universität wien

MASTERARBEIT / MASTER'S THESIS

Titel der Masterarbeit / Title of the Master's Thesis

Charging and routing strategies for electric vehicle routing considering flexible energy pricing patterns

verfasst von / submitted by

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angestrebter akademischer Grad / in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien, 2017 / Vienna, 2017

Studienkennzahl lt. Studienblatt / degree programme code as it appears on the student record sheet:	A 066 914
Studienrichtung lt. Studienblatt / degree programme as it appears on the student record sheet:	Masterstudium Internationale Betriebswirtschaft
Betreut von / Supervisor:	Univ.-Prof. Mag. Dr. Karl Franz Dörner, Privatdoz.

Abstract

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Charging and routing strategies for electric vehicle routing considering flexible energy pricing patterns

Urban freight distribution with electric powered vehicles has a high potential impact not only on distribution logistics, but also on energy supply, electricity distribution and grid utilization. Integrated solutions which combine benefits of several industries can lead to profitable cross-sector pricing strategies. The usage of day ahead information concerning energy prices and vehicle charge scheduling can lead to lower energy rates for fleet operators which can be reflected in smart and efficient charging and pricing policies. The proposed approach combines these findings and illustrates the effects on charging scheduling, grid integration and vehicle battery size. A mathematical model is developed for flexible energy prices and aims to synchronize vehicle scheduling and charging times. It attempts to find the optimal charging strategy for a given routing solution by using a commercial solver. Impacts on charging times at the depot as well as influences on the maximum state of charge are considered to evolve additional benefits. The evaluation is based on a practical goods distribution case incorporating six different scenarios to investigate the influence of various delivery strategies on potential enhancements for practitioners. The results show that variable energy prices can create desirable benefits for both vehicle operators and energy providers, such as financial benefits or geographically distributed charging.

Acknowledgements

I would not have been able to get to the point I am now and to write this thesis without the support of several individuals who I would to explicitly thank.

I would first like to thank the department of Production and Operations Management with International Focus and especially Prof. Karl Dörner for giving me the opportunity to write my thesis at his chair. Moreover, I would like to thank him for his input and support throughout my writing of the thesis.

Secondly, I would like to express my gratitude to Mag. Andreas Krawinkler and Mag. Karl Schneeberger for their support. Without their valuable contributions, guidance and encouragements I would not have been able to write my thesis to this extent. I would also like to thank them for introducing me to the topic and their support and patience whenever I encountered a problem.

Financial and professional support by the Climate and Energy Fund, the Austrian Research Promotion Agency (FFG) and the Environmental Support in Austria (UFI) in Austrian Electricity Mobility Flagship Projects (7th call, grant 853768) is gratefully acknowledged. I additionally have to express my appreciation to the practical partners and the Technical University of Vienna for their valuable input. The financial support by the Austrian Federal Ministry of Science, Research and Economy and the National Foundation for Research, Technology and Development is gratefully acknowledged.

Finally, I want to thank my parents and girlfriend for their continuous support not only during the writing of my thesis but throughout my entire studies. Their encouragement and support allowed me to focus solely on my work and studies. Moreover, they were always at my side and had an open ear and mind whenever I required their assistance or guidance.

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List of Abbreviations

BEV	**B**attery **E**lectric **V**ehicle
EPEX	**E**uropean-**P**ower-**Ex**change
EV	**E**lectric **V**ehicle
ICE	**I**nternal **C**ombustion **E**ngine
SoC	**S**tate-**o**f-**C**harge
TOU	**T**ime-**o**f-**u**se
TSP	**T**raveling **S**alesman **P**roblem
V2G	**V**ehicle-**t**o-**G**rid

1 Introduction

On the 11th of November 2015 the world community adopted a legally binding agreement to reduce the effects of climate change and keep the overall warming of the planet under 2°C (UNFCCC. Conference of the Parties (COP), 2015). In order to do so the agreement forces countries to reduce emissions. Especially, the transportation and electricity generation sectors need to undergo drastic changes to meet the proposed target. The road transport sector contributes about 21% to global CO_2 emissions, and is the second largest producer of emissions next to the electricity and heat production sector (Psaraftis, Minsaas, and Panagakos, 2013, p. 196). Alternative fuel vehicles and the shift to a renewable energy production create the opportunity for new business models that allow for joint benefits including the reduction of emissions. They thereby allow countries and companies to come one step closer to meeting the desired emission targets. Especially in the commercial transport sector new vehicle solutions have a large impact as proven solutions can be scaled up to a large vehicle fleet.

In addition to the changes mentioned above global energy markets also have seen dramatic alterations in the past decades from a shift to network neutrality (unbundling) over general market design and the integration of renewable energy sources (Glachant, 2013). The European energy markets such as the European Power Exchange (EPEX) provide two energy exchanges, a day-ahead trade where sellers and consumers are matched on a 15-min basis as well as intraday trading that is aimed at compensating production or consumption shortages and errors in forecasts (Graeber, 2014; EPEX, 2016a). For buyers and sellers of electricity this means that quantities need to be forecast on a day ahead-basis or at least 30-min before the electricity is needed. Day-ahead quantities are traded on a sport market and the clearing prices are determined through merit order. The above mentioned shift in the energy mix and the intermittency of the renewable energy sources has been shown to boost enormous price changes at the EPEX. Moreover, the lack of appropriate short-term storage technology make it even harder than with previous power plants to match consumption with production (Paraschiv, Erni, and Pietsch, 2014). This model aims at using these characteristics to integrate the energy prices into vehicle scheduling.

A study conducted by McKinsey in 2016 estimates that by 2030 up to 50% of newly registered vehicles could be electric, especially battery electric vehicles (BEV) may provide a viable storage opportunity. The above mentioned study was conducted in regard to consumers that use their vehicles for day to day transport. However, companies are also showing interest in transforming their commercial fleets (for transport or delivery) to all electric solutions (Trummer and Hafner, 2016; Lebeau et al., 2015). To contribute to stabilizing grid loads vehicles need to be intelligently integrated into the grid, as studies suggest that uncontrolled charging may put additional strain on the electricity grid (Hoog et al., 2015; Sundström and Binding, 2012). The coordination of charging times (smart-charging) for non-commercial vehicles is a new complicated problem that has been the center of many studies (García-Villalobos et al., 2014). A predefined energy consumption is important for utilities as unanticipated loads can lead to high costs of balancing energy a penalty that is charged at the energy markets. In order for utilities to determine viable storage and consumption patterns to optimize their electricity purchases synergies with the energy consumers need to be established and new business models generated. The optimization model proposed in this study focuses on producing a beneficial situation for both the BEV fleet operator and the energy provider. The model aligns information patterns between both partners and thereby is able to provide incentives to engage in a cooperation.

The thesis is organized as follows: First the related work in the sector of BEV routing and especially the smart integration of BEVs into the electricity grid will be discussed. In order to identify the practical implications the results of two expert interviews that were conducted in the scope of this thesis are then highlighted. Next the contributions both from a practical and theoretical perspective are presented. In the succeeding section an exact routing and charging model as well as a decomposition of the problem is presented. In the third part different scenarios to evaluate the benefits and effects of the proposed model based on a real-world study are introduced. The thesis ends with a conclusion and discussion of future applications and model extensions.

1.1 Related Work

Related research on EVs in the context of this thesis can be categorized by the purpose of the vehicles. Commercial distribution vehicles are typically used for the transport of goods or people whereas non-commercial vehicles are used for the day-to-day mobility behavior of individuals. While commercial trips are mainly planned ahead and are able to provide information concerning sequences, arrival times or travel times, non-commercial mobility is driven by personal demands and pricing incentives. Pelletier, Jabali, and Laporte, 2016 specifically explore the literature on electric vehicles in the distribution of goods. They classify the literature in three categories. Firstly, the strategic perspective encompasses all of the literature that deals with the issues of vehicle composition. In detail this means studies dealing with the size and type of battery and vehicle. Especially in the transition to an all-electric vehicle fleet several propulsion technologies may be operated simultaneously. It is therefore also important to deploy these different vehicles in a way that meet the requirements of the route profile. Moreover Pelletier, Jabali, and Laporte also allocate studies that integrate the decision to acquire / build charging equipment to this perspective. The tactical perspective looks into the day to day operation of an electric vehicle. Tactical decisions encompass charging strategies for instance in order to prolong the life of the battery. Finally, the operational perspective considers constraints and variations a vehicle faces in day-to-day operation. Factors such as breaks by the driver that can be used in order to charge the vehicle are considered. Advantages that are of technological nature or legislative nature are among the other topics that are considered these studies.

The following sections try to review the key findings of both the commercial and the non-commercial sectors and aim to align these approaches to the proposed problem. At the basis of the model is the routing of a commercial transport vehicle, therefore the literature on this subject and especially in regard to the deployment of electric vehicles in this context shall be reviewed. Models which incorporate energy consumption factors of BEVs, such as load dependent and non-load dependent energy consumption are considered. As the model also provides a refueling/recharging optimization this subject is addressed in the next section. The vantage point in this section is literature on optimal vehicle refueling, which has been conducted for regular diesel vehicles. The proposed model aims at finding joint benefits for both the electricity provider and electric fleet operator and therefore touches on literature on EV grid integration and the routing of vehicles in consideration of costs. This has largely been addressed in non-commercial literature and therefore these findings shall be highlighted. The last section looks at the minimization of energy consumption for BEVs and highlights the measures and technology that can be deployed in regard to this goal. Based on this four main areas are implicitly or explicitly addressed by the projected model. A strict separation of these sectors is not always possible as many of the discussed problems are interrelated, consequently the presented studies do not solely address only one issue.

1.1.1 Routing

The routing of commercial vehicles has been studied extensively in literature with the first study dating back more than 50 years (Dantzig and Ramser, 1959). Laporte, 2009 defines the vehicle routing problem as the design of a minimal cost route to a number of customers from a depot. With the introduction of BEVs to routing literature new characteristics and constraints are added to traditional models and novel solution techniques need to be considered. The work by Pelletier, Jabali, and Laporte, 2016 suggests that recent studies examine new objectives such as emission costs (Omidvar and Tavakkoli-Moghaddam, 2012) and also incorporate vehicle characteristics as for instance battery health (Moura, 2011) or waiting and recharging time (Bruglieri et al., 2015). Building on the knowledge of these newer studies consider variations of parameters such partial recharging or add additional constraints imposed by more realistic charging patterns or vehicle consumption (Keskin and Çatay, 2016). Non-commercial studies largely tackle the integration of consumer electric vehicles into the electricity grid. The underlying problem of these studies is the uncertainty of BEV charge times which need to be coordinated (Alonso et al., 2014). Vehicles are sometimes implicitly routed through price incentives, however more often the general focus lies not on coordinating the vehicle locations but on controlling the charging patterns (i.e. through price incentives) when vehicles are connected to the grid (Sundström and Binding, 2012; Cao et al., 2012). Flath et al., 2014 try to spatially coordinate charging in order to improve the utilization of area specific loads and to reduce stress on the transformer level of the grid.

1.1.2 Grid Integration

The combination of grid aspects with the routing or charging problem of BEVs has been addressed mainly in non-commercial literature, where it can be categorized into two general approaches depending on the centralization or decentralization of control. Both research streams largely tackle the problem of the integration of consumer BEVs into the electricity grid. In these scenarios vehicles can be actively integrated into the grid in three major ways, as described by García-Villalobos et al., 2014. Figure 1.1 shows examples of controlled charging strategies as proposed by García-Villalobos et al., 2014. The gray part displays the average energy consumption throughout the day. The black part of the graphs indicate additional loads. In this case additional loads induced through BEV charging. A pure off-peak charging aims at charging vehicles during times when overall grid consumption is low largely through voluntary participation of vehicle owners. This measure can easily be implemented as it does not require any smart technology. This however is also one of the weaknesses of this measure as it is unable to react to changes in grid utilization. Next to this strategy there are also so called smart-charging strategies. In these scenarios the vehicle charge can be actively controlled by the grid operator or a third party and adapted to the requirements of the grid. The first strategy is valley-filling. As can be observed in Figure 1.1 the idea is to shift the consumption of vehicles actively to times of low grid utilization and potential production surplus. A second smart charging strategy is peak shaving. This strategy also incorporates vehicle-to-grid (V2G) technology, which allows vehicles not only to charge but also to discharge surplus energy back to grid. Figure 1.1 highlights this strategy. The peak demand that is shaded out is supplied by the vehicle consequently this energy is then charged in lower demand periods. This allows BEVs to actively shift loads by storing and feeding energy back to the grid. Low energy demands at specific times lead to overproduction and low prices. The synchronization with these valleys can improve grid stability and lead to potential low energy consumption prices (García-Villalobos et al., 2014). In order to achieve the load-shifts induced by BEV charging vehicle owners need to be motivated. This can be achieved through time-of-use (TOU) prices. These prices are synchronized with the current utilization of the grid. This means that in instances where there is a surplus of production and shortage of consumption the prices for consumers will be lower in order to encourage charging to save energy costs. An example of this technique can be found in Cao et al., 2012 who introduced (TOU) prices in order to encourage the shift of loads during the daytime.

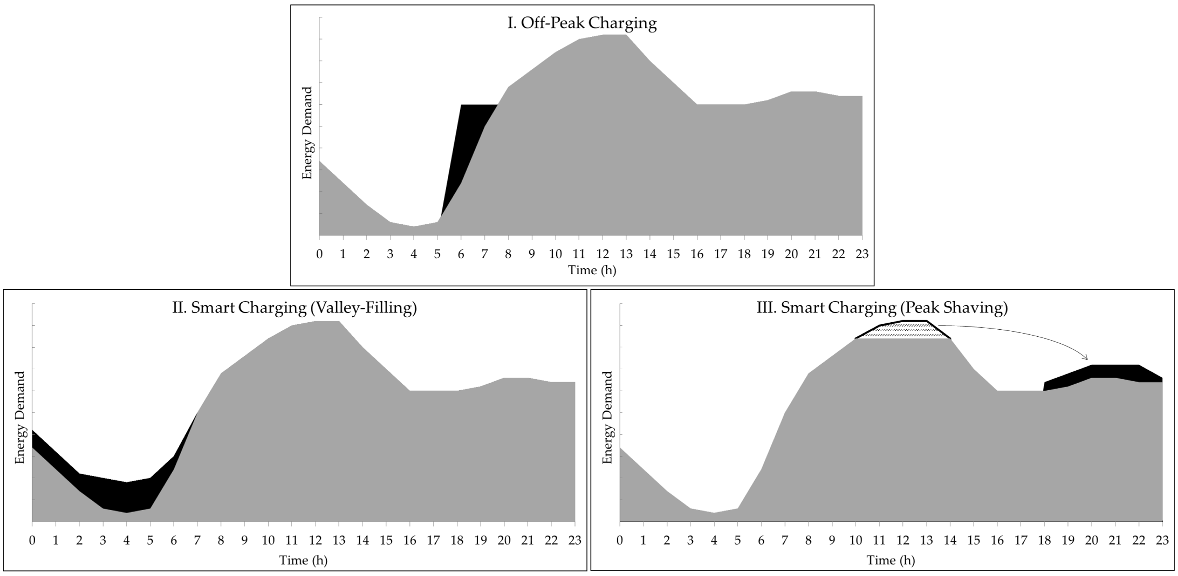

FIGURE 1.1: Three variations of electric vehicle charging

In a decentralized scenario individual vehicles are independent from the grid, i.e. the decision to charge or discharge is made independently by every vehicle. The motivation is provided though certain price incentives. The centralized models however also incorporate an aggregator which is responsible for a fleet of vehicles. The main task of the aggregator is to synchronize the individual needs of the vehicles, i.e. state of charge (SoC) or charging at minimal costs (Bessa et al., 2011) with the power and needs supplies. When comparing both, the centralized and decentralized approach studies found, a centralized scenario produces better results in terms of reducing the strains on the network (Gonzalez Vaya and Andersson, 2012). A decentralized approach however may be easier to implement and scale up as it does not require the exact knowledge of vehicle behavior (Logenthiran and Srinivasan, 2011).

The focus of commercial literature on BEVs has largely been on routing vehicles in order to achieve attained result. However, some studies also incorporate grid aspects and time-of-use prices. For instance the study by Sassi, Cherif, and Oulamara, 2015 is the first originating out of the commercial sector to incorporate time dependent charging costs in their model the objective of their model is the minimization of charging and routing costs. In a strategic outlook they try to find the optimal composition of a fleet with both EVs and conventional vehicles. The focus of their studies is on finding an optimal heuristic for solving their model (Sassi, Cherif-Khettaf, and Oulamara, 2015b; Sassi, Cherif-Khettaf, and Oulamara, 2015a). A second study of the commercial sector that integrates prices into their model was conducted by (Yang et al., 2015). The authors consider three different time charging zones with different prices in order to induce of peak-charging. Both of these studies incorporate different energy prices to improve the practicality of their models.

1.1.3 Charging / Refueling Optimization

The cost optimal refueling of vehicle has been explored since the early 1990s originally being of interest to practitioners it has its origins in the trucking sector where large quantities of fuel are usually purchased in one stop and therefore optimizing refueling to regard price can generate high cost savings (Suzuki, 2009; Hong Lin, Gertsch, and Russell, 2007). For instance the model by Suzuki, 2009 tries to minimize the costs of refueling. These are dependent on the price of gasoline at the gas stations that are selected for refueling based on a given route. The prices at every stop are discontinuous and the dynamic programming model also incorporates a stochastic component that incorporates future gasoline prices. Due to the advent of BEVs and especially due to their limited range and long charging times this type of optimization is regaining the interest to scientists. In their non-commercial application BEVs are parked during most of the day, either at home or at the workplace (Alonso et al., 2014). The idle time is therefore available for charging or discharging vehicles for V2G applications. Commercial vehicles however are heavily utilized during the daytime, and therefore charging times need to be integrated into the route profile. New charging strategies incorporate vehicle characteristics and for instance aim at prolonging battery life (Bashash, Moura, and Fathy, 2010) or minimizing the waiting time that is incurred during the route (Zhang et al., 2014).

Battery life is also an important consideration for commercial deployment of BEVs, as the battery is still the main cost driver in BEVs. Lithium-ion batteries that are used in current vehicles show a certain degradation over time and with increased charging and discharging. The battery health is influenced mainly by three components, the current with which it is charged, the maximal state of charge and discharge and lastly the temperature of the battery (Padovani et al., 2013; Ning and Popov, 2004). For instance as found by Millner, 2010 temperature differences of 10°C can have a significant influence on the degradation of the battery, EV manufacturers are tackling this problem through temperature controlling vehicle batteries. The study also found that operating BEVs in between 30 % - 90 % can lead to an improvement in the lifetime of the battery, in comparison to charging and discharging the vehicle battery fully. Due to the significance these variables have on the degradation of a battery during its life-cycle studies for instance as published by Sweda, Dolinskaya, and Klabjan, 2016 explore this problem and present an algorithm to find an optimal recharging schedule for EVs.

In addition to new characteristics of the vehicles recharging stations are also significantly different from conventional vehicle fueling. Firstly, every customer with an accessible power outlet is a potential (slow) charge point. However, the charging of the vehicle is also more complex as it is dependent on the current SoC of the vehicle (Sweda, Dolinskaya, and Klabjan, 2016). Lastly, and most importantly the currently installed charge technologies still require long charging times (Shareef, Islam, and Mohamed, 2016).

