MASTER THESIS REPORT

FACILITATING DISTRIBUTION FLEET ELECTRIFICATION

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COMPLEX SYSTEMS ENGINEERING AND MANAGEMENT

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Determining the most cost-effective electric infrastructure composition and operations to facilitate the electrification of heavy truck fleets for distribution centres in grid congested areas

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This thesis represents the final deliverable of my MSC degree Complex Systems Engineering & Management at the TU Delft and concludes my academic journey. From high school I have been passionate about sustainable technologies, which along the way has been focussed on electric mobility. I'm proud to have been able to support the energy transition and thankful for the amazing times that I have had in the academic world the past seven years, even though the process hasn't always been easy and multiple delay causing roadblocks were encountered. However, due to all that I have learned in numerous courses I'm able to do things that I couldn't have ever imagined, like the formulation of a mathematical optimization model in a programming language, as done in this thesis. This thesis was written during an internship at Recoy, which specializes in energy flexibility valorisation and energy system software solutions. An opportunity presented itself for a national project with a supermarket company which wanted to electrify its truck fleet but was limited by the grid capacity available at their distribution centre. This thesis provides a Mixed-Integer Linear Programming optimization model that can advise on the optimal infrastructural composition and operation of the system to facilitate an electric truck fleet regardless of the power grid constraints. Before this thesis commences, I would like to thank the people that have helped and supported me during the process.

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Executive summary

Emission-free zones are being instituted in cities in the Netherlands to combat the emissions caused by transportation activity, as they are responsible for a significant part of global CO2 emission due to fuel combustion. Operators of large commercial vehicle fleets are looking at alternatives for fossil fuel trucks, like e-trucks, to be able to keep servicing locations in cities where the emission free zones are instituted. E-truck fleets need sufficient charging infrastructure and power capacity at the distribution centres they operate from, of which the availability is not guaranteed. The issue of actors not being able to access the power grid capacity they require to electrify their delivery vehicle fleet cannot be solved in the short run by the grid operators. As the capacity of actors' connection to the power grid is constrained, solutions behind the electricity meter are necessary to either increase local supply or reduce momentary demand.

The problem is that these energy generation and storage components are expensive, and the distribution centres often are bounded by strict route schedules which cannot be shifted. Finding the most cost-effective solution is not easy as both the supply and demand side of the problem influence each other, and various timeframes and variations need to be considered. A distribution centre can be seen as small local system within a larger regional system like the power grid or the supply chains. Research into the composition of electricity generation or storage components and the scheduling of demand has previously been done for small local systems within the larger power grid system. The combined optimization of infrastructural composition and operational scheduling has not been performed earlier in the literature for distribution centres, while no similar use case has been studied in the Netherlands or its general region. This thesis' aim is to analyse the characteristics of both sides of the problem and interactions between them by development of an integrated optimization model.

To work towards this thesis' objective, a main research question is formulated: *"What is the most cost-effective electric infrastructural composition and operation to facilitate the electrification of heavy truck fleets of large-scale distribution centres in grid congested areas in various scenarios to ensure that the route schedules can be driven?"* Several sub research questions were formulated to aid in answering the main research question. The research approach and methods concern literature research, expert interviews, application of an optimization model to various scenarios of a real-life case study and rigorous verification and validation to scientifically answer the subquestions and main research question. The proposed mathematical model is a MILP model which optimizes the composition and operation of the electric infrastructure of a distribution centre, while considering the periodic energy balance, for various scenarios in the electrification process. After the model is constructed and verified, and the behaviour of the model has been analysed, a case study will be performed to acquire managerial insights and to test if the model is applicable to a real-world case.

This thesis solely considers the local system of a distribution centre, in which photovoltaic panels, wind turbines, battery storage and charging stations can be installed to facilitate the charging demand of the e-trucks on top of the power demand of the distribution centre. While the optimization of the infrastructural composition and the operation can be tackled separately, the way in which the charging of the EVs interacts with the infrastructural components make it essential to consider both problems simultaneously. Because both sides of the problem act on the same system and are reasonably homogeneous in function, they can be combined into a single mathematical problem formulation. The simultaneous optimization is facilitated by incorporating the sum of the number of each infrastructural component installed times their associated cost in the objective function of a MILP model and the resulting positive and negative power flows in the primary equality constraint, which represents the energy balance of the system. The primary positive power available is the electricity that can be bought

from the grid, which is however limited by the maximum grid connection. The power of the photovoltaic panels, wind turbines and discharge of the battery storage are the other positive power flows, while the charging of the battery storage, charging demand of the e-trucks and power demand of the distribution centre are the negative power flows. Due to this formulation the model minimizes the number of infrastructural components installed upfront and thus the total costs, while having to make sure that sufficient positive power is generated or available from storage, on top of the power from the grid, to facilitate the negative power flows. The power demand of the distribution centre is fixed but the model can smartly schedule the charging demand of the e-trucks to minimize the peak demand and avoid exceeding the power available from the grid as much as possible, to minimize the number of infrastructural components required. With the implementation approach of the problem in the mathematical model a high number of mixed-integer decision variables are used, causing the model to be high-dimensional and thus computationally difficult to solve. This thesis uses a literary substantiated method of making a highly dimensional problem implementation work by reducing the time period of the problem, as the number of decision variables scales with the number of time periods. This is done by considering a typical day per month for a total of 12 days, reducing the problem size but still incorporating seasonal variation.

The proposed mathematical model was tested by means of a case study and various scenarios for a supermarket company operating a distribution centre to analyse the models' behaviour in a practical setting. The case study subject is a distribution centre operated by a supermarket company and is located in the Randstad. The distribution centre of the specific supermarket company was chosen as subject for the case study as it already has experience with e-trucks, it has space available for the installation of electric infrastructure components, and supermarket companies have control over a consistent supply chain. The distribution centre would need to substitute 60 fossil fuel trucks with e-trucks in 2025, when the first zero-emission zones are instituted, and 120 e-trucks would be necessary in 2030 to facilitate all deliveries to retail locations in zero-emission zones. The data that was used as input for the parameters in the model was partly derived from literature and partly from experts, like the ones participating in the case study. The 3 main scenarios defined pertain to the number of e-trucks in the electrification process, with 5 e-trucks in the first, 60 in the second and 120 in the third. Each main scenario has 3 subscenarios, in which the first only looks at the optimal infrastructural composition combined with greedy, unscheduled charging. The second subscenario looks at both the optimal infrastructural composition and operation, while the third also optimizes both simultaneously, but with variable electricity prices based on the day-ahead market instead of fixed prices.

Before the model was applied to the real-world case, it was verified using a recalculable numerical test and validated using linear regression analysis. The results of the numerical test verifiably show that the model optimizes both the installation and the operation of the infrastructural components, to minimize the costs while adhering to the constraints. The results from the linear regression analysis show that a specific method is necessary to determine the typical days per month, as using the same day for every month is not statistically representative. To determine the most typical days per month the K-medoids method was chosen, in which for each cluster the data point with the lowest dissimilarity to all other points in the cluster is determined. The literature substantiating the K-Medoid method, and the resulting data indicate it is a respectable method to choose the most typical days, with the goal to simulate a whole year within a more manageable timeframe.

With the implementation of the mathematical model in the case study, the results show that within each of the three main scenario's, from the greedy charging subscenario to the variable electricity prices subscenario, the main pattern is that the model is able to decrease the total costs and the number of infrastructure components required. The model is able to reduce the cost from subscenario 1 to subscenario 3, for main scenario 1 by 2.2%, for main scenario 2 by 12.8% and for main scenario 3 by 19.4%. The greedy nature of the charging demand in subscenario 1 in combination with the pattern of the demand of the distribution centre causes the model to need an expansive infrastructural composition to facilitate the required power demand in exceedance of the maximum power of the grid connection. In subscenario 3 the number of infrastructural components is significantly reduced from the greedy subscenario 1, due to the ability of the model to smartly schedule charging demand to try to avoid peak power demand in exceedance of the maximum grid connection and to capture low electricity prices instead of high ones. The infrastructure investment steps in the electrification process to take, would be to install consecutively or collectively 1, 3 and 7 charging stations and 994, 1623 and 4340 PV panels in 2022, 2025 and 2030, leading to a PV installation with a total rated power of 1.562 MW, which proved to be the more cost-effective than wind turbines and battery storage. To study how the uncertainties in the model's input parameters affect the outcome of the model, sensitivity analysis using the one at a time method was done, in which each factor is varied in turn while keeping all other factors fixed at their original indicated value. The sensitivity analysis showed that the maximum grid connection and the electricity price had the biggest effect on the total costs. The results of the scenarios, the graphs and the sensitivity analysis show that the model is effectively able to optimize the infrastructural composition and operation to minimize the cost in all cases, giving managerial insights into the decisions that need to be made in all steps of the fleet electrification process.

During the formulation process of the mathematical model, which involved the problem description, conceptual modelling, validation and verification, various assumptions have been made to enable the model's development. For the yield of the renewable electricity sources as well as the demand of the distribution centre itself and electricity market prices it is assumed that historical data is representative for the future. To reduce the computational complexity of the model, the historic data of 2021 was comprised to a typical day per month using the K-medoid method, with a modelling resolution of hourly time period, for a total of 288 time periods. Regarding the infrastructural components, for the integration into the model a selection was made, and it was assumed that the characteristics of the different infrastructural components scale linearly with the number of units installed. All these assumptions affect real-life representability, and while case study results themselves cannot be directly generalized for other distribution centres, after testing of the mathematical model it can reliably be used to generate results for distribution centres in other cases.

This thesis provides a mathematical model which can determine the most cost-effective infrastructural composition and operation for not only distribution centres, but also other behind-the-meter systems, which have to electrify their truck fleet but are hindered by low charging capacity due to their kWmax. Based on the results of the case study and the performance of the mathematical model some general and some specific conclusions can be made. The most cost-effective infrastructural composition and operation is dependent on the characteristics and the demand of the distribution centre in question and the number of e-trucks and the intensity of their route schedules. The comparison of the simultaneous optimization of operation and infrastructure with the greedy base subscenario, in which the charging demand is fixed and only the infrastructural composition can be optimized, shows the value of the mathematical model and the cost-effectiveness of the operational optimization. With these general conclusions considered in the main scenarios of the case study, specific advice was given on the infrastructural and operational needs in the various steps of the electrification process.

In regard to further research recommendations, a first recommendation is to test the proposed mathematical model in other cases, with distribution centres with different characteristics and power demand. A very interesting topic for further research would be the possibility for not only scheduling the charging demand but also the possibility off rescheduling the transportation demand. Another interesting research direction is also limited by computational complexity and concerns the running of the model with a smaller resolution or over a bigger horizon, as this would increase the reliability.

Nomenclature

Abs	Absorbed
BET	Battery electric trucks
BS	Battery system
CAP	Capacity
CHP	Combined-heat power
CS	Charging station
Cur	Curtailment
DAM	Day-ahead market
DC	Distribution centre
DOD	Depth of discharge
EV	Electric vehicle
FLC	Fuzzy logic controller
GHG	Greenhouse gasses
ICE	Internal combustion engine
IDE	Integrated development environment
Inj	Injected
LCOE	Levelized cost of energy
MILP	Mixed-integer linear programming
NSGA	Non-dominated sorting genetic algorithm
OAT	One at a time
PG	Power grid
PSO	Particle swarm optimization
PV	Photovoltaic
SOC	State of charge
WT	Wind turbine

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1. Introduction

Emission-free zones are being instituted in cities in the Netherlands to combat the emissions caused by transportation activity, as these are responsible for a significant part of global CO2 emission due to fuel combustion (IEA, 2020a; 2020b; Panteia, 2021). The Dutch government has joined the Paris climate agreement and is therefore committed to reducing its greenhouse gas emissions by 49% in 2030 and 95% in 2050 compared to emissions levels in the Netherlands in 1990 (Rijksoverheid, 2021). On a municipal level even stricter milestones are set, with 30 cities planning to instate emission-free zones in the city centre for commercial vehicles from 2025 and personal vehicles from 2030, with emission zones being instituted in 10 more cities in 2030 as well (Panteia, 2021; TLN, 2021).

Operators of large commercial vehicle fleets are looking at alternatives for fossil fuel trucks, like e-trucks, to be able to keep servicing locations in cities where the emission free zones are instituted. Battery-electric trucks or e-trucks have the potential for lower life cycle greenhouse gas emissions and total lifetime costs (Zhou et al., 2017). Furthermore, electric trucks do not produce tail-pipe emissions and can have greater tank-to-wheels efficiency than internal combustion engine trucks in city delivery operations (Lee et al., 2013). Hydrogen trucks are also an option, as they have a higher range and refuelling speed, in which e-trucks lack (Hall & Lutsey, 2019). E-trucks are however improving on these points and currently seem the dominant choice for truck fleet operators (Koornneef, 2020).

E-truck fleets need sufficient charging infrastructure and power capacity at the distribution centres they operate from, of which the availability is not guaranteed. The issue is that the national and regional power grids in the Netherlands are too congested, due to the growing amount of decentral generation of solar panels and the switch to electric heating and transportation (Netbeheer Nederland, 2021). This means that even though distribution centre companies want to switch the delivery fleet that they operate to e-trucks, they might not be able to receive sufficient power from the grid at the moment they want to charge their e-trucks.

The issue of actors not being able to access the power grid capacity they require to electrify their delivery vehicle fleet cannot be solved in the short run by the grid operators and is growing more in size and number of affected entities as time goes on. This is evident by the recent Dutch Parliament letter concerning the total stop on the grid connection of new and existing companies for the coming years in two provinces due to congestion on the power grid (Rijksoverheid, 2022). Stops on new or existing grid connections have occurred earlier in other provinces as well (AD, 2021; Case data, 2021). Grid operator maps show that grid congestion is a problem across the Netherlands, both on the supply and demand side (Netbeheer Nederland, 2021).

As the capacity of actors’ connection to the power grid are constrained, solutions behind the electricity meter are necessary to either increase local power supply or reduce momentary power demand. These so-called behind-the-meter solutions derive their name from their position in regard to the private electricity meter that is used to measure the energy and power usage (Bayram & Ustun, 2017). The two solution avenues to excessive power demand are either the installation of local energy generation and storage components, or possibly the smart scheduling of the demand, to smooth out the demand peaks. Both solution avenues can also be utilized simultaneously, if one cannot solve the problem on its own or when its more economical to use both.

The challenge is that these energy generation and storage components are expensive, and the distribution centres often are bounded by strict route schedules which cannot be altered, hindering the fleet electrification process (Case data, 2021). It would thus be helpful to be able to determine the minimum size of the generation and storage components and at what time the e-trucks need to be charged, as this can actually be scheduled smartly within a truck's downtime. The degree to which the charging of the e-trucks can be spread in time also determines how many charging stations are necessary, which is another cost factor.

Finding the most cost-effective solution is not easy as both the supply and demand side of the problem influence each other, and hourly, daily, monthly and yearly timeframes and variations need to be considered. It might for example be cheaper to install more charging stations to use the free electricity from renewable generation, or it might be cheaper to install more renewable generation components to be able to spread the charging of the e-trucks more (Hoarau & Perez, 2018). Investment decisions for the electric infrastructural behind-the-meter generation and storage components need to be made up front even though the operational performance needs to be considered as well, as the yield of renewable electricity generation can vary daily and seasonally. The conjunction of both an infrastructural and operational problem, combined with all relevant factors make it far from a trivial problem to solve.

The socio-technical system considered in this thesis is a distribution centre with its own power demand as well as the additional charging demand, with the boundaries of the system defined by the factors within the distribution centre company's control. A distribution centre can be seen as small local system within a larger regional system like the power grid or the supply chains, but for this thesis solely the installation of infrastructural components and operational optimization on the terrain of the distribution centre is considered. The system can be pictured as a warehouse where on the supply side solar panels and wind turbines can be installed to generate power and facilitate the demand side, at which the e-trucks can be smartly charged in between their fixed routes. Further description and visualization of the system will be done in chapter 4. Distribution centres are a clear example of a complex multi-actor socio-technical system, as they involve complex physical-technical systems and networks of interdependent actors (Ottens et al., 2006). The complexity comes from the heterogeneity and numerousness of the components. This is increased by the addition of the generation and storage components to the collection of technical elements of the distribution centre itself (Behdani, 2012).

The combined optimization of infrastructure composition and operational scheduling as far as known has not been performed earlier in the literature for distribution centres, while no similar use case has been studied in the Netherlands or its general region. However, various locational factors, like meteorological and energy market dynamics, do influence both the supply and demand side. A significant knowledge gap is thus evident in regard to finding the most cost-effective electric infrastructure composition for large-scale commercial applications, like distribution centres, combined with the smart operation of large EVs, like e-trucks, which the distribution centre company directly controls. While research into the composition of generation or storage components and the scheduling of demand has previously been done for small local systems within the larger regional power grid system, no literature exists that considers all factors of interest. While some papers do incorporate a fixed electricity price, this thesis will also include variable prices. Akram et al. (2018) and O'Shaughnessy et al. (2018) among others researched the required size of generating and storage components to service a certain residential area in Saudi Arabia and the United States respectively, while Dai et al. (2019) researched the composition of a commercial charging station in China. Chandra Mouli et al. (2016) do study the operation of a given infrastructure with solar panels and batteries for an office parking lot servicing small electric vehicles in the Netherlands. However, not only differs the power demand of a distribution centre itself from the other researched use-cases, but because the distribution centre company has control over the operation of the e-trucks it can smartly schedule the charging, which might reduce the number of generation and storage components required. The different demand than other use-cases and the control over the e-truck fleet makes the case for distribution centres unique.

This thesis' aim is to analyse the characteristics of both the infrastructural and operational side of the problem and the interactions between them by the development of an integrated optimization model. The optimization model will consider the dynamic energy balance between the demand at the distribution centre and the supply of the electric behind-the-meter components for all time periods, while minimizing the total combined costs of all these static components and the charging stations. The operational cost of buying electricity from the power grid or revenue from selling to it will also be incorporated. The model is run in a setting with deterministic demand and supply over time. Therefor it should be able to find the most cost-effective electric infrastructure composition of the behind-the-meter components for the distribution centre, as well as the optimal charging schedule of the e-trucks.

The optimization model will be verified, validated and implemented into a specific case study, after which extensive sensitivity analysis will be done. The sensitivity analysis will help provide managerial insights for application, to determine which factors influence the results the most and which factors are the biggest risk or opportunity. A case study which is build around the distribution centre of a large supermarket company is used to test the model in a practical setting, which will aid in the validation of the model. Moreover, the case study will be useful to see the interaction of both the infrastructural and the operational side of the problem in practice.

The remains of this thesis will be structured as follows. The next chapter defines the key concepts establishing the cause and composition of the research problem, which can then be used to find relevant literature. The literature will then be reviewed to increase the understanding of the scientific problem at hand, and an overview will be given of the results from literature compared to the research problem under consideration. Consequently, a knowledge gap can be identified and the direction and scientific relevance of this research can be substantiated. Chapter 3 will detail the research objective, formulate the research questions and propose the research approach to answer these questions. Chapter 4 will give a more in-depth description of the problem, beginning with the business relevance and ending with a formal problem description. The formal problem description will aid in the formulation of the conceptual model and mathematical model that will be presented in chapter 5. In Chapter 6 the case study will be introduced and the model input data partly following from the case study will be detailed. Subsequently, in chapter 7 the proposed mathematical model will be verified and validated, with the use of data input from literature and the case study. This will give a first insight into the behaviour of the model. In chapter 8 the model will then be implemented to run the scenarios contained in the case study and present the results. In chapter 9 the research process will be discussed, diving into the research assumptions and limitations. The managerial insights and recommendations that follow from the case study results will also be discussed. In chapter 10 the thesis will be concluded, the research questions will be answered and recommendations for future research will be provided.

2. Literature review and knowledge gap

The purpose of the literature review is to gain methodological insights and establish a knowledge gap, in which this research can provide scientific value, and to examine how other scientific papers have tackled similar problems to the one under consideration in this research (Randolph, 2009). The context of the literature review is provided by four core concepts, which are also partly incorporated into the search term (Knopf, 2006). First the core concepts will be introduced and detailed, after which the literature review is performed.

2.1. Core concepts

There are four important concepts, which influence and bound the topic. These core concepts can have multiple interpretations or definitions, making it important to clearly define these concepts and explain their inner workings and effect on the topic (Sheppard, 2020). The core concepts are fleet electrification, grid congestion, behind-the-meter systems and infrastructure composition optimization.

2.1.1 Fleet electrification & scheduling

With fleet electrification the switch from fossil fuel vehicles to electric vehicles is meant for operators of a vehicle fleet, due to the introduction of zero emission zones. In 2025 emission-free zones will be established in 30 cities in the Netherlands, while in 2030 a total of 40 cities will have emission free zones (Panteia, 2021). Fleet operators servicing those cities will have no choice but to switch to zero emission vehicles like electric ones (TLN, 2021). The electrification of the truck fleet could be instantaneous or stepwise, according to the stepwise introduction of the emission-free zones, meaning for one or multiple scenario's the electric infrastructure required needs to be planned.

Besides acquisition and charging costs, fleet electrification will also increase grid congestion on the demand side, causing the need for smart scheduling of the charging (Stawski et al., 2021). The more electric vehicles are charged at the same time, the higher the peak demand is. To stay below the available power capacity, the charging of the vehicles could be smartly scheduled to spread out the charging demand. This smart scheduling of loads is also called demand response, as the demand is altered in response to the available supply (Feuerriegel & Neumann, 2014). How much the charging of the e-trucks can be shifted is dependent on the route schedules and working hours of the drivers.

2.1.2 Grid congestion and connection

Grid congestion entails the excessive demand for the transmission of electricity beyond the guaranteed capacity of the power grid (O'Connell et al., 2012). Grid congestion can be divided into excessive demand and supply. Excessive demand is caused amongst others by the increasing electrification of heating and transportation, while excessive supply is caused by the increasing decentral generation of renewable energy (Stawski et al., 2021). The degree of grid congestion is dependent on a number of factors including local grid rating, number of generating and consuming units, and the time (O'Connell et al., 2012). The electricity grid has to be able to deal with these so-called supply and demand peaks.

The presence of regional grid congestion has a direct effect on the businesses in that region, as they might not be able to satisfy their power demand with electricity from the power grid (AD, 2021; Rijksoverheid, 2022). The amount of power that a business or anyone in the Netherlands can supply or demand is constraint by the capacity of their grid connection, which is called the kWmax. It is measured by multiplication of the highest energy flow in a quarter hour with a factor four to simulate the instantaneous power demand (Overheid, 2022). Due to regional grid congestion grid operators are however currently denying request for new connections or expansions in many regions (AD, 2021; Rijksoverheid, 2022). This complicates a business' electrification process.

2.1.3. Behind-the-meter systems

A behind-the-meter system refers to a renewable energy system at a specific location owned by a single entity, usually operated with distributed generation and storage units to facilitate a user's energy demand. These so called behind-the-meter solutions, as they are situated behind the meter at the grid connection that measures the maximum peak demand, would entail on-site renewable energy generation, like solar panels or a wind turbine, and on-site energy storage (Bayram & Ustun, 2017). These components can be seen as electric infrastructure and will be referred to as infrastructural components. In the literature review it will be examined which components are used in each paper.

Behind-the-meter systems can be divided into three interacting layers: the technology layer, the economic layer and the social layer. The technical layer pertains to the stability and reliability of the system, supported by the infrastructural components like renewable energy generation and storage. The economic layer pertains to the optimization and scheduling of the system. The social layer refers to the people working within the system and the characteristics of the organization. Layer interactions for example are the organization that composes the technical layer, the technical layer in turn constrains the optimization within the economic layer and the optimization and scheduling steers the people within the organization (Bayram & Ustun, 2017).

2.1.4. Infrastructure composition optimization

In the context of this research infrastructure composition optimization means finding the optimal combination and size of infrastructural components, while minimizing the cost but achieving the required minimal performance. Infrastructure has been used to refer to telecom or physical facilities, but in this research, infrastructure refers to the on-site electrical grid and components, like solar panels, wind turbines, battery systems and charging stations. Simultaneously with the infrastructure composition, the operation needs to be optimized as well, as both influence each other.

In the identification of an optimization problem the electric infrastructure investment decision can essentially be seen a knapsack problem, while demand response or smart charge scheduling can possibly be interpreted as a job shop problem or a bin packing problem (Ferguson et al., 2018; Hsieh & Liu, 2004). Knowledge of the knapsack, job shop and bin packing problem will aid in recognizing these problems in literature if they are researched and differentiated between. The presence of a knapsack or scheduling optimization problem will be examined and filtered in the literature, to evaluate which paper's models could be useful inspiration for the construction of this thesis' model. The specific characteristics of the optimization problems will be discussed in the corresponding chapter 5: Mathematical model design

2.2. Literature review

A literature review is conducted according to a certain methodology, presenting a summary of all the literature found, followed by analysis to subsequently specify a knowledge gap (Timmins & McCabe, 2005). The methodology pertains to the scope, search term and database used. For the search of literature both the SCOPUS and Web of Science database were used. The search term used was 'Infrastructure optimization AND electric vehicle charging AND PV AND storage AND grid.' With the exclusion of conference notes this resulted in 26 papers. The search terms 'infrastructure optimization AND electric vehicle charging' are integral to the potential research direction. The other terms coupled by the AND function, while leading to a long search term, are necessary to limit the scope and avoid superabundant research of decreasing relevancy (Webster & Watson, 2002). More use-case specific search terms like 'electric truck/transport' were considered but didn't yield any results.

2.2.1. Literature summary

The subject of a smaller electric system within a larger one is not new to the literature and is often referred to as a microgrid. A microgrid can be defined as a group of interconnected loads and energy resources within electrical boundaries that can be controlled as a single entity (Ton & Smith, 2012). Microgrids are however not necessarily owned by a single entity and do not necessarily consider the larger system in which they function, which would be the general power grid. Thus, the term does not fully describe the smaller electric system owned by a single entity in a larger electric system, and the earlier introduced key concept of behind-the-meter provides a better frame of reference.

The term behind-the-meter was defined in 1992 by Hendriks and as the term refers to the connection to the general power system, it inherently considers the smaller electric system within the larger one (Hendriks, 1992). The first time behind-the-meter systems are mentioned in the literature is in 2005, in a survey about community wind power development (Bolinger, 2005). in 2009 the actual effect of a behind-the-meter wind power installation on electricity demand charges was studied (Hildreth & Kildegaard, 2009). It is not until later that the composition and operation of behind-the-meter systems is studied to match local energy demand and supply.

Of the papers found in this literature review the first ones to optimize the electric infrastructure composition originate from China and focus on commercial applications without optimizing the scheduling of power demand factors. Riu et al. (2012) focus on a battery swapping station for commercial EVs in China and try to match the size of a solar PV installation to the capacity. Zhang et al. (2013) also consider a commercial charging station in China but look at cable EV charging instead of battery swapping and give the model the option to install wind power as well. This increases the complexity of the problem as they cannot just charge on-site batteries for when EVs arrive, but have to prepare enough capacity, choosing from multiple generating components, to facilitate the stochastic demand of arriving EVs. Dai et al. (2019) and Liu and Dai. (2020) try to optimize the electric infrastructure of a commercial charging station in China as well. Dai et al. (2019) however, look at the multi-actor cooperation and competition to minimize the cost of energy instead of infrastructural costs. Liu and Dai (2020) reduce the solution set by evaluating a selection of behind-the-meter system alternatives, which reduces the complexity but increases the inaccuracy of the optimization.

In western countries after 2015 the infrastructure composition problem was approached analytically in less commercially oriented use-cases like parking lot charging, which presents different characteristics compared to a commercial charging station. With parking lot chargers, the demand is more predictable, but the demand is present for longer durations. Other locational factors like meteorological dynamics and energy market structure also differ in western countries compared to China. Chandra Mouli et al. (2016) designed an integrated PV panel and battery installation for an electric vehicle office parking spot in the Netherlands. They conclude that local battery storage does not eliminate power grid dependence of an EV charger in combination with PV panels in the Netherlands, but it would mitigate day to day solar variation and reduce grid energy exchange by 25%. Blasius et al. (2016) and Esfandyari et al. (2015) use a similar approach to study university parking lots in Germany and Ireland respectively but are only able to suggest a suitable range of battery capacity. Bhatti et al. (2018) study parking lot charging in Pakistan, where the PV generation is actually sufficient to facilitate the charging demand. They also identify a counterbalance between profits and grid burden depending on the ratio between PV panels and battery capacity installed.

From 2018 onwards the papers in this literature review consider more diverse electric infrastructure components and more heterogenous use-cases, like residential areas. Residential areas have many heterogenous demand factors, like appliances, electric heating and mobility and continuously fluctuating demand, dependent on social factors. Akram et al. (2018) try to find the optimal infrastructure composition for a residential area in Saudi-Arabia, considering PV panels, wind turbines, a battery system, electric vehicles and a back-up diesel generator. The number of components increases the complexity of the problem, but also offers more solution options. Modarresi and Olamaei (2019) also incorporate a diesel generator for their commercial charging station design in Saudi-Arabia. Akram et al. (2018) do evaluate different load shifting scenarios, but both papers don't optimize the operation of their system. Finding the optimal infrastructure composition of a commercial charging station or residential area, without optimizing the operation of the system, is also done by Ban et al. (2019) and Yan & Ma. (2020) in China, by Baik et al. (2018) in South-Korea and by Chatterji and Bazillian (2020), Lui et al. (2020), O'Shaughnesy et al. (2018), Trevizan et al. (2020) in the United States and Mohseni and Moghaddas (2018) in Iran.

The operation of a present behind-the-meter system and the smart scheduling of demand is done by Golpîra et al. (2018) for a manufacturing plant, but in this literature review Bracco et al. (2019) are the first to simultaneously optimize the electric infrastructure composition and operation of a behind-the-meter system. They consider PV panels, battery models and consumer electric vehicles for a parking lot in Italy. Mirhoseini and Ghaffarzadeh (2020) and Wang et al. (2020) also simultaneously optimize the infrastructure composition and operation of a commercial charging station in Iran and China respectively, while Melendez et al. (2020) do so for multiple parking lots for a ride sharing service. These later papers are able to solve such a high-dimensional problem of simultaneous infrastructure composition and operation optimization by reducing the modelling period. This thesis will draw inspiration from their research approaches.

2.2.2. Literature analysis

The research papers are processed in a concept-centric table, showing the characteristics of each paper and their activity in the topics of analysis (Klopper et al., 2007). The characteristics of the papers pertain to the authors, year of publication, and the geographical location were the data originated from. It is useful to evaluate the geographical locations the research papers examined, as different locations lead to different renewable energy generation and ultimately different results (Mazzeo et al., 2020). The topics of analysis, following partly from the core concepts, are the use-case of each paper, the use of a knapsack or scheduling problem formulation, the inclusion of a kWmax or energy balance constraint, the infrastructural components considered, the research method used, and the incorporation of electricity prices. The results can be seen in table 1.

The most distinctive categorizations concern the use-case of the research papers and their geographical origin, as this affects the power demand profile and available supply respectively. Is a commercial charging station or residential area considered, or does the research focus on office or university parking lots? Commercial charging stations can have completely random power demand, such as stochastically modelled by Mirhoseini and Ghaffarzadeh (2020) while residential areas can have a more predictable demand (Yan & Ma, 2020; Chatterji & Bazilian, 2020). Table 1 shows that a third of literature is rooted in Asia, roughly a fifth in the US. Four papers have a middle eastern origin, three papers concern Northern-Europe and one paper for both Southern-Europe and Australia. An integrated system of energy storage, photovoltaic and electric vehicle charging is more often analysed for commercial and residential use than for office or university parking lots, based on this literature review. Most noticeably, no research was found that looks at the electric infrastructure of distribution centres or business parks in general, in the Netherlands or somewhere similar.

Authors	Date	Location	Use-case	Knap sack	Sched-uling	Energy balance	kW max	Components	Method	Electricity price
Akram et al.	2018	Saudi Arabia	Residential area	●		●		PV/BS/EV/WT/DG	MILP	Only capital costs
Baik et al.	2018	South-Korea	Commercial station	●		●		PV/BS/EV	MILP	Fixed profile
Ban et al.	2019	China	Commercial station	●				PV/BS	MILP	Only capital costs
Bhatti et al.	2018	Pakistan	Parking lot (office)					PV/BS/EV	PSO	Hypothetical fixed
Blasius et al.	2016	Germany	Parking lot (university)			●		PV/BS/EV	Statistical analysis	Only capital costs
Bracco et al.	2019	Italy	Parking lot (general)	●	●	●	●	PV/BS/EV	MILP	Fixed prices
Chandra M. et al.	2016	Netherlands	Parking lot (office)			●		PV/BS/EV	Statistical analysis	Fixed prices
Chatterji & …	2020	USA	Residential area	●		●		PV/BS/EV	MILP	Fixed profile
Dai et al.	2019	China	Commercial station			●	●	PV/BS/EV	MAPSO	Internally modelled
Esfandyari et al.	2015	Ireland	Parking lot (university)					PV/BS/EV	Statistical analysis	Only capital costs
Fathabadi.	2018	Nonspecific	Not applicable					PV/BS/EV	Simulink & prototype	Not applicable
Ferguson et al.	2018	USA	Parking lot (office)		●			EV	Cost-benefit analysis	Historical dynamic
Golpîra et al.	2018	Nonspecific	Not applicable		●	●		BS/WT	MILP	Varying fixed price
Islam et al.	2018	Australia	Parking lot (university)			●		PV/BS/EV	Suitability analysis	Internally modelled
Liu & Dai.	2020	China	Commercial station					PV/BS/EV	MOPSO	Only cost constraint
Liu et al.	2020	USA	Residential area	●		●	●	PV/BS/EV	MILP	Fixed profile
Mazzeo et al.	2020	Worldwide	Not applicable			●		PV/BS/WT	Scenario simulation	Not applicable
Mazzeo.	2018	Italy	Residential area			●		PV/BS/EV	Feasibility analysis	Average hourly cost
Melendez et al.	2020	USA	Not applicable	●	●	●		PV/BS/EV	MILP	Historical DAM prices
Mirhoseini & …	2020	Iran	Commercial station	●	●	●	●	PV/BS/EV	MILP to LP	Fixed profile
Modarresi & …	2019	Saudi Arabia	Commercial station	●		●		PV/BS/EV/DG	LP	Fixed profile
Mohseni & …	2018	Iran	Residential area					PV/BS/EV	MAPSO	Fixed prices
O'Shaughn et al.	2018	USA	Residential area					PV/BS	ReOpt	Reference costs
Riu et al.	2012	China	Commercial station	●		●		PV/BS	NSGA multi objective	Fixed profile
Trevizan et al.	2020	USA	Commercial station					PV/BS/EV	LP	Fixed profile
Wang et al.	2020	China	Commercial station	●	●	●		PV/BS/EV	LP	Internally modelled
Worighi et al.	2019	Belgium	Residential area					PV/BS	FLC	Fixed prices
Yan & Ma.	2020	China	Commercial station			●		PV/BS/EV	NLCP	Fixed profile
Zhang et al.	2013	China	Commercial station					PV/EV/WT	DE	Fixed profile
This thesis	2022	Netherlands	Distribution centre	●	●	●	●	PV/BS/EV/WT	MILP	Historical DAM prices

Table 1. The table shows the characteristics of all papers reviewed and their activity in the topics of analysis. Component abbreviations represent photovoltaic (PV), battery storage (BT), electric vehicles (EV), wind turbines (WT) and diesel generators (DG). Appendix A shows a more detailed version.

