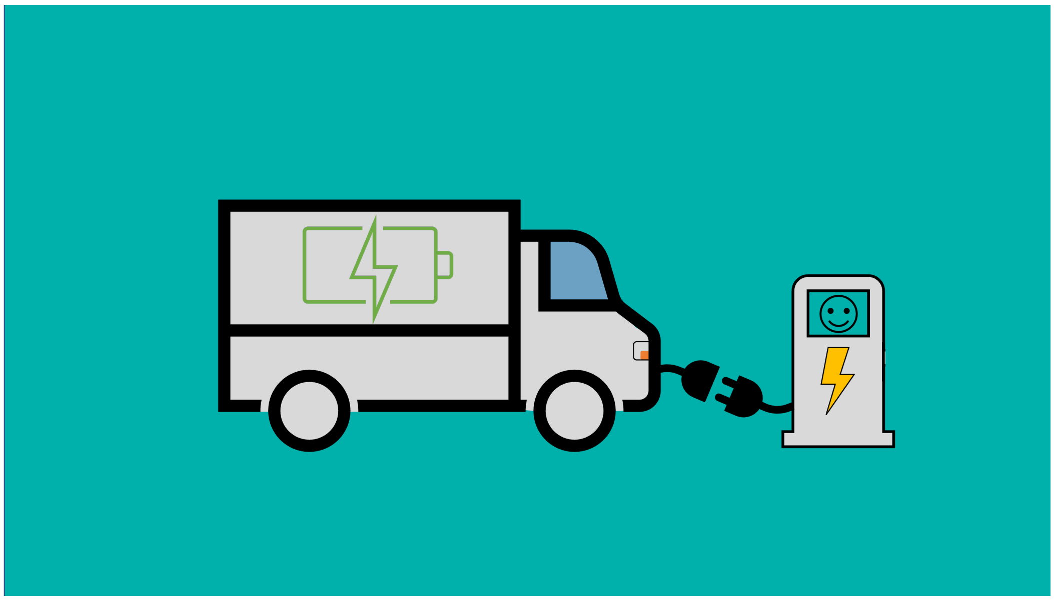

Optimizing heavy duty vehicle battery size and its impact on charging strategy

Master's thesis in Sustainable Energy Systems

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CHALMERS UNIVERSITY OF TECHNOLOGY
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Cover: Visualization of a battery electric heavy duty truck charging.

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Abstract

The electrification of heavy-duty trucks plays an important role in carbonizing the transport sector, although there are many crucial variables that needs further research before reaching a market penetration. This thesis focuses on the battery size, driving profile and charging behaviors of heavy-duty battery electric vehicles (HD-BEV). Characteristic driving profiles for six different vocations were created from aggregated driving data. A cost-minimizing optimization model was created to determine the battery sizes of the different vocations for a characteristic week. The model also cost-optimizes the charging pattern of the different vocations divided among charging powers ranging from 22 kW to 1000 kW. The results show that the battery sizes range from 188 kWh to 632 kWh for the various vocations. Furthermore, it is found that most of the electricity charged comes from the 22 kW charger for all but one long-distance vocation where most of the electricity is charged using a 350 kW fast charger. Although the 350 kW to 1000 kW chargers are never used in the base cases. The results also suggest that for half of the vocations, charging is equally distributed between night and daytime and that the other half charges the majority of their energy during night time. Sensitivity analyses suggests that the cost of battery has a relatively small effect on battery size and charging strategy. In contrast, vehicle consumption had a significant impact on battery size and charging strategy where the use of 500 kW and 1 MW chargers is observed.

Keywords: battery electric trucks, battery size, driving profiles, charging infrastructure, heavy-duty, optimization

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William Huynh, Gothenburg, May 2022

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Introduction

1.1 Background

In order to limit global warming the United Nations (UN) agreed on reducing greenhouse gas emissions (GHG emissions) through the Paris Agreement of year 2015. The goal is to act towards a decarbonized system throughout a majority of the sectors by 2030 [1]. In 2021 the transport sector accounted for 37% of the CO_2 emissions from end-use sectors globally, while road transport made up more than 76% of the CO_2 emissions from the transport sector [2].The European Union (EU) climate policy is to reduce the GHG emissions by 55% by 2030 compared to 1990 levels [3]. The city of Gothenburg aims to reduce GHG emissions from transportation by at least 90% compared to 2010 levels by 2030 [4]. As road transport make up a large share of the GHG emissions it is therefore of importance to decarbonize this sector. One way of doing so is by replacing fossil fuels with other, carbon-neutral energy sources such as electricity and batteries and biofuels accompanied by respective compatible powertrains [5]. For instance, electric motors powered by CO_2-neutral electricity in order to propel battery electric vehicles (BEV:s). BEV among other technologies plays a part in the solution to carbonizing the road transport sector and this report aims study this technology further [6]. Other technologies with the potential to substitute fossil fuels and propel vehicles from carbon neutral energy source are hydrogen fueled vehicles and electric road systems (ERS).

Although the electrification of personal vehicles have gone a long way in the past decade, the electrification of heavy duty battery electric vehicles (HD-BEV) is still in its initial stages. For the same reason it is of great interest to investigate the potentials and challenges of electrifying heavy duty vehicles (HDVs). HDVs are defined by the European Commission as freight vehicles of more than 3.5 ton or passenger transport vehicles of 8 or more seats [7]. As a large share of HDVs are yet to be electrified little is known about the of electricity demand and systemic behaviors it opposes to the energy system.

1.2 Literature Study

The literature study aims to focus on three main fields important to the background of the thesis. Namely the battery size of of HD-BEV:s, charging infrastructure for HD-BEV:s and finally the impact on the power grid.

1.2.1 Battery size

In electrifying road transport the battery size is regarded as one of the most crucial aspects from a consumer point of view when deciding whether to purchase an electric vehicle (EV) or an internal combustion engine (ICE) vehicle due to the phenomenon so called range anxiety i.e., the fear of range scarcity [8]. From a techno-economic standpoint it is therefore important to optimize the battery size to avoid insufficient capacity but also to avoid over dimension as they require rare earth metals (REM).

The battery sizes that Volvo have announced for their BEV:s ranges from 264 kWh to 540 kWh installed capacity [9]. Scania's battery size at 624 kWh installed capacity and promises a range of 350 km at 40 t load [10]. The Volvo FH Eletric model has a designed GCW of 44 t equipped with a 540 kWh battery weighing 3 t [11]. The battery pack could make up to 9 % of the load capacity.

The technical feasibility of BEV:s are gaining more and more recognition lately [12]. Although, this generally refers to battery electrification of passenger vehicles and not heavy duty vehicles. Nykvist and Olsson [13] disproves the argument that battery weight to capacity ratios and energy density of HD-BEV:s have a hard time competing with conventional diesel fueled HDV:s. They present results against these assertions by analyzing HD-BEV feasibility looking at factors as fast charging, payload i.e., the weight transported over distance as well as analyzing other factors of which the result is sensitive of. This was done by developing a model where all costs were included for a wide range of truck sized from 10 t to 100 t GVW. Constraints and driving characteristics are derived from studying and analyzing existing road transport patterns in terms of distances and payload. They have modeled a vehicle driving for 4.5 h followed by charging for 40 min and then drives another 4.5 h. In their model fast charging up to 1 MW is included in order to facilitate smaller batteries and shorter charging time. The model explores three scenarios where the main battery parameter sets (PS), battery cost, cycle life and specific energy are varied. PS1 represents a case where lithium-ion (Li-ion) batteries are assumed to cost 300 USD kWh^{-1}, a cycle life of 1000 cycles and a specific energy of 125 Wh kg^{-1}. The prices are slightly higher than 2021 values, when the report is published. PS2 resembles a near-future optimistic case with a battery cost of 100 USD kWh^{-1}, 5000 cycles and 175 Wh kg^{-1}. Lastly PS3, a case created from the arithmetic mean of the two former cases. It was found that the competitiveness of HD-HEV:s compared to diesel trucks per km depends greatly on gross vehicle weight (GVW) and battery parameters. If the cost instead is modeled per ton-km it is found that competitiveness is increased per GVW regardless of case and battery parameters. Moreover, if the battery parameter values of the optimistic case is achieved results indicates that HD-BEV:s can be competitive regardless both in terms of per km and per ton-km. Nykvist and Olsson also carried out an sensitivity analysis using the weighted case as a baseline and varying each parameter ± 30 % which further confirmed the results by the model i.e., on a per km basis parameters are highly sensitive to parameter assumptions while per ton-km basis the competitiveness increases for most cases. Even though Nykvist and Olsson presents data that contradicts the dogmas of HD-BEV:s they don't explicitly quantify the total cost of ownership (TCO) of HD-BEV:s or other technical issues such as what battery sized are economically feasible. Furthermore, the study simplifies and generalizes many parameters to derive average values hence not being specific to any market [13].

Gnann et. al., found that the market share of battery electric trucks (BET:s) increases with the battery size. By using a model that varies the input variables and calculates TCO, Gnann et. al., identifies the market diffusion of various drive train types including BET:s. The input variables, battery capacity and high power charging stations, are randomly varied 1000 times 100 kWh to 500 kWh and 0 stations to 677 stations respectively in year 2030. Their driving profile data for trucks includes the vehicle weight and annual mileage hence simplified although being individual driving profiles [14].

Link and Plötz evaluates in their 2022 study the feasibility of HD-BEV based on individual driving data. Based on recorded diesel truck driving patterns of one month in 2021 within a 220 km radius of Berlin in the Northeast of Germany, 224 trucks were sampled. About 9500 tours are modeled for battery sized ranging from 100 kWh to 800 kWh in order to determine whether or not it is technically feasibly to fully to substitute the diesel truck for a BET. The BET:s considered are 18 t rigid truck, 26 t rigid truck, tractor trailer combinations and truck trailer combinations. The criteria for technical feasibility being that the energy required for a route is less than the modeled gross battery size for at least 95 % of the simulations. It was concluded that 400 kWh batteries could electrify 52 % of the entire fleet while 600 kWh batteries would be sufficient to electrify 62 % fleet within and lastly 800 kWh would replace 68 %. Higher rates of BET replaceability are found within metropolitan areas. The importance of examining each vehicle driving profile in order to optimize battery size is highlighted. Link and Plötz don't optimize charging or battery sizes but models the planned routes strictly. In this study, individual driving patterns will be derived from aggregated driving data to represent multiple categories of BET:s. The objective aims to minimize the TCO thus finding a cost optimal solution that satisfies existing driving demands. [12]

Baek et. al. does so in proposing a nonlinear lithium-ion battery model to optimize truck batteries for parcel deliveries within a 100×100 km^2 area. The constrains are given by a working schedule where the daily active hours are limited and the vehicle has to make it back to its base. The battery model considers degradation from cycling, revenues and profits to optimize the battery size against cost. The model was ran for working hours of 6, 8, 10 and 12 hours per day where the optimal battery size maximizing the profit were 1.0 kAh, 1.1 kAh, 1.2 kAh, 1.4 kAh respectively. Translating to kWh, 1000 kAh at 350 Ω corresponds to 350 kWh as the authors assume the power train of a Tesla Model 3. The time horizon for the vehicles was then extended consequently requiring some batteries to be replaced. The results showed that as the time horizon went from 1 week to 1 year the optimal battery size went from approximately1.0 kAh to almost 1.5 kAh for all vehicle working hours. The first battery replacements were present after 3 and 5 years resulting in two optima at around 1.0 kAh and 1.5 kAh despite additional cost of replacing batteries. Baek et. al. estimates the profit of battery sizing up tp 56%. [15].

The non-profit organization Power Circle uses the same data as Trafikverket in order to electrify heavy duty traffic along the Öresund-Kattegatt-Skagerrak-region (ÖKS-region) which stretches along the Swedish west coast from the Danish-Swedish border to the Norwegian-Swedish border.Power Circle also estimates the batty sizes of each vehicle type based on the daily average driving distance to 250 kwh, 300 kWh and 500 kWh for heavy trucks operating locally, regional and long-haul respectively [16].

1.2.2 Charging infrastructure

HD-BEVs are being introduced to the market but their market share of sold trucks is still relative small. In 2021 there were approximately 66 000 registered HD-BEVs constituting 0,1% of the global truck market share.[2]. Even though the technology is present the system lacks charging infrastructure enough to carry a significant share of HD-BEVs on the road. Power Circle expects the HD-BEVs to increase from 121 registered trucks in year 2022 in all of Sweden to 5745 in ÖKS-region by year 2030 [16].

Plötz and Speth identifies truck stop locations from a logistics point of view in Europe using a unique data set of driving patterns from about 400 000 trucks. The truck stop data set distinguishes HD-BEV operating both long-haul from regionally operating trucks. Plötz and Speth evaluates the country coverage of their data by looking at the relation between No. of stop locations and target No. of locations. The same is done for urban nodes to ensure coverage of urban nodes in Europe. Furthermore, the representativeness of the data is evaluated by comparing comparing the distribution of stop locations to various variables such as number of stops versus number of location per country in order to see both variation and correlation between sizes of countries and traffic flow. In order to identify potential future charging stations, Plötz and Speth characterizes the top 10 percent most common long-haul truck stop locations using Open Street Mat data as well as their distance to to motorway. Additionally the top 10 percent long-haul truck stop locations were scanned identifying and labeling nearby objects within a 200 m radius in order to further characterize stops using "Here API". Stops and stop duration are presented and analyzed as a source for charging infrastructure. The result acts as an initial source for establishing charging infrastructure for battery electric trucks. Long-haul trucks in Europe are well represented by the results whereas regional trucks in eastern Europe aren't fully represent. Plötz states that the results have been conducted from a logistical point of view thus not considered what type of chargers, the amount and whether or not it can be sustained by the power grid [17].

Table 1.1: The power required to charge each vehicle type during their longest and second longest stop using charging strategy 2.

