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Industrial Electrical Engineering and Automation

Energy in the transportation system

A comparison of charging infrastructure scenarios

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Abstract

A functioning charging infrastructure is crucial for achieving full-scale national electrification within the transport sector. The system is likely to consist of different charging technologies, all with the main objective of providing efficient energy replenishment services. Careful planning for the deployment of this infrastructure is of high importance. The consumer segments are diverse, each with their own requirements and desires, but all sharing a common request: partly in the form of sufficient driving range. To prevent further increases in battery sizes, it is vital to address EV range anxiety by establishing a robust charging network.

The objective of this thesis is to determine the total energy requirement, in terms of batteries, for the transportation system when implementing a charging infrastructure based on battery swapping and slow charging. The results are compared with fast charging and electric road system scenarios, analyzing the usage of the proposed charging technologies for long-distance travel by cars and trucks. If the system solely consisted of battery swapping stations, the total battery capacity would be 420 GWh for cars and 32 GWh for trucks. In an electric road system scenario, these numbers would be 167 GWh and 12 GWh respectively. When compared to a fast charging solution, battery swapping would result in an increase of 0.4% for cars and 7.8% for trucks. In contrast, electric road systems would lead to a reduction of 60% for both cars and trucks.

Keywords: Charging infrastructure, road transport electrification, battery capacity need, electric vehicles

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Lastly, I would like to thank you who are about to read this paper. It is the product of the most rewarding months of my education, and I am proud of the outcome. I hope you find it interesting.

Lund, June 2023
Judith Lai Jakobsson

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1 Introduction

Global climate change is calling for urgent action, and there are initiatives across several sectors to pivot towards technological solutions for mitigation and adaptation to this change. The Intergovernmental Panel on Climate Change (IPCC) is urging to keep global warming limited to 1.5°C above pre-industrial levels to avoid irreversible and unforeseeable consequences for ecosystems, human societies, and global economic systems [20]. The majority of countries around the world entered the Paris Agreement in 2015, committing to pursuing efforts to maintain global warming below 1.5°C. According to IPCC, doing so involves limiting anthropogenic long-lived greenhouse gases (GHG).

The yearly development of global GHG emissions by sector is shown in figure 1, where electricity and heat can be seen to constitute the largest contributing sector, while transportation comes second [1]. To reach the 1.5°C target, overall GHG emissions have to be reduced by 45 percent until 2030 [21]. Transitioning to a low-carbon economy for the major emitting sectors could result in a significant emission reduction.

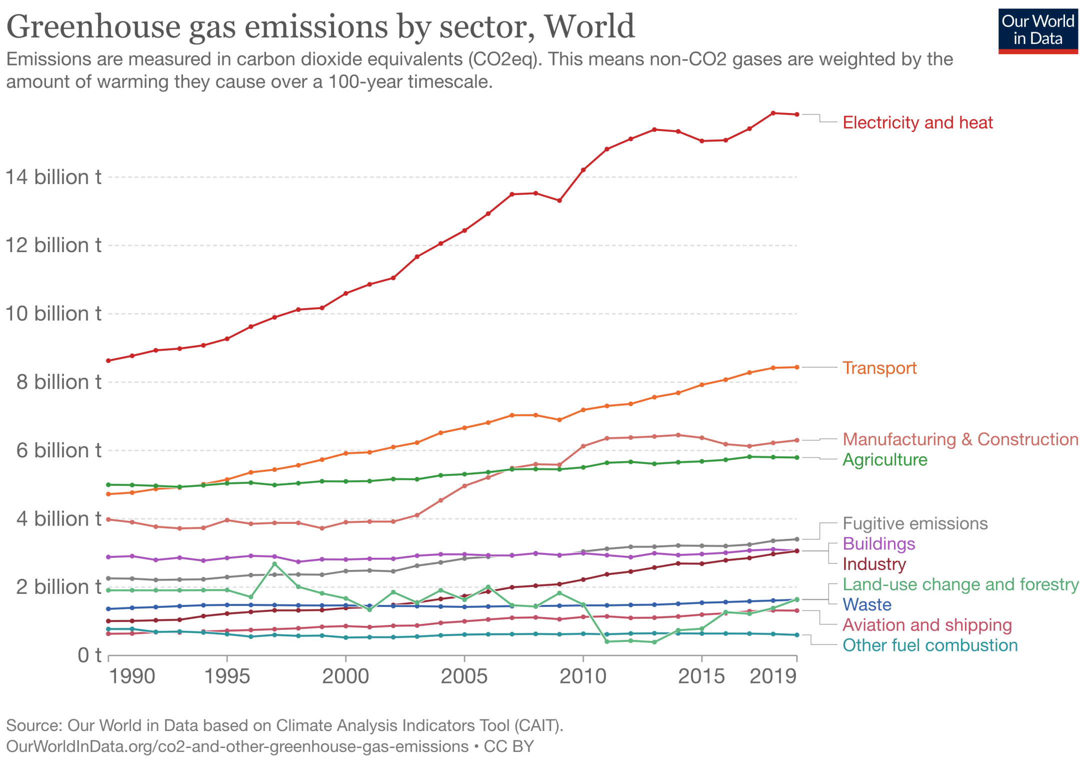

Figure 1: Greenhouse gas emissions by sector globally [1].

The International Energy Agency has developed three scenarios for future energy trend analyses: Net Zero Emissions by 2050 (NZE) Scenario, Announced Pledges Scenario (APS), and Stated

Policies Scenario (STEPS) [22]. In the NZE Scenario, all carbon dioxide emissions related to global energy use are zero by 2050, while the definition of the APS is that all climate commitments are met in full and on time. The STEPS is meant to reflect current policy settings for each sector and country around the world. According to the NZE Scenario, being the most ambitious of the three, the emissions of the transport sector have to be reduced by 20 percent until 2030, or three percent annually [23]. The IPCC, however, points out that the GHG emissions from transports are currently growing faster than many other sectors, and that without any actions taken, these emissions could increase by 65 percent until 2050 [24]. Successful strategies could reduce these sectoral emissions sufficiently enough to reach the 1.5°C limit. The main key to reaching full decarbonization is a combination of technological innovation and societal change, where strategies at regime scales are necessary.

In 2021, the average Swede emitted 3.42 tonnes of carbon dioxide per capita, compared to 4.69 tonnes of carbon dioxide per capita at a global average, assuming no correction for traded goods in either case [25]. The Swedish GHG emission distribution can be seen in figure 2. In this case, more than twice as much as the second largest sector, electricity and heat, was attributed to transports [2]. Although the emissions per capita are lower than the global average, the national climate ambitions put a lot of pressure on reducing this number. In 2017, the Swedish government decided on a climate policy framework including a climate act, climate goals, and a climate policy council, with the Paris Agreement as background [26]. The target is to have zero net emissions of GHG by 2045, to then achieve negative emissions by carbon sequestration, carbon capture and storage technologies, and/or involvement in emission reductions outside the Swedish borders. Part of this reform is climate goals, in which domestic transport is included. A 70 percent GHG emission reduction within the transport sector until 2030, compared to 2010 levels is aimed for, which covers all vehicle segments except for domestic flights.

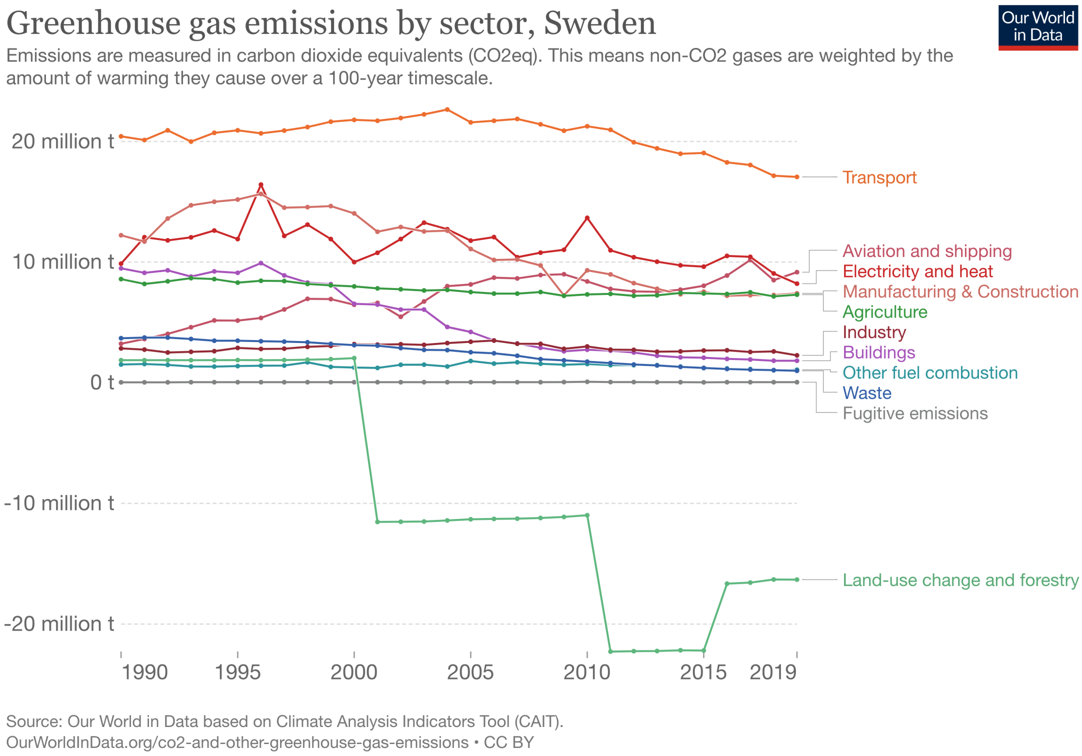

Figure 2: Greenhouse gas emissions by sector globally [2].

1.1 Decarbonizing transports

Mobility and goods transportation are two of the backbones of today's society, and as the number of vehicles and transports increases, a direct correlation can be seen with numerous challenges, including rising emissions. Traditionally, vehicles have been powered by fossil fuels, the emissions from which we know cause several environmental issues. Apart from causing global warming, the impacts of air pollution from the road transport sector on the national economy, human health, and residential welfare have shown to be severe [27].

No quick fix can be done to decarbonize the entire transport sector, but one of the main contenders for part of the solution is electric vehicles (EVs). The total environmental impact of EVs is not zero, as battery manufacturing and distribution are not negligible. Moreover, particulate matter (PM) emissions from tires and brakes, as well as road surface wear are emitted from both EVs and conventional fuel vehicles [28]. Nevertheless, an EV has greater efficiency compared to vehicles with internal combustion engines (ICE), and can make use of regenerative braking [29]. Additionally, EVs have zero tailpipe emissions and may give rise to reduced GHG emissions, provided that they are charged by clean power. Clean energy is by all means important to reduce these emissions in both leading sectors in figure 1.

The revolutionizing of the transport sector is not without its challenges. The worldwide adoption of EVs brings concern regarding charging infrastructure. Charging infrastructure is not only a necessity to power the vehicles, but also one of the causes, and solutions, to the EV range anxiety (EVRA) phenomenon [30]. Studies show that there are several issues related to existing charging networks, such as waiting queues and a lack of reliability in available charging stations [31]. This, together with the currently longer charging times compared to filling a gas tank, is one of the main barriers to full transition into electromobility today.

1.1.1 EVs today

In general, the growth of electric vehicle sales, if sustained, is in line with the NZE Scenario [32]. These sales numbers are however not spread evenly around the globe, but rather concentrated to specific regions. China, the United States, and Europe are the main markets, and there is an uneven distribution within the European market too. As for developing and emerging countries, high purchase costs and scarce access to charging infrastructure are holding back EV penetration, while this is not as much the case in developed countries. The EU has decided upon a regulation that stipulates a zero tailpipe requirement of all cars sold from 2035 and onward [23]. The status in 2021 was that electric cars accounted for about 9 percent of global car sales and 17 percent of European sales [33]. Subsidies for purchasing and tax reductions are considered part of the reasons for this overall increase. As mentioned, these sales are more concentrated in some parts of the continent, with national new EV sale shares of 85 percent in Norway, 72 percent in Iceland, and 43 percent in Sweden. Only 8 percent were new EV sale shares in Spain, having the seventh highest sales share of all European countries. In order to stay in line with the NZE Scenario, the electric car sales have to increase by approximately 6 percentage points per year, to reach a number of 60 percent new car sales in 2030 [32].

When it comes to commercial medium- and heavy-duty vehicles (hereafter denoted as heavy vehicles), an absence of policy support is one of the reasons for the historically slow electrical transition when compared to light-duty vehicles [34]. In 2021, electric trucks accounted for 0.3 percent of global truck sales, a number that should reach 30 percent according to the IEA NZE Scenario [23]. Close to 90 percent of all electric truck sales in 2021 were accounted for by China, although other markets are also expanding their shares as a result of increasing policies. In 2022, 0.4 percent (equal to 13 000 trucks) of the truck sales in China were electric, and 0.2 percent (equal to 1 000 trucks) in Europe. [33]

1.1.2 Charging technologies

The EV dilemma is referred to by some as a classic chicken and egg situation. Investors await large-scale EV adoption to get high utilization and return of investment of deployed charging infrastructure, while consumers are holding back until the accessibility of charging options is sufficient enough to avoid a depleted battery in the middle of nowhere [35]. The EVRA phenomenon has shown to be a significant reason as to why a vehicle owner would rather choose an ICE vehicle before an EV [30]. Worrying about battery depletion can make drivers only take trips less than the actual driving range, to save power in case of any unpredictable travel distance and/or energy consumption. Studies have however shown that EV utility currently being held down by EVRA can be increased by higher access to charging infrastructure.

The development of charging technologies has resulted in several viable options. This section seeks to introduce some of today's main technologies. Battery swapping as a method of energy replenishment is more thoroughly explained in section 2.

Static cable charging
The most common solution to EV charging today is conductive cable charging via a charging point. The market offers a variety of chargers with different mounting interfaces and power levels, from slow AC charging to fast DC charging. A standard power level for a home charging point is 11 kW, which today will have a car charged overnight. Lower levels of about 3 kW are possible from a standard power outlet. Fast charging options can be available at charging stations, with DC power levels from 22 kW and higher. [36] Some of the concerns regarding fast charging are related to the grid impact when a large enough scale of charging stations has been reached. When many fast chargers are connected at once, the high load on the power grid can cause issues, as the current infrastructure might not be dimensioned for these levels. Some companies have therefore started looking for solutions, and are now running trials on having a complementary battery system connected to the chargers [37], [38], [39]. Some battery packs and chargers are fixed at a charging station, while others are providing a mobile fast charging solution. This is faster to implement, and can also be cheaper, than reinforcing the grid [40]. As an example from these pilot studies, two fast chargers of 175 kW each can be supported by a 300 kW/360 kWh battery system.

Static inductive charging
Wireless (inductive) static charging happens by energy transfer induced by a magnetic field from a transmitter in the ground to a receiver on the vehicle. [36]

Dynamic inductive and conductive charging
Dynamic charging implies that energy can be transferred to the vehicle while moving, from which can generally be categorized as electric road systems (ERS). There are different ERS technology concepts, where three main ones can be identified: wireless induction, catenary technology, and conductive rails [41]. Dynamic wireless inductive charging works similarly to its static counterpart. Between coils installed in the road and the vehicle receiver, electricity is magnetically induced. This is compatible with any vehicle having a receiver. Catenaries, or overhead lines, is a concept similar to railway technology. Via conductive pantographs, the driving vehicle connects to the overhead lines to charge. This technology is only working with large vehicles within reach of the lines, thus passenger cars are not able to charge via this setup. Conductive rails are commonly installed in or upon the road surface, or alongside the road. Again similarly to the static case, electricity can be transferred from the rail via a pick-up under the vehicle and can be used by both light and heavy vehicles with this installment.

Smart charging and Vehicle-to-X
The background to smart charging and vehicle-to-X (V2X) is the concerns about power grid stability and the challenge of peak energy consumption hours in relation to extensive EV charging needs following a higher EV adoption rate. Smart charging and V2X enable a controlled and dynamic charging process, weighing in the interests of the vehicle owners, the market, and the grid [42]. Unidirectional, controlled (smart) charging can be called vehicle-one-grid (V1G), meaning that the vehicle is charged from the grid at a managed pace based on the requirements.

Bidirectional controlled charging, on the other hand, is when energy can also be drawn from the vehicle into another system. Some common concepts are vehicle-to-grid (V2G), vehicle-to-home (V2H), and vehicle-to-business (V2B). More than this, EVs can sometimes also charge each other if the equipment is available. By V2G, ancillary services to the power grid can be provided, which can give an extra income for the owner, and also turn a parked EV into a functional part of the grid flexibility. This is especially relevant as more renewable energy sources are in the power mix. Vehicles connected to the grid with V2G can help balance the supply fluctuations that may arise from intermittent power production. Ancillary services are defined as backup reserves to help maintain a balanced power grid by for instance managing disturbances. Examples of these services are different kinds of frequency regulation and power reserves [43]. Some require instant activation, while endurance is more important for other reserves.

Although the technologies for charging are mature, deployment is slow. Studies have shown that the lagging charging infrastructure to a large extent is due to a lack of policies and incentives to invest in such [44]. With the necessary political decisiveness to support the transformation, more rapid electrification could take place.

1.2 Road transports

The Swedish road transport fleet consists of several different vehicle types with different missions and requirements. This section aims at introducing the main vehicle groups and their respective requirements.

1.2.1 Vehicle segments' charging needs

Cars

Private passenger cars and *business cars* both have two different travel needs to satisfy: the short commuting and the long trips [36]. Most of the trips are shorter than the battery driving range, which means slow charging during parking is sufficient. For the longer trips, however, the battery capacity may not be enough, and the vehicle will have to stop for energy replenishment. Behavioral aspects come into play here, as the time a driver is willing to wait for charging is individual. For some, an hour might be perfect to catch a break from driving, while others want to drive the entire distance at once. Preferred battery sizes and charging infrastructure would most probably differ depending on which driver is asked.
Taxis' profits are depending on how many trips are being charged for, and standing still for recharging means losing valuable time that could have been used for driving passengers. There are however places where taxis tend to stay longer, such as by airports and railway stations, where charging could be done while waiting for the next customer.

Trucks

Local and *regional distribution trucks* start their missions relatively close to the destination, which can in many cases be managed without a recharge during the time of operation. Depending on the battery size and the number of trips in a day, nighttime charging can be sufficient. If not, charging during loading and/or unloading is preferable. The main differences between local and regional distribution trucks and *long-haul trucks* are the travel distances and the payloads. Long-distance trucks are heavier, and either require a very large battery or have to stop to charge along the way. For this segment, time is money, and unless charging happens during driving breaks, long charging stops are expensive. For long-haul trucks, the main obstacles towards full electrification where all trucks charge by cable are related to three things [45]. First, the large battery needed to fulfill the operating range requirements reduces the maximum payload capacity. Second, charging has to be planned according to operational schedules in order to not lose valuable driving time. Lastly, to fully recharge a depleted battery of large size during a limited time requires high power, which enforces challenges to the power grid stability and capacity.

Others
Buses have to follow a timetable and can be either local, regional, or long-haul, with different energy needs [36]. Suitable charging points for local and regional buses would be at bus stops and at the depot. The routes and ability to charge at bus stops determine the battery needed in order for the bus to be able to fulfill its mission. Long-haul buses are different in that they have to travel far without stops, and charging would then preferably be scheduled so as to coincide with the driving breaks. For all buses, dynamic charging would also be a suitable option.
Emergency vehicles have special requirements that need consideration. There have to always be available vehicles, so charging has to be planned so as to always have fully-charged batteries for some. The missions can differ depending on geographic location and situation, and emergency vehicles vary in size and service. Some of the vehicles are almost always in operation, and waiting times for charging might have more significant consequences than money. Furthermore, these vehicles have to be able to operate during times of crisis, which might include power disruption. Total electrification of this segment requires the most thorough planning.

1.2.2 Battery needs for passenger cars and heavy trucks

The Swedish fleet size of cars, medium- and heavy-duty trucks can be seen in table 1.

Table 1: Swedish registered vehicles in use by the end of 2022 [9].

Vehicle segment	**Fleet size (2022)**
Private cars	4 980 543
Heavy trucks (> 3 500 kg)	86 060

If the entire fleet was to be electrified, it would result in a total battery need that depends on the variety of vehicle sizes and driving range needs. More about the battery size distributions can be found in section 3. The battery needs can be expected to differ depending on which charging technology is dominating, especially when considering long trips. Vehicles traveling far distances are to a larger extent depending on some kind of energy replenishment along the way. Fast charging today requires relatively long charging times, which results in a need for rather large batteries to drive as far as possible on one charge. Electric road systems on the other hand can decrease the need for stored energy in batteries, as it can be drawn from the road system. Different numbers are proposed in terms of the decrease, but somewhere around a 60 percent lower overall battery capacity for vehicles on long distances, when compared to a fast charging scenario, is assumed in this work [6]. If instead, battery swapping would be the dominating technology in Sweden, it would result in another total battery need. An analysis of this scenario is the core of this project, and it is also compared to the fast charging and electric road system scenario.

1.3 Objectives

The objectives of this project are to determine the required amount of energy, in the form of batteries, needed to sustain a functional charging infrastructure based on battery swapping, and how this compares to scenarios of fast charging and electric road systems. A battery swapping model is developed primarily focusing on the overall battery capacity. Additionally, it includes a brief analysis of battery life degradation, provision of ancillary services, battery utilization rates, peak power demand, and land occupation. The main research questions (RQs) that are investigated are:
RQ1: How could a Swedish battery swapping system for cars and heavy trucks be dimensioned? To which extent could this system provide grid services, maintain battery health and peak power levels, and efficient use of space?
RQ2: How does the overall battery capacity vary depending on different charging technologies?

1.4 Methodology

To find the answers to the RQs, two main means of methodology were used, a bibliographic review and MATLAB modeling. A literature review was conducted by searching in academic databases and on the Internet. By studying earlier scientific reports and information found on company websites, enough theory was gathered to build a realistic model. During the fall of 2022, a pre-study was performed, which laid the groundwork for much of the theoretical background. The model was built in MATLAB, and was developed in a step-wise manner, with the aim of constructing a synthetic model to represent a battery swapping system in Sweden. As a basis for the model was input data provided by two doctoral students at the Division of Industrial Electrical Engineering and Automation (IEA) at Lund University, Hamoun Pourroshanfekr Arabani and Mattias Ingelström. This data consists of charging activities based on Pourroshanfekr Arabani's and Ingelström's own simulation models. An extensive description of the data and the model can be found in section 3. A sensitivity analysis of some of the model parameters was carried out, the details of which are elaborated upon in section 5. Lastly, in section 6, the background and results from the comparative study of the three selected charging technologies are declared. Three scenarios were established, one of which was derived from the battery swapping MATLAB model, and their total respective battery capacity needs were compared. The sensitivity analysis, as well as the comparative study, were both executed in MATLAB.

1.5 Delimitations

The aim of this work is to evaluate charging technologies from the Swedish context, hence is the model and analysis developed from this perspective. There is a wide variety of vehicle types, all important to include in the transformation towards electromobility. The scope of this study is however limited to cover cars, medium-, and heavy-duty trucks. Furthermore, the development of charging technologies is ongoing, and there are several proposed solutions. The three technologies included are the, by the author, main contenders today. Other technologies should however not by any means be counted out, and the future may hold new ways of implementation of as well battery swapping, as fast charging and electric road systems.

The study focuses solely on the overall battery capacity connected to the mobility sector of the selected segments. This includes batteries in vehicles on the road and batteries in charging. Other uses of batteries, such as in their second life or other kinds of energy storage, for instance a complementary battery system to fast chargers, are not included in the model. Additionally, whilst other aspects such as grid impact and prolonging of battery life are of high relevance, they are only briefly touched upon. Neither are business models, nor operational efficiency included.

In the development of the model, a severe set of assumptions are made. These constraints are limitations of the model, and are explained in section 3.

1.6 Thesis disposition

The remaining of this report comprises seven main sections. In section 2, battery swapping theory is presented, and the development of a battery swapping model in MATLAB is explained in section 3. The results are described and analyzed in section 4, while section 5 contains a sensitivity analysis performed on the model. Section 6 presents the results of the comparative study between battery swapping, fast charging, and electric road systems. Lastly, a discussion can be found in section 7, and section 8 concludes the key findings and suggestions for future research.

1.7 Clarifying note

In this work, the expressions *charging activities* and *charging locations* are frequently used. A charging activity is referred to as an action of energy replenishment, and a charging location is a site providing this service. The word *charging* is not linked to any specific technology and should not be mistaken for slow or fast charging, which specifically refers to cable charging.

2 Battery swapping

Battery swapping can be divided into two main aspects, the swapping service and the charging service [46]. The former occurs as the vehicle enters the swapping station, in which the discharged battery is exchanged for a fully charged one. When the swap has been performed, the charging service takes place and the depleted battery gets recharged at a monitored pace with consideration to battery health and power grid system balance.

This section aims to provide the necessary theoretical background of battery swapping that serves as a foundation for the reasoning behind the development of the battery swapping model and the conclusions drawn from it. First, a historical background leading up to the current battery swapping technology and its market is presented. Following this, the concept of Battery as a Service (BaaS) is described. The general benefits and challenges, as well as a collection of earlier studies, are presented, and finally concluded with the realized research gap being the reason for this thesis.

2.1 Development until today

The concept of battery swapping dates all the way back to the late 1800s when it was first presented. It was executed by some companies during the 1990s, including Mercedes Benz [13]. In 2007, an Israeli company called Better Place reinvented the technology and put it into practice. It started out successfully, and by the same time, the US company Tesla also adopted the technology, promoting it as a complement to cable charging. By then, however, the time had not yet come for battery swapping. Better Place filed for bankruptcy in 2013, and the idea was abandoned by Tesla. The reasons for this were that the EV penetration rate was still low, and the market not ripe enough for it to be economically viable considering the high capital and battery costs without any institutional support. Additionally, there was still a lack of standardization, value chain collaboration, and safety measurements.

Today, numerous initiatives and developments are in progress. Companies and authorities are showing interest in battery swapping technology, and both demonstration projects, as well as full-scale operations, are ongoing. This new-found interest has occurred as a result of the numerous benefits of this technology, combined with rising EV sales. Nonetheless, although the technology is mature there are also drawbacks to it, and adoption varies widely across the globe. Whether or not battery swapping will gain traction in a region depends on a variety of aspects. Electrifying the transportation system is a multidimensional and complex challenge, and has to be treated as such. Thus, a readiness index model, used for analyzing the readiness level of a country to adopt a transportation electrification system solution, is of great benefit [47]. The index depends on four subsystems, mutually dependent and interacting to form an entire system, which are technology, economic, political, and societal readiness levels. Conclusions drawn after analyzing eight different countries from three continents are that political processes and decisiveness are the most important factors, followed by societal and economic, and finally technology. This index implies that any commercialization of a new charging technology will only happen if there is political support for it.

There is however proof of concept. China had, by the end of 2021, approximately 1 400 BSSs, of which about 53 percent were for passenger vehicles and the rest for commercial vehicles [48].

By the end of 2023, the number of BSSs is estimated to surpass 11 000. Globally, China has a strong lead in the development of both EVs and EV charging infrastructure in general. As seen in figure 3, China had by the end of 2022 a 58 percent share of the global battery electric car stock, while Europe and the United States followed by 24 and 11 percent respectively [3]. For electric heavy-duty trucks, China accounted for almost 90 percent of the global registrations in 2021 [49]. Furthermore, following the high EV stock, China also has a large share of the EV charging infrastructure. In 2021, China had around 85 and 55 percent of the global public fast and slow chargers respectively.

