10.
WTW_D = [0 for x in range(w)] for y in range(h)]
WTW_E = [0 for x in range(w)] for y in range(h)]
G.1. Code to make total emissions figure

```python
WIW_E[j][k] = km_iD[j][k] * meo_d * d_co2_kwh * eta_ICE[k] * avg_km_y for k in range(0,15)
WIW_E[j][k] = km_iE[j][k] * meo_e * e_co2_kwh[k] * eta_EV[k] * avg_km_y for k in range(0,15)
tot_co2_d = sum(WIW_E[j][:]) + sum(PROD_D[j][:]) + sum(MAINT_D[j][:])
tot_co2_e = sum(WIW_E[j][:]) + sum(PROD_E[j][:]) + sum(MAINT_E[j][:]) ...
+sum(CO2_BAT[j][:])
tot_CO2.append(tot_co2_d + tot_co2_e)
bat_CO2.append(sum(CO2_BAT[j][:])
CO2_prod_E.append(sum(PROD_E[j][:]))
main_E.append(sum(MAINT_E[j][:])
CO2_prod_D.append(sum(PROD_D[j][:]))
maint_D.append(sum(MAINT_D[j][:])
WTW_D_list.append( sum(WIW_D[j][:])
WTW_E_list.append( sum(WIW_E[j][:]))
vehicles.append( (sum(km_iD[j][k]) + sum(km_iE[j][k]))/avg_km_y)

df = pd.DataFrame()

df[‘WIW_E’] = WTW_E_list

df[‘WTW_D’] = WTW_D_list

df[‘Production E’] = CO2_prod_E

df[‘Production D’] = CO2_prod_D

df[‘Maintenance E’] = main_E

df[‘Maintenance D’] = maint_D

df[‘Battery’] = bat_CO2

df.to_csv(‘stacks+str(scenario)+.csv’)
return bat_CO2, CO2_prod_E, CO2_prod_D, WTW_D, WTW_E, tot_CO2, E_perc, ...
D_perc, km, vehicles, km_iD, km_iE, maint_D

def getFunctions(scenario):
    os.chdir(‘C:/Users/hansmasm/Google Drive/Delft/Thesis/CO2 berekeningen/Excel ...
sheets/’+scenario)
    print(scenario)
    df = pd.read_csv(‘failurecurve2.csv’, delimiter = ‘;’, header=1)
    z = np.polynomial.fit(df[‘X’], df[‘Y’],30)
    failure = np.polynomial1d(z)
    rate_fail = []
    rate_fail.append( (failure(i)/100.) for i in range(0,15) )
    df = pd.read_csv(‘fuelusageincreaseICE.csv’, delimiter = ‘;’, header=1)
    # df[‘Y’] = 100
    eff_ICE_rate = df[‘Y’]/100.
    df = pd.read_csv(‘electricity_co2.csv’, delimiter = ‘;’, header=1)
    #df[‘Y’] = 0.364
    co2_kwh_e = df[‘Y’]
    df = pd.read_csv(‘fleetsize.csv’, delimiter = ‘;’, header=1)
    fleet_increase = df[‘Y’]/100.
    # Moderate entrance
    df = pd.read_csv(‘adoptioncurve.csv’, delimiter = ‘;’, header=1)
    adoption = df[‘Y’]/100.
    df = pd.read_csv(‘fuelusageincreaseEV.csv’, delimiter = ‘;’, header=1)
    # df[‘Y’] = 100
    eff_EV_rate = df[‘Y’]/100.
    return [rate_fail, eff_ICE_rate, eff_EV_rate, adoption, fleet_increase, co2_kwh_e]

plt.close(‘all’)
rates = getFunctions(‘BAU’)
bat, prod_E, prod_D, WTW_D, WTW_E, tot_co2, E_perc, D_perc, km_iD, km_iE, ...
maintD= calculate(rates, ‘BAU’)
rates1 = getFunctions(‘Moderate’)
```
bat1, prod_E1, prod_D1, WIW_DL, WIW_E1, tot_co2_1, E_perc_1, D_perc_1, KM_1, v1, ...
km_iD1, km_iE1, maintD1 = calculate(rates1, 'Moderate')

rates2 = getFunctions('Progressive')
bat2, prod_E2, prod_D2, WIW_DL, WIW_E2, tot_co2_2, E_perc_2, D_perc_2, KM_2, v2, km_iD2, ...
km_iE2, maintD2 = calculate(rates2, 'Progressive')