1.1.4 Minimization of Energy Consumption

Closely tied to the routing literature are studies concerning the minimization of the energy consumption of the vehicles. This issue has attained interest of both practitioners and theoretical studies. Due to the current range limitations of BEVs, it is important to optimally use the available energy. Additionally, the range of the vehicles depends on vehicle characteristics and driving behavior and in consequence can vary by more than 50% (Hayes et al., 2011). More importantly in the commercial sector the load of the vehicle can have a significant influence on vehicle consumption which is additionally directly reflected in the ecological impact (Demir, Bektas, and Laporte, 2014).

As Bruglieri et al. (2015) state BEVs allow a energy cost reduction in comparison to Internal Combustion Engine (ICE) vehicles of up to 90%. Additionally, this energy consumption can be further reduced for instance through the use of regenerative breaking which allows to regain up to 15% of the energy used for propulsion.

1.2 Practical Input / Expert Interviews

Next to the extensive literature research that was presented above two expert interviews were conducted, in order to incorporate real world data into the model and to integrate and solve a real world related problem.

1.2.1 Logistics Company

The first interview was conducted on 13.05.2016 with Markus Döhn who is responsible for electric mobility at a logistics company operating in the German market. The company delivers 64 million letters and 3.5 million packages each day in this market, however it is also present in 220 other countries. The main topic of the interview was the sustainability goals of the company and their practical implementation. The company pursues an improvement of its CO_2-efficiency by 30% in the next 4 years. The parcel and letter delivery business can be subdivided into four main sections. In the pre-run phase the parcels are picked up from their drop-off locations and transported to a regional distribution center. Here they are a sorted and in the main-run forwarded to a regional distribution center that is responsible for the final delivery area. In the post-run the parcels are then delivered to a local delivery center. From here the packages are distributed in the final delivery. In the final delivery the majority of vehicles is deployed by the company. This is due to the fact that a delivery to the final customer in rural areas occurs using smaller vehicles while the main run and post run is executed using trucks and lorries. In total more than 17 times as many vehicles are deployed in the final delivery in comparison to the main and post-run. The company has therefore decided that in order to attain their pursued goal the final delivery should be tackled first.

As has been shown in the case study conducted by Trummer and Hafner, 2016 electric vehicles have become a viable solution for the reduction of CO_2-emissions in the transportation sector. The company also decided to conduct their final deliveries using an electric vehicle. The initial problem they faced was to find a vehicle that meet both their technological and financial requirements. Firstly, the vehicle would have to be able to replace the diesel vehicles that were used up to this point and secondly the vehicles also needs to be able to compete with the diesel vehicle on a financial amortization basis. As can be observed in the study by Lebeau et al., 2015 there is already is wide selection of electric vehicles for the transport sector. However the problems with the available solutions mainly were that the necessary quantities could not be delivered in the required time and the vehicles were still too expensive to be able to complete with conventional vehicles. Out of this reason the company developed their own vehicle to meet these requirements. The usable capacity of the vehicle is 27 kWh and the overall payload capacity is 650 kg.

Due to the requirements to use the electric vehicle as a replacement for the conventional diesel vehicle and the characteristics of the BEV some problems arise for the company. First of all the charging infrastructure has a big influence on the usability of the BEV. Especially the charging infrastructure at the depot needs to be sufficient to accommodate all vehicles. Closely, connected to this issue is the smart charging of vehicles. This is seen as one of the key challenges that need to be overcome, as the energy supply at the depot is expected to be the main bottlenecks at least in the short term. The smart charging of vehicles is also important to consider to prolong the life of the battery. As Millner, 2010 pointed out a controlled charging can have a big impact on the longevity of the battery's life. This is also recognized by the logistics company who are interested in operating their vehicles in a way that preserves battery health.

Next to the changes to the vehicle fleet the company is also looking for new delivery solutions for the last mile deliveries. To do so it is considering approaches such as a "rolling-depot". In this scenario the delivery vehicle is parked inside the city at certain nodes. The vehicles final delivery to the customer then occurs cargo bikes and other non-motorized transport vehicles.

1.2.2 Utility / Charging station operator

A second interview was conducted with Roman Prager on 04.05.2016. He is responsible for operational management at a large Austrian utility firm and also oversaw parts of the firm's business that is connected to the charging infrastructure for BEVs, that is also provided by the firm. The interview was conducted with him in order to determine the key challenges for energy providers, in terms of BEV charging.

The first challenge the company faces stems from the requirements of the electricity grid to always be balanced. This means that supply and demand always have to meet. On the energy markets this is ensured through so called balancing groups which balance the energy used by consumers and producers in order to align consumption and production. In case

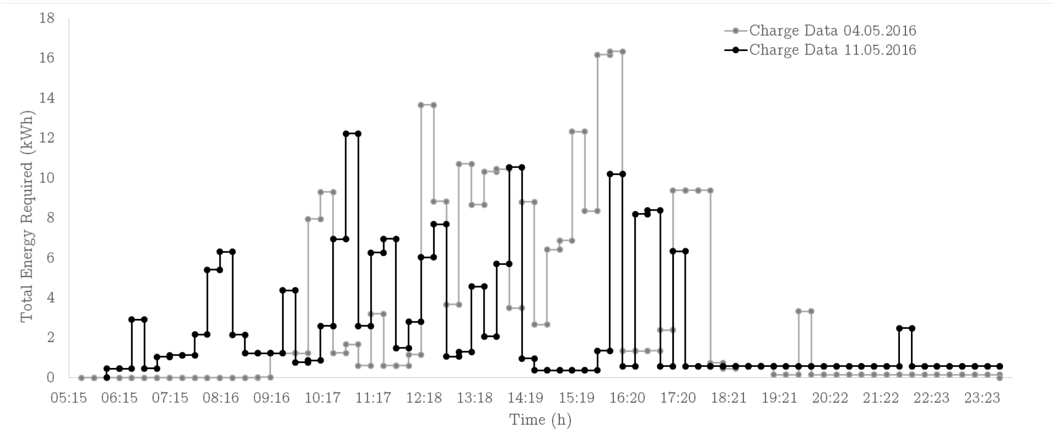

FIGURE 1.2: Required load of electric vehicle charging station for two days

this equilibrium is not achieved a operating reserve of energy is required to either lower consumption or increase production. For every participant of the energy markets the ordered energy and actual consumption have to be balanced on a 15-min interval. If this is not the case the utility is required to pay for the necessary balancing energy. This cross-control area balancing energy price is calculated in 15-min intervals and dependent on the utilization of the grid. This setup can create instances where the penalty in the form of balancing energy may be more expensive than the actual consumption of the energy (i.e. when there is a surplus in the energy that was ordered). To determine the required energy and purchase it on a day-ahead basis a prognosis based on historic data is therefore made.

In Figure 1.2 charge data obtained from the company is depicted. The figure shows the required load at all of the charging stations supplied by the utility company in fifteen minute intervals for two weekdays. The charges of all charging stations is summed up in 15-min intervals. As can be observed, the load varies for each 15-min interval. Moreover, there is a baseload for the charge data from 17:20 till the end of the day for the data of the 11th of May, which stems from a BEV that is charging at a slow charging outlet. The chargers include slow-level one chargers as well as fast charging with a power output of up to 50 kW. Vehicles can charge at any station with whatever power output that is provided at the station. As customers can begin charging at any time this means the company has to predict how much energy they will require. For companies that operate charging stations in different balancing groups a geographic prediction of charging may also be necessary.

Next to this problem for the utility company problems may also arise in terms of grid stability if the power output of charging stations increases. Moreover, the uncoordinated charging times paired with the volatility of renewable energy production can lead to further discrepancies between energy consumption and production.

2 Contribution

As the literature suggests new business models can be created through the newly established link between the transport and energy production sector. Especially for delivery companies and their vehicles it may be possible to integrate charging stops into their planning of regular tours. This would allow them to pass charging information (i.e. charging time and required charge) on to utility companies. To encourage the transport company to do so the utility company could forward the grid prices instead of charging a flat tariff. This would also allow for the company to decrease energy costs by charging in times of low energy prices.

The contribution of the proposed model is to introduce energy efficient charging through the use of valley filling and time-of-use (TOU) tariffs to commercial electric vehicle literature. While TOU-tariffs and valley filling have been addressed in non-commercial literature they have only been touched upon by commercial vehicle studies. The objectives of both parties need to be aligned to establish a practical realization of the model. Table 2.1 summarizes the benefits that are generated by the model for the utility and transport company as well as the grid. The model is based on the fact that the vehicle operator is charged a variable price. Though a utilization of low cost charging zones overall cost decreases can be achieved. The model considers decentralized charging of vehicles. As it has been shown in various studies that solely charging vehicles in one location in a uncontrolled way can lead to power losses or congestion in the transformer lines (García-Villalobos et al., 2014). Consequently, for an operator of an electric vehicle fleet it may not be possible to fully charge a large number of vehicles overnight. Through decentralized charging this issue may be overcome. Lastly, costly waiting times related to charging behavior on route is reduced through the main objective of working time reduction. For the utility company receiving fixed consumption values is paramount in order to avoid balancing energy. By receiving the necessary quantities ahead of time, these can be purchased appropriately and the energy providers do not need to rely on the prognosis of quantities. Finally, the utility operator may be able to gain additional profits in the intraday market, as pay-as bid method can lead to lower costs than the 15-min merit-order price. For the grid the link between supply and demand through price can lead

TABLE 2.1: Model benefits

Vehicle Operator	Utility / Grid
- Achieve a demand shift to low cost periods - Shift charge from the depot to the route - Decrease size of battery through charging on route - Use service times as charging times to minimize charging related waiting time on route	- Receive fixed consumption values from its client - Avoid to be charged balancing energy for incorrect prognosis - Shift energy demand to renewable energy sources - Gain additional profits in the intraday market

to a shift of consumption from high cost (high-demand / low-production) to low cost (low-demand / high-production). This may also lead to an increased consumption of renewable energy (Paraschiv, Erni, and Pietsch, 2014) and a better utilization of grid capacity.

The summarized effects of flexible tariff zones and adapted vehicle scheduling are visualized in Figure 2.1 which shows a comparison of fixed and flexible starting times of a given route based on a flexible energy prices. The figure illustrates the described effects of flexible energy prices combined with synchronized charging strategies. Due to shift of the starting point increased usage of low tariff zones as well as reductions in the maximum state of charge can be achieved. The scheduling of the route with fixed starting time leads to a narrow availability of tariff zones below the average price and therefore to limited reduction of the variable charging costs. As in the example shown only a few of the available stops are actually used for charging in contrast to the flexible starting time. In this case the route and its stops are scheduled aligned to the most beneficial usage of low charging prices. Therefore the charge at the depot can be shifted to the tour without extending travel times. This additionally leads to a lower maximum SoC which is required to execute the given tour. As shown in the second part of the figure this can further lead to a reduction of the battery size. In summary the main benefits of the model are 3-fold:

1. Reduction of variable charge related costs
2. Shifting vehicle charge away from the depot
3. Improved utilization of energy and grid capacity

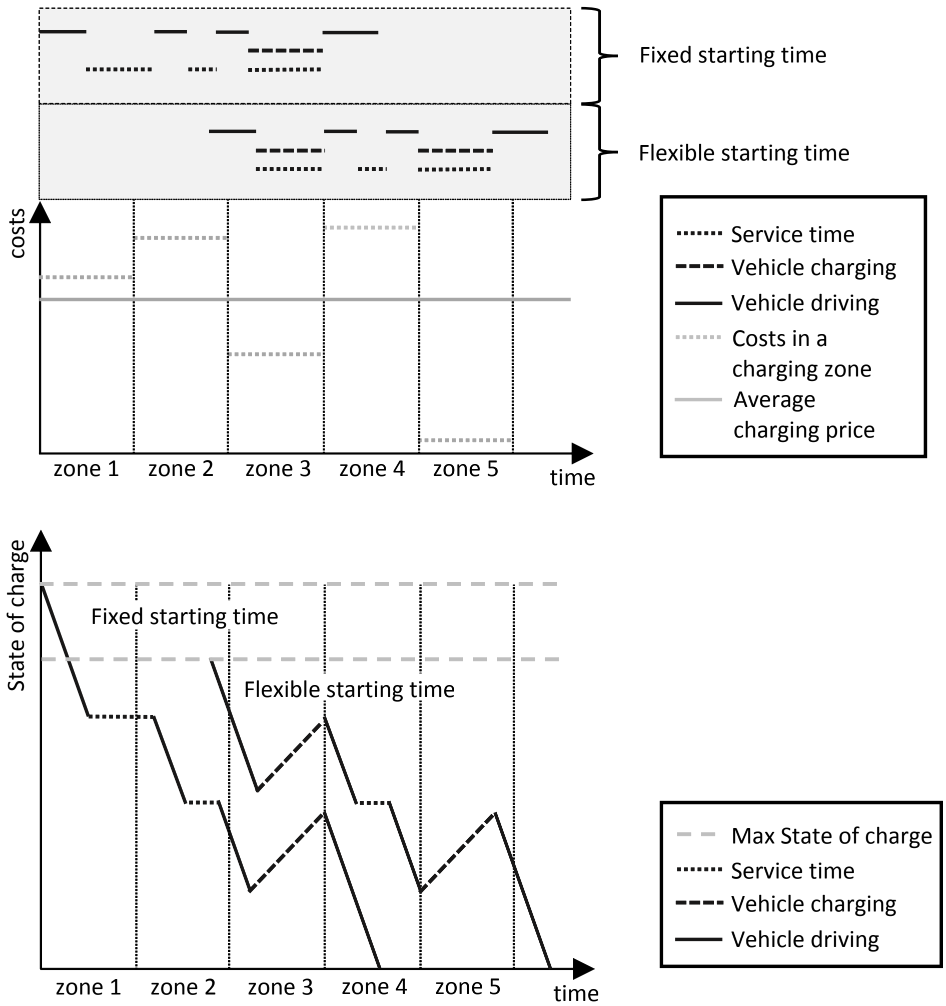

FIGURE 2.1: Model findings and functionality

3 Problem Formulation

The basic model initially aims to construct a route for a given set of customer locations departing from a depot and returning to this location (see Figure 3.1).The main objective is to reduce the driving time and the charging costs however the wage costs are assumed to account for the largest portion of delivery costs. The travel time from one customer to the next is predefined and may not necessarily have to be relational to the travel distance. For instance the travel time could increase due to congestion, speed limitation on a certain route or other external factors. The transport vehicle has a certain driving range which is dependent on the driven distance and the transported load. The initial driving range is determined by the charge that is conducted at the depot. The vehicle can generally be charged from 0 - 100% SoC however the maximum charge may be restricted to conform to possible charge limitations at the depot. If this driving range is not sufficient to satisfy the energy demand the vehicle is required to recharge during the tour. It is assumed that a vehicle can charge at any customer location. At every customer location packages are delivered to the customers. The time it takes for the driver to deliver these goods to their final locations is the service time and can be used for charging the vehicle. During the service time several customers can also be delivered by foot. There are certain instances where an increase of the total travel time is possible. Firstly, the vehicle may not have enough range to reach all customer locations and cannot recharge the required charge during the given service times or secondly, the costs for charging at a specific location offset the additional travel time. This is possible, as the charging costs are time dependent (TOU-prices).

There are two types of costs associated with charging that are induced by the objective of the model. Firstly, the total time should be minimized. This is the time the driver departs from the depot and arrives back at it. The charging time coordination is impacted by this as the total delivery time can be extended if charging times are longer than service times. This could be observed in the example presented above at node 5. The second type of costs originate out of the charging zones and the time dependency of these. There is a savings potential if the costs for charging at a specific charging station are lower than the average

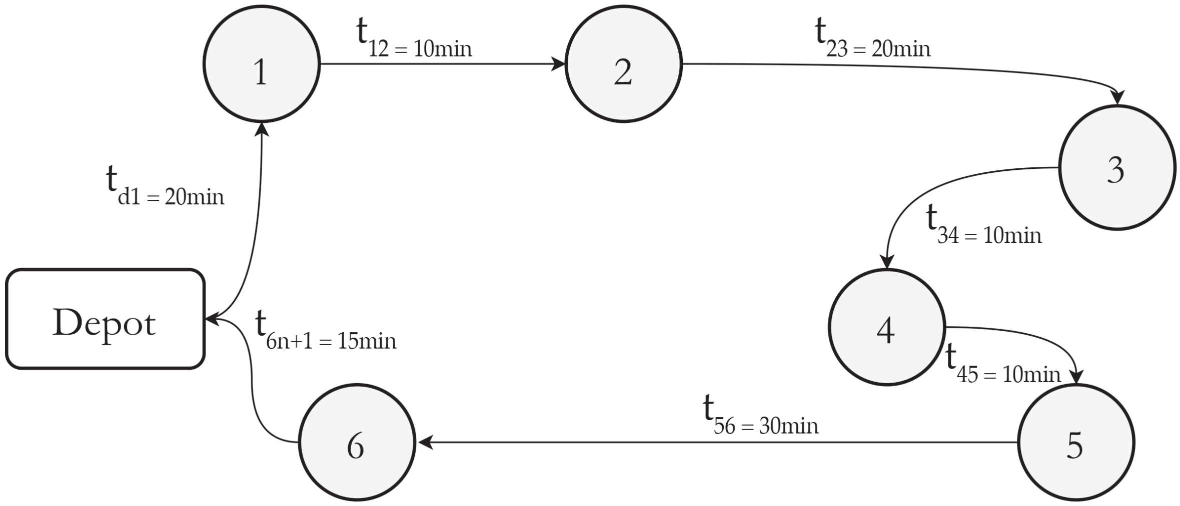

FIGURE 3.1: TSP illustration: Finding the shortest route

TABLE 3.1: Simplified model example

Node	Service Time	**Charging Time**	State of Charge	**Starting Time**
Depot Departure	-	CT_{d0}: 1h 30min	SoC_d: 50%	ST_d: 10:00
1	se_1: 10min	CT_{1c}: 10min	SoC_1: 35%	ST_1: 10:30
2	se_2: 15min	CT_{2c}: -	SoC_2: 30%	ST_2: 10:55
3	se_3: 13min	CT_{3c}: 10min	SoC_3: 10%	ST_3: 11:28
4	se_4: 20min	CT_{4c}: -	SoC_4: 15%	ST_4: 11:58
5	se_5: 5min	CT_{5c}: 10min	SoC_5: 10%	ST_5: 12:18
6	se_6: 12min	CT_{6c}: -	SoC_6: 15 %	ST_6: 13:00
Depot Arrival	-	-	SoC_{n+1}: 0 %	ST_{n+1}: 13:15

costs that the vehicle pays at the depot. The savings during the route should be maximized and this means the model will determined the optimal time to leave from the depot and the SoC that allows for the greatest cost savings while still being able to execute the route without the charge dropping below the minimum SoC. The time a vehicle arrives at a charging station is important for the determination of the charge costs. This means charging times will also be synchronized with low cost charging zones.