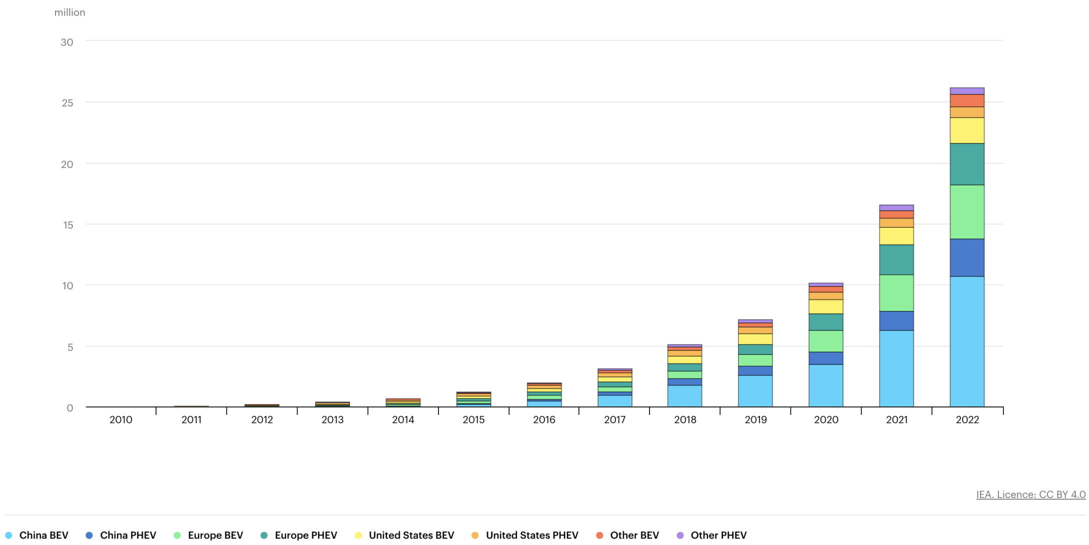

Figure 3: Global electric car stock, 2010-2022 [3].

As for new sales, China is in the lead too. Figure 4 shows that, out of all new truck registrations in 2022, electric trucks accounted for 3.9 percent in China, and only 0.5 percent or less in the other regions [4].

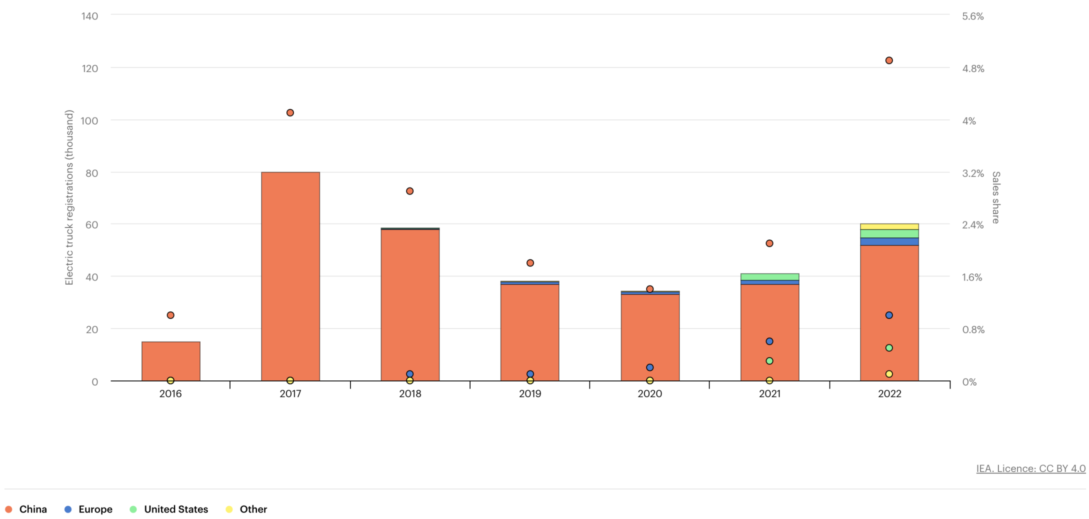

Figure 4: Electric truck registrations and sales share by region, 2015-2022 [4].

As explained by these numbers, a large part of the global EV charging development is happening in China. Battery swapping has only been deployed to a significant extent for cars and heavy trucks in China, which is why the coverage of battery swapping in this work is much based on Chinese solutions.

2.2 Swapping today

Today, battery swapping has again been put into practice, and there are several operators within the different vehicle segments. Except for cars and trucks, two- and three-wheelers are target groups for battery swapping. This section is a summary of the current situation in the battery swapping market for cars and heavy trucks, and is the result of the author's pre-study.

With numerous solutions, standardization levels vary. Some original equipment manufacturers (OEMs) limit their battery swapping business to their own vehicles, while others have aimed for a more common solution. Development, deployment, and operation of battery swapping stations (BSSs) can be carried out by either multiple parties or a single entity. Vehicle manufacturers that have their own battery swapping technology can produce compatible vehicles, whilst third-party BSS operators are more reliant on cooperative agreements with OEMs. NIO is an automaker that operates its own battery swapping technology, called NIO Power Swap Station [12], while Aulton New Energy Automotive Technology (Aulton) is a BSS operator collaborating with OEMs [19].

Other strategic partnerships are relevant for BSS operators, such as energy giants and taxi fleets. One example is NIO's agreement with Shell, allowing them to use Shell's well-situated gas stations to place BSSs along highways [50]. Furthermore, many battery swapping projects are directed toward ride-sharing or taxi fleets. Here, the interest from the fleet owners is due to the benefits of quick energy replenishment, compared to the lost profit by standing still by a charger. Ample is one of the battery swapping companies founded in the United States, being a BSS operator in agreement with the ride-sharing company Uber [51].

As mentioned, operators have different solutions. When it comes to batteries, some have one or several battery sizes for the drivers to choose from, while others have opted for modular battery packs. The concept of this is based on that several blocks fit in a standardized interface, and the total battery capacity can be varied as preferred. Ample and Contemporary Amperex Technology Co., Limited (CATL) are two of the companies providing this solution [52], [16]. In terms of reassuring there is a battery, some companies offer the possibility to search for BSSs with available batteries, and announce arrival or book a battery beforehand. The batteries are maintained by the BSS operators, where for instance NIO claim they keep the batteries at a temperature of 20°C and only charge to a 90 percent state of charge (SoC) [50]. Some operators have also implemented the vehicle-to-station-to-grid (V2S2G) technology in their stations [53].

Table 2 and 3 present a summary of some of the currently largest BSS operators for cars and trucks and their solutions. All companies have not revealed complete information about the stations' specifications, and there are numerous operators in addition to the ones listed. The presented properties are number of battery slots per station, the occupied area of one BSS, the total number of swaps performed in a day, and the duration of a swap. Important to note to these figures is that they may vary between projects and regions. Furthermore, although a station may fit a certain number of batteries, all stations are not always fully equipped. The BSS specifications refer to the highest capacity of a station, but less batteries may suffice to meet the swapping demand. When it comes to space requirements, only hardware is considered. This means that the necessary area for queuing and exiting the station is excluded. Lastly, the time per swap refers to the entire swapping process, including driving in and out of the stations. These times are what the companies have claimed to manage, although they might differ in reality.

Table 2: A selection of car BSS operators [10], [11], [12], [13], [14], [15], [16].

Operator	**# slots**	**Area** $[m^2]$	**Swaps/day**	**Time/swap [min]**
NIO	21	66*	408	3.5**
Aulton 3.0	28	155	1 000	1
Geely E-Energee	39	126	1 000	1
BAIC BluePark	60	75	400-500	1.5
Ample	-	30***	-	< 10
CATL EVOGO	48	45***	-	1 (per block)

Table 3: A selection of truck BSS operators [17], [18], [19].

Operator	# slots	Area $[m^2]$	Time/swap [min]
Enneagon****	7-8	240	3-5
SPIC	-	-	5
Aulton	-	90	1
Sany 3.0	-	123	1.9
Foton	7	120	3-4

** average dimensions of a double garage are assumed to be 7.3x9.1 m^2 [54]*
*** calculated total time per full swap based on 408 swaps per 24 hours*
**** average dimensions of a parking space are assumed to be 2.7x5.5 m^2 [55]*
***** data from truck battery swapping projects, large variations may occur*

In a car, the battery is swapped from underneath via, in most cases, an automatic mechanism. For electric trucks, the battery placement can vary. The main positions are behind the driver cab, sideways, under the chassis, in the tractor front, or in a specific battery trailer. Of these, the most common placement is behind the cab [17]. Battery swapping for trucks has come less far in deployment, but there are several projects ongoing, on which most of the data in table 3 is based.

2.3 Battery as a Service

BaaS is a business model where the customers purchase or lease the car without the battery. Instead, the battery is made available for lease, and the cost is determined by the energy requirements of the user. Additionally, many battery swapping services offer a range of battery capacities to choose from. This flexibility allows drivers to use a smaller battery for local commuting, and then upgrade to a larger capacity when needed. This way, drivers only pay for the energy actually used, rather than buying a large battery that is only fully utilized occasionally. One notable advantage of separating the battery from the vehicle is that the vehicle owners are also relieved of concerns related to the battery depreciation and disposal.

This model is a way to make battery swapping interesting for both OEMs and customers. The battery accounts for a large part of the cost of the vehicle, and this solution separates these costs from the vehicle body. Different business models have been presented in China. Cost sharing is determined by partnerships between e.g. OEMs, energy companies, and battery swapping service companies. Due to governmental policies, there are incentives to accelerate the establishment of charging infrastructure, and BaaS has shown effective. [56]

2.4 Benefits and challenges

One of the main benefits of the battery swapping technology is addressing one of the concerns for EV owners, being the time of energy replenishment. A swap can be performed in three to five minutes [18], compared to the present fast DC charging rates (C-rates) of 30-60 minutes (1-2C), or even 15 minutes (4C) with a supercharger [57]. Instead of recharging the battery with the driver waiting, it is possible to have it slowly charged during off-peak periods with low charging costs [58]. This allows for centralized charging control, and during times of low swapping frequencies, it is possible to avoid high power grid strain. In contrary, instant charging or electric road systems draw energy directly from the grid in most cases. Furthermore, integration of a BSS in a power grid system consisting of an increasing share of intermittent renewable power can be well suited [59]. The swapping station can function as both a swapping service unit, and an energy storage unit to act as a reserve during peak energy demands or power grid disturbances. A case study has shown that the equipment used for wind power energy storage in a BSS can have a utilization rate above 80 percent, compared to 8 percent for an energy storage unit connected to only the power plant [18].

Over time, the battery state of health (SoH) decreases. This reduces the vehicle's second-hand market value, which commonly makes an EV an expensive investment that rarely is returned by selling it. Via the separation of the battery and the vehicle, a financial burden that can often hinder an EV purchase can be relieved, and the vehicle lifetime is increased as the battery is not included [60]. BaaS has benefits both from a consumer and a supplier perspective [56]. Not only is the time for recharging decreased for the driver, but the costs and maintenance of the battery are also decoupled from the vehicle ownership. As the battery utilization rates are increased, the environmental impact is reduced as a result of the more efficient use of raw material resources.

Furthermore, automakers like NIO have introduced flexible battery leasing, currently offering two options of battery capacity, 75 kWh and 100 kWh [61]. When buying or leasing the vehicle, a battery lease contract is entered, where the customer may choose either of the battery sizes as a standard for the long-term agreement based on the expected needs. Later on, the customer may temporarily up or downgrade to another battery size on short-term rates. This can also improve battery utilization, but the cost benefits and total battery need compared to only having one option on battery size are not yet calculated.

Some of the challenges of introducing battery swapping are related to high investment costs and customers' inertia against adopting the technology, leading to a low infrastructural utilization rate [62]. The lack of standardization is also an obstacle to full-scale deployment of battery swapping infrastructure, but policies and unified standards would highly accelerate commercialization [56]. Lastly, the rapid development in battery technology is a risk for high investments in charging infrastructure. Better ranges due to higher energy density could result in that battery swapping becoming an outdated technology in the future.

2.5 Earlier studies

Existing literature on battery swapping for light- and heavy-duty vehicles is focusing on four main aspects - business models, operational efficiency, infrastructure planning, and adoption and policies. This section aims to summarize some of the earlier studies on the subject.

2.5.1 Operational efficiency

Battery swapping has several functions, and charging the batteries is one of them. Simulations have been done to develop optimized charging and discharging schedules of the batteries in regard to for instance the stochastic arrival of EVs and battery health.

The traffic behavior of EV drivers is a focus area, both in the work of operation management and BSS inventory planning. One proposal is an incentive- and penalty-based BSS operation, where EV drivers are presented with either a better or worse offer for swapping based on the operation schedule [63]. This schedule would then be dynamic and coordinated with forecasting of the EV charging demand schedule. There are also studies on how to maximize the BSS revenue by optimizing operation parameters such as batteries per station, number of charging slots, and the charging speed [64]. Increased profits could be reached by implementing a BSS battery distribution strategy based on SoH rather than on random allocation [65].

When it comes to preventing battery degradation, C-rates and storage conditions are two areas of interest. The battery lifespan is shortened faster as a result of high charge or discharge rates [66], while too long storage duration also causes the battery SoH to decrease [67]. Battery charging schedules make it possible to avoid charging during power grid peak hours, having an effect known as valley filling [68], and avoid too long storage times. Nonetheless, batteries are usually kept in the BSS for some time. The battery bank of a BSS can then function as an energy storage unit for the power grid, and by implementing battery-to-grid technology (B2G), peak shaving can be performed during the hours of high load on the grid, and BSS revenues may increase. Other studies have investigated the use of second-life batteries (i.e., batteries that have reached the end of their technical first life in cars) in an energy storage system (ESS), integrated with a BSS [69], [70]. The ESS could have three modes: backup, charging, and discharging mode. It would function as a buffer system, charging the ESS batteries during times of low electricity prices, and discharging them into the grid or into the BSS when needed. Due to that the ESS batteries are not aimed for first-life usage in cars, storing energy longer is not as much of a concern as for first-life batteries. Furthermore, integrating a BSS with renewable energy sources at a large scale or in a microgrid is a possibility to increase the battery utilization rates compared to only serving in a BSS or in an ESS [71], and to increase the profit [72]. Challenges to this are related to uncertainties due to the non-dispatchable characteristics of renewable energy sources, to be managed together with the uncertainties of EV arrival time and rates [73].

Several operational battery swapping modes exist. Except for the decentralized swapping and charging mode primarily considered in this thesis project, separate devices for centralized battery charging and distributed battery swapping can be used [74], [75].

2.5.2 Business models

As the concept of battery swapping differs from conventional energy replenishment technologies, business models form new shapes. The customer payments are often based on two parts: the cost of the energy and the cost of the service. There are different pricing strategies, and two of these are the pay-per-swap and subscription payments [76]. Another tool is tiered pricing, which can help optimize the BSS revenue as well as encourage customers to use the service at a time of beneficial prices for them too [77]. This could mean that customers are either economically rewarded if using the swapping service when batteries have been charged during power grid valley states, or penalized for doing the opposite. Having a tiered pricing scheme in effect could maximize battery utilization and reduce the power grid load.

2.5.3 Infrastructure planning

Siting of BSSs depends on multiple factors, such as power network constraints [78] and EV charging demands [79], and based on which criteria have to be met, different solutions are required. BSS deployment at proper locations is important to ensure service efficiency and a good return on investment ratio. Different methods to decide suitable locations have been presented, such as using a Geographic Information System (GIS) [80].

2.5.4 Adoption and policies

Battery swapping has been put into practice in several parts of the world, and different vehicle types have been subject to it. The technology is applicable for two-, three-, and four-wheelers of different kinds, and the main topic of discussion is the economic viability compared to other charging solutions. For heavy-duty trucks, a study shows that the high investment costs of battery swapping result in a breaking point for battery swapping to outperform fast charging at a 43 percent utilization rate [81]. Furthermore, the driving range most optimal is according to the same study between 156 and 252 kilometers. For electric taxis, one of the obstacles is slow energy replenishment, as they are rather time-sensitive and rarely earn money by standing still. This is one of the great advantages of battery swapping, as with optimal layout the taxi industry could remain at about 98 percent of its original (non-EV) capacity while reducing carbon dioxide emissions by 44 percent [82].

One of the main barriers to large-scale adoption of battery swapping technology is argued to be the limited political incentives. Political readiness is one of the most important drivers for implementing new technical solutions, and the results from a multidimensional readiness index model show that China scores higher in political readiness than most European countries. The total score of the study shows that different countries positions differently in the development of transportation electrification, China scores 97%, Norway 89%, Germany 81%, and Sweden 78% [47]. This is calculated by a sum of the scores (0-9) in four categories: technological readiness, political readiness, societal readiness, and economic readiness. Policy improvements are discussed in different terms, some of them being consumer versus provider subsidies [83], [84]. Provider subsidies are argued by some to be the most effective, but the impact of incentive actions varies. Subsidization should be carried out in a market where the opportunity cost is low, and it will reduce the service prices to enhance the technology's competitiveness. These subsidies should however not be sustained for a too long time. As the industry is mature and has a self-sustained development they should be adjusted so as not to interfere and prevent a healthy market, and instead harm other charging options.

2.6 Research gap and contributions

A wide variety of studies have been carried out on battery swapping, and a common solution has not been concluded in either economical, operational, or political aspects. One of the reasons can be the regional differences across the world that make no one solution fit all cases. These are severe, and, with the charging infrastructure development in its cradle for many parts of the world, different charging technologies should be thoroughly compared by several parameters. Here, a gap in the research on charging technologies can be found in the total battery capacity needed. To the author's knowledge, no studies on the total overall capacity needed for battery swapping have been conducted to this date. With such an analysis, comparisons to other charging technologies can be done in order to estimate the total overall battery cost, materials consumption, etc., which are relevant aspects to address. The contribution of this work is to objectively investigate the above matter, with the hope of having it included in future discussions on the subject of Sweden's charging infrastructure.

3 Battery swapping model

The model representing a battery swapping system is built in MATLAB. It relies on data derived from two simulation projects conducted by Hamoun Pourroshanfekr Arabani [5] and Mattias Ingelström [7] at IEA, Lund University. Named projects are aimed at developing a methodology to identify candidate locations for fast charging stations across Sweden based on charging needs for a synthetic population of cars and trucks with predetermined EV properties and travel intentions. Assuming the same driving patterns and vehicle specifications, the locations are considered valid in the battery swapping case as well. Candidate locations and the charging activities linked to each location are used to form the battery swapping system. The model consists of two main sections, namely determining the number of BSSs per location, and the circulation and quantity of batteries in a BSS. Having established these, peak power levels, utilization rates, and land usage are analyzed. Two assumptions to begin with are:

- Standardization is not an issue. All charging technologies are assumed to be compatible with all vehicles within the scope, in regard to mechanical dimensions and mounting, and electrical connections.
- The fleets, by the size they are today (see table 1) are fully electrified.

The remainder of the section aims at explaining the reasoning behind the input data and the modeling. The purpose is to describe the model in terms of its functionality and assumptions, beginning with the input data, followed by the MATLAB scripts.

3.1 Input data, Cars

The data is resulting from a Multi-Agent Transport Simulation (MATSim), in which all EVs are modeled and tracked by their movements on the transportation network, energy consumption, and charging activities.

3.1.1 The synthetic population

The annual average daily traffic of passenger cars is collected from SAMPERS, and disaggregated into individual agents. By combining the origin and destination (OD) information and Corine Land Cover Data, each agent is assigned specific OD locations.

Within the car fleet, three vehicle types are considered: small, medium and SUV, each equipped with batteries as specified in table 4. This distribution is assumed to be consistent across all cars in the fleet. Assuming an energy consumption rate of 0.2 kWh per kilometer [85], and utilizing approximately 80 percent of the battery capacity, these vehicles have driving ranges of 240, 320, and 400 kilometers, respectively.

Table 4: Vehicle specifications.

Vehicle type	**Battery capacity [kWh]**	**Population share [%]**
Small	60	15
Medium	80	50
SUV	100	35

The representative selection of agents is based on the OD route length, where only one-way trips longer than 150 kilometers are included. Shorter trips are assumed to be covered by slow charging and are therefore not subject to either fast charging, battery swapping, or electric road systems. The SAMPERS dataset also provides a distinction between private and business trips, which, together with trip distance, determines the starting times of an agent. Table 5 shows the number of long trips per day and segment. Based on driver segment and trip distance, the agents' departure times vary according to table 6, 7, and 8.

Table 5: Trips longer than 150 kilometers divided by segment.

Driver segment	**Number of trips**
Private trips	76 727
Business trips	15 409
Total	92 136

Table 6: Departure times, trips exceeding 1 000 kilometers.

Departure time [hh:mm]	**Trips exceeding 1 000 kilometers [%]**
08:00-10:00	100 (random distribution)

Table 7: Departure times, private trips.

Departure time [hh:mm]	**Private trips [%]**
05:00-12:00	70
12:00-16:00	20
16:00-	10

Table 8: Departure times, business trips.

Departure time [hh:mm]	**Business trips [%]**
05:00-10:00	80
10:00-	20

3.1.2 The charging activities

Before each MATSim iteration, each agent is appointed specific charging activities together with the travel plan. The locations of these activities are determined by the distance of the trip when taking the shortest route, the energy consumption profile, the battery capacity, and the initial SoC. The SoC when initiating a charging activity has a distribution according to table 9, which indicates the point at which the agent starts searching for a charging location. This implies that the actual SoC when reaching a charging station is slightly less than in table 9, depending on the distance to the charging location. Nevertheless, the SoC levels are assumed accurate enough and are therefore later used for when analyzing the incoming batteries to the BSS.

Table 9: SoC distribution for when initiating a charging activity.

SoC [%]	**Population share [%]**
20-30	80
30-50	20

3.1.3 The candidate locations for charging infrastructure

To identify candidate locations for EV charging stations, an iterative simulation is performed. Initially, it is assumed that no charging stations exist. The SoC when commencing a trip has a randomly assigned distribution according to table 10. For the first iteration only, the lower bounds of the SoC levels are set.

Table 10: SoC distribution for when initiating a trip.

SoC [%]	**Population share [%]**
50-70	20
70-90	30
90-100	50

The locations for where the EV batteries reach SoC = 0, called a Missing Energy Event (MEE), are identified. All MEEs within a 30-kilometer radius are aggregated and the agents are assigned to recharge at one location in the area. Consequently, there will be only one candidate location within such a zone. From this, the 100 locations with the highest MEE frequency are selected, and a new iteration with charging infrastructure in place at these locations is started. Running the simulation again, new areas with MEEs appear, and the candidate locations with the highest frequencies are selected. These steps are repeated as long as the rate of successful trips is below 90 percent. Here, a successful trip implies a completed trip where any MEEs have been avoided due to adequate charging infrastructure. If an EV battery is not charged within 90 minutes from arriving at its assigned charging location, it is considered an unsuccessful trip. A fast charge with a maximum power of 175 kW takes on average about 30 minutes according to the data, though this duration varies with battery size and SoC. In the dataset, locations to cover 78 percent of the trips are generated. This limited success rate is due to that adding more stations to cover the last percentages is not considered realistic from an economical and environmental aspect. In total, 337 locations are established, at which the total number of charging activities can be seen in table 11. The number of charging activities exceeds the number of successful trips, indicating that some jouneys require more than one charging stop to reach their final destination.

Table 11: Trips and charging activities.

Long trips	Successful long trips	Charging activities
92 136	71 866	75 583

For the dimensioning of each charging station, the probability of the number of charging activities at each location is considered. Figure 5 shows that, in more than 80 percent of all cases, there occur a maximum of 30 MEEs at the same place and time. Hence, a limit of 30 charging points is set, allowing for a maximum of 30 arriving vehicles per given instance.

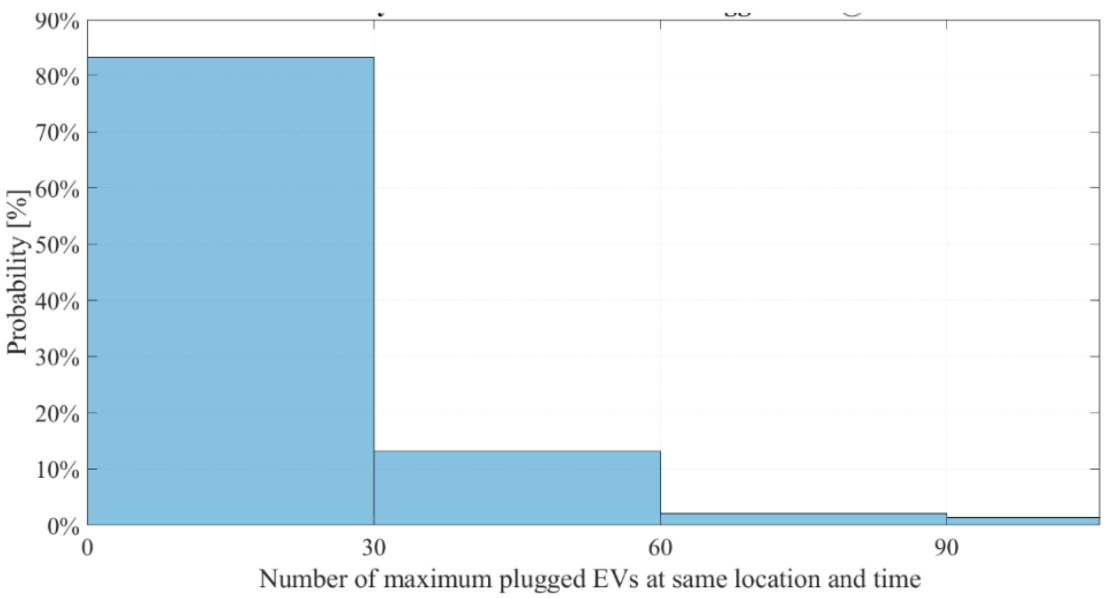

Figure 5: Probability of the maximum amount of charging activities at one location and point in time [5].

3.2 Input data, Trucks

The data for trucks is, as the car data, resulting from a MATSim model. The simulation models have similarities, but also significant differences.

3.2.1 The synthetic original and modified population

The traffic flows of medium- and heavy-duty trucks are retrieved from SAMGODS. The data provides travel statistics for one day, which is considered to be representative of an average day of the year. It is based on inter-zonal freight trips between 588 different zones [86], of which the data for the 290 domestic zones is applied in this project.

The SAMGODS data is divided into four truck weight classes, two medium- and two heavy-duty truck (MDT and HDT) models. Properties such as battery capacities, engine power, and geometrical specifications are collected from truck manufacturing companies. The weight classes, their assigned battery capacities, and their respective shares within the synthetic population are summarized in table 12.

Table 12: Vehicle specifications and synthetic population distribution, original data.

Weight class [tonnes]	**Battery capacity [kWh]**	**Population share [%]**
3.5-16 (MDT)	180	1.5
16-24 (MDT)	300	8.5
25-40 (HDT)	400	36
40-60 (HDT)	500	54

The dataset contains individual events longer than 300 kilometers. One limitation of the SAMGODS tool is that it provides distinct data on all continuous trips, without regard to that they may be part of a longer trip with several stops. A consequence of this is that consecutive events of the same agent, driving a total distance that may exceed 300 kilometers in a day, are not accounted for. Henceforth, it is difficult to extract information on the total number of trucks on long trips. This quantity is of importance when determining the overall battery capacity need in the vehicles and BSSs. Additionally, there is reason to assume that the dataset does not contain all trucks operating in a day. The total number of daily trips in SAMGODS, including those of a distance shorter than 300 kilometers, is 23 720. Meanwhile, vehicle statistics data by the Swedish government agency Transport Analysis reports that the national stock of trucks in use was counted to 86 060 by the end of 2022 [9]. By comparing the number of trips to the number of trucks, the conclusion would be that more than two-thirds of all trucks would stand still on a normal day.

To work around this discrepancy, data based on real measurements handed by Professor Mats Alaküla at Lund University [6] was used to estimate the actual number of long-haul trucks categorized by weight class. The distribution can be seen in figure 6. The bounds of the weight classes differ from the SAMGODS original data in table 12, and the four classes are merged into two, MDTs and HDTs. The figure shows that 52 percent of all MDTs and 95 percent of all HDTs travel farther than 300 kilometers in a day. When combined with the number of Swedish registered trucks in use of each weight class, it results in a total of 32 510 MDTs and 21 835 HDTs [9]. Trucks weighing between 3 500 and 10 000 kg are assumed to have the same distribution as MDTs in the upper plot of figure 6, although they are not included in the data.