Vehicle type	Charging power longest stop	Charging power second longest stop
LD-BEV	5 kW	-
HD-BEV Local	16 kW	-
HD-BEV Regional	19 kW	-
HD-BEV Contracting, farming and forestry	30 kW	40 kW
HD-BEV Long-haul	67 kW	100 kW

1.2.3 Impact on power grid

Stops and stop duration data is important for not only charging infrastructure but also to assess the impact on the power grid. Plötz and Speth studies the distribution of stops which, also, is of importance to the power grid design [17]. Trafikverket also evaluates the stop duration and when the stops are initiated (stop start time) for the longest and second longest stop. Trafikverket presents power suggestions for semi-public, public and terminal charging but no concrete conclusions whether how the status or layout of the power grid may be affected [18]. Power Circle created power profiles of charging using different charging strategies and then estimates the additional peak power demand in different regions of Sweden. They assume fixed battery sizes of 300 kWh and 550 kWh for regional and long-haul HD-BEV:s respectively. Two methods for charging of HD-EV:s are derived from their study. Method one is divided into two cases (1a & 1b) where they're treated differently during their second longest stop. The longest stop is treated equally where HD-BEV and LD-BEV are charged with 11 kW and 22 kW respectively. For method 1a the vehicles in need of complementary charging in order to suffice daily transport are charged during their second longest stop. The same goes for method 1b but the vehicles are charged with public charging using power ratings from 350 to 1000 kW in order to predict an increase in daytime charging. The second method uses daily energy demand and stop duration to calculate the average charging power required to fully charge the vehicle during the longest and second longest stop. By combining data of what time of the day the stops are and share of fleet moving, the share of vehicles stopped and available for charging could be estimated. Vehicles not able to fulfill their daily distance were charged with a power large enough such do so during the second longest stop. It was found that vehicles could charge with powers ranging from 5 kW to 67 kW during its longest stop depending on type of vehicle with light LD-BEV and long-haul HD-BEV are on the either side of the spectrum. Long-haul- and contracting, farming, and forestry HD-BEV:s was found to require complementary charging ranging from 40 kW to 100 kW according to table 1.1. Whereas charging method 1a does not take smart charging into account but rather uses the facility available at the given time, strategy 2 aims to smart charge using the lowest possible power rate whilst fulfilling the daily demand. Consequently, charging strategy 2 results in lower peak power demand than the rest of the strategies. Strategy 1b simulates so called opportunity charging where vehicles top up their energy banks as a safety measure. Opportunity charging is expected mainly during day time resulting in increased peak power demands. The power required to charge each vehicle type during their longest and second longest stop using charging strategy 2 is presented in table 1.1 [16].

The Swedish Transport Administration (STA), *Trafikverket*, released a report in early 2021 where charging infrastructure of heavy duty battery electric vehicles (HD-BEV) was evaluated. The aim of the report was to identify the expected fast charging infrastructure of HD-BEV along the main roads of Sweden along with the proposal of business model as well as other benefits and consequences. The material has been provided by Volvo trucks and Scania as aggregated and measured vehicle data. Together, Volvo trucks and Scania constitute a significant share of HDVs on the Swedish market. Based on the given data and daily average driving distances Trafikverket estimates the dimensioning distance to 350 km to 400 km and 600 km to 625 km for regional and long-haul trucks respectively [19].

The analysis concludes that the main contributor to an increased power demand are LD-BEV:s. The estimated peak power demands are presented in table 1.2 [16].

Region	Strategy 1a	Strategy 1b	Strategy 2
Skåne	300 MW	250 MW	200 MW
Västra Götaland	400 MW	340 MW	250 MW
Halland	60 MW	55 MW	40 MW
Total	760 MW	645 MW	490 MW

Table 1.2: The additional peak power demand in three regions in Sweden by charging strategy according to PowerCircle.

1.3 Aim

The objective of this master's thesis work is to evaluate battery size and charging of heavy duty vehicles based on current driving patterns with the objective to minimize total cost of ownership. This is done by creating driving profiles together with an optimization model.

- What driving behaviors can be expected for heavy duty battery electric trucks?
- What is the optimal battery size for a heavy duty battery electric truck?
- What charging infrastructure factors are crucial for the feasibility of heavy duty battery electric trucks?

1.3.1 Boundaries

This thesis will only study battery electric heavy duty vehicles and therefore not consider other electric vehicle propulsion techniques such as electrofuels or electric roads. Nor will it consider passenger vehicles or others not classified as heavy duty. The primarily focus is a techno-economic and technological assessment.

2

Method

In this section the methods used to carry out this project are described in detail. The first part of the master's thesis consists of normalizing aggregated driving data. The second part, creating characteristic driving profiles from the derived data and making assumptions related to vehicle types. The final and third part of the method consists of creating an investment model using GAMS (General algebraic modeling system) and solving the linear mathematical problem for optimal solution. In addition, sensitivity analyses of various parameters are presented. Figure 2.1 illustrates the method used in this study.

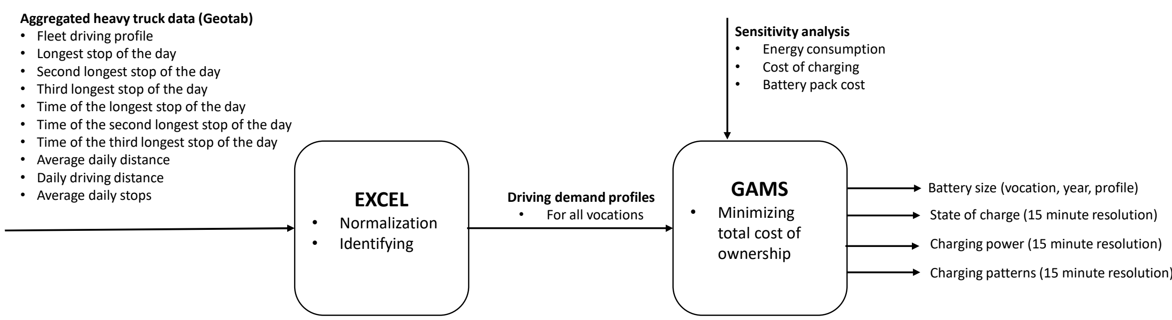

Figure 2.1: Coupled parts of the method.

2.1 Aggregated driving data

The data set which has been used in the methods is given by Geotab, a company which provides telematics hardware and fleet managing services. Presented in figure 2.1, are the aggregated and curated data sets provided by Geotab. When creating the data, Geotab identified trucks in North America with similar driving patterns. Driving behaviors among tens to hundreds of thousand vehicles which possesses the same characteristic driving profiles are aggregated into creating a vocation. The vocations are listed in table 2.1 where their respective average weekly distance, average weekly driving time and average speed are specified. The two long distance vocations named, LongDistance24 and LongDistance9to5 are assumed to drive mostly highway and carrying a relative high payload. LongDistance24 and LongDistance9to5 are characterized by a significantly larger average daily driving distance and average daily driving time. Similar to LongDistance9to5, the vocation LongStop9to5 is mostly active during daytime although characterized by it's long stops indicating multiple destinations along the route therefore driving about the same distance as LongDistance9to5 with a longer daily driving time. The vocation HubShort is characterized by many short stops and is, after the vocations containing after. The truck operates from a hub to a destination where a quick stop is carried out before returning to the hub. The vocation named Routed drives a significant distance throughout the day where the distance between the origin and destination is not direct. This vocation generally idles more than drives. Unknown is a vocation containing a profile with enough similar driving patterns but not any significant characteristic. The vocations and some characteristics are presented in table 2.1.

The data is collected by Geotab for the full month of February, similar driving patterns are aggregated and sorted by weekday, also carried out by Geotab prior to use. The data is then merged by weekdays into creating a representative week for the month of February. In some data and some cases there is a lack of available data points which have been assigned a negative value. These are set to zero such that the available data is normalized to a representative weekday and vocation. The result is a representative week of the month of February. The amount of missing values would be in the range of 1 % of the data points typically. The vehicle activity varies very little from month-to-month according to measured data by Volvo Group [20]. The different vocations have been categorized as either long haul, regional or local HD-BEV depending on their distances, the amount of stops and their driving profile. The different categories differ in electric motor power presented in section 2.3.1.

Table 2.1: Presented in the table are the following characteristics of each vocation, average daily driving distance, average daily driving time, average speed, classification and finally a short description.

Vocation	Average daily driving distance	Average daily driving time	Description
LongDistance9to5	372 km	6 h	LongDistance24 and LongDistance9to5 are assumed to drive mostly highway.
Unknown	120 km	4 h	
Routed	160 km	4 h	LongDistance24 and LongDistance9to5 are characterized by a significantly
LongStop9to5	400 km	8 h	larger average daily driving distance and average daily driving time.
LongDistance24	1080 km	18 h	
HubShort	300 km	6 h	LongStop9to5 is mostly active during daytime although characterized
			by it's long stops indicating multiple destinations along the route
			therefore driving half as far as LongDistance9to5 in just as many hours.

The data sets given are used to create driving profiles and to identify characteristics of each vocation and consequently estimate plausible vehicle parameters used in the vehicle modeling section. The data sets are described in the section below first in general, then with respect to variations between vocations and lastly with respect to variations between weekdays.

Longest stop of the day indicates the length of the longest stop of the day for the different vocations normalized by vocation and weekday. Usually when a from chauffeur parks the vehicle for the day until a it's operated again next day. The longest duration varies greatly with vocation and weekday. Typically the longest stop is around 14 h to 15 h indicating a typical eight to five day. Although some vocations (all but HubShort and LongStop9to5) around 1 % have their longest stops as 1 h long. There is a wide variation in how long the vehicles are stopped. The share of vehicles that have the same stopped time each weekday is up to 6 %. Meaning that the remaining 94 % of the fleet have different stopping behavior, although they're a bit less common. In general Routed has the highest density i.e., common fleet behavior among the vocations with an average density of 9 % on weekdays meaning a large share of its fleet acts accordingly. In contrast, LongDistance24 averages the lowest most common value during weekdays at just below 5 % with longest stops that are either about 30 min or 10 h long. Since the long and short stops are almost as common as one another, the values are in more evenly distributed creating two peaks for LongDistance24. The longest stop duration varies with the day of the week as well. Friday and Saturday are different as the vehicle can be parked either over night until Saturday, until Sunday or until Monday next week. This typically generates up to four peaks: a short one, an over night, one over two nights and one over three nights. In the second longest and third longest stop duration the shape of the curve acts as the function of $y(x) = x^{-e}$. The most common stops are much shorter ranging from 15 min to 60 min. The largest value of Routed are now ranging from 30 % to 60 % whereas the rest of the vocations are between 20 % to 40 %. Also given is the second and third longest duration. The most common value is about 5 % to 10 %, 20 % to 50 % and 30 % to

80 % for the longest, second longest and third longest stop duration respectively.

Table 2.2: The range for the most common values of longest, second longest and third longest stop duration as well as for longest, second longest and third longest start stop hour. Single values are weekly averages.

Vocation	Longest stop	2^{nd} longest stop	3^{rd} longest stop	Time of longest stop	Time of 2^{nd} longest stop	Time of 3^{rd} longest stop
LongDistance9to5	6 %	17 to 27 %	30 to 50 %	4.0 %	3.0 %	2.5 %
Unknown	7 %	20 to 40 %	38 to 65 %	3.6 %	3.2 %	3.0 %
Routed	10 %	30 to 51 %	47 to 83 %	4.6 %	4.8 %	5.5 %
LongStop9to5	8 %	18 to 21 %	35 %	4.8 %	3.0 %	3.0 %
LongDistance24	5 %	26 %	37 %	2.0 %	1.7 %	1.9 %
HubShort	6.5 %	15 to 25 %	30 to 45 %	5.5 %	2.5 %	3.0 %

Time of the longest stop of the day is the time of which the longest, second longest or third longest stop is initiated. Presented as a distribution over the time of a day and normalized by weekday and vocation. Most vocations initiate their daily longest stop when the working day for a chauffeur is over, sometime in the afternoon. The exception is LongDistance24 that is active around the clock a significant amount of time starts its longest stop around midnight. The time of the second and third longest stop of the day usually occurs in the morning and during lunch time. The most common value varies from 2 % to 10 % depending on vocation. HubShort have among the largest values during weekdays and LongDistance24 the smallest also during weekdays. During the weekend a greater range of variation occurs where HubShort decreases and Routed increases. Besides weekdays and weekends the variations are quite small.

Aggregated data representing driving distances are found in **"average daily total distance"** and **"total daily driving distance"** where the former presents the average driving distance for each vocation and weekday. The weekly average daily total driving distance and total daily driving distance for each vocation are presented in table 2.1. The standard deviation in average total daily distance is found larger in LongDistance9to5 and LongDistance24 since they drive longer distances. The standard deviation relative to their distances it is found larger in Hub Short than other vocations as can be seen in table 2.3.

Table 2.3: Standard deviation and standard deviation share of average of average weekly total driving distance.

Vocation	Standard deviation	Standard deviation % of average
LongDistance9To5	20.18	8%
Unknown	1.77	1%
Routed	6.46	6%
LongStop9To5	13.57	11%
LongDistance24	34.82	8%
HubShort	14.02	14%

The latter, total daily driving distance, presents the total driving distance for each vocation and weekday divided into 25 km bins. Hence the share of fleet that drives 0 km to 24.99 km can be distinguished from the share of fleet driving 25 km to 49.99 km and so on. The share of fleet total daily driving distance starts at a high value (mostly around 10 % to 20 %, on occation around 30 %) and decreases quickly indicating that only a small share of the fleet drives a longer distance relative to the rest of the fleet. Vocations such as LongDistance24 and LongDistance9to5 stagnates faster and maintains a higher level for a longer time before approaching zero, indicating that they drive longer distances. The day to day variance is quite small except weekend where the density levels are higher indicating that a larger share of vehicles drive shorter distances during the weekend.

Average daily stops presents the stop frequency for stop durations below 300 s, between 300 to 1800 s and 1800 s and above. The number of stops in each time category varies with greatly with vocation. Fewest number of stops per day are carried out by LongDistance24, LongDistance9to5, LongStop9to5 and HubShort averaging a couple of stops in each category per day. This indicates that these vocations drives towards their designated destinations with very few detours along the way. Routed and Unknown have 30 to 10 short stops shorter than 5 min per day respectively. During the weekend the number of stops in each category is approximately doubled for Routed and Unknown while the rest are halved. This data set includes the longest, second and third longest stop as well.