Figure 3.2 shows a small example of the charging behavior described above. The charging costs are illustrated by the dark gray columns. Furthermore the average charging costs, charging time, and service time are shown. As can be observed the charging times are synchronized with the service time in the time interval from 10:30 - 10:45. This is also the charging zone with the lowest charging costs and therefore allows for the greatest cost savings. It can also be observed that the vehicle can charge within a charging zone multiple

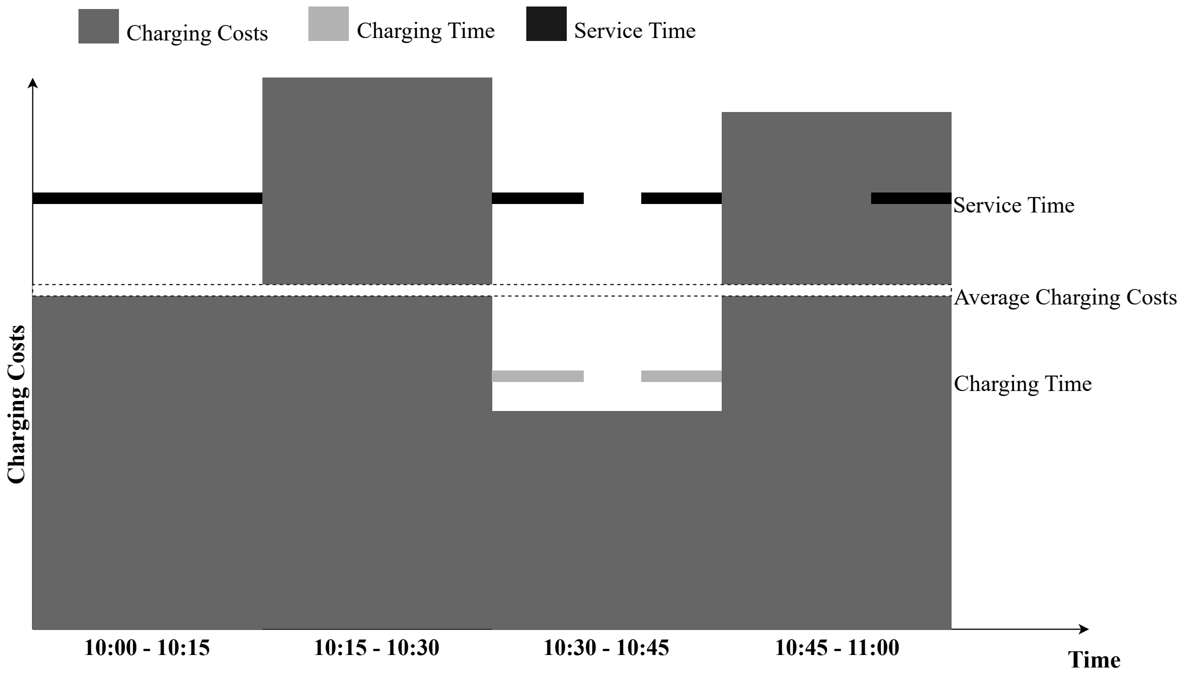

FIGURE 3.2: Example of the charging behavior

times, as there is a short driving break in between the two charges in the charging zone.

To incorporate all of the requirements described above a linear programming model was created. The model can be divided into two logical parts. The first part of the model incorporates the vehicle routing (Constraints 3.2 – 3.7). The sequence the customers are visited is determined by this part of the model. In the second part of the model the vehicle charging as well as departure and arrival times of the vehicle are determined (Constraints 3.9 – 3.25). The model considers the following input data (Table 3.2) and decision variables (Table 3.3). The small example in Figure 3.1 and the corresponding values for the decision variables (in bold) are summarized in Table 3.1. The example illustrates the main components of the model. Firstly, the starting time, the time of departure from a node to another is set. This time has an influence on the overall costs due to the time dependency of the costs. Secondly, the model determines the charging locations and times. The variable charging time summarizes and simplifies the more complex approach taken in the model that will be described in further detail below. The example also illustrates the calculation of the starting time at a node. This is dependent on the previous starting time, plus the travel time and service time or charging time. If the charging time is longer than the service time (for instance in node five) the total time, i.e. departure from the depot and arrival at the depot is increased. Finally, the SoC of the vehicle always has to be positive and is relational to the total charge time and the travel distance between the customers.

3.1 Objective Function

The Objective Function (3.1) minimizes the total variable costs for the delivery. These costs include the wage costs of the driver and the costs of charging the vehicle. ST_{MIN} is the time the driver leaves the depot and $ST_{N_{n+1}}$ is the time the driver arrives at the end depot.

$$min \quad (ST_{n+1} - ST^{MIN})w + \sum_{j \in N_0} \sum_{c \in C} CT_{jc} c_c ce + CT_{00} c^{av} ce \tag{3.1}$$

The first term therefore calculates the actual working time of the employee, which is multiplied by a wage factor.
Due to the structure of the pricing at electricity markets, which is time dependent, the charging costs c_c are subdivided into several zones of different charging costs. In the upper part of figure 2.1 an illustration of the different zones and can be observed. The decision variable CT_{jc} represents the actual time that the vehicle spends at customer j to charge the vehicle in charging zone c. This factor is multiplied with the costs of this cost-zone and the charging rate (ce) in kWh. The costs that are incurred for charging at the depot are weighted with an average cost factor c^{av}. The average cost per kWh is the mean of all charging zone prices.

3.2 Vehicle Routing

The first part of the constraints (3.2 - 3.7) determine the vehicle routing, which is formulated as traveling salesman problem (TSP). Constraints 3.2 ensure, that all demands are covered. Constraints 3.3 represent the flow constraint in the model. The load of the vehicle is subject to Constraints 3.5 and Constraints 3.6 where L_i and L_j represents the load of the vehicle at node i and node j. This determines the load dependent energy consumption of the vehicle. The delivery quantity at the individual nodes L_j needs to be greater than the quantity delivered to the preceding customer L_i minus the amount that was delivered to this customer d_j. Additionally, the load of the vehicle at every individual node may not be greater than the maximal load of the vehicle L^{MAX} and also needs to be greater than zero. In 3.6 the sum

TABLE 3.2: Input data for the considered model formulation.

Name	Description
$i \in N$	Set of customers
$i{\in}N_0, i{\in}N_{n+1}, i{\in}N, i{\in}N_{0,n+1}$	Set of customers, charging stations, and the start depot (0) or the end depot $(n+1)$, $i \in I \cup C \cup 0$ or $i \in I \cup C \cup n+1$
$c \in C$	Set of different charging costs Euro per kWh
c^{av}	Average charging costs Euro per kWh
$dist_{ij}$	Costs for traveling from node i to j (km)
ecl	Load dependent energy consumption
ece_{ij}	Empty vehicle energy consumption
L^{max}	Maximum capacity of vehicle
d_j	Demand of customer j (kg)
se_j	Service time of customer j (kg)
ce	Charging power for vehicle (kWh)
M	Big-M
w	Wage of driver (Euro per hour)
$costs_c$	Cost in charging zone c (Euro per kWh)
t_{ij}	Travel time from customer i to j (hours)
SoC^{max}	Maximum state of charge of the vehicle (kW)
CZA_c	Time of charging zone availability
DC^{max}	Percentage of total charge that may be charged at the depot

TABLE 3.3: Decision variables for the considered model formulation.

Name	Description
x_{ij}	If arc i to j is used(1) or not(0)
SoC_i	State of charge at node i
Li	Load of vehicle after visiting customer i
ST_i	Starting time at node i
CT_{ic}	Charging time in charging zone c at node i
ST^{MIN}	Minimum starting time i.e. when driver starts working
CTS_{ic}	Charging time start in charging zone c at node i
CTE_{ic}	Charging time end in charging zone c at node i
CH_{ic}	Binary variable if charging zone c at node i is used (1) or not (0)

of $X_{n,n+1}$ over all i and X_{0j} over all j need to be equal to one. This constraint ensures, that both the first start node and the designated end node are visited. The charging costs are time dependent and therefore the model also incorporates a time factor in the variable ST_i which is the starting time of the tour before visiting customer i. To this starting time a service time se_i is added this time accounts for the length of the stop.

$$s.t \quad d_j \leq \sum_{i \in N_0 : i \neq j} x_{ij} M \qquad \forall\, j \in I, \tag{3.2}$$

$$\sum_{i \in N_0 : i \neq j} x_{ij} = \sum_{i \in N_{n+1} : i \neq j} x_{ji} \qquad \forall\, j \in N \tag{3.3}$$

$$\sum_{j \in N_{n+1}} x_{0j} = \sum_{i \in N_0} x_{i,n+1} = 1 \qquad \forall\, j \in N \tag{3.4}$$

$$L_j \leq L_i - d_i x_{ij} + L^{max}(1 - x_{ij}) \qquad \forall\, i \in N_0, j \in N_{n+1} : i \neq j \tag{3.5}$$

$$0 \leq L_i \leq L^{max} \qquad \forall\, i \in N_{0,n+1} \tag{3.6}$$

3.3 Charging

Constraints 3.7 to 3.26 mirror the charging and discharging behavior of the vehicle. The following starting time at the next customer i.e. the customer at node j needs to be greater or equal to this time plus the service time and travel time from node i to the node j (t_{ij}), this is considered in Constraints 3.7.

In the model the day is divided into several charging zones. In these zones prices vary according to daily price changes at the EPEX. For every charging zone there is a charging time start (CTS_{ic}), charging time end (CTE_{ic}) and a binary variable that indicates if the vehicle charges in this charging zone at a specific node. CH_{ic} is a binary variable (Constraint 3.25), which is set to 1 if the charge occurs at a specific charging zone and node. Lastly, the actual charging time is tracked using the variable (CT_{ic}).

Constraint 3.9 specifies that the SoC of the successor needs to be greater or equal to the charge at the predecessor minus the necessary energy consumption and plus the energy charged at that node. The consumption of the vehicle is made up of two components, firstly

an empty vehicle energy consumption, this is dependent on the distance driven by the vehicle, secondly a load specific factor which increases the empty consumption dependent on the load and kilometers driven. Speed based energy consumption is not considered in this model because the load dependent energy consumption is based on an average inner city driving circle. Constraints 3.10 are similarly structured as the previous constraints and limits the charging to values greater than zero and smaller than the maximal charge. Charging at the depot is allowed prior to departure. In 3.11 the SoC at departure at the depot needs to be equal to the actual charging times that occur at the depot node. The model lets the solution flexibility select the starting charge as long as it is greater than zero and smaller than a predefined threshold (CH^{max}) (Constraint 3.12). The minimal starting time is set using Constraints 3.13. The charging zones dictate the prices at a certain point in time, in order to bind them to specific times the charging zones availability variable (CZA^c) stores the individual time intervals during which charging can be conducted in a specific charging zone. In an example with real life EPEX data this is restricted to 15-min intervals This means, that in case a charging zone is utilized ($CH_{ic} = 1$) the starting and end time of charging (CTS_{ic}, CTE_{ic}) needs to be in between the time interval that the charging zone is active (Constraints 3.15, 3.16). The actual charging time in a charging zone c is the time when charging ended minus the time charging started (3.17), this time may only be greater than zero in case the charging zone is actually used ($CH_{ic} = 1$) (3.18). The vehicle may commence charging once it has reached the customer location, therefore the travel time (t_{ij}) is added to the time the vehicle leaves the predecessor (3.18).
Constraints 3.19 - 3.24 are logical constrains which ensure the charging time of the next node does not begin or end before the previous one ended (3.20, 3.21), the SoC, starting and end time of charging is always positive (3.22), (3.23) (3.24). Constraints (3.25) and (3.26) represents the variable domain definition.

$$ST_j \geq ST_i + t_{ij}x_{ij} + se_j - M(1 - x_{ij}) \qquad \forall\, i \in N_0, j \in N_{n+1} : i \neq j \tag{3.7}$$

$$ST_j \geq CTE_{jc} \qquad \forall\, j \in N_{n+1} \tag{3.8}$$

$$SoC_j \leq \begin{pmatrix} SoC_i - ece_{ij}X_{ij} - dist_{ij}L_jecl \\ +M(1 - x_{ij}) + \sum_{c \in C} CT_{ic}ce \end{pmatrix} \qquad \forall\, i \in N_0, j \in N_{n+1} : i > 1 \tag{3.9}$$

$$SoC^{MAX} \geq \begin{pmatrix} SoC_i - ece_{ij}x_{ij} \\ -dist_{ij}L_jecl + \sum_{c \in C} CT_{ic}ce \end{pmatrix} \qquad \forall\, i \in N_0, j \in N_{n+1} : c \in C \tag{3.10}$$

$$SoC_0 = \sum_{c \in C} CT_{00}ce \qquad \forall\, c \in C \tag{3.11}$$

$$SoC_{Max}DC^{Max} \geq SoC_0 \tag{3.12}$$

$$ST^{Min} \leq ST_i - t_{0i} \qquad \forall\, i \in N \tag{3.13}$$

$$0 \leq \sum_{c \in C} CT_{jc}ce \leq SoC^{MAX} \qquad \forall\, i \in N_0, j \in N_{n+1} : c \in C \tag{3.14}$$

$$CZA_cCH_{ic} \leq CTS_{ic} \leq CZA_{c+1}CH_{ic} \qquad \forall\, i \in I, c \in C : c < C \tag{3.15}$$

$$CZA_cCH_{ic} \leq CTE_{ic} \leq CZA_{c+1}CH_{ic} \qquad \forall\, i \in I, c \in C : c < C \tag{3.16}$$

$$CT_{ic} = CTE_{ic} - CTS_{ic} \qquad \forall\, i \in I, c \in C : c < C \tag{3.17}$$

$$CT_{ic} \leq CH_{ic}M \qquad \forall\, i \in I, c \in C : c < C \tag{3.18}$$

$$CTS_{jc} \geq ST_i + t_{ij}x_{ij} \qquad \forall\, i \in I, c \in C \neq j \tag{3.19}$$

$$CTS_{ic+1} \geq CTE_{ic} \qquad \forall\, i \in I, c \in C : c < C \tag{3.20}$$

$$CTE_{ic+1} \geq CTE_{ic} \qquad \forall\, i \in I, c \in C : c < C \tag{3.21}$$

$$SoC_i \geq 0 \qquad \forall\, i \in N_{0,n+1} \tag{3.22}$$

$$CTS_{ic} \geq 0 \qquad \forall\, i \in I, c \in C \tag{3.23}$$

$$CTE_{ic} \geq 0 \qquad \forall\, i \in I, c \in C \tag{3.24}$$

$$CH_{ic} \in \{0, 1\} \qquad \forall\, i \in I, c \in C \tag{3.25}$$

$$x_{i,j} \in \{0, 1\} \qquad \forall\, i \in N_0, j \in N_{n+1} \tag{3.26}$$

4 Implementation

As described in the problem formulation the model incorporates a TSP and a recharging optimization. There are two cost components in the model the wage costs, which are dependent on the total tour time and the charging costs which depend on the energy charged and price at this point in time. The wage costs are considered to be an hourly rate and the maximum working time is based on legal restrictions. For the energy costs the day-ahead prices at the EPEX are used. The main objective of the model will always be to firstly, minimize the total working time. In initial trial runs this was also verified. In order to find a solution to the model described above the a decomposition is therefore conducted, where the TSP provides the sequence of customers that are visited by the vehicle and in a second step the charging times are adapted to minimize the charging cost of the predefined route. The TSP has been solved exact by many studies (Laporte, 1992) and therefore the solution to this problem is largely factored out in the solution approach. The focus is directed to the optimal charging strategies for a given route.

The implementation first uses the given real-world tour data provided by the practitioner. In a second step this data is then used to optimize the recharging of the vehicle. To do so the model was solved exact by implementing it in IBM ILOG CPLEX Optimization Studio 12.6.3. Following this procedure solutions were found for relatively large test instances within a reasonable calculation time. In a second step the tour data is optimized using a savings algorithm and local search.

4.1 Tour data optimization

To optimize the tours provided by the practitioner first new tours were created, using a savings-algorithm. The savings algorithm is a heuristic which was first introduced by Clarke and Wright in 1964. The basic procedure of the heuristic can be broken down into three steps. In a first step tours from the depot to each individual customer are created (see Figure 4.1). In a second step these individual tours are merged in order to obtain savings. The succession

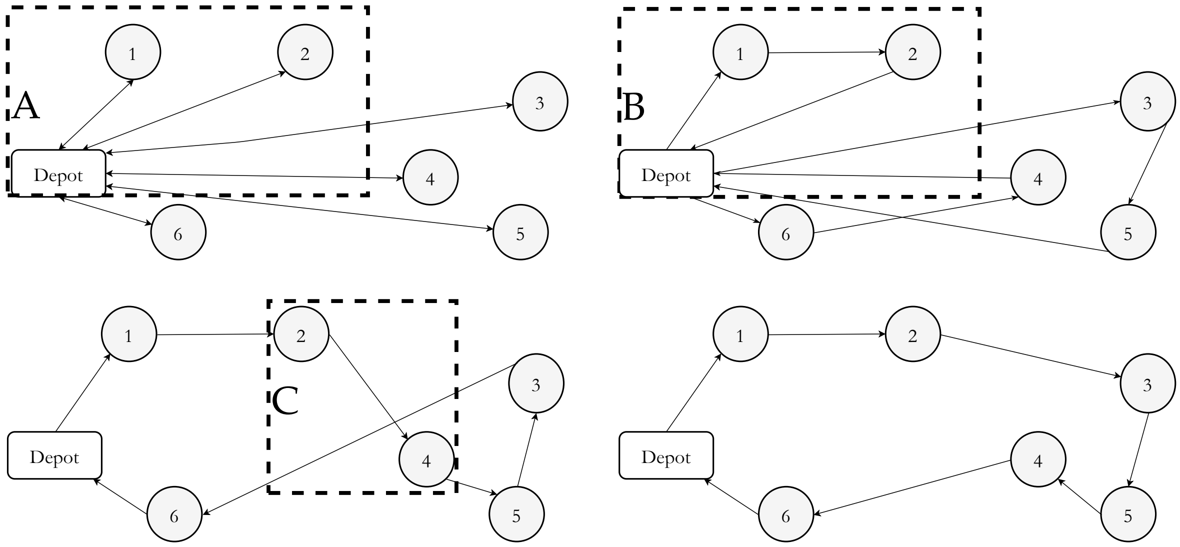

FIGURE 4.1: Illustration of a savings tour calculation with local search improvement

of the merge is determined by the extent of the savings. To determine these the savings for each route are calculated by adding the additional travel distance or time and subtracting the saved distances and times. For the example presented in Figure 4.1 (from route A to route B) the savings values are calculated for the travel time as has been conducted for the practical case. First the initial route costs are calculated:

1. $TravelTimeRoute_A$ = t_{d1} + t_{1d} + t_{d2}+ t_{2d}
2. $TravelTimeRoute_B$ = t_{d1} + t_{12} + t_{2d}
3. $Savings_{1-2}$ = t_{1d} + t_{d2} - t_{12}

By subtracting the additionally driven time from the no longer driven time the savings value can be determined (3). If these savings are grated than zero this means the total tour time is reduced and the two separated customers should be delivered during one tour. These calculations are conducted for all possible tour merges and the values are listed in a descending order. Tour merges are conducted until all tours have been merged or a constraint is violated. In the practical example this means that the total travel time may not be greater than the total possible work time and the transported load in kg may not exceed the total capacity. The vehicle range as determined by the charge do not restrict the savings heuristic as they are later considered in the calculation of charge times. In case a further merging of tours is not possible due to a violation of one of the constraints a new tour is created.