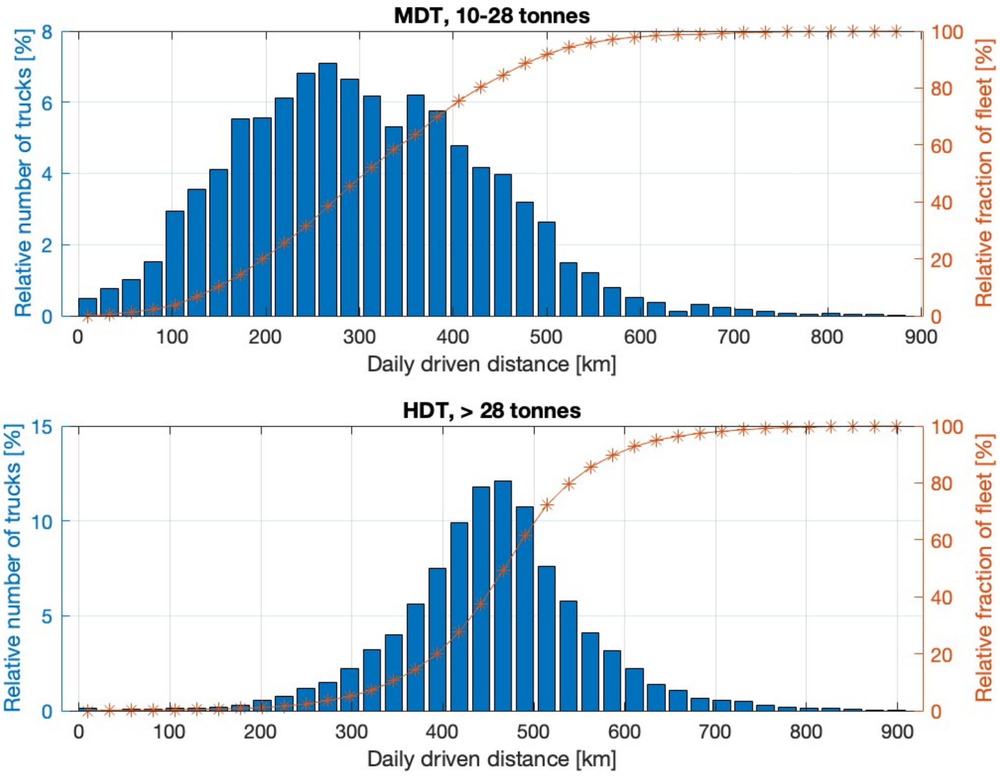

Figure 6: Trip distances, medium- and heavy-duty trucks [6].

The modified population differs from that in table 12. The share of MDTs exceeds that of HDTs, indicating that the missing consecutive trips exceeding 300 kilometers in the SAMGODS data might be significant. An updated distribution can be seen in table 13. The battery size allocation within the medium- and heavy-duty weight classes respectively remain the same, with 1.5/10 of the modified MDT fleet with a 180 kWh battery and the remaining with a 300 kWh battery. In the HDT fleet, 36/90 have a 400 kWh battery, and the rest have a 500 kWh battery.

Table 13: Vehicle specifications and synthetic population distribution, modified data.

Weight class [tonnes]	**Battery capacity [kWh]**	**Population share [%]**
3.5-16 (MDT)	180	8
16-24 (MDT)	300	52
25-40 (HDT)	400	16
40-60 (HDT)	500	24

Modifications also extend to charging activities. With more trucks embarking on long trips, the need for energy replenishment increases. The process of identifying charging locations in MATSim is based on the SAMGODS estimated traffic flow. From this, 69.3 percent successful trips resulted in 2 512 long-haul trips, prompting 4 561 charging activities as can be read from table 14. For the modified data, the number of long trips are calculated by using figure 6. The same rate of successful trips is maintained, as the added trips are assumed to go on the same routes as the original trips. If instead assuming 100 percent successful trips, additional routes, thus requirements for charging locations in new areas, could appear. By keeping the same rate, the number of charging activities per location is calculated by multiplying the original number by 13.8, which is how many more trips were estimated. In other words, the routes are assumed to remain the same but the number of trips, and consequently charging activities, are increased. The number of locations are also kept the same due to the inability at the time to change the simulation data. Furthermore, the distribution of SoC levels when reaching a charging station is assumed to not change, but the overall battery size distribution differs as a result of the increased share of MDTs.

Table 14: Trips and charging activities, original and modified data.

	Long trips	**Successful long trips**	**Charging activities**
Original data	3 625	2 512	4 561
Modified data	54 354	37 667	68 389

While this modification simplifies real-world complexities, it is considered an appropriate adjustment to capture the entire fleet within the model. Apart from these changes, all other assumptions from the original simulation remain applicable.

The departure times of all trucks follow a random distribution as illustrated in figure 7, and each agent is assigned specific OD information.

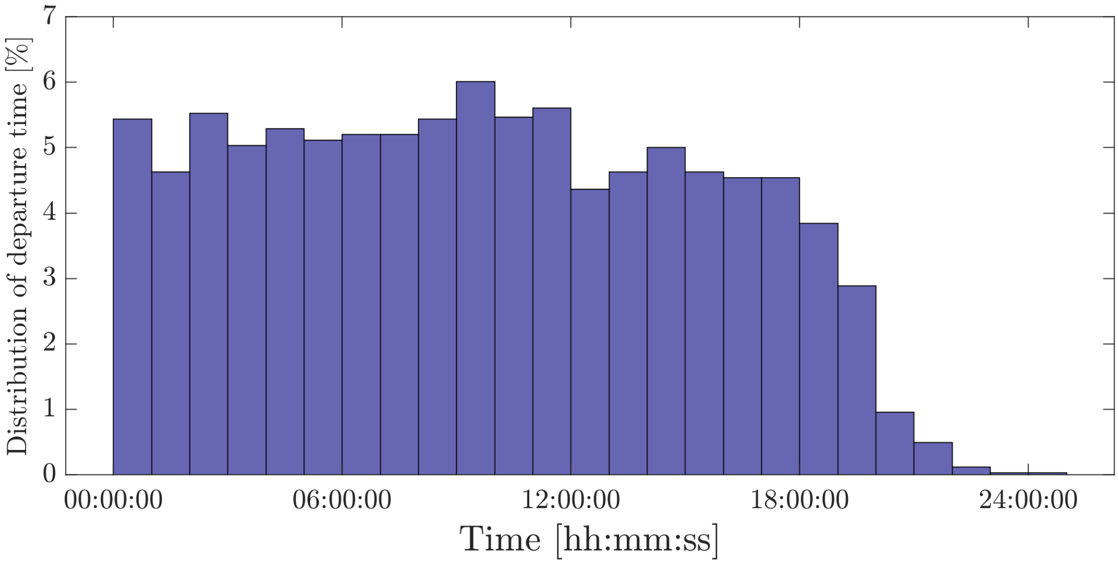

Figure 7: Departure times, all trucks [7].

3.2.2 The charging activities

Similar to cars, all agents are assigned charging activities before each iteration. These activities are based on the shortest route to the final destination, and the energy consumption profile together with the battery capacity and the initial SoC at departure. In between iterations, agents with charging activities next to a neighboring zone with an introduced charging station can adjust the travel plan to access it. However, this is only possible if the charging need appears within an adjacent zone, thus too large detours are avoided. This strategy optimizes coverage with fewer charging locations.

A charging activity is triggered by meeting one of two conditions: either the battery reaches a SoC level of 20 percent, or the truck has been in operation for 4.5 hours. For heavy vehicles with large batteries, the driving hours primarily determine charging needs. The SoC levels of the truck batteries upon reaching the station vary as a result of the different criteria for initiating a charging activity, and the variations in distance from the point of triggering to the nearest BSS. The SoC levels for the trucks reaching a charging location before reaching SoC = 0 are detailed in table 15. This data is based on actual simulation data for when the vehicles arrive at the location, in contrast to the same figures for cars presented in table 9, which reflects the charge levels at the initiation of a charging activity. Nonetheless, these numbers are used in the same manner.

Table 15: Battery SoC when swapped.

SoC [%]	Population share [%]
20-30	72
30-50	22
50-	6

3.2.3 The candidate locations for charging infrastructure

Relevant locations for charging are identified by running MATSim and gathering the geographical coordinates from instances of Low Energy Events (LEEs) or the events of vehicles running out of driving time. The distinction between MEEs and LEEs is that the former indicates a completely depleted battery, while the latter refers to when a battery reaches a SoC level of 20 percent. The truck data was obtained at a later stage of the MATSim development than the car data, which explains this alternative approach. The reason for instead using LEEs as a determining factor for charging station placements is that it gives the vehicles a margin to seek and find a station before completely exhausting their charge. This is of relevance as the MEEs or LEEs might occur at some distance from an available station.

The process for station placement involves multiple iterations, in which all trips start with fully charged batteries. Commencing with an initial iteration assuming no charging accessibility, the simulation is run and LEEs are gathered and aggregated within zones of a 30-kilometer radius. The zones are then ranked, with the top three in terms of LEE density selected for placement of charging stations before starting the next iteration. Each zone accommodates one station, ensuring an approximate distance of 60 kilometers between two adjacent stations, in alignment with the European Council's road map [87]. A charging station is placed in the direction of the closest road segment allowing higher speeds than 90 km/h.

Trips are deemed successful when vehicles reach their final destinations without running out of charge. Conversely, if a battery does run empty, either due to the truck being too far away from the nearest charging location, or that it has to wait for too long in queue and does not have enough time to swap, the trip is considered unsuccessful. In this context, the maximum time a truck can spend at a location is set to 45 minutes for all cases, including queuing and charging. This is aligned with regulations stipulating that a driver can only drive for 4.5 hours until a obligatory 45-minute break [88]. Other rules apply for trucks with multiple drivers, and after two sets of driving hours, but these exceptions are not taken into account. The trucks that do not reach 4.5 hours of driving time, but instead are constrained by reaching SoC = 20% do not actually need a break of 45 minutes. As the input data, however, does not contain information on which condition is the driving factor for initiating a charging activity, a long break is decided for all. This is an assumption inherited from the simulation data, and is based on that the majority of the trucks in the original population have a large battery that will not reach SoC = 20% before driving 4.5 hours. At each location, a maximum of 14 charging points with a plug power of 700 kW each is established, driven by assumed power grid limitations. In the original data, the maximum number of arriving trucks per given instant is therefore 14. Due to the manual population upscaling after running the simulation, however, this constraint is irrelevant. The average duration of a fast charging stop is approximately 45 minutes.

Within the dataset, successful trips comprise 69.3 percent of the total, which are covered by 29 established charging locations within the Swedish borders. An important note is that neither the SAMGODS nor the simulation data contains information on the time requirements of a mission. Due to this, the operational time aspect is neglected in the model, although it is highly relevant for a truck company from a business standpoint. The main concern that could interfere with this interest is the allowable waiting time, which is therefore a parameter subject to further analysis in the sensitivity study.

3.3 MATLAB model

The input data is a file consisting of all charging events arising from successful trips in a day. This dataset includes specifications on location, start and end time, duration, and the amount of energy transmitted. As the data is generated from a fast charging simulation, not all details of the events are directly applicable to the battery swapping case. However, the charging locations and start times remain valid on the premises that the same assumptions regarding the trips and vehicles are maintained. The data is sorted, and all events are aggregated into tables, each representing a five-minute resolution span within a day.

3.3.1 The number of swapping stations

The number of BSSs per location is determined by the flow of vehicles at each location and the established longest allowable waiting time. The waiting time refers to the duration until the vehicle enters the BSS, excluding the swapping process. The queuing system is assumed to be a single cumulative line, which can reduce waiting times compared to separate lines for each service spot [89]. The accepted waiting duration depends on various factors, such as driver characteristics, the driving mission, and the availability of station amenities like restaurants or kiosks. For cars, the acceptable waiting time is calculated based on a weighted average of travel time uncertainties affecting the total journey duration. The reasoning behind this is as follows: uncertainties in travel times vary according to traffic conditions, with prediction errors averaging between 8 and 19 percent on busy highways [90]. When planning a trip, drivers usually account for a margin to accommodate these uncertainties. Any deviation beyond this margin becomes uncomfortable, and a change of the original plan is often required. Consequently, a queuing time within this acceptable range ensures that the charging event falls within an agreeable time window without necessitating any travel plan changes. Assuming an uncertainty of ± 14 percent of the total travel time and an average speed of 100 km/h, the allowable waiting times are as detailed in table 16. The lower bound of each distance range is selected to establish the allowable waiting time, and only one battery swap per trip is assumed. Based on the SAMPERS data on travel distances, the population shares of each time frame are known. Out of every 100 cars, approximately 37 would accept a 13.5-minute wait, 24 cars will tolerate an 18-minute wait, and so on. By weighing these proportions, the average acceptable waiting time for all cars is calculated, resulting in a value of 20 minutes, which is employed in the model. Conversely, the waiting time for trucks, set at 45 minutes, is instead determined by driving regulations, as elaborated in section 3.2.2. For both cars and trucks, there are uncertainties associated with this parameter, which is why its impact on the results is investigated in the sensitivity analysis.

Table 16: Allowable waiting times depending on total travel time, cars.

Driving distance [km]	**Travel time**	**Waiting time**	**Population share [%]**
150-200	1h 30 min	13.5 min	36.8
200-250	2h	18 min	24.3
250-300	2h 30 min	22.5 min	12.6
300-350	3h	27 min	8.1
350-400	3h 30 min	31.5 min	5.3
>400	4h	36 min	13.0

The number of stations is determined exclusively by limiting the queue, which explicitly means that there will be a free swapping spot available in no more than 20 (cars) and 45 (trucks) minutes after arrival. However, the overall time allocation includes more than just the waiting time; it also includes the duration of a swap. This accounts for driving into the BSS, the swapping process, and leaving room for the next vehicle. For cars, this time is set at 3.5 minutes based on reported figures from one of the car BSS operators at the forefront, NIO [91]. Similarly, the total swap time for trucks is assumed to be 5 minutes, in accordance with the solutions offered by Enneagon, the BSS operator with the greatest number of truck service stations [17]. These figures are presented in table 2 and 3, and the implications of this parameter are further discussed in the sensitivity analysis.

3.3.2 The batteries and their way through the BSS

Within each BSS, a fixed number of batteries circulate while charging at a consistent rate of 0.5C. A car or truck station is assumed to have the ability to swap all vehicle sizes within the segment, as well as charge batteries regardless of their capacity. This kind of charging necessitates a planning schedule that takes the battery diversity and power outputs into account, which is a topic of ongoing research [92]. The battery stock within a BSS is assumed to mirror the distribution of battery sizes present in the fleet. Consequently, during periods of high swapping activity, it might not be possible for the driver to select a preferred battery size.

The total number of batteries in a station is a function of the average C-rate, the duration of a swap, and the difference between max and min DoD, according to equation 1.

$$\text{batteries per BSS} = \frac{\frac{60\text{ min}}{\text{C-rate}}}{\text{time of a swap}} * \frac{\Delta\text{DoD}}{100} \tag{1}$$

In this particular part of the model, the lowest SoC of the incoming batteries, 20 percent in accordance with table 9 and 15, is assumed. Choosing the lowest value ensures coverage of all scenarios. All batteries start charging immediately upon entry to the station, and are considered fully charged when reaching SoC = 90%. This results in a total number of 24 and 17 batteries per BSS for cars and trucks respectively. All BSSs are equal in size, which means that all are equipped with enough batteries to sustain the highest swapping service level given the physical constraints, i.e. the duration of a swap. This is a model simplification, and since the peak and mean load at each site is different, it is unlikely to reflect the reality. Instead of having a fixed number of batteries for all stations, the stock size would be probably be customized for the need at each location.

Furthermore, a simple model illustrating the theoretical life degradation of batteries charging within a BSS is constructed based on the logic in figure 8. Although the batteries most commonly used in vehicles today are other than LiFePO4, the reasoning is considered valid. The implications of this simplification is further addressed in the Discussion, section 7. A correlation can be seen between the battery cycling depths, the rates of (dis-)charge, and the battery SoH. Cycles involving deep discharges or high C-rates over time contribute to decreased total charge cycles, ultimately shortening battery lifespan.

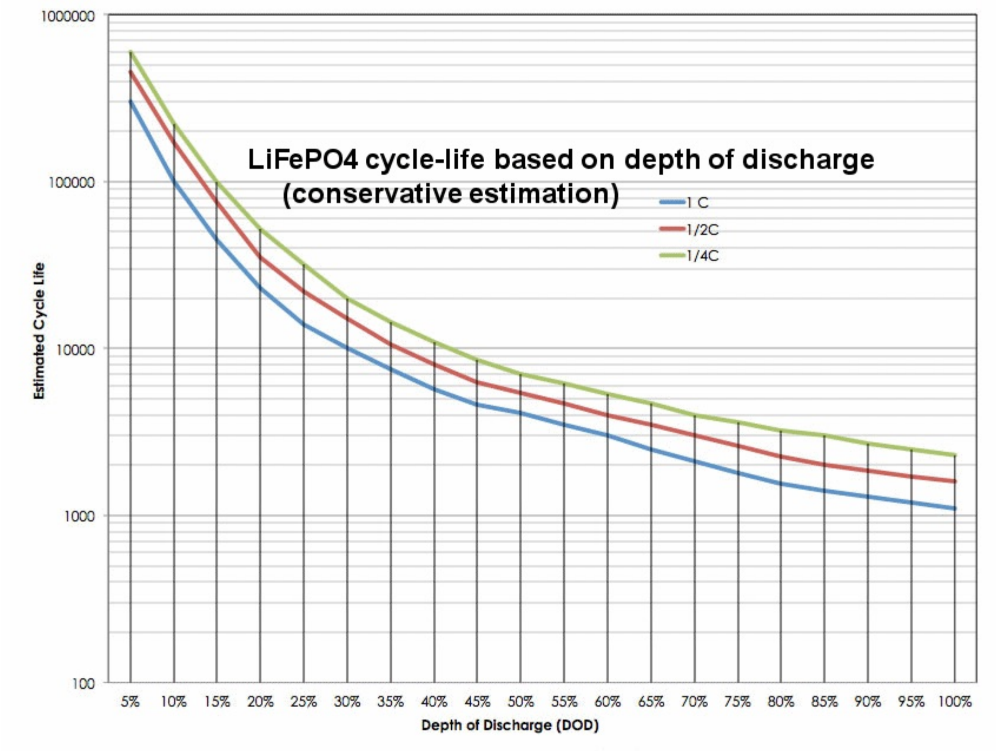

Figure 8: Estimations of the life-cycle of a LiFePO4 battery based on the depth of discharge and discharge rate [8].

Other mechanisms of battery degradation, related to storage conditions and charging temperatures, are outside the scope of this thesis. Cycle aging is a result of battery cycling, while calendar aging is associated with battery storage. The developed model only accounts for cycle aging of the batteries in charging mode, meaning that calendar aging and aging due to other cycling are neglected. Additional charge- and discharge cycles may occur via B2G services, but due to the added complexity of ancillary service modeling, these are excluded. Furthermore, although the battery health is known to decrease over time, a SoH = 100% is assumed for all batteries. As a result, the batteries' full capacity according to specifications can be utilized. Based upon this reasoning, the model is used to calculate the total battery life degradation per hour and BSS. From this, the consumed battery life of an individual battery is derived using equation 2.

$$\text{degradation} = \frac{1}{0.5\text{C}} \frac{\text{total BSS degradation}}{\text{number of batteries in BSS}} \tag{2}$$

In addition to an available swapping spot, a sufficiently charged battery must be available. Upon vehicle arrival, they join a queue. As many vehicles as possible - limited by the amount of free swapping spots and fully charged batteries - are swapped, while the rest remain in the queue. The number of batteries in a BSS is established to maintain the highest swapping frequency, corresponding to the time of a swap, determined by the fixed C-rate and incoming SoC levels. As a result, there will always be fully charged batteries available to swap at the highest frequency physically possible (constrained by the time of a swap and available spots). All batteries within a station follow the "first in - first out" (FIFO) priority rule, with all batteries exiting the BSS fully charged. Although the number of batteries per BSS and life degradation is based on SoC = 20%, the incoming batteries have a spread according to table 9 and 15.

3.3.3 The utilization rates, ancillary services, peak power, and land usage

As the frequency of charging events fluctuates during the day due to the predetermined starting times in table 7, 8, and 6, and figure 7, battery utilization within vehicles varies throughout the day. The utilization rate is determined by the number of batteries leaving the BSS immediately upon full charging. Consequently, the highest rates are achieved when batteries are instantly swapped as they reach a full charge. If not swapped directly, they can instead serve ancillary services to support the grid. This availability applies only to non-charging batteries.

During periods of high swapping frequencies, multiple batteries are in charging mode at the same time. Accounting for the various battery sizes and assuming a uniform C-rate, the required power supply differs for different charging outlets. A model simplification is that the charging batteries have a size distribution based on the fleet specifications (see table 4 and 13). This results in an average car battery capacity of 84 kWh, whereas the same number for trucks stands at 355 kWh. This translates to power connections of 42 kW and 177 kW per battery for cars and trucks, respectively, with a C-rate of 0.5. The power supply is assumed to remain constant until the charging process of a battery is complete, which means that the declining power levels when approaching high SoC levels are not considered.

Land usage plays an important role when analyzing the viability of the results, particularly in the context of large-scale charging infrastructure deployment. Hardware equipment dimensions and the necessary space around it vary among manufacturers. In car calculations, a fast charging spot is assumed to have a minimum area of 2.7x5.5 square meters [93], while a NIO BSS occupies the space of a double garage [11]. The average size of such a garage is assumed to be approximately 7.3x9.1 square meters [54]. Additionally, a parking space, with the approximate dimensions of 2.5x5 square meters [94], is often allocated for cars to use before initiating a swap. For trucks, BSS land usage can vary widely depending on the project, as briefly exemplified in table 3. One of Enneagon's projects, where the BSS occupies an area of 240 square meters, is used as a reference for calculations. This construction had, at the time of documentation, only one lane for swapping, but with space for another one [17]. Henceforth, these numbers are used assuming an operational capacity of two trucks at a time. Fast charging calculations are based on a truck's maximum size in Sweden, 2.6x24 square meters [95], and Heliox Energy's ultra-fast charger dimensions of 4.8x0.8 square meters [96]. These measurements include only the hardware equipment and area for charging or swapping, but space for entering and leaving the area is also required. These are assumed roughly the same for both battery swapping and fast charging.

The number of batteries in a BSS is exclusively determined based on the criteria of maintaining high-quality swapping services throughout the day. As a result, dimensions related to battery utilization, power demand, and land usage are not optimized in this study. Maximizing profit by varying the number of batteries per BSS, and BSS per location remains a topic for further research.

4 Results and Analysis

4.1 Cars

4.1.1 The number of swapping stations

All charging activities are covered by 337 locations. Their usage frequencies during a representative day are illustrated in figure 9. Although there is a cap of maximum 30 vehicles at the same time and location it is occasionally exceeded, which is due to that all activities within five minutes are aggregated.

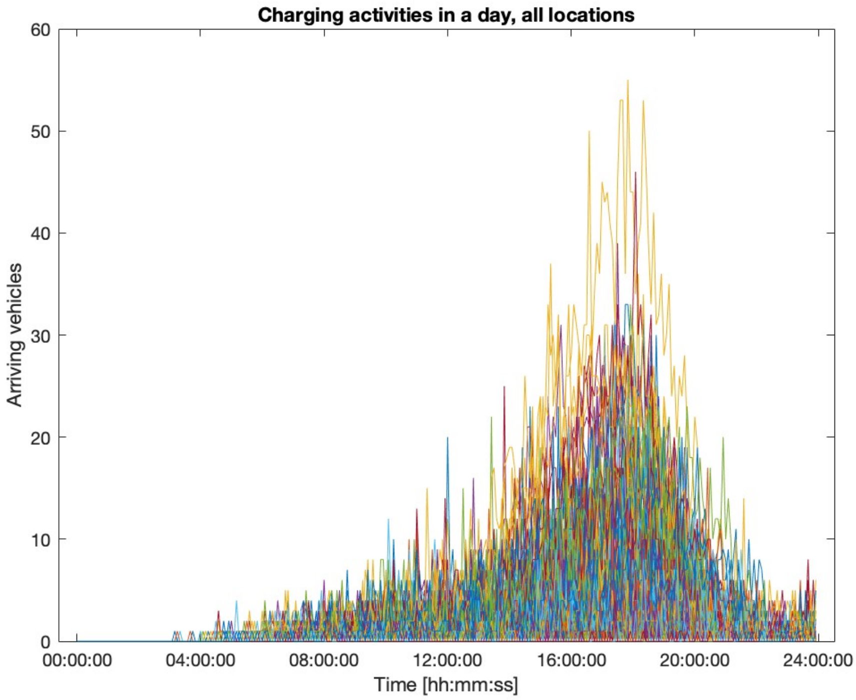

Figure 9: Aggregated charging needs at all locations during a day.

For each location, the model has established a minimum number of BSSs necessary to meet the maximum queue requirement, and these findings are illustrated in figure 10. For over 190 locations, which account for more than 55 percent of all, a single station suffice. Two stations cover about 74 percent of all locations, whereas 81 percent maintain adequate service levels with three stations. The exact results are listed in figure 11.

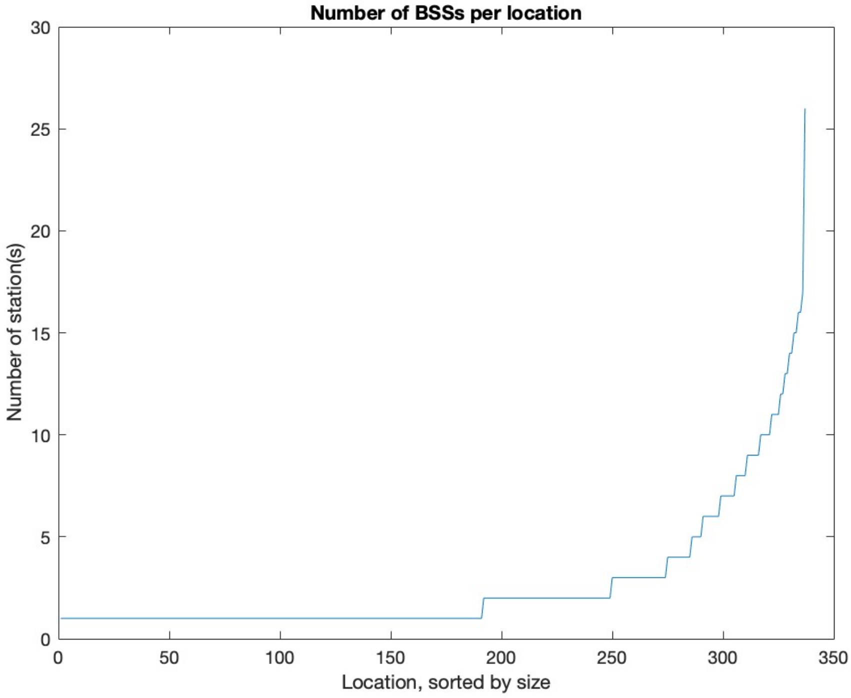

Figure 10: Number of BSSs per location to satisfy the car queue requirement, sorted by size.

Number of BSSs	1	2	3	4	5	6	7	8	9
Locations	191	58	25	11	5	8	7	5	6
Number of BSSs	10	11	12	13	14	15	16	17	26
Locations	5	4	2	2	2	2	2	1	1

Figure 11: Number of BSSs per location.

The locations requiring many BSSs have very high charging demands during the afternoon, as evident from the peak values in figure 9. For instance, at the location with the highest demand, depicted in figure 12, 55 cars arrive between 17:50 and 17:55, and 44 cars arrive in the next five minutes. To prevent congestion during these critical periods, the model proposes a high number of BSSs.

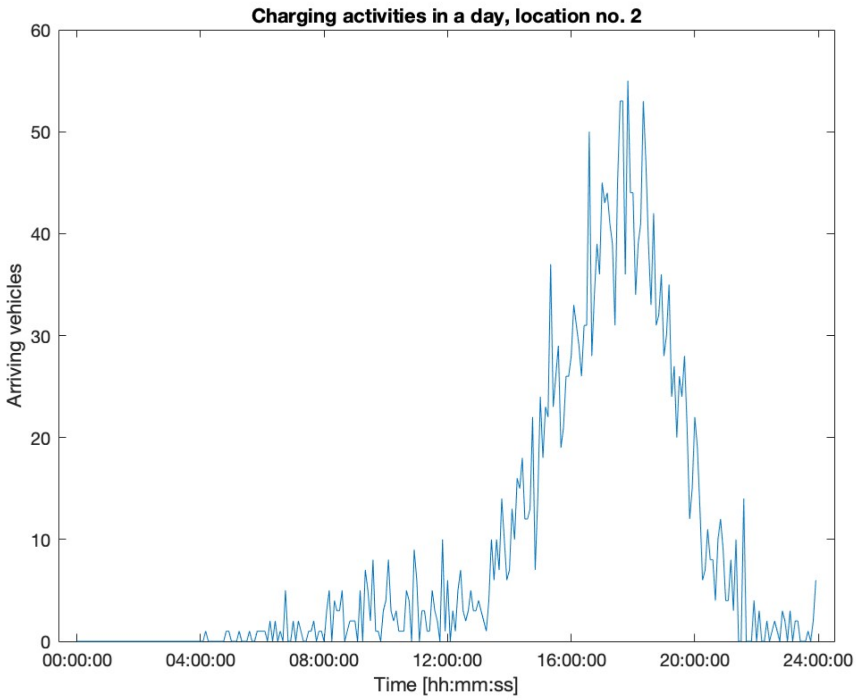

Figure 12: Aggregated charging activities at the busiest location.