2.2 Creating driving profiles

In this section the method of creating the driving profiles characteristic to each vocation is explained. The restrictions, assumptions and use of data for creating the driving profile scenarios are explained. An explanation of the different vocations based on their driving profiles follows the above mentioned.

According to European Union (EU) legislative regulation the driver is obliged to rest for at least 45 min for every 4.5 h of driving. The 45 min break can be split into two breaks of 15 and 30 min within the span of 4.5 h of driving. The driving profiles have been arranged as to comply with these regulations along with their respective common "start time of stop" as well as the "duration of the stop". Weekly and day-to-day regulations are not considered as it is assumed that drivers take shifts hence ignoring weekly limits [18]. In contrast, according to the United Stated department of transportation, the federal motor carrier safety association (FMCSA), there is a 30 min break for each 8 consecutive hours driven [21]. As the European constrains are stricter they will be applied to the model. Therefore, one of the constrains to the driving profiles are that there are no shifts that exceeds 4.5 h of driving. For every 4.5 h or driving, either a 45 min or 30 + 15 min is inserted depending on whether there is a longest, second longest or third longest stop already.

Remaining breaks that chauffeurs have to take are scheduled in the driving profile based on the data sets *time of the longest stop of the day*, *time of the second longest stop of the day* and *time of the third longest stop of the day* together with *longest*, *second longest* and *third longest stop of the day* respectively. This is done for each vocation and each weekday in order to create a characteristic driving profile of a representative week for each vocation.

The top three longest stops are not the only stops that are carried out. From the data set *average daily stops* the number of stops shorter than 5 min, between 5 min and 30 min and above 30 minutes that a vocation does on average per weekday is presented. These stops, shorter than 30 min, have not been taken into account when constructing the driving profile as these stops are considered too short to facilitate charging. These stops usually coincide with delivery stops and assuming charging possibilities of all charging rates at each delivery point is considered too optimistic as of today.

Driving profile

The base profile reflects the most common driving profile of each vocation and weekday. In the following description to how they are created it is referred back to figure 2.2.

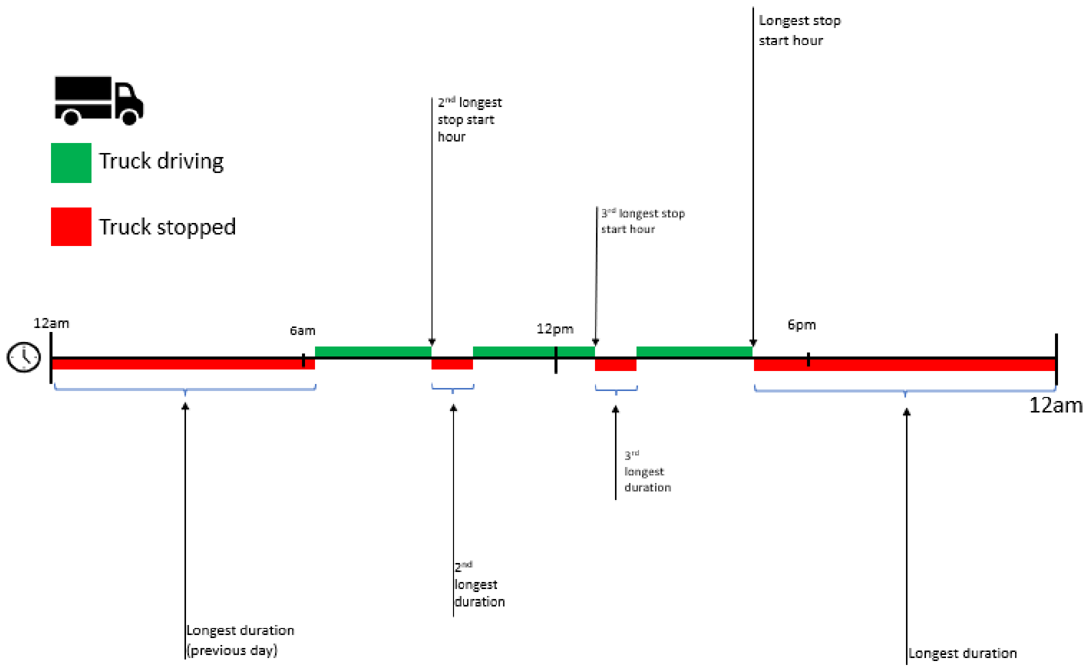

Figure 2.2: Here it is shown where the different data sets have been used to identify driving patterns and as a result, an characteristic profile is created.

- Most common *longest*, *second longest* and *third longest stop start hour* is identified for each vocation and each weekday.
- The start time of the *longest*, *second longest* and *third longest stop duration* is identified for each vocation and each weekday.
- The *longest stop duration* is placed after the *longest stop start hour* in the timeline. This is done for the second and third longest as well.
- If the start stop hour occurs when the vehicle already is stopped the next time slot is tested until one is found where the vehicle is not already stopped.
- Mandatory resting time according to EU legislations are included in the driving profile. For every 4.5 h of driving, 45 min of stop is scheduled.
- The profile is written in a binary format and fed to GAMS as input. For further reading, see section 2.3.

The driving profile is created from the most common driving patterns of each vocation for each weekday. These data points have been chosen based on the data point with the highest density or in other words, how most of the vehicles that have the same driving patters in a vocation are driving. The longest, second and third longest stop start hour, i.e., the time at which the truck begin its stop, is marked out on the timeline. The length of the stops namely longest, second longest and third longest stop are then marked out on the timeline respectively as can be seen from the green bars in figure 2.2. The magnitude of the most common behavior varies depending on data set, vocation and weekday. Some parameters have larger variations than other depending on their driving behavior. Table 2.2 presents the size range of the most common behavior of the fleet for each data set. For instance, Routed tends to have larger weekly average values although a relative large variation between the most common values. Whereas LongDistance24 tends to have a relative small variation and smaller most common value relative to the other vocations. This indicates that stops are more evenly distributed of LongDistance24 while the stops of routed are more concentrated to some specific length of stop. The density of the most common value increases as one goes from longest stop to second and third longest dataset. Meaning that as stops get shorter they approach the same length. For instance, the longest stop is usually over night while the second and third longest stop time is around 0.5 h to 1 h.

2.3 GAMS model

In the following section the GAMS model aiming to minimize the total cost of ownership (TCO) is presented in detail. In minimizing TCO the model uses a mixed integrer programming (MIP) solver with a temporal resolution of a quarter (q) of an hour which is run for a characteristic week in February. The model meets the driving demand by charging the battery using the available chargers and invests in battery pack capacity with the objective of minimizing the TCO.

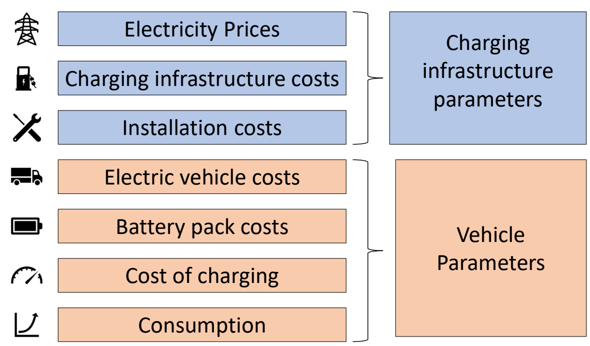

Figure 2.3: Parameters that goes under the category charging infrastructure and vehicle respectively.

2.3.1 Model parameter assumptions

Parameters, scalars and other values that have been feed to the optimization model are listed in table 2.4 and explained in this section. The section is divided into charging infrastructure parameters followed by parameters related to the vehicles. Costs that have been found in USD have been exchanged to Swedish Krona (SEK) at an exhange rate of 10 SEK/USD which is reflects the average exchange rate in year 2022.

Charging infrastructure parameters

Various charging power rates are implemented in the model based on their likeliness to be implemented in the medium-term future and the estimated required charging powers according to Power Circle [16]. The charging power ranges from 22 kW to 350 kW according to table 2.4. The 1 MW and 500 kW charger is used as an alternative for the model to find a solution and therefore the cost of using that charger was set to 15 SEK kWh^{-1} and 12.0 SEK kWh^{-1}. These prices reflect public charging prices in and around Gothenburg, Sweden in January 2023.

The chargers listed in table 2.5 are are assumed to be equipped with communication facilitating payment through WiFi or cellular which a vast majority of all public chargers according to the ICCT. This is feature is one of the main cost drivers and also reflected on the prices. The installation cost of chargers are based on installing at least 6 chargers per site as in 2018 the majority of chargers per site were six and above. It is assumed that the hardware expenses of chargers decline by 3% per year [27].

Table 2.4: List of parameters used in the optimization model. In cases where multiple sources have been used to determine parameter value an average has been used.

Parameter	Value	Unit	Source
Charging cost 22 kW	6.25	SEK kWh^{-1}	[22] [23]
Charging cost 50 kW	7.43	SEK kWh^{-1}	[24] [22] [23]
Charging cost 150 kW	8.00	SEK kWh^{-1}	[22] [25]
Charging cost 350 kW	8.87	SEK kWh^{-1}	[23] [26] [25]
Charging cost 500 kW	12.00	SEK kWh^{-1}	[25]
Charging cost 1 MW	15.00	SEK kWh^{-1}	

Table 2.5: Cost parameters of charging stations.

Type	Annualized Investment Cost
50 kW	224 638 SEK
150 kW	540 000 SEK
350 kW	241 948 SEK
500 kW	345 640 SEK
1 MW	691 279 SEK

Vehicle parameters

Listed below in tables are the vehicle related parameters such as cost of components for electric trucks and consumption parameters used as input for minimizing the TCO. in figure 2.4 the different parts contributing to the TCO are presented.

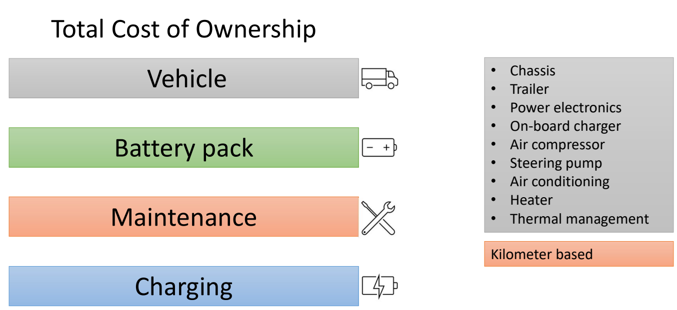

Figure 2.4: The parameters that are considered in the TCO and their respective components.

Table 2.6: Specifications i.e., required component power for a HD-BEV, specific cost (per kW cost) of that component and finally the total cost of the component for the different vehicle classes.

Component	Specifications (kW)	Specific Cost (€/kW)	Total Cost (€)
Chassis	-	-	25 375
Trailer	-	-	33 000
Power electronics	350	22.5	7875
On-board charger	44	60	2640
Air compressor	6	1250	7500
Steering pump	9	240	2160
Air-conditioning	10	58	580
Heater	10	63	630
Thermal management	350	18	6300
Electric powertrain (LongDistance9to5)	500	77	15 400
Electric powertrain (Unknown)	200	77	38 500
Electric powertrain (Routed)	200	77	38 500
Electric powertrain (LongStop9to5)	200	77	38 500
Electric powertrain (LongDistance24)	500	77	15 400
Electric powertrain (HubShort)	150	77	11 550
Total cost excl. battery (LongDistance9to5)	-	-	258 890
Total cost excl. battery (Unknown)	-	-	235 790
Total cost excl. battery (Routed)	-	-	235 790
Total cost excl. battery (LongStop9to5)	-	-	235 790
Total cost excl. battery (LongDistance24)	-	-	258 890
Total cost excl. battery (HubShort)	-	-	231 940

Table 2.7: Consumption parameters of HD-BEV:s.

Parameter	Value	Unit	Source
Consumption "Low Loss"	1.33	$\mathrm{kWh\,km^{-1}}$	[28]
Consumption "Average Loss"	1.83	$\mathrm{kWh\,km^{-1}}$	[28]
Consumption "More Aero"	1.15	$\mathrm{kWh\,km^{-1}}$	[29]
Consumption "Less Aero"	1.45	$\mathrm{kWh\,km^{-1}}$	[29]
Consumption "Local 2030"	0.82	$\mathrm{kWh\,km^{-1}}$	[18]
Consumption "Regional 2030"	1.06	$\mathrm{kWh\,km^{-1}}$	[18]
Consumption "Long-haul 2030"	1.38	$\mathrm{kWh\,km^{-1}}$	[18]
Consumption final "LongDistance9to5"	1.127	$\mathrm{kWh\,km^{-1}}$	
Consumption final "Unknown"	0.862	$\mathrm{kWh\,km^{-1}}$	
Consumption final "Routed"	0.862	$\mathrm{kWh\,km^{-1}}$	
Consumption final "LongStop9to5"	0.862	$\mathrm{kWh\,km^{-1}}$	
Consumption final "LongDistance24"	1.127	$\mathrm{kWh\,km^{-1}}$	
Consumption final "HubShort"	0.669	$\mathrm{kWh\,km^{-1}}$	

In table 2.7 the different consumption parameters from various studies are presented. These values have been used to weigh the final consumption values i.e., those used in the model. Mareev et al., simulates two scenarios consisting of a *low loss* and *average loss* scenario for a heavy-duty semi-trailer with a gross weight of 40 000 kg across the German highways in order to derive two different energy consumption parameters. The low loss case has a 24 % lower air drag coefficient and a 43 % lower rolling resistance than the average case. The resulting energy consumptions are $1.33\,\mathrm{kWh\,km^{-1}}$ and $1.83\,\mathrm{kWh\,km^{-1}}$ for the low loss and average loss case respectively [28]. Earl et al., too, simulates a HD-BET of 40 000 kg for two different aerodynamic cases resulting in an energy consumption of $0.98\,\mathrm{kWh\,km^{-1}}$ and $1.23\,\mathrm{kWh\,km^{-1}}$ for the more and the less aerodynamic HD-BET respectively. This is the required energy to propel the HD-BEV on a flat road without considering the total drive train efficiency. Earl et al., estimates the total drive train efficiency to 85 % [29]. In table 2.7 the drive train efficiency has been taken into account. The Swedish Transport Agency also estimates some consumption parameters for vehicles classed as local, regional and long-haul assuming an electric motor power of 150, 200 and 500 kW respectively. Additionally the Swedish Transport Agency Assumes battery sizes of 150, 375 and 600 kWh for local, regional and long-haul HD-BEV respectively. The consumption of each vocation are therefore according to the classifications in table 2.7. The final consumption parameters used are presented as *final consumption* in the table 2.7 and are based on all mentioned above and own assumptions. Moreover, costs for investing in HD-BEV:s are presented in table 2.6 [25]. The costs listed are direct manufacturer costs for year 2020. The capital expenditures (CAPEX) of the HD-BEV is given by equation 2.1 where v denotes the vocation, $C_{tot.excl.bat.,v}$ is the total cost of the vehicle excluding battery price accordint to table 2.6 in EUR, Cap_{bat} is the battery capacity in kWh and $C_{P,bat}$ the specific battery cost in EUR/kWh. The CAPEX is then annualized according to equation 2.2 where r is the rate and TL is he technical lifetime of the HD-BEV. The AIC is consequently divided by 52 in order to represent a characteristic week which is the time range of the model.

$$CAPEX = C_{tot.excl.bat.,v} + C_{maint.} + Cap_{bat} \times C_{P,bat} \tag{2.1}$$

$$AIC = CAPEX \times \frac{r}{1 - (1 + r)^{-TL}} \tag{2.2}$$

Table 2.8: Parameters used to calculate the TCO of HD-BEV:s.