The third constellation in the bottom left corner of Figure 4.1 shows the final route produced by the savings algorithm. As can be seen in section C the route crosses in this section and this may not be optimal. For further optimization of the obtained tours an improvement heuristic was used in the form of a local search heuristic. The 2-opt heuristic a special form of the k-opt was used. This heuristic was introduced by Croes (1958) and can be found in many variations. The main idea of the heuristic is to cut out certain parts of the tours rearrange this part of the tour and then ad it back to the tour. In case the total tour length decreases this swap is executed. For the example presented in Figure 4.1 in the bottom right part of the figure the 2-opt has been executed. The section between node 2 and 6 (4-5-3) is extracted and reinserted in reverse order (3-5-4).

4.2 Numerical Study

As input for the model real-world data was used. The data can be broadly subdivided into two major categories. The first category is related to the specifications of the simulated vehicle, while the second encompasses the tour specific variables, such as tour length, number of test tours and charging costs at a node. The following two subsection describe the data, that is also depicted in Table 4.1 in more detail.

TABLE 4.1: Numerical Study Input Data

No. of Customers	24 - 664
No. of Tours	1 - 11
Wage costs (€)	14
Max Vehicle payload (kg)	600
Max Vehicle Charge (kWh)	65
Min Vehicle Charge (kWh)	0
No. of charging zones	56
Begin Tour time	6
End tour time	20
Load specific energy consumption (kWh per km)	0.000056
Charging power (kW)	3.7, 11, 22, 50, 100
Empty Vehicle Consumption (kWh per km)	0.27322

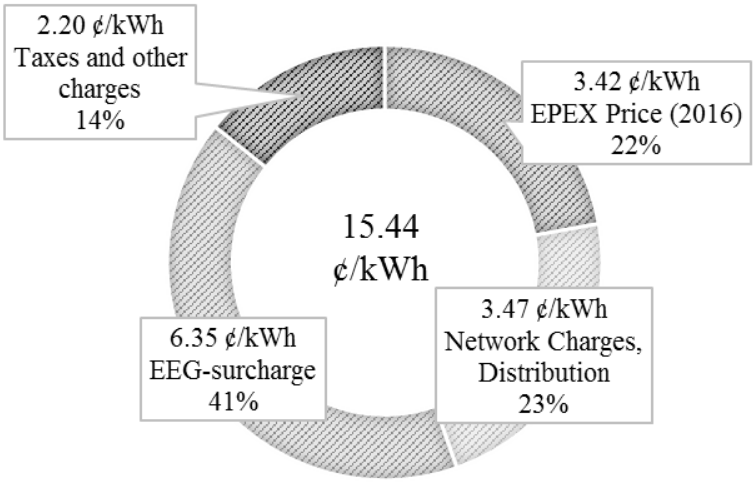

FIGURE 4.2: Components of the German electricity price for industrial customers for 2016 (Statista, 2016a; Statista, 2016b)

4.2.1 Tour specific information

The real world driving data was obtained from a company conducting the delivery of perishable goods in the business to customer sector. The daily execution is based on template tours with short-cutting. Street network distances and asymmetric travel time matrix based on average speeds are used. Through incorporating this input data, the model becomes a asymmetric TSP. Demands of the customers, service times and the tours are provided by the company. Lastly, the data also includes clustered routes where several customer deliveries are combined into one stop. This data is available in four different degrees of consolidation (50 m, 100 m, 150 m, 200 m). The data encompasses the consolidated service times and delivery quantities of each customer. Including the unclustered case the total number of test routes considered is 330. The maximum number of customers in a test case is 664 and the smallest number of customers in a test case is 24 executed by one vehicle with 200 m clustering. The average tour length is 89.74km. Using the travel time matrix, demand data and service time the routes were also optimized using a savings and local search. Here the number of routes increases to 346, however the maximum number of vehicles needed decreases to 10 (see table 5.5 for further route information).

As input data for the charging costs EPEX Spot continuous values were used (EPEX, 2016b). To compare the calculated scenarios and for the charge at the depot the average costs are set as the average price of the used EPEX dataset. The EPEX data is available in 15-min intervals. The possible working time begins at 6am and ends at 8pm. For this time interval there are therefore 56 individual charging zones. The wage costs were set according to the current conditions of the practical partner. Figure 4.2 shows the different components of the electricity price of Germany for an industrial customer. It can be seen than the EPEX price only makes up a small fraction of the total electricity costs, however this part of the energy price is the only one that can be actively controlled, therefore the model omits various taxes and surcharges that normally have to be paid. These are also omitted for the average price, which is calculated based on the EPEX values.

4.2.2 Vehicle Data

Generally electric vehicles do not only encompass BEVs but also include other vehicles that store energy in different forms, for instance fuel cell electric vehicles use hydrogen to store energy and generate electricity using a fuel cell when needed Chan, 2007. This thesis focuses on BEVs as this vehicle technology is more promising from a technological and economical viewpoint for the proposed use-case of urban deliveries (Offer et al., 2010). Especially, the conversion losses which are more than 45% smaller for BEV in comparison to a fuel cell vehicle enable the vehicle to play a key role in the stabilizing of grid power (Eaves and Eaves, 2004).

The vehicle data is also derived from actual fleet of the partner. Empty vehicle consumption as well as load dependent vehicle consumption were obtained by the partner using a longitudinal vehicle dynamics simulation. Figure 4.3 shows the general procedure. In a first step, vehicle data was recorded. This data was used in a second step to generate a motor consumption map, which is compared with measured energy consumption. To do so the engine load and rotational speed are inserted into an engine model. By iteratively adjusting the motor consumption map a representative motor consumption model was generated. Based on the vehicle and delivery data a vehicle model was created and used to tune the model to correspond to the previously measured driving cycles. A fully fine-tuned vehicle model thereby is able to accurately reproduce the vehicle energy consumption solely based on the driving profile and delivery stops. Data for both a conventional internal combustion engine vehicle as well as BEV was obtained using this method.

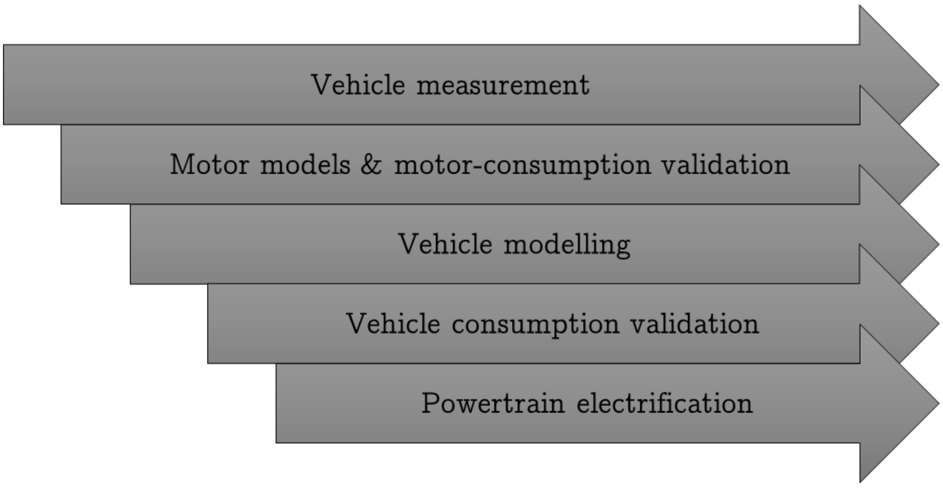

FIGURE 4.3: Process of longitudal vehicle dynamic simulation

In terms of charging technology there is a variety of technologies and standards that are currently used. On this basis, a distinction can be made between direct current (DC) and alternating current (AC) charging. There is a discrepancy between how energy is transported in the grid (AC) and how energy is currently stored in a battery (DC), therefore all of the currently available vehicles have an on-board AC-DC converter (Capasso and Veneri, 2015). Due to the limited space inside a vehicle and costs associated with these converters the capacity of these are limited to a maximum output of 43 kW (McKinsey, 2014). DC charging on the other hand can currently achieve greater charging power. In this setting the required conversion technology is located outside of the vehicle at the charging station and therefore does not suffer from the special limitations of the vehicle. This technology is currently able to reach a charging power of more than 100 kW (Shareef, Islam, and Mohamed, 2016). Moreover the capacity of this technology have not yet been reached as companies are currently building a charging infrastructure than can achieve a charge of above 300 kW (Daimler, 2016). In the scenarios three variations of charging speeds are therefore used to account for slow (3.7 kW, 11 kW, 22 kW), fast (50 kW) and ultra-fast charging (100kW).

5 Results

Based on the input data described in the previous sections the solution approach was verified on the different test instances and the results are summarized in six different scenarios. The numerical findings are focused on the charging strategies, benefits of adapted delivery behavior and implications on depot charging requirements, as determined by the model, battery sizes and charging power. Figure 5.1 shows the different scenarios. Variations to the previous scenarios are framed and can be grouped into four areas. In the first scenario a diesel case is also included in addition to a comparison between the flat tariff case and variable tariff, which is at the basis of the other scenarios. In scenario II the results of integrating clustered data (i.e 50 m - 200 m), as provided by the practitioner are also observed. The number of stops per cluster is reduced to one and the final delivery is made on foot. The delivery time consequently increases by the service time per customer. The vehicle traveled distance (in km) however is decreased as short driving distances are conducted on foot. Starting from the third scenario flexible starting times are allowed. This means the vehicle can depart at any time beginning from 6am as long as it returns back to the depot by 8pm. The fourth scenario looks at the impact of the optimized routes. Finally two further factors are analyzed in scenario five and six. Scenario V looks at the changes in battery size caused by the variations in the scenarios described above. In the final scenario the charging power is changed in five different stages and the impact on the individual route as well as overall impacts are analyzed.

Scenario	Vehicle Technology/ Price Model	Starting Time Fixed / Flex	Data Type	Type of Tour data	Additional variations
Scenario I:	Diesel / BEV-Flat / BEV-Variable	Fixed Start	Unclustered	Prefefined Tours	
Scenario II:	BEV-Flat / BEV-Variable	Fixed Start	Clustered	Prefefined Tours	
Scenario III:	BEV-Flat / BEV-Variable	Flex Start	Clustered	Prefefined Tours	
Scenario IV:	BEV-Flat / BEV-Variable	Flex Start	Clustered	Savings Tours	
Scenario V:	BEV-Flat / BEV-Variable	Flex Start	Clustered	Prefefined Tours	Battery Size
Scenario VI:	BEV-Flat / BEV-Variable	Flex Start	Clustered	Prefefined Tours	Charge Speed

FIGURE 5.1: Scenarios Overview

5.1 Scenario I: Diesel - BEV comparison

The first scenario includes a comparison of a conventional diesel vehicle with combustion engine and a battery powered vehicle which was adapted to the requirements of the diesel vehicle. The assumption is made, that the diesel vehicle is fully fueled and does not have to be refueled during the trip. For the BEV two price patterns are used. In the first version the electricity prices are set fixed as the average of the EPEX values. This means no matter when the vehicle is charged the same costs occur. In a second version, the electricity prices are set according to the real time prices of the EPEX. The Table 5.1 shows the results obtained from the model for the diesel vehicle, and electric vehicle with the two electricity tariff options. The data for the diesel vehicle include the objective value and energy consumption, while the BEV values also include BEV specific data and a comparison between the energy costs of both tariffs (Energy Cost reduction).

The results depicted in Table 5.1 for Scenario I also support our choice of solution strategy, as it can be observed, that the energy consumption for the BEV regardless of fixed or variable tariff obtains less than 1% (0.75-9.13 €) of the objective value. In comparison it makes up more than 10% (10.31-124.29 €) for the diesel vehicle. For the diesel vehicle a price of 1 € was considered. These results also show the large cost gap between the energy consumption costs of a conventional diesel vehicle and BEV. Additionally, further key results can be observed in this scenario that are important to consider for the next scenarios. First, there is only a small reduction of the energy costs from the flat tariff to the variable tariff. The average savings between the two test cases is equal to 2.26%. This effect arises due to short service times and sparsely availability of low rates during the morning. Nevertheless the vehicle does charge outside of the depot for the variable tariff. On average the vehicle charges 19.72% of the total charge during the tour. In consequence the maximum SoC during the tour is also reduced, on average by 8.35 kWh. In accordance with the second part of the objective function this energy is charged during charging zones that exhibit lower than average costs.

An example of the charging and driving behavior of the BEV with a variable electricity tariff is shown in Figure 5.2 (See A.1 for more detail). It can observed that the variable price only drops below the average price in a few instances. Moreover the figure shows that the vehicle only charges during the service time, there is no instance, where the charge prolongs the service time, this is due to the high impact of the wage costs described above.

TABLE 5.1: Scenario I: Diesel - BEV comparison - Results

	Diesel		BEV Flat Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Max SoC [kw]	Charged on Tour (%)
1_0_11	1162.12	124.29 (10.69%)	1046.96	9.13 (0.87%)	41.94	0%
2_0_10	1086.72	115.43 (10.62%)	979.78	8.48 (0.87%)	41.94	0%
3_0_9	1022.34	107.84 (10.55%)	922.43	7.93 (0.86%)	41.94	0%
4_0_8	885.76	93.14 (10.51%)	799.47	6.85 (0.86%)	41.94	0%
5_0_7	790.88	83.62 (10.57%)	713.41	6.15 (0.86%)	41.94	0%
6_0_6	710.27	73.46 (10.34%)	642.22	5.41 (0.84%)	41.94	0%
7_0_5	597.74	63.27 (10.58%)	539.13	4.66 (0.86%)	41.94	0%
8_0_4	453.41	46.02 (10.15%)	410.77	3.39 (0.82%)	35.84	0%
9_0_3	332.23	34.51 (10.39%)	300.26	2.54 (0.85%)	35.84	0%
10_0_2	196.73	19.74 (10.04%)	178.44	1.45 (0.81%)	24.97	0%
11_0_1	95.41	10.31 (10.8%)	85.86	0.76 (0.88%)	24.97	0%
Average	**666.69**	**70.15 (10.48%)**	**601.70**	**5.16 (0.85%)**	**37.75**	**0%**

	BEV Variable Tariff					
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	1046.75	8.92 (0.85%)	19.74%	32.47	209 (664)	2.23%
2_0_10	979.57	8.28 (0.85%)	20.55%	32.47	202 (637)	2.39%
3_0_9	922.23	7.73 (0.84%)	21.20%	32.47	194 (597)	2.53%
4_0_8	799.31	6.69 (0.84%)	20.23%	32.47	158 (523)	2.37%
5_0_7	713.27	6.01 (0.84%)	20.04%	32.47	142 (468)	2.28%
6_0_6	642.08	5.27 (0.82%)	21.13%	32.47	132 (437)	2.56%
7_0_5	539.00	4.53 (0.84%)	21.82%	26.68	115 (366)	2.80%
8_0_4	410.69	3.3 (0.8%)	21.53%	26.68	91 (300)	2.63%
9_0_3	300.21	2.48 (0.83%)	20.08%	21.32	64 (213)	2.14%
10_0_2	178.42	1.43 (0.8%)	15.99%	21.32	29 (133)	1.47%
11_0_1	85.85	0.75 (0.87%)	14.64%	31.28	14 (64)	1.48%
Average	**601.58**	**5.03 (0.83%)**	**19.72%**	**29.28**	**122.73 (400.18)**	**2.26%**

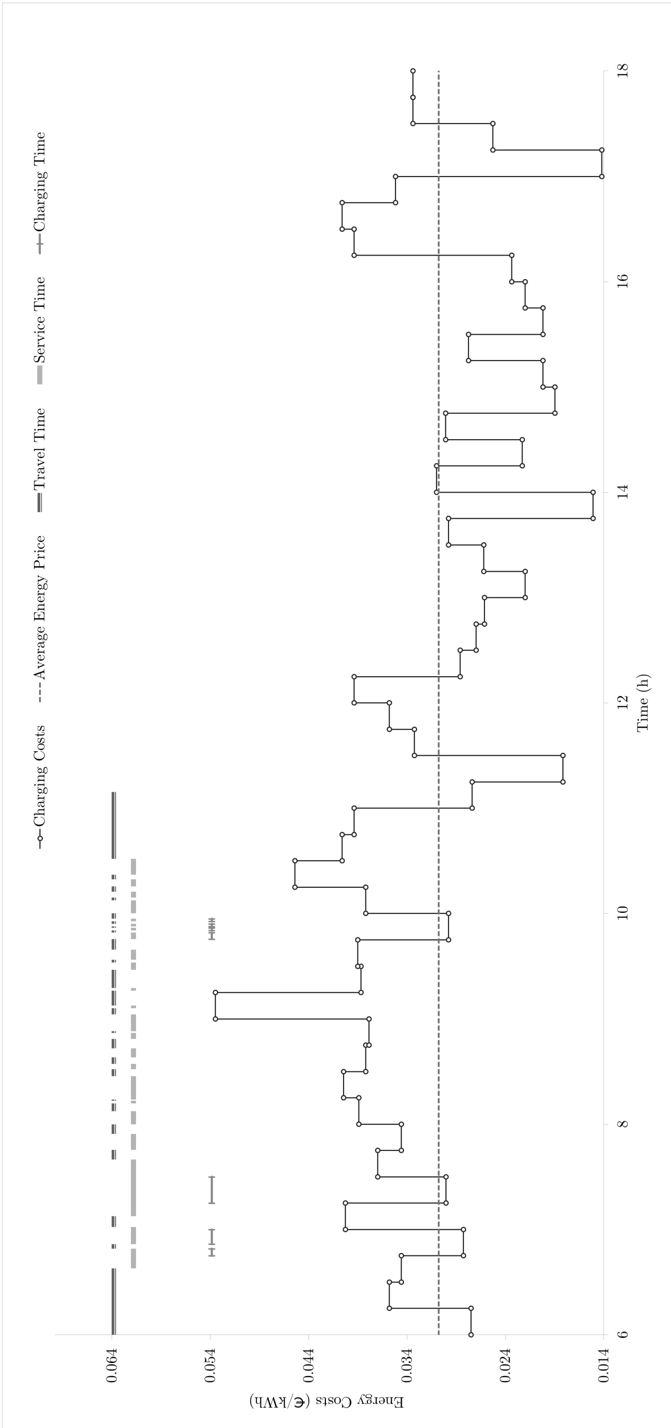

FIGURE 5.2: Scenario I: Extract of a Tours charging and driving behavior

This means that tours will not become longer. Lastly, this also holds the wage costs constant for every vehicle type. It can also be seen that through the fixed starting time, potential charging times are restricted to a time of day where the price only drops below the average price in a view instances. Finally, there is also a high number of charges for every tour. For instance in test tour 11_0_1 that only incorporates one tour the vehicle charges 14 times. Which is at nearly every third customer. This is caused by the short service times in the un-clustered data instances.