4.1.2 The batteries and their way through the BSS

The number of batteries in each, and all, BSSs can be seen in table 17, together with the summarized battery capacity. Knowing that the total amount of batteries in cars on successful long trips is 71 866, the batteries in BSSs account for a 31 percent increase in batteries and energy. Furthermore, when compared to the entire car fleet, the increase in batteries of the car transportation system amounts to 0.44 percent.

Table 17: Batteries in BSSs.

Number of batteries/BSS	24
Number of locations	337
Total number of batteries in BSSs	22 056
Total battery capacity in BSSs	1.853 GWh

The established battery life degradation is shown in table 18. The maximum DoD is considered for these results, being from SoC = 90% to SoC = 20%. Some batteries have more shallow discharge cycles, which results in prolonged total life.

Table 18: Life degradation.

Life degradation per BSS and hour	0.0057
Life degradation, one battery charge cycle	0.00048
Total number of cycles in life, one battery	2 100

4.1.3 The utilization rates, ancillary services, peak power, and land usage

Figure 13 shows the number of fully charged batteries and their total energy when not used for swapping services, and can instead be used for ancillary services when necessary. It mirrors the trend seen in figure 9, where the highest overall swapping frequencies occur around 18:00 and 20:00.

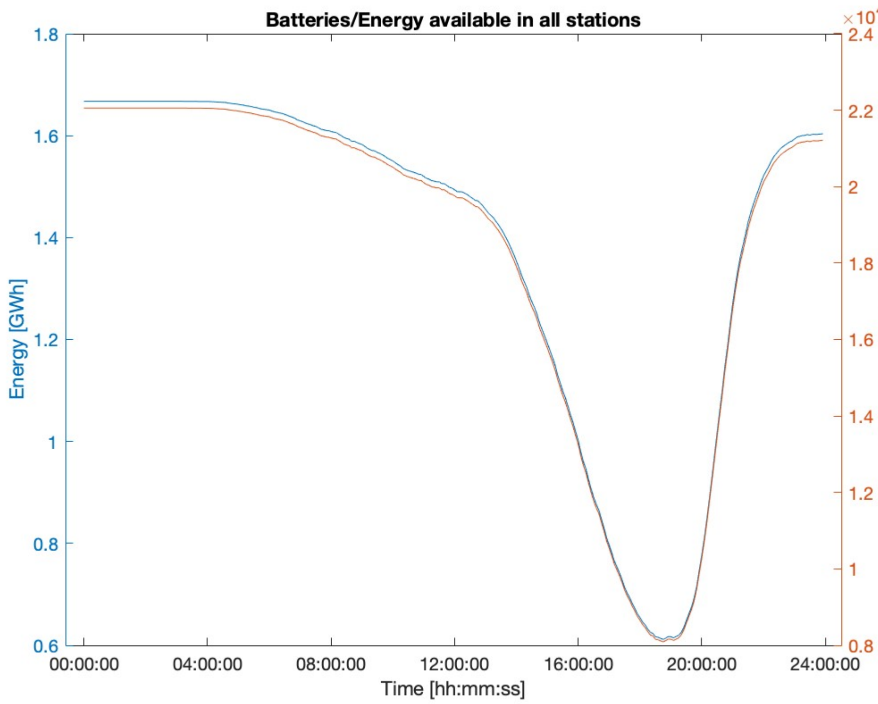

Figure 13: Fully charged batteries stored in BSSs.

The amount of energy stored in the stations indicates that the rates at which the batteries are swapped into EVs vary significantly during a day. This is evident by figure 14, where both the maximum and mean utilization rates are presented on the left. The low mean values can be explained by referring to figure 13, where it is shown that a large part of the battery stock remains underutilized for swapping purposes over the course of a day. This value would increase if a model of the battery utilization for ancillary services would have been incorporated. Furthermore, any correlation between the maximum utilization rate and the number of BSSs at a location is shown in the right diagram. For numerous locations equipped with only one BSS, the maximum utilization rate falls below the 30 percent mark. This can be explained by the fact that these locations experience only a few charging activities per day, and rarely no more than two at once. This means that a BSS equipped with 24 batteries is substantially over-dimensioned. A more appropriate, lower amount of batteries in these stations would increase the utilization rates.

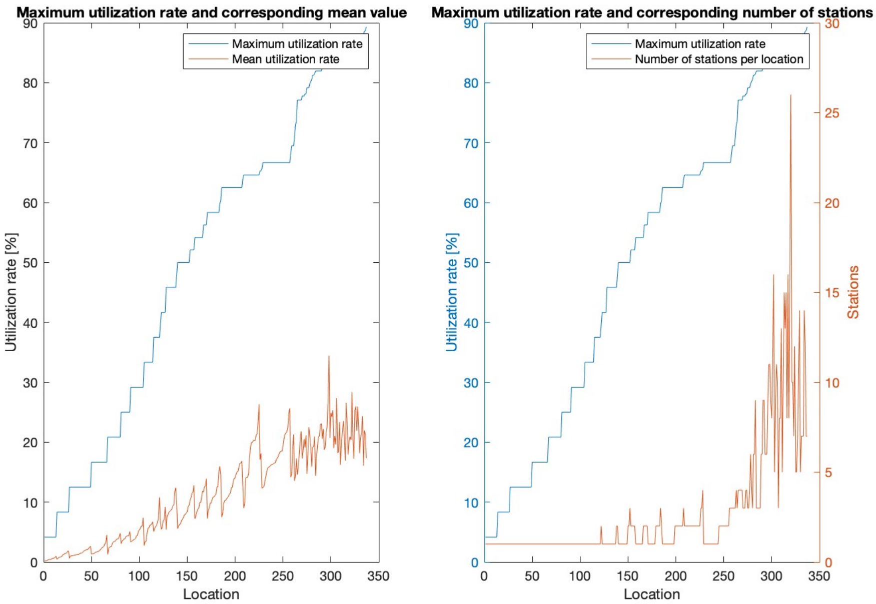

Figure 14: Maximum utilization rate (sorted by size), mean utilization rate, and number of stations.

The peak power levels for each location are shown in figure 15, and the relation to the number of BSSs per location, seen in figure 10, is clear. The maximum level is 22.5 MW for the location with 26 BSSs, although 96 percent of all locations require a power connection lower than 10 MW, and 88 percent is good with 5 MW.

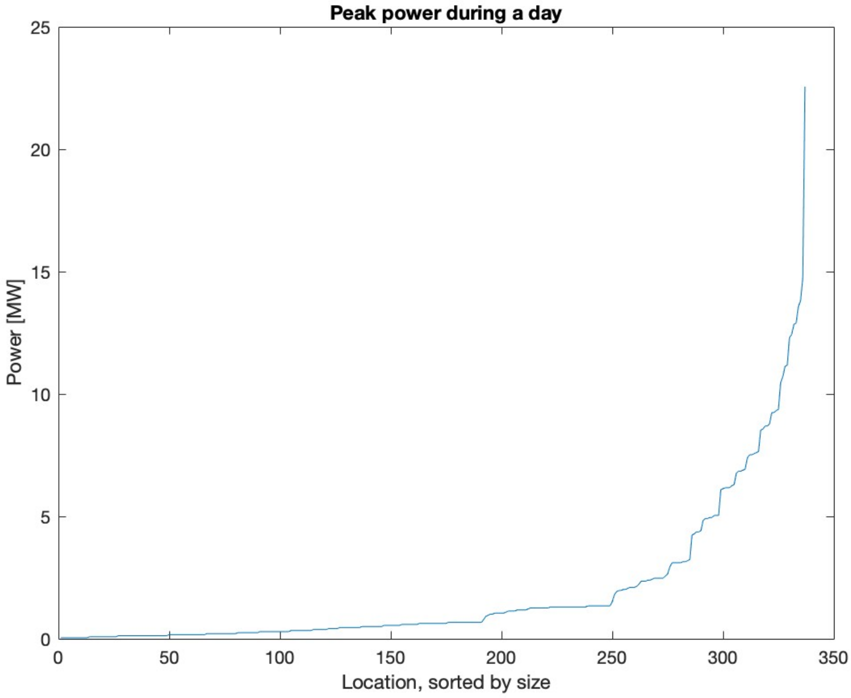

Figure 15: Peak power levels per location in a day, sorted by size.

The land usage is visually represented in figure 16. Within the same area as one BSS, five fast chargers can be accommodated. If considering an instance where the same area is designated for either battery swapping or fast charging, the number of served cars differs. In the battery swapping scenario, taking 3.5 minutes per swap translates into 17 swapped car batteries in an hour. Within the same timeframe, fast chargers would facilitate the charging of 10 EVs, with a 30-minute duration for each. In both cases, it is assumed that the vehicle leaves the area immediately after a full energy replenishment. Furthermore, spacing for waiting lines depends on how long of a line a driver will accept to stand in. If, as assumed in the battery swapping case, the average driver can accept 20 minutes of waiting and a swap is performed by one station every 3.5 minutes, that equals a maximum line of five cars. In the fast charging alternative, two cases can be considered: where the driver is accepting 30 minutes of waiting, or none at all. If 30 minutes is accepted, aligning with the 30-minute charging duration, a queue of five cars can exist since there are five fast charging spots. If none, or less than 30 minutes of queuing is accepted, then the line will be the same or shorter. This means, that for the same area in both the battery swapping and fast charging scenario, the space required for queuing will be the same.

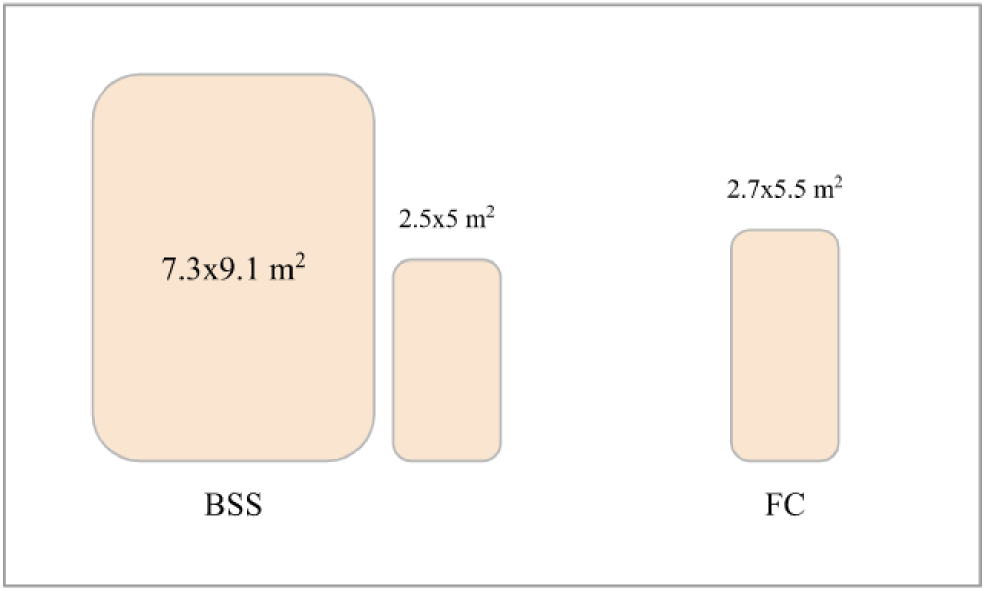

Figure 16: Land usage for the BSS, a parking spot, and a fast charging spot.

4.2 Trucks

4.2.1 The number of swapping stations

A total of 29 locations are established based on the original input data. The frequency of original charging activities can be seen in figure 17. The locations cover the charging needs of all 2 512 successful trips. In total, 4 561 charging activities are managed, which indicates a need for more than one charging stop within domestic borders per trip for some trucks.

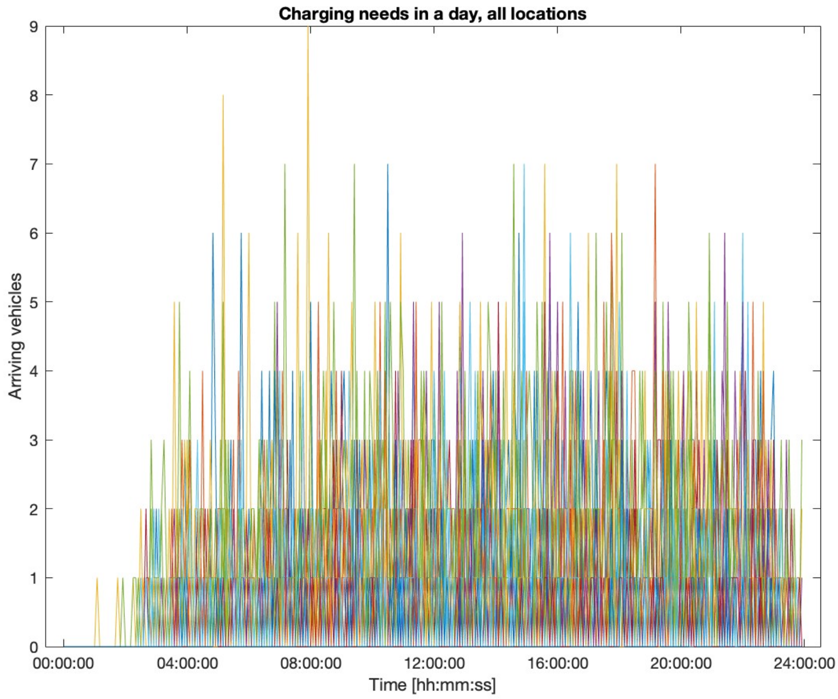

Figure 17: Aggregated charging activities at all locations during a day, original data.

Figure 17 does not include all trips due to the data discrepancy, so the modified data can be seen in figure 18. Noting from the modified scenario is that the number of locations is not scaled to fit the new population. One of the locations accommodates almost 130 trucks within a five-minute period. Comparing figure 18 to its car counterpart, figure 9, reveals a more evenly distributed flow of charging activities throughout the day for trucks. This increases the average utilization of a location's assets within a day, which is evident by the results in section 4.2.3. Drawing further conclusions regarding the load distributions at the locations is challenging, more than that additional charging locations are necessary. The following results are only presented for the modified population and charging activities, unless explicitly stated otherwise.

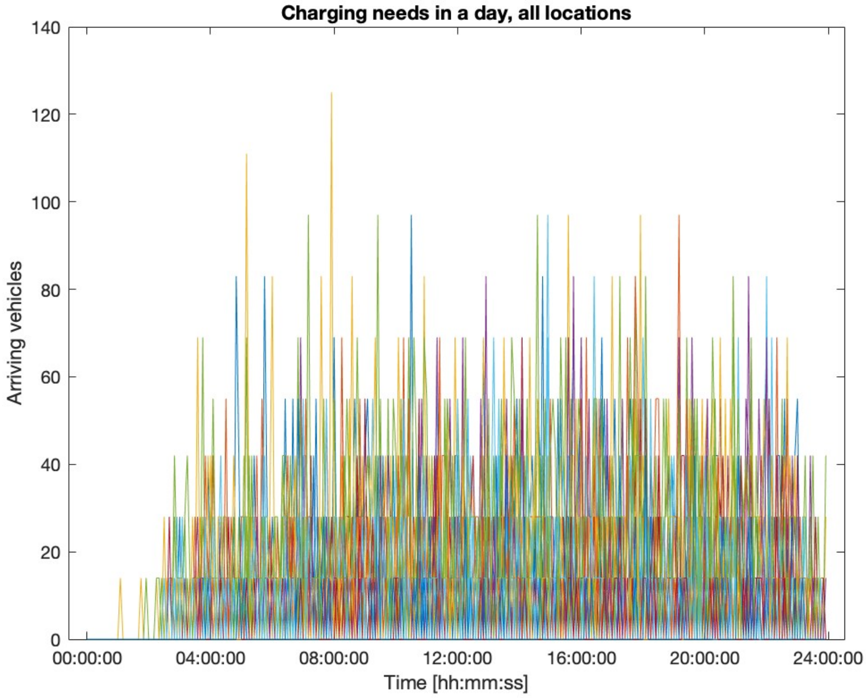

Figure 18: Aggregated charging activities at all locations during a day, trucks modified data.

For each location, a minimum number of BSSs to meet the maximum queue requirement are found, and the results can be seen in figure 19. Notably, around 30 percent of all locations need fewer than 10 BSSs, while 83 percent require fewer than 20 BSSs. Nonetheless, this is a significant amount of stations to fit within one location and its plausibility is evaluated in section 4.2.3, where the land usage of one truck BSS is assessed. Comparatively, in the original case, 62 percent of all locations would have effectively maintained good service with only one BSS, and the remainder with two BSSs. This could hold true also for the modified population if additional charging locations were placed.

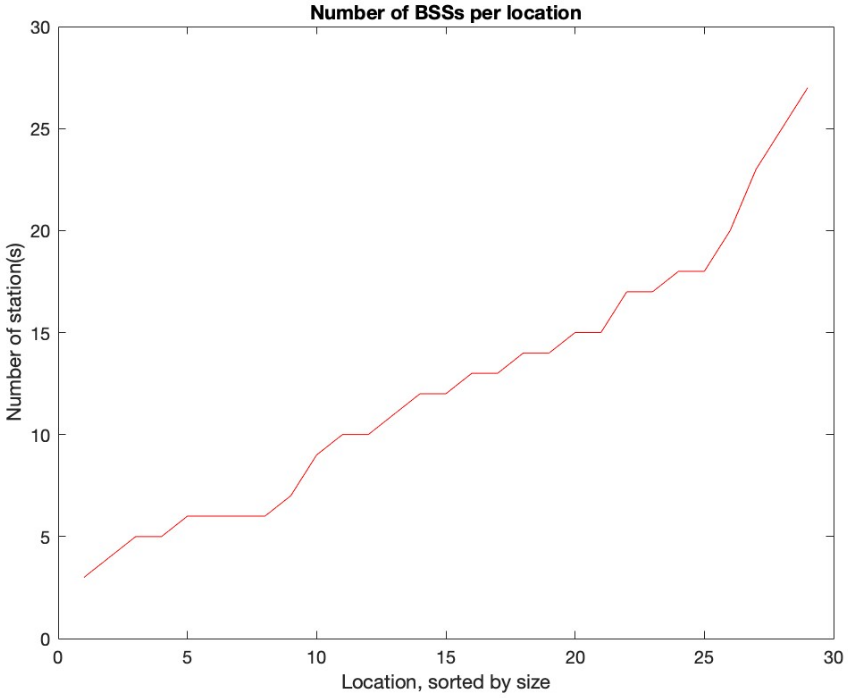

Figure 19: Number of BSSs per location to satisfy the truck queue requirement, sorted by size.

4.2.2 The batteries and their way through the BSS

The number of batteries and their total energy can be seen in table 19. The overall number of batteries on the trucks on successful long trips is 37 667, which means that the batteries in the stations account for 17 percent of additional batteries and energy. If compared to the batteries in the total domestic heavy truck fleet, consisting of 86 070 trucks, the batteries in the BSSs give an increase of 8 percent.

Table 19: Batteries in BSSs.

Number of batteries/BSS	17
Number of locations	29
Total number of batteries in BSSs	6 579
Total battery capacity in BSSs	2.33 GWh

Life degradation and the impact on total life is presented in table 20. It shows similar results as for cars (table 18), and the conclusions remain the same. More shallow cycling extends battery lifespan. Furthermore, it is important to note that the impact of battery cycling associated with ancillary services is not accounted for, as it is not included in the model. Some reasoning on the subject can be found in the Discussion, section 7.

Table 20: Life degradation.

Life degradation per BSS and hour	0.0040
Life degradation, one battery charge cycle	0.00048
Total number of cycles in life, one battery	2 100

4.2.3 The utilization rates, ancillary services, peak power, and land usage

Figure 20 depicts the number of fully charged batteries and their total energy when not utilized for swapping services. As expected, the batteries start fully charged, and the peak levels of stored energy are reached during the earliest hours. During the day, however, the energy levels are relatively low when compared to the same figure for cars, figure 13. This has a significant effect on the battery utilization outcomes. What can also be noted from the figure is that all batteries are not fully charged at the end of the day. From the last hour of the day, to around 03:00 in the morning, the swapping activity is very low, and the batteries will remain stored in the stations for a while. By the time of increased swapping activity, they will have recharged fully. In other words, a sustainable steady state is achieved.

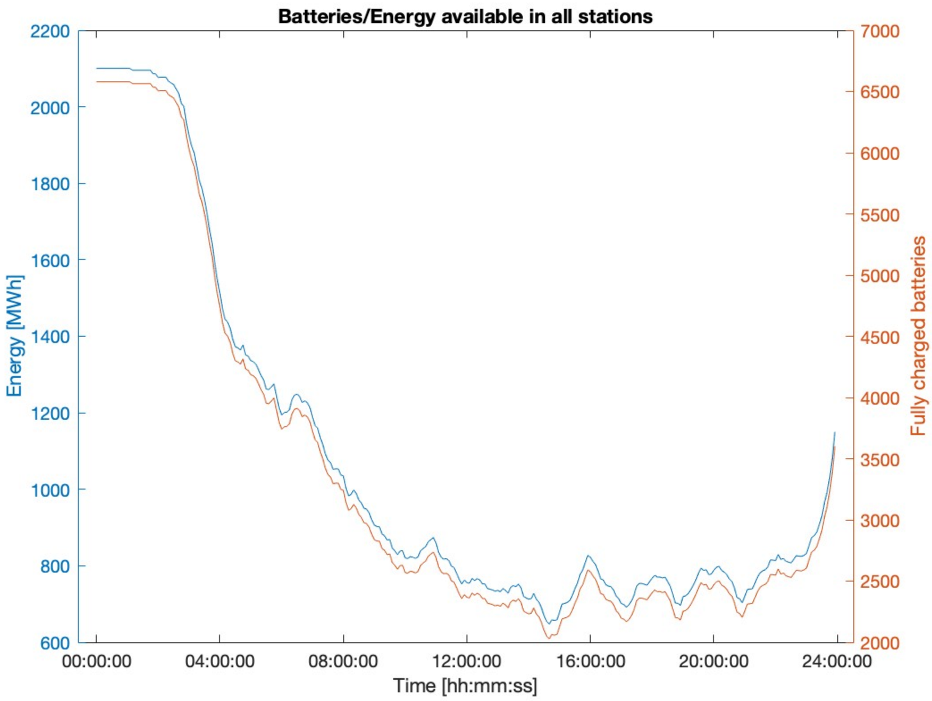

Figure 20: Batteries stored in BSSs.

The left diagram of figure 21 shows the maximum and mean utilization rate for each location. On the right-hand side of the figure, any correlations between the maximum utilization rates and the number of BSSs are illustrated. Both maximum and mean values are higher for most truck locations than for cars (see figure 14), which has several explanations. Due to the increased number of charging activities per location, the number of batteries per BSS is more rarely excessive than for a location with a more balanced, i.e. lower, flow of charging activities. Furthermore, the departure times of trucks have a higher degree of variation compared to cars. This results in a more consistent flow of charging activities throughout the day. Most locations have a mean utilization rate ranging between 35 and 60 percent, although there are some lower values too. The dips in mean values on the left-hand side of the figure coincide with the low points in the number of BSSs seen on the figure's right-hand side. This correlation suggests that there are still locations where 17 batteries per station are excessive during most parts of the day. Adjusting the number of batteries to match the actual demands could be a solution to this issue. The results of doing so could however impact service levels during peak load hours, as the maximum utilization rate curve indicates that during periods of high demand, most of the batteries are actually used.

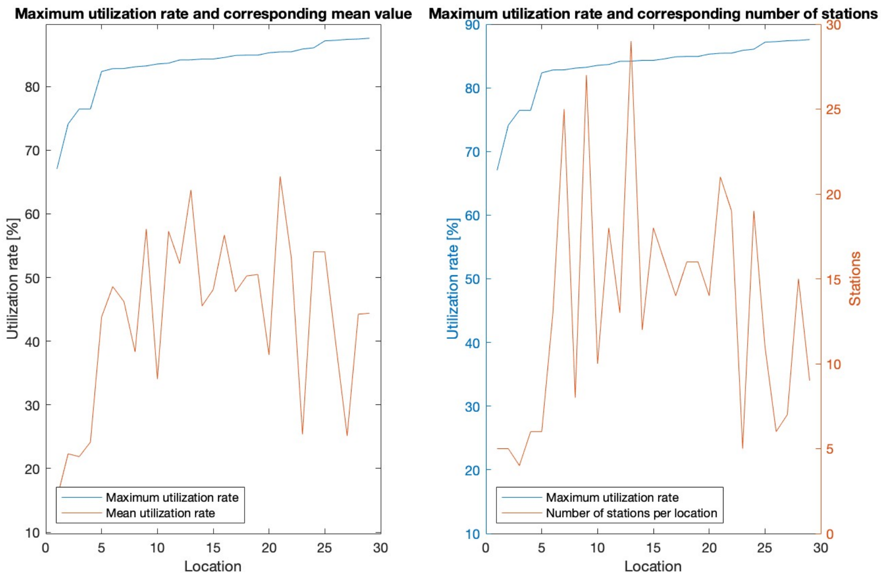

Figure 21: Maximum utilization rate (sorted by size), mean utilization rate, and number of BSSs.

The peak power levels across all locations are illustrated in figure 22. The power demands are high at most locations, with only one site below 10 MW. This is a result of the increased number of charging activities without adding any charging locations. Most of these power levels are too high, and should not be confused with actual numbers in real-world projects. Worth noting is that one of the advantages of battery swapping is that relatively low power levels can be maintained during most of the day, at least when compared to power levels of fast charging stations. This is however not observed in this study due to the above reasons.

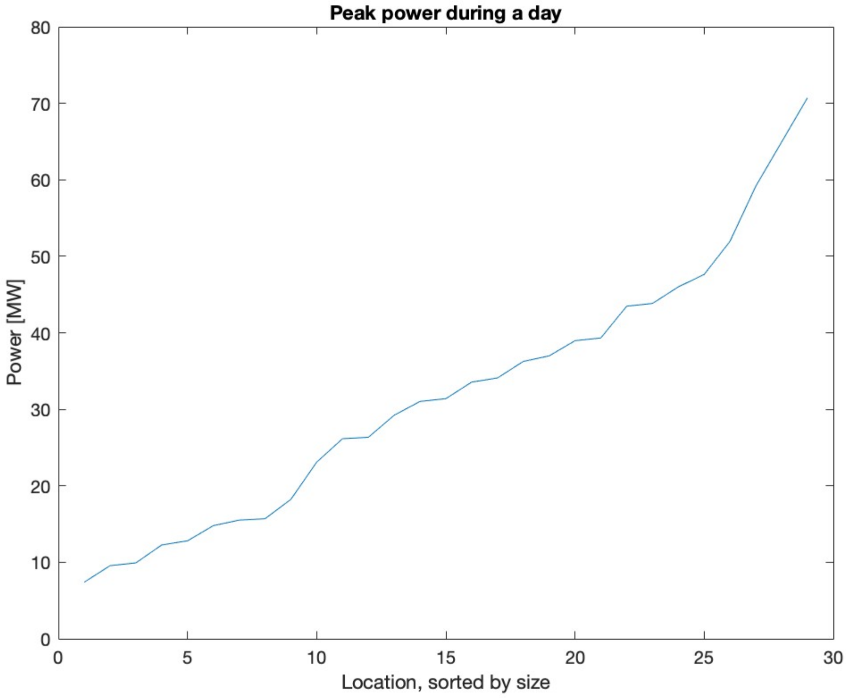

Figure 22: Peak power levels per location in a day, sorted by size.

In terms of land usage, a single BSS occupies an area of 240 square meters. Conversely, approximately three fast charging spots, each covering 66 square meters, can fit within the same area. A challenge in comparing these numbers is that it is unknown whether the BSS covers the entire truck or only part of it. This depends on how the station is constructed, and it is likely that a part of the trailer might remain outside the BSS's roof while swapping. If this is the case, additional space required for the remaining part of the truck needs considering. A rough estimate could involve assuming that half of the truck, if equipped with a trailer of maximum allowed length, remains outside of the BSS. This would add 30 square meters to the BSS area, and four fast charging stations could instead fit within this space. Comparing the efficiency and capacity of the technologies becomes relevant. Given a swapping time of five minutes and a fast charging time of 45 minutes per truck, it is estimated that 12 trucks could be swapped in an hour, while fast charging four trucks within the same timeframe. Despite the approximation regarding land usage, the significantly faster swapping time translates to a higher number of trucks per hour and area unit than fast charging.