The manner in which the infrastructure optimization problem is defined as a knapsack problem with an energy balance constraint is recognized in a third of the literature. Of those only Ban et al. (2019) don't use an energy balance equation but use the value of lost load. Some statistical analysis papers, like by Blasius et al. (2016), Chandra Mouli et al. (2016), Islam et al. (2018), Mazzeo et al. (2020) and Mazzeo (2018), do consider the energy balance, but are not knapsack problems as they don't use an optimization research method. A quarter of the papers include some form of scheduling optimization, but only Golpîra et al. (2018) and Melendez et al. (2020) use a job shop problem formulation. Golpîra et al. (2018) does not consider electric vehicles however and Melendez et al. (2020) varies the driving schedule of autonomous vehicles, while in the case of this thesis the charging needs to be scheduled.

The operational side of the problem, in which the charging of electric vehicles can be scheduled smartly to reduce the peak demand, is incorporated differently in the eight papers that consider it. Ferguson et al. (2018) use a strict bin packing problem formulation but use heuristics to perform it as a cost-benefit analysis, because they state that for a large number of EVs the problem would be high-dimensional and thus computationally difficult to solve. However, Bracco et al. (2018), Mirhoseini and Ghaffarzadeh (2020) and Wang et al. (2020) make a high dimensional bin packing problem work by reducing the time period of the problem. Bracco et al. (2018) do this by considering a typical day per month, reducing the problem size but still incorporating seasonal variation. Interestingly enough, these papers combine an infrastructural knapsack problem formulation with a temporal bin packing formulation, where minimizing the number of bins per period in this context pertains to reducing the number of charging stations that are required simultaneously.

Regarding the infrastructural components, PV panels and battery energy storage are almost always considered, with the exception of Ferguson et al. (2018) and Golpîra et al. (2019), as this combination for electric infrastructure optimization purposes is the main proposition (Worighi et al., 2019). Direct electric vehicle charging is excluded from the two residential oriented papers by O'Shaughnesy et al.

(2018) and Worighi et al. (2010), the battery swapping station papers from Ban et al. (2019) and Riu et al. (2012), and the climate impact paper by Mazzeo et al. (2020), while for this research facilitating electric vehicle charging is the main focus. Three papers consider wind turbines besides photovoltaic generation (Akram et al., 2018; Mazzeo et al., 2020; Zhang et al., 2013). Only the papers by Akram et al. (2018) and Modarresi and Olamaei (2019) consider a back-up diesel generator. So, while the words PV and storage were included in the search term, the resulting papers organically introduced the consideration of power from wind turbines and a diesel generator. Golpîra et al. (2018) also include a combined-heat power (CHP) plant, but for this research solely electric infrastructure is considered

When it comes to the research method optimization methods are most often used, with almost half of the papers using some form of programming. Modarresi and Olamaei (2019), Trevizan et al. (2020) and Wang et al. (2020) use linear programming, while Mirhoseini and Ghaffarzadeh (2020), Akram et al. (2018), Chatterji and Bazillian (2020), Ban et al. (2019), Melendez et al. (2020) and Liu et al. (2020) use mixed-integer linear programming (MILP). Yan and Ma (2020) use non-linear convex programming. With (non-) linear programming a (non-) linear objective function is optimized under certain constraints to minimize or maximize a specific variable, usually the cost (Alevras et al., 2001). Bhatti et al. (2018) use particle swarm optimization (PSO), while Liu and Dai. (2020) use multi-objective PSO and Dai et al. (2019) and Mohseni and Moghaddas (2018) use multi-actor PSO. Chandra Mouli et al. (2016), Blasius et al. (2016) and Esfandyari et al. (2015) use statistical analysis. Mazzeo (2018) and Islam et al. (2018) use a qualitative approach with a feasibility and suitability analysis. Ferguson et al. (2018) perform a cost-benefit analysis to determine how many charging stations are required and where, but only consider electric vehicles. the remaining papers use specific models, like ReOpt, Fuzzy Logic Controller (FLC), or a Non-dominated Sorting Genetic Algorithm (NSGA).

The electricity price is a significant cost factor in large scale electrification and different incorporation approaches with varying levels of practical accuracy are used in the literature (Wang et al., 2020). Some don’t consider it at all and only consider the capital cost of infrastructure investment (Akram et al., 2018; Ban et al., 2019; Blasius et al., 2016; Esfandyari et al., 2015; Liu & Dai, 2020). Others use a strictly fixed price, a fixed price profile, or a seasonal or time-of-use (TOU) price profile. Other papers like Islam et al. (2018) use a load based internal electricity price model, while Bhatti et al. (2018) and O'Shaughnesy et al. (2018) escalate or multiply historical price data with a certain parity factor. Melendez et al. (2020) uses historical Day-Ahead Market (DAM) data to incorporate the electricity prices, while Ferguson et al. (2018) also use historical dynamic prices. This is an interesting approach as the day ahead market price varies across the year and is determined by the bids of all generating units. This opens the door for arbitrage opportunities with battery storage systems and might increase attractiveness of combining renewable generation with such storage systems (Gomes et al., 2017).

2.3. Knowledge gap

What is most noticeable from the literature review is that no use-case similar to electrification of a fleet of trucks of a large-scale distribution centre is focused on by the research papers. As mentioned, more use-case specific search terms like ‘electric truck/transport’ were tried but didn’t yield any results. Distribution centres itself have a very different fixed demand profile than residential or commercial use-cases. The route schedules of the e-trucks are also fixed, but the charging of the e-trucks in the downtime presents a more flexible and controllable opportunity than present in other use-cases (Case data, 2021; Koornneef, 2020; RVO, 2020). This knowledge gap presents a unique research opportunity that coincides with the problem analysis. Furthermore, only three papers considered wind turbines, while only the one paper by Akram et al. (2018) considered a back-up diesel generator. While wind as a renewable energy source is an interesting research addition, a diesel generator will not be considered in this research, as it causes GHG emissions.

While many papers study a smaller electric system within a larger electric system, what makes the case of a large-scale fleet operator like a distribution centre unique is that it has complete control over the operation of the EVs to optimally schedule the charging. Only Bracco et al. (2019), Mirhoseini and Ghaffarzadeh (2020), Wang et al. (2020) and Melendez et al. (2020) simultaneously optimize the electric infrastructure composition and the operation of a behind-the-meter system. However, the only consider small private EVs as an external stochastic demand, meaning the operation of the system can only be optimized up to a certain level. With knowledge of the future route schedules and sole control over the charging of the e-trucks, optimization of the operation on a distribution centre has more potential to reduce the overall power demand and total costs. Insights on this potential couldn't be found in the papers of this literature review, presenting an interesting knowledge gap.

A maximum to the grid connection is not often used in the literature, especially not in combination with fixed route schedules that have to be driven and subsequently making it essential to recharge the EVs sufficiently, while it is precisely due this combination of factors that a behind-the-meter system is required. Only Bracco et al. (2019), Dai et al. (2019), Lui et al. (2020) and Mirhoseini and Ghaffarzadeh (2020) use a kWmax, without forced transportation demand, but the first three papers are oriented on residential parking with Dai et al. (2019) only using a kWmax in scenarios, while Mirhoseini and Ghaffarzadeh (2020) solely evaluate a microgrid. In this thesis a large commercial application of e-trucks with a strict power capacity of the connection to the medium voltage grid is evaluated, which couldn't be found elsewhere in literature of this review.

In the large-scale electrification of delivery trucks electricity cost plays a significant part in the total cost, but some research papers don't even consider electricity cost and only consider capital infrastructure cost (Akram et al., 2018; Ban et al., 2019; Blasius et al., 2016; Esfandyari et al., 2015; Liu & Dai, 2020). Most papers incorporate a fixed price, or fixed price profile. Only Trevizan et al. (2020) considers seasonal price changes and Melendez et al. (2020) uses historic data. These papers originate from California and Florida respectively. Only Ferguson et al. (2018) and Melendez et al. (2020) use historical dynamic prices, but the former only considers EVs and charging stations while the latter optimizes the route schedules. In this research the electric infrastructure composition of a distribution centre needs to be optimized to handle a fixed route schedule, varying the times in which the vehicles are charged. On the basis of this literature review it seems that how dynamic prices effect the value of infrastructure components in a composition optimization has not been studied earlier in literature.

Few papers originate and use data from West-Europe and even fewer from the Netherlands specifically, while variable input parameters like the electricity price and yield of the renewable electricity generation differ from other parts of the world. Blasius et al. (2016) and Worighi et al. (2019) study a parking lot in Germany and a residential are in Belgium respectively, but only use local data to model the PV yield. Chandra Mouli et al. (2016) use data originating from the Netherlands specifically, which shows that PV energy generation comparing summer and winter differs a factor of five, but also don't include local wind power yield or variable electricity prices. The lack of research on electric infrastructure composition optimization, consisting of both solar and wind power generation in combination with energy storage and EV charging, in the Netherlands and Europe as a whole presents a researchable knowledge gap that can result in a realistic evaluation of the use-case in the Netherlands.

3. Research approach

The research approach describes the methodology used to scientifically answer the determined research questions to subsequently complete the research objective. At the highest level, research approaches can be divided into three types: deductive, inductive and abductive (Bryman & Bell, 2015). The research at hand can be defined as an inductive one, as several known premises are taken as true, where after in the remaining research space a framework will be built to solve the problem (Saunders et al., 2012). This entails the zero-emission transportation transition on the distribution centre. With the research type defined, first the research objective and main research question will be introduced. Thereafter the subquestions will be listed and explained. Finally, the research method and approach will be laid out.

3.1. Research objective & questions

The objective of this thesis is to solve the identified research gap by proposing a MILP model which optimizes the composition and operation of the electric infrastructure of a distribution centre, while considering the periodic energy balance, for various scenarios in the electrification process. Besides the main objective concerning the optimization model that this thesis proposes, there is also a secondary objective, namely applying the optimization model to a real-life situation by means of a case study. In this thesis the case study will be carried out for a large-scale distribution centre of a supermarket company, located in the Randstad. The secondary research objective of application to a case study will help to assess whether the proposed model can eventually be used in real-life by distribution centres to determine the best electric infrastructure composition for their situation.

The main and sub research questions determined to reach the research objective incorporate the core concepts and the knowledge gap identified in the literature review. The main research question states the research objective and aims to find the solution to the stated problem, while the sub research questions should help the process in answering the main question (Sheppard, 2020). The main question is as follows:

MQ: *"What is the most cost-effective electric infrastructural composition and operation to facilitate the electrification of heavy truck fleets of large-scale distribution centres in grid congested areas in various scenarios to ensure that the route schedules can be driven?"*

The following sub-research questions are formulated following the research boundaries set by the core concepts and the knowledge gap identified in the literature review:

SQ1: *"What are the different stages and scenarios of the fleet electrification process?"*
SQ2: *"Which infrastructural components should be considered and what are their characteristics?"*
SQ3: *"What are the costs factors of the components and how can they be implemented in the model?"*
SQ4: *"How can the infrastructural and operational side of the problem be integrated into a single, simultaneous optimization model?"*
SQ5: *"How do variations in the models' input parameter values affect the outcome of the proposed model and which have the biggest impact?"*
SQ6: *"To what extend does the model reflect the real-life scenario?"*

The subquestions are formulated in sequential ordered, in which the findings of earlier subquestions will help answer later questions. By answering all the subquestions the main question should be able to be answered. Different sub research questions require different research methods. Which research methods will be used to find the answer to which sub research question will be discussed next, as well as the overall research approach that will be used to answer the main research question.

3.2. Research approach & methods

The research approach and methods concern further literature research, expert interviews, application of an optimization model to various scenarios of a real-life case study and rigorous verification and validation to scientifically answer each research question. Different research questions need different methods. The first 4 subquestions will be answered by literature research. Some information has already been shared in the literature review, meaning some subquestions can already be answered. Another avenue that will be used to answer the subquestions 2 and 3 is through interviews. By speaking to experts in the field or key employees of distribution centres useful information can be acquired that would be harder to find in the literature. For the subquestions 4 and 5 an optimization modelling approach will be chosen, while for subquestion 6 a case study will be performed. Next the research methods will be discussed individually.

3.2.1. Literature research

Literature research is used for both the literature review and the answering of specific sub research questions, namely the first 4 subquestions. The literature review was performed in the previous chapter, since it presents the basis on which the research methodology is build. The core concepts were established, namely grid congestion, fleet electrification, behind-the-meter and infrastructure optimization. With the core concepts defined a literature review was performed and a knowledge gap was established. Besides the growth of theoretic knowledge and the determination of a knowledge gap, some subquestions can already be answered by the literature research performed thus far. This pertains to subquestions 1 and 2.

The problem and system description in chapter 4 will further use the literature to determine the characteristics of all infrastructure components and the interactions between them, to incorporate them in a formal problem description in preparation for construction of the mathematical model. In the literature review the infrastructural components most commonly considered besides EVs were PV panels and battery storage systems, with the addition of wind turbines as another renewable energy source. Diesel generators are excluded in the consideration of a strictly zero-emission system.

3.2.2. Modelling approach

The optimization technique that will be used is mixed-integer linear programming (MILP). Benefits of MILP are that it can guarantee the global optimality of the solution, it provides a more direct measure of optimality, and it is flexible and can enhance modelling capabilities and adaptability. A downside is that it can have poor performance in scalability (Ban et al., 2019). These downsides can be remedied by clever selection of the modelling horizon and resolution. This will be explained in chapter 5 concerning the mathematical model.

After the choice is made to use MILP to solve the problem and the mathematical formulation is worked out, several other technical decisions need to be made to implement and solve the MILP problem. These choices concern the solver to use, the software or programming language to write the problem in, and the environment to use. IBM ILOG CPLEX is chosen as the main solver for this research. The programming language that the problem will be written in is Python. The IDE of choice is Jupyter Notebook. Further analysis in support of these decisions can be found in appendix B.

3.2.3. Verification and validation

After the mathematical model is constructed it needs to be verified and validated to scientifically test its credibility before it can be applied to the real-world problem. The case study will be introduced beforehand to supply the data necessary for validation of the model, but the case study will only be performed after the verification and validation chapter. The difference between verification and validation is that with verification the model's representation of the conceptual description is evaluated and that with validation the model's representation of the real system it tries to simulate is evaluated (Carson et al., 2002; Thacker et al., 2004). Both steps will be further explained in chapter 7: Model verification and validation.

Both verification and validation will be done by means of scientifically proven frameworks and methods, with use of the overarching framework by Mitre (2022). First this framework will be discussed. Then the model will be verified by use of a simple numerical test, of which the results can be evaluated through manual calculations. The model will be validated with the framework from Carson et al. (2002) and by use of linear regression analysis. As mentioned earlier, the verification and validation happen between the introduction of the case study and the results of the case study.

3.2.4. Case study

After the model is constructed and verified, and the behaviour of the model has been analysed, a case study with various scenarios will be performed to acquire managerial insights and to test if the model is applicable to a real-world case. Because input data from the case study is necessary for the verification and validation, the model will already be introduced beforehand. When the verification and validation process has been concluded successfully, the model can be implemented on the case study. Specific data about distribution centres is hard to find, but as the differences between them are small, a case study is an excellent tool to evaluate the sector. In this thesis a single case will be studied, with the subject being the distribution centre of a large supermarket company, to gain useful insights into the case itself and distribution centres in similar situations. While the evaluation of a single case might provide less reliable results compared to using multiple cases, the evaluation of a single case is less time-consuming and allows for a deeper understanding of the topic (Gustafsson, 2017).

The zero-emission zones will be introduced stepwise, meaning the number of fossil fuel trucks that are necessary to substitute for e-trucks will also increase stepwise, leading to multiple scenarios. Literature research shows that zero-emission zones will be established in 30 large cities in the Netherlands in 2025, while a total of 40 zero-emission zones will be present in 2030 (TLN, 2021). Literature research shows that grid congestions is a serious issue, and many distribution centres might not be able to increase their grid connection. The steps that happen in the electrification process can be seen in figure 1, which shows the e-truck numbers needed in the case study. The specific scenarios evaluating these e-truck numbers will be further detailed in chapter 6: Case study and data input.

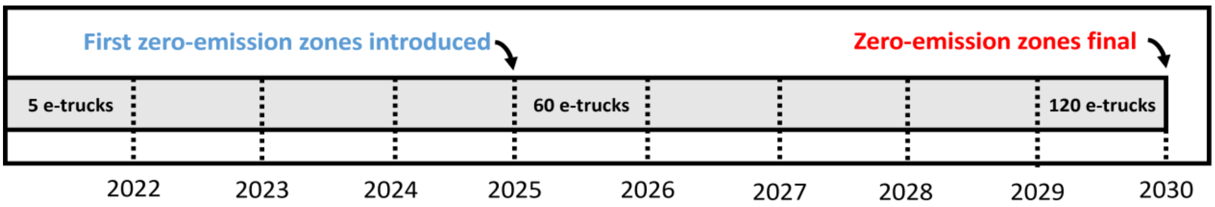


Figure 1. Timeline of the introduction of the zero-emission zones and the gradual adoption of e-trucks.

The iterative process of constructing the case study will be aided by employees of the supermarket company that operates the distribution centre. Interviews and data sheets will be used to the exact information necessary to set up the context in which the model will be tested. The distribution centre in question is situated in the Randstad, which is a dense urban area with grid congestion, as can be seen in appendix D. All relevant data of the case study will be incorporated into the model, while market conform data will be used in parts where exact data cannot be acquired. All the data input will be detailed in chapter 6: Case study and data input. After the verification and validation, the case study will be performed, and the obtained results will be analysed to acquire managerial insights. Analysis of the results of the case study should enable the answering of subquestion 5 and also partly subquestion 6. When all subquestions are answered, the answer to the main questions can be found as well.

4. Problem and system description

In this chapter the background and context of the problem will be elaborated on and the distribution centre as the system of interest will be described in more detail. First the general business relevance of the problem will be discussed. The business relevance will show the necessity of solving the problem. Secondly, the infrastructural composition and operational side of the problem will be described formally and in more detail. The formal problem description lays the foundation for the mathematical model and will help to fully understand the problem and what steps and assumptions were made while the mathematical model was constructed. The assumptions will be specified separately as well after the formal problem description.

4.1 Business relevance

Due to the creation of zero emission zones in most cities in the Netherlands from 2025 and 2030 onwards, fleet operators servicing those cities will have no choice but to switch to zero emission vehicles like electric ones, as explained in the core concept of fleet electrification (Panteia, 2021; TLN, 2021). Distribution centres will thus have to substitute all the fossil fuel-based trucks with non-emitting trucks on their route schedules servicing areas within emission free zones. As it takes some time to acquire e-trucks and the required infrastructure and get everything up and running, fleet operators and so too distribution centre companies will need to progressively switch to electric vehicles in the years running up to 2030 (Panteia, 2021). This means that in the fleet electrification process there will be various stages in which an increasing number of fossil fuel trucks will be substituted with e-trucks.

In an ideal scenario, disregarding potential profitability of renewable energy sources independently, distribution centre companies would be able to simply get all the required electricity from the power grid and be able to sufficiently charge the e-trucks in a minimal amount of time so that they can fulfil their route schedule. In reality however, both getting sufficient power from the grid and charging the e-trucks sufficiently in minimal amount of time is often hardly possible (Case data, 2021; Koornneef, 2020; RVO, 2020). First, the scheduling of the charging and the charging stations required will be discussed. This pertains to the operational part of the problem. Secondly, the addition of behind-the-meter components to supplement the insufficient power from the grid will be discussed. This pertains to the infrastructural part of the problem.

4.1.1. Operational side of the problem

Fossil fuel-based trucks and e-trucks are not directly interchangeable and route schedules have to be adjusted or sufficient charging stations have to be installed to account for the decreased operating range (Koffrie, 2020). This means that e-trucks have to make more frequent and shorter trips and the batteries of the e-trucks need to be recharged in between trips (Koornneef, 2020). If the breaks between trips were to coincide for all e-trucks, there would need to be a charging station for every vehicle and the demand on the grid connection capacity would be maximal. Financially it makes more sense to have less charging stations and use them for multiple vehicles consecutively, spreading the power demand at the same time.

The route schedules between the operating hours can be shifted a little bit, but still significant investment in charging infrastructure is required (Koffrie, 2020). It is during the night-time, outside of normal working hours when most e-trucks are stationary, that the smart charge scheduling potential is the greatest. When a large group of e-trucks is stationary for a prolonged amount of time, the charging can be spread maximally to minimize the number of charging stations and amount of capacity required. It only needs to be ensured that when every vehicle starts their route schedule again, they are sufficiently recharged. This is illustrated in figure 2.

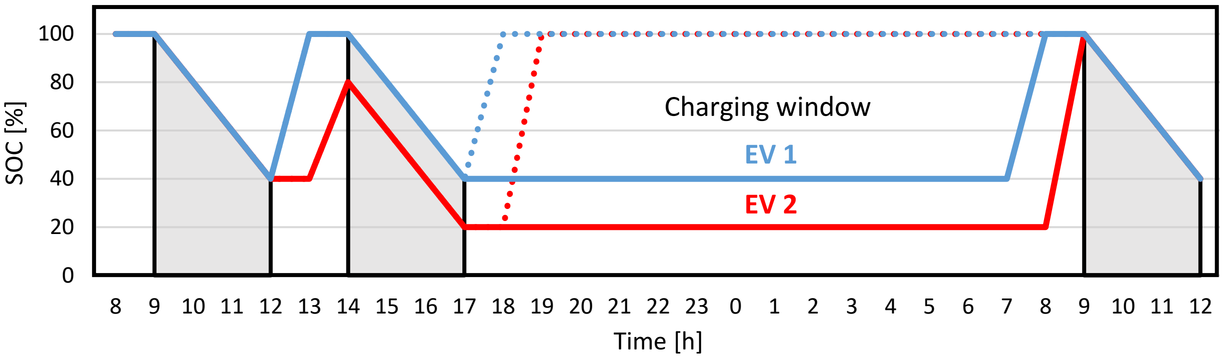


Figure 2. This figure shows the state of charge of two EVs over the course of 28 hours. The grey areas indicate when both vehicles have an equal transportation demand, due to which their SOC decreases equally. The dotted lines show the area in which the SOC could be, if alternative charging strategies were used. Figure is adapted from Case data (2020) and Koornneef (2020).

There are various strategies concerning the smart charging of a fleet of electric vehicles, as illustrated by figure 2 for a set of electric vehicles. Both have the same route schedules, within the normal working hours of 9 to 5. As the SOCs of both vehicles fall below half of their capacity after the first route, they both need to be recharged between their routes. Even in the limited time available their charging demand can be separated, so the same charging station can be used subsequently, and the charging demand minimized. An additional strategy could be to charge an electric vehicle to less than full, as shown with the bottom line, if it is not required for the next route. This would reduce the charging demand in that specific time period even further.

In the prolonged period between the last route of an e-truck and the first route of the next day any time period could be chosen to charge the electric vehicle to a sufficient level for the first route, as shown by the area between the dotted and solid lines, called the charging window. In theory the charging of 17 electric vehicles could be spread over the 17 hours, such that only one charging station is required. In reality there will be vehicles with differing route schedules, and additional demand and supply factors to consider, but this is the instance in which the bin packing problem formulation can be applied to minimize the number of bins, which is the number of charging stations, by fitting the required items, namely the charging demand of every vehicle.

4.1.2. Infrastructural side of the problem

The power required for the combined charging demand of the electric vehicles, on top of the electricity demand of the distribution centre itself, can often not be supplied sufficiently solely by power from the grid at distribution centres with a limited grid connection (Case data, 2021). If a distribution centre is located in a grid congested area it is also often not possible to increase the capacity of the grid connection. Other solutions are required behind the meter to supplement the power available from the grid connection and facilitate the overrunning charging demand. These infrastructural components can consist of renewable energy generation, like solar panels or wind turbines, or of energy storage technologies, like a battery.

Renewable energy generation presents an additional power source next to the power grid, which can be used to accommodate the charging demand. Renewable power sources like solar and wind are only available variably in specific time periods, due to meteorological factors. Energy storage technologies, like batteries, can store energy attained in previous periods and use it in future periods. The factors influencing the power yield of these sources and the operation of a battery will be discussed in the next subchapter. The effect and value of these behind-the-meter infrastructural components on the day-to-day operations is illustrated in figure 3. In the figure it is assumed that the combined charging demand is fixed, and the distribution centre demand has a day-night fluctuation.

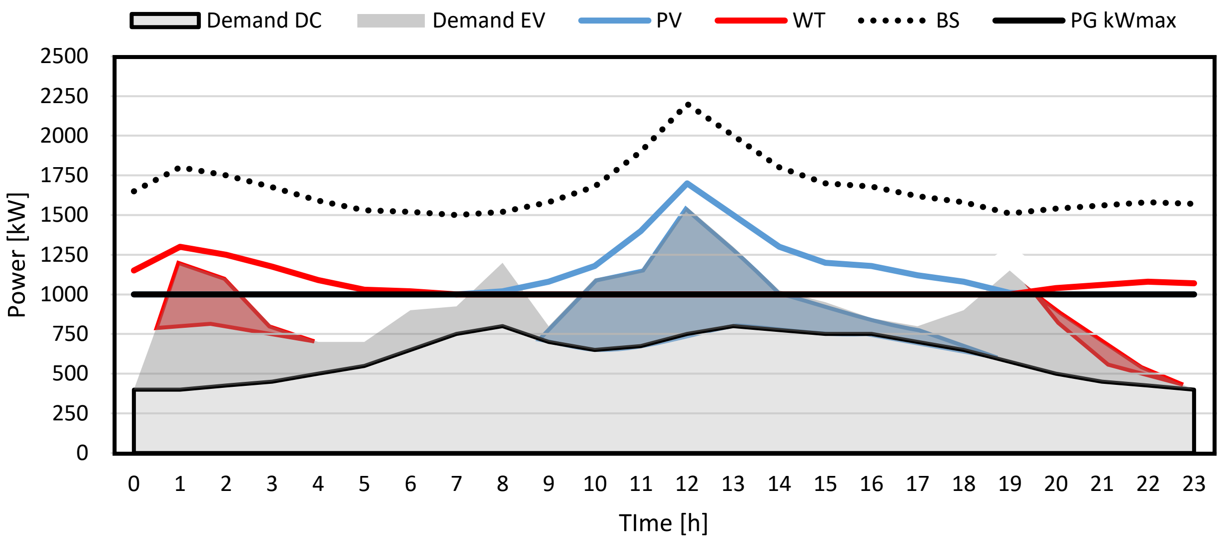


Figure 3. This figure illustrates the matching of power supply to the demand. The power demand of the distribution centre itself is shown with darker grey and the combined fixed charging demand of the EVs on top in lighter grey. The blue and red line represent the power yield of PV panels and wind turbines respectively, and the black and dotted line the power supply potential of the power grid and battery system. The filled areas represent the actual supply by the components corresponding to the colours to match the demand. Adapted from Budischak et al. (2013) and O'Shaughnessy et al. (2018).

In figure 3 it is illustrated that the charging demand of all EVs combined, on top of the existing demand of the distribution centre itself, can exceed the amount of power the grid connection can supply. On two occasions the extra demand can be supplied by wind and solar energy generation respectively, represented by the filled area underneath the demand curve, with the colour corresponding to the energy source but on two occasions the demand exceeds the maximum grid connection while there is also insufficient renewable energy generation. Of course, it would be preferable to shift the demand to earlier or later time periods when more capacity is available, as discussed about the operational problem in the previous section, but a strict route schedule may not allow it. In these situations, an energy storage system like a battery becomes useful, as it can store energy from previous time periods and use it in future high demand time periods. The dotted line shows the extra capacity that a 1 MW/1 MWh battery could offer, while for the white peaks in figure 3 only about 200 kW is required. The same goes for the photovoltaic and wind turbine yield, of which not all is necessary to facilitate the demand exceeding the maximum grid connection. The extra generated electricity is then used instead of electricity from the power grid.

Figure 3 only illustrates the infrastructural problem for 1 day, while on other days the demand might be higher or the yield of the renewable generation lower, underscoring the complexity of the problem. The question that then arises is how much of each infrastructural component would be necessary and effective to install and to what extent do the costs and benefits weigh up against buying the power from the grid. This is where the knapsack problem description comes in, where the electricity demand over the modelling horizon represents the knapsack, which can be filled with the power from the infrastructural components for a certain associated cost, with the goal to minimize the total system costs. The modelling horizon should be sufficiently long to capture the day-night and seasonal variations in demand and supply. Peak demand days should be considered to ensure that the infrastructural composition that the model presents is sufficiently robust.

4.1.3. Simultaneous optimization

While the two described sides of the problem can be tackled separately, the way in which the charging of the EVs interacts with the infrastructural components makes it essential to consider both problems simultaneously. With more renewable generation installed it might be possible to spread the charging more and require fewer charging stations, or more charging stations might be cost-effective instead of a battery system to capture time periods with high yield from renewable generation (Hoarau & Perez, 2018). Considering the problems separately may lead to a sub-optimal solution (Yan & Ma, 2020). The synergies between the smart charging in the operational side of the problem and the infrastructural components in the other side of the problem can reduce the demand on the grid and potentially improve the profitability, allowing for discovery of a global system optimum (Hoarau & Perez, 2018).

Because both sides of the problem act on the same system and are reasonably homogeneous in function, they can be combined into a single mathematical problem formulation. The charging station can be incorporated as an infrastructural component with the others in the objective function, while the operational optimization happens in the constraints. This is done for example by Bracco et al. (2019) and will be explained in more detail in the mathematical problem formulation chapter.

4.2. System and components description

Before a formal problem description is formulated it is important to understand and describe the system and its components. As aspects like the power grid (PG) and route schedules are discussed separately, this mostly concerns the infrastructural components, consisting of photovoltaic panels (PV), wind turbines (WT), battery system (BS) and charging stations (CS). An overview of the system, which is based around the distribution centre itself, and the role of the infrastructural components and the smart charge scheduling in solving the discussed problem can be seen in figure 4.

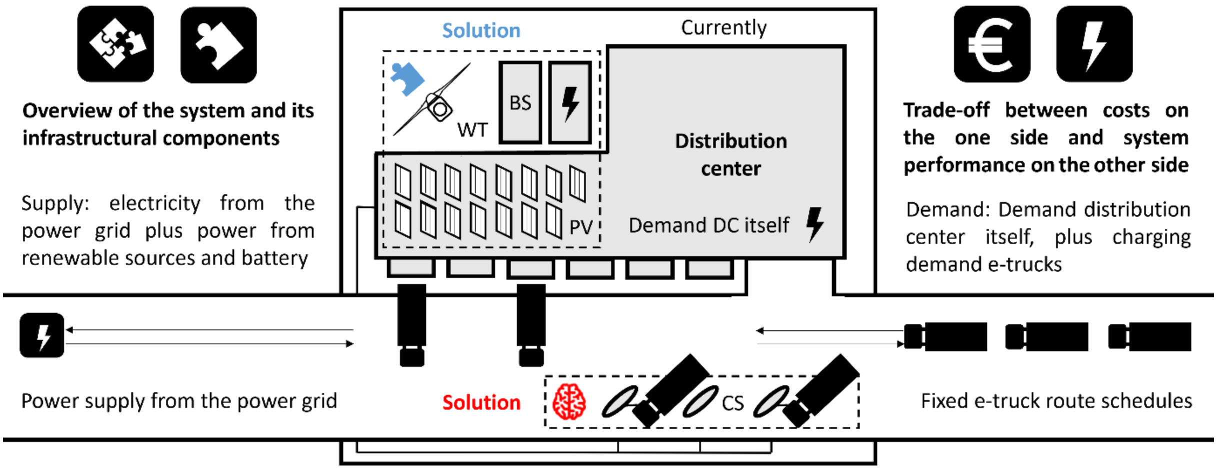


Figure 4. This figure gives an overview of the distribution centre as the main system, with roughly on the left the supply side and on the right the demand side. The upper solution box contains the infrastructural components for renewable electricity generation and storage, while the bottom one represents the potential smart scheduling of the charging of the e-trucks.

Figure 4 gives an overview of the distribution centre as the system and the interaction between the components it contains currently and components that can be added as solution to the introduced problem of facilitating the increasing charging demand of a growing e-truck fleet. The first solution in blue pertains to the installation of additional generation and storage components, while the second solution in red pertains to the smart scheduling of the charging, also explained earlier as demand response. Next the characteristics of the infrastructural components and the aspects that influence their functioning and interaction with the other components will be discussed.

4.2.1. Photovoltaic installation

Photovoltaic electricity generation by use of solar panels is one of the most attractive options for decentral electricity generation, with the yield being dependent on various factors. Solar panels have increasingly lower cost and are also highly scalable, making them suitable for homeowners as well as large commercial parties, like distribution centres. The power output of a solar PV system depends on several factors, like the solar irradiation, area and efficiency of the PV array, angle of incidence, and atmospheric temperature (Akram et al., 2018). The context of these values and the process of the calculations can be found in appendix C.

The infrastructural components all have multiple costs, like the purchase costs, installation costs and maintenance costs (Bracco et al., 2019). But while for the maintenance costs simply the costs made over the modelling period can be taken, for the purchase and installation costs this cannot be done directly. The one-off costs act over the entire lifetime of the component, while the period that will be modelled is much smaller. To adapt these costs to the modelling period, a so-called capital recovery or annualization formula will be used, also done by Bracco et al. (2019), Dai et al. (2019) and Liu et al. (2020). The calculation process can be found in appendix C. This allows for the calculation of a total per unit cost for each component, for which the values will be specified in the data input chapter.

4.2.2. Wind turbine power

Another interesting energy source due to its characteristics that can be harnessed locally with wind turbines is wind energy, again dependent on various factors. Advantages over solar power are that the wind can blow during the day but also during the night and that while solar power yield is higher in the summer, wind power yield is generally larger in the winter. It could be said that solar and wind power generation are somewhat synergetic (EWEA, 2009). That makes it an interesting technology to include in the model, as the variability of renewable energy sources hampers the reliability, which this seasonal synergy can reduce. The power that a wind turbine can generate is dependent on the product of factors like the efficiency of the wind turbine, or so-called power coefficient, the surface area of the rotor, the density of air and the velocity of air (EWEA, 2009). Again, same as for the PV panels, the factors will be combined into a single yield per wind turbine for incorporation into the mathematical model, and the process of these calculations can be found in appendix C.