5.2 Scenario II: Clustered data

In Scenario II the effect on charging of the clustered input data is examined. The data are clustered in four stages 50 m, 100 m, 150 m and 200 m. The clustering influences the charging costs that decrease with increased clustering due to a shorter driving distance. Table 5.2 shows how clustering changes the tour values. Firstly, the total driven distance decreases with increased clustering. In total from 6467.68 km to 5531.88 km. While the total distance and energy consumption decrease in every case the total tour time increases from the 150 m cluster to the 200 m cluster. This means that after a certain degree of clustering the benefits from a decrease in driving time are outweighed by increased deliver time on foot. This can also be observed in the objective value, which is lowest for the 150 m cluster and increases for the 200 m cluster.

TABLE 5.2: Scenario II: Clustered Data Summary

	0m	50m	100m	150m	200m
Total Energy Consumption (kWh)	1872.00	1763.05	1690.52	1642.60	1601.40
Objective Value (€)	6617.37	6250.25	6089.30	5960.05	6022.71
Total driven distance (km)	6467.68	6093.60	5844.83	5675.90	5531.88
Total Tour Time w/o service Time	342h 42min	308h 9min	287h 48min	267h 28min	256h 17min
Service Time	126h 7min	133h 14min	143h 24min	154h 34min	170h 50min
Total Tour Time	468h 49min	442h 23min	431h 11min	422h 2min	426h 7min

The results for the model calculations using the savings and local search optimized tours are summarized in Table 5.3. The number of charge stops decreases and on average there are significant less charging stops in the clustered case. Between the no clustering and maximal clustered case there is a difference of 8.6 stops (i.e. on average 14.27 stops per tour). This effect arises due to increased service time and reduction of stops. The minimum number of stops for a tour is 6 in contrast to the no-cluster case, where the minimum number of stops on one tour was equal to 14. The effect of large decreases in the number of charge stops does not prevail for further clustering scenarios after the 50m cluster. There is a decrease in the amount of charge stops, however the average decrease falls to 0.16 from 1.85 for the next consecutive clusters. The average cost reduction between flat and variable tariff over all instances of clustered data is 2.26%. There is no clear tendency for the cost differences in terms of increased clustering. The total charge outside the depot however increases to a maximum of 29.92% for the case where the clustering is increased to 200m. The average amount of charge that is shifted outside of the depot over all of these cases is 407.32 kWh.

TABLE 5.3: Scenario II: Clustered Data - Results

Clustering	Energy Costs (Flat) [€]	Energy Costs (Var) [€]	Energy Cost Reduction BEV Flat / BEV Var
0m	56.74	55.38	2.26%
50m	53.44	52.20	2.09%
100m	51.24	50.13	2.01%
150m	49.79	48.54	2.33%
200m	48.54	47.17	2.63%
Average	**51.95**	**50.68**	**2.26%**
Clustering	Average no of charging stops / Tour	Charge outside of Depot (%)	Charge outside of Depot (kWh)
0m	20.45	20.42%	382.22
50m	14.58	22.06%	388.99
100m	12.33	22.08%	373.24
150m	12.15	25.14%	412.98
200m	11.85	29.92%	479.19
Average	**14.27**	**23.92%**	**407.32**

5.3 Scenario III: Flexible Starting Time

As can be seen in seen in Figure 5.2 the tour is restricted to a charging interval and the model only determines if a charge is conducted at a location or not. This restricts the potential savings significantly. In Scenario III therefore the model may also decide when the vehicle leaves the depot, as long as the tour time stays within the specified time interval. The effect of this change is displayed in Table 5.4. Firstly, the energy cost savings increase on average to 18.27%. Secondly, the charge outside of the depot more than doubles in every case. In comparison to the results of Scenario II where it was only 407.32 kWh or 29.92% of total charge it increases on average to 998.77 kWh or to 58.33% of the total charge. The maximum energy cost reduction between the flat and the variable charging costs of 20.35% are achieved for the greatest clustering. With increased clustering the proportional savings and charge outside of the depot is also increased. The lowest savings occur at the maximum clustering. This is not only caused by a lower driving distance but also occur due to a higher savings of the variable tariff in comparison to the flat tariff. The charge outside of the depot is also equal to the total charge below the average costs. The effect of releasing the starting time can be observed in Figure 5.3. Figure A.2 shows the same Scenario in more detail. Additionally Figure A.5 - A.8 show the complete results.

TABLE 5.4: Scenario III: Clustered Data / Flexible Starting Time - Results

Clustering	Energy Costs (Flat) [€]	Energy Costs (Var) [€]	Energy Cost Reduction BEV Flat / BEV Var
0m	56.74	48.42	15.30%
50m	53.44	44.51	17.56%
100m	51.24	42.05	18.74%
150m	49.79	40.57	19.39%
200m	48.54	39.02	20.35%
Average	**51.95**	**42.91**	**18.27%**
Clustering	Average no of charging stops / Tour	Charge outside of Depot (%)	Charge outside of Depot (kWh)
0m	54.64	56.63%	1060.08
50m	37.14	57.87%	1020.26
100m	30.61	58.77%	993.57
150m	25.97	58.52%	961.29
200m	22.32	59.86%	958.64
Average	**34.13**	**58.33%**	**998.77**

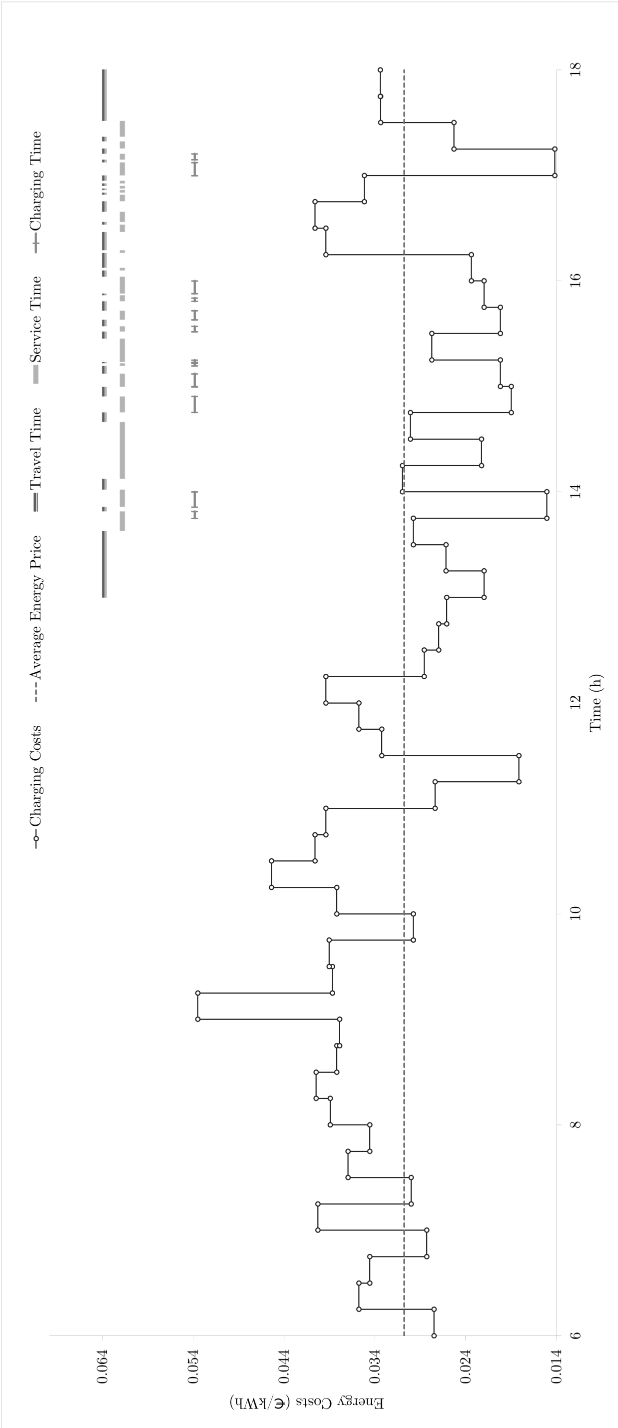

FIGURE 5.3: Scenario III: Tour Charging Patterns

The tour time is shifted to a later starting time. During this time-interval energy costs are reduced by the higher availability of low tariff zones. Moreover long service times are synchronized with low energy costs.

5.4 Scenario IV: Savings Tours as Input Data

In Scenario IV, the predefined routes are optimized using savings and local search. The improvements are summarized in Table 5.6. The table shows the cumulated values over all tours and degrees of clustering. Overall the results show that there is a great opportunity for improvement for the predefined tours. On the one hand a decrease in travel time can be obtained and on the other hand the maximum number of vehicles decreases. The average savings from an optimized route to the predefined route achieved through shorter travel distance is 13.35 (from 51.94 to 38.59). The total energy savings are equal to 145.86 kWh (from 1713.19 kWh to 1567.33 kWh). In regard to the charging pattern the results of Scenario II prevail. These are shown in 5.5. The objective value decreases largely due to the reduction in travel time. The charge outside of the depot on average is equal to 59.88% or 938.32 kWh. The cost savings between the variable and flat tariff increase with clustering with maximum savings of 20.63%.

TABLE 5.5: Scenario IV: Clustered Data / Savings Routes - Results

Clustering	Energy Costs (Flat) [€]	Energy Costs (Var) [€]	Energy Cost Reduction BEV Flat / BEV Var
0m	50.64	41.94	17.56%
50m	47.99	39.32	18.53%
100m	46.55	37.69	19.49%
150m	46.46	37.45	19.86%
200m	45.88	36.56	20.63%
Average	**47.50**	**38.59**	**19.21%**
Clustering	Average no of charging stops / Tour	Charge outside of Depot (%)	Charge outside of Depot (kWh)
0m	46.89	59.46%	993.41
50m	33.43	59.21%	937.41
100m	29.00	61.31%	941.57
150m	23.72	59.62%	913.98
200m	19.83	59.80%	905.24
Average	**30.63**	**59.88%**	**938.32**

TABLE 5.6: Scenario IV: Differences of Predefined Tours to Savings and local search

	Tour Length			
	Max Tour Length	Min Tour Length	Mean Tour Length	Sum Tour Length
Predefined	143.69 km	54.35 km	89.74 km	29613.89 km
Savings + LS	117.74 km	51.19 km	78.51 km	27163.35 km
Difference	-18.06%	-5.81%	-12.52%	-8.27%
	Tour Time			
	Max Tour Time	Min Tour Time	Mean Tour Time	Sum Tour Time
Predefined	6h 7min	2h 2min	4h 4min	1463h 23min
Savings + LS	5h 6min	1h 2min	3h 4min	1241h 41min
Difference	-12.56%	-23.47%	-19.09%	-15.17%

5.5 Scenario V: Battery Size considerations

Charging outside the depot also has an influence on the maximum SoC that a vehicle has during a tour. This is illustrated in Figure 5.4.

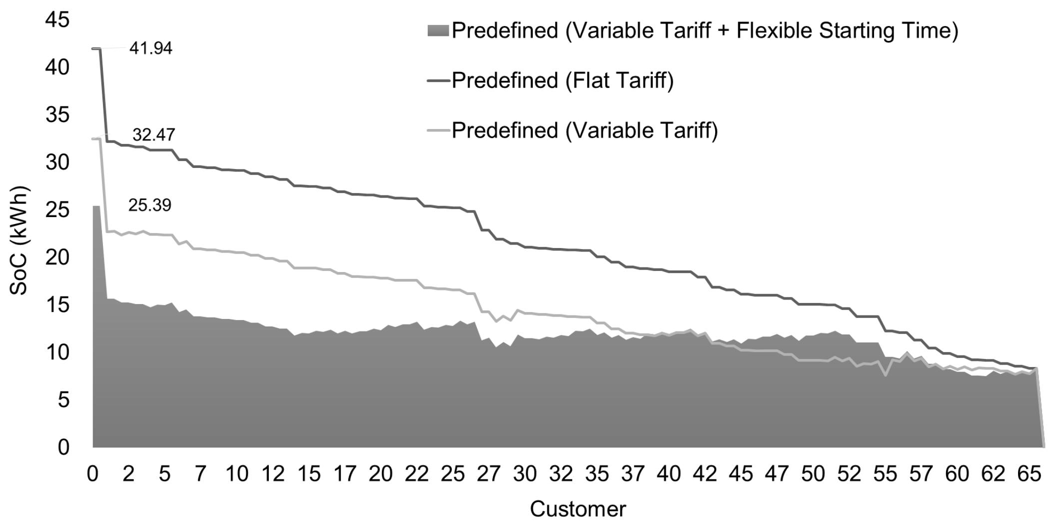

FIGURE 5.4: Scenario V: Charging/Discharging pattern under different scenarios

For all three scenarios the maximum SoC is occurs at the depot. Thereafter vehicles discharge during the tour. While the charging behavior during the tour creates different charging and discharging patterns it can be seen that the vehicle is discharged to the same level at customer 64. The remaining charge is set to cover the remaining distance and to arrive at the depot with a SoC of zero. It can be observed, that the discharge is reduced for the variable tariff and increases the greatest from customer 55 to 57. A greater charge can be observed in case of a flexible charging time. For instance from customer 15 to 25. In this scenario the SoC and thereby also the size of the vehicle battery is decreased the most. In comparison to the flat tariff a vehicle with a 22.58% (41.94 vs 32.58 kWh) smaller battery can be deployed in case of the variable tariff. If the starting time is released this is decreased to 25.39kWh or only 60.53% of the fixed pricing scenarios battery size is required. This is caused by the increased charging throughout the tour which can also be observed in Figure 5.4.

5.6 Scenario VI: Charge Power Variation

Up to this point the charging power has been set at 11 kW for all previous scenarios. In this scenario the charging power will be increased up to a speed of 100 kW and the impact on overall model results presented. In detail five variations where tested, three AC-charging scenarios (3.7 kW, 11 kW, 22 kW), which correspond to a level 1 to level 2 charger and two fast charging cases which correspond to a fast DC charger (50 kW, 100 kW).

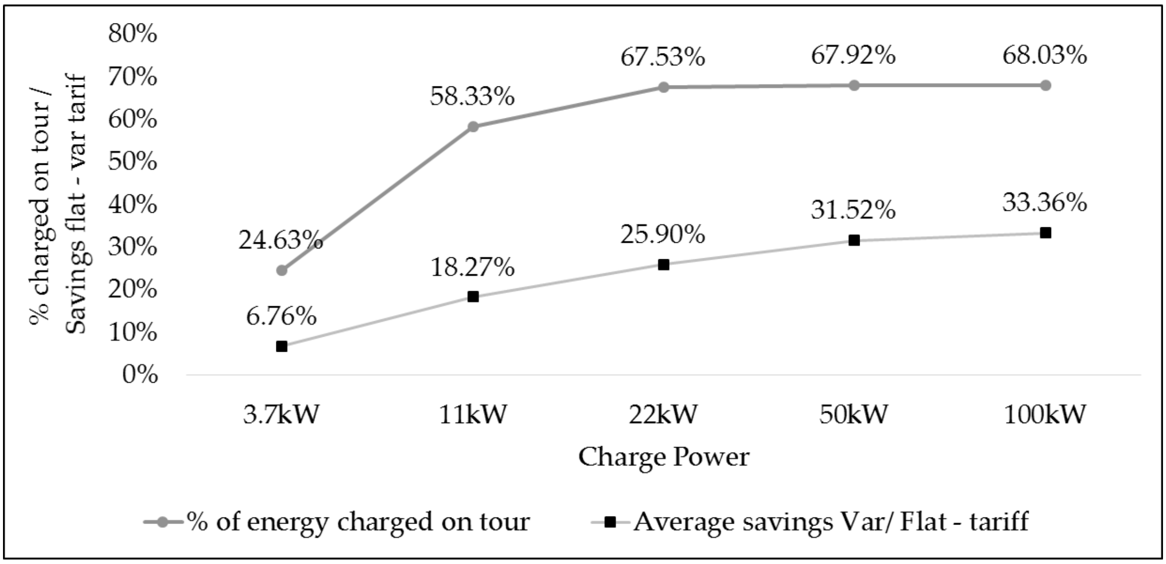

FIGURE 5.5: Scenario VI: Charge on tour and average savings for changing charging power

In Figure 5.5 the charge during the tour in % and the total savings between the scenarios are illustrated. For the former it can be observed that the average charge on tour increases with a greater charging power. However it can also be seen, that the increases stagnate when the charging power is increased above 22 kW. The reason for this trend can be observed when looking at the charging and discharging pattern. Figure 5.6 shows four cases of the charging behavior during the tour. For the 11kW case 10.93 kWh are charged at the depot and rest outside of it. If the charging power is increased to 22 kW and higher the total charge at the depot is 7.90 kWh in every case. This is the required charge to arrive at the first customer. Consequently, the vehicles arrive with a battery at minimum allowed SoC at the first customer and recharge at this location. While the charging pattern change for the different charge power cases above 22kW the amount charged at the depot remains unchanged. This explains the shape of the graph showing the percentage charged on tour in Figure 5.5. The second graph in Figure 5.5 shows the average savings between the flat and variable tariff. In the case of this data it can also be observed, that the average savings increase with an increase in charging power however the increases decline with greater charging power. While the energy charged on tour stays unchanged after the power is increased above 11 kW there are still increases for the savings. This effect can again be explained by the charging pattern depicted in Figure 5.6. With increased charging power a greater charge can occur within the same time-frame. This can also be observed in the charge graph where larger vertical jumps indicate this. This also means that the more energy can be charged for lower energy prices.