The large spaces needed for battery swapping should, however, not be overlooked. By these numbers, 10 BSSs would require an area of approximately 1 200 square meters. For reference, this is equal to about five tennis courts. This calculation only accounts for the hardware equipment, meaning that the lanes for driving in and out of a BSS are not included. With more BSSs, additional lanes are necessary. Altogether, it results in rather large spaces that might not be available everywhere along the transportation network. Instead, establishing several distributed locations with fewer BSSs at each site could be a less complex solution.

5 Sensitivity analysis

A sensitivity analysis can be defined as an analysis of how the model's outputs react to changes in the inputs and/or structure of the model [97]. It serves several purposes, one of which is to identify model uncertainties that may call for additional research or data input [98]. The analysis can also aid in validating and verifying the model, as well as evaluating its robustness [99] [100]. This section aims to describe and motivate the methodology employed for the sensitivity analysis of the MATLAB model. It subsequently presents the results comprehensively, and concludes with general remarks on the analysis.

5.1 Methodology

There are several techniques for conducting sensitivity analyses, each with different levels of applicability to a specific model. These methods can be categorized in various ways, such as mathematical, statistical, and graphical methods [101]. Mathematical techniques can be useful for providing insight into the impact of input variables on the output, often by varying the input parameters within a representative range and calculating the outputs. Some mathematical methods are valuable for validating and verifying the model, as well as identifying the need for complementary data or research. These methods are often suitable for deterministic models, while probabilistic models can be better analyzed with statistics. Statistical methods can for instance be applied when the goal is to compare the interactions between multiple inputs and their impact on the output. Graphical methods are often used best in combination with other techniques. They can provide visual insight into dependencies and offer a comprehensive view of how outputs vary with inputs. Thus, they can serve as a first step in a deeper analysis or complement an analysis with a graphical representation.

In this model, an important source of uncertainty is related to the input parameters. The parameters are decided through estimation or actual values from real systems, and understanding their impact on the results is important. Of particular interest are the parameters that are estimated to have the greatest impact, as they cause the most uncertainty in the model. The chosen method involves mathematical analysis complemented by graphical representation. This approach is suitable, as the model is deterministic. This means that average values are applied to a large population without random deviations [102], in contrast to stochastic models. It also differentiates from a probabilistic model as it gives a single output for each input, rather than a probabilistic characterization of the uncertainties [103]. The method is relatively simple to apply and understand, and it fits well with linear models. It is effective when the range of each selected input is known, and any number of inputs is possible. While more sophisticated methods exist, this approach is considered reasonable to establish a basis for discussing and drawing conclusions about the model's uncertainties related to the input parameters. Each input is varied while keeping all other parameters constant according to the base scenario. Their absolute, as well as relative, impact on the outputs is investigated and plotted. A sensitivity coefficient can be used to show the sensitivity of the results to a change in the input parameter [104]. This coefficient is calculated by dividing the change in the results by the change in the input parameter, as seen in equation 3. The change is measured relative to the reference values from the base scenario. For ease of interpretation, the sensitivity coefficients are described in absolute values.

$$\text{sensitivity coefficient} = \frac{\Delta \text{ output}}{\Delta \text{ input}} \tag{3}$$

Four results are analyzed: the total number of batteries and, consequently, the total battery capacity, across all BSSs; the hourly battery life degradation in one BSS; the mean stored energy across all locations; and the maximum utilization rates for all batteries within the battery swapping system. The stored energy varies throughout the day, and neither the maximum nor minimum values are considered optimal representations of a day. Therefore, a mean value of the energy across all locations during the day is chosen to show the average energy capacity available for grid services. Similarly, utilization rates fluctuate, and the analysis focuses on the averages of the maximum values across all locations as a function of the input parameters. Naturally, utilization rates are not constant during a day due to traffic flow variations. Identifying which parameters have the most significant impact on maximizing overall utilization rates is of interest, particularly since some numbers are very low. Although mean utilization rates are also of interest and would be useful for an even deeper analysis, they are not included in this study.

The results are functions of four main input parameters: the battery SoC when leaving the BSS (SOCdep), the recharge C-rate for the batteries (C), the accepted waiting time (WT), and the time for a swap (ST). The reference values for these have been estimated based on current technology and may vary. These variations can lead to different final outcomes, and this sensitivity analysis is used as a tool to determine the absolute and relative impact that each parameter has on the output when varied within a chosen range.

5.1.1 Input parameters

Table 21: Input parameter ranges, cars.

SOCdep [%]	**C [C]**	**WT [min]**	**ST [min]**
50 - 90	0.5 - 1.5	13 - 36	1 - 10

Table 22: Input parameter ranges, trucks.

SOCdep [%]	**C [C]**	**WT [min]**	**ST [min]**
70 - 90	0.5 - 1.5	5-45	1 - 10

The ranges within which each parameter is analyzed are presented in table 21 and 22.

The SoC level of the batteries upon departing the BSS, SOCdep, spans from 50% to 90% for cars. This range accounts for the flexibility in battery swapping options where drivers can select batteries of lower SoC. The lower bound is decided by estimation and is a low value that may, or may not be economically viable for the BSS operator and satisfactory for the customers. A lower SoC could be a solution to the inability to choose battery size. For instance, a driver who desires a 60 kWh battery may instead receive a 100 kWh battery and could be satisfied with a

SOCdep value of 50%. On the other hand, for trucks, the range is narrower due to the assumed reluctance of trucks to accept a lower SoC. This stems from the economic significance of reducing the number of charging stops and meeting delivery deadlines. The lower bound, 70%, is set by estimation. Decreasing the SOCdep parameter might necessitate additional charging activities to avoid running out of charge, but this aspect is not included in the sensitivity analysis since it would require modifying the input data from MATSim. If the battery is considered to be sufficiently charged at a low SoC, it will have a shorter charging time, which affects the number of required batteries per station. Additionally, battery life degradation, which is a function of cycle depth, also changes with SOCdep. Furthermore, lower SOCdep impacts utilization rates and the available energy stored in the stations. If the batteries are planned to stay in the station for a longer time, it can be preferable to keep the battery at lower SOCdep levels in order to maintain good battery health. This correlation is however not reflected in the sensitivity analysis, as battery health is not analyzed from an energy storage point of view, but solely by looking at the charging cycles.

C affects all four results, and is varied between 0.5 and 1.5 for both cars and trucks. This range is chosen to capture how the results are affected by fast charging of the batteries. The upper limit is a rather high rate at which the batteries will be fully charged in 40 minutes, nearly the same time as an average fast charge for cars in the model. The lower bound aligns with the default value, but should not be regarded as an absolute minimum.

The range of WT for cars is drawn from the data represented in table 16, where the lowest value ensures that all agents receive a fully charged battery in the ideal time, while the highest value only satisfies agents covering the longest distances. For trucks, this parameter is important to analyze due to the base scenario assumption that all trucks would accept a long break. Since not all trucks adhere to this, as some agents still have driving time left before the mandatory break, a WT as low as possible, five minutes, is set as the lower bound. The lowest value of WT, combined with the highest values of ST, allows for no queuing at all by always having a swapping spot ready for the next truck. WT influences all results except life degradation, as the parameter has no relation to battery charging, but only to the number of BSSs per station.

ST is the only parameter that has an impact on both the number of batteries per station and the number of BSSs per location, which is an interesting relation. It ranges from 1 to 10, based on the common market solutions for cars today according to table 2. As truck applications vary widely, not all are represented in table 3, thus the same range as for cars is applied. Both ends of the range are on edge of what is reasonable, and should be seen as an attempt to capture as many cases as possible. The reality is most likely to end up somewhere in the middle.

5.2 Results: Cars

The max and min values for when each parameter is varied individually are presented in table 23 and 24.

Table 23: Car results sensitivity analysis, min-max values.

Output param.	**$50 \leq$ SOCdep ≤ 90**	**$0.5 \leq$ C ≤ 1.5**
Total no. of batteries	10 109 - 22 056	22 056 - 7 352
Life degr. per BSS [/h]	0.0008 - 0.0057	0.0057 - 0.0062
Stored energy [GWh]	0.425 - 1.385	1.385 - 0.468
Utilization rates [%]	0 - 49.98	49.51- 56.29

Table 24: Continued car results sensitivity analysis, min-max values.

Output param.	**$13 \leq$ WT ≤ 36**	**$1 \leq$ ST ≤ 10**
Total no. of batteries	23 832 - 20 256	37 548 - 19 332
Life degr. per BSS [/h]	No impact	0.02 - 0.0021
Stored energy [GWh]	1.519 - 1.249	2.556 - 1.183
Utilization [%]	47.95 - 50.61	32.90 - 57.39

5.2.1 Input parameter: SOCdep

The relative change in output with varying input, compared to the reference values, is shown in figure 23. Furthermore, the absolute results can be seen in figure 24 and 25.

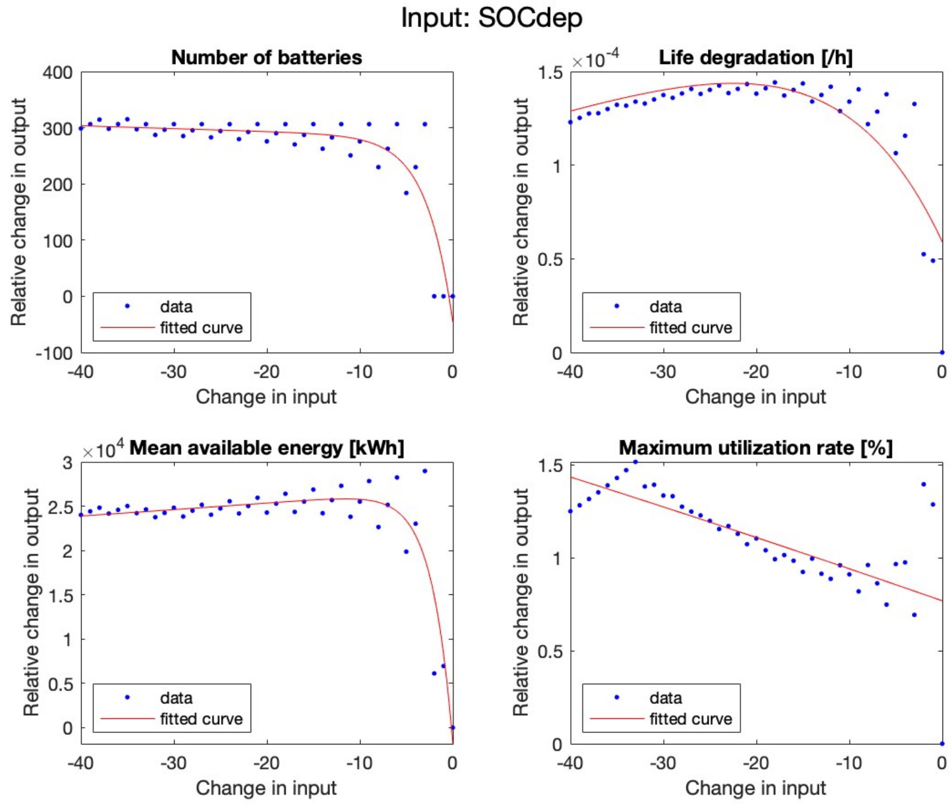

Figure 23: Relative change in output (absolute values) to input, SOCdep.

The number of batteries decreases in a step-wise manner with decreasing SOCdep, as depicted in the upper part of figure 24. While individual percent shifts do not make a major difference, when looking at intervals of three percent, a change of about 1 000 batteries is observed. This is validated by the upper left graph in figure 23, where each step of the input gives a relative change of about 300 to the number of batteries. The three data points at zero relative change in the same graph stem from that the input variables, including the reference value, return no change in output values. The decrease of batteries due to lower values of SOCdep is a result of the shortened residence time of each battery while charging. Because of this, a lower battery stock is needed to serve all customers. The total difference within the selected input range is 11 947 batteries.

When it comes to battery life degradation, illustrated in the bottom graph of figure 24, it increases with increasing SOCdep. This is due to the deepening battery charging cycles, and the life degradation spans between 0.0008 and 0.0057 per hour and BSS within the total range. Lower SOCdep values are linked with shallower charge cycles, hence leading to the lower degradation values at these points. As seen in the upper right graph of figure 23, one change in input gives a relative change in output of about 0.0001-0.00015. Overall, the life degradation ranges from its lowest point of 0.0008 at SOCdep = 50 to its peak of 0.0057 at the default SOCdep value, and the total difference within the range amounts to 0.0049. These results are from the perspective of a BSS, where the hourly battery health reduction is assessed. The pattern shown in the bottom of figure 24 mirrors that of an individual battery, albeit on a larger scale.

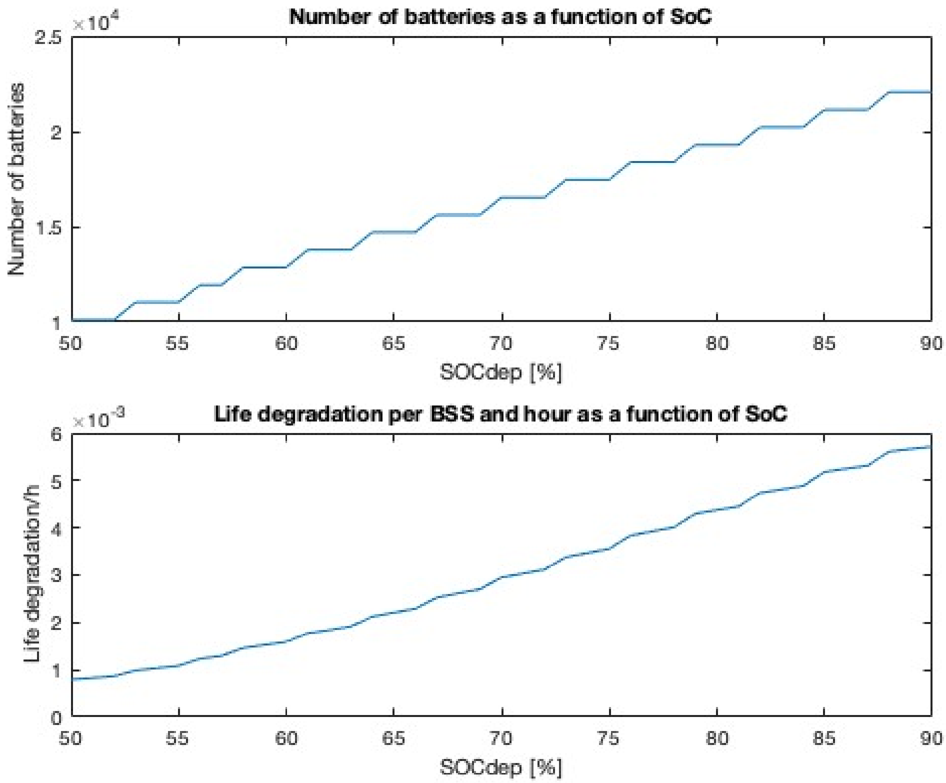

Figure 24: Number of batteries and life degradation, SOCdep.

The mean energy stored in BSSs is displayed in the upper part of figure 25, and ranges between approximately 0.4 and 1.4 GWh. It is shown to increase as the number of batteries increases, yielding a similar pattern to the upper graph of figure 24. These energy levels are calculated for batteries considered to have reached a ”full” charge, depending on the value of SOCdep. Hence, lower SOCdep values result in that batteries get fully charged faster and thus are earlier available for grid services. Nonetheless, this potential increase in available energy is not high enough to reverse the curve. This is due to the fewer batteries housed within a station, coupled with the reduced amount of energy in the batteries if only charged to low SOCdep values. Figure 23 indicates an average relative change of the output of about 25 MWh per alteration in input. A total difference of 0.96 GWh is observed within the selected range.

Maximum utilization rates are zero for the lowest values of SOCdep. This signifies that most batteries in the battery swapping stations attain full charge and remain in the station for extended periods. However, at a SOCdep value of 58, an increased utilization rate can be seen as the input increases. This increase is declining as SOCdep approaches the reference input value, which can be seen in figure 23. For each change in input, there is a corresponding output change of approximately 0.7-1.5 percent. With the highest point of the utilization curve being reached at the default SOCdep value, the total difference in utilization rate amounts to 50.0% within the selected range.

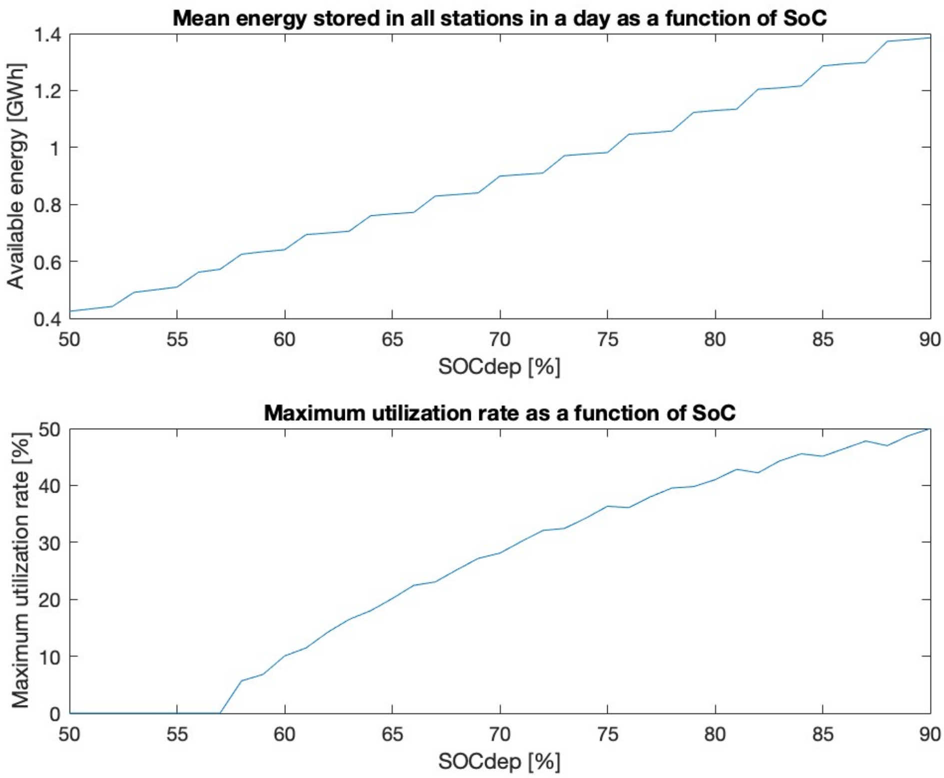

Figure 25: Available energy and utilization rate, SOCdep.

5.2.2 Input parameter: C

When varying C within the range of 0.5 to 1.5, the change of output relative to that of input is shown in figure 26. The absolute results are illustrated in figure 27 and 28.

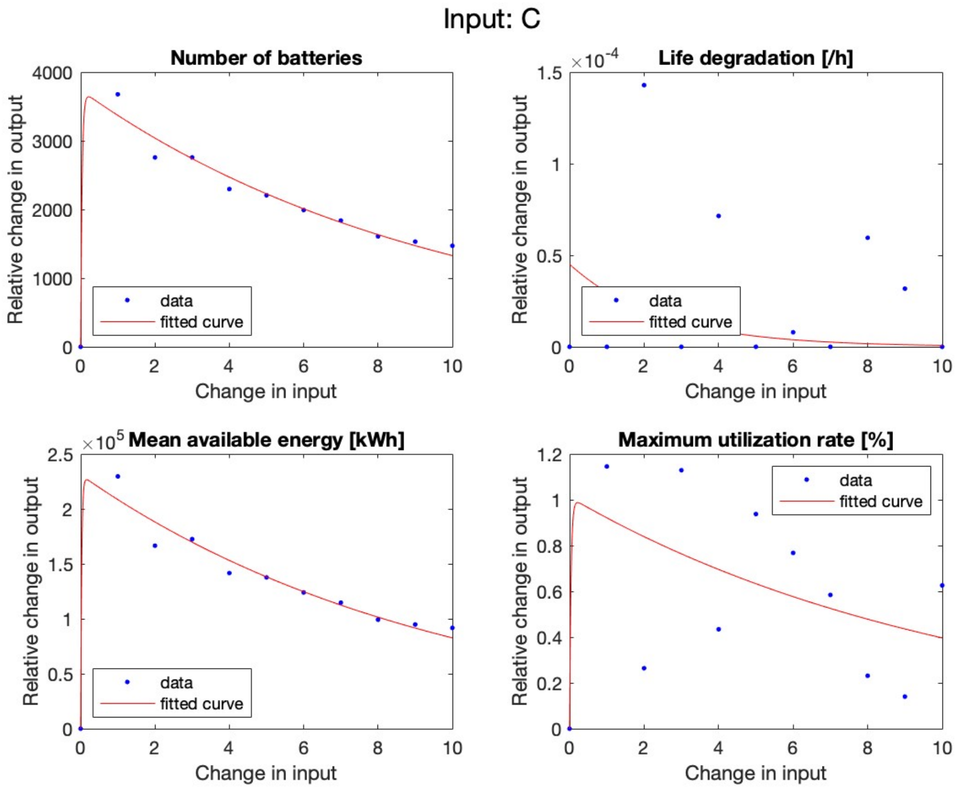

Figure 26: Relative change in output (absolute values) to input, C. C has been multiplied by 10 for a better graphical interpretation.

The number of batteries required per station demonstrates a reduction as the value of C increases, as per the upper graph of figure 27. This outcome results from higher charging rates leading to shorter residence times for batteries, making them available for swapping sooner. Within the selected range of input parameters, the total difference counts up to 14 704 batteries. As seen in figure 26, the rate of decrease is not constant, but declining.

The profile of life degradation as a function of C is non-linear, as shown in the lower graph of figure 27. A pronounced peak occurs at $C = 1.3$, although any distinct trends are difficult to discern from this figure, as well as from the relative change in figure 26. The reason for this is that the illustrated values represent the total life degradation in a BSS per hour. This is dependent on two factors: the number of batteries in a BSS, and the degradation profile of an individual battery. The battery wear per charge cycle as a function of rising C is known to increase according to figure 8. This, together with the decreasing number of batteries with increasing C, may explain the fluctuations at the bottom of figure 26. In total, the difference in life degradation varies by 0.0005 within the selected range.

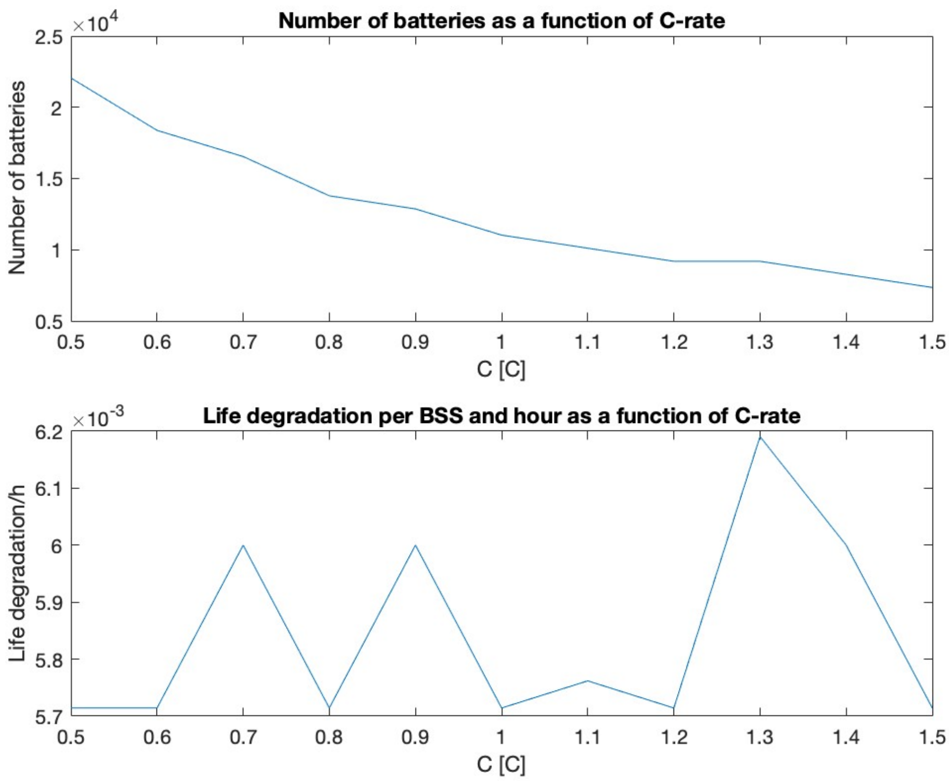

Figure 27: Number of batteries and life degradation, C.

The mean energy stored in the stations exhibits a decline by increasing value of C. This is mainly a consequence of the decreasing amount of batteries seen in figure 27. This correlation is further illustrated in figure 26, where the patterns of the upper left (number of batteries) and bottom left (available energy) figures bear a significant resemblance. The result ranges between 0.5 and 1.4 GWh, which is a similar outcome as for the SOCdep parameter.

The maximum utilization rate, presented in the lower graph of figure 28, has an overall increasing trend associated with increasing C. However, it is a non-linear function that varies between approximately 50% and 56%. Two aspects of the C parameter contribute to the utilization rate: the number of batteries per station, and the charging time. By increasing C, the number of batteries per station decreases as the batteries are fully charged faster. Normally, a reduced number of batteries per station would increase the utilization rate due to that the batteries may be used more efficiently. On the other hand, if the batteries are fully charged faster and not swapped immediately, the utilization rate decreases due to a higher number of fully charged batteries being stored in the station. The overall trend leans toward an increase, implying that the reduced amount of batteries is the more dominating factor. Nevertheless, there seem to be some inputs where the batteries are fully charged faster, but the number of batteries per station is not decreased. This gives a lowered utilization rate, which could explain the downturns observed at, for example, C = 0.7 and C = 0.9.

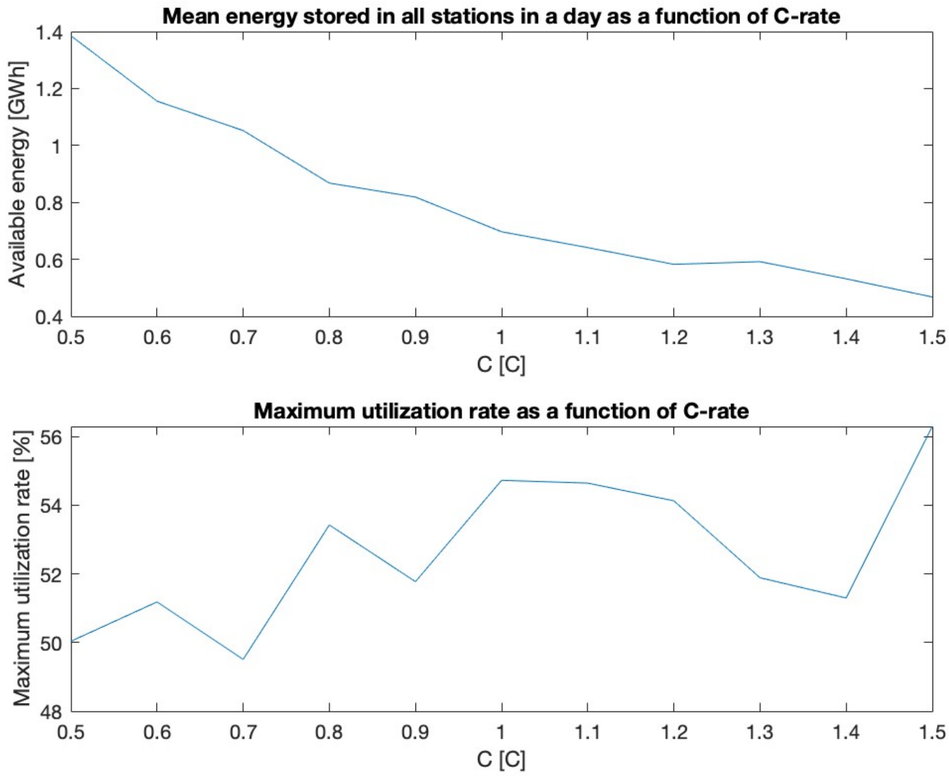

Figure 28: Available energy and utilization rate, C.

5.2.3 Input parameter: WT

The parameter WT is varied between 13 and 36 minutes, which has an impact on all selected outputs except life degradation. The sensitivity coefficients are illustrated in figure 29, whereas the absolute results can be seen in figure 30 and 31.