fig, ax = plt.subplots()
ax.plot(range(2016,2031,1), E_perc, label = 'EV [%]', color = 'purple')
ax.plot(range(2016,2031,1), E_perc_1, color = 'mediumorchid', linestyle = ':')
#ax.plot(range(2016,2031,1), E_perc_2, color = 'blueviolet', linestyle = '--')
#ax.plot(range(2016,2031,1), D_perc, label = 'ICV [%]', color = 'navy')
#ax.plot(range(2016,2031,1), D_perc_1, color = 'royalblue', linestyle = ':')
#ax.plot(range(2016,2031,1), D_perc_2, color = 'c', linestyle = '--')
plt.legend()
plt.ylabel('Year')
plt.xlabel('Market share [%]')

plt.subplots()  
plt.plot(range(2016,2031,1),tot_co2_bau, label = 'BAU')
plt.plot(range(2016,2031,1),tot_co2_1, label = 'Moderate')
plt.plot(range(2016,2031,1),tot_co2_2, label = 'Progressive')
plt.legend()
plt.ylabel('Year')
plt.xlabel('Total emitted CO$_{2}$ eq kg')

fig, ax = plt.subplots()
plt.plot(range(2016,2031,1),KM, label = 'BAU')
plt.plot(range(2016,2031,1),KM_1, label = 'Moderate')
plt.plot(range(2016,2031,1),KM_2, label = 'Progressive')
plt.ylabel('Year')
plt.xlabel('Fleet growth, e_co2_kwh = rates')
plt.subplots()
ylabels = ['Survival rate [%]', 'Emission factor [CO$_{2}$ eq kg/kWh]', 'Fuel decrease [%]', 'Fuel decrease [%]', 'Techno. adoption curve [%]', 'Techno. adoption curve [%]', 'Techno. adoption curve [%]']
xrange = range(2016,2031)
e_co2_kwh = [x/100. for x in e_co2_kwh ]
rates = [ failure_e_co2_kwh[0:16], eta_ICE[0:16], eta_EV[0:16], fleet_growth, ...
adapt[0:16],adapt1[0:16], adapt2[0:16]]
num = [ 1, 2, 3, 3, 4, 5, 5, 5]
true = [ False, False, False, True, False, False, True, True]
lables = ['$\eta_{\text{ICE}}$\% $\eta_{\text{EV}}$\% $\text{BAU}$ $\text{Moderate}$ $\text{Progressive}$]
colors = [ 'grey', 'green', 'red', 'green']
for r, ylabel, i, topl, label, c in zip(rates,ylables, num, true, labels, colors):
    r = [x*100 for x in r]
    plotCurve2(xrange,r[0:15], ylable, i, topl,label,c)
G.3. Code for capacity and charging rate figure

```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
def makeStack(scenario):
    os.chdir("C:/Users/huisman/Gdrive/Delft/Thesis/CO2 berekeningen/Excel ... sheets/"+scenario)
    df = pd.read_csv(’stacks’+scenario+’.csv’, delimiter=’,’, header=0)
    l = list(df)
    df[1[0]] = df[1[0]] +2016
    df1 = df.loc[[0.,4.,14.],[1.0].. , [1.2,1.4,1.6,1.7]]
    df2 = df.loc[[0.,4.,14.],[1.0].. , [1.1,1.3,1.5,1.7]]
    df1.columns = [’Year’, ’WIW’, ’Production’, ’Maintenance’, ’Battery’]
    df1[’Battery’] = 0
    df2.columns = [’Year’, ’WIW’, ’Production’, ’Maintenance’, ’Battery’]
    df1[’Type’] = ’D’
    df2[’Type’] = ’E’
    dfs = [df1, df2]
    df_tot = pd.concat(dfs)
    df_tot = df_tot.sort_index()
    bottom = [0,0,0]
b = 0
ind = np.arange(6)
width=0.35
plt.minorticks_on()
plt.grid(b=True, which=’minor’, alpha = 0.2, linestyle=’-.’)
plt.grid(b=True, which=’major’, alpha = 0.5)
plt.bar(ind, df_tot[’WIW’], width, align=’center’, label=’WIW emissions’)
plt.bar(ind, df_tot[’Production’], width, align=’center’,bottom=df_tot[’WIW’], label=’Production related emissions’)
plt.bar(ind, df_tot[’Battery’], width, align=’center’,bottom=df_tot[’Production’]+df_tot[’WIW’], label=’Battery related emissions’)
plt.bar(ind, df_tot[’Maintenance’], width, align=’center’,bottom=df_tot[’Battery’]+df_tot[’Production’]+df_tot[’WIW’], label=’Maintenance related emissions’)
plt.ylim([0,8979492373.380154])
plt.xticks(ind, [’’,’’,’’,’’,’’,’’,’’,’’,’’])
#plt.legend(loc=’upper right’)
fig, ax = plt.subplots(figsize=(10,4))
plt.subplot(3,1,1)
plt.title(’CO2 [eq]$ emissions \text{ [kg]}$’, y=1.3)
makeStack(’BAU’)
plt.legend(loc=’upper center’, bbox_to_anchor=(0.5,1.4), prop={’size’: 9}, frameon=False, ncol=4)
plt.subplots_adjust() 
plt.subplot(3,1,2)
makeStack(’Moderate’)
plt.subplot(3,1,3)
makeStack(’Progressive’)
ind = np.arange(6)
plt.xticks(ind, [’Diesel 2016’,’Electricity 2016’,’Diesel 2020’,’Electricity 2020’,’Diesel 2030’,’Electricity 2030’])
```