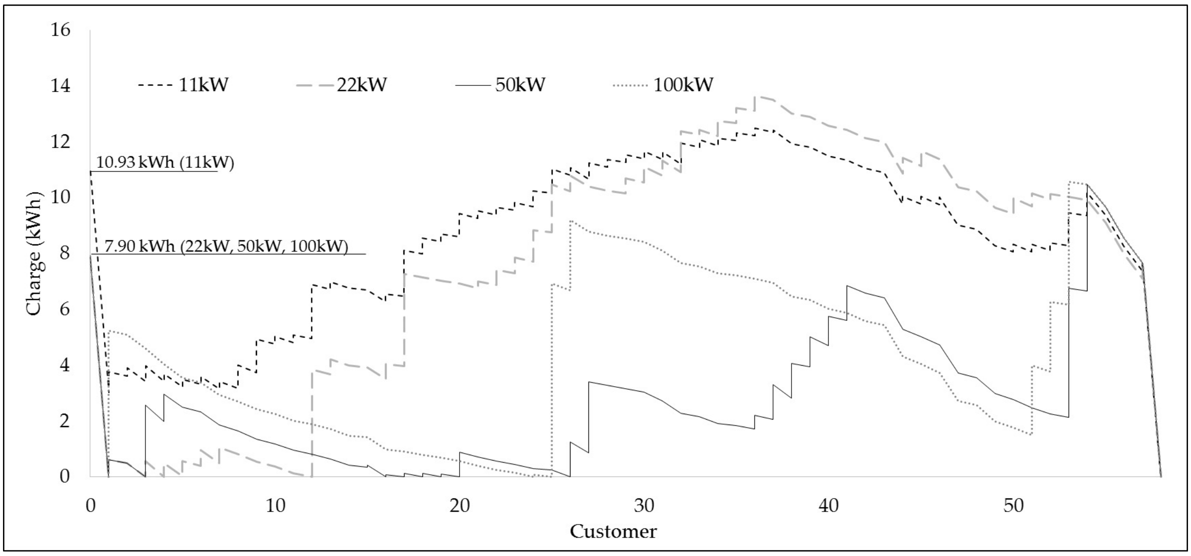

FIGURE 5.6: Scenario VI: Charging Pattern under different charging power

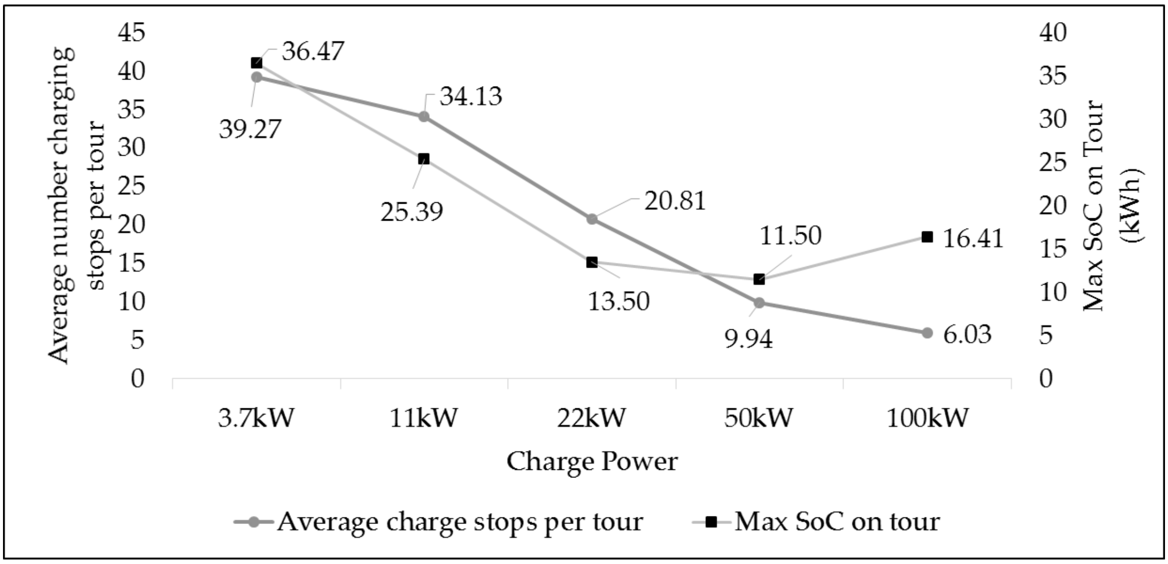

FIGURE 5.7: Scenario VI: Charge stops per Tour and max SoC for changing charging power

Figure 5.7 shows the changes in charges per stop and the maximal SoC with increased charge power. The average charge stops decrease with increases in charge stops. The smallest average amount of charge stops occurs with a charging power of 100 kW at about 6 stops. The biggest decrease occurs if the charging power is increased from 22 kW to 50 kW. As could be seen in Figure 5.5 the charge outside of the depot only decreases to a certain power level. The results for the max SoC are depicted in Figure 5.7. They show a similar pattern to the average number of charge stops until 22 kW, however deviate thereafter. First the max SoC decreases become smaller and reach their minimum at 50 kW. For the highest charging power the max SoC again increases. Since the vehicle can charge more in a shorter amount of time the charges during cheap time intervals increases. If these charging zones are at the beginning of the route the vehicle will charge more cheap energy to offset later increases in costs. In certain cases it may be possible that the SoC within these time intervals is greater than the SoC that the vehicle had when it left the depot. Table A.9 to A.12 show the results of this scenario in more detail. For the results of the 11 kW case see Scenario III.

5.7 Findings

A diesel vehicles energy consumption makes up more than 10% of the objective value in the proposed optimization model. For BEVs, these only make up less than 1%. This means for the optimization of the energy costs to become viable additional benefits need to be generated. Scenario I showed that even though only small cost savings between both the variable and flat tariff are possible the vehicle charges almost 20% of energy outside of the depot. This may reduce the stress on the charge bottleneck. Another benefit that derives from the shift of charging behavior is that the battery can be operated with a lower battery capacity which leads to lower initial purchase costs. The following scenarios further examine and try to improve on this baseline scenario. Scenario II showed that input data and especially service times have significant impact on the results obtained in Scenario I. Scenario II also shows that the clustering only has a positive impact on the objective value as well as total tour time to a certain extent. When the walking time becomes greater than the savings that are generated by not driving certain distance the objective value increases. This is also related to the predominance of the wage costs in comparison to the energy cost.

Clustering of the customers does not only proof to be effective in lowering the tour time and driving distance but also lead to more reasonable number of charging stops. This is especially important for a practical implementation of the model. The best way to synchronize charging times with energy prices is by letting a vehicle execute the predefined route within a certain time interval rather than setting a fixed starting time. Although this increases the average number of stops, the increases in energy cost reductions and charge outside of the depot increase substantially. Scenario IV shows that the overall savings are still greatest when route optimization is considered in comparison to energy optimization. Different factors within the scenarios were also shown to have an impact on the charging pattern and battery size, as for instance shown in Scenario V. The smallest required battery size is required with a variable tariff and a flexible starting time. Finally the last Scenario shows that the charging speed also has an impact on all of the results described above. It could however also be observed that this is only true until a certain extent as the route characteristics required a certain initial charge to reach the first customer. Additionally, a greater charging power can also increase the max battery size. This is caused by an increased charge in cheap charging zones. However other benefits such as a lower number of charging stops or average savings where shown to still prevail.

6 Conclusion

The efficient integration of BEVs into the grid can generate significant benefits on numerous levels. In this chapter a short conclusion shall be presented in order to highlight these benefits as well as present the implications of these findings define future research directions and model extensions.

6.1 Contributions and Implications

The presented model and scenarios address the problem of a smart integration of BEV transport vehicles into the grid pricing patterns with a predefined route. This is done through smart charging with a valley-filling approach. The approach merges previously separate research streams and applies them to the electric vehicle recharging problem. The idea also builds on previous studies of different sectors, for instance the work of Suzuki, 2009 who introduced the vehicle refueling problem for conventional diesel trucks in a similar manner. In this study the model is also solved through a decomposition of route composition and timing of refueling. The results show that offering a variable tariff to transport firms can induce charging outside of the depot. In a best case scenario this charge can even be greater than the charge at the depot. The results of the test cases further illustrate that setting variable prices can create desired benefits. Firstly, the charge costs for the transport firm are reduced. In a best case by about 20.63% per day, which constitute a high return and therefore good incentive for the company. Secondly, more than half of the required energy is charged outside of the depot. This is both a benefit for the transport firm that is able to shift energy consumption from the depot and thereby avoid an energy shortage but also for the utility and grid as loads are shifted to low cost i.e. production surplus zones and distributed over time and geographic location. The differences in the input data also show that some scenarios are better suited for a practical implementation. For instance, longer service times increased the above described benefits. This can be achieved by clustering customers. By far the greatest impact however could be observed when tour times allowed to be flexible. By incorporating real world the model is able to show how incentives for all of the involved partners can be generated. This is a key component for a practical implementation. The expert interviews that were conducted revealed that both the transport firm and utility firm are looking for new ways to integrate BEV charging into their existing infrastructure. While the model creates benefits such as a load shift and reduces the capacity required at the depot the savings produced by the model would be an additional motivation for the partner to consider a decentralized charging of vehicles. Further results can be obtained for the battery size and required charging infrastructure. By implementing the model the required battery size of the vehicle is decreased, which leads to a lower initial investment and thereby also a faster return on investment. In terms of the required charging infrastructure the different scenarios that were presented show that a greater charging power does not necessarily generate proportionate increases in savings and other benefits. In summary the model touches on all three levels (strategic, operational, tactical) as described by Pelletier, Jabali, and Laporte (2016)

The implications of the obtained results are multiple. Firstly, the model shows that purely on a energy cost perspective an electric vehicle is superior to a conventional diesel vehicle. When all other costs are held constant it is favorable for transport firms to switch to all BEV for the delivery of goods. Additional benefits such as reduction in emissions may even offset a higher total cost of acquisition The results also showed that it is favorable in terms of charging outside of the depot to cluster customers. This is both favorable from an energy efficiency standpoint but also reduces overall tour time and therefore has the potential to reduce costs. Clustering can be beneficiary to a certain extent in this case until a cluster of 150m. With a further expansion of the radius some values such as the total delivery time or objective value can increase. For a practical implementation however clustering is an effective way to increase service times and thereby extend potential charging times. The optimized predefined routes make it obvious that in this case this optimization still promises the greatest savings. This means that both that this optimization step is essential and should not be omitted. The reduction of battery size due to an increased charging during the route is a valuable result and implies that smaller battery sizes may be sufficient to meet the requirements of the route. This is an in important consideration for strategic decisions in a firm. Lastly, the variation of the charging power showed that for the presented cases faster charging technologies do not necessarily yield a substantially higher increase of the benefits. The implication is that current charging technology are sufficient for an implementation.

6.2 Model Extensions and Further Research

While the model yields many results that create important implications for a real world application further research needs to be conducted to allow for an easier application and implementation. These can generally be divided into recommendations that are connected to model extensions and general further research in the area of dynamic pricing of electric delivery vehicles. A simple modification could be undertaken in the varying the input data of the model. By changing the route profile for instance by shifting the depot location to be in a more central location new implications for vehicle characteristics such as battery size may be gained. It could also be interesting to restrict charging to a few customer locations and to have different charging speeds at these locations. Another adaption would be to cluster the provided data with different approaches. By differentiating between these styles the impact could be determined. Furthermore it would be possible to apply this method to cluster customer nodes at real world charging stations. In terms of the real world application it may also be important to consider additional time for engaging and disengaging the charge of the vehicle. This is however dependent on future developments as technologies such as inductive charging would not require this kind of driver input.

The model does not consider any conversion losses as these don't have an influence on the effect imposed by the a different tariff structure. However to increase the degree of realism of the model these should also be considered. An extension of this consideration would be to also include charge specific components in the charging of vehicles, as for instance vehicles can charge faster in if they the battery is not fully depleted. This may lead to different results in terms of the battery size and SoC throughout the tour. In the current model only the latest arrival and departure time are predetermined. However delivery drivers mostly work in shifts, for example 7 hours long. In the presented scenarios this would mean that the actual delivery time of the driver would always smaller than the actual working time. Two extensions are possible in this regard firstly, a vehicle could be able to return to the depot and reload and head out for another tour or a flat-rate for the driver could be set. This would enable the vehicle to have charging stops that are longer than the service time without incurring a penalty in the form of an increased wage. The effect of instability in driving times, for instance caused by congestion or longer/shorter service times, also needs to be investigated. This could be incorporated by only allowing a charge inside a charging zone with a time certain buffer.

While the model is able to stimulate a load shift on the grid level more decentralized optimization strategies may also need to be considered. In a first step this means, that proxies for lower level grid energy consumption and utilization should be integrated to analyze the effects that the proposed pricing model has on this level of the grid. Additionally, a real time vehicle charge management could be considered in a next step. This may be able overcome some of the limitations of the proposed model. In this scenario vehicles could be used to offset a capacity surplus for the utility or even provide balancing energy in a V2G scenario, as it has been shown in non-commercial vehicle literature. To show the potential of coordinating production and consumption through price incentives a further more direct applications could also be created by integrating the real time production of regenerative power plants. Furthermore it would also be interesting to consider and integrate a scenario that considers autonomous driving, as this would offset the need for a driver and would have a significant impact on the objective function and the overall model.

A Appendix

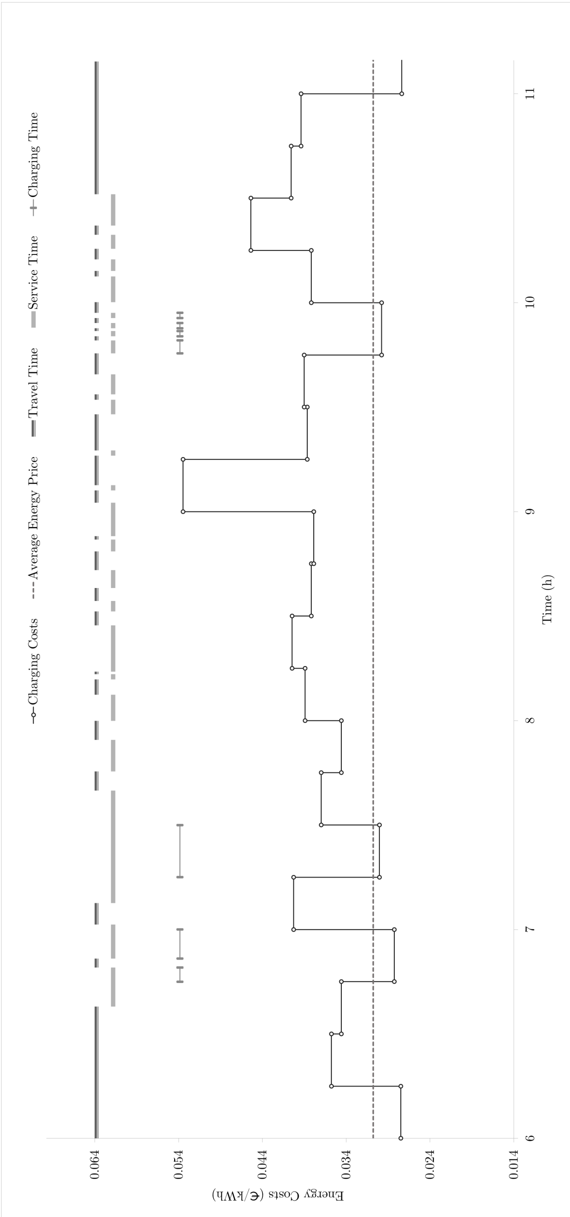

FIGURE A.1: Scenario I: Example tour charging patterns detailed view

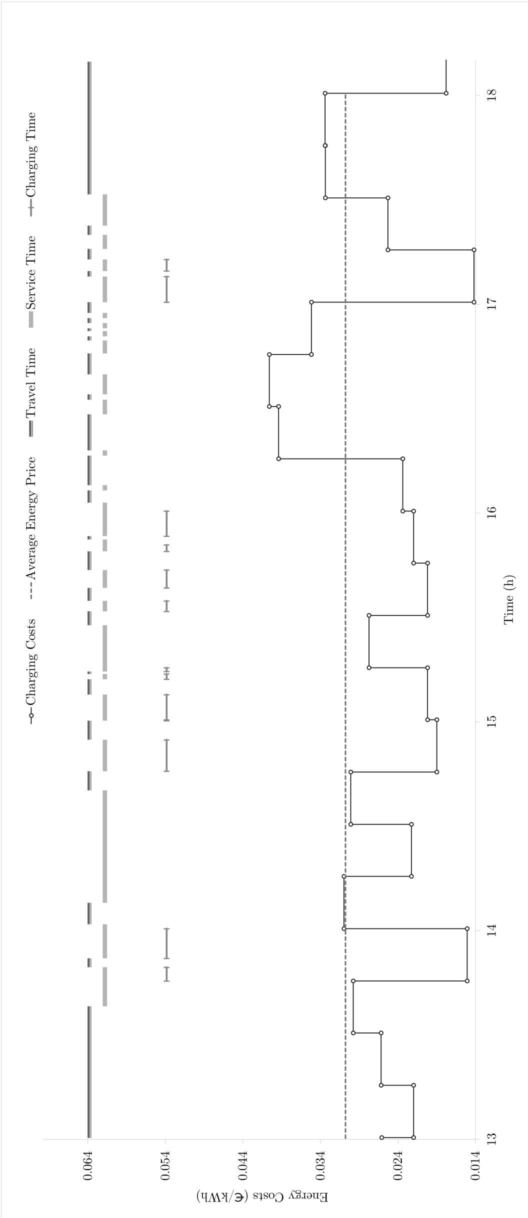

FIGURE A.2: Scenario III: Example tour charging patterns detailed view

TABLE A.1: ScenarioI Clustering 50m: Results

	Diesel		BEV Flat Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Max SoC [kw]	Charged on Tour (%)
1_0_11	1098.60	117.4 (10.69%)	989.82	8.62 (0.77%)	40.43	0%
2_0_10	1022.95	108.54 (10.61%)	922.38	7.98 (0.86%)	40.43	0%
3_0_9	965.32	101.78 (10.54%)	871.02	7.48 (0.85%)	40.43	0%
4_0_8	835.44	87.76 (10.5%)	754.13	6.45 (0.84%)	40.43	0%
5_0_7	748.83	79.14 (10.57%)	675.51	5.82 (0.84%)	40.43	0%
6_0_6	668.10	68.96 (10.32%)	604.22	5.08 (0.84%)	40.43	0%
7_0_5	567.57	59.76 (10.53%)	512.21	4.4 (0.84%)	40.43	0%
8_0_4	426.97	43.13 (10.1%)	387.02	3.18 (0.82%)	35.11	0%
9_0_3	319.02	32.82 (10.29%)	288.61	2.41 (0.84%)	35.11	0%
10_0_2	186.09	18.36 (9.86%)	169.08	1.35 (0.8%)	22.41	0%
11_0_1	85.95	9.13 (10.63%)	77.48	0.67 (0.81%)	22.12	0%
Average	**629.53**	**66.07 (10.42%)**	**568.32**	**4.86 (0.85%)**	**36.16**	**0%**

			BEV Variable Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	989.63	8.43 (0.85%)	21.13%	31.28	154 (511)	2.17%
2_0_10	922.20	7.79 (0.84%)	22.08%	31.28	147 (486)	2.33%
3_0_9	870.84	7.31 (0.84%)	22.02%	31.28	139 (462)	2.35%
4_0_8	753.99	6.3 (0.84%)	22.10%	31.28	114 (397)	2.28%
5_0_7	675.36	5.68 (0.84%)	22.36%	31.28	105 (357)	2.47%
6_0_6	604.08	4.93 (0.82%)	23.86%	31.28	95 (328)	2.80%
7_0_5	512.09	4.28 (0.84%)	23.03%	31.28	82 (279)	2.78%
8_0_4	386.95	3.1 (0.8%)	23.18%	25.77	58 (219)	2.32%
9_0_3	288.57	2.37 (0.82%)	21.68%	25.77	45 (160)	1.84%
10_0_2	169.07	1.33 (0.79%)	17.80%	18.55	17 (91)	1.17%
11_0_1	77.48	0.67 (0.86%)	16.18%	18.55	6 (42)	0.44%
Average	**568.20**	**4.75 (0.83%)**	**21.40%**	**27.96**	**87.45 (302.91)**	**2.09%**