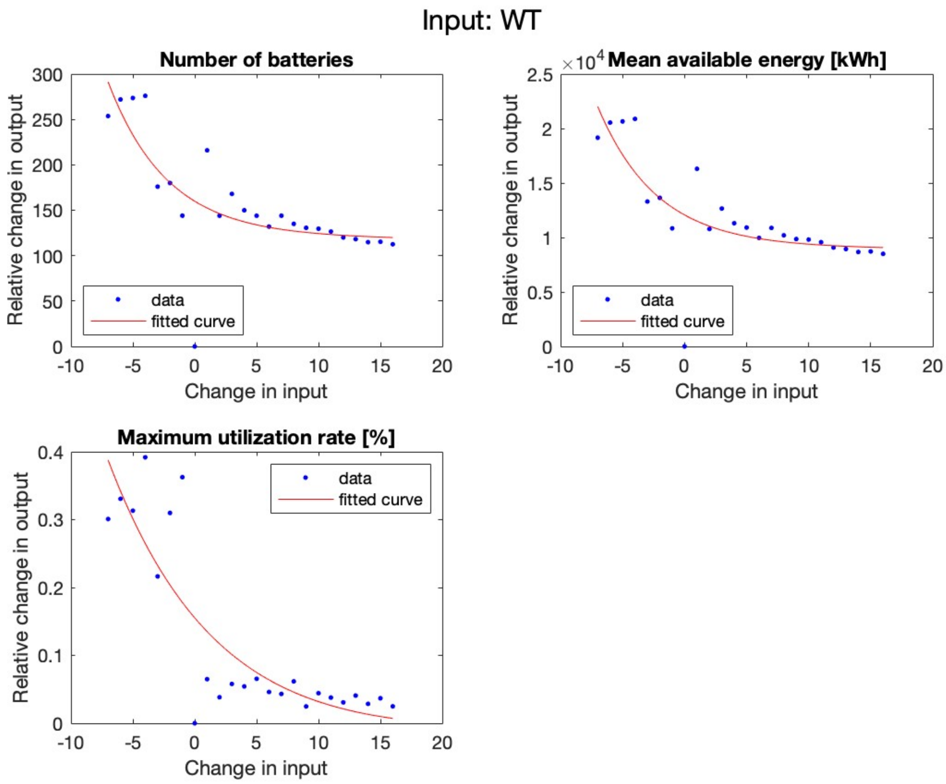

Figure 29: Relative change in output (absolute values) to input, WT.

The total number of batteries decreases by increasing WT. This is due to a lowered number of BSSs per location as a function of longer accepted waiting times. As per figure 30, the output varies with a total difference of 3 600 in total. The most significant rate of decline is observed between WT = 16 and WT = 17, a trend mirrored in the top left corner of figure 29. In the same figure, it can be noted that the average relative change in output is between 100 and 200 batteries per unit change in input.

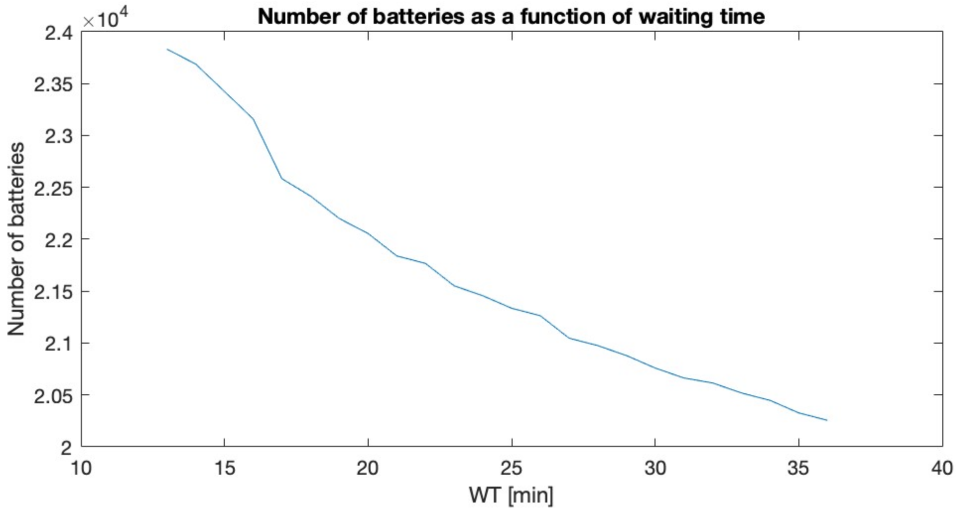

Figure 30: Number of batteries, WT.

The mean available energy decreases as WT increases, as seen in the upper part of figure 31. Across all locations in a day, the mean available energy ranges between 1.25 and 1.52 GWh as a function of WT. This is a direct consequence of the reduction in the number of batteries, which can be seen by comparing the upper two graphs of figure 29. The data on relative change shows the exact same pattern for both figures.

The maximum utilization rate has an overall increasing trend by increasing WT, fluctuating between approximately 48% and 51% within the selected input range. The relative change of output to input is largest at low values of WT, mainly below the reference value, as visualized in figure 29. This increase is a result of the lower amount of BSSs per location. When WT is set to a low value, a larger number of BSSs is required to meet the peak-hour demand. During times of less charging activities, some of the BSSs will be used less, if even at all. In contrast, allowing for longer waiting times leads to a reduction in the number of BSSs. During peak hours, the longest allowed waiting times will occur, but during other times, there will be shorter queuing.

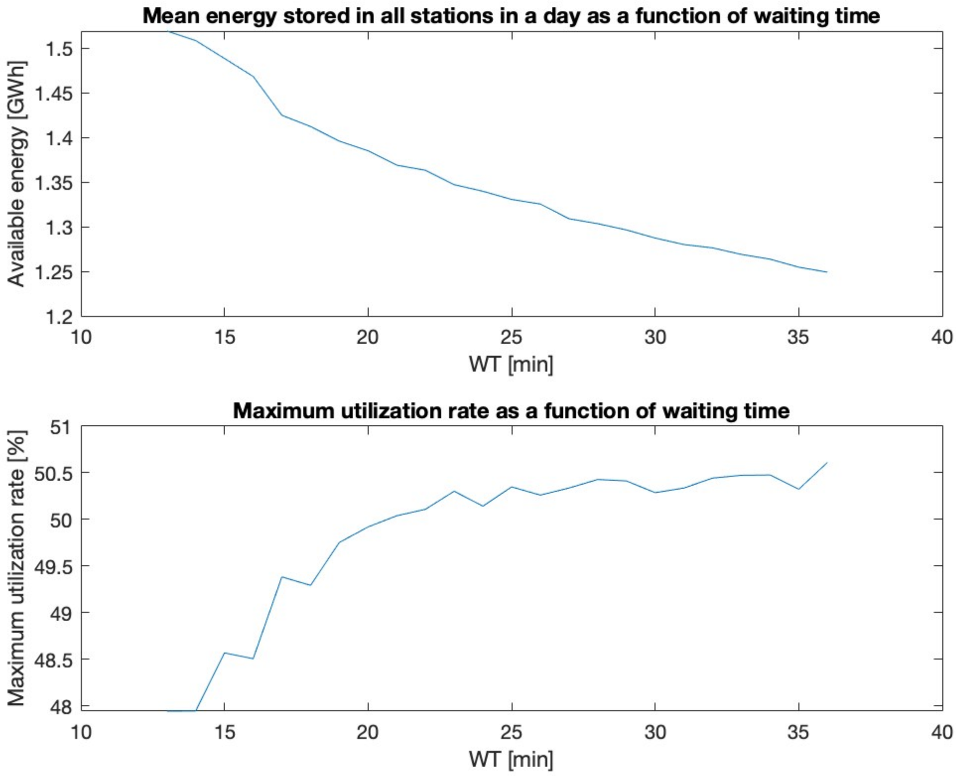

Figure 31: Available energy and utilization rate, WT.

5.2.4 Input parameter: ST

ST is varied between 1 and 10 minutes, and has an impact on both number of batteries per station and the total number of stations. These two factors influence the total number of batteries differently, and the result is interesting to analyze. The sensitivity coefficients for all outputs can be seen in figure 32. Figure 33 illustrates the resulting number of batteries, and figure 34 is included to visually present how this number is affected by the battery-per-station and BSSs-per-location count respectively. Furthermore, figure 35 shows the life degradation as a function of ST, while figure 36 represents the mean energy stored and utilization rates.

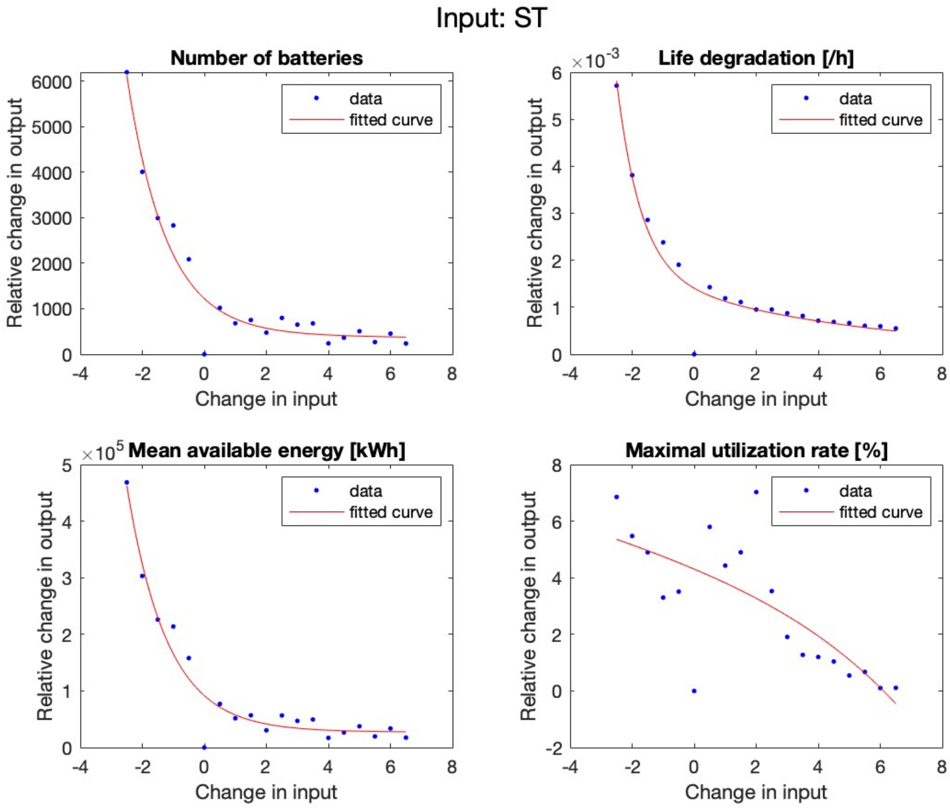

Figure 32: Relative change in output (absolute values) to input, ST.

In the upper diagram of figure 33, the total number of batteries is depicted as a product of the total number of stations and the number of batteries per station. The two parts are illustrated separately in the lower diagram. From this, it is seen that the total number of batteries for low values of ST primarily is influenced by the number of batteries per station, as it decreases rapidly with low values of ST. When ST increases, the growing number of stations becomes more pronounced in the overall total number of batteries.

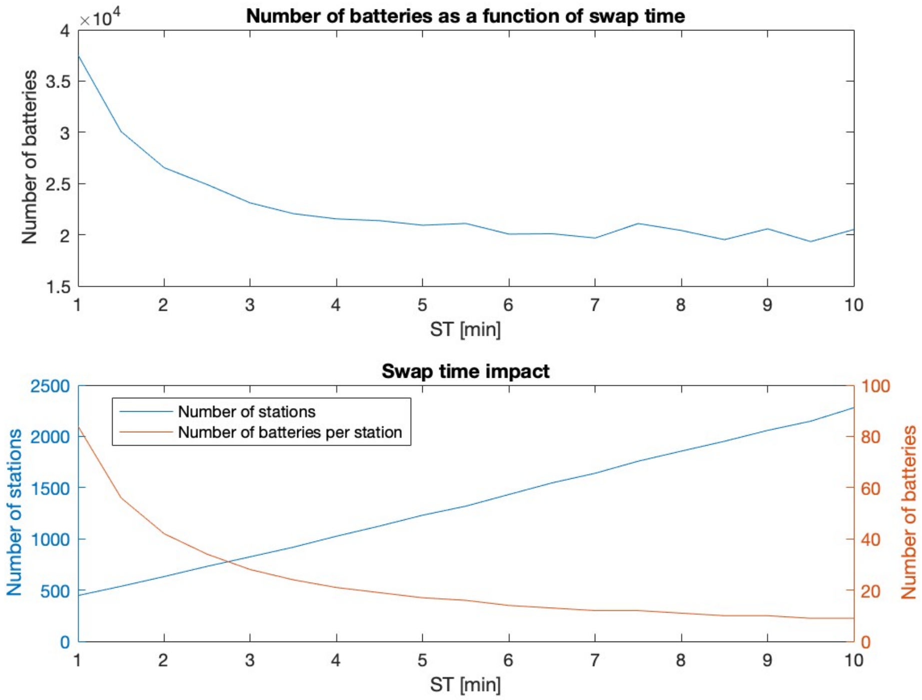

Figure 33: Number of batteries, ST.

This behavior becomes more evident as ST is increased further, as illustrated in figure 34, where the input range is extended. Here, it is clear that the dominant factor for the lowest values of ST is the number of batteries, while the number of stations has a greater influence for larger values. Within the original range, the number of batteries varies between approximately 19 300 and 37 500. It should be noted that the steepest gradient appears for the lowest values of ST, while the curve flattens around ST = 3, as is also emphasized by figure 32. There is a sharp increase of batteries for low input values, while the relative change plateaus at around 1 000 batteries above the reference value.

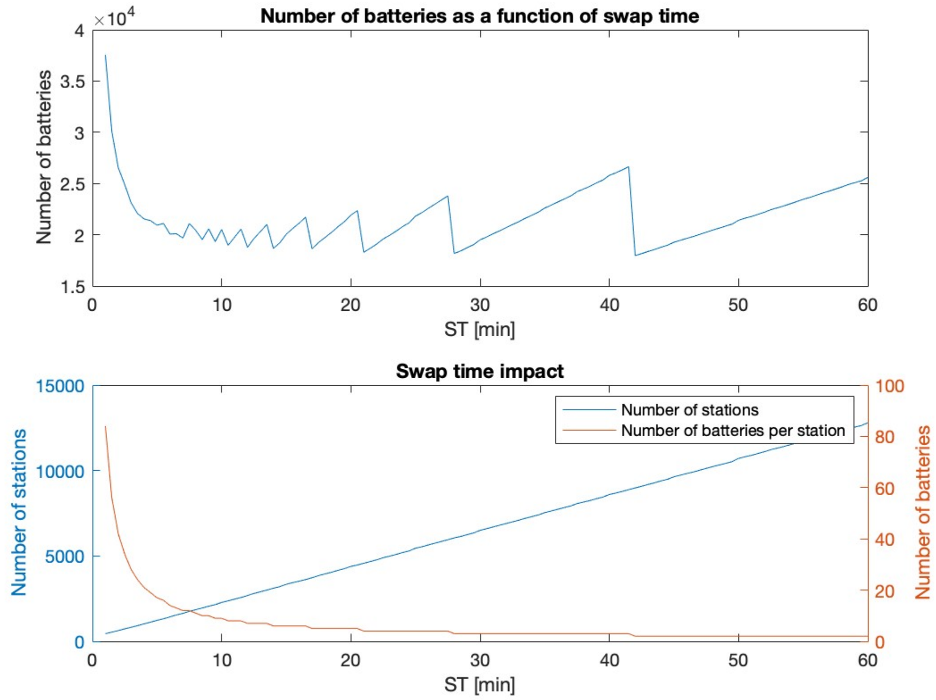

Figure 34: Number of batteries, ST (extended range).

Life degradation decreases by increasing ST, as per figure 35. This outcome arises from the fact that the measured quantity represents the aggregated decay per BSS. Consequently, by a decreasing number of batteries per station, the total life degradation per station is reduced. The relative change in output has a similar pattern for both upper diagrams of figure 32, and the variation in life degradation ranges from 0.9x10^{-4} to 0.8x10^{-5} per change in ST. The change throughout the entire range of input values extends from 0.002 to 0.02.

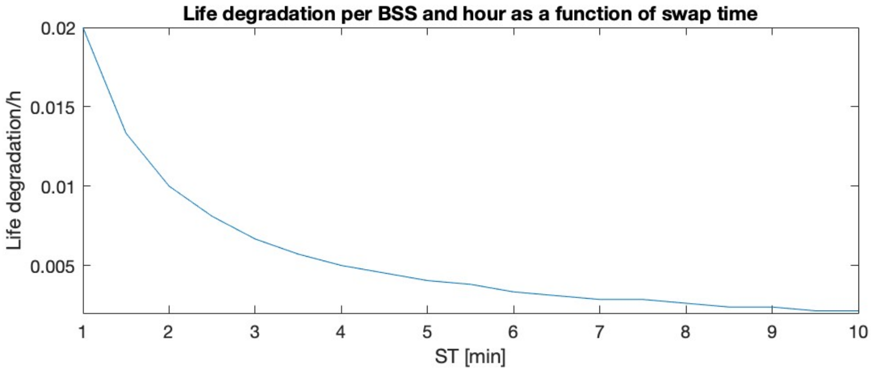

Figure 35: Life degradation, ST.

The mean stored energy as a function of ST exhibits a profile similar to the number of batteries seen in the upper diagram of figure 33. It ranges between 1.2 and 2.6 GWh, and shows a steep decline for ST values below the reference value, as seen in figure 32, and a flattening trend for higher values.

Utilization rates, within the selected range of input values, vary between 33% and 58%, as per figure 36. This substantial variation can be attributed to the fact that a small value of ST results in a need for a high number of batteries per station to provide charged batteries at this frequency. This pace of swapping will mainly be used during peak load hours, with the batteries remaining stored for long periods of time throughout other parts of the day. Furthermore, the number of BSSs also affects the utilization rate, as a higher ST value requires more BSSs to meet the demand. A peak is reached at ST = 5, indicating an optimum balance of BSSs in a location and batteries per BSS at this value. A trend of declination in the change of output to input can be seen in figure 32.

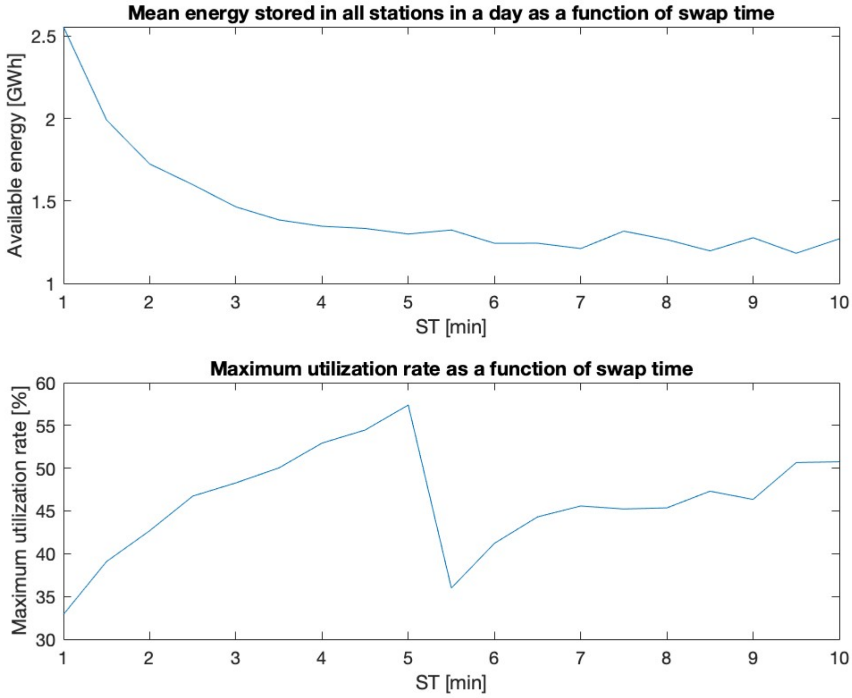

Figure 36: Available energy and utilization rate, ST.

5.3 Results: Trucks

The max and min values for when each parameter is varied individually are presented in table 25 and 26.

Table 25: Truck results sensitivity analysis, min-max values.

Output param.	**70 $\leq$ SOCdep $\leq$ 90**	**0.5 $\leq$ C $\leq$ 1.5**
Total no. of batteries	4 332 - 6 137	6 137 - 2 166
Life degr. per BSS [/h]	0.002 - 0.004	0.004 - 0.0043
Stored energy [GWh]	0.893 - 1.134	1.018 - 0.377
Utilization rates [%]	41.99 - 83.34	85.03 - 78.62

Table 26: Continued truck results sensitivity analysis, min-max values.

Output param.	$5 \leq$ WT ≤ 45	$1 \leq$ ST ≤ 10
Total no. of batteries	16 864 - 6 137	6 972 - 5 916
Life degr. per BSS [/h]	No impact	0.02 - 0.002
Stored energy [GWh]	4.498 - 1.019	1.288 - 0.950
Utilization rates [%]	37.32 - 83.69	83.27 - 75.46

5.3.1 Input parameter: SOCdep

The relative changes in outputs when varying SOCdep between 70% and 90% are seen in figure 37. The absolute results are found in figure 38 and 39.

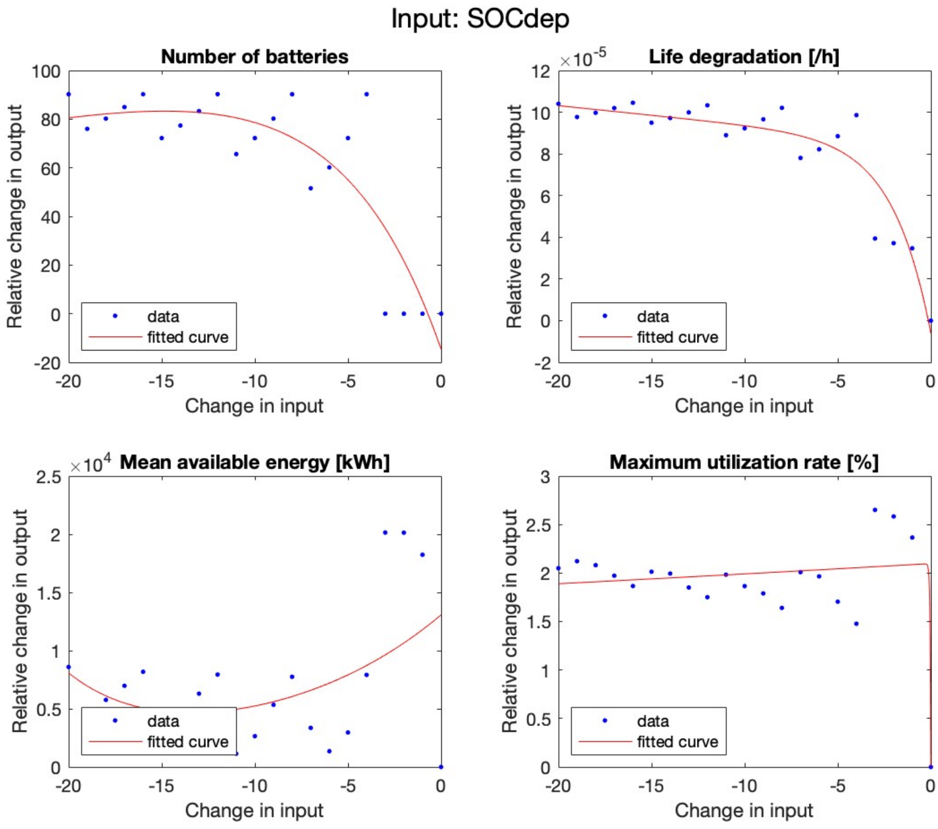

Figure 37: Relative change in output (absolute values) to input, SOCdep.

Shown in the upper part of figure 38, is that the number of batteries increases with SOCdep, with a total difference of 1 805 batteries within the selected input range. The relative change in output is on average approximately 80 batteries per step, as indicated in the upper left of figure 37. As both figures reveal, however, there is only a change in the number of batteries every fourth step through the input vector.

In the lower part of figure 38, life degradation can be observed to also increase with SOCdep. Across the range from lowest to highest values, it varies by 0.0021 per BSS and hour. If translated into a total number of charge cycles for a single battery, the lowest value of SOCdep would result in approximately 3 050 cycles, whereas the highest value leads to 2 100 cycles, likewise the reference scenario. Furthermore, figure 37 suggests that the relative change is declining with increasing SOCdep, from approximately 0.0001 to 0.00008 per step.

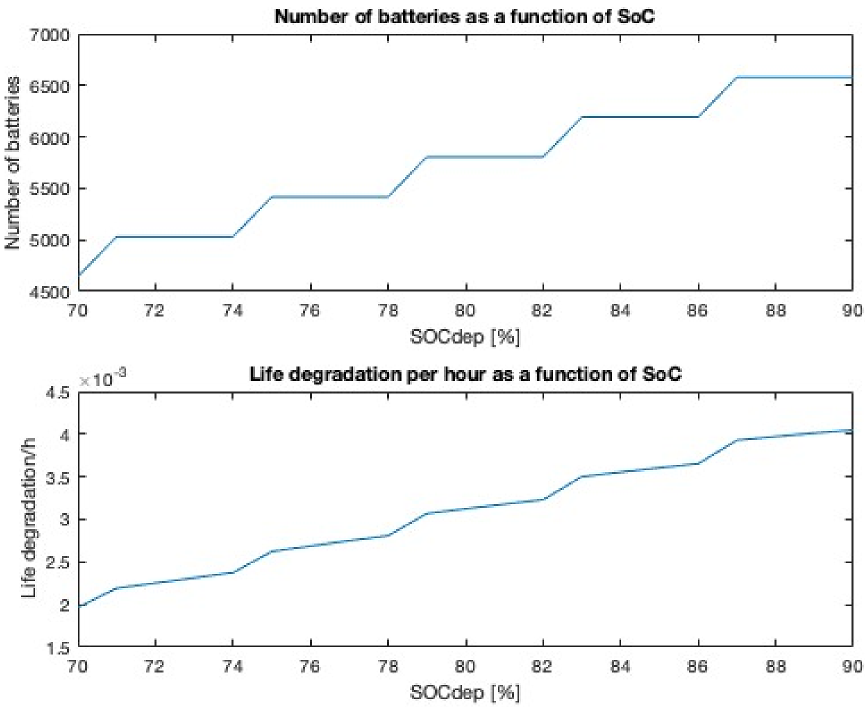

Figure 38: Number of batteries and life degradation, SOCdep.

The mean energy stored across all locations as a function of varying SOCdep is depicted in figure 39. This pattern can be explained by looking at the change in the number of batteries in figure 38. The energy levels drop between each peak due to the constant number of batteries while the time of recharging increases. Consequently, the residence time for fully charged batteries decreases. The overall increasing trend with an increasing value of SOCdep is also a result of the higher maximum charge level, which determines the amount of stored energy in one battery. As can be seen in figure 37, the relative change is around 1 and 10 MWh.

Regarding utilization rates, they range from 42 to 84 percent, as evident in the lower part of figure 39. This is a significant difference and can be somewhat explained by the fact that the batteries are fully charged more quickly and stored for longer durations when not in use. As per the diagram in the bottom right corner of figure 37, the relative change is on average 2 percent per change of SOCdep.

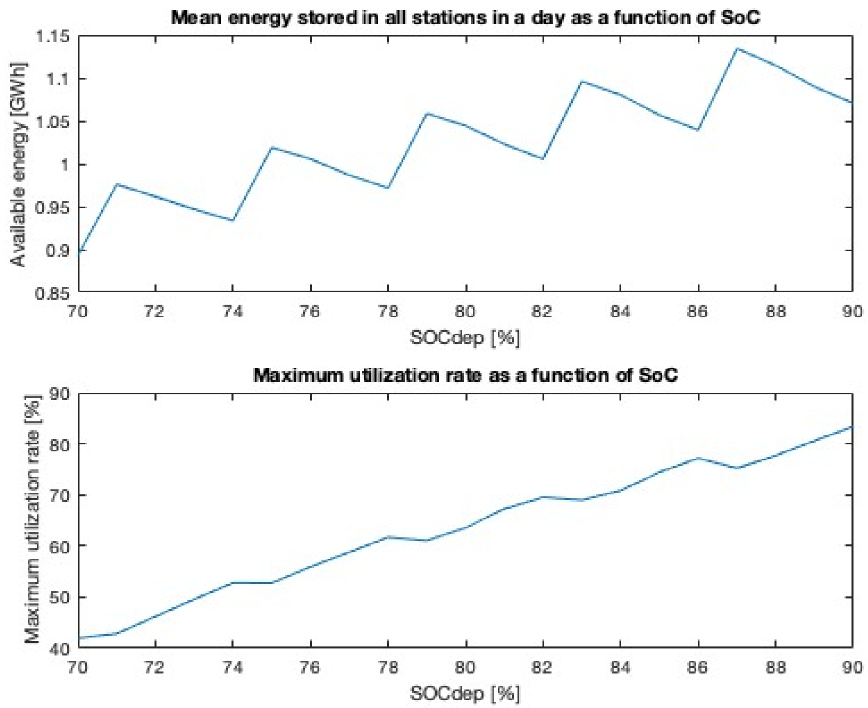

Figure 39: Available energy and utilization rate, SOCdep.