4.2.3. Battery storage system

Battery storage systems are installations that enable storage of generated electricity from renewables, like solar PV panels and wind, that can be released later on when the system needs it (National Grid, 2022). Battery storage technologies allow the use of renewable generated energy even when the sun isn’t shining, or the wind has stopped blowing. By storing renewably generated energy for later use a battery is already alleviating the demand on the grid connection, but a battery could also be gradually charged via the power grid to facilitate a large charging demand from multiple e-trucks at a later moment, that the grid connection wouldn’t have been able to facilitate with its own capacity.

Battery energy storage systems can even be used to trade on the electricity markets, buying electricity when the price is low or even negative and selling when the price is high, which helps the stabilization of the regional and national power grids. However, despite decreasing costs, battery energy storage systems are still expensive, often not being profitable when not supplying enough benefit. In this case they might just be what is necessary to integrate the e-trucks into the distribution centre’s electricity grid. Just as the other grid components the battery installation can be build modular with linearly increasing size. Other factors influencing the interaction within the system are the capacity of such a battery module, the charging capacity and the charging and discharging efficiency. The values of these factors will also be introduced in the data input chapter.

4.2.4. Charging stations

Charging stations are an essential interface between the local electricity grid and the EVs, as they authorize and manage the charging sessions. While the connectors for EV charging have been standardized, the charging stations themselves come in various number of sizes and specifications. The biggest categorial factor within charging stations is whether they supply AC or DC electricity, with AC chargers only having power to slow charge while DC chargers enable fast charging (Parchomiuk et al., 2019; Virta, 2022). Besides charging speed/power another specification that is important is the charging efficiency. The exact values used in the modelling will be detailed in the data input chapter.

4.3. Formal problem description

The formal problem description will provide a more detailed, modelling oriented description of the problems under consideration. The formal problem description will be used as the starting point for the mathematical problem formulation that will be introduced in the next chapter. The power demand and supply side always have to be in balance and in the model consist of various parameters and decision variables, which for clarity sake are shown in figure 5 and will be explained in the next sections.

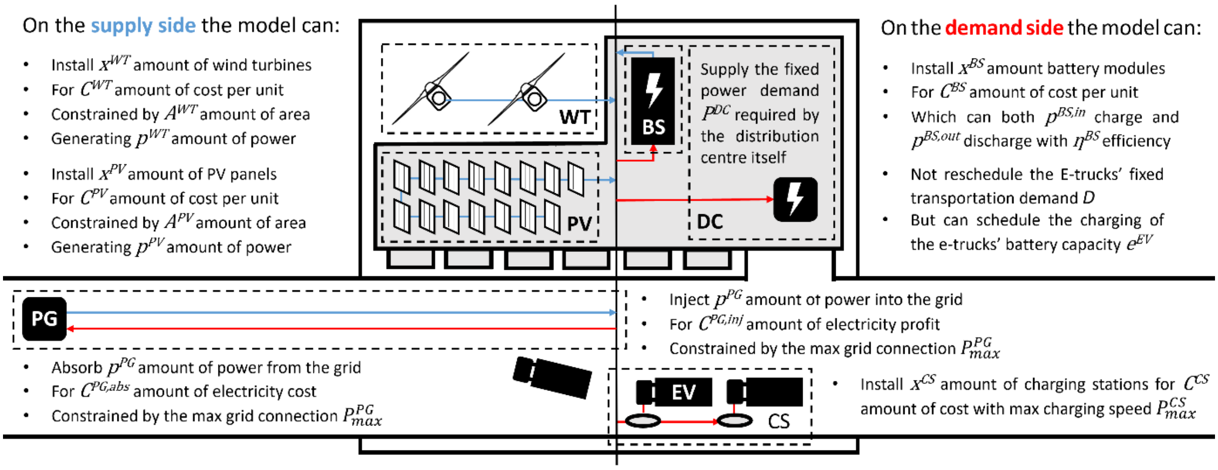


Figure 5. Schematic of the parameters and decision variables on the supply and demand side on a DC.

4.3.1. Demand side

For this problem a distribution centre company that distributes its goods according to a fixed delivery schedule is considered, as schematically seen in figure 5. The delivery schedule is specified per e-truck and is converted to a transportation demand D for every time period t. The transportation demand is then multiplied with the average consumption F of heavy-duty e-trucks to get a decrease in the state of charge e^{EV} for every vehicle in every time period t. The state of charge of the e-trucks is bounded by the minimum E^{EV}_{min} and maximum capacity E^{EV}_{max} of the battery of the e-trucks. This means that the state of charge of the e-trucks needs a positive inflow to counteract the negative outflow caused by the transportation demand, to keep the state of charge between its minimum and maximum bounds.

Every time period t that the transportation demand of an e-truck is 0, ergo when it is not driving, the model can decide to charge the specific e-truck. The charging p^{CS} of the e-trucks is bounded by the maximum charge speed of the e-truck or the charging station P^{CS}_{max}, whichever value is the lowest, and multiplied with charging efficiency η^{CS}. The model counts how many e-trucks charge simultaneously in every time period t, and the time period wherein the maximum number of e-trucks need to charge simultaneously decides the minimum number x^{CS} of charging stations required. The charging stations have an associated cost C^{CS}, therefore the model tries to spread the charging of the e-trucks over all time periods, to minimize the number of charging stations required and thus the total cost. So beforehand the model has an unknown amount of power demand for the e-trucks per time period t.

The electricity demand that is known beforehand however, is the demand P^{DC} of the distribution centre itself. The values of the electricity demand of a distribution centre and the level of its maximum grid connection will be detailed in the data input chapter. The model can also decide to charge the battery system or sell excess electricity and inject it back into the power grid for every time period t, falling under the demand denominator as both are negative power flows. The power $p^{BS,in}$ going to the battery system is multiplied with the charging efficiency $\eta^{BS,in}$ and added to the SOC e^{BS} of the battery of the previous period $t-1$. How much energy the battery system can contain is bounded by the max capacity E^{BS}_{max} and how much it can be charged in a single time period t is bounded by the charging capacity P^{BS}_{max}. The power injected into the grid $p^{PG,inj}$ is multiplied with a selling price $C^{PG,inj}$ to valorise the power outflow and is constraint by the maximum capacity of the grid connection P^{PG}_{max}. With the demand components of the system known, next the supply components can be discussed.

4.3.2. Supply side

It is imperative that the electrical system is always in balance, meaning the supply of electricity should be equal to the demand, shown by the blue and red power flow lines in in figure 5 respectively. This will be ensured by use of an energy balance constraint, in which is stated that the sum of all negative power flows and all positive power flows should be equal to 0. The main and already existing supply component is the connection of the distribution centre to the power grid. Per time period t the model can decide to absorb electricity $p^{PG,abs}$ from the grid to balance the system for a certain buying price $C^{PG,abs}$. As discussed earlier however, the maximum amount of electricity that can be absorbed from the grid is bounded by the capacity of the grid connection P^{PG}_{max}, called the kWmax. To counteract the insufficiency of the grid connection to supply the power for the exceeding demand, infrastructural components like solar panels, wind turbines and batteries can be installed.

The model knows beforehand how much power a wind turbine or PV panel will yield for every time period t, based on a deterministic modelling approach of using historical data. The power yield P^{PV} and P^{WT} for every time period t is multiplied with the number of PV panels x^{PV} or wind turbines x^{WT} that is installed. Knowing this the model can evaluate how many of each component it is necessary or cost-effective to install. The power that the PV panels and wind turbines yield is not directly valorised, but rather added as positive power flows to the energy balance constraint. Other positive power flows can then be reduced, or negative power flows can be increased, like the power bought from or sold to the grid respectively. If in certain time periods this is not possible, but the installed PV and wind turbine capacity is still necessary for other time periods, the excess power p^{cur} can be curtailed. The PV panels and wind turbines do have an associated per unit cost C^{PV} and C^{WT}, meaning the model tries to balance the installation with cost savings or profits made through other components. How many solar panels or wind turbines can be installed is constrained by the area available A^{PV}_{max} and A^{WT}_{max}.

The final supply component is the battery system, which can be discharged to supply a positive power flow $p^{BS,out}$ per time period t. The power discharged is multiplied with the inverse of the discharging efficiency $\eta^{BS,out}$ to calculate the electricity that is subtracted from the battery's SOC e^{BS}. The discharging power flow is bounded by the discharging capacity P^{BS}_{max}. The battery system also has an associated per module costs C^{BS}, so the model tries to minimize the installation. The maximum capacity of the battery system is however the product of the capacity of a single module E^{BS}_{max} multiplied with the number of modules x^{BS} installed in the battery system. Therefore, if the model needs to store more electricity it needs to install more modules.

To summarize the modelling of the costs, all per unit costs C of the infrastructural components are multiplied with the number of units x installed, and the revenue and costs of selling electricity to and buying from the power grid is summed for all time periods t and added to the cost equation. This will be detailed further in the conceptual model in chapter 5: model design.

4.4. Problem assumptions

In the modelling activities that are performed to conduct this research some assumptions are made in regard to the methodology and the data used. These assumptions make it feasible to translate the complex real-life situation into a mathematical model that can be solved computationally. For a large number of decision variables, the problem would be high-dimensional and thus computationally difficult to solve (Ferguson et al., 2018). But while there are ways to reduce the complexity, this also reduces the real-life applicability. This is recognized in Fowler's (1997) modelling principle: "Models are not right or wrong; they are more or less useful." If too many compromises are made in the modelling activities the model and results will not be representative of and applicable to the real-life situation. That is why the aim of this thesis is to propose a model which is solvable, but at the same time gives an accurate representation of the system and provide useful insights into the composition of the electrical infrastructure and operation at distribution centres. A number of assumptions were made for the infrastructural and operational problem to accomplish this. These assumptions will be detailed and reasoned next.

The first few assumptions concern the fact that solely the distribution centre itself and the activities within its area are taken as the system with its associated boundaries. This means that the route schedules of the e-trucks are fixed and not influenced by changing demand of retail locations. Furthermore, it is assumed that the route schedules do not change over the different scenarios that will be run. In the different scenarios an increasing number of e-trucks are introduced. The implementation of the e-trucks itself is not considered, but rather the number of route schedules will be increased to accommodate the number of e-trucks. The assumption is thus made that the number of e-trucks is synonymous and represented by the number of route schedules. It is also assumed that the e-trucks start the simulations with a full battery. Also outside the control of the distribution centre is the assumption that there is local grid congestion, due to which the grid connection is constrained and unupgradable. This is a reasonable assumption as proven in the literature review (Case data, 2021; Netbeheer Nederland, 2021).

Historical data will be used for the yield of the renewable electricity sources, for the demand of the distribution centre itself and for the day-ahead market electricity prices. As mentioned before, typical days will be chosen to represent the months to reduce the size of the mathematical model. The assumption that this subset is representative for the whole year will be verified in the chapter 7: verification and validation. This method is also used in many papers from the literature review (Bracco et al., 2019; Dai et al., 2019; Liu et al., 2020). For all scenario's, which in real-life would happen in different years, the historical data from the same year will be used. While this assumption can be valid for the renewable electricity generation and electricity market prices due to the inherent variability even within years, the demand data of the distribution centre is also used for every scenario. This can be explained by the fact that within the fleet electrification process the fossil fuel trucks are substituted with e-trucks. This means that the size of the operation at the distribution centre stays the same and the same yearly demand data can be used in the different scenarios.

It is further assumed that the characteristics of the different infrastructural components scale linearly with the number of units installed. For some elements, like the yield of the PV panels and the capacity of the battery system this holds scientifically true, while for others like the yield of the wind turbines and the battery (dis)charging rate this is a reasonable assumption. It is of main importance to consider all assumptions during evaluation of the results, where conclusions can be made on the basis that a certain level of a characteristic is simply required, even if it does not scale perfectly linear. With the formal problem description and necessary assumptions having been presented, the mathematical model will be proposed in the next chapter.

5. Mathematical model design

This chapter will discuss the mathematical model that will be used in this research. First a conceptual overview of the model will be given, which helps by visualizing the interactions of the model and the context of its operation. Thereafter the modelling horizon and resolution will be discussed. Finally, the mathematical model itself will be presented, of which the parameters, decision variables and equations will be detailed and discussed.

5.1. Conceptual model

A conceptual model is a helpful tool to understand how the input parameters are being used to optimize the objective function of the model under study within the given constraints. Additionally, the conceptual model forms the basis of the models' verification steps later in this chapter. The conceptual modelling phase succeeds the system description of chapter four which is in line with the model design steps from Robinson (2011) that are as depicted in Figure 6. The use of a conceptual model can help to understand how the input parameters are utilized in the optimization of the objective function under the constraints specified. Furthermore, the conceptual model provides a framework, which the mathematical model and its description can be structured on. The position of the conceptual model in the whole modelling process can be seen in figure 6, adapted from Robinson (2017). The knowledge acquisition, assumptions and system description have already been detailed, so now the conceptual model can be worked out.

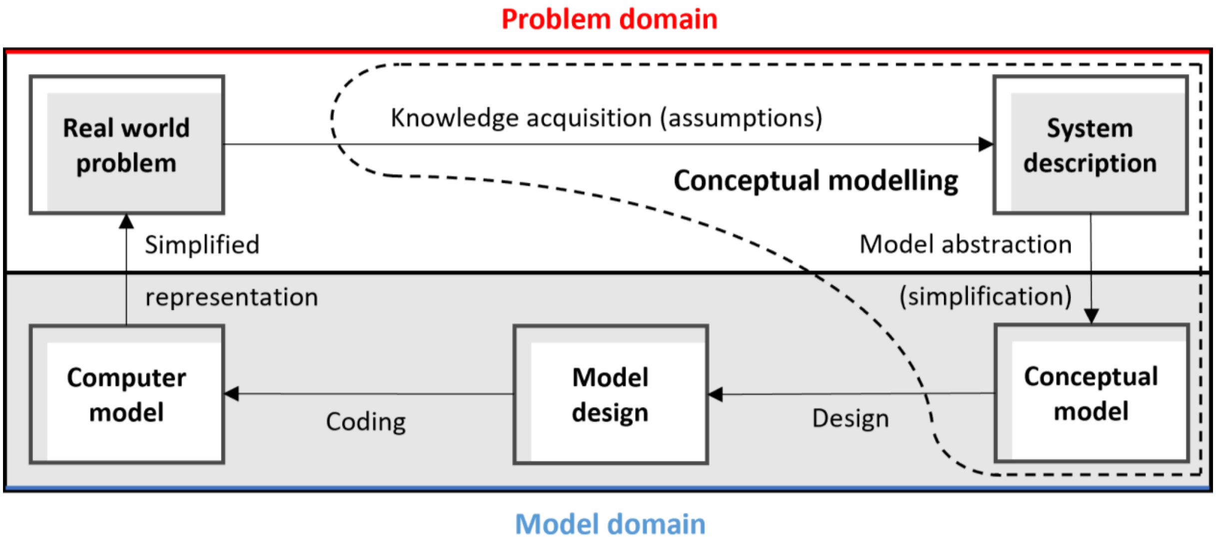


Figure 6. The steps and activities of the conceptual model design. Adapted from Robinson (2017).

5.1.1. Similar optimization problems

Instead of creating a conceptual model from scratch, insights gained from the literature review will be used to study papers which pertain to a similar optimization problem as is considered in this thesis. The papers in the literature review were evaluated based on their activity regarding either infrastructure composition optimization, system operation optimization, or both. Found mathematical optimization models allude to a knapsack problem for the infrastructure investment problem, and to a job shop or bin packing problem for the system operation problem.

The electric infrastructure investment decision can essentially be seen as a knapsack problem (Hsieh & Liu, 2004). The knapsack problem can be explained as a portion of space needing to be filled with objects, each having a value and size, with the objective to find the most valuable filling. In the context of this research the fillable space would refer to the electricity required, and the value would be the costs of the electrical components. A knapsack problem can be unbounded or bounded, meaning the components can go up to any size or the components have a maximum size to which they can be included in the knapsack problem. In the case of the electric infrastructure problem at hand it would be a bounded problem, as not only technical boundaries like the kWmax are considered but also spatial boundaries limiting the amount of solar and wind generation that can be installed.

Demand response or smart charge scheduling can possibly be interpreted as a job shop problem or a bin packing problem (Ferguson et al., 2018; Golpîra et al., 2018). In a job shop problem, the inputs are a list of jobs that need to be done and a list of machines to fulfil those jobs. The required output is a schedule in which the jobs are assigned to certain machines, while the overall cost minimized or profit maximized (Croce et al., 1995). In the context of this research the jobs would be the transportation schedule while the machines would be the charging stations, possibly supported by local renewable generation, with the goal of finding the optimal charging schedule. In a bin packing problem item of various sizes must be packed into a finite number of bins with a fixed capacity (Bilaut et al., 2013). In the context of this research the bins would be the various time periods with more or less capacity available in which charging activity can be scheduled. In a bin packing problem, the goal is to minimize the number of bins used (Bilaut et al., 2013). By spreading the charging of the e-trucks instead of all charging simultaneously the number of charging stations needed can be minimized, as researched by Ferguson et al. (2018). Knowledge of both the job shop and bin packing problem will aid in converting the formal problem formulation into the mathematical model.

5.1.2. General conceptual model

The conceptual model shown in figure 7 provides a general framework for the model domain introduced in figure 6, to aid the translation of the formulated problem into the mathematical model. This general conceptual model is applicable to all cases that could arise within the stated problem space, concerning the electrification of large vehicle fleets in the logistical sector.

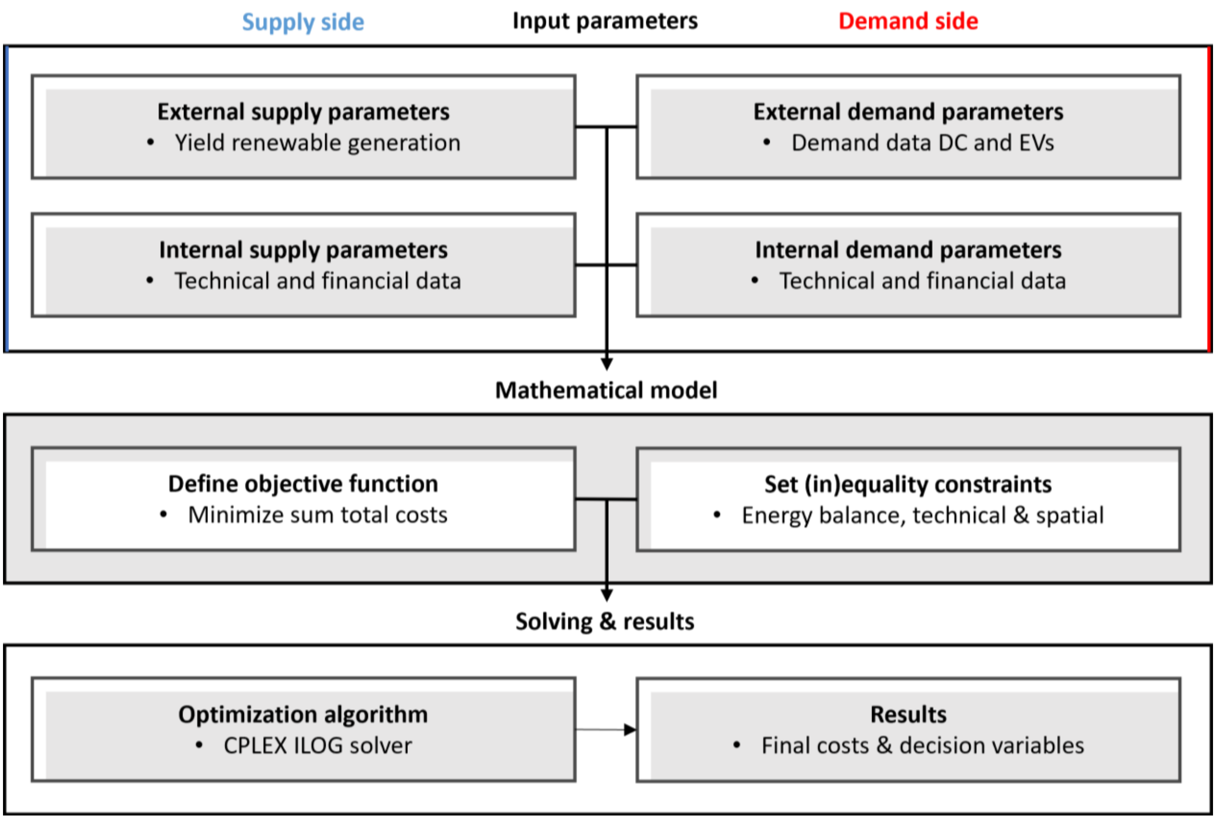


Figure 7. General conceptual model showing the sequential steps involved in the model domain

The conceptual model in figure 7 is divided into the input parameters, the mathematical model and the subsequent solving and results. The input parameters can be divided into the supply and demand parameters, both with external and internal ones. The external input parameters are parameters that are outside of the control of the distribution centre. For the supply side this concerns the yield of the renewable electricity generation, which is dependent on meteorological activity. On the demand side this concerns the transportation demand of the EVs and the electricity demand of the DC itself, which technically is under control of DC but is assumed as fixed due to outside demand of the retail locations. The internal parameters pertain to the technical specifications and costs of the components that are considered in the model, which the DC has control over. A conceptual version of the mathematical model, in which the external and internal supply and demand factors are fitted, will be discussed next.

5.1.3. Mathematical conceptual model

The mathematical conceptual model shown in figure 8 illustrates the positioning and interaction of the input parameters and decision variables, introduced in the formal problem description, when they are placed within the objective function and constraints. It concentrates on the mathematical model step from the general conceptual model and essentially shows the translation process of the individual mathematical terms into the formulas of the mathematical model. While the mathematical terms have from the formal problem formulation onwards been divided into demand and supply factors, the balancing act between them is harder to grasp. Figure 8 aims to illustrate how the energy balance per time period and the influence of the upfront investment in the static infrastructural components on the energy balance can be understood.

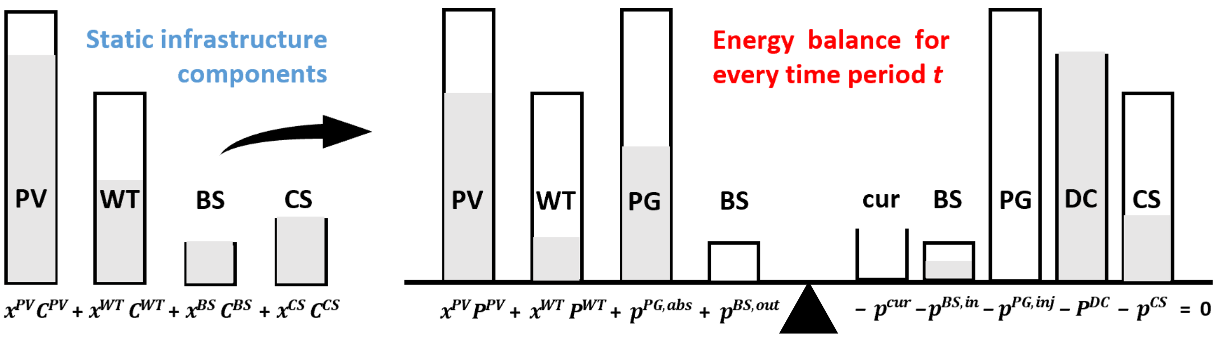


Figure 8. Conceptual model serving as overview for the mathematical model that will be proposed. This figure visualized the optimization of the static infrastructure components on the left, based on the energy balance on the right, which needs to be maintained for every time period.

What must be understood is that the real-time power flows, apart from the demand of the DC, are indirectly caused by the number and type of infrastructural components installed independent of time. For example, a certain number of PV panels installed thus leads to a certain power yield per time period, dependent on the solar irradiation. Figure 8 shows the static optimization of the infrastructural components on the left, where it can be seen that the installation of PV and wind is constrained and only as much is installed as necessary or cost-effective for power generation, shown by the grey filled part. The installation of the battery modules and charging stations is unconstrained. The total costs are then calculated by summing the products of the costs C and the number x of a component installed, with the objective to minimize the total costs.

On the right of figure 8, the energy balance is visualized, understating that the positive power flows should negate the negative power flows, thus the sum of all power flows p should be 0. The grey filled part in the bars represents the amount of power which is active of the max, indirectly caused or constraint by the number of each specific infrastructural component installed. The amount of power that can be taken out from or put into the battery system BS will explicitly be constrained in the model, as well as the power that can be absorbed from or injected into the power grid PG. It is visualized in the figure that the BS cannot be charged and discharged simultaneously, and neither can the PG. The power that can be generated by the PV panels or the wind turbines WT is not explicitly constrained but rather by the number of units that is installed by the model, just as the power that can be charged to the EVs is constrained by how empty the batteries of all the EVs are. The power that can be curtailed or that is needed for the demand of the distribution centre is unconstrained. Curtailment is unconstrained but throws away value, so the model should mostly avoid this, hence the bar being empty. The demand of the distribution centre is known, so therefore the whole bar is grey in the figure.

To summarize the conceptual mathematical model, in the objective function the number and type of infrastructural components installed can be optimized to supply or store the required power in the energy balance constraint. Operationally the model can also optimize the size of all the different power flows, within the prescribed constraints, to maintain the balance for every time period. This is especially the case for the charging demand of the e-trucks, which the model can smartly schedule.

5.2. Modelling horizon and resolution

While the parts of the infrastructural components of the model's calculations are fixed, a lot of the operational constraint and intermediary calculations are modelled for every month m = 1…m and every time period t = 1…T. The resolution of the modelling can be decided by taking the time period as days, hours, minutes or even seconds. For this research the time period was set at hours, as this sufficiently considers the day and night variation of renewable electricity generation. Modelling for every minute or second would also severely increase the total number of variables and constraints, therefore hampering performance. A time period of an hour also allows for the normalization of the power and energy terms, as the amount of power expressed in kW in an hour is equal to the amount of energy expressed in kWh. The characteristics and relations of the different timescales can be seen in figure 9.

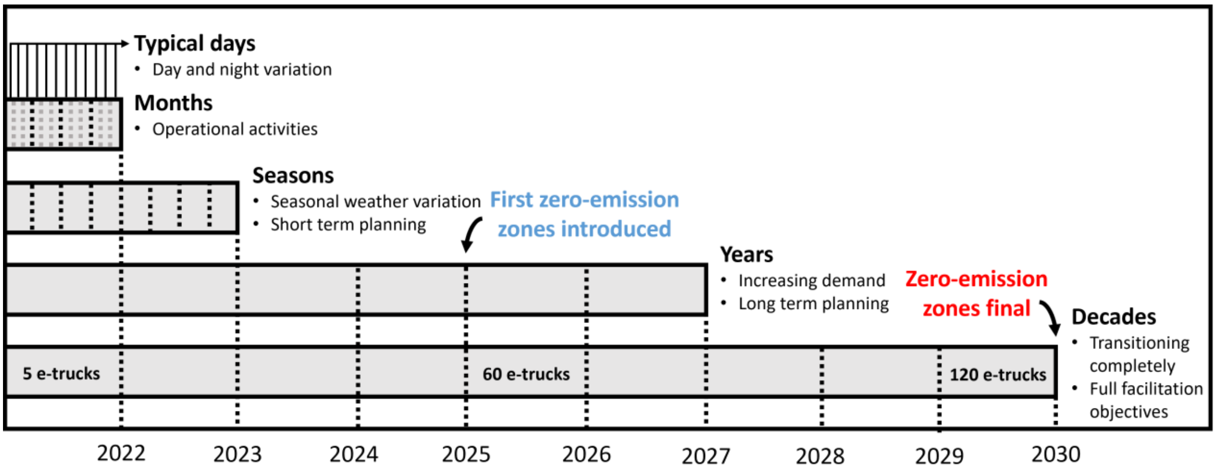


Figure 9. Diagram showing and naming the different timelines and their characteristics.

The separation of the time period and months is useful because it allows the model to be run for a typical day for every month, reducing the number of variables and constraint by approximately 30. Instead of running the model for every day in the year, the model will run for a typical day in every month, for a total of 12 days. This approach is also used by Bracco et al. (2019) and Dominguez-Munoz et al. (2011) to reduce the computational intensity of the model. This leads to a total of 12 times 24 is 288 time periods. This approach disregards variation within months, possibly leading to the exclusion of rare weather events like the Dunkelflaute, in which for an extended period of time solar irradiation as well as wind is marginal but is necessary for the sake of model performance (Li et al, 2020). Which days are typical for the months will be examined further in the verification and validation chapter.

5.3. Mathematical model

Insights from the formal problem description and the model conceptualization form the basis for the mathematical model proposed next. First the infrastructure optimization model will be introduced, after which the parameters will be detailed. After that the decision variables will be listed. Finally, the objective function and constraints will be defined, and the interpretation of the model will be given.

5.3.1. Introduction optimization model

The objective function captures the different cost factors for the infrastructure optimization of the distribution centre. The first part of the objective function captures the static infrastructural components, which the model can install for a certain associated cost. The second part of the objective function is summed for every month m in M and every period t in T, while the final part is also summed for every charging station s in S.

The constraints are listed below the objective function and represent conditions that the optimal solution must satisfy. The constraints represent both practical distribution centre constraints as well as variable and parameter constraints. The individual constraints will be elaborated on more thoroughly below the mathematical model. Next the parameters and variables will be defined for every subgroup of the infrastructural components.

5.3.2. Parameters

- $\eta^{BS,in}$: charging efficiency of a battery module [%]
- $\eta^{BS,out}$: discharging efficiency of a battery module [%]
- η^{CS}: charging efficiency of charging station [%]
- A^{PV}: ground surface area of a photovoltaic panel [m^2]
- A^{WT}: ground surface area of wind turbine [m^2]
- A^{PV}_{max}: maximum surface available for all photovoltaic panels [m^2]
- A^{WT}_{max}: maximum surface available for all wind turbines [m^2]
- C^{BS}: total annual cost of battery module [€]
- C^{CS}: total annual cost of charging station [€]
- C^{PV}: total annual cost of a photovoltaic panel [€]
- C^{WT}: total annual cost of a wind turbine [€]
- $C^{PG,abs}_{m,t}$: price of buying electricity in month $\mathrm{m} \in M$, at time $t \in T$ [€/kWh]
- $C^{PG,inj}_{m,t}$: price of selling electricity in month $\mathrm{m} \in M$, at time $t \in T$ [€/kWh]
- $P^{DC}_{m,t}$: power demand from distribution centre in month $\mathrm{m} \in M$, at time $t \in T$ [kW]
- $D_{v,m,t}$: transportation demand of vehicle $\mathrm{v} \in V$, in month $\mathrm{m} \in M$, at time $t \in T$ [km]
- E^{BS}_{max}: maximum energy level of battery [kWh]
- E^{EV}_{max}: maximum energy level of the electric vehicles [kWh]
- E^{EV}_{min}: minimum energy level of the electric vehicles [kWh]
- $E^{EV}_{v,m,t=0}$: energy level of vehicle $\mathrm{v} \in V$ in month $\mathrm{m} \in M$, at time $t = 0$ [kWh]
- $P^{PV}_{m,t}$: yield for photovoltaic panel in month $\mathrm{m} \in M$, at time $t \in T$ [kW]
- $P^{WT}_{m,t}$: wind yield for turbine in month $\mathrm{m} \in M$, at time $t \in T$ [kW]
- P^{BS}_{max}: maximum charging and discharging speed of battery [kW]
- P^{CS}_{max}: maximum charging speed of charging station [kW]
- P^{PG}_{max}: max amount of electricity that can be absorbed from or injected into power grid [kW]
- F: Mean consumption of the vehicles [kWh/km]
- K: Mean number of days in a month [-]
- Q: Sufficiently large number [-]

5.3.3. Decision variables

- $e^{BS}_{m,|t|}$: energy level of battery in the last time period $t = |t|$ [kWh]
- $e^{BS}_{m,t}$: energy level of battery in month $\mathrm{m} \in M$, at time $t \in T$ [kWh]
- $e^{EV}_{v,m,|t|}$: energy level of vehicle $\mathrm{v} \in V$ in month $\mathrm{m} \in M$, in the last time period $t = |t|$ [kWh]
- $e^{EV}_{v,m,t}$: energy level of vehicle $\mathrm{v} \in V$ in month $\mathrm{m} \in M$, at time $t \in T - 1$ [kWh]
- $p^{BS,in}_{m,t}$: power charged into battery in month $\mathrm{m} \in M$, at time $t \in T$ [kW]
- $p^{BS,out}_{m,t}$: power discharged from battery in month $\mathrm{m} \in M$, time $t \in T$ [kW]
- $p^{CS}_{s,v,m,t}$: power from charging station $s \in S$ to vehicle $v \in V$, month $\mathrm{m} \in M$, time $t \in T$ [kW]
- $p^{cur}_{m,t}$: amount of power that is curtailed in month $\mathrm{m} \in M$, at time $t \in T$ [kW]
- $p^{PG,abs}_{m,t}$: amount of power absorbed from the grid in month $\mathrm{m} \in M$, at time $t \in T$ [kW]
- $p^{PG,inj}_{m,t}$: amount of power injected to the grid in month $\mathrm{m} \in M$, at time $t \in T$ [kW]
- x^{BS} : number of battery modules to install [-]
- x^{CS}: number of charging stations to install [-]
- x^{PV}: number of photovoltaic panels to install [-]
- x^{WT}: number of wind turbines to install [-]
- $y^{BS,in}_{m,t}$: binary variable equal to 1 if battery system is charging in month $m \in M$, at time $t \in T$, and equal to 0 otherwise [-]
- $y^{BS,out}_{m,t}$: binary variable equal to 1 if the battery system is discharging in month $\mathrm{m} \in M$, at time $t \in T$, and equal to 0 otherwise [-]
- $y^{CS}_{s,v,m,t}$: binary variable equal to 1 if power is transferred from charging station $s \in S$ to vehicle $v \in V$, in month $\mathrm{m} \in \mathrm{M}$, at time $t \in T$, and equal to 0 otherwise [-]
- $y^{PG,abs}_{m,t}$: binary variable equal to 1 if power is absorbed from the grid in month $m \in M$, at time $t \in T$, and equal to 0 otherwise [-]
- $y^{PG,inj}_{m,t}$: binary variable equal to 1 if power is injected into the grid in month $m \in M$, at time $t \in T$, and equal to 0 otherwise [-]

5.3.4. Objective function and constraints

As the model shows great potential for commercial implementation, the exact mathematical formulation becomes somewhat confidential, as to avoid competitors copying the model. Hopefully the model description and the decision variable and parameter list do give a good impression of the model. The complete mathematical model was moved to confidential appendix E.