Symbol	Component	Value	Unit	Source
C_{bat}	Battery pack price	1351	SEK kWh^{-1}	[19] [30]
C_{bat}	Battery pack price "2030" (75%)	1013	SEK kWh^{-1}	[25]
C_{bat}	Battery pack price "2050" (55%)	743	SEK kWh^{-1}	[25]
TL	Technical lifetime of HD-BEV	8	years	[31]
r	Rate	5	%	[19]
$C_{maint.}$	Specific cost of maintenance	1.324	SEK km^{-1}	[25]

In order to determine the electric energy consumed by the HD-BEV the specific energy consumption is established according to table 2.7. Furthermore, an average speed is derived for each vocation. This speed will be proportionate to the energy consumed by the vehicle. As this parameter will heavily influence the energy consumed it is based on the average distance traveled by each vocation. In order to derive an average speed, a time is required which is extracted from the existing driving profile. These profiles have not taken all stops, mainly stops shorter than 30 minutes into account. The number of stops shorter than 5 min, between 5 min to 30 min and above 30 min are given as a data set. The time of these stops are subtracted from the daily driving time of each vocation and a new daily driving time is formed. Combining the average driving distance and the daily hours driven from the driving profile, an average speed is derived. An example of the principle is portrayed in figure 2.5.

2.3.2 Charging of vehicles & total cost of ownership

This section aims to describe how the charging dynamics and equations relate to the driving profile in order for the model to decide a battery size. The binary driving profile is included in GAMS indicating whether or not there's a driving demand. Hence, the charging of the vehicle is described by equation 2.3 where $Ch_{t,v}$ is the charging of each vocation v, at each time step t and $DP^{inv}_{t,v}$ is a binary parameter indicating the inverse driving profile i.e., the parameter equals one if the vehicle is parked and zero if the vehicle is driving. This prevents the model from charging the vehicle while it is driving. The vocation is charged using either a 22 kW, 50 kW, 150 kW, 350 kW, 500 kW or 1 MW charger denoted by

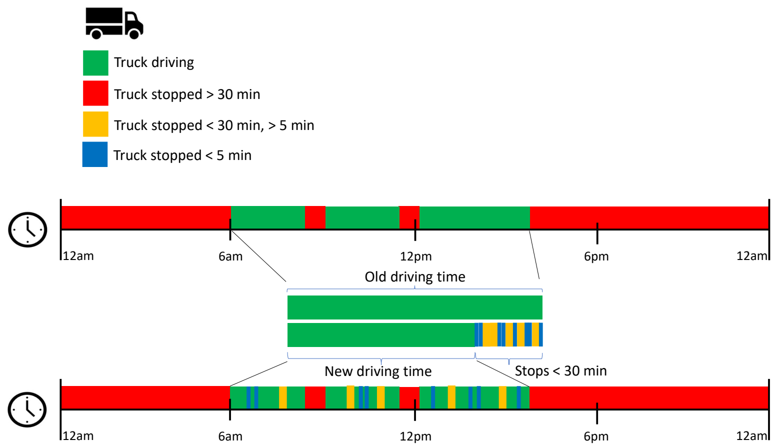

Figure 2.5: Schematic figure picturing the daily driving profile of an arbitrary vocation. Here all stops are included showing the new driving time acquired (bottom timeline) compared to the old driving time (top timeline).

$Ch^{22}_{t,v}$, $Ch^{50}_{t,v}$, $Ch^{150}_{t,v}$, $Ch^{350}_{t,v}$ and $Ch^{1000}_{t,v}$ respectively. The superscript indicate the power being charged.

Each charging power rate is described by equation 2.4 where $Ch^{P}_{t,v}$ is the energy charged for vocation v, during the time step t, power rate P. $BIN^{P}_{t,v}$ is the binary variable indicating whether or not vocation v is being charged using a charger of power P at time step t. Equation 2.5 limits the vocations to only charge using one specific charger for each time step. Hence for all charging powers there can be up to one (or none) charger active per vocation and time step.

For each time step the vehicle is either charged, discharged or neither. When the vehicle is charged or discharged the battery SoC in either increased or decreased respectively. When the vehicle is standing still and not charged the battery SoC reamains unchanged. The model considers the battery SoC according to equation 2.6 where $SoC_{t+1,v}$ is the battery SoC of vocation v at time t+1 i.e., next time step until the last time step thus creating a continuous loop. $SoC_{t,v}$ is the battery SoC at current time t and $D_{t,v}$ the energy demand generated from driving vocation v at time step t. Equation 2.7 describes the driving energy demand where FE_v is the fuel economy of each vocation, $\bar{u}_v$ is the average vehicle velocity of each vocation. The capacity of the battery pack is defined by equation 2.8. Finally, equation 2.9 describes the objective function i.e., the TCO for all vocations which includes the cost of charging and total cost of vehicle which are defined by equation 2.10 and 2.11 respectively.

$$Ch_{t,v} = DP^{inv}_{t,v} \times \sum_{P_i}^{P_n} Ch^{P}_{t,v} \tag{2.3}$$

$$Ch^{P}_{t,v} \leq BIN^{P}_{t,v} \times \frac{1}{4} \times P \tag{2.4}$$

$$\sum_{P_i}^{P_n} BIN^{P}_{t,v} \leq 1 \tag{2.5}$$

$$SoC_{t++1,v} \leq SoC_{t,v} + Ch_{t,v} - D_{t,v} \tag{2.6}$$

$$D_{t,v} = DP_{t,v} \times FE_v \times \frac{1}{4} \times \bar{u}_v \tag{2.7}$$

$$Cap_v \geq SoC_{t,v} \tag{2.8}$$

$$min\left(TCO = \sum_{v_i}^{V_n} Cap_v \times C^{bat} + C_v^{vehicle} + CC_v\right) \tag{2.9}$$

$$CC_v = \sum_{t_i}^{t_n} \sum_{P_i}^{P_n} Ch_{t,v}^P \times C_P \times \frac{1}{4} \tag{2.10}$$

$$C_v^{vehicle} = C_v^{ex.bat.} + C_v^{maint} \tag{2.11}$$

Table 2.9: The sets, parameters and variables from equation 2.9 to 2.8 sorted in that order, separated by a horisontal line.

Symbol	Description
t	Set ot timesteps
v	Set of vocations
TCO	Total cost of ownership for all vocations over modeled time period
$DP_{t,v}^{inv}$	Inverted driving profile for vocation v at time t
$D_{t,v}$	Driving demand per vocation v and time t
FE_v	Fuel economy of vocation v
$\bar{u}_v$	Average speed of vocation v
C^{bat}	Cost of battery pack (annualized divided by 52)
$C_v^{vehicle}$	Cost of vehicle for vocation v (annualized divided by 52)
$C_v^{ex.bat.}$	Cost of vehicle excluding battery cost for vocation v (annualized divided by 52)
C^{maint}	Cost of maintenance (annualized divided by 52)
C^P	Cost of charging using power P
P	Power of chargers
Cap_v	Battery pack capacity for vocation v
CC_v	Cost of charging for vocation v
$Ch_{t,v}$	Energy charged to battery at time t for vocation v
$Ch_{t,v}^P$	Energy charged to battery at time t for vocation v using charger of power P
$BIN_{t,v}^P$	Binary variable indicating if vehicle v, at time t, is charging with power P
$SoC_{t,v}$	Battery electric state of charge of vocation v, at time t

2.3.3 Sensitivity analyses

In this subsection the sensitivity analyses parameters are described in detail. The parameters varied are specified as well as changes required by the model to perform these. First the sensitivity analyses of the parameter vehicle consumption is presented followed by a sensitivity analyses of battery costs.

Consumption value parameters

Here two extreme values of the vehicle consumption parameter is tested. On the lower side a consumption of 0.9 kWh km^{-1} is assumed for LongDistance24 which is a very optimistic value given that efficiency measures aggressively advances in the near future. It is to some extent unlikely but not an impossible projection according to the Swedish transport agency [18]. On the other extreme, a consumption of 2.1 kWh km^{-1}h is tested for LongDistance24 as it is not a unrealistic scenario where trucks have to drive in winter road conditions for a lager part of their journey in northern Sweden for instance. These results are compared to the base consumption value of 1.2 kWh km^{-1}. Finally, as a sensitivity analyses the consumption value parameter will be increased to 175 % of base case and decreased to 75 % of base case of each vocation. For the high consumption parameter case a battery size cap is added to the model. Equation 2.12 describes how the battery size is limited to 1000 kWh for all vocations.

$$SoC_{t,v} \leq 1000 \tag{2.12}$$

Battery cost parameters

A near future projection of battery prices have been the decline below 1000 SEK kWh^{-1} in the 2030s. This thesis analyses the impact of battery prices above and below the model base value of 1351 SEK kWh^{-1}. The optimistic projection expects a battery pack cost of 743 SEK kWh^{-1} which isn't impossible considering the previous trends in battery pack prices and electrification rate of vehicles. On the other hand due to limited resources and the high demand in electrifying vehicles a bottleneck in the production chain could be a possible outcome causing prices to increase. Therefore, a battery pack cost of 2094 SEK kWh^{-1} is analyzed.

3
Results

In the following section the results are presented in order to answer the reasearch question established. First the results from modeling the base scenario are presented followed by the results from the sensitivity analyses.

3.1 Base model results

The modeled battery sizes for each vocation are presented in table 3.1. The battery sizes that have been modeled seem to concur with the battery sizes that are currently produced or will be produced in the near future. As the battery size increases the cargo capacity decreases. In order to compensate for the added battery weight the EU has increased the gross combination weight (GCW) of HD-BEV:s with 1 t [32]. Hence the battery sizes modeled are not out of range compared to current and near future HD-BEV battery sizes.

The number of battery cycles per modeled week is also presented in table 3.1. LongDistance24 is cycled more than the other vocation at more than 12 cycles per week. LongStop9to5 and HubShort are cycled 5.7 times per week and the remaining vocations are cycled 6.8 to 8.5 times during the same time period.

Table 3.1: The modeled battery sizes and the amount of battery cycles that are ran per modeled week for each vocation.

Vocation	Battery size [kWh]	Number of battery cycles per week
LongDistance9to5	426	6.8
Unknown	189	7.3
Routed	224	8.5
LongStop9to5	262	5.7
LongDistance24	632	12.3
HubShort	188	5.7

Figure 3.1 shows the charging energy duration of the vocation in kWh 15min^{-1}. 87.5, 37.5, 12.5 and 5.5 kWh 15min^{-1} corresponds to 350, 150, 50, 22 kWh h^{-1} respectively. As the 1 MW and 500 kWh chargers are not utilized for any vocation they are not shown in the figure. The results in figure 3.2 shows the relative amount of energy charged by each vocation. It is evident that the long distance vocations LongDistance24 is the major consumers of the energy from the somewhat faster chargers such as 350 kW and 150 kW. LongDistance9to5 is also a large consumer of the 150 kW charger. All vocations but LongDistance24 receive the majority of their energy from the 22 kW charger. The lines in figure 3.1 are overlapping thus not always visible. The final driving profiles can be found in Appendix A.

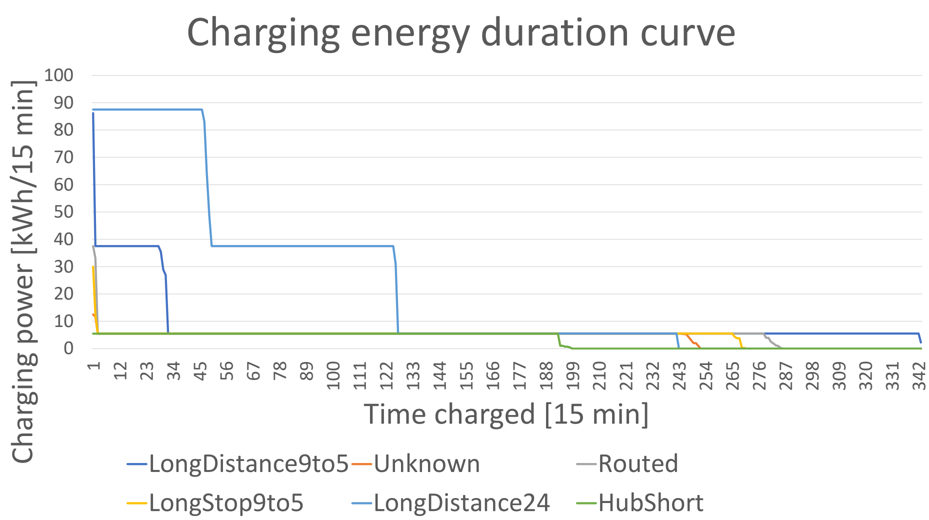

Figure 3.1: The charging energy duration of all vocations in 15 min slots for a charcteristic week.