5.3.2 Input parameter: C

When varying C within the range of 0.5 to 1.5, the sensitivity coefficients can be seen in 40, and the absolute values are shown in figure 41 and 42.

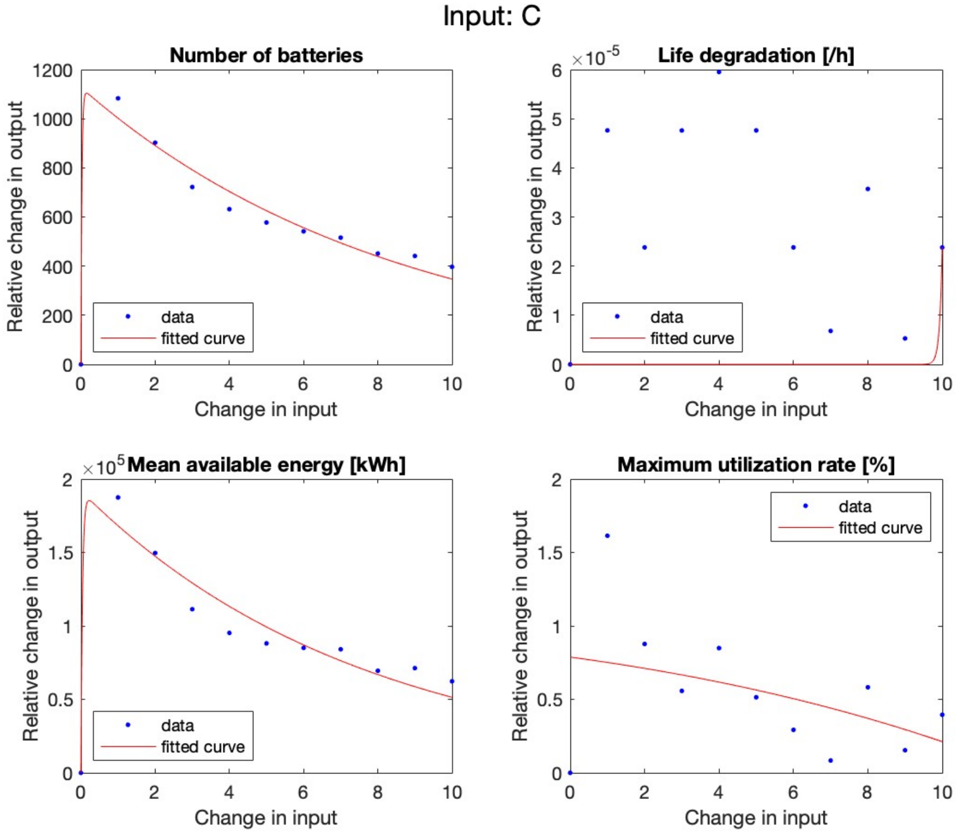

Figure 40: Relative change in output (absolute values) to input, C. C has been multiplied by 10 for a better graphical interpretation.

The number of batteries decreases with an increasing value of C. The top plot of figure 41 indicates an approximate difference of 4 000 batteries between both ends of the range. Figure 40 reveals that the increase is declining when iterating through the input vector.

Analyzing the impact of C on life degradation solely based on figure 41 is challenging. The initial conclusion might suggest that the C-rate does not have any impact, but it is known from figure 8 that this statement would be inaccurate. While interpreting figure 41, it is important to bear in mind that life degradation is presented for an entire BSS. Consequently, it heavily relies on the number of batteries per station. While the individual battery life is decreased by increasing value of C, the overall degradation per BSS rises linearly with the number of batteries. As per figure 40, the degradation varies by 0.0001-0.0005 per BSS and hour.

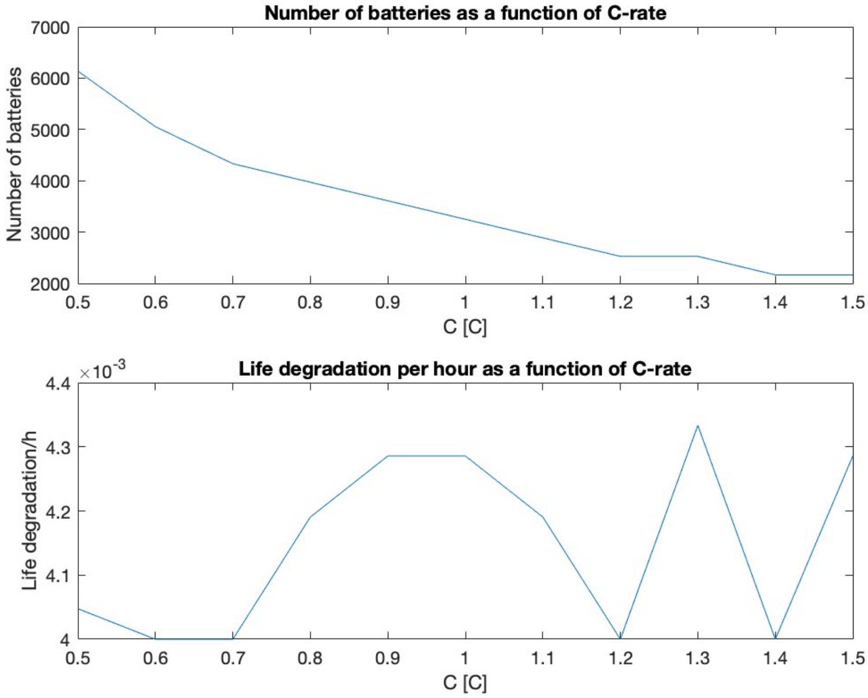

Figure 41: Number of batteries and life degradation, C.

The mean stored energy across all locations is decreasing from 1 GWh to 0.4 GWh with increasing C, as seen in figure 42. This is a result of the reduction in the total number of batteries. Although the batteries charge more rapidly by increasing C, and hence could be available as stored energy for a longer time, this effect is barely reflected in the overall energy levels due to the more substantial impact of the battery reduction. The bottom left plot in figure 40 shows that the decrease is declining, with a very similar pattern to the top right plot of the number of batteries.

Maximum utilization rates in relation to C are depicted at the bottom of figure 42. The maximum value reaches 85 percent, while the minimum is measured at approximately 79 percent. The curve's non-linearity arises from its dependence on both the number of batteries in a BSS, and the residence time of a fully charged battery. The decrease in battery stock has an increasing influence on the utilization rate, while the faster recharging times prolong the batteries' time as fully charged in the BSS. In this case, the overall trend is more determined by the latter factor, reducing the utilization rates as the C-rate increases. The bottom right plot of figure 40 shows a slight overall declining trend in relative change.

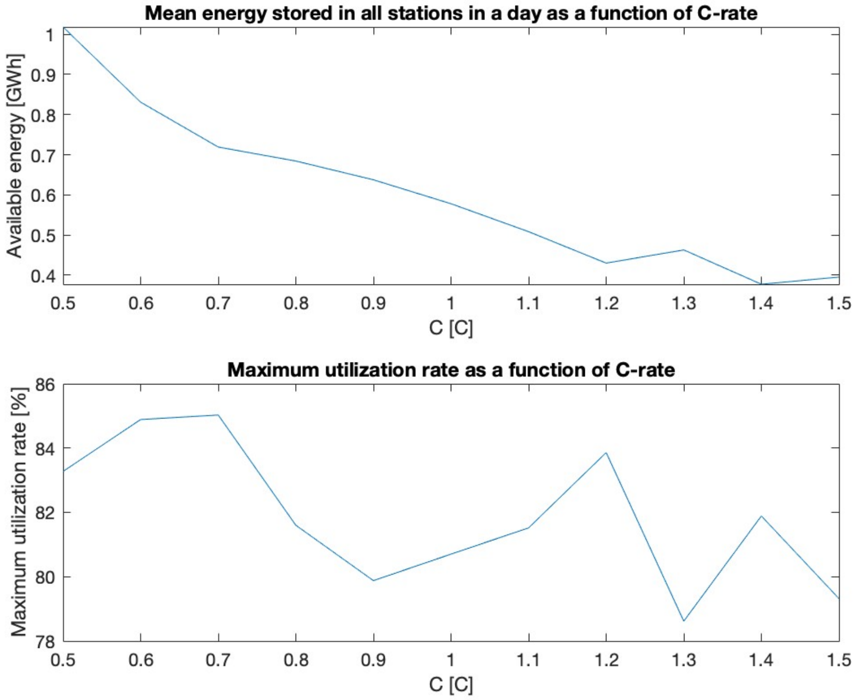

Figure 42: Available energy and utilization rate, C.

5.3.3 Input parameter: WT

WT is assessed across a range spanning from 5 and 45 minutes, having an effect on all analyzed outputs except life degradation. The relative change in output as a result of the change of input is illustrated in figure 43, and the absolute results can be seen in figure 44 and 45.

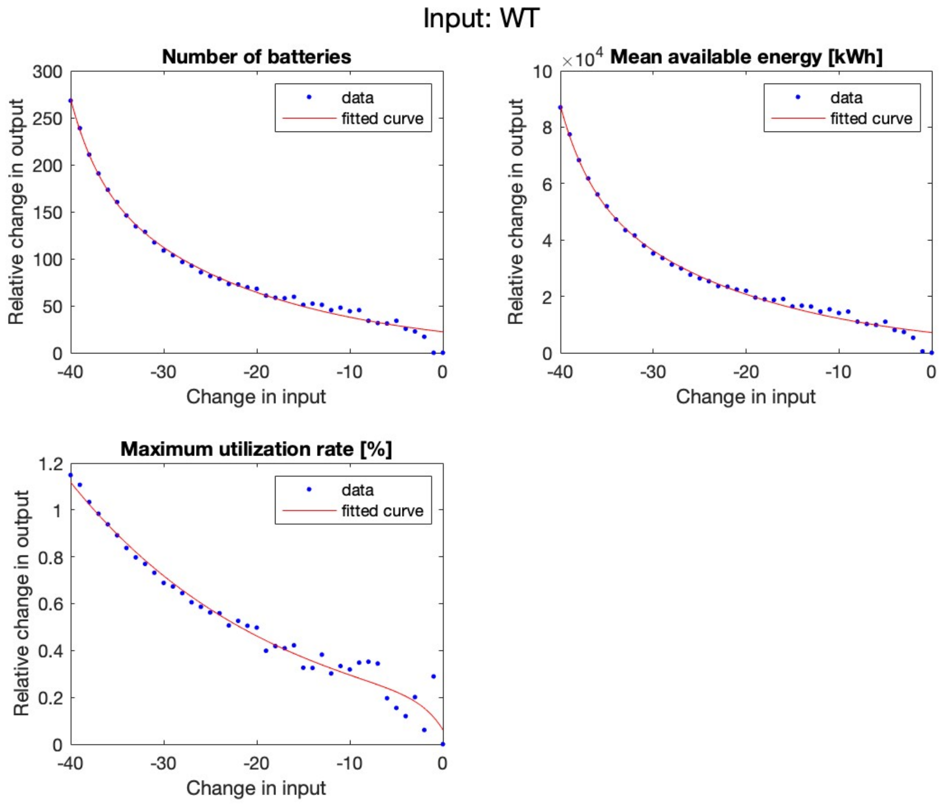

Figure 43: Relative change in output (absolute values) to input, WT.

The accepted waiting time significantly influences the number of batteries, as illustrated in figure 44, particularly when looking at the lower bound of the WT values. The total difference between the two ends of the spectra amounts to approximately 10 000 batteries, which is more than the entire battery stock in BSSs for the reference scenario. This substantial difference is partly because of the large span, and based on the upper left plot of figure 43, it is apparent that the inclining number of batteries is largest for the smallest values of WT, with a relative change of about 200-275 batteries. Furthermore, waiting time as an input parameter impacts the number of BSSs per location. Keeping all other parameters at default values, the time of a swap is five minutes. Consequently, for allowable waiting times lower than 10 minutes, there has to be one BSS per arriving vehicle, which explains the peak at the left end of the figures. Furthermore, the number of batteries per BSS is fixed, which leads to many batteries being added as a result of the need for swapping slots. This is also evident by the figures of stored energy in figure 45.

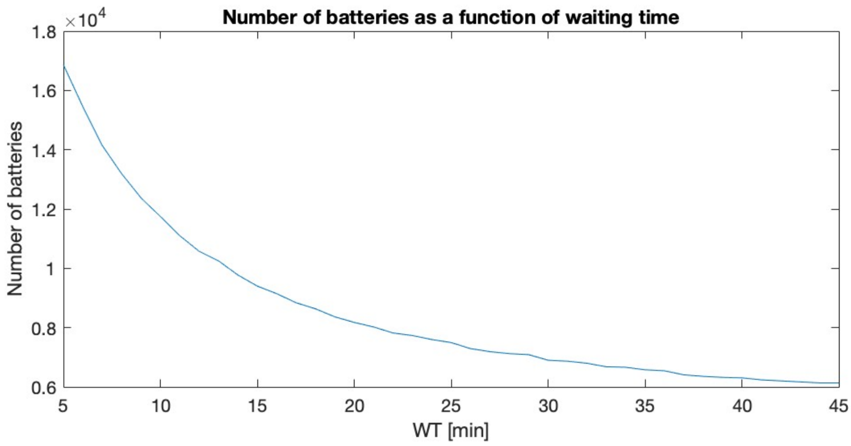

Figure 44: Number of batteries, WT.

As mentioned, WT determines the number of BSSs per location. For every additional BSS required due to reduced queuing times, a fixed number of batteries follows. In other words, these batteries are not added because of increased battery capacity demands, but merely to accommodate the need for more swapping slots. This leads to a scenario where, for low values of WT, the stored energy reaches very high levels, while utilization rates remain relatively low, as seen in figure 45. The stored energy ranges from 1 GWh to 4.5 GWh, and has the highest relative change for the lowest values of WT. The lowest utilization rate reaches 37 percent, whereas the highest attains the 83 percent mark (as per the reference scenario). The same declining trend is mirrored in the relative change displayed in figure 43.

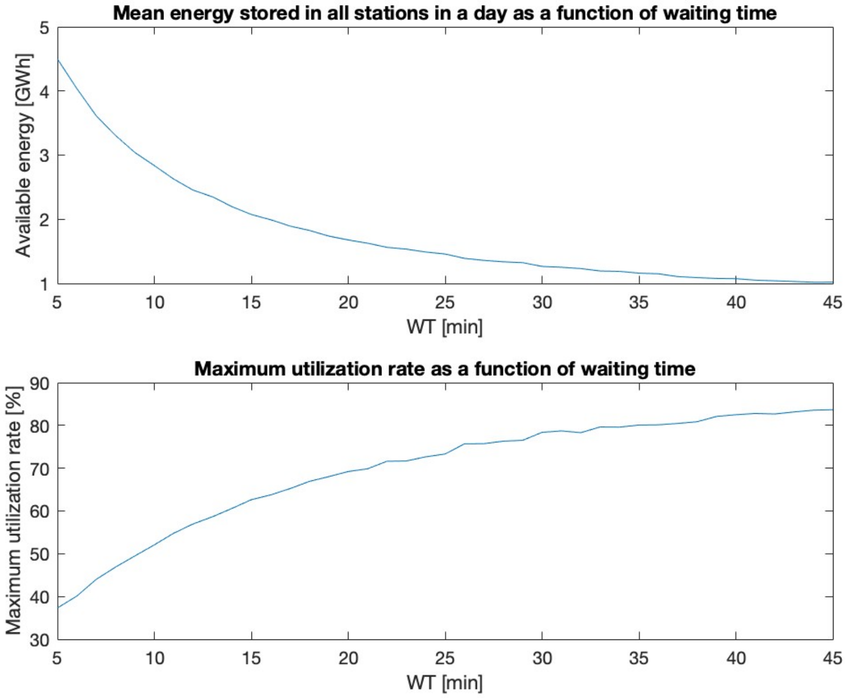

Figure 45: Available energy and utilization rate, WT.

5.3.4 Input parameter: ST

ST is varied between 1 and 10 minutes, and figure 46 illustrates the relative change in output corresponding to each input. Furthermore, the result of the number of batteries is in figure 47 broken down into two constitutive parts: the number of batteries per BSS and the number of BSSs. Life degradation can be seen in figure 48, whereas the mean stored energy and maximum utilization rates across all locations are depicted in figure 49.

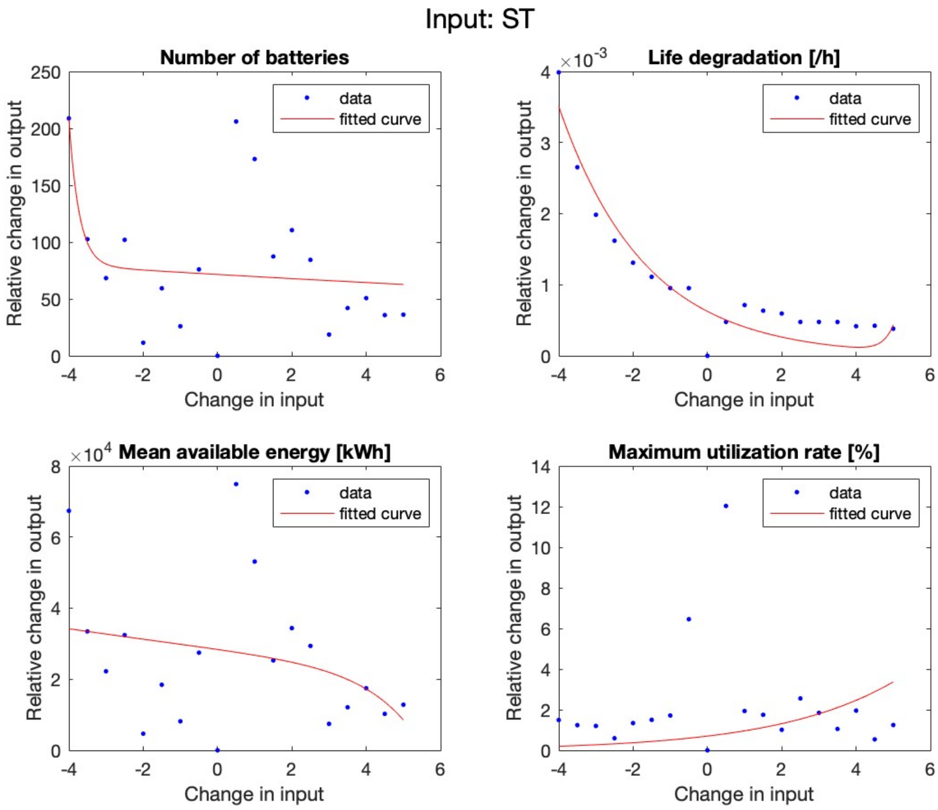

Figure 46: Relative change in output (absolute values) to input, ST

The total number of batteries is a product of the number of batteries per BSS and the total number of BSSs. Both aspects are visually represented in the two plots of figure 47, which illustrates the resulting total and its two parts separately. The influence of the number of batteries per BSS is particularly pronounced for the lowest ST values, while as ST increases, the impact of the number of BSSs appears to be more significant. An extended range of ST is shown for cars in figure 34, and a similar trend can be expected for trucks. In total, the count of batteries varies from a minimum of 6 000 to a maximum of 7 000. Figure 46 shows that the relative change in output typically ranges between 50 and 100 batteries per adjustment in ST.

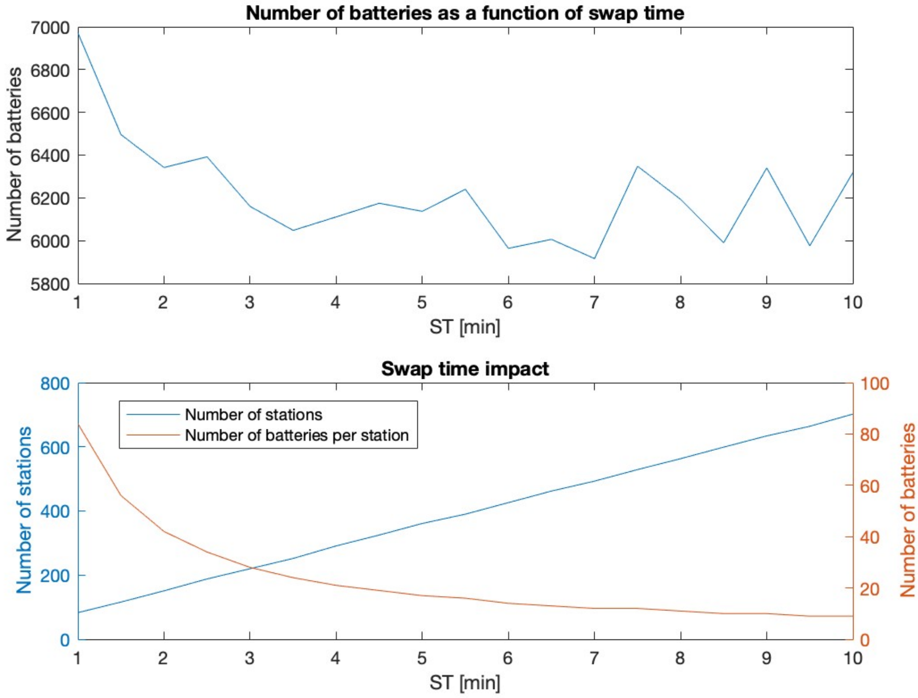

Figure 47: Number of batteries, ST.

Life degradation as a function of ST is shown in figure 48. This range spans from 0.002 to 0.02, and it is important to remember what the figure represents. It is measured for an entire BSS, meaning that a higher number of batteries being cycled leads to increased overall degradation. ST does not influence an individual battery's life degradation, it only impacts all batteries as a group by determining the group's size. However, the trend is not identical to that of the battery stock. This discrepancy is due to that figure 48 depicts the degradation of a single BSS, while figure 47 shows all locations. Thus, the life degradation corresponds only to the orange graph of figure 47, which represents the number of batteries in a BSS. The relative change of life degradation per BSS and hour ranges between 0.0005 and 0.003 for each input, as seen in the upper right corner of figure 46.

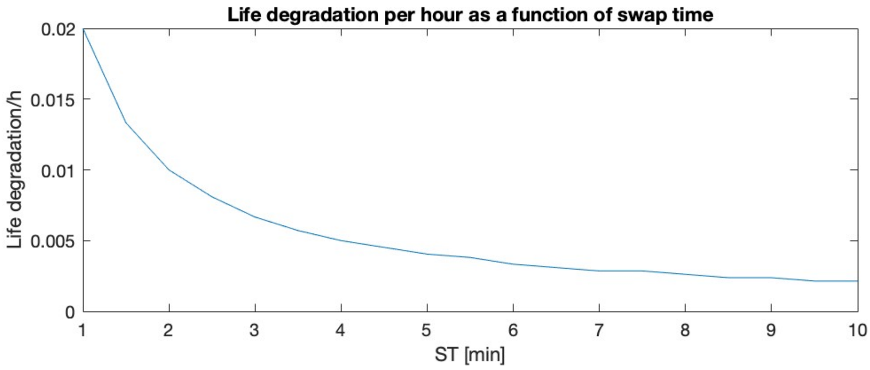

Figure 48: Life degradation, ST.

The upper plot in figure 49, as well as the bottom left plot in figure 46, illustrates how the mean energy stored completely tracks the total number of batteries. This pattern arises because there are no other components altering energy levels in this case, since both SOCdep and C remain fixed at reference values.

The utilization rates range between 75 and 83 percent. Notably, upon comparing the upper and lower plots of figure 49, it is evident that for the upper half of the ST range, the curves have opposite gradients. As energy storage increases, utilization decreases, and vice versa. The relative change in output remains almost consistently around 2 percent for all values, as depicted in figure 46.

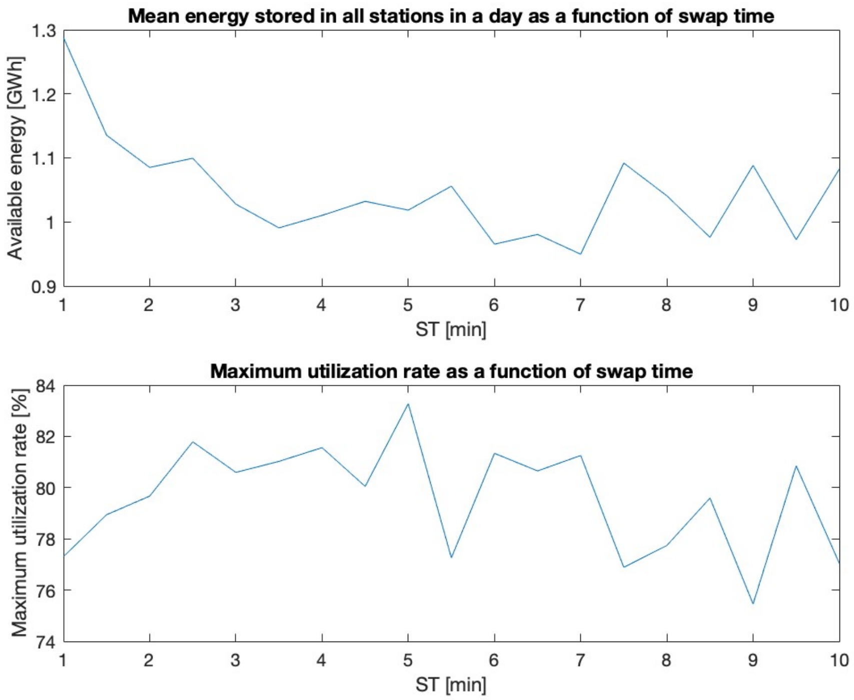

Figure 49: Available energy and utilization rate, ST.

5.4 Evaluation

Table 27 presents a summary of the input parameters with the largest impact on each output. The absolute differences are highly correlated with the range within which the parameters are varied, while relative values, the sensitivity coefficients, explain how a change in input affects the output.

Table 27: Evaluation of input parameter impact, absolute and relative values.

Output	Cars (abs.)	Cars (rel.)	Trucks (abs.)	Trucks (rel.)
Total no. of batteries	ST	ST/C	WT	C
Life degr. per BSS	ST	ST	ST	ST
Stored energy	ST	ST/C	WT	C
Utilization rates	SOCdep	ST	WT	ST/SOCdep

The relative change in the number of batteries is the largest for increasing C or decreasing ST from reference values. The former reduces the amount, while the latter leads to an increase. This means that the number of batteries can be most efficiently reduced by increasing the charge rate. When looking at the absolute differences within the entire ranges, the largest is found by varying ST or WT for cars and trucks respectively. The large difference is solely due to the very high numbers achieved, as the number of batteries increases by both lower ends of ST and WT.

An analysis of life degradation would be interesting if it included numbers for the individual battery wear as well. Unfortunately, this is not done due to time limitations. ST does not affect individual batteries, so the conclusion that can be drawn is that ST is the dominating parameter only due to the accumulated life degradation. The degradation of one battery due to changing the charge rate, C, for instance, does not seem to have as much effect on the overall results.

The stored energy is also a result of the total number of batteries, and the two results in table 27 are identical. It is evident, although not very surprising, that the size of the battery stock determines the energy available for ancillary services more than e.g. the available capacity due to changing SOCdep.

The largest impact on absolute utilization rates is due to variations in SOCdep and WT for cars and trucks respectively. In the car scenario, a reduced SOCdep means that batteries are fully charged earlier, and are kept stored in the BSSs for a longer time during most of the day. For trucks, a decreased WT results in an increased number of BSSs due to the need for swapping spots. With each station comes a fixed number of batteries, which are not all needed and utilized.

A conclusion from the sensitivity analysis is that these four input variables affect the results, some of them significantly. Nonetheless, the results of absolute differences should be analyzed by remembering that a rather wide range has been chosen to capture as many cases as possible. This does not mean that all values are plausible today.

6 Comparative study

Three scenarios are formulated to evaluate the energy requirements in terms of batteries, depending on the dominating charging infrastructure. These scenarios are battery swapping (BS), fast charging (FC), and electric road systems (ERS). It is considered in each scenario that only one of the charging technologies is available. While these represent three cases on the extreme end, it is important to acknowledge that the future most likely will feature a mix of several charging options. This charging infrastructure is assumed to be utilized by cars, medium-, and heavy-duty trucks on long trips, and the considered populations are the same as described in section 3. For shorter trips, the vehicles are assumed to be able to operate on their battery only. Slow charging is assumed for both groups during times prior to and after trips. This section initially presents the distinct scenarios for cars and trucks, and is concluded with the presentation and comparison of the results.