5.3.5. Model interpretation

The objective function (1) captures the cost drivers of the infrastructure optimization over the modelled year. The first part of the objective function pertains to the optimal number of the static infrastructural components multiplied with their associated total unit costs. The second part concerns the sum of the dynamic cost drivers like the power absorbed from the grid and injected to the grid multiplied with the associated buy and sell price as well as the compensation for the renewable fuel units. The SOC of all batteries and vehicles in the last time period |t| are summed and also multiplied with the electricity cell price in the last time period, to include the value of the excess SOC and avoid unrealistic model behaviour in which it tries to end the simulation with minimal SOCs across the board.

The most important equality constraint (2) pertains to the energy balance of the system, in which the power flows of all components are summed. For the system to be in balance the positive power flows, like the generated power from the photovoltaic installation and wind turbines, as well as the power that is absorbed from the grid or taken out of the battery, should be equal to the negative power flows. The negative power flows are the power that is put into the battery, injected unto the grid, power that is curtailed or used by the distribution centre, as well as the sum of all EVs charging that happens in a specific moment. The sum of equation should be zero for every time period t in every month m.

Equality constraint (3) and (4) show the calculations of the energy levels inside the battery system and electric vehicles for the next period. They start quite similarly, stating that the energy level or SOC for the next period is the SOC of the previous period, plus the amount of energy that is charged into the battery or EV times the charging efficiency in time period Δt. However, while the discharging of the battery system with the associated efficiency is considered, the discharging of the EVs, or so-called vehicle to grid (V2G) is not considered in this research. Energy is used by the EVs though for their transportation demand D, given in kilometres, and is multiplied by the average consumption F to calculate the reduction in the SOC of the EVs.

While equality constraints are used to ensure that an equation equals a certain value, inequality constraints are used to ensure that an equation or decision variable is between a certain range. Inequality constraints are often used to define a certain capacity, stating that a decision variable should stay between its minimum and maximum values, applicable to the power flows. As can be seen in inequality constraint (5) to (12), the minimum of the power flows is 0, meaning the power flows should always be equal to or higher than 0 or a designated minimum value. Maximum power flows of the photovoltaic panels, wind turbines and battery system components are given per unit and are multiplied by the number of units installed to get the total maximum power flow for each installation respectively. In constraint (12) it is expressed that power can only flow from the charging station to the electric vehicles if the associated binary variable $y^{CS}_{s,v,m,t}$ is 1. The maximum charging speed is calculated again by a derivation of the quadratic formula, by which the lowest charging speed of either the electric or the charging station is selected. The curtailment power constraint (7) has no maximum.

Inequality constraints can also be used to ensure that the model adheres to the physical boundaries in the system, like how much space is available on the roof for the PV panels, or on the land for the wind turbines in constraint (13) and (14), wherein the surface area of one unit, times the total number of units should not exceed the maximum surface available. Finally, inequality constraints are used to make the binary variables represent the on and off state of the associated decision variable. In constraint (15) to (18) Q represents a significantly large number, forcing the binary variables to turn 1 if any non-zero power flow were to happen. Constraint (19) and (20) thereafter state that non-zero power in- and outflow of the PG and BS cannot happen simultaneously, otherwise the sum of both binary variables in the on state would exceed 1.

The final inequality constraints (21) and (22) concern the charging and installation of sufficient charging stations. In constraint (21) Q again represents a sufficiently large number, ensuring that if an EV has a non-zero transportation demand the sum of the binary variables for that vehicle with all charging stations should be 0. Constraint (21) essentially expresses that if a vehicle is driving it can’t be charged. In constraint (12) it was expressed that if the model wants to charge an EV the associated binary variable should be 1. If for every time period and month the binary variables of all vehicles are summed, then the number of vehicles that would need to charge simultaneously in every period is calculated. This is precisely what constraint (22) does. By stating that the number of charging stations to be installed, indicated by the fixed decision variable x^{CS}, should be equal to or larger than the simultaneous charging demand in every time period, sufficient charging stations will be installed to handle the period with the maximum number of simultaneous charging sessions.

6. Case study and data input

The model proposed in the previous chapter will be tested by means of a case study and various scenarios for a supermarket company operating a distribution centre to analyse the models' behaviour in a practical setting. In this chapter the case study will be discussed. First the supermarket company under study will be introduced and the scope and specifics of the case study will be explained. The scenarios that will be evaluated by the model will also be explained in this chapter, as they are partly specific to the case study and depending on the companies' electrification process. Finally, the data to be used in the model will be detailed in this chapter as a large part of the input parameters are dependent on the geographical, spatial and technical characteristics of the distribution centre in the case study. That is why the case study is discussed first, before the model is verified and validated, as case study data is necessary to run the model and case specific data can then be verified and validated.

6.1. Case study subject and scenarios

The case study subject is the distribution centre operated by a supermarket company, located in the Randstad, which geographically has some interesting characteristics for this research. The first one is that due to its position between several city centres, most of its delivery location will be inside zero-emission zones in the future, meaning electrification of the truck fleet is essential. The second one is that due to its location in the dense urban area of the Randstad the local power grid is congested, as can be seen in the maps in appendix D, and the maximum contracted grid connection can't be increased. Finally, most of the distribution centres of this supermarket company are similarly situated in urban areas near city centres and facing the same issues. These factors make the distribution centre in the case study a suitable subject for this research and representative of the general sector, meaning the results of this case study can be applied to other distribution centres with similar conditions and issues.

The distribution centre of the specific supermarket company was chosen as subject for the case study as it already has experience with e-trucks, it has space available for the installation of electric infrastructure components, and supermarket companies have control over a consistent supply chain. Due to the lower range and higher cost of e-trucks, route schedules of fossil fuel trucks can't be directly used for e-trucks. The distribution centre in question already operates five e-trucks, which means accurate and representative route schedules can be acquired for the modelling. The distribution centre also has bounded space available on its roof for PV panels and on a nearby field for wind turbines, which means that the model in this case study has the option to install these infrastructural components up to a certain number. Another distribution centre from a different supermarket company was possible for a case study, but no space was available there for the installation of renewable energy generation components, meaning part of the model could not have been tested. Finally, as supermarket companies both operate their own distribution centres and retail locations, and the demand for delivery of goods is predictable, the route schedules of the e-trucks are consistent across the year. This means that a subset of route schedules used for the modelling would be representative for the whole year.

The distribution centre would need to substitute 60 fossil fuel trucks with e-trucks in 2025, when the first zero-emission zones are instituted, and 120 e-trucks would be necessary in 2030 to facilitate all deliveries to retail locations in zero-emission zones. Together with the 5 e-trucks they have now, these progressive steps in the electrification process will be considered as main scenarios to run in the model. The results of these scenarios will help decide on a cost-effective infrastructure planning for the distribution centre in the case study for the coming decade. For each main scenario 3 subscenarios are considered, of which the first only optimizes the infrastructural composition in a greedy charging nature, the second optimizes both, and third as well but then with variable electricity prices.

Scenario 1 2022	5 e-trucks	Only infrastructural optimization (greedy)	Fixed electricity price
	5 e-trucks	Infrastructural & operational optimization	Fixed electricity price
	5 e-trucks	Infrastructural & operational optimization	Variable electricity price
Scenario 2 2025	60 e-trucks	Only infrastructural optimization (greedy)	Fixed electricity price
	60 e-trucks	Infrastructural & operational optimization	Fixed electricity price
	60 e-trucks	Infrastructural & operational optimization	Variable electricity price
Scenario 3 2030	120 e-trucks	Only infrastructural optimization (greedy)	Fixed electricity price
	120 e-trucks	Infrastructural & operational optimization	Fixed electricity price
	120 e-trucks	Infrastructural & operational optimization	Variable electricity price

Table 2. The scenarios with the year the number of e-trucks considered and other characteristics.

6.2. Model data input

The data that will be used as input for the parameters in the model can partly be derived from literature and partly from experts, like the ones participating in the case study. For some infrastructural components data from the case study will be used, even though it could also be sourced from literature, to ensure that the case study accurately represents the real-world situation. Numerous configurations of the infrastructural components are available, like for example for the PV panels and charging stations, and it makes sense to include configurations in the model similar to what is already being implemented in real-life in the case study, to better let the model represent the reality. The meteorological data was gathered from Meteonorm and Soda-pro. All data input for the parameters can be seen in table 3, with the associated sources referenced. Data from the experts for the case study is referenced to Case data (2021) and was received via an information request Excel sheet. The expert data is supported by data found in the literature or online.

6.2.1. Fixed input parameters

Table 3 shows the input data for all fixed parameters, meaning they are constant for every time period. The symbols as used in the mathematical model and their definitions are presented first. The data that was gathered from the case study is confidential is moved to the confidential appendix E.

	Definition	**Value**	**Unit**	**Source**
$\eta^{BS,in}$	Charging efficiency BS	97.5	%	Alfen, 2022b; Valoen & Shoesmith, 2007
$\eta^{BS,out}$	Discharging efficiency BS	97.5	%	Alfen, 2022b; Valoen & Shoesmith, 2007
η^{CS}	Charging efficiency CS	Appendix E	%	EnelX, 2022; Case data, 2021
A^{PV}	Ground surface area PV	2	m^2	ENF, 2022; Secondsol; 2022
A^{WT}	Ground surface area WT	Appendix E	n/a	Case data, 2021
A^{PV}_{max}	Max area available PV	Appendix E	m^2	Case data, 2021
A^{WT}_{max}	Max area available WT	Appendix E	n/a	Case data, 2021
C^{BS}	Total costs BS unit	Appendix E	€	Mongird et al. 2020; NREL, 2021
C^{CS}	Total costs CS unit	Appendix E	€	Heliox, 2022; Case data, 2021
C^{PV}	Total costs PV unit	Appendix E	€	Case data, 2021
C^{WT}	Total costs WT unit	73847	€	EWEA, 2009; Taryani, 2021
E^{BS}_{max}	Max capacity BS unit	100	kWh	Raaijen, 2022; Alfen, 2022a
E^{EV}_{max}	Max capacity EV	Appendix E	kWh	DAF, 2022; Case data, 2021
E^{EV}_{min}	Min capacity EV	Appendix E	kWh	Case data, 2021; Kostopoulus, 2020
$E^{EV}_{v,m,t=0}$	Starting capacity EV	Appendix E	kWh	Case data, 2021
P^{BS}_{max}	Max (dis)charge power BS	100	kW	Raaijen, 2022; Alfen, 2022a
P^{CS}_{max}	Max charging power CS	Appendix E	kW	EnelX, 2022; Case data, 2021
P^{PG}_{max}	Max inject and absorb PG	Appendix E	kW	Case data, 2021
F	Average consumption EV	Appendix E	kWh/km	Earl et al., 2019; Case data, 2021
K	Mean days in month	30.475	d	Not applicable

Table 3. Table showing the input data for the parameters with the associated sources referenced.

All fixed input parameters are independent except the total cost parameters, which follow from multiple factors. The total cost per unit parameters is actually based on the purchase costs, installation costs and maintenance cost, multiplied with the earlier discussed annualization factor. The calculation process of the total costs parameters is further elaborated on in appendix C. There are however also multiple parameters that vary over time, like the electricity price, the power demand of the distribution centre itself, the transportation demand of the e-trucks and finally the power yield of the solar panels and wind turbines. Charts of these variable parameters will be presented next.

6.2.2. Variable input parameters

The data for the variable input parameters spans across a whole year and will be shown as such, while in the simulations a typical day for each month will be chosen and used. First the power demand of the distribution centre will be shown and discussed. Figure 10 clearly shows the day and night variation in the energy demand of the distribution centre. This makes sense as less work is being done in the night than during the day. The energy demand peaks in the morning when all activities start up, but interestingly enough already in the afternoon the energy demand decreases. In the weekends there is also less activity, which shows in the weekly variation of the demand as well. A slight seasonal variation can be seen too, where in the winter months the energy demand is slightly lower, while in the summer months it is slightly higher. This can be contributed to the cooling installations for food preservation, which require a lot of energy, more during the warm summer months than the cold winter months. The reverse energy demand of heating cannot be seen in the graph. This could be due to the heating installation running on gas.

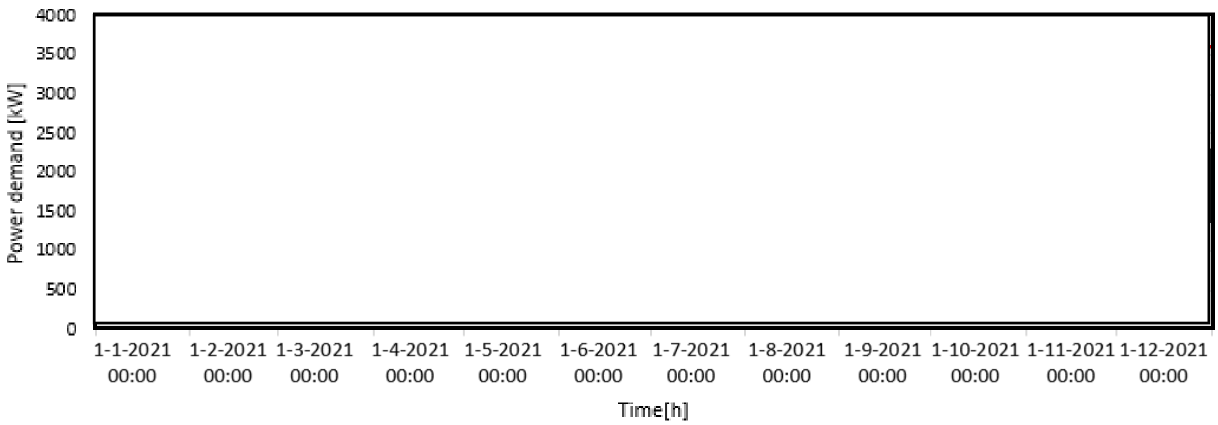


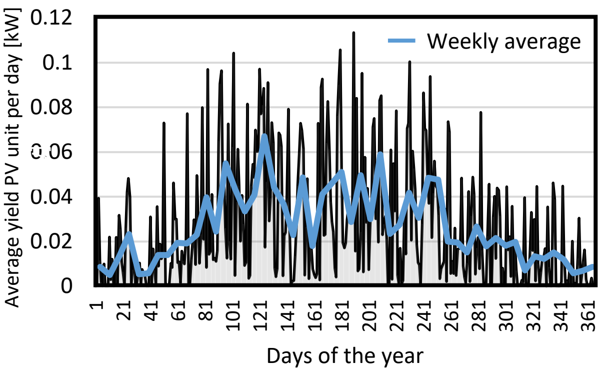
Figure 10. This figure shows the yearly local power demand data from the distribution centre in the case study, as well as its maximum grid connection. As it is confidential info it is moved to appendix E.

The next variable input parameter is the transportation demand of the e-trucks. Currently 5 e-trucks are operated at the distribution centre of the supermarket company represented in the case study. In total 30 representative daily route schedules could be distilled from the information that was received. The first 3 route schedules can be seen in table 4 to illustrate the transportation demand. All the route schedules can be found in appendix E. To simulate the incorporation of 5 e-trucks in the truck fleet the first 5 route schedules will be used. To simulate the incorporation of 60 and 120 e-trucks the route schedules will be repeated 2 and 4 times respectively. This means that e-truck 3 will have the same route schedule as e-truck 33, 63 and 93. In reality it could be more likely that all e-trucks are assigned unique routes. For this research however, the variation in different route schedules and the route schedules specifically being for e-trucks are the most important. The route schedules in table 4 are presented for a day and are repeated for all days in the simulation period. In the translation of the data received from the experts to the route schedules in table 4, trips that took for example 4 hours with a length of 96 km were converted to 4 time periods with 24 km transportation demand each.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Schedule 3	0	0	0	0	0	0	0	18	18	18	0	12	12	12	0	17	17	17	0	0	0	0	0	0
Schedule 2	0	0	0	0	0	0	0	10	10	10	10	0	20	20	20	0	12	12	12	0	0	0	0	0
Schedule 3	Schedule 1 & 2 give a good impression of a accurate route schedule. The actual route schedules are in confidential appendix E																							
Schedule ...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Table 4. On the y-axis are the different schedules and on the x-axis the hours of the day. The transportation demand is given in kilometres per time period. Complete table can be found in appendix E.

The next variable input parameters are the yield of the solar and wind installation. The data presented is calculated from various different factors and corresponding to the yield of one unit. For the PV panels the yield per panel is based on a common installation, namely a south-facing 360 Wp panel, under a tilt of 30 degrees, a surface area of 2 m^2 and a standard test efficiency of 18% (ENF, 2022; Secondsol; 2022). For the power yield of the wind unit a wind turbine with a rated power of 500 kW and rotor diameter of 42 m will be considered as a base. The average power yield per PV panel and base wind turbine over the year can be seen in figure 11 and 12, while for the simulation hourly data will be used.



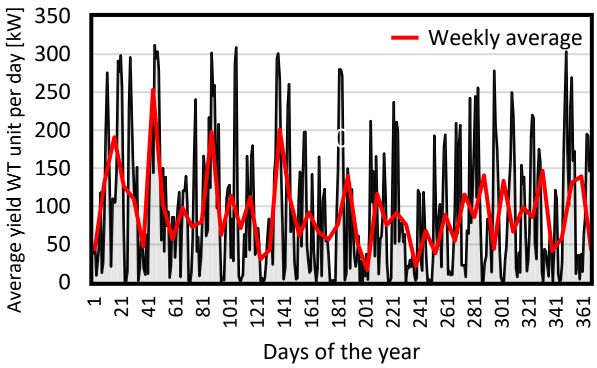


Figure 11 and 12. Figure 11 on the left shows the yield per PV panel across a whole year (8760 hours). Figure 12 on the right shows the wind power yield per unit across a whole year (Meteonorm, 2021).

Figures 11 and 12 clearly show the seasonal variation of solar and wind power yield per unit. For solar the yield peaks in the summer months and falls in the winter months. For wind power optimal wind speeds can occur across the whole year, but the occurrence of optimal wind speed is higher in the winter months than in the summer, meaning more power can be yielded in the winter than in the summer. The final variable input parameter is the historical data from the day-ahead electricity market, which can be seen in figure 13. Hourly data is shown even though the clarity is lower to showcase the variability and the occurrence of negative prices as well. For scenarios with a fixed electricity price the yearly average of 105 €/MWh will be used. With all fixed and variable input parameters detailed the actual functioning of the model can be verified and validated.

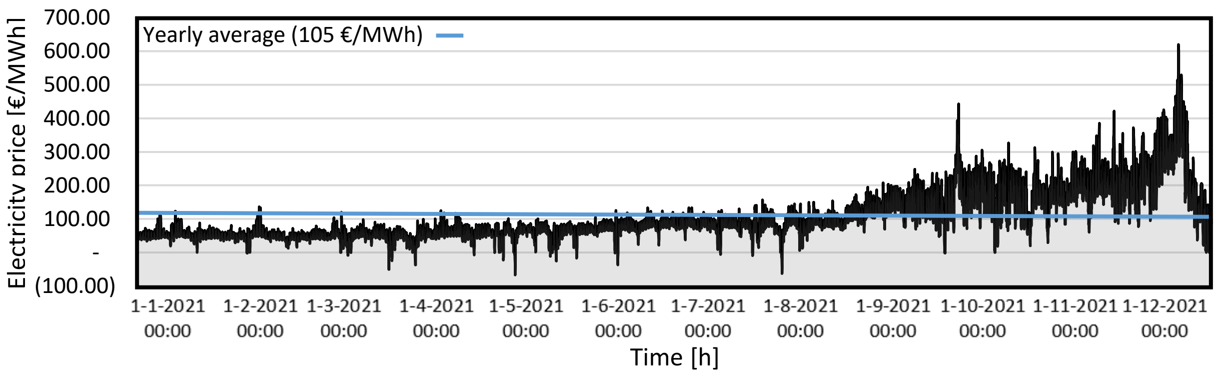


Figure 13. Chart of the day-ahead market electricity prices of 2021 (EPEX SPOT, 2021).

7. Model verification and validation

Before the model or its results are applied to the real-world problem it is important to verify and validate the model. Verification is the act of finding and fixing modelling errors and ensuring that the implementation of a model accurately represents the developer's conceptual description of the model (Thacker et al., 2004). Validation is the act of reviewing and evaluating how the model works and ensuring that the model accurately represents the real system it tries to simulate (Carson et al., 2002). Because a novel model is proposed it cannot simply be verified and validated by use of existing models. The model can however be compared to the real-life situation and the data input can be validated. Both verification and validation will be done by means of scientifically proven frameworks and methods, with use of the overarching framework by Mitre (2022), which will be discussed first. Then the model will be verified by use of a simple numerical test, of which the results can be ratified through manual calculations. The model will be validated with the framework from Carson et al. (2002) and by use of linear regression analysis. Finally, the results of the process will be discussed.

7.1. Verification and validation framework

The verification and validation process is an integral part of the development and implementation of a scientifically proven model, which is illustrated in Mitre's (2022) framework in figure 14. It presents a step-by-step guide on how to execute the process. After the development of the model, it first needs to be verified. The main questions in the verification process are if the model correctly represents the conceptual and mathematical model and if the outcomes of the model make sense based on the input parameters. Then, in combination with a prepared case study, it can be validated. The main questions in the validation process are if the model accurately represents the case study and if the outcomes of the model make sense based on the real-world scenarios. After the model is validated even more validation data can be gathered or the model can be adjusted for closer representation. Afterwards, analysis of the results will lead to further refinement of the model itself or possible implementation.

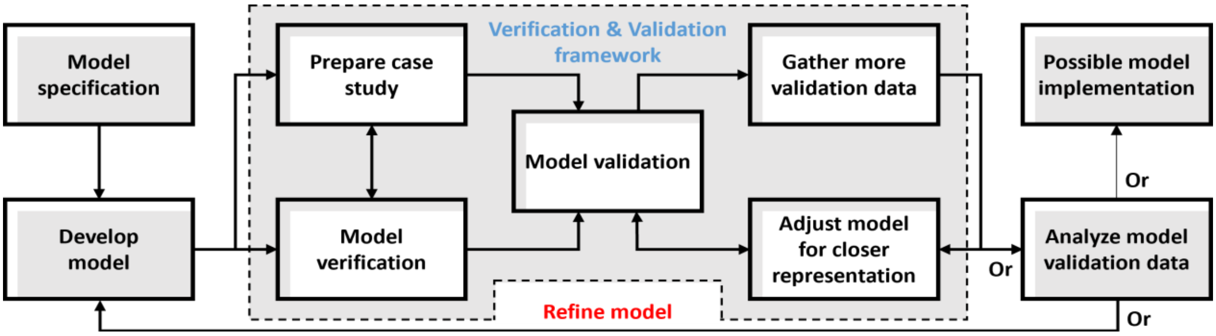


Figure 14. Diagram showing the verification and validation process, adapted from Mitre (2020).

The first two steps of the framework, specification and development of the model, have already been done in chapter 4: problem and system analysis, and chapter 5: mathematical model design. The case study and data input have also already been prepared and presented in chapter 6: case study and data input. Next the model will be verified by use of a simple numerical test.

7.2. Model verification through numerical test

With the use of a simple numerical test, which can also be evaluated by manual calculation, it can be verified that the results of the model accurately represent the conceptual and mathematical model. In the numerical test the model will be run for 1 day, meaning 24 hours, and with simpler input data for the parameters than in the case study. The fixed and variable input data will again be presented separately and can be found in table 5. All efficiencies will simply be taken as 100% and a maximum number will be used for the PV panels and wind turbines instead of maximum surface area.

	Max PV	Max WT	Cost PV	Cost WT	Cost BS	Cost CS	Max charge CS	Capacity BS	Capacity EV	kWmax	Consumption EV
Test value	100	10	100	10000	1000	1000	200	100	300	1000	2

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
E-truck 1	0	40	40	40	0	40	40	40	0	0	0	0	0	40	40	40	0	40	40	40	0	0	0	0
E-truck 2	0	30	30	30	0	30	30	30	0	0	0	0	0	30	30	30	0	30	30	30	0	0	0	0
E-truck 3	0	0	0	0	0	40	40	40	0	40	40	40	0	0	0	0	0	40	40	40	0	40	40	40
E-truck 4	0	0	0	0	0	30	30	30	0	30	30	30	0	0	0	0	0	30	30	30	0	30	30	30
PV yield	0	0	0	0	0	0	0	1	1	2	2	4	4	4	4	2	2	1	1	0	0	0	0	0
WT yield	100	100	200	200	100	100	100	50	50	50	50	100	100	50	50	0	0	0	0	0	0	0	0	0
DC demand	800	800	800	800	900	900	900	900	950	950	950	950	950	950	950	950	900	900	900	900	800	800	800	800
PG price	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 5. The top 2 rows show the values of all fixed input parameters that are considered in the numerical test. Below, the values for all 24 time periods of the variable input parameters are shown.

The input data for the numerical test in table 5 has been structured in such a way that all interactions between the decision variables and the adherence to the constraints can be tested. Just as with the data from the case study the transportation demand of the e-trucks in their route schedules is given in km and can be converted to kW/kWh with the average EV consumption. Again, the power in kW and energy in kWh are equalized with the choice of an hourlong time period. The E-trucks have a capacity of 300 kWh and an average consumption of 2 kWh/km. The battery capacity of E-truck 1 and 3 decreases with 240 kWh per route and the battery capacity of E-truck 2 and 4 with 180 kWh per route. In time period 4 and 16 e-truck 1 and 2 only have one time period in between their routes and therefore have to charge in that moment, likewise for e-truck 3 and 4 in time period 8 and 20. Between 8 and 13 the charging window for e-truck 1 and 2 is longer, as it is for e-truck 3 and 4 between 12 and 17, wherein the charging of the e-trucks can be scheduled smartly, according to renewable energy generation and variable electricity power grid prices.

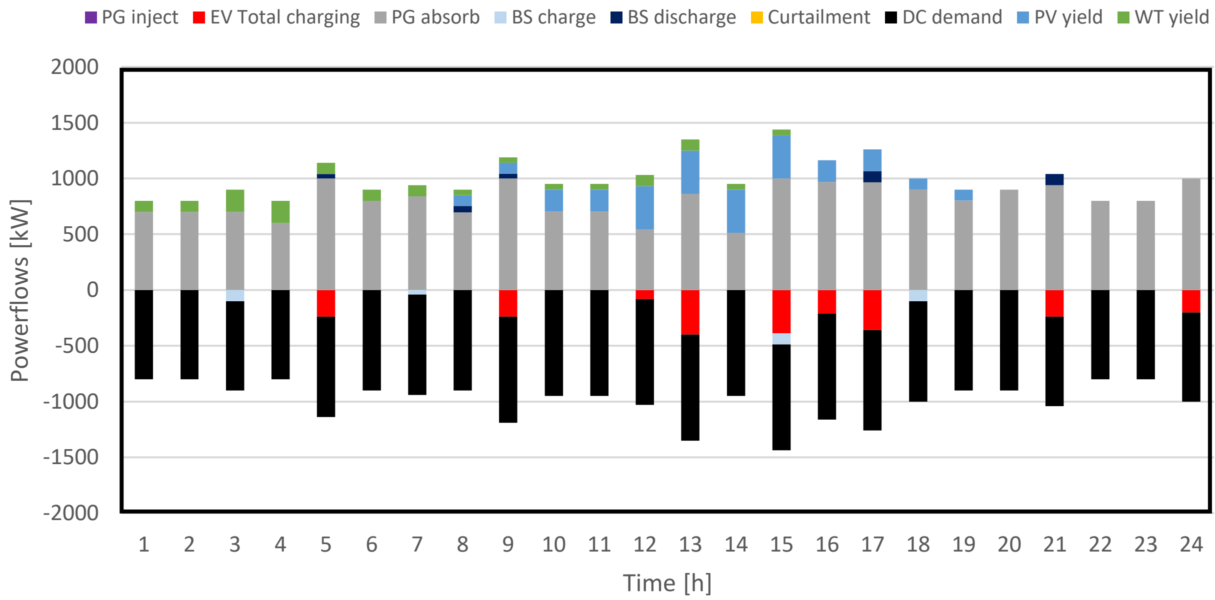


Figure 15. Resulting power flows per hour of the simple numerical test. Above the zero line all positive power flows are shown, and below the negative power flows. Of both the total is equal each hour.

The results of the numerical tests verifiably show that the model optimizes both the installation and the operation of the infrastructural components, to minimize the costs while adhering to the constraints. The operation of the system can be seen in figure 15, which gives a chronological overview of the positive and negative power flows. It can be seen that the absorption from the power grid in light grey never exceeds the 100 kW kWmax constraint. In regard to the infrastructural components 97 PV panels, 1 wind turbine, 1 battery module and 2 charging stations were installed by the model. When looking at the input data chronologically one would expect that the model needs to install at least 2 wind turbines and 100 PV panels to handle the charging demand in time period 5 and 9. However, because the model is deterministic, it knows that in time period 21 it needs a battery module to facilitate the charging demand which would exceed the kWmax, due to the lack of renewable electricity generation. The installation of infrastructure components happens statically and they can be used for every time period, meaning utilization of the battery module can reduce the need for PV panels and wind turbines in time period 5 and 9. The battery can be charged in an earlier time period, as shown in purple, and discharged in a later time period, as shown in orange, when extra power is required. This shows the cost minimization of the model as well as adherence to the SOC constraints of the e-trucks, as it makes sure they are charged full enough to fulfil their next routes. The numerical test also shows the arbitrage potential of battery storage due to the variable electricity prices, as the battery is charged in time period 7 and discharged in time period 8, when the prices are higher.

7.3. Model validation

Validation of the model, to evaluate how it works and how well it represents the real system it tries to simulate, will be done following a simple framework suggest by Carson et al. (2002), checking face validity and performing a linear regression analysis. The framework consists of three steps: test the model face validity, test the model over a range of input parameters and compare predictions of the model to actual past performance of the system; when verifying a new system, compare implemented model behaviour to assumptions and specifications. To aid in the first step Kleijnen's (1995) suggestion to 'divide and conquer' will be used, basically evaluating the model part by part. For the second and third step linear regression analysis will be used to evaluate the results of simulation runs over a range of input parameters. To run the simulations data from the case study will be used, which has been detailed in the previous chapter, ahead of the validation as shown in figure 14. With the data from the prepared case study and the insights from the verification the model can now be validated.

7.3.1. Model face validity

For the first point Carson et al. (2002) suggest running the model for a given scenario and examine if all the model's outputs are reasonable. This philosophy has actually been used throughout the development of the model, combined with an agile development approach, essentially incorporating Kleijnen's (1995) divide and conquer tactic. With an agile approach, short iterative development cycles are used to develop functioning modules of a model. An agile approach was used as it is more flexible and adaptable then traditional linear approaches. Agile development also facilitates learning through experimentation and exploration, which is ideal for this research (Dyba & Dingsoyr, 2009).

During the development of the individual modules of the model it was continuously checked whether the outputs were reasonable or not. Previously acquired knowledge or data found in references was for example used to check if the yield of the solar installation or wind turbines was calculated realistically. If the outputs of a module seemed unreasonable, the calculations were thoroughly checked to find the error. After rectification of these errors some checks were coded into the module to output an error message if the error were to occur again. This was especially useful when the different modules were integrated, as this could bring back bugs previously present in the model. Exact utilization of the automatic checks in the code can be seen in appendix F.

7.3.2. Linear regression analysis

With the implementation approach of the problem in the mathematical model a high number of mixed-integer decision variables are used, causing the model to be high-dimensional and thus computationally difficult to solve. Bracco et al. (2018), Mirhoseini and Ghaffarzadeh (2020), Riu et al. (2012) and Wang et al. (2020) make a highly dimensional problem implementation work by reducing the time period of the problem, as the number of decision variables scales with the number of time periods. Bracco et al. (2018) do this by considering a typical day per month, reducing the problem size but still incorporating seasonal variation.

The question then is what constitutes as a typical day? An easy approach would be to choose the same day for every month. Even though there is variation from day to day, under the hypothesis that days in the same month are reasonably similar and deviating days in one month are evened out by counter-deviating days in another month this could be an approach. To test this hypothesis a linear regression analysis is done, which is a statistical technique to determine if there is a linear correlation between certain response and predictor variables. In the case of this thesis the response variables are the number of infrastructural components installed and the predictor variables are the days in the month.

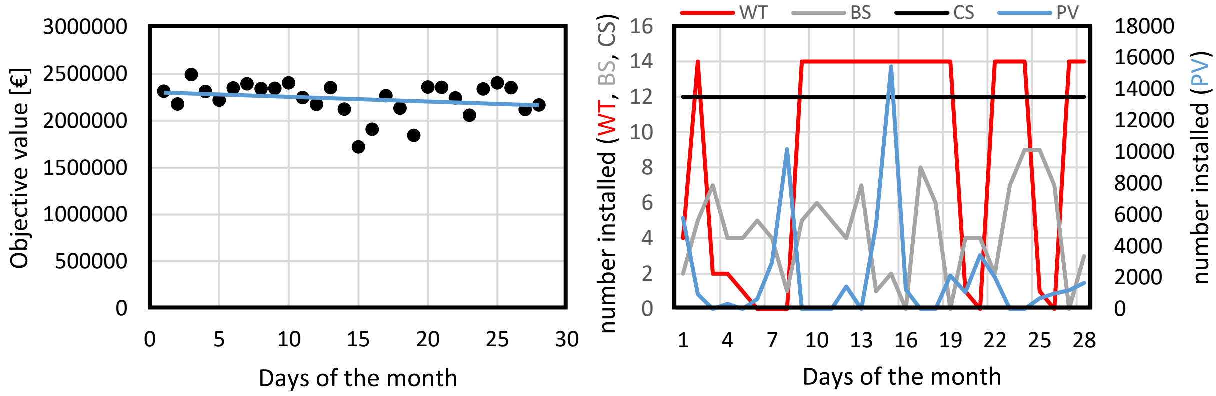


Figure 16 and 17. Figure 16 on the left shows the objective values of the model runs and the linear regression line, for each run changing which day of the months is used. Figure 17 on the right shows the resulting values of the decision variables. The left y-axis is used for the wind turbines, battery system and charging stations and the right y-axis is used for the PV panels.

Even though the linear regression line in figure 16 seems quite horizontal, the t-test will show if the results are statistically significant, meaning the samples would represent the dataset. The t-test statistic is calculated by dividing the difference between the hypothesised slope, which is 0, and the actual slope with the standard error for estimation (Das, 2022). The t-test value is -0.15, meaning that with a widely used standard of 0.05 for statistical significance the hypothesis is concluded as false. Another factor is that more than the potential costs the interest is in the most cost-effective electric infrastructure. Figure 17 shows that the results for the infrastructural components differ greatly depending on which day of the months is used in the model, meaning another method is required.