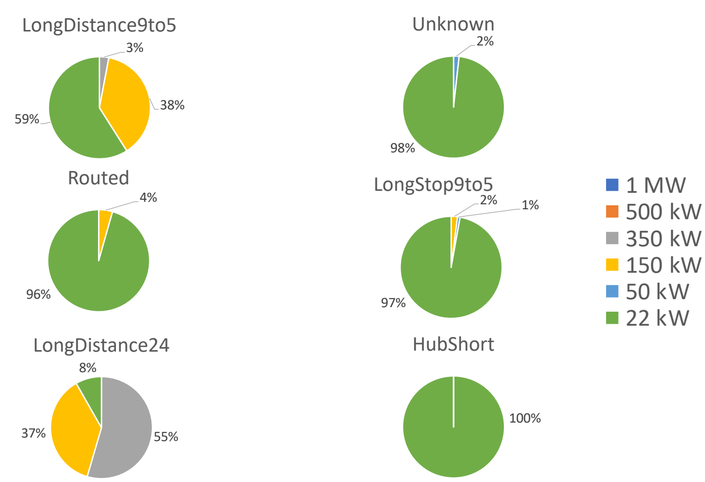

Figure 3.2: Charging power distribution based on total energy charged. The 1 MW charger is included although it's not used.

The results in Figure 3.3 show the distribution of charged energy between daytime and night-time which are defined as 6 h to 18 h and 18 h to 6 h respectively. It's found that the 22 kW charger is used throughout the day to different extents and dominates all but the LongDistance vocations (LongDistance9to5 and LongDistance24). It's also evident that the 22 kW uses most of the charged energy during night time when the majority of the vehicles are parked in general. LongDistance9to5 charges a very small amount using the 150 kW during night-time. Besides that, the long distance vocations stands out as they're the only vocation using other chargers than the 22 kW charger during night time. LongDistance24 uses the 350 kW and the 150 kW charger during night-time and it's also the only vocation that is driving throughout most of the night.

Figure 3.4 presents charged energy for each vocation daytime compared to night-time. Left image compares the total share of charged energy day vs. night-time relative to total charged energy. It can

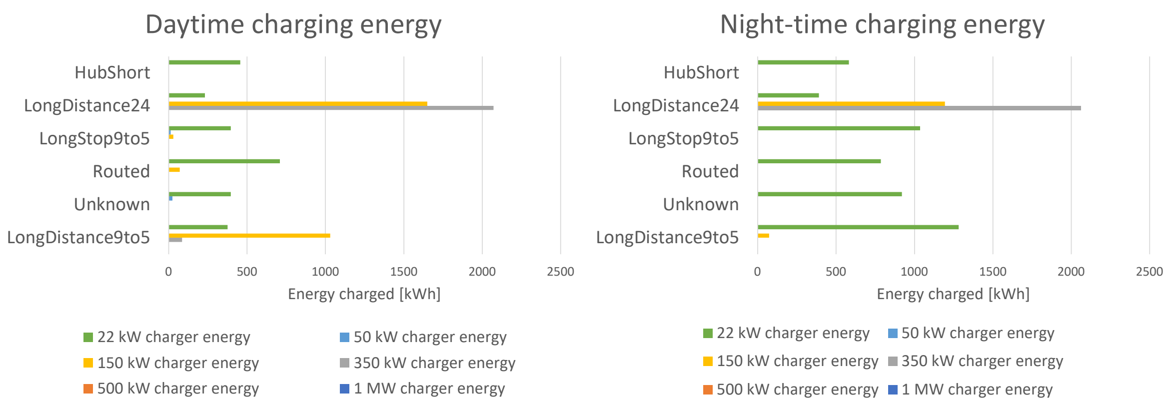

Figure 3.3: The charging energy per vocation and charging power during daytime (06-18) and night-time (18-06) for a characteristic week.

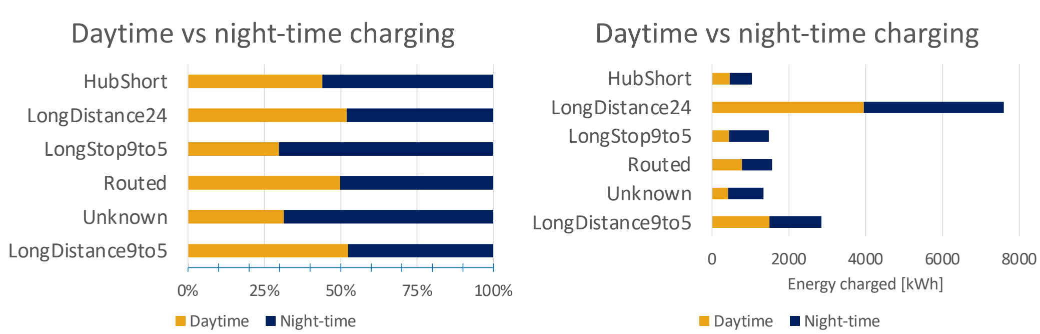

Figure 3.4: The charging energy per vocation during daytime(06-18)) compared to night-time (18-06) in terms of charged energy (left) and in terms of share of charged energy per vocation (right).

be seen that most of the energy is charged during night-time for HubShort, LongStop9to5 and Unknown. Routed, LongDistance24 and LongDistance9to5 charges equally between daytime and night-time. Right image compares total charging energy day vs. night-time where LongDistance clearly consumes the most electricity followed by LongDistance9to5.

Table 3.2 present the same information as in figure 3.2 but in absolute energy terms. Here it is found how much each vocation consumes from each charger. It is also found how much energy each charger produces and how much is produced in total, all within a characteristic week. The 1 MW and the 500 MW chargers are never used as table 3.2 presents. The charger that charges the most amount of energy is the 22 kW one followed by the 350 kW which is closely followed by the 150 kW charger. Lastly the charger that charges the least amount of energy is the 50 kW charger at 37 kWh. The 50 kW charger is probably too slow compared to faster chargers during shorter stops while the 22 kW charger is enough for the longer stops hence the low utilization rate. The vocations consuming the most energy within the modeled time period are LongDistance24, LongDistance9to5, Routed, LongStop9to5, Unknown and HubShort ranging from most to least energy consumed.

Table 3.2: Energy charged per vocation with respect to charging power. The total amount of charged energy per vocation and total energy that each charges has discharged is also presented.

	Energy Charged [kWh]						
Charger Power	LongDistance9to5	Unknown	Routed	LongStop9to5	LongDistance24	HubShort	Sum of energy charged per charger
1 MW	0	0	0	0	0	0	0
500 kW	0	0	0	0	0	0	0
350 kW	86	0	0	0	4221	0	4307
150 kW	1104	0	71	30	2881	0	4085
50 kW	0	24	0	13	0	0	37
22 kW	1713	1354	1533	1459	638	1065	7762
Sum of charged energy per vocation	2903	1378	1603	1501	7740	1065	16191

The SoC for all vocations are presented in figure 3.5. The SoC directly reflects the driving profile as it increases when charged and decreases as the vehicle is driven. Detailed figures of the SoC can be found in appendix B. The charged and discharged electricity to and from the battery can be found in detail in appendix C. LongDistance9to5, LongStop9to5 and HubShort are parked during the weekend. All vocations but LongDistance24 are showing consistent diurnal charging patterns as they're charged slowly during the night, complementary charged a few times during the day and finally the battery is drained before night time. LongDistance24 on the other hand uses 150 kW to 350 kW significantly more than the other vocations especially during night time. It also doesn't reach zero SoC as often as the other vocations.

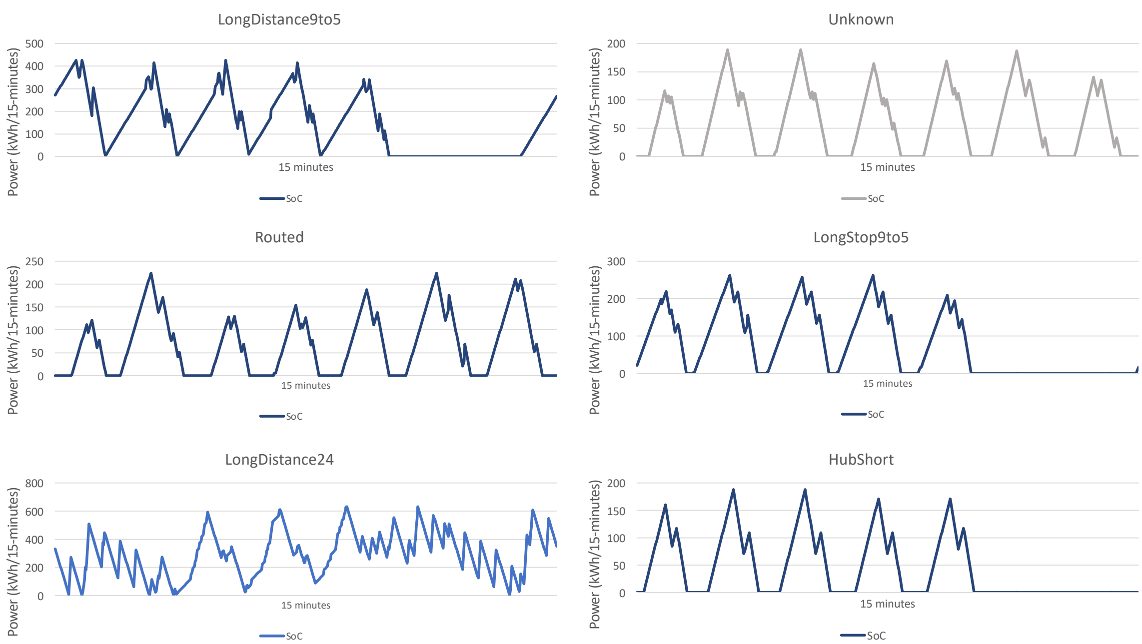

Figure 3.5: The SoC of each vocation for a characteristic week.

3.2 Sensitivity analyses results

Below the results from varying the two sensitivity analysis parameters are presented. First the cost of battery results is presented followed by the results from varying vehicle consumption.

3.2.1 Battery cost parameter

Table 3.3 presents the battery sizes from a low and high battery price scenario followed by the relative increase or decrease in battery size. It's found that when battery prices are lowered to 55 % of base case, the battery size of all vocations are the same or increased by up to 12 %. LongDistance9to5 battery size is increased the most to 112 % of base case whereas Routed and HubShort stayed the same. All other vocations increased to 102 % to 104 % of base case. In conclusion the battery sizes changes marginally with the battery price. This can be explained by the fact that the battery makes up about 4.7 % on average. Charging cost makes up a much larger share and therefore it's not as much worth investing in further battery capacity as in optimizing charging strategy. such as increasing the share of fast charging. This can be seen in figure 3.6.

Table 3.3: The battery size and percentage increase of battery size compared to base case for each vocation are presented in the table below.

Vocation	Battery size [kWh]: Low battery price		Battery size [kWh]: High battery price	
LongDistance9to5	475 kWh	112%	422 kWh	99%
Unknown	195 kWh	103%	175 kWh	93%
Routed	224 kWh	100%	192 kWh	86%
LongStop9to5	273 kWh	104%	225 kWh	86%
LongDistance24	643 kWh	102%	632 kWh	100%
HubShort	188 kWh	100%	174 kWh	93%

In figure 3.6 the difference in energy charged between each battery price case and the base case is presented for each vocation and charger power. In the case where the battery price is lower LongDistance9to5 consumes less electricity from the 350 kW and 150 kW charger and swaps it for the 50 kW and 22 kW chargers. A trend that swaps high power charging for low power charging. Similar is found in Unknown and LongStop9to5. LongDistance and Routed on the other hand swaps high and low power charging to intermediate power charging. HubShort remains unchanged.

In the case of high battery prices it is found that for low power charging is being replaced by higher power charging (50 and 150 kW) compared to the base case. The exceptions being LongDistance9to5 where charged energy from 150 kW and 22 kW is being replaced by the 50 kW charger and LongDistance24 that's unchanged.

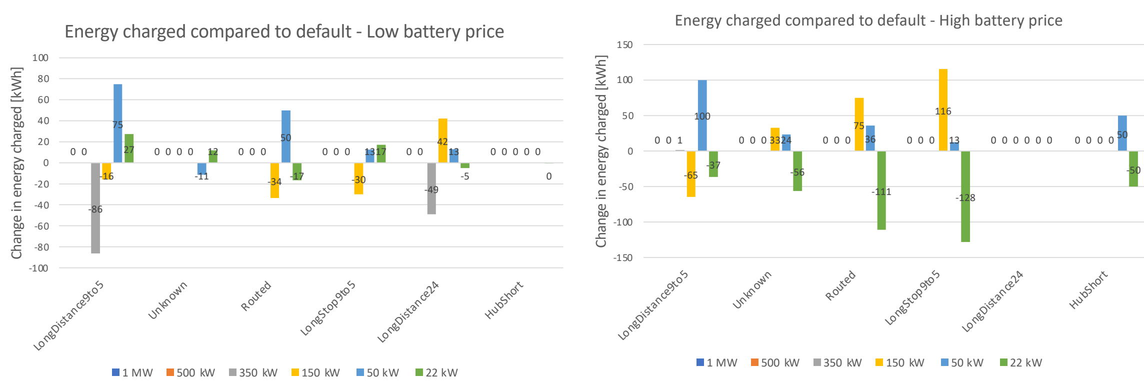

Figure 3.6: The difference in energy charged for each charger and vocation are presented for the low battery price case (left) and high battery price case (right) comapared to base case.