6.1 Cars

In all scenarios, there is a distinction between long and short trips. Long trips are defined as one-way journeys exceeding 150 kilometers, while trips of shorter distances are categorized as short trips. The distribution can be seen in table 28. The travel distance data is retrieved from the SAMPERS database, and include all forecasted trips longer than 100 kilometers [105]. There are a total of 165 967 trips in the dataset, of which 92 136 exceed 150 kilometers. Furthermore, there are a total of 4 980 543 Swedish registered cars in use [9]. This indicates that far from all cars are utilized for long distances based on the SAMPERS data. For cars not represented in the data, it is assumed that they cover distances between 0-100 kilometers per day, and thus, they are allocated to the group of short trips. This approach is employed to calculate the total battery capacity within the transportation system, accounting for cars that may not be used on a daily basis.

Table 28: The car fleet.

Total fleet	**Long trips**	**Short trips**
4 980 543	92 136	4 875 561

6.1.1 Battery swapping scenario

In the BS scenario, all cars are assumed to have a battery distribution according to table 4. This includes all cars on short and long trips, regardless of if they are considered successful in the battery swapping model. The battery swapping system is, however, only dimensioned to support the battery distribution of cars traveling long distances. As a result, one of the advantageous aspects of battery swapping technology is not taken into consideration: the potential for cars primarily used for short trips to operate with a smaller battery during most of the time, and upgrade to a larger one when necessary. Instead, all cars are assigned the same battery distribution, so that if cars would switch between driving long and short trips, the overall battery distribution will remain the same. This is further discussed in section 7.

The total battery capacity in the BS scenario consists of the batteries in the cars and the additional batteries in the BSSs. The locations and stations are described in detail in section 3.

6.1.2 Fast charging scenario

In the FC scenario, the entire fleet is assumed to have the battery size distribution according to table 4, and the sum of these batteries equals the total battery capacity of the car transportation system. The locations designated for fast charging remain consistent with those in the BS scenario, and the stations are configured with a maximum of 30 charging points per location. Each fast charger is equipped with a maximum plug power of 175 kW, which is a setup in accordance with Pourroshanfekr Arabani's work [5].

6.1.3 Electric road system scenario

The considered ERS is road bound and conductive, providing all cars with access to ERS on all National and European Roads. Studies present varying outcomes concerning the required total battery capacity need, resulting in potential scenario disparities. In this comparative study, a total battery capacity reduction of 60 percent for the entire fleet, when compared to the FC scenario, is assumed [6].

6.2 Trucks

In all truck scenarios, long and short trips are separated according to table 29, where the long trips are all farther than 300 kilometers. The distribution of driving ranges is based on data of trips in a day from real measured data, as depicted in figure 6, combined with data from the Swedish government agency Transport Analysis. Furthermore, for trucks traveling shorter distances, sufficient battery sizes are necessary. The short trips are divided into subgroups, as outlined in table 30, which builds upon the same measured data presented in figure 6. Without disaggregating the fleet further into different weight classes with distinct energy consumption profiles, an average value of 1 kWh/km is assumed for all [85]. 80 percent of the full battery capacity is assumed to be utilized, resulting in the estimated battery sizes provided in table 30.

Table 29: The truck fleet.

Total fleet	**Long trips**	**Short trips**
86 060	54 354	31 706

Table 30: Short trip distances and battery distribution.

Driving distance [km]	**Population share [%]**	**Battery capacity [kWh]**
0-150	20	180
150-200	20	300
200-300	60	400

6.2.1 Battery swapping scenario

The trucks traveling long distances are equipped with battery sizes as specified in table 13, whereas table 30 presents the battery sizes for shorter trips. The total battery capacity in the BS scenario comprises the batteries in the trucks as well as the additional batteries housed in the BSSs. This system is described in detail in section 3.

6.2.2 Fast charging scenario

In the FC scenario, truck battery capacities are assumed to be the same as in the battery swapping scenario. The sum of these batteries equals the total battery capacity in the truck transportation system. Fast charging stations are placed in the same locations as proposed in the BS scenario, with 14 charging points at each station and a plug power of 700 kW each [7]. These are the dimensions of the stations in Ingelström's fast charging simulation model for trucks.

6.2.3 Electric road system scenario

The ERS scenario is based on the assumption of a 60 percent reduction in battery capacity for all trucks, when compared to the FC scenario [6]. Similarly to cars, the trucks in this scenario also have access to ERS on all National and European Roads.

6.3 Results

The results of the scenarios for cars and trucks can be seen in table 31 and 32 respectively. When compared to the FC scenario, the BS scenario results in a battery capacity increase of 0.4 percent for cars, and 7.8 percent for trucks. By the same comparison, the ERS scenario results in a battery capacity reduction of 40 percent for both cars and trucks as expected by the preconditions.

Table 31: Total battery capacity in the transportation system, cars.

Scenario	**Battery capacity [GWh]**
BS	420.22
FC	418.37
ERS	167.35

Table 32: Total battery capacity in the transportation system, trucks.

Scenario	**Battery capacity [GWh]**
BS	32.22
FC	29.89
ERS	11.96

7 Discussion

The results are a consequence of a number of assumptions that are not by any means absolute truths. Furthermore, there are aspects not considered in the model, which implies that it does not capture the entire complexity of charging infrastructure planning. For instance, profit and business models are not included in the calculations. Doing so would mean introducing an economic perspective on battery utilization, grid services, and the overall return on investment. This section aims to provide a fuller picture of some crucial assumptions and their implications, as well as other aspects that are relevant to keep in mind when interpreting the results.

7.1 Battery preferences

The inability to choose battery size due to the FIFO priority rule means that some drivers might not receive their preferred battery. This priority system is chosen to simplify the model structure, but may not be necessary in reality at all times. Throughout much of the day, several fully charged batteries are available in the BSSs, which means it could be possible to choose from the fully charged battery stock. However, during times of high load, this option may not be available. The freedom of choice has not been incorporated in the model, and would likely result in a change of overall battery capacity stored in the BSSs. If allowing for the choice of battery size, choosing the right size should be encouraged. Due to the EVRA phenomenon, a driver is often likely to choose a large-sized battery even if a lower range would have been sufficient. If yearning for a certain size of battery, it could be possible to view the BSS stock to check the charging status of the preferred batteries. If a battery of the desired size is available but not fully charged, the option to pay an additional fee for faster charging to have it ready upon arrival could be offered.

On the other hand, choosing a battery that is not fully charged could also be possible. This is analyzed in the sensitivity analysis, where it showed to primarily impact the utilization rates. This could be beneficial for instances where the driver may not need the full capacity, and also be a solution for when an instantly available battery is needed. Another aspect is the ability to swap a battery even if it has not yet reached low charging levels. More shallow charging cycles would prolong battery life, which is positive in both environmental terms, and from an economical aspect for the investors. Since drivers would not directly benefit from this due to not owning the battery, incentives would likely be necessary to encourage careful battery use. However, any case where the driver uses less than the full capacity of a battery, either by own choice or not, could result in the need for additional charging activities due to reduced driving range. These extra events are not factored into the model, but for cars, originally approximately 5 percent of the trips require more than one charging stop. If this number were 15 percent instead, there would be an increase of about 7 000 charging activities from the current level. The extent to which the BSS infrastructure would need to expand due to these extra activities depends on when these events would occur. If it would be anytime except during peak hours, the existing system would likely suffice, and the mean utilization rates would increase. Would the new events be added to the current peak, however, additional locations and/or BSSs would probably be necessary. In the case of trucks, they are less likely to drive with decreased capacity or stop earlier than necessary for the reasons mentioned. This is due to the operational inefficiency of a charging stop, even if it is brief.

Effective communication with the BSSs requires a competent tool for the driver to announce arrival, check battery stock, and so on. This tool could also suggest alternative charging locations with fewer vehicles or more available batteries. It could facilitate trip planning and optimization for the drivers, giving them a sense of control over the trip and charging activities. This should not be overlooked, as it could affect a driver's attitude toward the EV transition. Understanding driver behaviors, particularly in electrified scenarios, is complex. Identifying the needs and characteristics of different drivers is crucial for developing a well-functioning charging infrastructure. Although interesting and important, this is beyond the scope of this thesis.

7.2 Traffic flow deviations

The model is dimensioned for trips on an average day, which means that deviations can occur. However, the assumption that there is not much variation between ordinary days is considered reasonable. When it comes to cars, people typically have their schedules and routines by which they use their cars. Trucks even more so, as the most profit is made when the trucks are in operation. Having trucks for specific businesses also implies that the driven routes are similar, even if not necessarily on a daily basis. It is however worth considering what happens to the car traffic flow profiles during special occasions, such as before, during, and after holidays. These are times when the number of cars traveling long distances increases. With more travel of this kind, more charging activities follow as a result. The battery swapping system is not sized for this, which means that large queues would occur at several locations. This would mainly be an issue along the busiest roads, but most locations would likely experience a higher load. As the mean utilization rates for most locations are rather low, these would have the capacity for increased traffic, but there is a risk that it is the traffic on already busy roads that would increase the most. In such cases, a good tool for route planning and thoughtful pricing incentives could relieve some of the stress on the charging infrastructure by encouraging drivers to swap at appropriate times and locations. The variations in truck traffic are not likely to be of the same magnitude, even though there may be some variations due to businesses' varying operating hours during holidays. The battery swapping system of the truck model is already saturated with the current traffic flow, and any variations that lead to a higher load would further emphasize the need for an expanded swapping network.

Another complexity of the real world not depicted in the model is the geographical distribution of batteries. The assumption that the BSSs will always have the same distribution as the fleet is a simplification. In reality, there may be more large batteries in cities that are commonly traveled to than in cities that are traveled from. For example, during skiing weeks, many people travel to the same destination during a specific period. Given that most Swedish ski resorts are located in the North, driving distances are long for many travelers. These drivers would likely prefer larger batteries to cover longer distances on a single charge, but it also depends on the characteristics of the individual travelers. Some want to arrive as quickly as possible, while others prefer a slower trip with breaks. Family trips might involve several breaks for meals and bathroom visits. However, this does not necessarily mean that they would choose a smaller battery for this trip. Given how long the trip is, having the option to drive far without having to stop to swap is probably preferred, even knowing that stops might be unavoidable. If children are asleep, drivers would likely want to cover as much distance as possible. Furthermore, the availability of BSSs might be lower up North due to the generally lower frequency of charging activities. Knowing this, most people would want to have a larger battery reserved in their cars to ensure its availability for the returning trip. Having many large batteries at skiing resorts during these weeks could create an uneven distribution in other parts of the system. This aspect is not considered in the model, but calculations would be required on how to ensure that the system remains stable and functional even during these times. One solution to this could be modular batteries, as already available to some extent in the market today. Using the same interface while varying the number of battery cells in a pack could create greater flexibility in battery sizes. By doing so, during skiing periods, it would only be necessary to ensure that there are enough battery modules for all, without regard to specific battery sizes. Nevertheless, a buffer would still be required to ensure a sufficient capacity to serve all.

7.3 The reality - a mix of several technologies

The model in this work has been developed to represent a scenario where the charging infrastructure in Sweden will solely be based on battery swapping technology and slow charging. This will almost certainly not be the case. Most vehicles compatible with battery swapping today also have the ability to use the fast charging network. Regardless of which other technologies will enter the market in the future, there is likely to be more than one option for drivers. A combination of fast chargers and BSSs is one solution. The results of the battery swapping model show that, during certain hours, the number of charging activities is very high. To avoid queues, more swapping slots are needed, and the model's solution is to add more BSSs. This also means adding more batteries, which remain stored during the rest of the day. When only needing more space, a fast charging spot could be an option due to its generally less required land usage. Additionally, by combining a fast charging station and a BSS, it could be possible to use energy from the stored batteries to avoid drawing power from the grid during times of high load. While this would not be possible at all times, as the batteries are not always full and stored, it could be a solution when more spots are needed and there is available energy in the batteries. Another option for accommodating many vehicles would be having a BSS with several swapping slots that share a common space for battery storage and charging. This would be space efficient in terms of hardware, but require more complex logistical arrangements at the site in general.

7.4 Waiting times

The actual accepted waiting times are subject to uncertainty, both for cars and trucks. For cars, the estimation is based on the assumption that the drivers already factor in a margin for travel time uncertainties based on the driving distance. As long as the waiting times fall within these time frames, there is no need to alter the travel plans due to the risk of encountering long queues or other disruptions. This is however a generalized simplification, as the real world is far more complex. The duration a driver is willing to wait depends on the type of trip and the individual driver. While no distinction has been made between business and private trips in this analysis, there may indeed be significant differences. Business drivers, even when covering long distances, might aim to reach their destination as quickly as possible and, ideally, even complete the entire journey without stopping. For this group of drivers, the assumed waiting times might not align favorably. However, considering that the majority of the business trips commence before 10:00, many could probably plan to reach an appropriate swapping station before the evening rush hours. As the maximum waiting times will only occur during these peak hours, any other time of the day will typically result in shorter, or even non-existing, queues at most locations. On the other hand, for the friends or family road trip, longer waiting times may be more acceptable. This group of travelers might prefer a break to stretch their legs and grab a bite to eat, so that the waiting is combined with other necessities. With integrated stations offering both fast charging and BSSs, travelers not in a rush could pick the slower option, leaving the fast lane for the ones in a hurry. To make such a system work as intended, appropriate pricing is necessary. The sensitivity analysis car results show that the impact of waiting times is limited within the selected range. This implies that if the queues would need to be shortened, it would not significantly increase the number of batteries. Nevertheless, it is important to keep in mind that shorter waiting times would increase the need for battery swapping slots, and consequently, according to the model, more BSSs. This could potentially be mitigated by introducing the dual-slot BSS, or the combined battery swapping and fast charging stations mentioned earlier.

For trucks, on the other hand, operational efficiency is one of the most important parameters. This entails driving from point A to point B within agreed lead times, avoiding unnecessary downtime. Unfortunately, the input data lacks information about the time aspect of the missions, but downtimes are possible to analyze. The MATSim model reveals that most trucks reach the 4.5-hour driving limit before depleting their charge. This suggests that they need to take the 45-minute break, and are thus accepting a queue within this time window. However, this is based on the original data, where the majority of trucks have a battery capacity of 400-500 kWh. In the modified data, the predominant weight class is MDT with a 300 kWh battery capacity. Assuming an energy consumption of approximately 1 kWh/km and an average speed of 90 km/h, using 80 percent of the battery capacity would allow for around 2 hours and 40 minutes of driving. This means that the driving factor for initiating a charging activity would be running out of charge. In this case, a 45-minute break is unlikely to be accepted, at least for the first stop of a trip. By the time of a second stop, the truck would almost have driven the entire driving time and queuing could be accepted. Incorporating the aspect of multiple stops, however, requires a higher level of model complexity, which is challenging due to the inability to distinguish the connection between respective agents and their charging activities. This is an area of improvement of the model, as the sensitivity analysis shows that waiting times have the largest impact on the results when varied from the minimum to maximum value.

Time is equivalent to money for trucks, while the value for the car segment is more complex. Nevertheless, it should be considered. Swapping operations are quicker than fast charging, enabling drivers to reach their final destination earlier. However, preferences vary from driver to driver, and swapping may not necessarily be the optimal option for all. The advantages of taking a longer break from driving should also be addressed. During a long journey, a break results in safer driving for most. There are numerous aspects to consider when valuing time, and these are relevant when assessing the impact of shorter or longer charging stops. Furthermore, swapping and fast charging might not look the same in the future. It may become more space and time efficient, which will paint a new picture.

7.5 The future may not look the same

The model and comparative study are based on what we know and have today. This applies to the size of the vehicle fleet, estimations of traffic flows, battery and charging technologies, and more. Due to the intricate nature of the transportation system, forecasting these parameters for a future scenario would introduce additional uncertainties when analyzing the model results. Hence, the decision was made to use data of today. It is, however, essential to keep in mind that the future is very likely to present a different scenario from today's. As previously mentioned, the battery swapping technology is presently under development for various application areas and regional constraints. At the same time, other charging technologies are emerging and maturing, and it is imperative to strive for a comprehensive understanding of the evolving landscape. On another note, battery technology is advancing. Improvements in energy density will lead to longer driving ranges without increasing in battery size. This would mean that the total energy need may not increase linearly with the increase of EVs. Moreover, the transition to EVs may affect the fleet sizes. While the number of cars, eventually going electric, is likely to continue increasing in line with population and GDP growth, this may not necessarily hold true for trucks. Old trucks still in use today might not be replaced with new ones, either due to changes in business dynamics or because the new electrical trucks can cover the need with fewer vehicles. Furthermore, driving patterns may change. Following the several restrictions due to COVID-19, many stayed at home more than usual. Those who were able to, arranged home office setups, which are still used to some extent. Remote working, along with digital meetings, reduced both long and short trips. The evolution of these trends over time will likely impact daily traffic flows.

A comprehensive study of multiple future scenarios within the same context would be interesting and likely more accurate, as the actual implementation of a fully scaled charging infrastructure remains in the future.

7.6 The use and wear of batteries

One concern is the low utilization rates for several locations, especially for cars. More than 100 sites have a maximum utilization rate lower than 50 percent, and the mean value of utilization for almost all locations is below 30 percent. This can be explained for some locations by the fact that the BSSs are oversized by the number of batteries. The fixed number of batteries per BSS results in always having as many batteries in the station as there are slots, regardless of the expected swapping need at the location. However, this is likely not how it is solved in reality. Instead, there are probably fewer batteries at a location where the swap frequency is low throughout the day. Yet, if there is one or a few times a day when the swap rate significantly increases compared to the rest of the day, the battery stock has to be large enough to cover these peak times. Optimizing the number of batteries per BSS, rather than setting a default value, would enhance the accuracy of the model. It would reduce the total number of batteries in BSSs, further narrowing the gap between the BS and FC scenarios in the comparative study.

Including ancillary services would increase the mean, and potentially the maximum, utilization rates. During periods of storage in the BSSs, the batteries could be employed to balance the grid. This implies that the utilization of the batteries is likely to be higher than what the model results show. The ability of station-to-grid (or station-to-X in general) is an important aspect of battery swapping, both from a business perspective and for ensuring grid stability. Hence, this function is likely to be integrated into a future battery swapping system. The reason for excluding this kind of dynamics from the model's scope is the added complexity they introduce.

When and how a BSS would act as an energy storage unit depends on its location, and the energy production and usage profiles. Integrating a fast charger with a BSS, as mentioned earlier, would also be relevant from this aspect. The diverse applications of the energy storage function of a BSS constitute a wide area of research on its own. An estimation suggests that BSSs located in southern Sweden could be valuable storage units due to the lower levels of local energy production. However, considering the battery swapping profiles of the locations, most experience peak loads during hours of high household energy use. During these times, BSS operators would most likely prioritize vehicle services over ancillary services, and might not be able to support the grid.

Bidirectional charging results in additional battery cycling, and the impact of such cycling on battery degradation is of relevance. As seen in figure 8, if maintaining the discharge cycles shallow for station-to-X functions, the impact is kept significantly lower than for the cycling in cars. This holds true when considering cycle aging alone, as calendar aging is not part of the model. Nonetheless, calendar aging is constantly occurring, especially as the batteries are charged to 90 percent in the base scenario. A model examining the impact of SoC on stored batteries would yield more detailed results on life degradation due to calendar aging.

When considering the degradation of batteries, it is essential to bear in mind that the applied degradation model refers to a LiFePO4 battery. This is not entirely accurate, as LiFePO4 batteries are not commonly used in EVs. A more realistic model of an EV battery would show a higher sensitivity to cycle depths, resulting in higher degradation rates with the current parameters. The implications for the results would be shorter battery lifespans and increased battery turnover. However, as the model does not account for the length of battery lives when calculating total battery capacity, it would not impact the comparative study.

From a business aspect of BSS operations, battery health has a value. With higher degradation rates, each cycle becomes more expensive due to the shortened lifespan. For instance, enabling deep discharge cycles for grid support is possible, but it comes at the expense of battery lifetime. Furthermore, batteries can be charged more rapidly to be ready for the next customer, also affecting the total number of charge cycles over a battery's lifespan. On the other hand, by increasing the overall C-rate, fewer batteries per BSS would be required. Pricing these measures is important, as is considering the environmental impact of accelerated battery consumption of fewer batteries compared to gentle usage of more batteries. Minimizing the number of battery cells, maintaining those within the system, and recycling batteries that have reached their end of life are some of the key actions for achieving a sustainable system.

7.7 Land usage and power connections

Land occupation is essential when analyzing the feasibility of a proposed solution. For the majority of the car sites, one to three BSSs are sufficient, and they could be accommodated by a similar area as some existing petrol stations. Approximately four car BSSs could fit in an area the size of a tennis court, excluding driving lanes. Locations requiring four or more BSSs would need the total area of a large parking lot. As the number of BSSs increases, so does the land needed for queuing to and exiting the stations. For the highest number of BSSs, a solution could be to integrate the stations with shopping malls. A shopping mall providing 500 parking spots could fit 26 BSSs (hardware only) by reducing the remaining number of parking spaces to approximately 400. Another solution to the high number of needed stations would be to distribute them within the predefined zone of a 30-kilometer radius. This would reduce long queues and prevent an excessive concentration of BSSs at a single location. For trucks, the number of BSSs per location is not reasonable. In this case, the shopping mall solution would not be feasible, and additional locations would be necessary. If a truck has several planned stops along the way, it might be possible to swap while discharging. Some studies have suggested portable swapping stations, which could be useful for these locations.

Furthermore, power constraints are crucial. Regardless of the charging infrastructure, more electrical energy will be required as the transport sector becomes electrified. Not only will there be an overall increased energy need, but also times of high power demand. Power peaks should be avoided to prevent stressing the power grid, but it may not always be possible to avoid them completely. The battery swapping system offers a benefit in that it allows for shifting the power demand in time. In reality, a battery does not have to be charged instantly, as modeled in this work. With smart charging, it can instead be initiated when prices are low and the grid is not under a high load. However, there are still some peak hours when the power need is high, as seen in the results. These represent times of high swap frequency, when many discharged batteries enter the BSSs and start charging immediately. In order to reduce the peak power levels, there could be price incentives to swap earlier or to plan the trip differently. Since all stations do not experience peak loads at the exact same time, moving some charging activities to new or nearby locations could flatten the peak in figure 9. The high peak powers at each location for trucks are due to the limited number of charging locations based on the original data. The assumption that the modified population will travel the same routes is not verified, and instead, new locations may be more relevant. This change would significantly reduce the peak power levels per location. If the new locations were situated within the same area, however, the distribution would not make much difference at a power grid level. Comparing the power levels of the BS and FC scenarios, it is shown that most car battery swapping locations require a smaller power connection than if they were fast charging stations. The maximum power connection needed at an FC location is calculated by the maximum plug power (175 kW) multiplied by the maximum number of charging points (30), resulting in 5.25 MW. Approximately 85 percent of all locations in the BS scenario have peak power levels below 5 MW. For trucks, on the other hand, the FC scenario allows for a maximum of 14 charging points per location, and a plug power of a maximum of 700 kW, resulting in 9.9 MW. Only one location in the BS scenario can provide good service throughout a whole day with a power connection below 10 MW.

Model constraints are important to remember when analyzing these results. Although the model is developed to represent a battery swapping system, simplifications are inevitable. One such simplification that affects power levels is the C-rate. It is assumed constant, although it reduces with higher SoC in reality. If these dynamics would have been accounted for in the model, the overall power need would have been slightly less than what is shown in the results.

7.8 MEEs, LEEs and starting times

The car and truck data differ in when they initiate a charging activity. Cars' charging activities are generated as a result of MEEs, while charging locations for trucks are placed based on LEEs. The difference is that MEEs occur at SoC = 0%, and LEEs occur at SoC = 20%. The truck data is based on LEEs as a modification from before, as LEEs mean that the vehicle still has some charge left to reach the nearest charging location. In contrast, the generated locations for cars being based on MEEs imply that this margin does not exist. Although an updated simulation based on LEEs might lead to a higher rate of successful trips due to the remaining battery capacity to reach a station, this has not been confirmed, and the car data based on MEEs is considered accurate enough.

Furthermore, the starting times significantly influence the occurrence of charging activities. This results in the peak of charging activities for cars in figure 9, while the same figure for trucks, figure 18, shows a more even flow. The starting times for both segments are reasonable. Long car trips would most likely start before lunch, and distinguishing between private and business trips is also logical. The model considers both weekdays and weekends for the starting times. This can be noticed especially for the car segment, as for instance private trips are initiated throughout the day, although most start before noon.

7.9 Short trips and total energy need

If short trips had been included in the car model for the BS and FC scenarios, the total energy needs would be different. In the BS scenario, vehicles primarily used for short distances could have a small battery during most of the time. If planning to drive farther, it would be possible to upgrade to a battery pack with greater capacity. However, this would require additional locations as the number of charging activities would increase, leading to the need for a larger battery stock. Furthermore, around holidays or other periods of increased traveling, there would be a higher number of small batteries at the stations. Ensuring a sufficient number of batteries of the right size to meet demand would hence become an important aspect. One solution already mentioned could be the use of modular batteries. Fitting several modules into the same battery pack could eliminate the risk of having only one size left. A buffer of modules would still be necessary, but this setup would reduce the need for a buffer of all different battery sizes. In the FC scenario, it is unlikely that vehicle owners would settle for a very small battery, even if its range would be sufficient for the short trips their cars are mostly used for. It would be inconvenient once the driver wants to go on a longer trip, which is why most would probably still choose a car with a large enough battery to enable longer travel. Consequently, the total battery stock of the FC scenario would not change.

Regarding trucks, including short trips would probably have minor implications on the results. In the BS scenario, if trucks traveling less than 300 kilometers would use the technology, they could reduce their battery capacities. However, trucks on daily short trips might not have the 45-minute obligatory break, which means that swapping would need to be quick enough to justify not keeping a large battery. This could present a challenge in terms of available space for additional BSSs. To reduce downtime in these cases, mobile BSSs could be an alternative for efficient swapping at warehouses or other truck stops. In the FC scenario, not much would change for trucks. As most trucks driving short distances do not have time for a full charging break as long as charging times are not shortened, they would prefer to keep the battery sizes sufficient to complete the mission in one charge.

In conclusion, including short trips would primarily lead to reduced battery capacities in the

BS scenario. Given the large proportion of both car and truck populations driving short distances, these reductions can have substantial impacts on the overall energy requirements. The ERS scenario already considers the entire fleets, resulting in a significantly less amount of battery capacity. Another factor that could impact the results of the comparative study is that some fast charging stations are opting towards installing complementary battery storage units to ease the grid load. This would mean an increase in batteries for the FC scenario. An interesting point to consider is that, for one fast charge, two batteries would be charged and discharged simultaneously, meaning that battery wear is doubled, and the consumption rate higher than in the BS scenario.

8 Conclusions and future research interests

What the future holds for the Swedish charging infrastructure remains undefined. Nevertheless, its development is imperative to achieve the national targets for transport electrification. Battery swapping is an option that can provide fast service, good battery maintenance, and grid support. However, this is only true if the system is dimensioned correctly. Otherwise, it may result in long queues, low battery utilization rates, and require large land areas. The results show that the battery swapping scenario for vehicles on long trips may not result in a significant increase in battery capacity compared to the fast charging scenario. The differences between the battery swapping and electric road system scenarios, on the other hand, are substantial. This gap could be expected to narrow if vehicles on shorter trips would have been included in the battery swapping scenario, as well as if the number of batteries per BSS would be determined individually based on the need at each site.

There are several notable areas for further research. Including short trips in a similar analysis would provide a more comprehensive picture of the future potential of battery swapping. Additionally, integrating ancillary services in a battery swapping model would be relevant in the Swedish setting due to the increasing share of intermittent energy sources. Lastly, an analysis of the value of time in the context of waiting to charge would offer an interesting perspective for comparing different charging technologies.

A question that must be addressed and goes beyond research interest, is one of the main obstacles for the battery swapping technology to gain further ground. It revolves around a crucial issue, being the lack of unified technical standards. Achieving such agreements could lead to reduced upfront costs and an increase in utilization rates. More than that, customers are more likely to embrace the concept of battery swapping if it improves travel convenience, rather than the other way around. The compatibility between vehicles and battery swapping operators could be the deciding factor in whether battery swapping becomes integrated into the Swedish charging infrastructure or not.

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