TABLE A.2: ScenarioI Clustering 100m: Results

	Diesel		BEV Flat Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Max SoC [kw]	Charged on Tour (%)
1_0_11	1066.84	112.63 (10.56%)	962.47	8.27 (0.77%)	38.95	0%
2_0_10	994.47	104.04 (10.46%)	898.07	7.64 (0.86%)	38.95	0%
3_0_9	933.26	97.18 (10.41%)	843.21	7.14 (0.85%)	38.95	0%
4_0_8	810.52	84.12 (10.38%)	732.58	6.18 (0.84%)	38.95	0%
5_0_7	730.22	76.11 (10.42%)	659.70	5.6 (0.84%)	38.95	0%
6_0_6	649.24	66 (10.17%)	588.09	4.86 (0.84%)	38.95	0%
7_0_5	557.70	57.72 (10.35%)	504.23	4.25 (0.84%)	38.95	0%
8_0_4	419.47	41.7 (9.94%)	380.83	3.07 (0.82%)	34.36	0%
9_0_3	309.98	31.27 (10.09%)	281.00	2.3 (0.84%)	34.36	0%
10_0_2	178.56	17.12 (9.59%)	162.70	1.26 (0.8%)	21.81	0%
11_0_1	85.88	9.03 (10.52%)	77.50	0.66 (0.81%)	21.88	0%
Average	**612.37**	**63.36 (10.26%)**	**553.67**	**4.66 (0.83%)**	**35.00**	**0%**

			BEV Variable Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	962.31	8.11 (0.84%)	20.79%	29.55	126 (435)	1.95%
2_0_10	897.91	7.48 (0.83%)	21.91%	29.55	120 (413)	2.10%
3_0_9	843.07	7 (0.83%)	21.66%	29.55	118 (395)	2.05%
4_0_8	732.45	6.05 (0.83%)	22.20%	29.55	100 (333)	2.14%
5_0_7	659.58	5.47 (0.83%)	21.61%	29.55	88 (299)	2.21%
6_0_6	587.97	4.74 (0.81%)	23.38%	29.55	80 (274)	2.51%
7_0_5	504.11	4.13 (0.82%)	23.59%	29.55	74 (239)	2.82%
8_0_4	380.76	3 (0.79%)	23.38%	25.81	49 (184)	2.36%
9_0_3	280.96	2.25 (0.8%)	23.06%	25.81	38 (136)	2.08%
10_0_2	162.69	1.24 (0.76%)	21.55%	17.71	15 (75)	1.29%
11_0_1	77.50	0.66 (0.85%)	19.68%	17.58	6 (37)	0.57%
Average	**553.57**	**4.56 (0.82%)**	**22.07%**	**26.71**	**74 (256.36)**	**2.01%**

TABLE A.3: ScenarioI Clustering 150m: Results

Route_Clustering _No-of-Tours	Diesel Objective Value (OV) [€]	Diesel Energy Consumption [€] (% of OV)	BEV Flat Tariff Objective Value (OV) [€]	BEV Flat Tariff Energy Consumption [€] (% of OV)	BEV Flat Tariff Max SoC [kw]	BEV Flat Tariff Charged on Tour (%)
1_0_11	1044.60	109.61 (10.49%)	943.03	8.05 (0.77%)	38.95	0%
2_0_10	975.60	101.28 (10.38%)	881.76	7.44 (0.86%)	38.95	0%
3_0_9	920.59	95 (10.32%)	832.57	6.98 (0.85%)	38.95	0%
4_0_8	796.47	81.95 (10.29%)	720.54	6.02 (0.84%)	38.95	0%
5_0_7	715.84	74.3 (10.38%)	647.01	5.46 (0.84%)	38.95	0%
6_0_6	634.89	64.22 (10.12%)	575.40	4.73 (0.84%)	38.95	0%
7_0_5	544.22	56.1 (10.31%)	492.25	4.13 (0.84%)	38.95	0%
8_0_4	405.78	40.05 (9.87%)	368.68	2.95 (0.82%)	34.32	0%
9_0_3	301.26	30.23 (10.03%)	273.26	2.22 (0.84%)	34.32	0%
10_0_2	169.56	16.09 (9.49%)	154.65	1.18 (0.8%)	19.99	0%
11_0_1	79.79	8.25 (10.33%)	72.15	0.61 (0.81%)	19.99	0%
Average	**598.96**	**61.55 (10.18%)**	**541.94**	**4.53 (0.83%)**	**34.66**	**0%**

Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	BEV Variable Tariff Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	942.86	7.87 (0.83%)	22.82%	29.55	117 (377)	2.20%
2_0_10	881.59	7.27 (0.82%)	24.34%	29.55	114 (356)	2.36%
3_0_9	832.40	6.82 (0.82%)	24.39%	29.55	111 (345)	2.39%
4_0_8	720.39	5.88 (0.82%)	24.92%	29.55	93 (288)	2.42%
5_0_7	646.86	5.32 (0.82%)	25.49%	29.55	90 (263)	2.69%
6_0_6	575.25	4.58 (0.8%)	27.58%	29.55	83 (239)	3.08%
7_0_5	492.11	4 (0.81%)	26.73%	29.55	77 (214)	3.27%
8_0_4	368.60	2.86 (0.78%)	28.25%	25.23	52 (159)	2.97%
9_0_3	273.21	2.17 (0.8%)	26.06%	25.23	41 (120)	2.23%
10_0_2	154.64	1.17 (0.76%)	25.68%	15.16	16 (61)	1.37%
11_0_1	72.15	0.6 (0.83%)	24.19%	15.16	8 (30)	0.61%
Average	**541.82**	**4.41 (0.81%)**	**25.50%**	**26.15**	**72.91 (222.91)**	**2.33%**

TABLE A.4: ScenarioI Clustering 200m: Results

	Diesel		BEV Flat Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Max SoC [kw]	Charged on Tour (%)
1_0_11	1047.74	106.89 (10.2%)	948.70	7.85 (0.77%)	37.93	0%
2_0_10	978.68	98.64 (10.08%)	887.28	7.25 (0.86%)	37.93	0%
3_0_9	922.49	92.73 (10.05%)	836.57	6.82 (0.85%)	37.93	0%
4_0_8	801.10	80.29 (10.02%)	726.71	5.9 (0.84%)	37.93	0%
5_0_7	720.52	72.66 (10.08%)	653.20	5.34 (0.84%)	37.93	0%
6_0_6	640.70	62.68 (9.78%)	582.63	4.62 (0.84%)	37.93	0%
7_0_5	550.44	54.52 (9.9%)	499.94	4.02 (0.84%)	37.93	0%
8_0_4	412.51	38.92 (9.43%)	376.46	2.87 (0.82%)	34.23	0%
9_0_3	306.82	29.56 (9.63%)	279.43	2.18 (0.84%)	34.23	0%
10_0_2	174.75	15.47 (8.85%)	160.42	1.14 (0.8%)	18.90	0%
11_0_1	79.85	7.69 (9.63%)	72.73	0.56 (0.81%)	18.64	0%
Average	**603.23**	**60 (9.79%)**	**547.64**	**4.41 (0.79%)**	**33.77**	**0%**

			BEV Variable Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	948.51	7.66 (0.81%)	25.61%	26.37	111 (331)	2.44%
2_0_10	887.09	7.06 (0.8%)	27.39%	26.37	108 (312)	2.63%
3_0_9	836.39	6.63 (0.79%)	29.02%	26.37	110 (304)	2.68%
4_0_8	726.55	5.74 (0.79%)	30.15%	26.37	94 (251)	2.71%
5_0_7	653.04	5.18 (0.79%)	30.48%	26.37	89 (229)	3.04%
6_0_6	582.47	4.46 (0.76%)	33.11%	26.37	82 (206)	3.48%
7_0_5	499.79	3.87 (0.77%)	33.19%	26.37	74 (183)	3.65%
8_0_4	376.37	2.78 (0.74%)	34.27%	23.45	51 (134)	3.08%
9_0_3	279.37	2.12 (0.76%)	32.78%	23.45	40 (104)	2.55%
10_0_2	160.40	1.12 (0.7%)	33.96%	12.69	16 (50)	1.82%
11_0_1	72.72	0.56 (0.77%)	35.06%	12.10	7 (24)	0.85%
Average	**547.52**	**4.29 (0.77%)**	**31.37%**	**23.30**	**71.09 (193.45)**	**2.63%**

TABLE A.5: ScenarioIII Clustering 50m: Results

	Diesel		BEV Flat Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Max SoC [kw]	Charged on Tour (%)
1_0_11	1098.60	117.4 (10.69%)	989.82	8.62 (0.77%)	40.43	0%
2_0_10	1022.95	108.54 (10.61%)	922.38	7.98 (0.86%)	40.43	0%
3_0_9	965.32	101.78 (10.54%)	871.02	7.48 (0.85%)	40.43	0%
4_0_8	835.44	87.76 (10.5%)	754.13	6.45 (0.84%)	40.43	0%
5_0_7	748.83	79.14 (10.57%)	675.51	5.82 (0.84%)	40.43	0%
6_0_6	668.10	68.96 (10.32%)	604.22	5.08 (0.84%)	40.43	0%
7_0_5	567.57	59.76 (10.53%)	512.21	4.4 (0.84%)	40.43	0%
8_0_4	426.97	43.13 (10.1%)	387.02	3.18 (0.82%)	35.11	0%
9_0_3	319.02	32.82 (10.29%)	288.61	2.41 (0.84%)	35.11	0%
10_0_2	186.09	18.36 (9.86%)	169.08	1.35 (0.8%)	22.41	0%
11_0_1	85.95	9.13 (10.63%)	77.48	0.67 (0.81%)	22.12	0%
Average	**629.53**	**66.07 (10.42%)**	**568.32**	**4.86 (0.85%)**	**36.16**	**0%**

			BEV Variable Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	989.63	8.43 (0.85%)	21.13%	31.28	154 (511)	2.17%
2_0_10	922.20	7.79 (0.84%)	22.08%	31.28	147 (486)	2.33%
3_0_9	870.84	7.31 (0.84%)	22.02%	31.28	139 (462)	2.35%
4_0_8	753.99	6.3 (0.84%)	22.10%	31.28	114 (397)	2.28%
5_0_7	675.36	5.68 (0.84%)	22.36%	31.28	105 (357)	2.47%
6_0_6	604.08	4.93 (0.82%)	23.86%	31.28	95 (328)	2.80%
7_0_5	512.09	4.28 (0.84%)	23.03%	31.28	82 (279)	2.78%
8_0_4	386.95	3.1 (0.8%)	23.18%	25.77	58 (219)	2.32%
9_0_3	288.57	2.37 (0.82%)	21.68%	25.77	45 (160)	1.84%
10_0_2	169.07	1.33 (0.79%)	17.80%	18.55	17 (91)	1.17%
11_0_1	77.48	0.67 (0.86%)	16.18%	18.55	6 (42)	0.44%
Average	**568.20**	**4.75 (0.83%)**	**21.40%**	**27.96**	**87.45 (302.91)**	**2.09%**

TABLE A.6: ScenarioIII Clustering 100m: Results

Route_Clustering _No-of-Tours	Diesel Objective Value (OV) [€]	Diesel Energy Consumption [€] (% of OV)	BEV Flat Tariff Objective Value (OV) [€]	BEV Flat Tariff Energy Consumption [€] (% of OV)	BEV Flat Tariff Max SoC [kw]	BEV Flat Tariff Charged on Tour (%)
1_0_11	1066.84	112.63 (10.56%)	962.47	8.27 (0.77%)	38.95	0%
2_0_10	994.47	104.04 (10.46%)	898.07	7.64 (0.86%)	38.95	0%
3_0_9	933.26	97.18 (10.41%)	843.21	7.14 (0.85%)	38.95	0%
4_0_8	810.52	84.12 (10.38%)	732.58	6.18 (0.84%)	38.95	0%
5_0_7	730.22	76.11 (10.42%)	659.70	5.6 (0.84%)	38.95	0%
6_0_6	649.24	66 (10.17%)	588.09	4.86 (0.84%)	38.95	0%
7_0_5	557.70	57.72 (10.35%)	504.23	4.25 (0.84%)	38.95	0%
8_0_4	419.47	41.7 (9.94%)	380.83	3.07 (0.82%)	34.36	0%
9_0_3	309.98	31.27 (10.09%)	281.00	2.3 (0.84%)	34.36	0%
10_0_2	178.56	17.12 (9.59%)	162.70	1.26 (0.8%)	21.81	0%
11_0_1	85.88	9.03 (10.52%)	77.50	0.66 (0.81%)	21.88	0%
Average	**612.37**	**63.36 (10.26%)**	**553.67**	**4.66 (0.83%)**	**35.00**	**0%**

Route_Clustering _No-of-Tours	BEV Variable Tariff Objective Value (OV) [€]	BEV Variable Tariff Energy Consumption [€] (% of OV)	BEV Variable Tariff Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	962.31	8.11 (0.84%)	20.79%	29.55	126 (435)	1.95%
2_0_10	897.91	7.48 (0.83%)	21.91%	29.55	120 (413)	2.10%
3_0_9	843.07	7 (0.83%)	21.66%	29.55	118 (395)	2.05%
4_0_8	732.45	6.05 (0.83%)	22.20%	29.55	100 (333)	2.14%
5_0_7	659.58	5.47 (0.83%)	21.61%	29.55	88 (299)	2.21%
6_0_6	587.97	4.74 (0.81%)	23.38%	29.55	80 (274)	2.51%
7_0_5	504.11	4.13 (0.82%)	23.59%	29.55	74 (239)	2.82%
8_0_4	380.76	3 (0.79%)	23.38%	25.81	49 (184)	2.36%
9_0_3	280.96	2.25 (0.8%)	23.06%	25.81	38 (136)	2.08%
10_0_2	162.69	1.24 (0.76%)	21.55%	17.71	15 (75)	1.29%
11_0_1	77.50	0.66 (0.85%)	19.68%	17.58	6 (37)	0.57%
Average	**553.57**	**4.56 (0.82%)**	**22.07%**	**26.71**	**74 (256.36)**	**2.01%**

TABLE A.7: ScenarioIII Clustering 150m: Results

	Diesel		BEV Flat Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Max SoC [kw]	Charged on Tour (%)
1_0_11	1044.60	109.61 (10.49%)	943.03	8.05 (0.77%)	38.95	0%
2_0_10	975.60	101.28 (10.38%)	881.76	7.44 (0.86%)	38.95	0%
3_0_9	920.59	95 (10.32%)	832.57	6.98 (0.85%)	38.95	0%
4_0_8	796.47	81.95 (10.29%)	720.54	6.02 (0.84%)	38.95	0%
5_0_7	715.84	74.3 (10.38%)	647.01	5.46 (0.84%)	38.95	0%
6_0_6	634.89	64.22 (10.12%)	575.40	4.73 (0.84%)	38.95	0%
7_0_5	544.22	56.1 (10.31%)	492.25	4.13 (0.84%)	38.95	0%
8_0_4	405.78	40.05 (9.87%)	368.68	2.95 (0.82%)	34.32	0%
9_0_3	301.26	30.23 (10.03%)	273.26	2.22 (0.84%)	34.32	0%
10_0_2	169.56	16.09 (9.49%)	154.65	1.18 (0.8%)	19.99	0%
11_0_1	79.79	8.25 (10.33%)	72.15	0.61 (0.81%)	19.99	0%
Average	**598.96**	**61.55 (10.18%)**	**541.94**	**4.53 (0.83%)**	**34.66**	**0%**

			BEV Variable Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	942.86	7.87 (0.83%)	22.82%	29.55	117 (377)	2.20%
2_0_10	881.59	7.27 (0.82%)	24.34%	29.55	114 (356)	2.36%
3_0_9	832.40	6.82 (0.82%)	24.39%	29.55	111 (345)	2.39%
4_0_8	720.39	5.88 (0.82%)	24.92%	29.55	93 (288)	2.42%
5_0_7	646.86	5.32 (0.82%)	25.49%	29.55	90 (263)	2.69%
6_0_6	575.25	4.58 (0.8%)	27.58%	29.55	83 (239)	3.08%
7_0_5	492.11	4 (0.81%)	26.73%	29.55	77 (214)	3.27%
8_0_4	368.60	2.86 (0.78%)	28.25%	25.23	52 (159)	2.97%
9_0_3	273.21	2.17 (0.8%)	26.06%	25.23	41 (120)	2.23%
10_0_2	154.64	1.17 (0.76%)	25.68%	15.16	16 (61)	1.37%
11_0_1	72.15	0.6 (0.83%)	24.19%	15.16	8 (30)	0.61%
Average	**541.82**	**4.41 (0.81%)**	**25.50%**	**26.15**	**72.91 (222.91)**	**2.33%**

TABLE A.8: ScenarioIII Clustering 200m: Results

	Diesel		BEV Flat Tariff			
Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	Max SoC [kw]	Charged on Tour (%)
1_0_11	1047.74	106.89 (10.2%)	948.70	7.85 (0.77%)	37.93	0%
2_0_10	978.68	98.64 (10.08%)	887.28	7.25 (0.86%)	37.93	0%
3_0_9	922.49	92.73 (10.05%)	836.57	6.82 (0.85%)	37.93	0%
4_0_8	801.10	80.29 (10.02%)	726.71	5.9 (0.84%)	37.93	0%
5_0_7	720.52	72.66 (10.08%)	653.20	5.34 (0.84%)	37.93	0%
6_0_6	640.70	62.68 (9.78%)	582.63	4.62 (0.84%)	37.93	0%
7_0_5	550.44	54.52 (9.9%)	499.94	4.02 (0.84%)	37.93	0%
8_0_4	412.51	38.92 (9.43%)	376.46	2.87 (0.82%)	34.23	0%
9_0_3	306.82	29.56 (9.63%)	279.43	2.18 (0.84%)	34.23	0%
10_0_2	174.75	15.47 (8.85%)	160.42	1.14 (0.8%)	18.90	0%
11_0_1	79.85	7.69 (9.63%)	72.73	0.56 (0.81%)	18.64	0%
Average	**603.23**	**60 (9.79%)**	**547.64**	**4.41 (0.79%)**	**33.77**	**0%**

Route_Clustering _No-of-Tours	Objective Value (OV) [€]	Energy Consumption [€] (% of OV)	BEV Variable Tariff Charged on Tour	Max SoC [kw]	Charge Times (No of total stops)	Energy Cost Savings BEV Flat Tariff / BEV Variable Tariff
1_0_11	948.51	7.66 (0.81%)	25.61%	26.37	111 (331)	2.44%
2_0_10	887.09	7.06 (0.8%)	27.39%	26.37	108 (312)	2.63%
3_0_9	836.39	6.63 (0.79%)	29.02%	26.37	110 (304)	2.68%
4_0_8	726.55	5.74 (0.79%)	30.15%	26.37	94 (251)	2.71%
5_0_7	653.04	5.18 (0.79%)	30.48%	26.37	89 (229)	3.04%
6_0_6	582.47	4.46 (0.76%)	33.11%	26.37	82 (206)	3.48%
7_0_5	499.79	3.87 (0.77%)	33.19%	26.37	74 (183)	3.65%
8_0_4	376.37	2.78 (0.74%)	34.27%	23.45	51 (134)	3.08%
9_0_3	279.37	2.12 (0.76%)	32.78%	23.45	40 (104)	2.55%
10_0_2	160.40	1.12 (0.7%)	33.96%	12.69	16 (50)	1.82%
11_0_1	72.72	0.56 (0.77%)	35.06%	12.10	7 (24)	0.85%
Average	**547.52**	**4.29 (0.77%)**	**31.37%**	**23.30**	**71.09 (193.45)**	**2.63%**