3.2.2 Consumption parameter

The battery sizes for the scenario with a low and high consumption parameter value are presented in table 3.4. The battery sizes are presented alongside the relative change in battery size compared to the base case. For the low consumption case all vocations decreased their battery size about 20 % to 35 %. The vocation which battery decreased the most was LongDistance24 and the vocation which battery decreased the least was LongDistance9to5. For the high consumption case the battery size increased between 31 % to 95 %. LongStop9to5 increased the least by 31 % while LongDistance9to5 and Routed increased the most with at an increase of 95 %. Without equation 2.12 limiting the battery size to 1000 kWh LongDistance9to5 was given a unreasonable big battery size of 3847 kWh.

Table 3.4: The battery size and percentage increase of battery size compared to base case for each vocation are presented in the table below. The second column shows results from a low consumption parameter scenario while right shows the results from a high consumption parameter scenario.

Vocation	Battery size [kWh]: Low consumption		Battery size [kWh]: High Consumption	
LongDistance9to5	335 kWh	79%	832 kWh	195%
Unknown	132 kWh	70%	360 kWh	190%
Routed	153 kWh	68%	410 kWh	195%
LongStop9to5	189 kWh	72%	340 kWh	131%
LongDistance24	411 kWh	65%	1000 kWh	158%
HubShort	131 kWh	70%	329 kWh	175%

The energy charged per vocation from each charger is presented in 3.7 for each consumption parameter case. In the case of low consumption parameters the vocations Unknown, Routed, LongStop9to5 and HubShort decreases charging from the 22 kW charger as it makes up at least 96 % of the charged energy for these vocations. LongDistance24 saw a great decrease in charging from 350 kW and a small increase from the 22 kW charger. LongDistance9to5 decreased in cast charging, 350 kW and above, as 50 kW charging increased. It's found that for a high consumption parameter value a net increased charging occurs mostly allocated to fast charging, 150 kW and above but also a significant increase in 22 kW charging. For LongDistance9to5 and LongDistance24 an increased fast charging from 150 kW and 350 kW to 150 kW chargers respectively is found. LongDistance24 also saw the use of 500 kW and 1 MW chargers. The vocations that didn't increase fast charging (Unknown, Routed, HubShort) saw an increased use of 22 kW charger instead. LongStop9to5 charging increased slightly from the 150 kW and 22 kW charger.

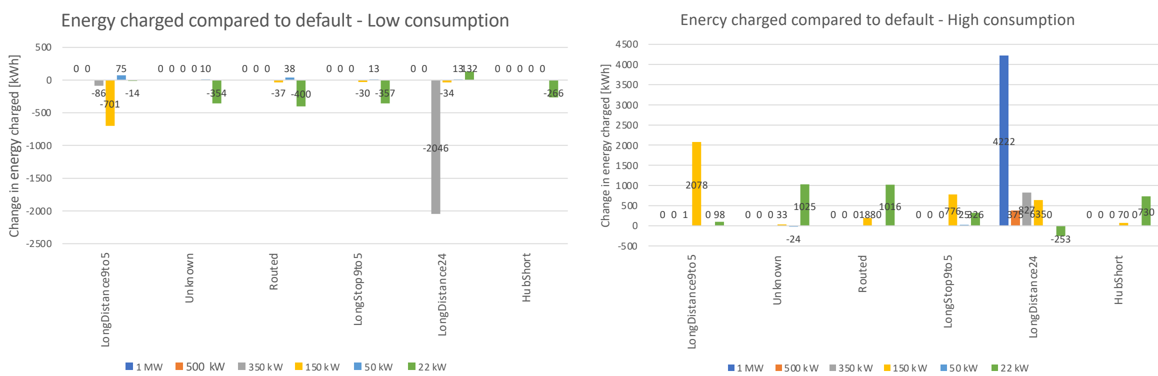

Figure 3.7: The difference in energy charged for each charger and vocation are presented for the low battery price case (left) and high battery price case (right). compared to base case

4 Discussion

The individual driving profiles per vocation has been created using aggregated data which results in a great generalization of each vocation. As tens of thousands of driving profiles have been categorized into six vocations a great variation within each vocation is found which is not entirely captured or accurately represented when converted into an individual driving profile. The most accurate way to describe the driving behaviors would to use individualized data where each vehicle would then be electrified. Another way would be to create additional vocations in order to gain more homogeneous driving profiles. This could distinguish between the vehicles that drive the most and least within a vocation thus resulting in more accurate results for e.g., battery sizes. In such a case where there are more vocations one might identify where there's a need of 500 kW and 1 MW charging especially in the case of individual data. In combination with a fleet population utilization rates for different chargers can be identified and additionally more precise costs of charging could be established.

As can be seen from the sensitivity analyses the effect that parameter values have on the system can be quite significant. Changes in market development, prices and technologies are difficult to predict and leaves uncertainties in the model. The parameters chosen to carry out a sensitivity analyses namely cost of battery pack and consumption parameter are two parameters that carry some uncertainties and volatility. The cost of battery has been predicted to further decrease but as issues regarding the unsustainable sourcing of REM:s and potential difficulties keeping up with Li-ion battery demands as the market expands the battery price could be facing an uncertain future. As for the consumption most vehicles are becoming ever more efficient.

Some argues that chargers in the range of 500 kW and 1 MW are needed in order for electric trucks to gain market share. The results from this show no such signs. Perhaps the cost of battery compared to the other parameters in the TCO is too small still.
For the current model the cost of chauffeur haven't been taken into account. Including this factor in a model that can choose whether to fast charge or pay more for chauffeurs waiting could have a significant impact on whether or not the model chooses to charge as well as what type of charger is utilized. As time standing still would be more expensive an increase in fast charging would be the probable outcome when taking chauffeur cost into account.

Cost of charging have been derived from literature and real time data which may apply only to general cases, time intervals or spatial restrictions. A dynamic charging cost model with geographic boundaries (e.g., energy areas in Sweden) would have been a more accurate assessment for the TCO. Although this would require assumptions regarding occupancy rate as this highly determines the cost of charging. Using a dynamic pricing model could minimize cost of charging thus avoiding charging during peak prices. This is expected to shift charging tonight-time from daytime as charging cost most probably will be higher during daytime. Charging at lower power rates when possible increases the battery cell life time compared to fast charging thus an expected reduction in TCO could be expected. In the current model battery cycling is presented as apart of the result in order to compare between vocations although the impact i.e., the degradation of the battery has not been taken into account when calculation the TCO.

What haven't been included in the assessment are the benefits from having no tailpipe emissions. The benefits associated to health and environment for instance. This could play a significant role if the EU decides to include the transport fleet in the EU emission trading system (EU ETS). This would probably give HD-BEV:s a significant benefit towards internal combustion engine (ICE) trucks.

The model used for this thesis studies the individual driving pattern, energy consumption and charging. Thus nothing is really said about the fleet perspective that the vehicles may have, which, too is important information for constructing future charging infrastructure. By adding a fleet population to each of the vocations in the model an estimated peak power demand could be obtained. Combining this with investments in charging infrastructure could help the design of a dynamic charging price model.

The amount of electricity consumed by each vehicle and vocation is determined by their daily driven distance and consumption. The daily driven distance assigned to each vocation is based on the average daily driven distance for each vocation meaning that the electricity consumed and consequently the battery size may not be completely representative for the vocation as a whole. Another way to accurately present the battery size result could be in terms of percentage of vocation electrified for a given battery size.

The lack of charging infrastructure creates a bottle neck in the transition from traditional ICE trucks to HD-BEV:s. The model assumes that there will be charging options available whenever there's a stop longer than 15 min therefore not taking realistic availability of charging into account as of the charging infrastructure of today. This could be the case when most companies and stops have chargers available to the vehicles stopping for delivery for instance. Depending on whether or not these spots can maintain a high utilization rate will determine if they can be of fast charging, i.e., 350 kW and up or if they'll have to be an over night type of charger. Besides privately, there's a demand for public charging infrastructure. Most vehicles are parked during night-time as when the majority of vehicles charge which creates a large demand of charging outlets, almost equal to the number of HD-BEV:s. Long-haul HD-BEV:s would also require fast charging on top of over night chargers further increasing the demand. Therefore, in order to facilitate the transition to an all electric HDV fleet an expansion in both capacity and quantity is required.

5 Conclusion

Driving profiles were created from aggregated diesel truck driving data for six different vocations in order to derive a battery size using a cost optimizing model as well as to study the charging patterns related to each driving profile. The battery sizes of the vocations, LongDistance9to5, Unknown, Routed, LongStop9to5, LongDistance24 and HubShort were 426, 189, 224, 262, 632 and 188 kWh respectively. For all vocations but LongDistance24 majority of the charging was done by using the 22 kW charger. For LongDistance24https://www.kuali.com/recipe/cook-with-anchor-dairy/black-sesame-basque-burnt-cheesecake/ the majority of the electricity charged was from using the 350 kW charger. The 150 kW charger is mainly used by LongDistance9to5 and LongDistance24 and makes up to 4 % of the electricity charged by the rest of the vocations. Even less used is the 50 kW charger. The 1 MW and 500 kW charger are never used in these scenarios. In terms of diurnal charging behaviors it was found that for all vocations but LongStop9to5 and Unknown, charging between night- and daytime is equal. For the mentioned vocations, about 70 % to 75 % of the charging takes place during night time.

A sensitivity analyses of battery cost and consumption parameters was carried out where it was found that for an approximate ±55 % increase/decrease in cost of battery pack there was little to no significant impact in invested battery capacity i.e., battery size. Although it was found that many vocations increased low power charging, in general 50 kW and below for a low battery price scenario and vice versa, 150 kW and above for a high battery price scenario. As for the scenario with a decreased consumption a decrease of battery size down to between 79 % to 65 % of the ordinary battery size was found. When the consumption was increased an increase in battery size from 31 % to 509 %. Here a decrease in all charging sizes is found for the low consumption case. Vocations as LongDistance9to5 and Routed also swaps fast charging for 50 kW charging. In the case of increased consumption a great increase in fast charging is found for LongDistance9to5, LongStop9to5 and LongDistance24. Furthermore, a increase in 22 kW charging is found too.

A

Driving profiles

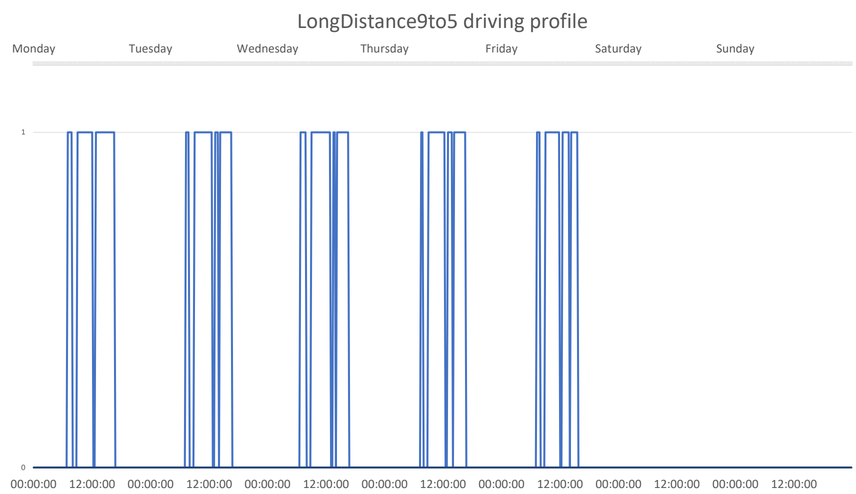

Figure A.1: Driving profile of vocation LongDistance9to5 for a characteristic week. The value 1 on the x-axis indicates that the vehicle is driving.

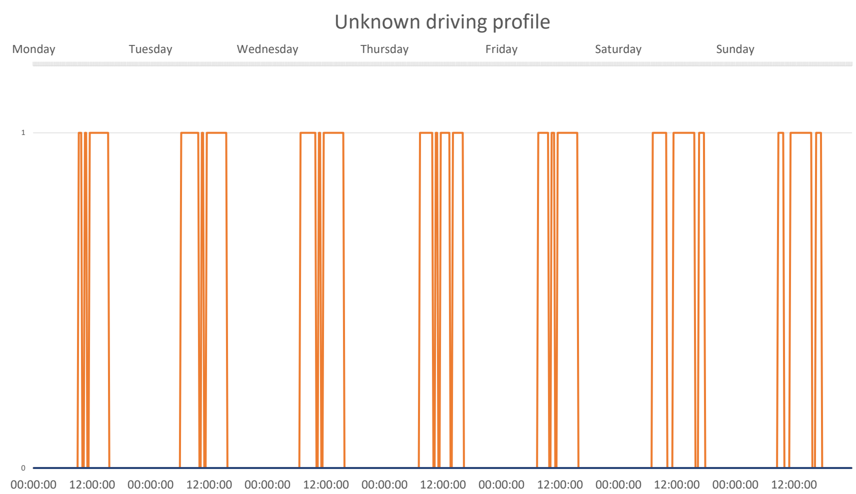

Figure A.2: Driving profile of vocation Unknown for a characteristic week. The value 1 on the x-axis indicates that the vehicle is driving.

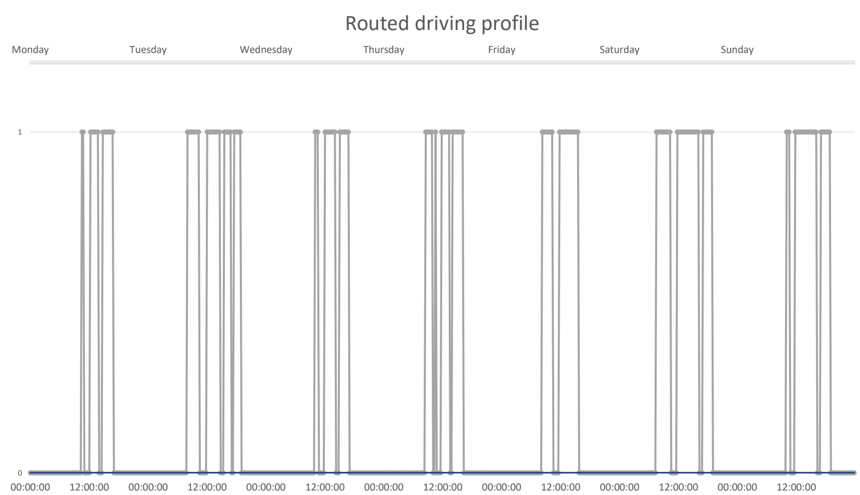

Figure A.3: Driving profile of vocation Routed for a characteristic week. The value 1 on the x-axis indicates that the vehicle is driving.