G.3. Code for capacity and charging rate figure

```bash
# -*- coding: utf-8 -*- 
***
Created on Sun Apr 29 16:35:49 2018
```

---

The code snippet provided demonstrates how to create a stacked bar chart using Python. The code is organized and formatted to ensure readability and to minimize the effort required to read and understand it. The comments within the code provide explanations for each section, making it easier to follow the logic and purpose of each part of the code. This approach is beneficial for both educational and practical purposes, as it enhances comprehension and facilitates debugging and modification of the script. The use of functions, such as `makeStack`, helps in organizing the code and separating the logic into manageable parts, which is a good practice in software engineering. The comments also serve as documentation, which is crucial for maintaining and contributing to the code in the future. Furthermore, the code snippet includes importing necessary libraries such as `matplotlib`, `numpy`, and `seaborn`, which are essential for creating the visualization. The use of `os` and `pandas` for file handling and data manipulation, respectively, demonstrates a comprehensive approach to creating a functional and maintainable code base. This structured and well-documented code is a testament to good coding practices, which are fundamental in software development.
```python
# Python code overview

@import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import os
from matplotlib import cm, pylab
from matplotlib.lines import Line2D

os.chdir('C:/Users/huismansm/Google Drive/Delft/Thesis/Optimization')
df = pd.read_excel('battery_3d_bar.xls', header=0, sheet_name='Sheet2')
cap_range = len(df)

# set up the figure and axes
fig = plt.figure()
ax1 = fig.add_subplot(111, projection='3d')

height_bar_floor = [x for x in df['Charge rate 45 min']]
list_height = []
list_index = []
counter = 0
for each in height_bar_floor:
    for i in range(0, int(each), 20):
        list_height.append(i)
        list_index.append(counter)
        counter = counter + 1

height_bar_floor1 = [x for x in df['Charge rate 15 min']]
list_height1 = []
list_index1 = []
counter = 0
for each in height_bar_floor1:
    for i in range(0, int(each), 20):
        list_height1.append(i)
        list_index1.append(counter)
        counter = counter + 1

xpos = list(range(0, cap_range, 1))
num_el_high = len(xpos)
xpos = xpos + list_index1 + list_index
ypos = [-1] * cap_range
ypos = ypos + list_height1 + list_height
num_elements = len(xpos)

zpos = [0] * num_elements
#zpos = zpos + [0]*6
dx = np.ones(num_elements)
dy = [100] * num_el_high + [20]*len(list_height1) + [20]*len(list_height)
dz = [x for x in df['Capacity needed[kWh]']] + [0]*len(list_height1) + ...
    [1]*len(list_height)
colormap = cm.jet
tmpcolor = [colormap(i) for i in np.linspace(0,0.9,5)]
tmpcolor1 = tmpcolor * 4 + ['w'] * len(list_height1) + ['b'] * len(list_height)
ax1.bar3d(xpos, ypos, zpos, dx, dy, dz, color=tmpcolor1)
ax1.set_zlabel('Capacity needed [kWh]')
plt.xticks([2.5, 8, 13, 18])
plt.yticks(range(0,max(list_height1)+500,500), fontsize=9)
ax1.set_xticklabels(['1', '2', '3', '4'], minor=False, fontsize=9)
ax1.set_xlabel('Mission profiles for different # of driving moments')
```
G.3. Code for capacity and charging rate figure

```
ax1.set_xlabel('Charging rate [kW]

custom_lines = [Line2D([0],[0], color=tmpcolor[4], lw=2), 
                 Line2D([0],[0], color='b', lw=2), 
                 Line2D([0],[0], color=tmpcolor[3], lw=2), 
                 Line2D([0],[0], color='grey', lw=2), 
                 Line2D([0],[0], color=tmpcolor[2], lw=2), 
                 Line2D([0],[0], color=tmpcolor[1], lw=2), 
                 Line2D([0],[0], color=tmpcolor[0], lw=2)]

ax1.legend(custom_lines, ['Far','45 min break','Germany','15 min break','...
                         'Belgium','National','Drayage'], loc='lower center',...
                         bbox_to_anchor=(0.5,-0.22), prop={'size': 8}, ncol=5, frameon=False)
```