7.3.3. Valid data selection

The results from the linear regression analysis show that a specific method is necessary to determine the typical days per month, as using the same day for every month is not statistically representative. An added complexity is that the typical day of a month can differ for each variable input parameter. What could be a typical day for PV yield, might not be a typical day for the demand of the distribution centre. A different method is to take the average value of each variable input parameter per month. This is the technique of the K-means clustering algorithm with which the centres from data clusters can be identified. The problem with the K-means method is that the final determined centres may not be associated with a specific datapoint, hampering the interpretability of the chosen data (Das, 2022).

Another method that can be used and is similar to the K-means method is the K-medoids methods, in which for each cluster the data point with the lowest dissimilarity to all other points in the cluster is chosen. This is exactly the method that Dominguez-Muñoz et al. (2011) use for the optimization of combined-heat powerplant, which is what Bracco et al. (2019) also cite in their methodology. While generally a clustering algorithm is used to sort the datapoint into clusters, In the context of this research the months will be taken as clusters for relatability and simplicity's sake, as Dominguez-Muñoz et al. (2011) also relate their clustered data to months of the year.

To calculate the dissimilarity between the days in the monthly clusters, the Euclidian distance between the values of all days is calculated per monthly cluster and sorted into a dissimilarity matrix. This was done this way for all variable input parameter data separately, except for the data selection of the electricity demand of the distribution centre. For the electricity demand of the distribution centre the most demanding day per month was chosen, to ensure the robustness of the infrastructure composition that the model will propose in handling the most extreme electricity demand days. The exact days that were used for each variable input parameter can be seen in table 6.

	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
PV yield	4	1	14	18	8	17	7	27	18	6	22	10
WT yield	16	28	10	7	1	2	31	13	10	12	21	27
DC demand	9	5	16	22	28	25	31	13	30	29	2	16
DAM prices	2	26	19	26	12	20	14	25	29	8	30	10

Table 6. Typical days, with the lowest dissimilarity for photovoltaic yield, wind power yield and day-ahead market prices and the highest distribution centre electricity demand days per month.

The literature substantiating the K-Medoid method, and the results indicate it is a respectable method to choose the most typical days, with the goal to simulate a whole year within a more manageable timeframe. What the typical day per month for the photovoltaic yield calculated with the K-Medoid method looks like in relation to the K-Means method and the rest of the days per month can be seen in figure 18. The modelling timeframe has 12 times 24 hours for a total of 288 time periods. All the days for January are indicated with the varying shaded grey lines between time period 0 and 23, for February between 24 and 47 and so onwards. What can be seen is that the K-Medoid days vary more hourly than the K-Mean data, which is unnaturally smooth. The total power yield per K-Medoid day is also slightly lower than the mean, as the mean also considers the outlier days with high yield, while the K-Medoid days are positioned more in between the gross number of days that are most similar. With the model verified and validated, the scenarios of the case study can now be run confidently.

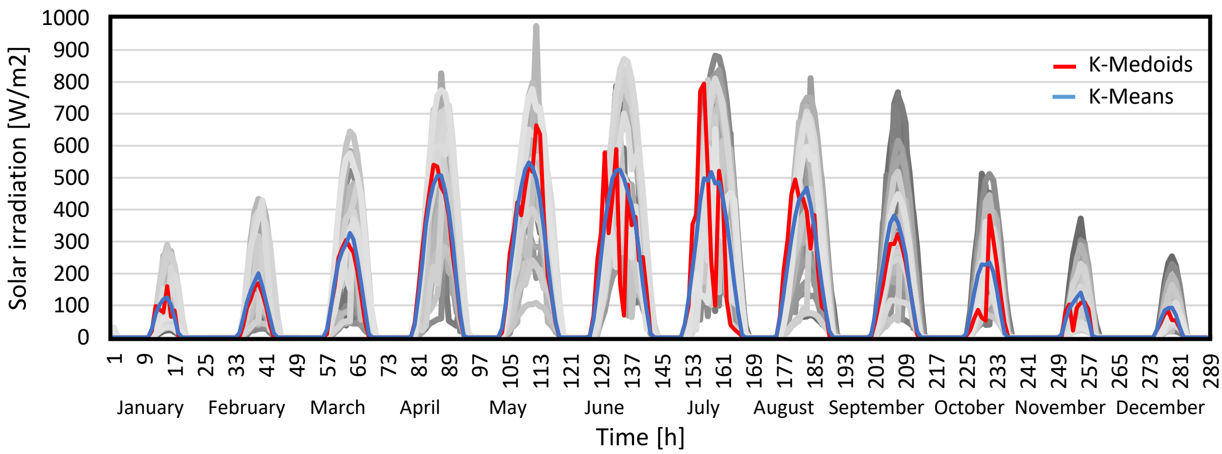


Figure 18. The typical days for PV yield calculated with the K-Medoid method are shown in red, the course of the K-Mean data is shown in blue. The rest of the days are shown in varying grey shades.

8. Model implementation and results

In this chapter the mathematical model will be used to evaluate the scenarios in the case study, to test the model's effectiveness and accuracy in simulating the infrastructural composition and operational application in each sequential step of the truck fleet electrification process. The three main scenarios pertain to the progressive electrification of the truck fleet, with 5 e-trucks in the first scenario, 60 in the second and 120 in the third. The scenario's each have three subscenarios of which the first one concerns solely optimization of the infrastructure composition with a fixed electricity price. This subscenario acts as a base case and relates to greedy charging, in which the e-trucks are charged immediately after returning to the DC and the charging can't be scheduled smartly. In the second subscenario the infrastructure composition and operation are optimized with a fixed electricity price. In the third subscenario the infrastructure composition and operation are optimized with variable DAM electricity prices. Besides the variation in these parameters the rest of the static input parameters are taken from the case study data detailed in chapter 6. For the variable input parameters, like the PV yield, WT Yield, DC demand and electricity prices, the hourly data of the whole year was presented in chapter 6. Data for the research approach of evaluating a typical day per month, for a total of 12 days or 288 hours was selected using the K-Medoid method detailed in chapter 7. The model was run using a 0.05 optimality gap, taking between 5 seconds for the first subscenario and 40 minutes for the last subscenario to solve, on a computer with an Intel i5-8250U Quadcore processor and 8 GB of RAM memory. After application and testing of the model in the main- and subscenarios, a sensitivity analysis will be performed to study the effect of each parameter and to gather managerial insights.

8.1. Results from the scenarios

The output of the model in each subscenario will be evaluated and compared to each other in regard to the objective value, the values of the decision variables, the power flows of the system and the activity of the charging station. The objective value is the sum of all cost factors included in the objective function of the model, which the model tries to minimize. In the model the infrastructural and operational costs are annualized, meaning the objective value represents the yearly costs that the distribution centre would have. The values of the static decision variables represent the amount of each infrastructural component that would be most cost-effective to install, while the values of the dynamic decision variables show the operation of the system. These values are visible in the power flows of the distribution centre, which will be graphically depicted for evaluation and comparison. The most important operational aspect is the smart scheduling of the e-truck charging, which will also be evaluated and compared by graphical depiction of the activity of the charging stations.

8.1.1. Overview results

The overview of the results shows that within each of the three main scenario's, from the greedy charging subscenario to the variable electricity prices scenario, the main pattern is that the model is able to decrease the total costs and the number of infrastructure components required. The overview of the results can be seen in table 7. In main scenario 1 only 5 e-trucks are considered, and 2 charging stations and 2038 PV panels are required if the e-trucks are to be charged immediately after returning, as is assumed in the greedy scenario 1.1. If besides the infrastructure composition the operation is optimized as well, the model can schedule the charging of the e-trucks smartly and spread the demand to reduce the number of charging stations to 1 and the number of PV panels to 994. These PV panels are still required as in time period 180 high demand of the DC coincides with a single time period of e-truck 3 between two longer routes in which it has to charge. The combined demand of the DC and e-truck 3 exceeds the kWmax and exactly enough PV panels are installed based on the solar irradiation at time period 180 to generate the required power. No battery storage and wind turbines are installed by the model, making PV panels the more cost-effective option to supply power in time period 180.

	Characteristics	E price	Objective value	CS	PV	BS	WT
Scenario 1.1	Only infra optimization	Fixed	2597975 €	2	2038	0	0
Scenario 1.2	Infra & operation opt.	Fixed	2576080 €	1	994	0	0
Scenario 1.3	Infra & operation opt.	Variable	2539289 €	1	0	1	0
Scenario 2.1	Only infra optimization	Fixed	3111700 €	14	9166	8	1
Scenario 2.2	Infra & operation opt.	Fixed	2886235 €	4	2617	0	0
Scenario 2.3	Infra & operation opt.	Variable	2712926 €	4	0	2	0
Scenario 3.1	Only infra optimization	Fixed	3913597 €	28	14951	33	7
Scenario 3.2	Infra & operation opt.	Fixed	3256250 €	7	5963	0	0
Scenario 3.3	Infra & operation opt.	Variable	3155301 €	11	5963	0	0

Table 7. This overview of the results of the scenarios shows the characteristics of the subscenarios, their corresponding objective value and the number of each infrastructural component installed.

The model weighs the cost of the electricity and the costs of each infrastructural component, leading to differing cost reductions and infrastructure compositions from the greedy subscenarios to the variable electricity subscenarios in main scenario 1 and 2, which both show a similar pattern. From subscenario 1.1 to subscenario 1.2 the cost reduction is 1%, while from subscenario 1.2 to 1.3 the cost reduction is 2.3%. The cost reductions may seem low, but the objective value represents the total yearly system costs, so the differences add up. In main scenario 1 the electricity costs represent 99% of the total costs. Even though the model can significantly reduce the required infrastructure components in subscenario 1.2 the variable electricity prices in subscenario 1.3 allow the model to reduce the total costs more, by shifting the charging demand to time periods with low electricity prices. The model also installs a battery module instead of PV panels in subscenario 1.3 as it is more cost-effective by taking advantage of arbitrage possibilities with the variable electricity price. This pattern is also visible in the subscenarios of main scenario 2, which considers 60 e-trucks. The model is able to significantly reduce the infrastructural components required in subscenario 2.2 due to operational optimization, compared to the greedy subscenario 2.1 in which solely infrastructure optimization is used. Besides 9385 PV panels and 14 charging stations even 8 battery modules and a wind turbine are necessary to facilitate the fixed charging demand, of which the peak is again at time period 180. Just as in subscenario 1.3 the model substitutes the PV panels for battery storage as the most cost-effective component in subscenario 2.3, due to the variable electricity prices. The shift from an infrastructure heavy composition in the greedy subscenario 2.1 with fixed charging demand, to a smartly scheduled system with flexible demand results in a cost reduction for the first year of 10.7%.

In main scenario 3 the increased charging demand of the considered 120 e-trucks leads to an enlarged continuation of the pattern established in main scenario 1 and 2, with a deviation in the third subscenario with variable electricity prices due to the limited grid connection. In subscenario 3.1 an expansive infrastructure composition is required for the fixed charging demand. The generation and storage need to be matched to the demand peak exceeding the kWmax, while the number of charging stations needs to be matched to the number of e-trucks simultaneously charging. Of both the PV panels and the wind turbines the maximum number due to spatial constraints is not reached, meaning that PV panels are more cost-effective for certain demand peaks, while wind turbines are for other. In general, both are not cost-effective looking at the first year as simulated, as the model reduces the costs and the number of infrastructure components required in subscenario 3.2, in which it can optimize the system's operation and smartly schedule the charging demand. In subscenario 3.3 with variable electricity prices the model does not substitute the PV panels with battery storage, as the cost-effectiveness of arbitrage possibilities is less than the PV power generation due to the increased demand of the larger e-truck fleet more often exceeding the kWmax. The model installs 4 more charging stations to maximally shift charging demand to periods with high PV power generation or low electricity prices and is able to reduce the total costs with 19.4% compared to subscenario 3.1

8.1.2. Comparison of the power flows

A graphical depiction of all the power flows gives insight into the operation of the distribution centre's system and shows the practical effect of the infrastructural components and the proportions and time-patterns of all the power flows in the various subscenarios. The power flows are depicted in a stacked bar chart in which the positive power flows, like generated or grid-absorbed power, can be found above zero, and the negative power flows, like the DC power and e-truck charging demand, can be found below zero. The electric system should always be in balance, so the positive and negative stacked bars are always of equal length. The simulation period is 12 typical days for 288 hours and the daily variance in power demand of the DC can be seen in the 12 waves present in this sub chapter's figures, with the valleys representing lower power demand during the night and the peaks higher demand during the day. This is also visible in the power yield of the PV panels, of which the proportion follows from the number of panels installed and the solar irradiation per time period that also has diurnal variation. Graphical representation of the power flows will be presented for the subscenarios of main scenario 3. With the highest charging demand due to the facilitation of 120 e-trucks the impact of the infrastructural components and the differences between the subscenarios will be most visible. Graphs of the power flows of the other subscenarios can be found in appendix G.

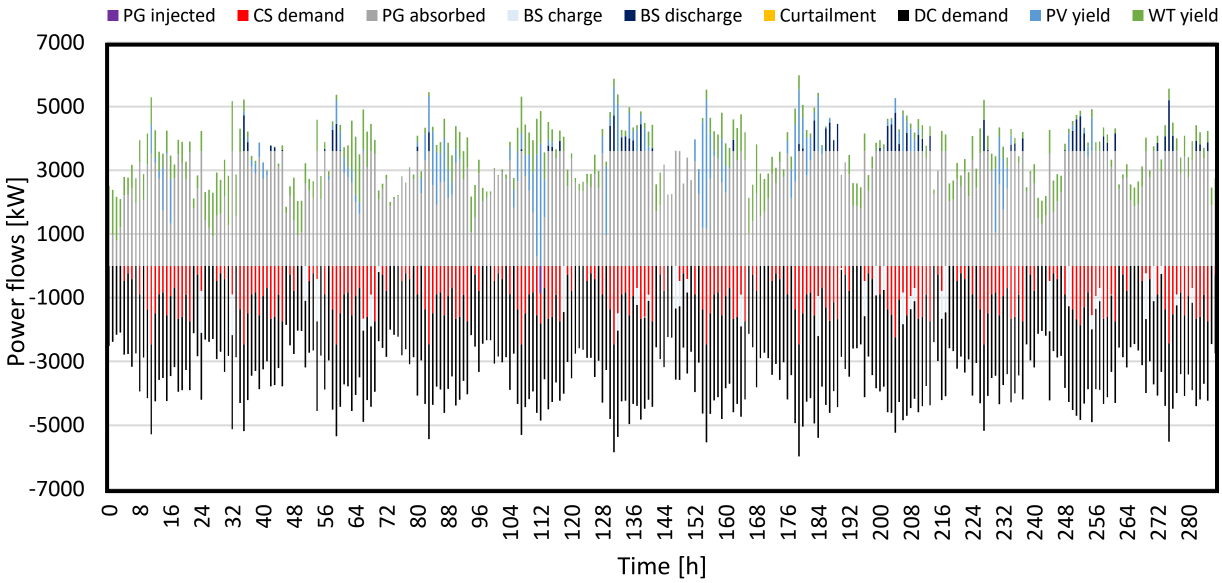


Figure 19. Power flows of the distribution centre's system in subscenario 3.1, in which the e-trucks are charged immediately after return and only the infrastructural composition is optimized.

The greedy nature of the charging demand in subscenario 3.1 in combination with the pattern of the demand of the distribution centre causes the model to need an expansive infrastructural composition to facilitate the required power demand in exceedance of the maximum power of the grid connection. The graph of distribution centre's power flows in subscenario 3.1 shown in figure 19 includes the demand of the DC itself, the power absorbed from the grid, the charging demand of 120 e-trucks, the power yield of 14951 PV panels and 7 wind turbines, and the activity of 33 battery storage modules. What can be seen in the figure is that the charging demand shows a constant pattern, due to the inflexible immediate charging of the e-trucks after their return to the DC. What also can be seen besides the diurnal demand of the DC is that the daily demand peaks in the summer months, due to increased demand of the cooling as explained in chapter 6 of the case study. Due to the greedy, inflexible charging demand that coincides with high demand of the DC, the model can't avoid that the power demand exceeds the kWmax 46% of the simulated time. The kWmax is the most important constraint and denotes the maximum contracted power that can be bought from the grid per period.

Even though in this subscenario the model can't optimize the scheduling of the charging, it can optimize the infrastructural composition of the electric system, which shows the differences between the characteristics of the components. Both the number of PV panels and wind turbines do not reach the maximum allowed due to spatial constraints, which show that both are cost-effective at different times. The numbers of each installed lead to 5382 kW rated power of PV panels and 3500 kW of wind turbines installed. When looking at the total power yield across the simulated period however, the PV panels generate 77226 kWh of power and the wind turbines 135388 kWh, caused by the favourable wind speeds in the Netherlands compared to solar irradiation. The yield can be multiplied with factor K, which denotes the mean number of monthly days, to annualize the resulting data from the K-medoid comprised simulation horizon. When the total yearly cost per infrastructural generation components is divided by the yearly generated power, the so-called levelized cost of energy (LCOE) of PV panels is around 0.14 €/kWh and of the wind turbines around 0.125 €/kWh, which strokes with reality (Badouard et al., 2022). The fact that despite the higher LCOE more rated power of PV panels is installed can be explained due to the fact that PV panels yield more power in the summer months, when demand is higher, and wind turbines more in the winter months, as shown in figure 11 and 12 in chapter 6. Battery storage is also used to store the wind turbine power generated during the night when the demand is lower, to later on supply power when the demand peaks. The combination of wind power and battery storage is however not that cost-effective to completely substitute PV power.

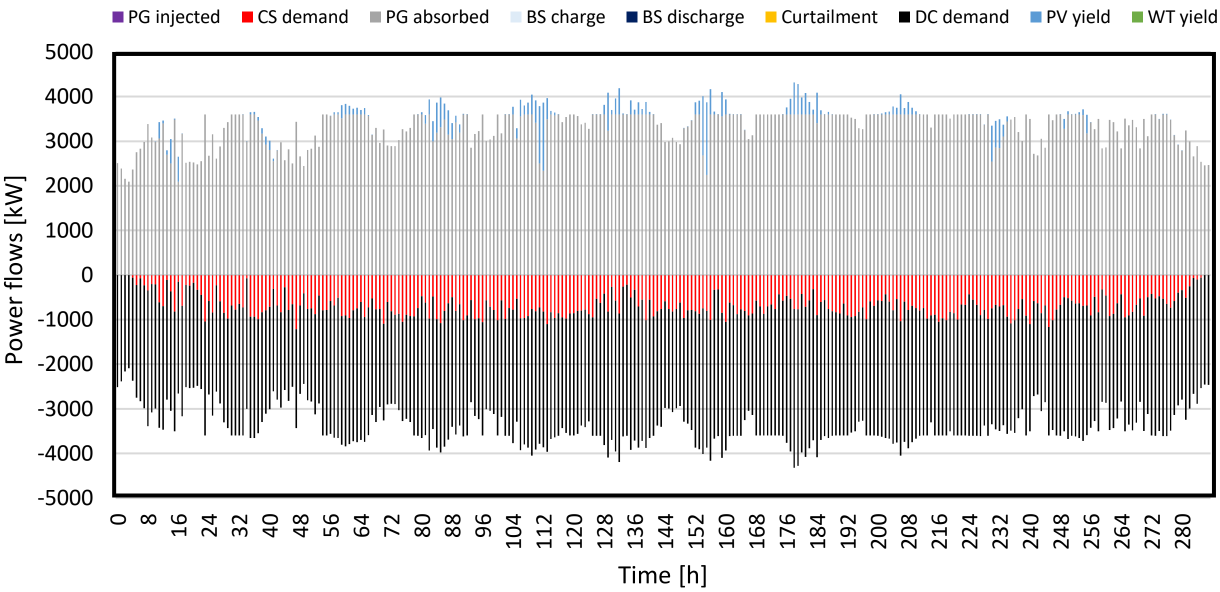


Figure 20. Power flows of the distribution centre's system in subscenario 3.2, in which both the infrastructural composition and the operation is optimize, by smartly scheduling the charging.

In subscenario 3.2 the number of infrastructural components is significantly reduced from the greedy subscenario 3.1, due to the ability of the model to smartly schedule charging demand to try to avoid coincident of charging with high demand of the DC and subsequent exceedance of the kWmax. In subscenario 3.2 the total demand only exceeds the kWmax 12% of the simulated time, because the model has spread the charging out more. The charging demand pattern of subscenario 3.2 in figure 20 is a lot flatter when compared to that in figure 20 of subscenario 3.1, with the model actually reducing the charging demand when the demand of the DC increases in the summer months. Due to the operational optimization only 7 charging stations and 5963 PV panels are required to facilitate 120 e-trucks. The flatness of the power absorbed from the grid shows that the model tries to use all power capacity available within the kWmax. Even though there are still periods where capacity is left over the model is not able to completely avoid the power demand exceedance of the kWmax. This is due to the intensity of the route schedules of some e-trucks with multiple routes per day.

When an e-truck has multiple long routes on a day with only a small charging period in between, the model has to charge the truck and can't shift or spread out the charging demand to avoid potential coincident with high power demand of the DC. This is especially the case with the route schedule of e-truck 3, which is repeated for e-truck 33, 66 and 99, because only 30 different route schedules were available in the case study to model the 120 e-trucks in main scenario 3. The route schedule of e-truck 3 shown in chapter 6 shows 2 longer routes with only on hour in between them at 12:00 of every day, in which it has to charge a minimum of 106 kWh. At 12:00 of August, which is time period 180, the demand of the DC is at its highest with 3554 kW. Exactly in that time the 4 e-trucks with route schedule 3 have to charge a combined 424 kW, which brings the total demand to 3978 kW, in exceedance of the kWmax with kW. This explains that besides the operation optimization still 5963 PV panels are installed, to exactly yield kW of power. Even though the LCOE of PV panels is higher than that of wind turbines, the power yield of the PV panels is also higher than wind turbines at time period 180 and during the months with peak DC power demand, making them the more cost-effective option.

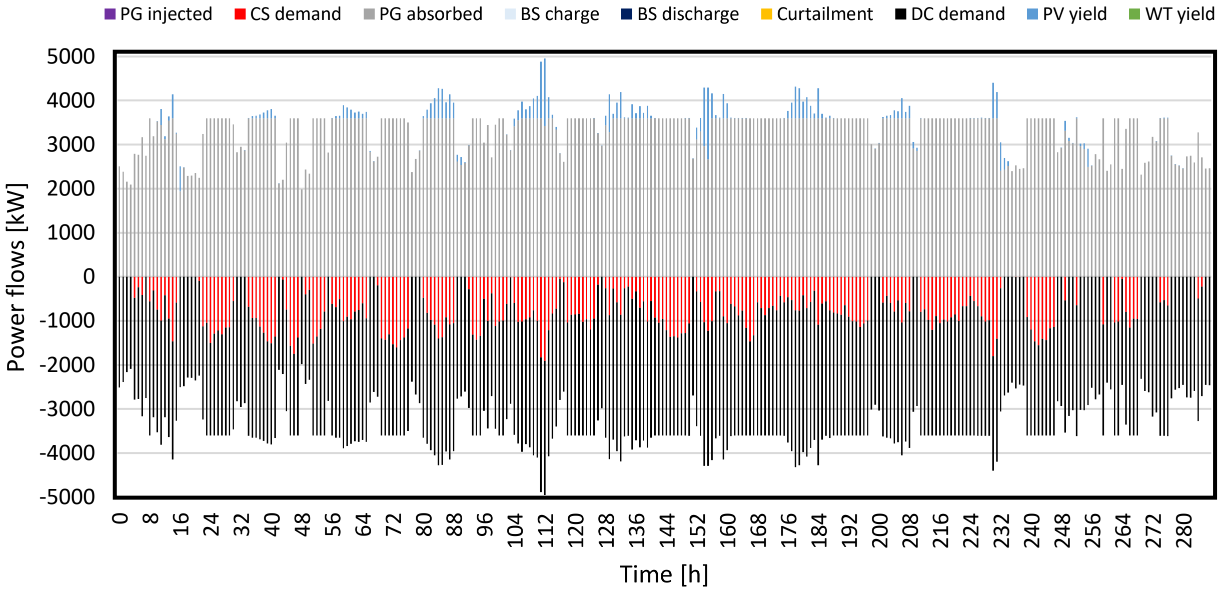


Figure 21. Power flows of the distribution centre's system in subscenario 3.3, in which the effect of a variable electricity price is considered on the infrastructural composition and operation.

The differences between the subscenario 3.2 and 3.3, in which the fixed electricity prices are substituted with variable DAM electricity prices, seem small, but the interesting part is that by the installation of more charging stations less total cost can be realised. In subscenario 3.3 the same amount of PV panels is required, but 11 charging stations instead of 7 are installed, which leads to 3.2% total cost reduction. Even though the additional charging stations add extra costs, the model uses them to optimally make use of periods in which PV power yield is high or the electricity prices are low. This is especially the case at t=112 and t=230. What is different in figure 21 of subscenario 3.3 compared to figure 20 of subscenario 3.2 is that the charging demand is less flat and more irregular, with the model avoiding charging when the electricity prices are high. This is especially the case in the later parts of the simulation period, in which the variable electricity price increases due to geopolitical factors. The total demand exceeds the kWmax 38% of the time, but only when there is excess power yield available from the 5963 PV panels that have to be installed regardless, due to the 4 e-trucks with route schedule 3. The full capacity of power that can be bought from the grid is used 63% of the time. This is also the reason that battery storage is not as cost-effective as in subscenario 1.3 and 2.3, as there is limited capacity left over for arbitrage possibilities. The in-depth smart scheduling of charging, to optimize the operation based on internal demand factors and external price factors, will be discussed next in the e-truck SOC and charging activity sub chapter.

8.1.3. Comparison of the charging activity

By graphically comparing the charging activity of a specific e-truck or of all charging stations in general for each subscenario the impact of the operational optimziation of the model can be seen in the way it smartly schedules the charging demand. Again, the subscenarios of main scenario 3 will be evaluated, with the greedy subscenario 3.1 in which the scheduling of the e-truck charging is not optimized acting as a base case. For the figures in this chapter not the continuous charging activity in kW will be evaluated but rather the binary charging activity of the charging stations, refering to their on or off state, will be evaluated, as this better shows the shifting of charging of e-trucks around. Figure 22 shows the charging activity of the e-trucks in greedy subscenario 3.1, in which the e-trucks are immediately cahrged after return to the DC. This results in 28 e-trucks of the 120 having to charge simultaneously, and the model needed to install 28 charging stations. Due to the fixed power demand the charging acitivity in figure 22 follows a constant pattern, with peaks during the days and valleys during the night.

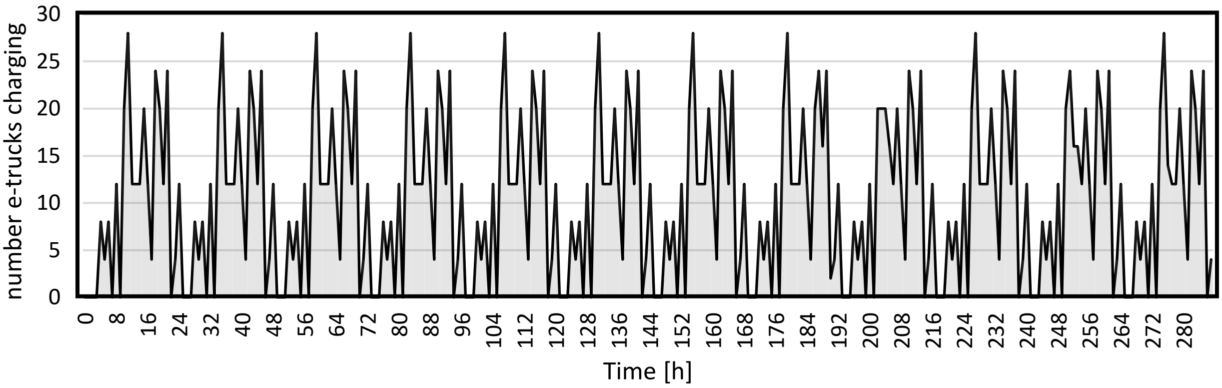


Figure 22. This graph shows the number of e-trucks that is simultaneously charging per time period and consequently how many of the charging stations are active in scenario 3.1 in each time period.

In subscenario 3.2 the number of charging stations is significantly reduced, the charging stations are used more often, and the charging activity changes according to the demand of the DC. The model balances the installation of the charging stations and the PV panels, depending on their corresponding costs, as the required number of charging stations and their operational power demand has effect on the required number of PV panels. In figure 23 it can be seen that the charging activity in the first 4 typical days up to time period 96 varies more than the charging activity in the next 4 days, which represent the months May to August. When compared to the pattern in figure 22 of the greedy subscenario 3.1, the model in subscenario 3.2 actually uses the charging windows of the e-trucks, in which it shifts and spreads the charging demand to avoid exceedance of the kWmax.

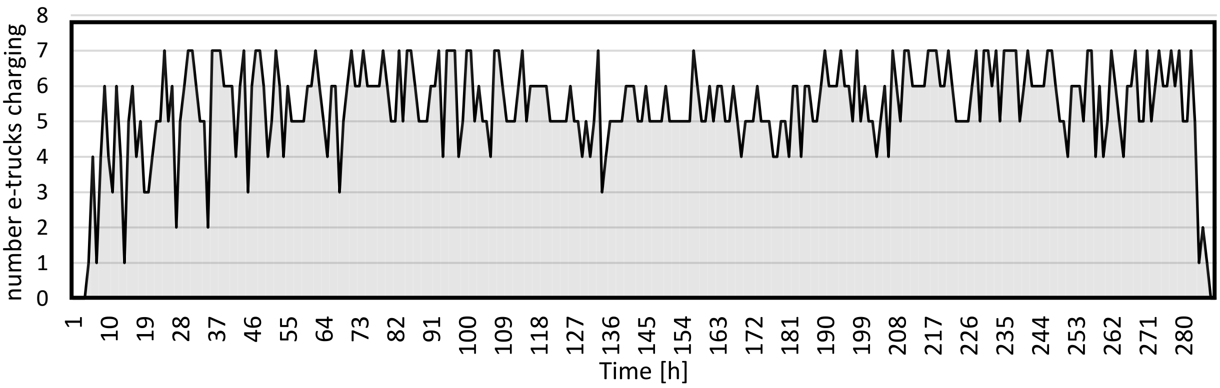


Figure 23. This graph shows the number of e-trucks that is simultaneously charging per time period and consequently how many charging stations are active in subscenario 3.2 in each time period.

The seventh charger is used less often in the typical days of these 4 months in the middle, while with the limited charging capacity one would expect the model to need al 7 chargers to spread the charging. However, the more e-trucks are charging simultaneously, the higher the charging demand can be, for which the model would need to install additional generation components. During the first 4 months the model can use the seven chargers without risk of exceeding the kWmax. During the 4 months in the middle when there is less charging capacity available due to high demand of the DC, the model only uses the number of charging stations and charging power as is necessary. This is the case for example at time period 180 when the 4 e-trucks with route schedule 3 have to charge in between routes, but no charging of additional e-trucks is done.

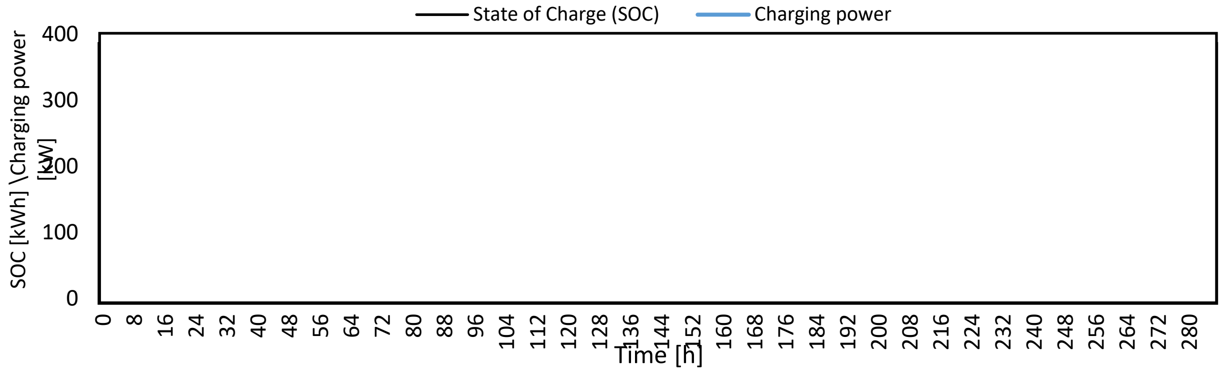


Figure 24. In the figure the SOC in kWh of e-truck 3 can be seen together with the charging activity in kW. The SOC decreases according to the transportation demand in route schedule 3, which is repeated for e-truck 33, 63, 93, and increases following the charging activity. The exact route schedule is confidential information, which is why the chart is moved to confidential appendix E.

The model optimizes the charging activity of the e-trucks by spreading or moving it during time periods with high DC demand and minimizing the number of e-trucks that need to charge simultaneously but is limited by the incident of high demand and the length of the charging windows of the e-trucks. In figure 24 the course of the SOC and the charging activity of e-truck 3 can be seen, which together with e-truck 33, 63 and 93 has the busiest route schedule. The route schedule has two longer routes with only 1 time period in between them per day, and a long charging window before and after the two routes. Even though in the single time period between routes the e-trucks have to charge, In the longer charging window the model can vary the charging activity, depending on the power demand of the DC or of the other e-trucks. This can be seen when the pattern of the first days, which is similar in the greedy charging subscenarios, is compared with variation in the charging activity in the middle months, when there is more risk of exceeding the kWmax.