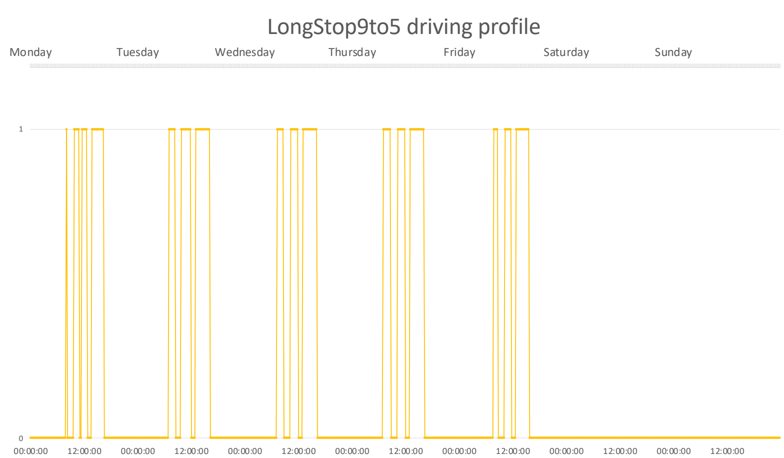

Figure A.4: Driving profile of vocation LongDistance9to5 for a characteristic week. The value 1 on the x-axis indicates that the vehicle is driving.

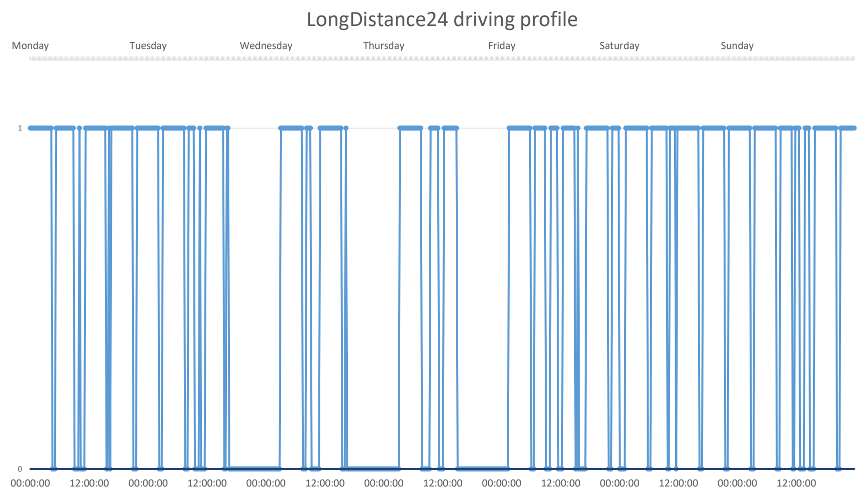

Figure A.5: Driving profile of vocation LongStop9to5 for a characteristic week. The value 1 on the x-axis indicates that the vehicle is driving.

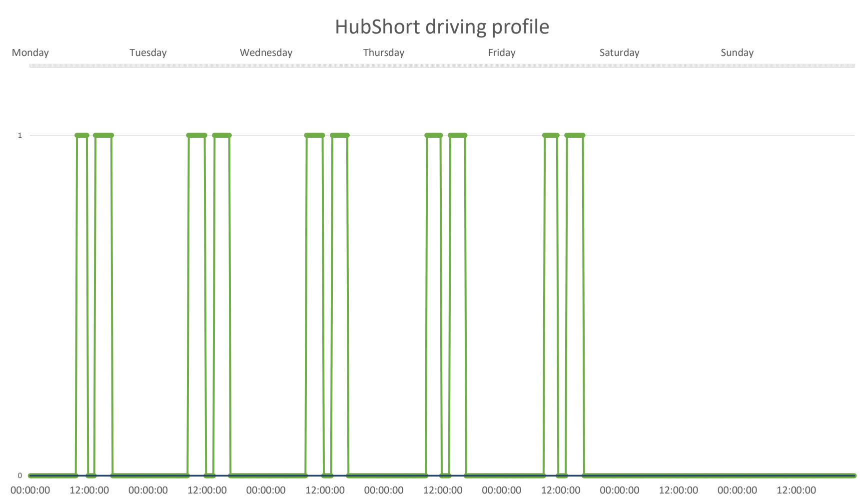

Figure A.6: Driving profile of vocation HubShort for a characteristic week. The value 1 on the x-axis indicates that the vehicle is driving.

B
SoC of battery

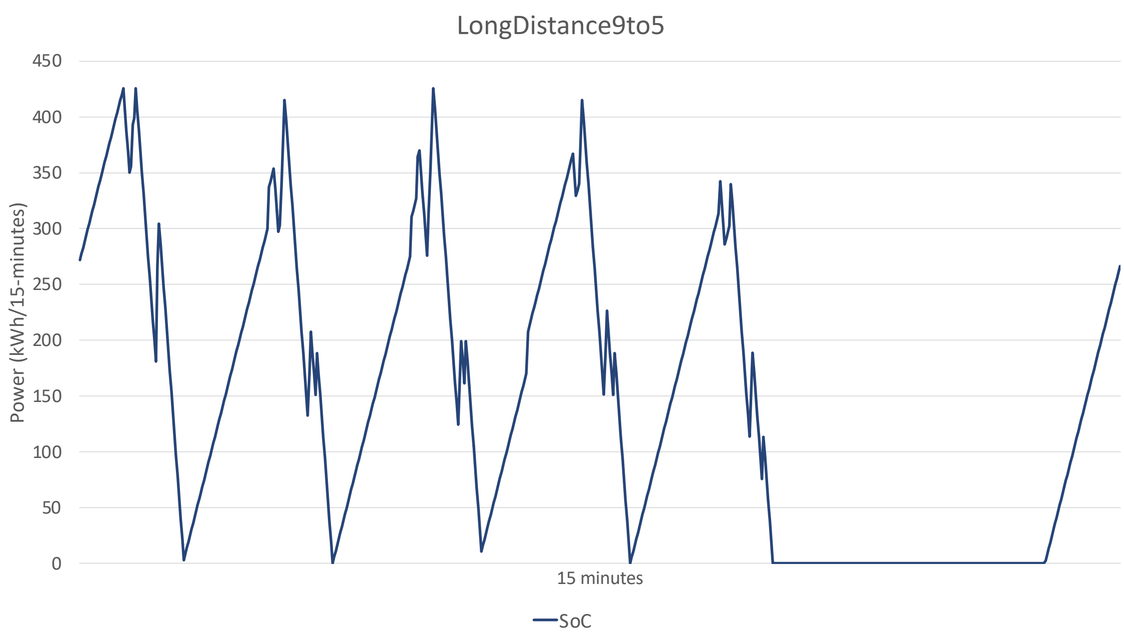

Figure B.1: The SoC of LongDistance9to5 for a characteristic week.

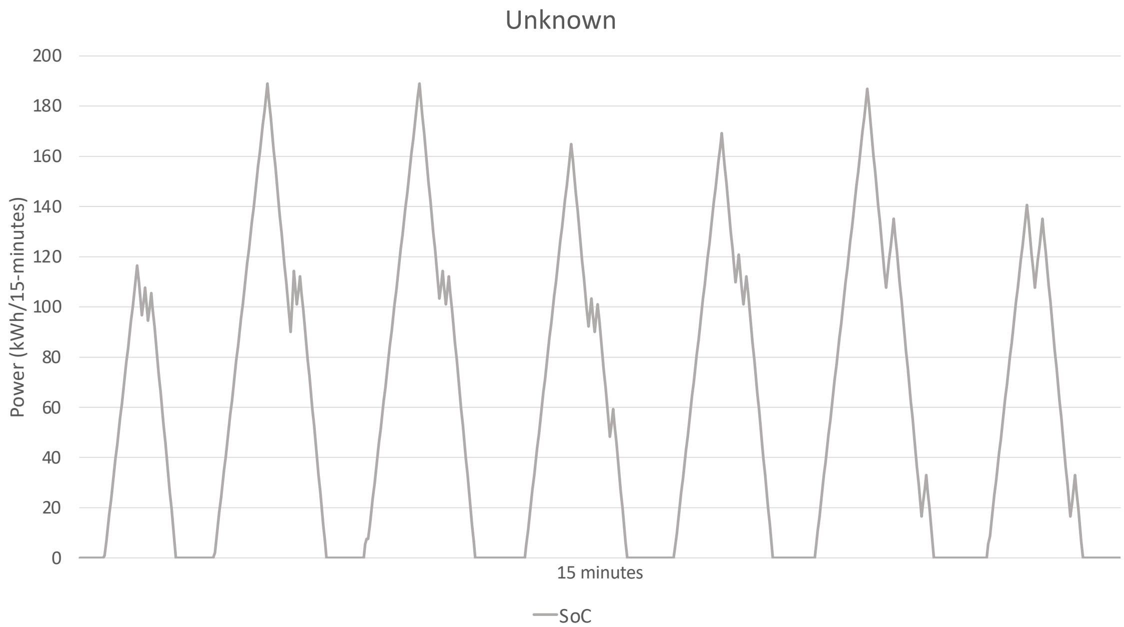

Figure B.2: The SoC of Unknown for a characteristic week.

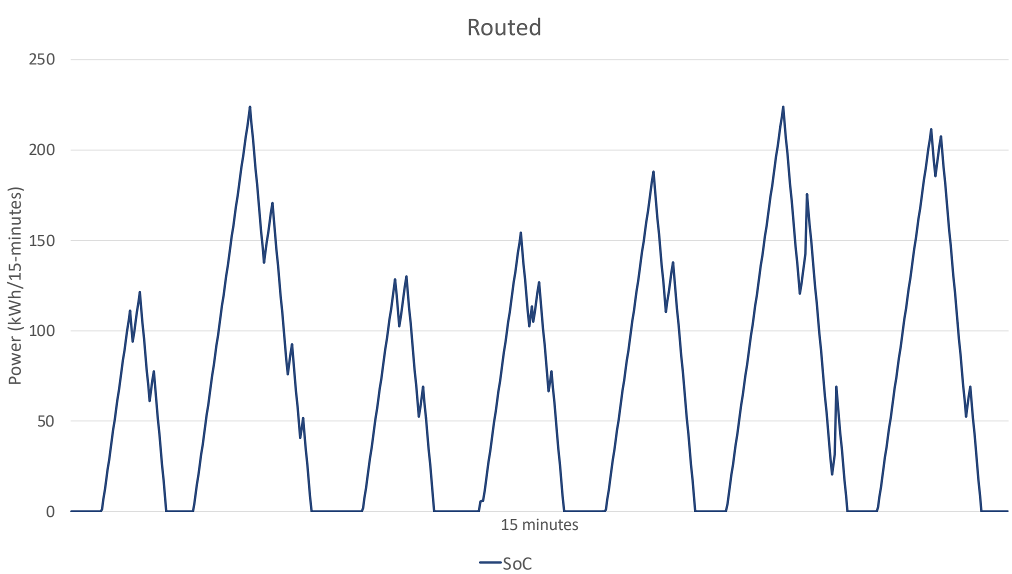

Figure B.3: The SoC of Routed for a characteristic week.

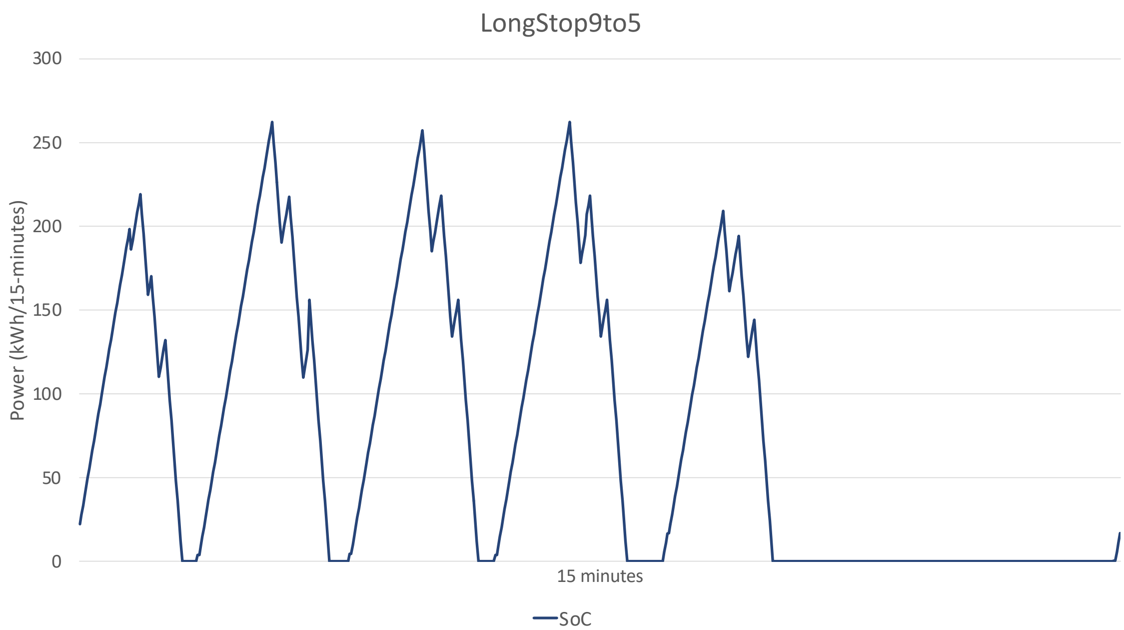

Figure B.4: The SoC of LongStop9to5 for a characteristic week.