TABLE A.9: Scenario VI: 3.7 kW charging power

Clustering	Energy Costs (Flat) [€]	Energy Costs (Var) [€]	Energy Cost Reduction BEV Flat / BEV Var
0m	56.74	53.96	5.11%
50m	53.44	50.41	5.94%
100m	51.24	47.93	6.76%
150m	49.79	46.25	7.48%
200m	48.54	44.67	8.50%
Average	**51.95**	**48.64**	**6.76%**
Clustering	Average no of charging stops / Tour	Charge outside of Depot (%)	Charge outside of Depot (kWh)
0m	55.44	19.38%	362.72
50m	41.79	21.94%	386.85
100m	36.67	24.74%	418.18
150m	32.83	27.24%	447.46
200m	29.64	29.86%	478.10
Average	**39.27**	**24.63%**	**418.66**

TABLE A.10: Scenario VI: 22 kW charging power

Clustering	Energy Costs (Flat) [€]	Energy Costs (Var) [€]	Energy Cost Reduction BEV Flat / BEV Var
0m	56.74	43.13	24.53%
50m	53.44	40.01	25.68%
100m	51.24	38.09	26.02%
150m	49.79	36.85	26.33%
200m	48.54	35.58	26.95%
Average	**51.95**	**38.73**	**25.90%**
Clustering	Average no of charging stops / Tour	Charge outside of Depot (%)	Charge outside of Depot (kWh)
0m	34.00	69.27%	1296.76
50m	23.42	68.13%	1201.08
100m	18.36	67.93%	1148.38
150m	15.44	66.75%	1096.48
200m	12.82	65.58%	1050.20
Average	**20.81**	**67.53%**	**1158.58**

TABLE A.11: Scenario VI: 50 kW charging power

Clustering	Energy Costs (Flat) [€]	Energy Costs (Var) [€]	Energy Cost Reduction BEV Flat / BEV Var
0m	56.74	39.24	31.01%
50m	53.44	36.45	32.07%
100m	51.24	34.90	32.01%
150m	49.79	34.12	31.49%
200m	48.54	33.36	31.03%
Average	**51.95**	**35.61**	**31.52%**
Clustering	Average no of charging stops / Tour	Charge outside of Depot (%)	Charge outside of Depot (kWh)
0m	16.06	70.49%	1319.66
50m	10.94	68.96%	1215.81
100m	8.67	67.83%	1146.61
150m	8.14	66.72%	1095.98
200m	5.91	65.62%	1050.79
Average	**9.94**	**67.92%**	**1165.77**

TABLE A.12: Scenario VI: 100 kW charging power

Clustering	Energy Costs (Flat) [€]	Energy Costs (Var) [€]	Energy Cost Reduction BEV Flat / BEV Var
0m	56.74	37.33	34.25%
50m	53.44	35.30	34.03%
100m	51.24	34.03	33.55%
150m	49.79	33.35	32.72%
200m	48.54	32.70	32.23%
Average	**51.95**	**34.54**	**33.36%**
Clustering	Average no of charging stops / Tour	Charge outside of Depot (%)	Charge outside of Depot (kWh)
0m	8.80	70.38%	1317.42
50m	6.80	68.95%	1215.62
100m	5.48	68.09%	1151.10
150m	5.02	66.90%	1098.96
200m	4.03	65.82%	1054.03
Average	**6.03**	**68.03%**	**1167.43**

Bibliography

Alonso, Monica et al. (2014). "Optimal Charging Scheduling of Electric Vehicles in Smart Grids by Heuristic Algorithms". In: *Energies* 7.4, pp. 2449–2475. ISSN: 1996-1073. DOI: 10.3390/en7042449.

Bashash, S., S J Moura, and H K Fathy (2010). "Charge trajectory optimization of plug-in hybrid electric vehicles for energy cost reduction and battery health enhancement". In: *Proceedings of the 2010 American Control Conference*. IEEE, pp. 5824–5831. ISBN: 978-1-4244-7427-1. DOI: 10.1109/ACC.2010.5530497.

Bessa, R. J. et al. (2011). "Models for the EV aggregation agent business". In: *2011 IEEE Trondheim PowerTech*. IEEE, pp. 1–8. ISBN: 978-1-4244-8418-8. DOI: 10.1109/PTC.2011.6019221.

Bruglieri, Maurizio et al. (2015). "A Variable Neighborhood Search Branching for the Electric Vehicle Routing Problem with Time Windows". In: *Electronic Notes in Discrete Mathematics* 47, pp. 221–228. ISSN: 15710653. DOI: 10.1016/j.endm.2014.11.029. arXiv: 1506.00211.

Cao, Yijia et al. (2012). "An optimized EV charging model considering TOU price and SOC curve". In: *IEEE Transactions on Smart Grid* 3.1, pp. 388–393. ISSN: 19493053. DOI: 10.1109/TSG.2011.2159630.

Capasso, Clemente and Ottorino Veneri (2015). "Experimental study of a DC charging station for full electric and plug in hybrid vehicles". In: *Applied Energy* 152, pp. 131–142. ISSN: 03062619. DOI: 10.1016/j.apenergy.2015.04.040.

Chan, C. C. (2007). "The State of the Art of Electric, Hybrid, and Fuel Cell Vehicles". In: *Proceedings of the IEEE* 95.4, pp. 704–718. ISSN: 0018-9219. DOI: 10.1109/JPROC.2007.892489.

Clarke, G. and J. W. Wright (1964). “Scheduling of Vehicles from a Central Depot to a Number of Delivery Points”. In: *Operations Research* 12.4, pp. 568–581. ISSN: 0030-364X. DOI: 10.1287/opre.12.4.568. arXiv: arXiv:1011.1669v3.

Croes, A (1958). “A Method for Solving Traveling-Salesman Problems”. In: *Operations Research* 6.6, pp. 791–812.

Daimler (2016). *A Joint Venture for Ultra-Fast, High-Power Charging Along*. URL: http://media.daimler.com/marsMediaSite/en/instance/ko/BMW-Group-Daimler-AG-Ford-Motor-Company-and-Volkswagen-Group.xhtml?oid=14866747 (visited on 01/07/2017).

Dantzig, G. B. and J. H. Ramser (1959). “The Truck Dispatching Problem”. In: *Management Science* 6.1, pp. 80–91. ISSN: 0025-1909. DOI: 10.1287/mnsc.6.1.80.

Demir, Emrah, Tolga Bektas, and Gilbert Laporte (2014). “The bi-objective Pollution-Routing Problem”. In: *European Journal of Operational Research* 232.3, pp. 464–478. ISSN: 03772217. DOI: 10.1016/j.ejor.2013.08.002.

Eaves, Stephen and James Eaves (2004). “A cost comparison of fuel-cell and battery electric vehicles”. In: *Journal of Power Sources* 130.1-2, pp. 208–212. ISSN: 03787753. DOI: 10.1016/j.jpowsour.2003.12.016.

EPEX (2016a). *Basics of the Power Market*. URL: https://www.epexspot.com/en/company-info/basics_of_the_power_market (visited on 10/11/2016).

— (2016b). *EPEX SPOT SE: Intraday Continuous Market Data*. URL: https://www.epexspot.com/en/market-data/intradaycontinuous (visited on 01/17/2017).

Flath, Christoph M et al. (2014). “Improving Electric Vehicle Charging Coordination Through Area Pricing”. In: *Transportation Science* 48.4, pp. 619–634. ISSN: 0041-1655. DOI: 10.1287/trsc.2013.0467.

García-Villalobos, J. et al. (2014). “Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches”. In: *Renewable and Sustainable Energy Reviews* 38, pp. 717–731. ISSN: 13640321. DOI: 10.1016/j.rser.2014.07.040.

Glachant, Jean-Michel (2013). “Epilogue”. In: *Evolution of Global Electricity Markets*. Elsevier, pp. 791–798. DOI: 10.1016/B978-0-12-397891-2.00037-7.

Gonzalez Vaya, M. and Goran Andersson (2012). “Centralized and decentralized approaches to smart charging of plug-in Vehicles”. In: *2012 IEEE Power and Energy Society General*

Meeting. IEEE, pp. 1–8. ISBN: 978-1-4673-2729-9. DOI: `10.1109/PESGM.2012.6344902`.

Graeber, Dietmar Richard (2014). "Vermarktung von Strom aus erneuerbaren Energien". In: *Handel mit Strom aus erneuerbaren Energien*, pp. 25–40. DOI: `10.1007/978-3-658-05941-5_4`.

Hayes, John G. et al. (2011). "Simplified electric vehicle power train models and range estimation". In: *2011 IEEE Vehicle Power and Propulsion Conference*. IEEE, pp. 1–5. ISBN: 978-1-61284-248-6. DOI: `10.1109/VPPC.2011.6043163`.

Hong Lin, Shieu Hong, Nate Gertsch, and Jennifer R. Russell (2007). "A linear-time algorithm for finding optimal vehicle refueling policies". In: *Operations Research Letters* 35.3, pp. 290–296. ISSN: 01676377. DOI: `10.1016/j.orl.2006.05.003`.

Hoog, Julian De et al. (2015). "Optimal Charging of Electric Vehicles Taking Distribution Network Constraints Into Account". In: *IEEE Transactions on Power Systems* 30.1, pp. 365–375.

Keskin, Merve and Bülent Çatay (2016). "Partial recharge strategies for the electric vehicle routing problem with time windows". In: *Transportation Research Part C: Emerging Technologies* 65, pp. 111–127. ISSN: 0968090X. DOI: `10.1016/j.trc.2016.01.013`.

Laporte, G (1992). "The traveling salesman problem: an overview of exact and approximate algorithms". In: *European Journal of Operational Research* 59, pp. 231–247.

Laporte, Gilbert (2009). "Fifty Years of Vehicle Routing". In: *Transportation Science* 43.4, pp. 408–416. ISSN: 0041-1655. DOI: `10.1287/trsc.1090.0301`.

Lebeau, Philippe et al. (2015). "Conventional, Hybrid, or Electric Vehicles: Which Technology for an Urban Distribution Centre?" In: *The Scientific World Journal* 2015, pp. 1–11. ISSN: 2356-6140. DOI: `10.1155/2015/302867`.

Logenthiran, T. and Dipti Srinivasan (2011). "Multi-agent system for managing a power distribution system with Plug-in Hybrid Electrical vehicles in smart grid". In: *ISGT2011-India*. Vol. 0954. IEEE, pp. 346–351. ISBN: 978-1-4673-0315-6. DOI: `10.1109/ISET-India.2011.6145339`.

McKinsey (2014). *EVolution Electric vehicles in Europe: gearing up for a new phase?* Tech. rep. April, p. 21.

McKinsey (2016). “Automotive revolution perspective towards 2030”. In: *Stanford University, PEEC Sustainable Transportation Seminar*. January 1st, pp. 1–20. DOI: 10.1365/s40112-016-1117-8.

Millner, Alan (2010). “Modeling Lithium Ion battery degradation in electric vehicles”. In: *2010 IEEE Conference on Innovative Technologies for an Efficient and Reliable Electricity Supply*. 4. IEEE, pp. 349–356. ISBN: 978-1-4244-6076-2. DOI: 10.1109/CITRES.2010.5619782.

Moura, Scott J (2011). “Techniques for Battery Health Conscious Power Management via Electrochemical Modeling and Optimal Control”. PhD thesis, pp. 1–152.

Ning, Gang and Branko N. Popov (2004). “Cycle Life Modeling of Lithium-Ion Batteries”. In: *Journal of The Electrochemical Society* 151.10, A1584. ISSN: 00134651. DOI: 10.1149/1.1787631.

Offer, G.J. et al. (2010). “Comparative analysis of battery electric, hydrogen fuel cell and hybrid vehicles in a future sustainable road transport system”. In: *Energy Policy* 38.1, pp. 24–29. ISSN: 03014215. DOI: 10.1016/j.enpol.2009.08.040.

Omidvar, A. and R. Tavakkoli-Moghaddam (2012). “Sustainable vehicle routing: Strategies for congestion management and refueling scheduling”. In: *2012 IEEE International Energy Conference and Exhibition (ENERGYCON)*. 4. IEEE, pp. 1089–1094. ISBN: 978-1-4673-1454-1. DOI: 10.1109/EnergyCon.2012.6347732.

Padovani, Thomas MIRO et al. (2013). “Optimal Energy Management Strategy including Battery Health through Thermal Management for Hybrid Vehicles”. In: *IFAC Proceedings Volumes* 46.21, pp. 384–389. ISSN: 14746670. DOI: 10.3182/20130904-4-JP-2042.00137.

Paraschiv, Florentina, David Erni, and Ralf Pietsch (2014). “The impact of renewable energies on day-ahead electricity prices”. In: *Energy Policy* 73, pp. 196–210. ISSN: 03014215. DOI: 10.1016/j.enpol.2014.05.004.

Pelletier, Samuel, Ola Jabali, and Gilbert Laporte (2016). “50th Anniversary Invited Article ”Goods Distribution with Electric Vehicles: Review and Research Perspectives”. In: *Transportation Science* 50.1, pp. 3–22. ISSN: 0041-1655. DOI: 10.1287/trsc.2015.0646.

Psaraftis, Harilaos, Atle Minsaas, and George Panagakos (2013). "Green Corridors in European Surface Freight Logistics". In: *Handbook of Global Logistics*. Vol. 181, pp. 193–218. ISBN: 978-1-4419-6131-0. DOI: 10.1007/978-1-4419-6132-7.

Sassi, Ons, Wahiba Ramdane Cherif, and Ammar Oulamara (2015). "Vehicle Routing Problem with Mixed fleet of conventional and heterogenous electric vehicles and time dependent charging costs". In: *International Journal of Mathematical, Computational, Physical, Electrical and Computer Engineering* 9.3, pp. 167–177.

Sassi, Ons, W. Ramdane Cherif-Khettaf, and Ammar Oulamara (2015a). "Multi-start Iterated Local Search for the Mixed Fleet Vehicle Routing Problem with Heterogenous Electric Vehicles". In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Vol. 9026, pp. 138–149. ISBN: 9783319164670. DOI: 10.1007/978-3-319-16468-7_12.

Sassi, Ons, Wahiba Ramdane Cherif-Khettaf, and Ammar Oulamara (2015b). "Iterated Tabu Search for the Mix Fleet Vehicle Routing Problem with Heterogenous Electric Vehicles". In: *Communications in Computer and Information Science*. Vol. 14, pp. 57–68. ISBN: 978-3-540-87476-8. DOI: 10.1007/978-3-319-18161-5_6. arXiv: arXiv:1011.1669v3.

Shareef, Hussain, Md Mainul Islam, and Azah Mohamed (2016). "A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles". In: *Renewable and Sustainable Energy Reviews* 64, pp. 403–420. ISSN: 13640321. DOI: 10.1016/j.rser.2016.06.033.

Statista (2016a). *Börsenstrompreis am EPEX-Spotmarkt für Deutschland bis 2016*. URL: https://de.statista.com/statistik/daten/studie/154012/umfrage/grosshandelspreise-fuer-strom-in-deutschland-seit-2008/ (visited on 01/15/2017).

— (2016b). *Zusammensetzung des Industriestrompreises in Deutschland bis 2016*. URL: https://de.statista.com/statistik/daten/studie/168571/umfrage/strompreis-fuer-die-industrie-in-deutschland-seit-1998/ (visited on 01/15/2017).

Sundström, Olle and Carl Binding (2012). "Flexible charging optimization for electric vehicles considering distribution grid constraints". In: *IEEE Transactions on Smart Grid* 3.1, pp. 26–37. ISSN: 19493053. DOI: 10.1109/TSG.2011.2168431.

Suzuki, Yoshinori (2009). “A decision support system of dynamic vehicle refueling”. In: *Decision Support Systems* 46.2, pp. 522–531. ISSN: 01679236. DOI: 10.1016/j.dss.2008.09.005.

Sweda, Timothy M., Irina S. Dolinskaya, and Diego Klabjan (2016). “Optimal Recharging Policies for Electric Vehicles”. In: *Transportation Science* 14, trsc.2015.0638. ISSN: 0041-1655. DOI: 10.1287/trsc.2015.0638.

Trummer, Wolfgang and Norbert Hafner (2016). “Potentials of e-Mobility for Companies in Urban Areas”. In: *Commercial Transport, Lecture Notes in Logistics*. Ed. by Uwe Clausen et al. Lecture Notes in Logistics. Cham: Springer International Publishing, pp. 129–139. ISBN: 978-3-319-21265-4. DOI: 10.1007/978-3-319-21266-1_8.

UNFCCC. Conference of the Parties (COP) (2015). “Adoption of the Paris Agreement. Proposal by the President.” In: *Paris Climate Change Conference - November 2015, COP 21* 21932.December, p. 32. ISSN: 1098-6596. DOI: FCCC/CP/2015/L.9/Rev.1. arXiv: arXiv:1011.1669v3. URL: http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf.

Yang, Hongming et al. (2015). “Electric vehicle route optimization considering time-of-use electricity price by learnable partheno-genetic algorithm”. In: *IEEE Transactions on Smart Grid* 6.2, pp. 657–666. ISSN: 19493053. DOI: 10.1109/TSG.2014.2382684.

Zhang, Tian et al. (2014). “Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price”. In: *IEEE Transactions on Vehicular Technology* 63.6, pp. 2600–2612. ISSN: 00189545. DOI: 10.1109/TVT.2013.2295591. arXiv: arXiv:1301.2457v1.

B Deutsche Zusammenfassung

Die städtische Frachtverteilung mit elektrisch-betriebenen Fahrzeugen wirkt sich nicht nur auf die Verteilungslogistik, sondern auch auf die Energieversorgung, die Stromverteilung und die Netznutzung aus. Integrierte Lösungen, die die Vorteile mehrerer Branchen miteinander kombinieren, können zu profitablen sektorübergreifenden Preisstrategien führen. Der Einsatz von Day-Ahead-Informationen bspw. von Energiepreisen und der Fahrzeugladeplanung kann zu niedrigeren Energiepreisen für Transportfirmen führen, die sich in einer intelligenten und effizienten Gebühren- und Preispolitik widerspiegeln.

Der vorgeschlagene Ansatz kombiniert diese Ergebnisse und veranschaulicht die Auswirkungen auf die Ladeplanung, Netzintegration und Fahrzeugbatteriegröße. Ein mathematisches Modell wird für flexible Energiepreise entwickelt und zielt auf die Synchronisation von Fahrzeugterminierungs- und Ladezeiten ab. Mittels eines kommerziellen Solvers wird versucht, die optimale Ladestrategie für eine gegebene Tour zu finden. Veränderungen der Ladezeiten im Depot sowie Einflüsse auf den maximalen Ladezustand werden als zusätzlicher Nutzen betrachtet. Die Evaluierung basiert auf einem praktischen Fall der Warenverteilung mit sechs verschiedenen Szenarien, um den Einfluss verschiedener Strategien auf mögliche Verbesserungen für Praktiker zu untersuchen. Die Ergebnisse zeigen, dass variable Energiepreise für Fahrzeugbetreiber und Energieversorger wünschenswerte Vorteile schaffen können, wie etwa finanzielle Vorteile oder geografisch verteiltes Laden.