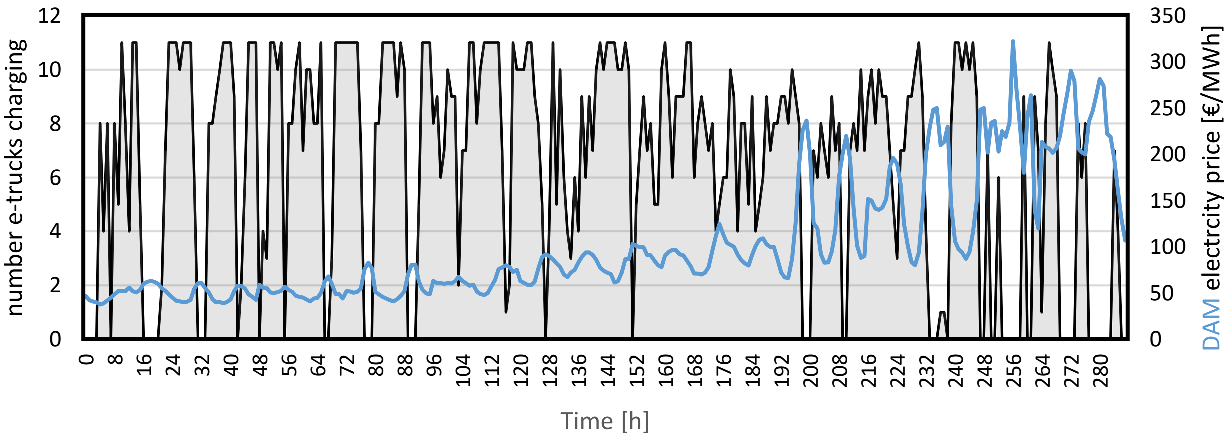


Figure 25. This graph shows the number of e-trucks that is simultaneously charging per time period, with the scale shown on the left y-axis and the DAM electricity prices in light blue on the right y-axis

In subscenario 3.3 the model installs 11 charging stations, which is 4 more than in subscenario 3.2, to take full advantage of the variable DAM electricity prices, due to which the charging activity fluctuates significantly more than in subscenario 3.2. In figure 25 it can be seen that the model avoids charging at all when the variable electricity prices are higher. The model then uses all 11 charging stations available when the prices are lower to charge as much as possible or required. Figure 25 shows why the model is able to reduce the total cost from subscenario 3.2 to subscenario 3.3, even though the infrastructural costs are higher with more charging stations installed. At the end of the simulation the variable DAM electricity prices increases significantly due to geopolitical reasons, at which point the model tries to charge as least as possible. The fact that the electricity prices for 2022 are higher than for the utilized data from 2021 will be discussed further in the sensitivity analysis, among other input parameter values which can vary and to which the sensitivity of the model will be tested.

8.2. Sensitivity analysis

To study how the uncertainties in the model's input parameters affect the outcome of the model, sensitivity analysis using the one at a time (OAT) method will be done, in which each factor is varied in turn while keeping all other factors fixed at their original indicated value. OAT can be defined as a local sensitivity analysis method as it studies the effect of one factor, while the interactions among factors are less visible, due to them not being varied simultaneously (Campolongo et al., 2011). However, because the model in this thesis is strictly linear, OAT is a valid approach for the sensitivity analysis and still gives insight into the balance of the infrastructural components and their effect on the total costs (Saltelli et al., 2006). The approach of the sensitivity analysis will be discussed next.

The input parameters that will be evaluated in the sensitivity analysis are the cost factors of the infrastructural components and the electricity price, as well as the parameters in the constraints that were active during the previously discussed scenarios. For the cost factors of the infrastructural components an average scalable price per unit was considered in the model, while in reality economies of scale or technological advancements could reduce the price in the future. Input parameters of the infrastructural components' characteristics, which have an effect on the power yield or storage, will not be varied. Ultimately the cost-benefit ratio is what matters, and that is already covered by varying the cost factors. For the parameters in the active constraints, it is interesting to both positively and negatively vary to relax and tighten the constraints respectively. Input parameters of inactive constraints, like the maximum number of PV panels due to spatial limits, will not be considered as they would have no effect. All the input parameters with their original value considered in the sensitivity analysis can be seen in the first column of table 8, with the varied value and percentage change compared to the original value beside them.

The sensitivity analysis will be performed within main scenario 2 with 60 e-truck, because it sits between main scenario 1 and 3. It has more representative charging demand than main scenario 1 but has less decision variables than main scenario 3, so it runs significantly faster which is important when a lot of simulations have to be run. In table 8 the results of the sensitivity analysis compared to the subscenario 2.2 can be seen. The various levels of optimization between the subscenarios can result in different levels of effect in the parameters varied, but ultimately the sensitivity metrics per parameter are similar between the subscenarios. The total costs and the number of each infrastructural component installed in subscenario 2.2 acts as a base for comparison and can be seen below the column headers in table 8. For each varied parameter value, the total cost of the simulation is given, with which the level of sensitivity can be calculated by dividing the percentage change in output by the percentage change in input. Finally, the resulting values of the decision variables are shown in the right 4 columns, which represent the number of each infrastructural component installed.

Base	Value	Change	Total cost	Change	Sensitivity	CS	PV	WT	BS
Scenario 2.2		None	2886235 €			4	2617	0	0
kWmax	4000 kW	%	2859894 €	-0.91%	-8.21%	3	0	0	0
	3400 kW	%	2911035 €	0.86%	-15.47%	4	4868	0	0
	3200 kW	%	2937719 €	1.78%	-16.05%	4	4710	1	3
CS cost	14540 €/unit	%	2910162 €	0.83%	3.02%	4	2617	0	0
	9152 €/unit	%	2867631 €	-0.64%	3.26%	4	2617	0	0
	7891 €/unit	%	2864263 €	-0.76%	2.47%	4	2617	0	0
PV cost	19 €/unit	%	2877923 €	-0.29%	2.11%	4	2617	0	0
	17.5 €/unit	%	2874598 €	-0.40%	1.97%	4	2617	0	0
	16 €/unit	%	2849416 €	-1.28%	4.68%	3	16187	0	0
WT cost	66025 €/unit	%	2883712 €	-0.09%	0.83%	4	0	3	0
	62113 €/unit	%	2871978 €	-0.49%	3.11%	4	0	3	0
	58202 €/unit	%	2808273 €	-2.70%	12.75%	3	0	14	0
BS cost	7793 €/unit	%	2885457 €	-0.03%	0.18%	4	1075	1	1
	6435 €/unit	%	2884031 €	-0.08%	0.26%	4	1076	0	1
	3717 €/unit	%	2878768 €	-0.26%	0.44%	4	0	0	2
EV capacity	370 kWh	%	2863964 €	-0.77%	-7.39%	3	1695	0	0
	300 kWh	%	2897095 €	0.38%	-3.60%	4	3539	0	0
	265 kWh	%	Infeasible €	-	-	-	-	-	-
CS power	225 kW	%	2886235 €	0.00%	0.00%	4	2617	0	0
	125 kW	%	2886235 €	0.00%	0.00%	4	2617	0	0
	100 kW	%	Infeasible €	-	-	-	-	-	-
EV consump	1.2 kWh/km	%	2824378 €	-2.14%	8.57%	8	0	0	0
	1.8 kWh/km	%	2947965 €	2.14%	17.11%	4	3228	1	0
	2 kWh/km	%	Infeasible €	-	-	-	-	-	-
PG price	0.115 €/kWh	10%	3139815 €	8.79%	92.25%	4	2617	0	0
0.105 €/kWh	0.125 €/kWh	19%	3295618 €	14.18%	74.47%	5	2762	0	0
	0.21 €/kWh	100%	4811324 €	66.70%	66.70%	3	16187	14	0

Table 8. Results from the sensitivity analysis that was performed with subscenario 2.2 as base case. The sensitivity analysis uses a lot confidential input values from the case study, which is why information is missing. A complete version of table 8 can be found in confidential appendix E

From the sign and the proportion of the sensitivity it can be seen what the relation of a specific input parameter is with the total costs. When the sign of the sensitivity is negative the input parameter is inversely related to the total cost, meaning if the input parameter value is increased the total cost decreases and vice versa. This is the case with the kWmax and the battery capacity of the e-trucks. More available capacity leads to less infrastructural components required, however in reality the grid connection and kWmax can often not be increased. What can be managerially decided is what battery capacity the e-trucks will have. Depending on the costs of the e-truck models, which are not considered in this thesis, either more expensive e-trucks could be bought to spend less on infrastructure, or less expensive e-trucks with less capacity could be bought for slightly more infrastructural costs. In that same sense the power required of the charging stations can be fine-tuned. The sensitivity analysis shows that faster charging stations provide no extra benefit, while 125 kW charging stations would be sufficient and in reality less expensive. Charging stations of 100 kW are not sufficient to facilitate the charging demand, while e-trucks with 265 kWh battery capacity are not able to service all transportation demand, shown by the infeasibility of the model to run the simulation with these parameter values with main scenario 2 as the basis.

All the cost factors, the average EV consumption and the PG electricity price are positively related to the total costs, which means that when the parameter input values are decreased or increased the total cost decreases or increases respectively as well. It can be seen that the cost of the charging stations has a subsequent effect on the total cost, but not on the infrastructural composition. The number of charging stations installed depends more on the values of other parameters than on the cost of the charging stations themselves. When looking at PV panels and wind turbines, reductions in the cost don't have much effect until a certain price parity point is reached at which the LCOE is lower than the electricity bought from the grid. The maximum number of 16187 PV panels and 14 wind turbines are installed and the effect on the total cost is larger than before the price parity. If the spatial constraints, limiting the number of each component installed, would not be in place, the only limiting factor would be the max power that can be injected back unto the grid. The model is not at all sensitive to the cost of battery modules, only installing them when necessary, even if the price is significantly reduced. This does not necessarily subtract from the general utility of battery storage. It can be explained by PV panels and wind turbines being more cost-effective and synergizing with each other. The PV panels generate more power during the day and the summer months and wind turbines more during the night and winter months. Because the model can smartly schedule the charging demand, the generated power can generally always be used immediately, and no residual energy is left to store.

The average EV consumption converts the transportation demand of the e-trucks to a decrease in the SOC of their battery per time period, which has to be recharged later. An average consumption of 2 kWh/km is infeasible because e-trucks would be unable to service their longer routes. The average consumption of the e-trucks thus indirectly effects the total charging demand, to which the model has to adjust the optimal infrastructural composition, increasing the sensitivity to this factor. The model is most sensitive to changes in the electricity price, because the cost for electricity bought from the grid represents between 70-98% of the total costs, depending on the amount of PV panels and wind installed. The results from the sensitivity analysis regarding the electricity price are of extra interest due to the average electricity price doubling in 2022 compared to 2021. Data from 2021 was used in this thesis as a whole year was available, but the results from the simulation run with 0.21 €/kWh, which is more in line with 2022 average electricity costs, underscore the original results of the model.

8.3. Managerial insights

The results of the scenarios, the graphs and the sensitivity analysis show that the model is effectively able to optimize the infrastructural composition and operation to minimize the cost in all cases, giving managerial insights into the decisions that need to be made in all steps of the fleet electrification process. The outlook of these managerial insights is in the first place on the case study itself. However, while the results of the case study cannot directly be applied to other cases, certain patterns and interactions can identified that would also hold in other cases. Regardless, with the mathematical model validated by the case study, the model itself can also be applied to other cases to generate specific results. The case specific and general managerial insights will be discussed next.

8.3.1. Managerial insights case study

The case specific managerial insights pertain to the interpretation of the results from the scenarios to determine the best infrastructure investment strategy in the fleet electrification process. This does not necessarily mean that the results from the cheapest scenario can directly be applied, but rather that according to additional qualitative wishes the most cost-effective components can be chosen. In the case study first 5 e-trucks have to be facilitated, then 60 in 2025 and 120 in 2030. When solely the data from the case study is considered, which concerns the static input parameters, the route schedules and the variable input parameter data from 2021, then the advisable steps to take would be to install consecutively or collectively 1, 3 and 7 charging stations and 994, 1623 and 4340 PV panels in 2022, 2025 and 2030. In the mathematical model 360 Wp PV panels are used, leading to an installation with a total rated power of 1.562 MW. In reality other PV panels can be installed as well, as long as the total rated power, the efficiency and orientation are equal. The operation of the e-trucks has to be optimized as well, to smartly charge the vehicles according to the available supply, as this significantly reduces the cost and otherwise the suggested infrastructure composition might not be sufficient. Even though in reality future energy demand and supply might be harder to accurately estimate, the model supplies the blueprint for how the e-trucks should be smartly charged. Possibly a variable electricity contract can be entered in lieu of an original electricity contract with fixed electricity prices, as the results show that with optimal scheduling of the charging the total costs can be further reduced. The PV panels are preferred over battery storage, even though subscenarios 1.3 and 2.3 with variable electricity prices use it, because in subscenario 3.3 ultimately PV panels are more cost-effective.

When the results from the sensitivity analysis are considered, original insights can be substantiated and additional insights and trade-offs can be determined. Currently the electricity price in 2022 is much higher, which was considered in the sensitivity analysis at the bottom of table 8. It can be seen that the choice for PV panels is still valid but the addition of wind turbines is cost-effective as well. Furthermore it was deduced from the sensitivity analysis that charging stations of 175 kW would be overkill and charging stations of 125 kW would be sufficient, which would reduce the infrastructure cost. The sensitivity analysis also shows that the size of the battery capacity of the e-trucks that are purchased has an effect on the required infrastructure and subsequent cost. The yearly costs of the system can be reduced by 22271 euros if e-trucks with a 370 kWh battery are acquired and if e-trucks with a 300 kWh battery are acquired the yearly costs of the system would increase with 10860 euros. If a service life of 10 years is assumed and the costs are divided by the 60 e-trucks considered in main scenario 2, then the 370 kWh e-truck should not have more than 3712 euro additional purchase cost compared to the base kWh version, for the bigger battery to make financial sense. The 300 kWh e-trucks would need to be more than 1810 euros less in purchase costs compared to the base kWh version. In reality the prices can fluctuate and vary per e-truck version and per manufacturer, but when a distribution centre company receives quotations for e-trucks with different battery capacities it can perform the calculation illustrated above and decide on the most cost-effective option.

Additional qualitative preferences, that could not directly be included into the quantitative model, can lead to the installation of more infrastructure components than required by the model. In subscenario 3.3 the full capacity of the grid connection is used 68% of the time. If the company wants to reduce the risk of exceeding the kWmax, it could decide to install battery storage next to the suggested infrastructure composition by the model anyway. Besides providing a buffer for any excess power demand, the battery can be even be used to trade on the electricity imbalance markets. Another operational, qualitative preference is that in reality logistical companies want to avoid physically shuffling e-trucks between charging stations. However, the results of the subscenarios show that the greedy charging strategy, in which the e-trucks are immediately charged after returning, is not most cost-effective. Software does exist to smartly schedule the charging, with multiple e-trucks connected to charging stations, but only a selection being charged at a time. This does however mean that more charging stations are required than minimally found by the model. A operational balance needs to be found between the minimally required number of charging stations and just installing a charging station for every e-truck, which is not cost-effective. This balance can be achieved by looking at the simulated charging profile of the model, and determining what the maximum number of e-trucks is that has to charge during the night, when the distribution centre company really can't usher e-trucks around. For the case study the maximum number of e-trucks that needs to be charged during a night is 23 (appendix G.4) meaning that with 23 charging stations the e-trucks would never have to be shuffled during the night. So, even though the model can advise on the most cost-effective infrastructural composition and operations, post analysis can be used to tailor the advice to additional preferences.

8.3.2. General managerial insights

First and foremost, it is important to note that the model can be applied to more use-cases than just distribution centres. The model can be applied to behind-the-meter systems of other use-cases with both on-site power demand and charging demand, or even to systems with only one of the two power demands. For logistical locations like bus depots or harbours the model can be used to determine the most-cost effective infrastructural composition and operations as well, based on the schedules of their electrified buses or cranes. Any manageable power demand can be operationally optimized by the model, meaning industrial or large-scale residential systems could possibly be evaluated as well. Even when no manageable power demand is present, the model can still be used to determine solely the most cost-effective infrastructural composition, based on the fixed on-site demand of any case.

While in this thesis solely a single case is studied, general managerial insights can be determined for other cases as well, for example when the values of the input parameters in other cases are similar. Some parameters can be directly controlled by the relevant party in a case, such as the battery capacity of their electric vehicles and the charging speed of the charging stations. Other factors, such as the costs of the infrastructural components and the electricity price, might be similar in a different use-case due them having access to the same regional market prices. Even when in the future prices of the infrastructural components will drop due to technological developments, the results of the sensitivity analysis already provide insight into the expected effect. What is however very case specific is the on-site power demand of the system, the schedule of the manageable power demand, and the maximum capacity of the grid connection. If a case in another part of the world than West-Europe is considered, market prices for the infrastructural components might differ as well.

When a case is studied for a system in another part of the world, so many input parameter values may differ that, aside from running the model for the specific case, only patterns and interactions from the results of the case study in this thesis can be useful. On an international level the variability in the purchasing power parities, which is a currency conversion metric that tries to equalise the purchasing power of different currencies, leads to differing costs for the infrastructural components across the world (OECD, 2022). The electricity costs in West-Europe are also some of the highest in the world, meaning that when cases in other parts of the world with a lower electricity cost are considered, renewable energy infrastructure components might be less attractive (Statista, 2021). However, besides cost factors meteorological factors differ across the world as well. When a case is studied in a country with higher solar potential, the results of the model show that PV panels are installed when price parity is reached with the electricity price. parameter variations can all be considered in the model and make it an internationally applicable tool.

Besides these internationally focussed insights, some general managerial insights that apply everywhere can also be found in the case results. The factor with the biggest impact is the maximum capacity of the grid connection in relation to the system's demand. The less residual capacity is left for the additional demand of the electrification process, the more investment in infrastructural components is required. The second factor influencing the cost is the level of flexibility in the manageable demand, of which the value was highlighted by the third subscenarios. Furthermore, the installation of generation components is more cost-effective than battery storage, if sufficient generation capacity can be installed and the yield coincides with the power demand. If peak demand occurs during the night or during the winter, and the potential for wind energy at the location is low, battery storage would be more cost-effective. Essentially the most cost-effective solution is the one in which the characteristics of the infrastructural components match the characteristics of the power demand. The model proposed in this thesis supplies a tool that not only inherently considers all these characteristics but can also advice on the number and type of infrastructural component required.

9. Discussion

In the interpretation of the outcomes of the model, it should be remembered that the results of the case study are not necessarily representative for other cases and generalization of the results of the case study should be done carefully, considering the assumptions and limitations. This chapter will discuss the main assumptions and their corresponding limitations, the limitations of the modelling approach and mathematical model and the validity of the model and the data. Finally, the overall generalizability of the model, the case study and the generated managerial insights can be discussed.

9.1. Main assumptions and limitations

During the formulation process of the mathematical model, which involved the problem description, conceptual modelling, validation and verification, various assumptions have been made to enable the model's development. In this section these assumptions, their reason and effect on the mathematical model will be elaborated upon, followed by a discussion on the research limitations.

9.1.1. Model assumptions and limitations

The proposed simultaneous infrastructure composition and operation optimization model represents the high-level electric system of a distribution centre and is formulated using both information from literature and from experts of the supermarket company in the case study. The combination of theoretical knowledge from the literature and practical knowledge from the supermarket company aims to let the formulated model closely represent the real-life distribution centre in the case study. However, some assumptions are required to make it feasible to translate the complex real-life situation into a mathematical model that can be solved computationally, within a reasonable amount of time. The modelling assumptions made beforehand affect the solution space, which may impinge on the real-life representability. Therefore, it is necessary to reflect on the assumptions made and the effect they may have on the model's outcome.

Looking back at the development process of the mathematical model the most challenging part was the computational intensity of the model and incorporating and aligning all the different timescales. Infrastructure investment decisions are made upfront for the next decade, while the operation of the distribution centre occurs live, changing every second. For the steps in the electrification process also specific years had to be evaluated, so eventually the decision was made to look at time periods of an hour over the length of a year. 8760 time periods proved to be to computationally intensive to solve, so a method had to be find to comprise the simulation length. Literature research presented a substantiated method with the K-medoid approach, which will be discussed further in subchapter 9.2.

The main assumption concerning the scope and boundaries of the system is that solely the distribution centre itself and the activities within its area are considered, which has an effect on site specific input data, like the route schedules, power demand of the DC, the kWmax and spatial constraints. The route schedules of the e-trucks are assumed to be fixed and not influenced by changing demand of retail locations, while in reality the intensity of the route schedules and the assignment to the e-trucks can differ. For formulation of the route schedules real-life data from the case study was used with the assumption that the average intensity of the route schedules is representative for the future. The validity of the route schedules could be reduced if in the future the operational strategy changes and the intensity increases. This is also the case with power demand of the DC, for which data from 2021 was used, but could increase in the future due to business expansion. While the spatial constraints in this case study are not bound to change, it is unknown when in the future the congestion on the grid is solved by the grid operators and the grid connection can be increased. This possibility is not considered in the scenarios but is discussed in the sensitivity analysis.

For the yield of the renewable electricity sources as well as the demand of the distribution centre itself and electricity market prices it is assumed that historical data is representative for the future. For all scenario's, which in real-life would happen in different years, the historical data from the same year was used. This assumption is valid for the renewable electricity generation and also for demand of the DC if the size of the operation stays the same, which in the absence of business expansion is valid because in the fleet electrification process e-trucks are substitutive and not additive. While normally historical electricity prices could also be representative for the near future, geopolitical factors have caused the average DAM electricity price to double in 2022. This circumstance could not be foreseen at the start of this thesis, but the possible effects were studied in the sensitivity analysis.

Regarding the infrastructural components, for the integration into the model a selection was made, and it was assumed that the characteristics of the different infrastructural components scale linearly with the number of units installed. A selection of infrastructural components reduces the solution space, which differs from the reality in which all technologies are a possibility. Things like a combined heat powerplant or diesel generator were not included but based on the literature the most sustainable and financially interesting technologies were selected. Literary substantiation increases the likely representativeness of model's optimal outcome. Real-life validity of characteristics of the PV panels and wind turbines like the LCOE were also checked during the research. Besides the selection of the infrastructural components, the costs and characteristics of the components also had to be assumed linearly for the MILP model. For some elements, like the yield of the PV panels and the capacity of the battery system this holds scientifically true, while for others like the yield of the wind turbines and the battery (dis)charging rate this is a reasonable assumption. However, for the component costs economies of scale conflict with the linear requirement. Small installations are relatively more expensive than bigger installations. This non-linear cost path was tried to capture in average cost prices considering the ranges of installation sizes that could occur. Due to the modularity of PV panels the size of the installation corresponds linearly to the number installed. With wind turbines various sizes with different rated power levels exist. That is why a 500 kW wind turbine was assumed as a base, and if 7 were installed this could be interpreted as a single wind turbine of 3.5 MW. The mathematical MILP model only considers quantitative factors, so post analysis is required regardless, to interpret the results according to qualitative wishes in a specific real-life case.

9.1.2. Research method limitation

The main aspects of the research method are that an optimization model is used to simultaneously optimize the infrastructural composition and the operation, that sequential electrification steps are incorporated in scenarios, containing multiple subscenarios, and that a real-life case study is evaluated. The limitations of the optimization model as discussed earlier are that it only considers the components within the selection, only a single financial objective is considered and that the modelling horizon is comprised of a larger dataset, due to computational intensity. The reasoning and substantiation for this method has already been explained, but possible improvements will be discussed in subchapter 10.3: recommendations for future research. Besides the modelling approach, a single case study was caried out. This can negatively affect the reliability of the outcomes of the model, but it reduces the time required and increases the focus on the specific case (Gustafsson, 2017). The research limitation of a single case study was also partly alleviated by analysing and testing the model in 3 main scenarios, with each having 3 subscenarios. The model has thus been tested and verified in 9 scenarios, but also repeatedly run in the sensitivity analysis, which increases the reliability of the model outcomes. Ideally, more real-life case studies would have been evaluated to further increase the model's reliability. This could have been done by evaluating case studies from other distribution centre companies. One other case of a distribution centre was looked at, and the model performed well in it, but no additional PV panels or wind turbines could be installed at that location.

9.2. Reflection on validity and generalizability

The validity of the model, as earlier discussed in chapter 7, concerns the level to which the model represents the real-life situation it tries to simulate. It effects the reliability of the model's outcomes and the generalizability of the model for other situations. While the validity of the model and data was ensured throughout the development and verification and validation process, this section will further elaborate on the reliability and generalizability of the model and its outcomes in the case study.

9.2.1. Validity

In the development of the model the validity was ensured by using methods which were sufficiently substantiated by scientific research, and implementing them on the objective and constraints that followed from the problem description and case study. By using general input parameters the model can also be applied to different cases. The validity of the data was again ensured by combining and comparing data from literature and from experts of the case study. With this approach both the reliability of the model's results and the generalizability of the model to other cases are accounted for.

The biggest challenge during the modelling was to find and validate the best method available to determine the most typical day per month. To reduce the computational complexity of the model, the historic data of 2021 was comprised to a typical day per month, with a modelling resolution of hourly time period, for a total of 288 time periods. This shortens the simulation period, which could negatively affect the validity if the subset is not representative for a whole year. While this method does consider diurnal and seasonal variation, circumstantial events could still occur which would invalidate the model's results. The earlier mentioned Dunkelflaute, in which prolonged periods of no wind and minimal solar irradiation occur, could cause the suggested infrastructural composition by the model to perform insufficiently (Li et al, 2020). Eventually the K-medoid method was chosen and used to determine the typical days of each month for each variable input parameter. The assumption that these subsets were representative for the whole year was verified in chapter 7: verification and validation. The scientific validity of this method for energy systems was also substantiated by three papers from the literature review (Bracco et al., 2019; Dai et al., 2019; Liu et al., 2020). All-in-all the validity of the model was continuously checked and the results show that the model accurately represents the real-life situation of the distribution centre in the case study.

9.2.2. Model generalizability

The specific results of the case study itself can't be directly applied to other distribution centres of supermarket companies or different ones, but after testing of the mathematical model it can reliably be used with other input parameter values to generate results for distribution centres in other cases. The case study results hold specifically for the used input parameter values which were based on real-life data from the supermarket company in the case study, and checked with literature. Changing the input parameter values will affect the model outcome as was demonstrated in the chapter 7: validation and verification and in subchapter 8.3: sensitivity analysis. The proposed model can however be used for other distribution centre companies to analyse the required infrastructure composition and operations during their fleet electrification process as the models' objective functions and constraints have been generally formulated. This general construction of the model makes it suitable to be used and tested for other case studies as well. The complexity of setting up and using the proposed model for other supermarket companies depends on the case study details that should be accounted for, such as the number of e-trucks per electrification step, the future route schedules of the e-trucks, the max grid connection or kWmax and the space available for the infrastructure components themselves. The model can even be applied to other behind-the-meters systems, as explained in the general managerial insights in chapter 8, but if other types of components with different characteristics are to be considered in the model, some formulas might have to be adapted to the specific component.

10. Conclusion

The purpose of this thesis' final chapter is to answer the main research question and conclude the research by summarizing the insights gathered. First the formulated sub research questions will be answered. Discussing them gives a good chronological summary of the whole thesis. Through combination of the answers to the sub research questions, a conclusive answer to the main research question can be formulated. Finally, recommendations for future research will be discussed.

10.1. Answers to the sub research questions

In this sub chapter the answers to the sub research question will be given and discussed. The sub-research questions were formulated following the research boundaries set by the core concepts and the knowledge gap identified in the literature review. The answers for the first 3 sub research questions follow partly from the literature and partly from the information received out of the case study.

SQ1: "What are the different stages and scenarios of the fleet electrification process?"

In the case study at the end of this year 5 e-trucks will need to be facilitated. In 2025 a total of 60 e-trucks will have to be facilitated in preparation for 2030, at which point 120 e-trucks need to be operational. These main stages were incorporated into three main scenarios, each evaluating the infrastructural and operational needs corresponding to the number of e-trucks that had to be facilitated. A model which could simultaneously optimize the infrastructural composition and the operation was the goal, but to have something to compare it to the concept of greedy charging was introduced. Finally, out of the literature review it appeared that variable electricity prices were an interesting aspect which had not previously been researched in the context of this thesis' topic. These three topics together formed the subscenarios contained within each main scenario.

SQ2: "Which infrastructural components should be considered and what are their characteristics?"

A lot of different technologies exist that can provide benefit to businesses. To explore which technologies and infrastructural components are often considered, especially in the context of this thesis' topic, all papers in the literature were evaluated on the components they consider. PV panels and charging stations were most often featured. Battery storage and wind turbines were also considered in multiple papers. Two inclusions of a diesel generator were found and one inclusion of a combined-heat power plant. It was decided to focus solely on electric sustainable components, dropping the diesel generator and the combined heat powerplant, as it also supplies heat.

The power output of a solar PV system depends on several factors, like the solar irradiation, area and efficiency of the PV array, angle of incidence, and atmospheric temperature. The power that a wind turbine can generate is dependent on the product of factors like the efficiency of the wind turbine, or so-called power coefficient, the surface area of the rotor, the density of air and the velocity of air. The performance of battery storage depends on the energy and power capacity per module and the round-trip efficiency. Finally, the performance of the charging stations depends on the charging speed and the charging efficiency. While not all factors are mentioned in the mathematical model and rather a comprehensive factor is given, all factors are included into the coded model as detailed in appendix C.

SQ3: "What are the costs factors of the components and how can they be implemented in the model?"

The cost per infrastructural component is build-up of various factors. The costs of all infrastructural components are consist of the purchase cost, installation cost and maintenance cost. For the PV panels and wind turbines even a cost per kW is used, so that units with varying characteristics can be easily implemented into the model. In the end a total per unit cost was calculated which is used in the model. The difficulty is that the lifetimes of the infrastructural components do not align with the simulation period of the model. To adapt these costs to the modelling period, a so-called capital recovery or annualization formula was used, a method which was substantiated by literature. The calculation process can be found in appendix C and involves the lifetime of the components and the discount rate.

SQ4: "How can the infrastructural and operational side of the problem be integrated into a single, simultaneous optimization model?"

It was found in the literature that the electric infrastructure investment decision can essentially be seen a knapsack problem, while demand response or smart charge scheduling can possibly be interpreted as a job shop problem or a bin packing problem. Combination of both these problem types into a single simultaneous optimization model is not trivial. Inspiration was taken from papers by Bracco et al. (2019), Mirhoseini and Ghaffarzadeh (2020) and Wang et al. (2020) which incorporate the static infrastructural optimization in the objective function of a MILP model, and the operational optimization in the constraints. This approach was used to construct a conceptual model for the specific topic of this thesis. In the eventual mathematical model, the objective function is built up with the sum of the total cost of each infrastructural component, multiplied with a decision variable indicating how many of that specific component the model installs. The model thus tries to minimize the total cost by minimizing the installation of each infrastructural component.

The operational optimization is primarily handled in the primary equality constraint, which pertains to the energy balance of this system. In this equation the positive and negative power flows are summed and have to be equal to zero, because the electrical system always has to be in balance. The positive power flows of the PV panels and wind turbines follow from the power yield per unit multiplied with the decision variables indicating the number of units of the component installed. The negative power flow of the DC demand follows from historical data and the negative power flow of the charging demand is a decision variable but has to respond to the SOC of each e-truck, which decreases according to its corresponding route schedule. A lot of other equations are also defined in chapter 6 of the mathematical model, but in the end the model tries to find the most cost-effective infrastructure composition to be able to sufficiently facilitate the total demand.

SQ5: "How do variations in the models' input parameter values affect the outcome of the model?"

How the model reacts to changes in the values of the input parameters was studied in the sensitivity analysis. All the cost factors, the average EV consumption and the PG electricity price are positively related to the total costs, which means that when the parameter input values are decreased or increased the total cost decreases or increases respectively as well. The kWmax and the battery capacity of the e-trucks were negatively related to the total costs, thus an increase or decrease in these values effects the total costs inversely. The kWmax and the electricity prices had the most significant effect on the total costs. The other parameters had insignificant effect on the lower cost, but interesting effect on the type and number of components installed. With PV and wind turbines a certain price point can be reached, after which it becomes more attractive to install this component type than the other or more attractive than buying power from the grid. The sensitivity analysis also allows for the finetuning of the capacity of e-trucks and charging speed of charging stations required.

SQ6: "To what extend does the model reflect the real-life scenario?"

While several assumptions have been made to aid the modelling of the problem, the reliability and generalizability as such have been detailed in the discussion. It is possible that certain input parameters could be different in reality, but this could differ on a case per case basis as well. The most important is that the base of the mathematical model, which are the objective function and the constraints, are valid in any case, as was verified in chapter 6. While the K-medoid method offers a literary substantiated method to determine the least dissimilar days, to comprise the simulation period from a whole year to 12 days, the subset has overall similarity but can't contain the same level of detail. So, while the model does reflect reality, certain edge-cases like a Dunkelflaute are not accounted for.

10.2. Answer to the main research question

By combining the answers of the sub research questions, an answer to the main research question could be formulated. The main research question entails:

MQ: ***"What is the most cost-effective electric infrastructural composition and operation to facilitate the electrification of truck fleets of large-scale distribution centres in grid congested areas in various scenarios of a case study to ensure that the route schedules can be driven?"***

The most cost-effective infrastructural composition and operation is dependent on the characteristics and the demand of the DC in question and the number of e-trucks and the intensity of their route schedules. The more charging capacity is available between the kWmax and the demand of the DC, the less the need for additional infrastructural components is. The number of e-trucks and the intensity of their route schedules influences the total charging demand. When the charging capacity is low due to the kWmax, and the total charging demand is high, optimal operation is to shift or spread out the charging as much as possible. If this is not possible and kWmax is exceeded due to coincident charging demand with high power demand of the DC, then additional infrastructural components are required.

The comparison of the simultaneous optimization of operation and infrastructure with the greedy base subscenario, in which the charging demand is fixed and only the infrastructural composition can be optimized, shows the value of the mathematical model and the cost-effectiveness of the operational optimization. It is thus always advisable to not simply charge the e-trucks upon return but actually schedule the charging demand, be it by physically switching the e-trucks connected to the chargers or by using software. In the managerial insights additional qualitative preferences were discussed, like reduction of the risk of exceeding the kWmax and the avoidance of shuffling the e-trucks around at night. For the first preference it can be managerially decided to install battery storage, even though it is not required by the model, as it can act as a buffer and can be used to trade on the electricity imbalance markets. To avoid the need to shuffle the e-trucks between the charging stations at night, it was determined based on the charging demand profile of the model that 28 charging stations would be the best balance between cost minimization and operational effectiveness.

When these general conclusions are considered with the main scenarios of the case study, then specific advice can be given on the infrastructural and operational needs in the various steps of the electrification process. In the first main scenario 5 e-trucks need to be facilitated and 1 charging station and 994 PV panels are required. Even though the charging demand of 5 e-trucks is small, the short charging window of an e-truck in which it has to charge coincides with high demand of the DC, causing an exceedance of the kWmax. The precise number of PV panels is installed by the model to yield exactly enough power to alleviate the exceeding demand. In the second main scenario 60 e-trucks have to be facilitated and 4 charging stations and 2617 PV panels are required, which means 3 more charging stations and 1623 more PV panels have to be installed. In the final step of the electrification process 120 e-trucks have to be operational and 11 charging stations and 5963 PV panels are required, meaning 7 additional charging stations and 3346 PV panels have to be installed. In the model PV panels of 360 Wp were considered, while in reality any PV panel can be used, as long they have the same efficiency and orientation and a total of 1.562 MW rated power is installed. Managerially the decision for charging stations of 125 kW can be made as they would be cheaper and were proven to be sufficient. Furthermore, e-trucks of with a battery capacity of 300 kWh were proven sufficient even though they slightly raise the infrastructural cost, if they are 1810 euros less in purchase costs compared to the base kWh, they would be the more cost-effective option. When the traditional contract with fixed electricity prices is replaced with a variable electricity price contract, the advice is to install the maximum amount of PV panels and wind turbines to achieve the lowest total costs.