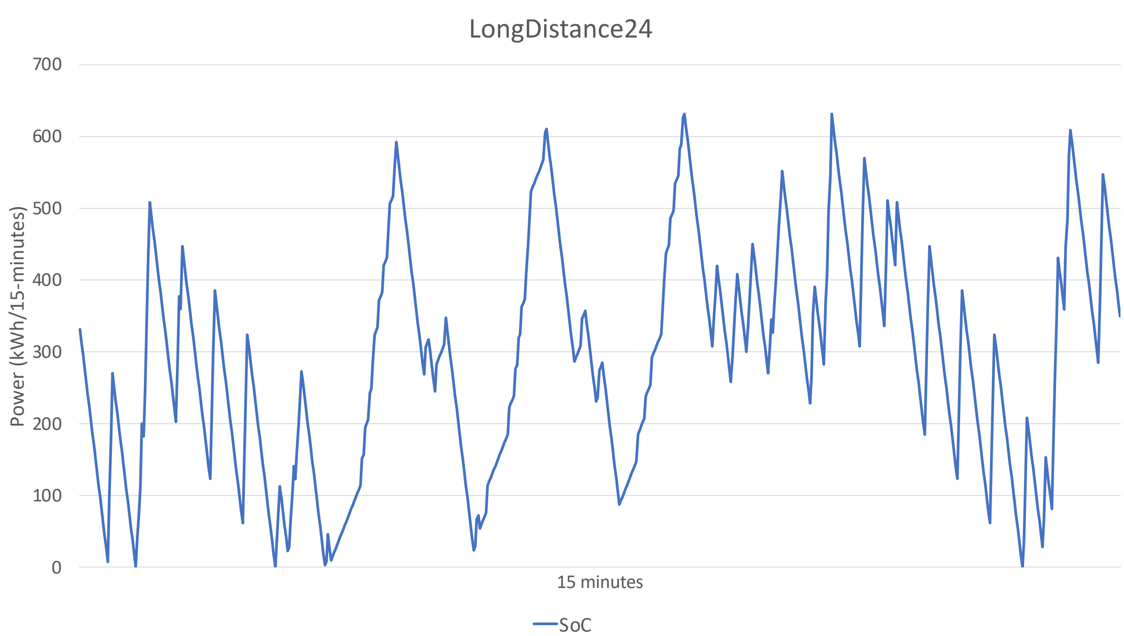

Figure B.5: The SoC of LongDistance24 for a characteristic week.

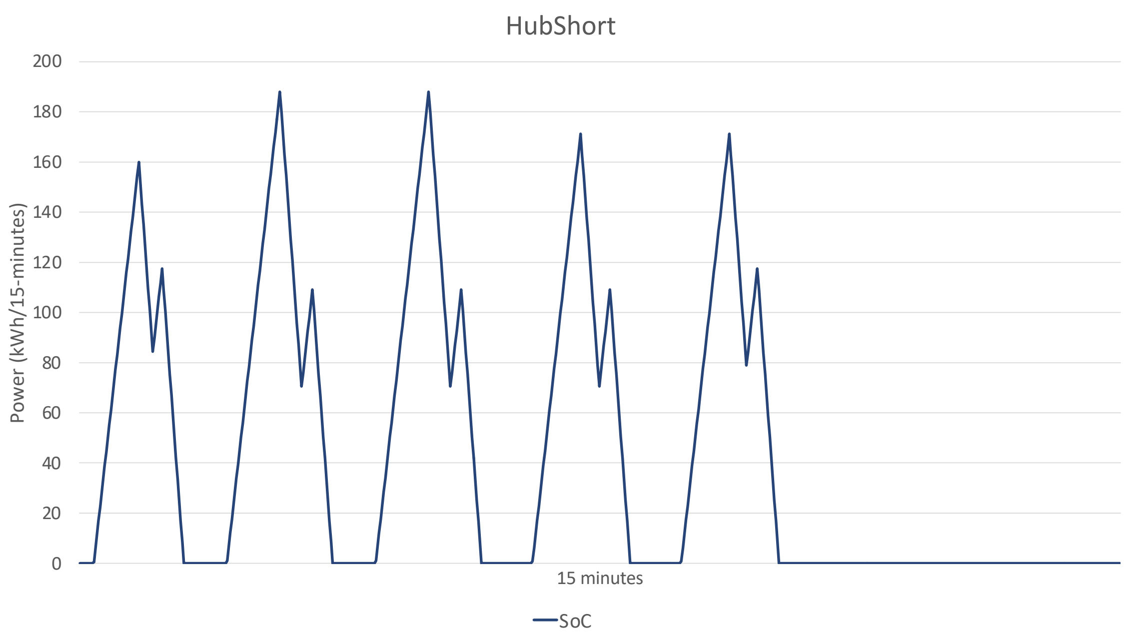

Figure B.6: The SoC of HubShort for a characteristic week.

C
Charging and discharging of battery

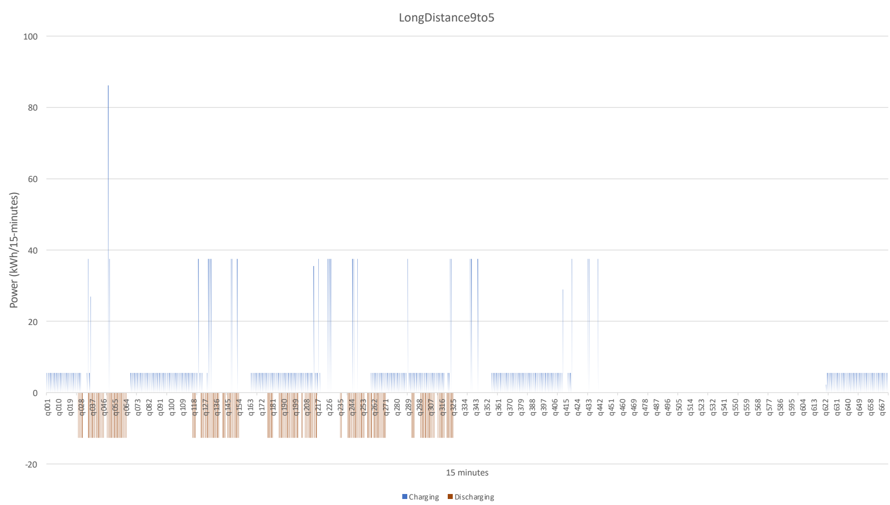

Figure C.1: The charged energy and discharged energy of LongDistance9to5 expressed in positive and negative values respectively for each quarter of a characteristic week.

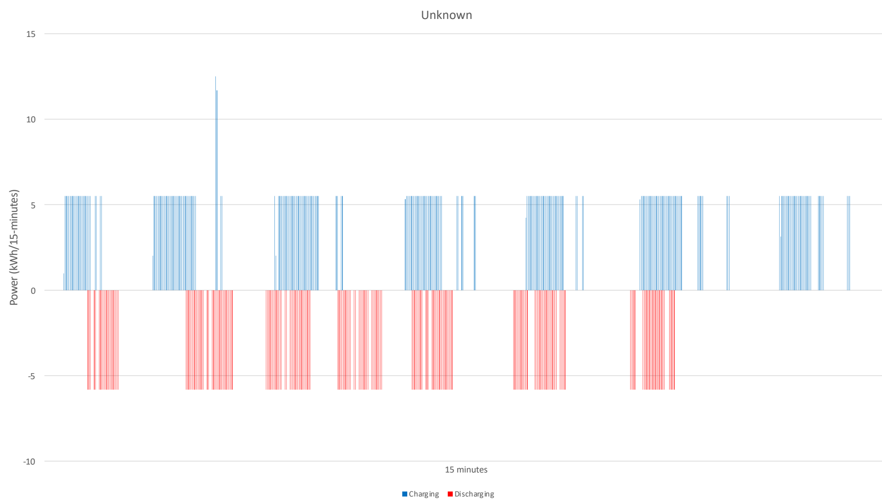

Figure C.2: The charged energy and discharged energy of Unknown expressed in positive and negative values respectively for each quarter of a characteristic week.

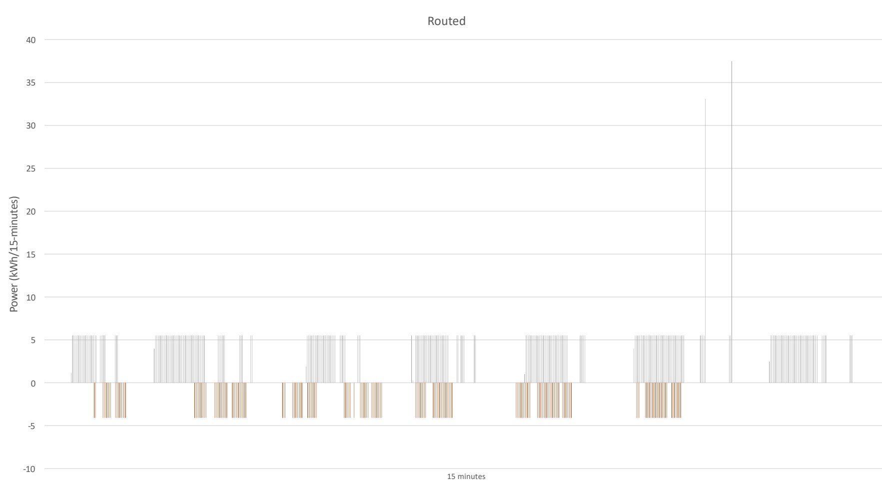

Figure C.3: The charged energy and discharged energy of Routed expressed in positive and negative values respectively for each quarter of a characteristic week.

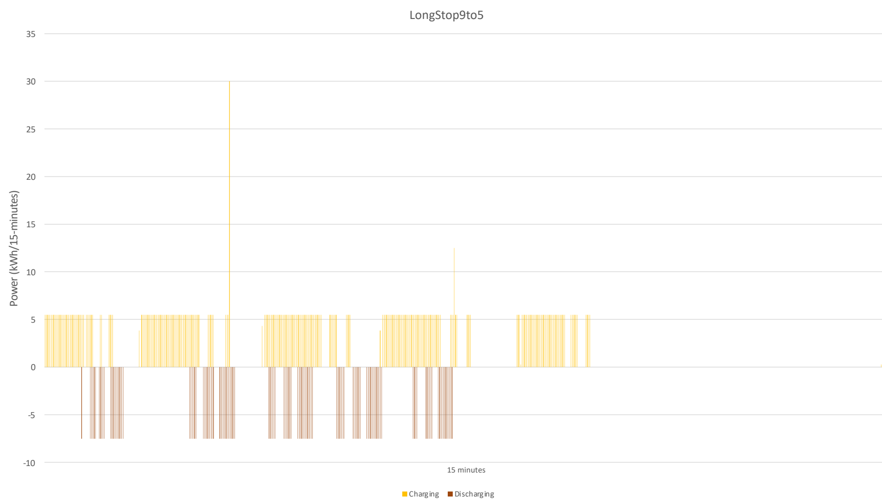

Figure C.4: The charged energy and discharged energy of LongStop9to5 expressed in positive and negative values respectively for each quarter of a characteristic week.

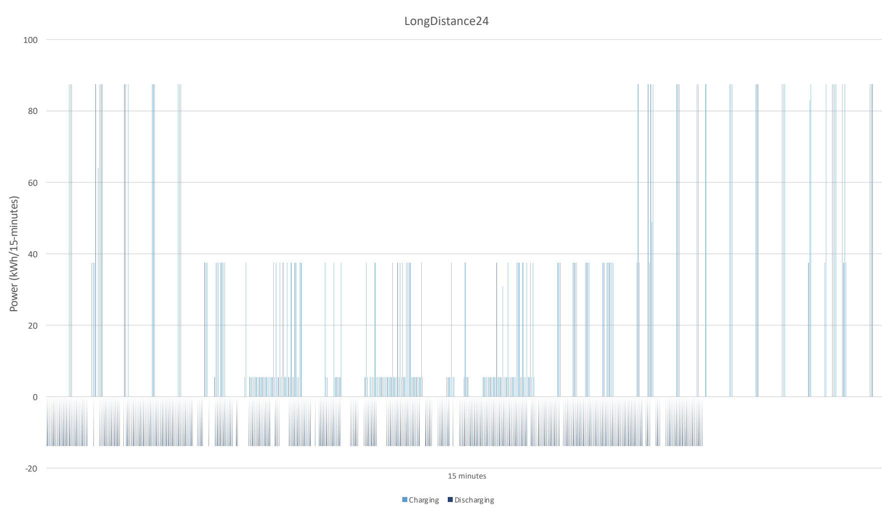

Figure C.5: The charged energy and discharged energy of LongDistance24 expressed in positive and negative values respectively for each quarter of a characteristic week.

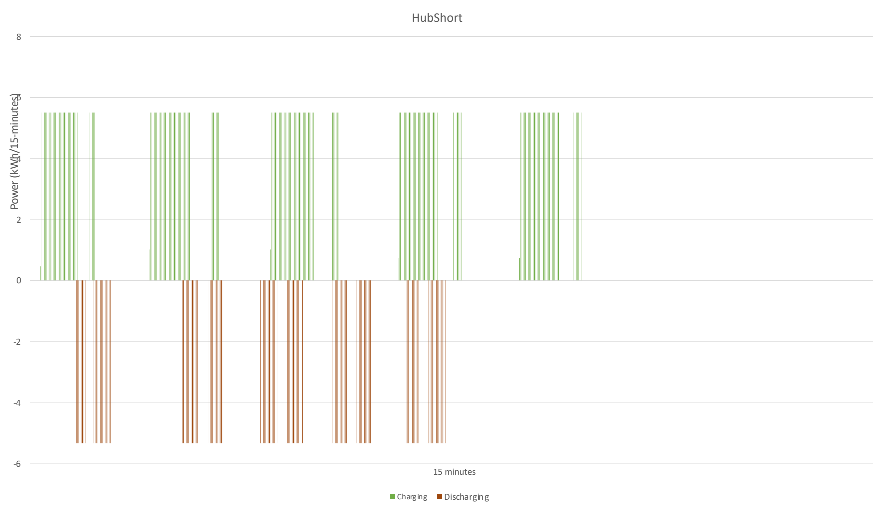

Figure C.6: The charged energy and discharged energy of HubShort expressed in positive and negative values respectively for each quarter of a characteristic week.

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