The analysis was done using data from 2021, while in 2022 the average electricity price more than doubles. The results from the sensitivity analysis show that the advice given above based on the data from 2021 is valid for 2022 as well. The value of the sustainable generation from PV panels and wind turbines is even greater in 2022. The installation of battery storage is found to be not cost-effective as the yield of the PV panels and wind turbines synergizes and the charging demand can be scheduled to always make use of the sustainably generated power. The optimal operation of the system in all steps of the electrification process has been shown in chapter 8 and entails the shifting or spreading of charging demand according to the power demand of the DC. In the scenarios with variable electricity prices the charging demand is even shifted to periods with low prices and avoided in periods with high prices. All in all, the model was able to supply the most cost-effective infrastructural composition for each electrification step and the optimal operational strategies.

Looking beyond the distribution centre in the case study, it can be stated that the model can be applied to more use-cases than just distribution centres and it can be used for other locations around the world, as it considers the parameters that can vary internationally. Any manageable power demand can be operationally optimized by the model, meaning industrial or large-scale residential systems could possibly be evaluated as well. For any case with just a fixed on-site energy demand just the infrastructural composition component of the model can be utilized as well. While in this thesis solely a single case is studied, general managerial insights were gained by determining the parameters that are controllable and evaluating the parameters that can vary across the world in the sensitivity analysis. When a case is studied for a system in another part of the world, the input parameter values may differ significantly. However, the patterns and interactions from the results of the case study in this thesis can still be informative and regardless, the model can be run with the data from the new case to generate specific results. Conclusively, the mathematical model provides a proven tool in which all important factors of specific infrastructural are considered, in which case specific data and constraints can be implemented, to determine the most cost-effective infrastructural composition and operations, suitable for similar behind-the-meter system cases around the world.

10.3. Recommendations for future research

This thesis provides a mathematical model which can find the most cost-effective infrastructural composition and operations for not only distribution centres, but also similar behind-the-meter systems, which have to electrify their truck fleet but are hindered by low charging capacity due to their kWmax. The model was tested in a case study of a large supermarket company in the Randstad, had sensitivity analysis done on it and was evaluated on its validity and generalizability. The model can be used as a tool in other cases for other behind-the-meter systems, to advise them on their most cost-effective infrastructural composition. The operational optimization can be used beforehand to get insight into the optimal charging schedule. Various assumptions were made, and limitations were determined, opening doors for future research to improve the model and bring it closer to real-life reliability. The recommendations for future research will be discussed below.

A first recommendation for future research is to test the proposed mathematical model in other cases, for distribution centres with different characteristics and power demand. Also, different numbers of e-trucks and intensities of route schedules can be tested. By testing the model in different real-life case studies, the model outcomes can be further validated. Also, the effects that the characteristics of different distribution centres have on the model's outcome can be compared. Continuing in this trend, other behind-the-meter systems could be evaluated with the model as well, to test the level of applicability of the model to different systems. The formulas might not be directly applicable when a different kind of manageable demand is considered instead of electric vehicles, but they provide the structure to which the new manageable demand can be added as a decision variable per time period.

Besides the possible addition of a different manageable demand, other infrastructural components can be added to the model as well. Firstly, alternatives of the same type of component can be added, to let the model itself decide which type of charging station or battery it prefers. The model could even decide to install a mix of them. Secondly, different types of infrastructure components could be added as well, like e-boilers, heat pumps, CHP plants or fuel cells. While for the calculations of the costs the same formulas can be used, for the inclusion of the characteristics new formulas are required. Other additional factors that could be included in the model are possible revenue streams from renewable fuel units or from trading on the imbalance markets. Both would make the installation of infrastructural components more attractive.

In this thesis solely the distribution centre itself was considered and the route schedules of the e-trucks were fixed, due to the persistent demand of retail locations. An interesting topic for further research would be the possibility for not only scheduling the charging demand but also the possibility of rescheduling the transportation demand. In reality the route schedules are very strict, as working hours of truck drivers and demand of retail locations have to be considered. But the value of the model being able to just shift a route schedule by 1 hour could be significant. The amount that the model shifts a route could then come with an associated cost, to let the model decide if the extra cost of rescheduling is worth the operational flexibility. A beginning was made with this addition to the model; however, the complexity of the model quickly increases with each possible route schedule alternative.

Another research direction that is also limited by computational complexity concerns the running of the model with a smaller resolution or over a bigger horizon. Using a smaller resolution allows the model to more precisely optimize the operation and increase the real-life representativeness, as in reality decisions are not only made for every hour. Evaluating a larger horizon would extend the simulation length and test the robustness of the infrastructural composition more. Ideally, it would be possible to run the simulation over a whole year, taking into consideration every variation and prolonged periods of similar conditions. The research approach used in this thesis, which uses a typical day per month, can then also be validated by checking if the results are similar in both cases.

Finally, while the proposed mathematical model in this thesis is deterministic and uses historical data, it would be interesting to try and apply the operation side of the model to live system optimization. While the model can provide a the optimal operation of the system based on historical data, In reality the exact future power supply and demand is not known. The uncertainty can be incorporated by introducing stochasticity to the variable input parameters. The uncertainty can be reduced by using forecast for only a few hours in the future, and by rerunning the model every minute to get the latest optimal schedule. This essentially pertains to the live smart charging of the e-trucks. All-in-all a wide field of interesting directions and topics can be further researched, highlighting the applicability and the power of the model.

References

AD. (2021, September 16). *Stroomnet noorden Noord-Holland in de knel: Geen elektriciteit voor nieuwe grootverbruikers*. AD.nl. https://www.ad.nl/noord-holland/stroomnet-noorden-noord-holland-in-de-knel-geen-elektriciteit-voor-nieuwe-grootverbruikers~afe70b7a/

Akram, U., Khalid, M., & Shafiq, S. (2018). An Improved Optimal Sizing Methodology for Future Autonomous Residential Smart Power Systems. *IEEE Access*, *6*, 5986–6000. https://doi.org/10.1109/ACCESS.2018.2792451

Alevras, D., Padberg, M., & Padberg, M. W. (2001). *Linear Optimization and Extensions: Problems and Solutions*. Springer Science & Business Media.

Alfen. (2022a). *TheBattery Specifications | Alfen Elkamo*. Retrieved 10 June 2022, from https://alfenelkamo.fi/en/energy-storage/thebattery-specifications

Alfen. (2022b). *TheBattery Elements*. Retrieved 10 June 2022, from https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwiAyerg0aL4AhXM3KQKHUJhDdkQFnoECAIQAQ&url=https%3A%2F%2Falfen.com%2Fde%2Ffile-download%2Fdownload%2Fpublic%2F1372&usg=AOvVaw1IOMp4DMamyMVFRrT5J_Tk

Badouard, T., de Oliveira, D.M., Yearwood, J. & Torres, P. (2020). *Final Report Cost of Energy (LCOE), Energy costs, taxes, and the impact of government interventions on investments*. Enerdata & Trinomics. https://energy.ec.europa.eu/system/files/2020-10/final_report_levelised_costs_0.pdf

Baik, S. H., Jin, Y. G., & Yoon, Y. T. (2018). Determining Equipment Capacity of Electric Vehicle Charging Station Operator for Profit Maximization. *Energies*, *11*(9), Article 9. https://doi.org/10.3390/en11092301

Ban, M., Yu, J., Shahidehpour, M., & Guo, D. (2019). Optimal sizing of PV and battery-based energy storage in an off-grid nanogrid supplying batteries to a battery swapping station. *Modern Power Systems and Clean Energy*, *7*(2), 309–320.https://doi.org/10.1007/s40565-018-0428-y

Bayram, I. S., & Ustun, T. S. (2017). A survey on behind the meter energy management systems in smart grid. *Renewable and Sustainable Energy Reviews*, *72*, 1208–1232. https://doi.org/10.1016/j.rser.2016.10.034

Behdani, B. (2012). Evaluation of paradigms for modelling supply chains as complex socio-technical systems. *Proceedings of the 2012 Winter Simulation Conference (WSC)*, 1–15. https://doi.org/10.1109/WSC.2012.6465109

Bhatti, A. R., Salam, Z., Sultana, B., Rasheed, N., Awan, A. B., Sultana, U., & Younas, M. (2019). Optimized sizing of photovoltaic grid-connected electric vehicle charging system using particle swarm optimization. *International Journal of Energy Research*, *43*(1), 500–522. https://doi.org/10.1002/er.4287

Billaut,J.C. Croce, F.D. & Grosso, A. (2013). A single machine scheduling problem with bin packing constraints. *14th International Conference on Project Management and Scheduling*, 40.

Blasius, E., Federau, E., Janik, P., & Leonowicz, Z. (2016). Heuristic Storage System Sizing for Optimal Operation of Electric Vehicles Powered by Photovoltaic Charging Station: *International Journal of Photoenergy*, *2016*, 1–12. https://doi.org/10.1155/2016/3980284

Bolinger, M. (2004). *A survey of state support for community wind power development*. http://www.regie-energie.qc.ca/audiences/3526-04/DocumentsAudi3526/CCVK_Annx_community_wind.pdf

Bolinger, M. A. (2005). Making European-style community wind power development work in the US. *Renewable and Sustainable Energy Reviews*, *9*(6), 556–575. https://doi.org/10.1016/j.rser.2004.04.002

Bracco, S., Delfino, F., Longo, M., & Siri, S. (2019). Electric Vehicles and Storage Systems Integrated within a Sustainable Urban District Fed by Solar Energy. *Journal of Advanced Transportation*, *2019*, 1–19. https://doi.org/10.1155/2019/9572746

Budischak, C., Sewell, D., Thomson, H., Mach, L., Veron, D. E., & Kempton, W. (2013). Cost-minimized combinations of wind power, solar power and electrochemical storage, powering the grid up to 99.9% of the time. *Journal of Power Sources*, *225*, 60–74. https://doi.org/10.1016/j.jpowsour.2012.09.054

Campolongo, F., Saltelli, A., & Cariboni, J. (2011). From screening to quantitative sensitivity analysis. A unified approach. *Computer Physics Communications*, *182*(4), 978–988. https://doi.org/10.1016/j.cpc.2010.12.039

Carson, J.S., Snowdon, Y. C., Yücesan, E., Chen, C. -h, Snowdon, J. L., & Charnes, J. M. (2002). *Model verification and validation*. Proceedings of the 2002 Winter Simulation Conference.

Case data. (2021). *Data from the case study, acquired through an Excel information request via the case study experts.* Anonymous authors and data.

Chandra Mouli, G. R., Bauer, P., & Zeman, M. (2016). System design for a solar powered electric vehicle charging station for workplaces. *Applied Energy*, *168*, 434–443. https://doi.org/10.1016/j.apenergy.2016.01.110

Chatterji, E., & Bazilian, M. D. (2020). Smart Meter Data to Optimize Combined Roof-Top Solar and Battery Systems Using a Stochastic Mixed Integer Programming Model. *IEEE Access*, *8*, 133843–133853. https://doi.org/10.1109/ACCESS.2020.3010919

DAF. (2022). *DAF CF ELECTRIC*. Retrieved 10 June 2022, from https://www.daf.com/en/about-daf/sustainability/alternative-fuels-and-drivelines/battery-electric-vehicles/daf-cf-electric

Dai, Q., Liu, J., & Wei, Q. (2019). Optimal Photovoltaic/Battery Energy Storage/Electric Vehicle Charging Station Design Based on Multi-Agent Particle Swarm Optimization Algorithm. *Sustainability*, *11*(7), Article 7. https://doi.org/10.3390/su11071973

Das, A. (2022, April 4). *K-Medoid Clustering (PAM)Algorithm in Python*. Medium. https://towardsdatascience.com/k-medoid-clustering-pam-algorithm-in-python-with-solved-example-c0dcb35b3f46

Della Croce, F., Tadei, R., & Volta, G. (1995). A genetic algorithm for the job shop problem. *Computers & Operations Research*, *22*(1), 15–24. https://doi.org/10.1016/0305-0548(93)E0015-L

Domínguez-Muñoz, F., Cejudo-López, J. M., Carrillo-Andrés, A., & Gallardo-Salazar, M. (2011). Selection of typical demand days for CHP optimization. *Energy and Buildings*, *43*(11), 3036–3043. https://doi.org/10.1016/j.enbuild.2011.07.024

Dyba, T., & Dingsoyr, T. (2009). What Do We Know about Agile Software Development? *IEEE Software*, *26*(5), 6–9. https://doi.org/10.1109/MS.2009.145

Earl, T., Mathieu, L., Cornelis, S., Kenny, S., Ambel, C. C., & Nix, J. (2019). *Analysis of long-haul battery electric trucks in EU*. 22.

EnelX. (2022). *JuicePump 175kW Commercial Charging Station ✓Learn More*. Retrieved 10 June 2022, from https://evcharging.enelx.com/store/commercial/juicepump-175kw

ENF. (2022). *Cell Solar Energy Co., Limited Solar Panel Series PERC Mono 360-380W/72 Cell. Detailed profile including pictures, certification details and manufacturer PDF*. Retrieved 10 June 2022, from https://www.enfsolar.com/pv/panel-datasheet/crystalline/43777

EPEX SPOT. (2021). *Day-Ahead Market Prices*. https://www.epexspot.com/en

Esfandyari, A., Norton, B., Conlon, M., & McCormack, S. J. (2015). *The Battery Energy Storage System (BESS) design option for on-campus Photovoltaic Charging Station (PV-CS)*. 1700–1709. Scopus. https://doi.org/10.18086/swc.2015.01.02

Fathabadi, H. (2018). Novel battery/photovoltaic hybrid power source for plug-in hybrid electric vehicles. *Solar Energy*, *159*, 243–250. https://doi.org/10.1016/j.solener.2017.10.071

Ferguson, B., Nagaraj, V., Kara, E. C., & Alizadeh, M. (2018). Optimal Planning of Workplace Electric Vehicle Charging Infrastructure with Smart Charging Opportunities. *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 1149–1154. https://doi.org/10.1109/ITSC.2018.8569299

Feuerriegel, S., & Neumann, D. (2014). Measuring the financial impact of demand response for electricity retailers. *Energy Policy*, *65*, 359–368. https://doi.org/10.1016/j.enpol.2013.10.012

Fowler, M. (1997). *Analysis Patterns: Reusable Object Models*. Addison-Wesley Professional.

Gearhart, J. L., Adair, K. L., Durfee, J. D., Jones, K. A., Martin, N., & Detry, R. J. (2013). *Comparison of open-source linear programming solvers.* (No. SAND2013-8847). Sandia National Lab. (SNL-NM), Albuquerque, NM (United States). https://doi.org/10.2172/1104761

Golpîra, H., Rehman Khan, S. A., & Zhang, Y. (2018). Robust Smart Energy Efficient Production Planning for a general Job-Shop Manufacturing System under combined demand and supply uncertainty in the presence of grid-connected microgrid. *Journal of Cleaner Production*, *202*, 649–665. https://doi.org/10.1016/j.jclepro.2018.08.151

Gustafsson, J. (2017). *Single case studies vs. Multiple case studies: A comparative study*. 15.

Hall, D., & Lutsey, N. (2019). Estimating the infrastructure needs and costs for the launch of zero-emission trucks. Int. Counc. Clean Transp, 1-31.

Hendriks, E. (1992). *Framework for energy consumption monitoring and control behind the meter. An inventory. Raamwerk energieverbruiksmeting en sturing achter de meter. Inventarisatie*. https://www.osti.gov/etdeweb/biblio/6933596

Hermans, L. M., & Thissen, W. A. H. (2009). Actor analysis methods and their use for public policy analysts. *European Journal of Operational Research*, *196*(2), 808–818. https://doi.org/10.1016/j.ejor.2008.03.040

Hildreth, L., & Kildegaard, A. (2009). Avoided demand charges and behind-the-meter wind: Insights from an application at the University of Minnesota. *Wind Energy*, *12*(4), 363–374. https://doi.org/10.1002/we.298

Hoarau, Q., & Perez, Y. (2018). Interactions between electric mobility and photovoltaic generation: A review. *Renewable and Sustainable Energy Reviews*, *94*, 510–522. https://doi.org/10.1016/j.rser.2018.06.039

IBM. (2022). *ILOG CPLEX Optimization Studio | IBM*. https://www.ibm.com/products/ilog-cplex-optimization-studio

Islam, M. S., Mithulananthan, N., & Lee, K. Y. (2018). Suitability of PV and Battery Storage in EV Charging at Business Premises. *IEEE Transactions on Power Systems*, *33*(4), 4382–4396. https://doi.org/10.1109/TPWRS.2017.2774361

Kleijnen. J.P.C. (1995). Verification and validation of simulation models. European Journal of Operational Research, 82 (1) (1995)

Klopper, R., Lubbe, S., & Rugbeer, H. (2007). The Matrix Method of Literature Review. *Alternation*, *14*(1), 262–276.

Koffrie, R. (2020). *DKTI-inventarisatie 0-emissie inzamelvoertuigen _ geleerde lessen en voorlopige conclusies*. TNO.

Koornneef, G.J. (2020). *DKTI lessons learned so far*. Retrieved 27 May 2022, from https://docplayer.nl/189308266-Dkti-lessons-learned-so-far-1-juli-2020-gertjan-koornneef.html

Kostopoulos, E. D., Spyropoulos, G. C., & Kaldellis, J. K. (2020). Real-world study for the optimal charging of electric vehicles. *Energy Reports*, *6*, 418–426. https://doi.org/10.1016/j.egyr.2019.12.008

Kuhlman, D. (2011). *A Python Book: Beginning Python, Advanced Python, and Python Exercises*. Platypus Global Media.

Lee, D.-Y., Thomas, V.M., Brown, M.A. (2013). Electric urban delivery trucks: energy use, greenhouse gas emissions, and cost-effectiveness. Environ. Sci. Technol., 47 (14) (2013), pp. 8022-8030

Li, B., Basu, S., Watson, S. J., & Russchenberg, H. W. (2020, September). Quantifying the predictability of a 'Dunkelflaute'event by utilizing a mesoscale model. In *Journal of Physics: Conference Series* (Vol. 1618, No. 6, p. 062042). IOP Publishing.

Liu, G., Xue, Y., Chinthavali, M. S., & Tomsovic, K. (2020). Optimal Sizing of PV and Energy Storage in an Electric Vehicle Extreme Fast Charging Station. *2020 IEEE Power Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, 1–5. https://doi.org/10.1109/ISGT45199.2020.9087792

Liu, J., & Dai, Q. (2020). Portfolio Optimization of Photovoltaic/Battery Energy Storage/Electric Vehicle Charging Stations with Sustainability Perspective Based on Cumulative Prospect Theory and MOPSO. *Sustainability*, *12*(3), Article 3. https://doi.org/10.3390/su12030985

Masmoudi, O., Delorme, X., & Gianessi, P. (2019). Job-shop scheduling problem with energy consideration. *International Journal of Production Economics*, *216*, 12–22. https://doi.org/10.1016/j.ijpe.2019.03.021

Mazzeo, D. (2019). Nocturnal electric vehicle charging interacting with a residential photovoltaic-battery system: A 3E (energy, economic and environmental) analysis. *Energy*, *168*, 310–331. https://doi.org/10.1016/j.energy.2018.11.057

Mazzeo, D., Baglivo, C., Matera, N., Congedo, P. M., & Oliveti, G. (2020). Impact of climatic conditions of different world zones on the energy performance of the photovoltaic-wind-battery hybrid system. *IOP Conference Series: Earth and Environmental Science*, *410*, 012044. https://doi.org/10.1088/1755-1315/410/1/012044

McKinney, W. (2012). *Python for Data Analysis: Data Wrangling with Pandas, NumPy, and IPython*. O'Reilly Media, Inc.

Meindl, B., & Templ, M. (2013). *Analysis of commercial and free and open-source solvers for linear optimization problems*.

Melendez, K. A., Das, T. K., & Kwon, C. (2020). Optimal operation of a system of charging hubs and a fleet of shared autonomous electric vehicles. *Applied Energy*, *279*, 115861. https://doi.org/10.1016/j.apenergy.2020.115861

Mirhoseini, P., & Ghaffarzadeh, N. (2020). Economic battery sizing and power dispatch in a grid-connected charging station using convex method. *Journal of Energy Storage*, *31*, 101651. https://doi.org/10.1016/j.est.2020.101651

Mitchell, S., Consulting, S. M., & Dunning, I. (2011). *PuLP: A Linear Programming Toolkit for Python*.

Mitre. (2013). *Verification and Validation of Simulation Models*. https://www.mitre.org/publications/systems-engineering-guide/se-lifecycle-building-blocks/other-se-lifecycle-building-blocks-articles/verification-and-validation-of-simulation-models

Modarresi Ghazvini, A., & Olamaei, J. (2019). Optimal sizing of autonomous hybrid PV system with considerations for V2G parking lot as controllable load based on a heuristic optimization algorithm. *Solar Energy*, *184*, 30–39. https://doi.org/10.1016/j.solener.2019.03.087

Mohseni, S., & Moghaddas-Tafreshi, S. M. (2018). A multi-agent system for optimal sizing of a cooperative self-sustainable multi-carrier microgrid. *Sustainable Cities and Society*, *38*, 452–465. https://doi.org/10.1016/j.scs.2018.01.016

Mongird, K., Viswanathan, V., Alam, J., Vartanian, C. & Sprenkle, V. (2020). 2020 grid energy storage technology cost and performance assessment. PNNL. US Dep. Energy. Retrieved 14 November, from https://www.pnnl.gov/sites/default/files/media/file/Final%20-%20ESGC%20Cost%20Performance%20Report%2012-11-2020.pdf

National Grid. (2022). *How does solar power work? | National Grid Group.* Retrieved 14 November 2022, https://www.nationalgrid.com/stories/energy-explained/how-does-solar-power-work

Netbeheer Nederland. (2022). Capaciteitskaart Afname en voeding in Nederland. Retrieved 14 November, from https://capaciteitskaart.netbeheernederland.nl

O'Shaughnessy, E., Cutler, D., Ardani, K., & Margolis, R. (2018). Solar plus: Optimization of distributed solar PV through battery storage and dispatchable load in residential buildings. *Applied Energy*, *213*, 11–21. https://doi.org/10.1016/j.apenergy.2017.12.118

OECD. (2022). *Conversion rates—Purchasing power parities (PPP)—OECD Data. TheOECD*. Retrieved 14 November 2022, from http://data.oecd.org/conversion/purchasing-power-parities-ppp.htm

Orlowska, A., Chrysoulas, C., Jaroucheh, Z., & Liu, X. (2021). Programming Languages: A Usage-based Statistical Analysis and Visualization. *2021 The 4th International Conference on Information Science and Systems*, 143–148. https://doi.org/10.1145/3459955.3460614

Ottens, M., Franssen, M., Kroes, P., & Van De Poel, I. (2006). Modelling infrastructures as socio-technical systems. *International Journal of Critical Infrastructures*, *2*(2–3), 133–145. https://doi.org/10.1504/IJCIS.2006.009433

Overheid, M. van B. Z. en. (2022). *Begrippencode elektriciteit* [Zbo]. Retrieved 15 June 2022, from https://wetten.overheid.nl/BWBR0037938/2022-05-18

Pandey, Y. N., Rastogi, A., Kainkaryam, S., Bhattacharya, S., & Saputelli, L. (2020). Python Programming Primer. In Y. N. Pandey, A. Rastogi, S. Kainkaryam, S. Bhattacharya, & L. Saputelli (Eds.), *Machine Learning in the Oil and Gas Industry: Including Geosciences, Reservoir Engineering, and Production Engineering with Python* (pp. 41–73). Apress. https://doi.org/10.1007/978-1-4842-6094-4_2

Panteia. (2021). *Ingroeipad Zero Emission Trucks*. https://open.overheid.nl/repository/ronl-4ace3ab3-c916-4f30-aaa5-3bcd0a45d7cb/1/PDF/eindrapportage-ingroeipad-ze-trucks.PDF

Parchomiuk, M., Moradewicz, A., & Gawiński, H. (2019). An Overview of Electric Vehicles Fast Charging Infrastructure. *2019 Progress in Applied Electrical Engineering (PAEE)*, 1–5. https://doi.org/10.1109/PAEE.2019.8788983

PULP. (2022). *Optimization with PuLP — PuLP 2.6.0 documentation*. https://coin-or.github.io/pulp/

Raaijen, E. (2021). *Toepassingen van batterij energieopslag systemen*. https://www.topsectorenergie.nl/sites/default/files/uploads/Urban%20energy/Bijlages%20bij%20evenementen/Netinpassing%20-%20Evert%20Raaijen%20-%20Alfen.pdf

RAENG. (2021). *Calculating wind turbine power yield*. Royal Academy of Engineers. https://raeng.org.uk/publications/other/23-wind-turbine

Randolph, J. (2009). *A Guide to Writing the Dissertation Literature Review*. https://doi.org/10.7275/B0AZ-8T74

Rijksoverheid. (2022, June 8). *Kamerbrief congestie op het elektriciteitsnet in Limburg en Noord-Brabant—Kamerstuk—Rijksoverheid.nl* [Kamerstuk]. Ministerie van Algemene Zaken. https://www.rijksoverheid.nl/documenten/kamerstukken/2022/06/08/congestie-op-het-elektriciteitsnet-in-limburg-en-noord-brabant

Robinson, S. (2017). A tutorial on simulation conceptual modelling. *2017 Winter Simulation Conference (WSC)*, 565–579. https://doi.org/10.1109/WSC.2017.8247815

Rui, X., Nian, L., Jingyan, Y., & Yingda, Z. (2012). Multi-Objective Optimal Sizing of EV Battery-exchange Stations System with Photovoltaic Generation Using NSGA-II. In B. J. Chen, V. Hu, & D. Kong, *Electronic Information & Electrical Engineering* (Vol. 19, pp. 184–188). Atlantis Press.

RVO. (2020). *DKTI uitgelicht period 2017-2020*. https://www.rvo.nl/sites/default/files/2021/02/DKTI-Uitgelicht-2017-2020.pdf

Saltelli, A., Ratto, M., Tarantola, S., & Campolongo, F. (2006). Sensitivity analysis practices: Strategies for model-based inference. *Reliability Engineering & System Safety*, *91*(10–11), 1109–1125. https://doi.org/10.1016/j.ress.2005.11.014

Schäfer, C. (2021). Data Types, Variables, Lists, Strings, Dictionaries, and Operators. In C. Schäfer (Ed.), *Quickstart Python: An Introduction to Programming for STEM Students* (pp. 13–24). Springer Fachmedien. https://doi.org/10.1007/978-3-658-33552-6_5

Secondsol. (2022). *Mono Sharp—NUSC360 360 W*. Secondsol Der Photovoltaik Marktplatz. Retrieved 10 June 2022, from httpshttps://www.secondsol.com/en/anzeige/17167/photovoltaic-modules/monocrystalline-modules/sharp/nusc360-360-w

Statista. (2021). *Electricity prices worldwide 2021.* Statista. Retrieved 14 November 2022, from https://www.statista.com/statistics/263492/electricity-prices-in-selected-countries/

Stawska, A., Romero, N., de Weerdt, M., & Verzijlbergh, R. (2021). Demand response: For congestion management or for grid balancing? *Energy Policy*, *148*, 111920. https://doi.org/10.1016/j.enpol.2020.111920

Taryani, K. (2021, December 20). *Wind Turbine Cost: Worth the Million-Dollar Price In 2022?* https://weatherguardwind.com/how-much-does-wind-turbine-cost-worth-it/

Thacker, B. H., Doebling, S. W., Hemez, F. M., Anderson, M. C., Pepin, J. E., & Rodriguez, E. A. (2004). *Concepts of Model Verification and Validation* (p. 41).

Timmins, F., & Mccabe, C. (2005). How to conduct an effective literature search. *Nursing Standard (Royal College of Nursing (Great Britain): 1987)*, *20*, 41–47. https://doi.org/10.7748/ns2005.11.20.11.41.c4010

TLN. (2021, March 17). *Update—Nóg meer steden maken zero-emissie zone bekend*. Transport en Logistiek Nederland. https://www.tln.nl/nieuws/steeds-meer-steden-maken-zero-emissie-zone-bekend/

Ton, D. T., & Smith, M. A. (2012). The U.S. Department of Energy's Microgrid Initiative. *The Electricity Journal*, *25*(8), 84–94. https://doi.org/10.1016/j.tej.2012.09.013

Trevizan, R. D., Nguyen, T. A., & Byrne, R. H. (2020). Sizing Behind-the-Meter Energy Storage and Solar for Electric Vehicle Fast-Charging Stations. *2020 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM)*, 583–588. https://doi.org/10.1109/SPEEDAM48782.2020.9161848

Valoen, L. O., & Shoesmith, M. I. (2007). *The effect of PHEV and HEV duty cycles on battery and battery pack performance*. https://www.osti.gov/etdeweb/biblio/21007769

Vasconcellos, P.H. (2018, December 21). *Python IDE Tutorial: The Top 5 Python IDEs for Data Science*. DataCamp. https://www.datacamp.com/community/tutorials/data-science-python-ide

Virta. (2020). *AC, DC Chargers: Their EV Charging Capacities | Virta*. Retrieved 3 June 2022, from https://www.virta.global/blog/ev-charging-and-basics-of-electricity

Wang, C., Tian, L., Zhang, F., & Cheng, L. (2020). Optimal Sizing of Photovoltaic and Battery Energy Storage of Electric Vehicle Charging Station Based on Two-part Electricity Pricing. *2020 IEEE*

Sustainable Power and Energy Conference (ISPEC), 1379–1384. https://doi.org/10.1109/iSPEC50848.2020.9351007

Wang, N., Heijnen, P. W., & Imhof, P. (2020). A multi-actor perspective on multi-objective regional energy system planning. *Energy Policy*, *143*. https://doi.org/10.1016/j.enpol.2020.111578

Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly*, *26*(2), xiii–xxiii.

Worighi, I., Geury, T., El Baghdadi, M., Van Mierlo, J., Hegazy, O., & Maach, A. (2019). Optimal Design of Hybrid PV-Battery System in Residential Buildings: End-User Economics, and PV Penetration. *Applied Sciences-Basel*, *9*(5), 1022. https://doi.org/10.3390/app9051022

Yan, D., & Ma, C. (2020). Stochastic planning of electric vehicle charging station integrated with photovoltaic and battery systems. *IET Generation, Transmission & Distribution*, *14*(19), 4217–4224. https://doi.org/10.1049/iet-gtd.2019.1737

Zhang, Y.-D., Liu, N., Zhang, J.-H., & Li, Y. (2013). Optimum sizing of a stand-alone hybrid PV/wind generation system integrated with electric vehicle charging stations. *Dianli Xitong Baohu Yu Kongzhi/Power System Protection and Control*, *41*(15), 126–134. Scopus.

Zhou, T., Roorda, M.J., Maclean, H.L., Luk. J. (2017). Life cycle GHG emissions and lifetime costs of medium-duty diesel and battery electric trucks in Toronto Canada. Transp. Res. Part D, 55 (2017), pp. 91-98, 10.1016/j.trd.2017.06.019

Appendix A. Literature review table

Authors	Date	Location	Area	Use case	knap-sack	Sched-uling	Energy balance	kW max	Components	Method	Electricity price
Akram et al.	2018	Saudi Arabia	Dammam	Residential area	•		•		PV/BS/EV/WT/DG	Mixed-interger linear programming	No electricity costs, only capital infrastructure
Baik et al.	2018	South-Korea	Seoul	Commercial station	•		•		PV/BS/EV	Mixed-interger linear programming	Fixed electricity price profile
Ban et al.	2019	China	Harbin	Commercial station	•				PV/BS	Mixed-interger linear programming	No electricity costs, only capital infrastructure
Bhatti et al.	2018	Pakistan	Faisalabad	Parking lot (office)					PV/BS/EV	Particle swarm optimization	Hypothetical prices multiply parity factor
Blasius et al.	2016	Germany	Cottbus	Parking lot (university)			•		PV/BS/EV	Statistical analysis	No electricity costs, only capital infrastructure
Bracco et al.	2019	Italy	Liguria	Parking lot (general)	•	•	•	•	PV/BS/EV	Mixed-interger linear programming	Fixed prices
Chandra Mouli et al.	2016	The Netherlands	Randstad	Parking lot (office)			•		PV/BS/EV	Statistical analysis	Fixed industrial electricity price
Chatterji & Bazilian.	2020	USA	Potomac	Residential area	•		•		PV/BS/EV	Mixed-interger linear programming	Fixed/flat tariff, TOU tariff
Dai et al.	2019	China	Shanghai	Commercial station			•	•	PV/BS/EV	Multi-actor particle swarm optimization	Internal price modelling
Esfandyari et al.	2015	Ireland	Dublin	Parking lot (university)					PV/BS/EV	Statistical analysis	No electricity costs, only capital infrastructure
Fathabadi.	2018	Non specific	Non specific	Not applicable					PV/BS/EV	Simulink & prototype	Not applicable
Ferguson et al.	2018	USA	California	Parking lot (office)		•	•		EV	Cost-benefit analysis	Historical dynamic prices
Golpîra et al.	2018	Non specific	Non specific	Not applicable		•	•		BS/WT	Mixed-interger linear programming	Varying electricity fixed prices
Islam et al.	2018	Australia	Queensland	Parking lot (university)			•		PV/BS/EV	Suitability analysis	Internal price modelling
Liu & Dai.	2020	China	Southern area	Commercial station					PV/BS/EV	Multi-objective particle swarm optimization	Only cost constraint
Liu et al.	2020	USA	Oak ridge	Residential area	•		•	•	PV/BS/EV	Mixed-interger linear programming	Fixed electricity price profile
Mazzeo et al.	2020	Worldwide	Worldwide	Not applicable			•		PV/BS/WT	Scenario simulation	Not applicable
Mazzeo.	2018	Italy	Cosenza	Residential area			•		PV/BS/EV	Feasibility analysis	Average hourly cost of electricity
Melendez et al.	2020	USA	Tampa	Not applicable	•	•	•		PV/BS/EV	Mixed-interger linear programming	Historical day-ahead market electricity prices
Mirhoseini & Ghaffarzadeh.	2020	Iran	Qazvin	Commercial station	•	•	•	•	PV/BS/EV	Mixed-interger linear programming	Fixed electricity price profile
Modarresi & Olamaei.	2019	Saudi Arabia	Yanbu	Commercial station	•		•		PV/BS/EV/DG	Linear programming	Fixed electricity price profile
Mohseni & Moghaddas	2018	Iran	Hendurabi island	Residential area					PV/BS/EV	Multi-actor particle swarm optimization	Fixed electricity price
O'Shaughnesy et al.	2018	USA	Hawaii	Residential area					PV/BS	ReOpt linear progragmming	Reference electricity costs escalated
Riu et al.	2012	China	Beijing	Commercial station	•		•		PV/BS	Non-dominated sorting genetic algorithm	Fixed electricity price profile
Trevizan et al.	2020	USA	Los Angeles	Commercial station					PV/BS/EV	Linear programming	seasonal and TOU electricity price profile
Wang et al.	2020	China	Beijing	Commercial station	•	•	•		PV/BS/EV	Linear programming	Internal TOU price modelling
Worighi et al.	2019	Belgium	Brussels	Residential area					PV/BS	Fuzzy logic controller	Fixed TOU electricity prices
Yan & Ma.	2020	China	Shanghai	Commercial station			•		PV/BS/EV	Non-convex linear programming	Fixed electricity price profile
Zhang et al.	2013	China	Beijing	Commercial station					PV/EV/WT	Differential evolution algorithm	Fixed electricity price profile
This thesis	2022	The Netherlands	Grid congested	Distribution center	•	•	•	•	PV/BS/EV/WT	Mixed-interger linear programming	Historical day-ahead market electricity prices

Appendix B. Programming choices

After the choice is made to use MILP to solve the problem and the mathematical formulation is worked out, several other decisions need to be made to implement and solve the MILP problem. These choices concern the solver to use, the software or programming language to write the problem in, and the environment to use. The options, pros and cons and final decisions for each choice will be detailed.

For linear programming a multitude of solvers have been developed which can be divided in free or open-source solvers and commercial solvers. The main free solvers are GLPK, LP_SOLVE, CLP, SCIP and SoPlex (Meindl & Templ, 2012). The advantage of free or open-source solvers is that they can be used at no cost. Open-source solvers can also be managed and improved upon by the concerned community. The disadvantage of free solvers is that they are often less powerful and take longer to solve problems (Gearhart et al., 2013; Meindl & Templ, 2012). The main commercial solvers are CPLEX, Xpress and Gurobi. The advantages of commercial solvers are that they are powerful and faster than free solvers. A study by Gearhart et al. (2013) found that no open-source solver could outperform CPLEX for example, which shows the power that these commercial solvers have. The software behind commercial solvers is more reliable and the companies behind the software can offer more support than is available for free solvers. The disadvantage of commercial solvers is that they are expensive to acquire for companies. Luckily academic licenses are available for Gurobi and CPLEX, making them free of charge for academic use. Analysis by Meindl and Templ (2012) shows that again the performance of the commercial solvers far surpasses the performance of free solvers. The performance of Gurobi and CPLEX are similar. CPLEX is designed to tackle large scale mixed integer problems, such as the problem at hand, and the academic license is easier to acquire, thus CPLEX is chosen as the main solver for this research. With open-source solvers the code is released to the public domain, which means that the solvers can be used in any software without any restrictions, making it possible to compile the solvers on different platforms and architectures (Meindl & Templ, 2012). With commercial solvers the available options are dependent on what the developing company offers. The CPLEX solver is currently developed by IBM and offered through its own proprietary software, IBM ILOG CPLEX Optimization Studio (IBM, 2022). The software however offers several application interfaces (API) making it possible to use the solver in different programming languages and programs (Meindl & Templ, 2012).

That programming language that the problem will be written in is Python. Python is one of the most popular programming languages right now (Orlowska et al., 2021). Previous experience with the language, its ease of use and the supportive packages available are the reasons for this decision. Python is a high-level, open source, object-oriented programming language, with the use of significant indentation and clarity in syntax, making programming in python more forgiving and easier to read (Kuhlman, 2011; Mitchell et al., 2011). CPLEX also offers an API for python to connect to the solver (IBM, 2022; Meindl & Templ, 2012). Code is often written in an integrative development platform (IDE). IDEs are tools that improve the writing, testing and debugging of code, by offering code completion, highlighting and debugging (Vasconcellos, 2018). The IDE of choice is one recommended by Vasconcellos (2018), namely Jupyter Notebook. Jupyter facilitates a structured way of coding and data visualization directly in its notebooks, allowing for continuous and accurate data analysis. Python doesn't facilitate intuitive writing of linear programming problems directly, but because Python is open source a lot of packages are developed and released for it, so too for linear programming (Mitchell et al., 2011). Packages in Python are a collection of modules that together offer functionality in a condensed, sort of black box, format (Kuhlman, 2011). The package that will be used for linear programming in python is PuLP. PuLP prescribes a specific, textual and intuitive way of writing the linear programming problem, after which it converts to the raw, mathematical formulation, which is needed for the solver to be able to interpret it (Mitchell et al., 2011).

Appendix C. Component characteristics and costs

C.1. Component characteristics

Even though the PV and WT power flows and BS and EV power levels were earlier defined as decision variables, the model does not consider them as such but more as indirectly influenced by the other decision variables. The power flows for PV and WT calculated by

$$P_{m,t}^{PV} = x^{PV} \cdot \eta_{m,t}^{PV} \cdot I_{m,t} \cdot A^{PV} \cdot R^{PV}, \ \forall\, m \in M, t \in T, \tag{1}$$

$$P_{m,t}^{WT} = x^{WT} \cdot \frac{1}{2} \cdot \eta_{m,t}^{WT} \cdot A^{WT} \cdot \rho^{air} \cdot v^3, \ \forall\, m \in M, t \in T, \tag{2}$$

are mostly dependent on the decision variables $x^{PV}$and x^{WT}, denoting how many units of each technology are installed respectively. In equation 1 $\eta_{m,t}^{PV}$ represents the efficiency of the solar panels, $I_{m,t}$ the irradiation of the sun, A^{PV} the surface area of the solar panel and $R^{PV}$the performance ratio of the whole PV installation. In equation 2 $\eta_{m,t}^{WT}$ represents the efficiency of the wind turbine(s), A^{WT} the area swept by the rotor and ρ^{air} and v the density and velocity of the air.

C.2. Component costs

Because the model does not run for the whole lifetime of the infrastructural components, the purchase and installation costs should be amortized over the lifetime of the asset, after which the costs for the first year can be considered. Of course, costs are made in the following years as well, but the utility of the assets is then also experienced. The annualization factor based on amortization formulae can be seen in equation 4, in which r is the discount rate and L^i the lifetime of asset i.

$$\omega^i = r(1+r)^{L^i} / ((1+r)^{L^i} - 1). \tag{4}$$

The total costs for the infrastructural components like the solar installation, wind installation, battery systems and charging stations are calculated quite comparable. The capital C with a capital I subscript are the purchase and installation cost of the asset. Only for the charging stations these costs are a fixed amount which is multiplied with the annualization factor. For the other components the purchase and installation cost are taken as €/kW(h) and multiplied with the rated power W or capacity, after which these costs are also multiplied with the annualization factor. The maintenance costs C^M are based per year. The total cost per unit of a component is finally multiplied with the amount of units the model wants to install, denoted by the decision variables x.

$$C^{PV,tot} = x^{PV}(\omega^{PV} \cdot C^{PV,I} \cdot W^{PV,I} + C^{PV,M}); \tag{5}$$

$$C^{WT,tot} = x^{WT}(\omega^{WT} \cdot C^{WT,I} \cdot W^{WT,I} + C^{WT,M}); \tag{6}$$

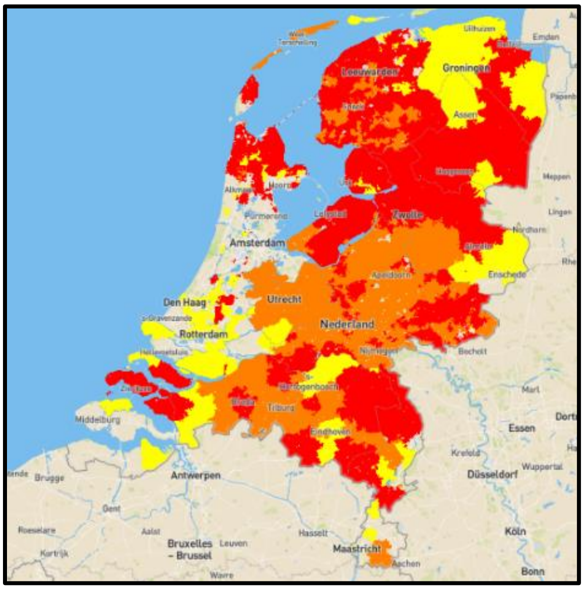
$$C^{BS,tot} = x^{BS}(\omega^{BS} \cdot C^{BS,I} \cdot CAP^{BS} + C^{BS,M}); \tag{7}$$

$$C^{CS,tot} = x^{CS}(\omega^{CS} \cdot C^{CS,I} + C^{CS,M}); \tag{8}$$

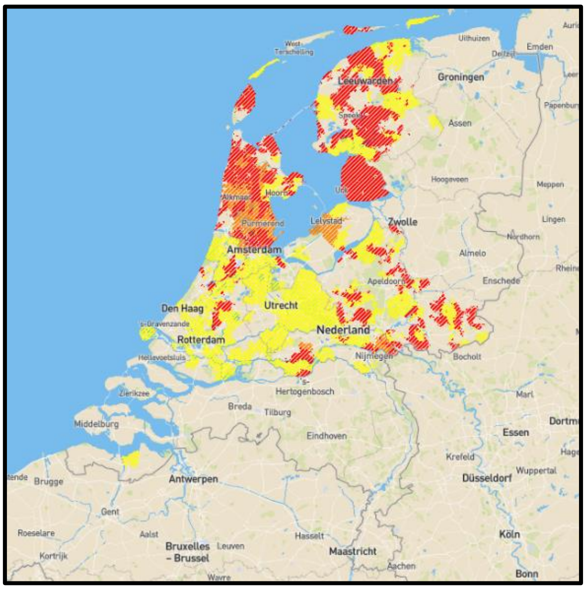
$$C^{PG,tot} = x^{PG} \cdot C^{PG,I} + K \cdot \sum_{m=1}^{M} \sum_{t=1}^{T} \Delta t \left(P_{m,t}^{PG,abs} \cdot p_{m,t}^{buy} - P_{m,t}^{PG,inj} \cdot p_{m,t}^{sell}\right). \tag{9}$$

The total costs for the power grid calculated in equation 5 consists firstly of the amount stepwise increases in the grid connection the model wants to install, times the installation cost per such a step. Secondly, all the power that is absorbed from the grid is summed and multiplied with the buy price and all the power that is injected into the grid is summed and multiplied with the sell price. These costs and profits are multiplied with K, which represents the mean number of days in a month, to stretch the profit/costs of the 12 typical days across the whole year. Factor K is important as it makes the final cost calculations more realistic, and it also enables the investments to earn themselves back more, otherwise the yearly costs of a component will not earn itself back in 12 days.

Appendix D. Congestion maps



Regional grid supply congestion



Regional grid demand congestion

Appendix E. Case data & model formulas (confidential)

All the data from the case study and the formulas of the mathematical model were consolidated in this confidential appendix. As not everybody can just have access to this data unfortunately the contents of this appendix will not be shown in the public version of this thesis. If you have any questions in regards to the part of the model that is deemed confidential you can try to contact Recoy B.V.

Appendix F. Structure model code

On the highest level there is the structure of the code itself. Instead of a single, continuous code file Jupyter Notebook works with code blocks or cells, which can be run individually. Code needs to be written sequentially, meaning that variables, constants and input values need to be defined before they can be used in equations of functions. On the lower level there is the structure of the data captured in the code. Data structures like lists, series and dictionaries can be used.

F.1. Structure of the code

First the necessary packages are imported and the connection to the solvers API is established. Secondly the necessary data files are loaded in the modelling horizon characteristics are set. Before the model is written first the external and internal input values are defined, from the loaded data files, case study data and literary sources. Then the decision variables can be defined in the PuLP syntax and the intermediary calculations can be written. The objective function and constraints are the defined in the PuLP syntax as well. Finally, the solver is called to acquire the results, automatic error tests are implemented, and the results are visualized.

F.2. Structure of the data

There are several types of data collection formats that are used within Python with pros and cons, but also specific use-cases. Here is a comparison by Kuhlman (2011) of the different types of collection in python and their characteristics:

- String: ordered, characters, immutable,
- Tuple: ordered, heterogeneous, immutable,
- List: ordered, heterogeneous, mutable,
- Dictionary: unordered, key/values pairs, mutable,
- Set: unordered, heterogeneous, mutable, unique values.

As we need a mutable data collection format that can store numeric values, the choice is between lists and dictionaries. A set data structure is not applicable as the values that will be used are not necessarily unique. A list is a series of items that can be indexed, appended and performed calculations on. Dictionaries are a collection of key-value pairs. These key-value pairs can also be appended and with dictionaries specific key-value pairs can be called and performed calculations on (Kuhlman, 2011; Pandey et al., 2020; Schäfer, 2021). Dictionaries work as follows:

```
dictionary = {}

dictionary[key] = value

print(dictionary[key])
```

In the first line of code a dictionary, indicated by the curly brackets, with the name dictionary is created. In the second line a key-value pair is added to the dictionary. Square brackets are used to specify a certain key. In the third line the specific dictionary key is called, and the value printed. Dictionaries can also be nested, essentially a dictionary within a dictionary:

```
dictionary[key_1] = {}

dictionary[key_1][key_2] = value

print(dictionary[key_1][key_2])
```

This is especially useful if a data collection has multiple indices. In this research not only is data associated with time but also with a specific vehicle. So, a dictionary can be created in which the first key is $v \in V$, and for every v there is a nested dictionary with the second key being $t \in T$ (Pandey et al., 2020). To write equations that are performed for every key-value pair in a dictionary, for loops can be used to iterate over all key-value pairs:

```
for key_1, value in dictionary:
       for key_2, value in dictionary[key_1]:
              new_dictionary[key_1][key_2] = dictionary[key_1][key_2] * 2
new_dictionary[key_1][key_2] = dictionary[key_1][key_2] * other_dictionary[key_1][key_2]
```

The first loop iterates over every key_1, while the second loop iterates over every key_2 for each key_1 exclusively. New nested dictionaries can be created with the same indices, while the values of a nested key can be multiplied by constants or with other dictionaries with the same indices. With this approach in calculations, the interactions of the values of the time periods will be with the corresponding ones between dictionaries. How this approach is used to implement the mathematical model in Python will be explained in the next subchapter.

F.4. Initializing the model

To run the model, first the required packages need to be imported and the model horizon characteristics need to be set. Besides the PuLP package, Matplotlib is used for data visualization and Numpy and Pandas are widely used data analysis packages (McKinney, 2012).

```
In[1]: import pandas as pd
import matplotlib.pyplot as plt
import pulp as pl
import numpy as np
In[2]: pl.listSolvers(onlyAvailable = True)
solver = pl.apis.CPLEX_CMD(mip = True, msg = True, gapRel = 0.10, gapAbs = 0.05, timeLimit = None)
```

PuLP is abbreviated to 'pl' in the model and used in the second code cell, indicated by the second input tag 'In[2]', to connect to the CPLEX solver. Here the characteristics of the solver can be specified. The model's horizon characteristics also need to be specified.

```
In[3]: days = 12
hours = range(days * 24)
SufficientlyLarge = 10000
vehicles = range(1,101)
vehicle_schedules = len(vehicles) * 3
K = 30.437 # mean days in a month
```

Modelling horizon characteristics pertain to the scope or boundaries of the simulation, in this case the timeframe and the number of vehicles. By specifying this at the top of the model the modelling horizon can be easily changed for different running different scenarios.

F.5. Defining the input values

The input values can roughly be divided in external and internal values; internal if they are within control and external if they are outside of control. The extraneous input values mostly concern meteorological data, but also the electricity market prices and the distribution center kWh meter data. All this data was consolidated in an Excel file and loaded in using Pandas.

```
In[4]: xl = pd.ExcelFile(r"C:\Users\Christiaan\Documents\thesis\input_data.xlsx")

input_data = xl.parse('input_data')

In[10]: GHI = dict(zip(hours, input_data.iloc[0:1 + len(hours), 6]))
```

From the loaded Excel file data columns are selected and immediately made into a dictionary with the hours as index. The data in the Excel file is over a longer period, so the time period specified decides the length of the column that is selected.

```
In[12]: PV_dr = 0.08 # discount rate

PV_life = 25 # useful lifetime

PV_cr = (PV_dr * (1 + PV_dr) ** PV_life) / (-1 + (1 + PV_dr) ** PV_life)

PV_purchase = 800 # purchase and installation costs per kW
```

The intraneous input values can simply by defined in the model, as partly shown above for the photovoltaic installation. The exact input values will be discussed in chapter x.

F.6. Defining the decision variables

For the definition of the decision variables the exact syntax that PuLP prescribes should be used. Documentation can be found on the PuLP (2022) website. In the model static and dynamic decision variables are used, dynamic meaning that a specific decision variable acts in every time period. Dictionaries are used to give these dynamic decision variables their time index, for which PuLP has a designated function.

```
In[25]: PG = pl.LpVariable('PG', lowBound = 0, cat = 'Integer')

PG_abs = pl.LpVariable.dicts('PG_abs', hours, lowBound = 0, cat = 'Continuous')

for v in vehicles:

CS_power[v] = pl.LpVariable.dicts('CS_power' + str(v), hours, lowBound = 0, cat =
'Continuous')
```

The decision variables are specified with a name, boundaries, possible index for dictionary decision variables and with a value category, either continuous, integer or binary. For the charging decision variables first a loop over the vehicles is used, after which a nested dictionary is created.

F.7. Intermediary calculations

Intermediary calculations pertain to calculations that are specified after the decision variables are defined, but before the objective function and constraints are defined. The intermediary calculations specify the framework of interactions between the variables and input values, over which the solver calculates the objective functions, adhering to the constraints. One example of intermediary calculations is that of the SOC of the EVs. The SOC of the BS is calculated in a similar way.

```
In[35]: EV_soc = {}

for v in vehicles:

            EV_soc[v] = {}

for key in sorted(EV_delta[v]):

if key != 0:
```

```
EV_soc[v][key] = EV_delta[v][key] + EV_soc[v][key - 1]
            else:
EV_soc[v] = {key: value + EV_capacity for key, value in EV_delta[v].items()}
```

First the dictionary for the EV SOC is created, after which the loop iterates over every vehicle. Then a nested dictionary and a loop over the sorted keys of EV_delta are created, iterating over the chronological time index. EV_delta is dictionary where for every hour the charging power is added, and the transportation demand subtracted. The IF statement states that if it is not the first time period, the EV SOC is the SOC of the EV of the previous time period plus the EV delta, as detailed in equation x. However, if it is the first time period the capacity of the EVs and the EV delta are added, to simulate the fact that the EVs start with a full battery.

F.8. Defining the objective function and the constraints

After all the variables are defined and the whole framework of interactions is written, finally the core of the (mixed-integer) linear programming model can be defined. First the objective, to minimize the or maximize is specified. Then the objective function, the sum of all costs, is expressed.

```
In[50]:model = pl.LpProblem("total_costs", pl.LpMinimize)
model += pl.lpSum(PV_cost + WP_cost + BS_cost + CS_cost + PG_cost + EV_cost)
model += PV * PV_surface <= PV_maxsurface
for v in vehicles:
for h in hours:
model += EV_soc[v][h] <= EV_capacity
```

An example of a static constraint as well as a dynamic constraint, which holds for every time period and every vehicle, is given. In the full model a lot more constraints are specified and used, but the examples give an idea of the full model and the PuLP syntax that is essential to use.

F.9. Verification of the model

During the development of the individual modules of the model it was continuously checked if the outputs were reasonable. Previously acquired knowledge or data found in references was for example used to check if the yield of the solar installation or wind turbines was calculated realistically. If the outputs of a module seemed unreasonable, the calculations were thoroughly checked to find the error. After rectification of these errors some checks were coded into the module to output an error message if the error were to occur again. This was especially useful when the different modules were integrated, as this could bring back bugs previously present in the model.

```
In[82]:for h in hours:
if PG_inj[h].varValue * PG_abs[h].varValue != 0:
print("{}{}".format('Error: Coincident in- & outflow PG at h =', h))
```

This code block automatically checks if there is now simultaneous absorption from and injection to the power grid in the same time period. If one of them is zero the if condition is not triggered, but if both of them are non-zero the result is non-zero and the error message with the time period of occurrence is printed. More of these automatic tests were written and included in the complete model, and the outputs of every module individually and together were checked on reasonability.

Appendix G. Graphs other scenarios

G.1. Results scenario 1.2.

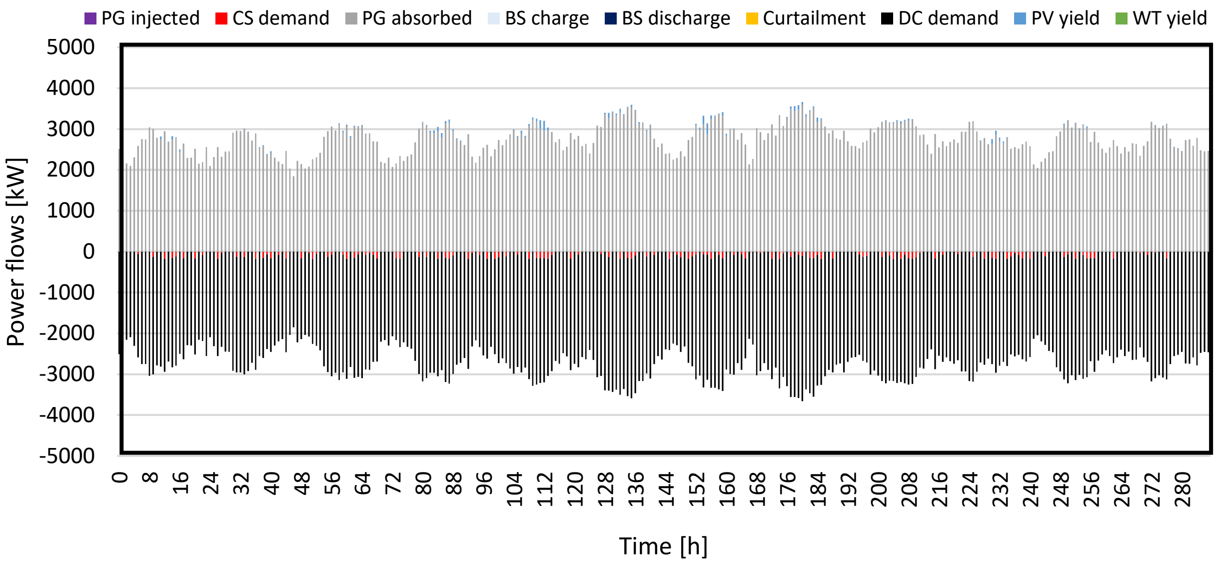


Figure G1. Power flows of the distribution centre's system in subscenario 1.2.

G.2. Results scenario 2.2.

In the second scenario 60 e-trucks need to be facilitated, increasing the total costs and number of infrastructural components required, giving insight into the preparations that need to be done for the intermediate step in the electrification process around 2025. The objective value or total cost for the simulated year is 2886235, which is 12% higher than in scenario 1.2. In scenario 2.2 the costs consist for 96% of electricity costs and thus for 4% of infrastructural component costs. In the second scenario 4 charging stations are required and 2617 PV panels, meaning 3 more charging stations and 1623 more PV panels are necessary compared to scenario 1.2. No wind turbines or battery storage are determined profitable in this scenario as well. The maximum constraint on the number of PV panels is still inactive. The effects of infrastructural components on the operational power flows can be seen in figure G2.

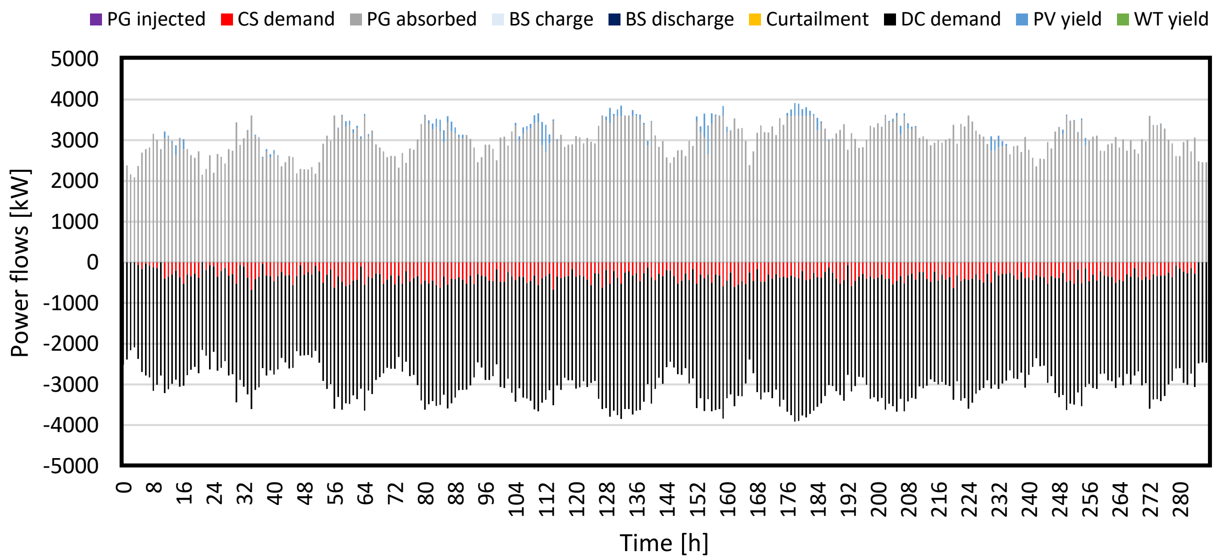


Figure G2. Power flows of the distribution centre's system in scenario 2.2

The charging demand with 60 e-trucks constitutes for 13% of the total power demand and shows significant effect on the infrastructural components required and the extensivity of the smart scheduling in the operation. More PV panels are used to supply the additional power required above the kWmax to charge the e-trucks. It can be seen in figure G2 that from period 130 to 136 and 176 to 183 the full capacity up to the kWmax is used to buy electricity for continuous periods of time, with multiple other points in the simulation were the kWmax is also incidentally reached. The periods of time were the kWmax is continuously reached are indicative of the smart scheduling operations by the model, as it tries to spread the charging demand over the time and use all capacity that is available. If it didn't spread the charging demand around, it would be more variable and higher demand peaks would occur, requiring the installation of more generation components. In the previous scenario peak total demand was caused by high demand of the DC and simultaneously necessary charging demand of an e-truck. In this scenario peak demand can also be caused by a group of e-trucks with small charging windows of a few time periods, if those charging windows coincide with a few time periods of high DC power demand. Even if the model spreads the charging demand out in the charging windows, the total charging demand in those few time periods can exceed the total charging capacity available between the high DC power demand and the kWmax.

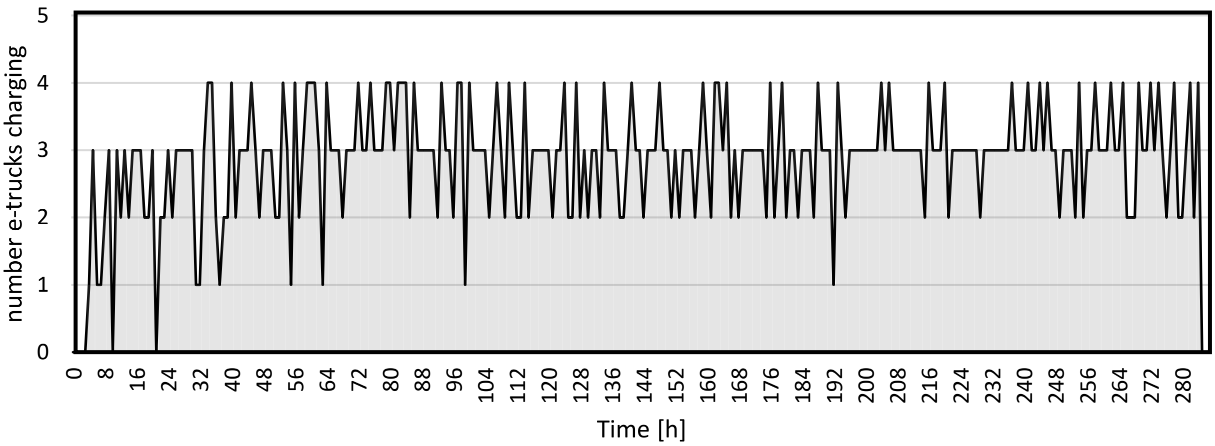


Figure G3. This graph shows the number of e-trucks that is simultaneously charging per time period and consequently how many of the charging stations are active in scenario 2.2 in each time period.

Instead of zooming in on the charging activity of a single e-truck, by looking at the charging activity of all charging stations the extend of the smart scheduling can be seen, making it possible to facilitate 60 e-trucks with only 4 charging stations. Figure G3 shows that at all times 2 charging stations are active. A third charging station is active most of the time and the fourth one for halve of the time. If the charging was not scheduled smartly by the model, considers both the charging station cost and the available power capacity, and the e-trucks would be charged directly after their return to the DC, then the number of charging stations required and power demand peaks would be higher. The model does assume that there are always people available to switch the e-truck that are connected to the charging stations. In reality the shunting of e-trucks is not always possible, and the DC has other operational requirements. This will be discussed more in the discussion.

G.3. Results scenario 2.3

Scenario 2.3 is identical to scenario 2.2 in the facilitation of 60 e-trucks and while the only difference is that the fixed electricity price is replaced by hourly DAM electricity prices, the effect of the electricity price variability is visible in the recommended infrastructure composition. In scenario 2.3 the same number of charging stations as in scenario 2.2 are necessary with 4 pieces. However, instead of installing 2617 PV panels the model installs 2 battery modules, for a total capacity of 200 kWh, to handle the charging demand in excess of the kWmax at t=180. In scenario 2.2 the installation of PV panels to handle this peak demand was more cost-effective, as the power yield could be used in other time periods as well. In scenario 2.3 the installation of battery storage allows the model to handle peak demand, but also utilize arbitrage possibilities as can be seen in figure G4, charging when the DAM electricity prices are low and discharging when the prices are high. Besides the operational optimization of the battery the model is also able to shift the charging demand to time periods when the electricity prices are low. This results in an objective value and total costs of 2779883, which is 4% lower than in scenario 2.2.

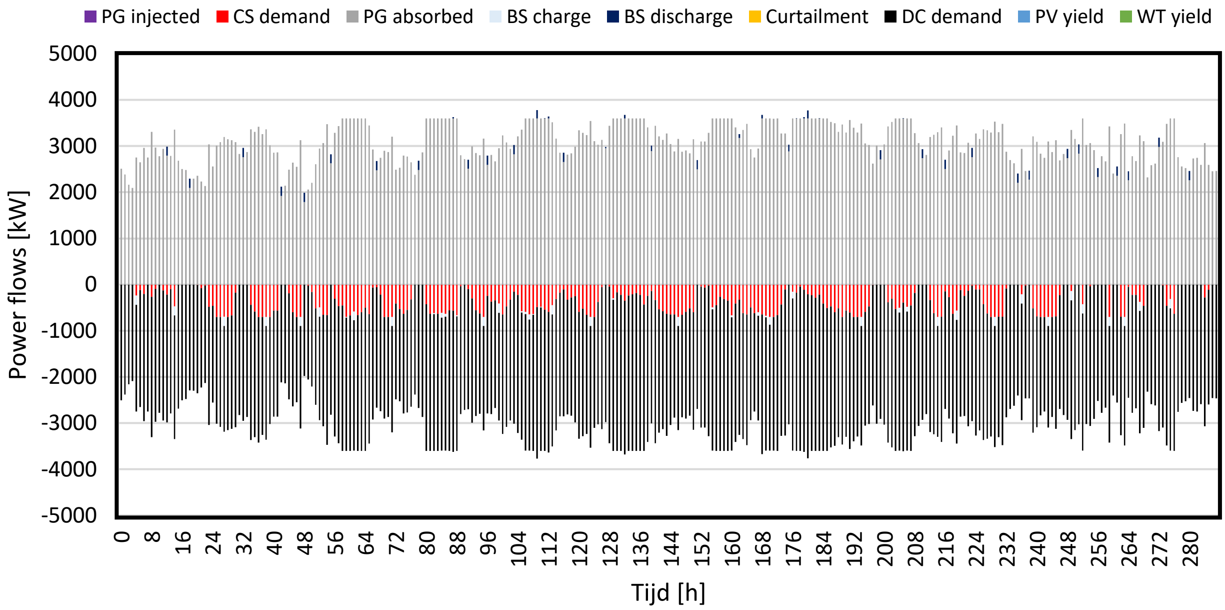


Figure G4. Power flows of the distribution centre's system in scenario 2.3

G.4. Number of e-trucks that need to be charged per typical day

In reality logistical companies do not want to physically shuffle e-trucks between charging stations. Software does exist to smartly schedule the charging, so that all e-trucks can be connected to charging stations, but only a selection is charged at a time. This does however mean that more charging stations are required than minimally found by the model. For the case study in this thesis the maximum number of e-trucks that need to be charged in the night, during which the distribution centre doesn't want to usher e-trucks around, can be seen in figure G5.

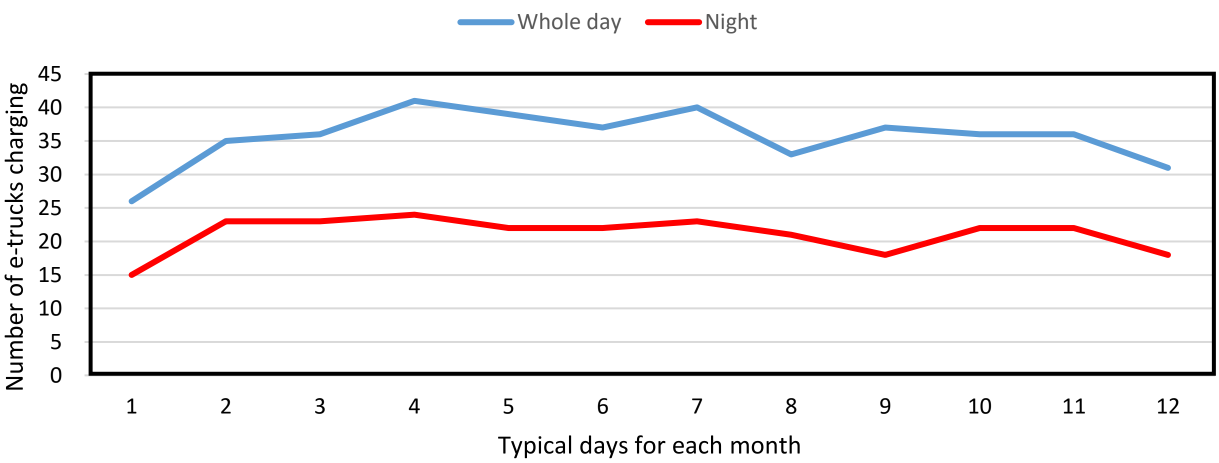


Figure G5. Number of e-trucks that have to charge per typical day or only considering the night.