Charge Scheduling of Electric Vehicles in Last-mile Distribution

A Case Study at Picnic

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Master of Science Thesis

Delft University of Technology

Transport Engineering and Logistics (TEL)

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Summary

Freight transportation, currently dominated by fossil fuelled vehicles, contributes largely to sustainability problems, including noise and air pollution, global warming and oil dependency. The adoption of electric vehicles (EVs) could solve these problems by enabling much cleaner and efficient transport [1]. However, substituting conventional internal combustion engine (ICE) vehicles with EVs within the transportation and logistics sector is not straightforward. In contrast to ICE vehicles, EVs have to refuel frequently due to the relatively low energy content of their batteries. Moreover, the recharging process of an EV is a lot more time consuming than refuelling a conventional ICE vehicle. In order to successfully adopt EVs in last-mile distribution processes, the range and recharging limitations should be addressed adequately.

In this contribution, the range and recharging limitations of EVs are addressed during the depot charge scheduling of a fleet of EVs. The use of EVs is considered in the context of a last-mile delivery process while operating a multi-shift schedule, which means that vehicles can be used to execute multiple trips per day. It is assumed that individual trips, which span a number of customer orders, do not exceed vehicle range. Consequently, charging outside of the home depot is not needed. Many last-mile distribution service providers operate a large fleet of vehicles from one depot location. Due to the high investment cost that is associated with installing charging infrastructure, there are typically less chargers than vehicles. Moreover, grid capacity constraints limit the peak power that can be drawn from the grid on a specific depot location. Both factors should be taken into account during the construction of a charge schedule.

The aim of this work is threefold: (1) to develop a model to optimise the charge schedule for a fleet of EVs while considering labour, battery degradation and energy cost and taking into account constraints related to the vehicle, charging infrastructure and grid, (2) to investigate the impact of the three different shift schedules on charging cost and (3) to study the impact of adapting the configuration of both the vehicle and charging infrastructure on charging cost. The impact of charge scheduling optimisation on charging cost is investigated in a real-life case study for Dutch e-grocer Picnic, that currently operates a last-mile delivery process with over 700 EVs [2].

A MIP model for the charge scheduling problem is proposed. Two important conditions related to the problem are that (1) the assignment of vehicles to trips is determined preceding to the charge schedule optimisation and (2) the energy requirements of all trips are known. In a real-life context, this would mean that the energy requirement of trips should be predicted using certain trip characteristics. A step wise approach is used to introduce the problem. First, the problem formulation for the charge scheduling problem without the incorporation of battery degradation cost is given. Subsequently, the model is extended to be able to account for battery degradation cost, using a discrete battery wear model from Han et al (2014) [3]. Model adjustments that enable coordinated charging, which resembles the use of smart chargers are introduced last. The implementation of the proposed model is verified in order check whether the problem is formulated and implemented correctly.

Three different aspects of the case study of e-grocer Picnic are analysed. This outlines the necessary information to set up the experimental study. The following subjects are discussed in consecutive order: the energy demand of the fleet, the current charge scheduling process of Picnic and characteristics of the vehicle charging characteristics and charging infrastructure

The model is implemented in Gurobi and solved using an exact solver. In order to asses its performance, the proposed model is compared to the benchmark, which is determined using operational data. The proposed model outperforms the benchmark by 25.2% in total cost and all cost components are reduced individually. This confirms that the implementation of charge schedule optimisation provides high economical benefits in last-mile services using EVs. An immediate consequence of reduced battery wear cost is that expected lifetime of the vehicles batteries is extended (19.0%). Furthermore, the impact of three different shift schedule types, the increase in vehicle battery size, the addition of coordinated charging and the implementation of fast chargers is investigated. It turns out that more energy demanding shift schedules result in higher average charging cost per charged amount of energy. This can be explained by the decrease in charging flexibility in these shift schedules. The introduction of a larger battery size, shows potential for decreasing cost related to charging (10%). Moreover, coordinated charging yields a large reduction of charging cost (7%). The best tested configuration combines larger battery size with coordinated charging and this yields a decrease in charging cost of 6.6%, 12.7% and 15.1% for the CS, MS and FS schedule when compared to current configuration.

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Nomenclature

AC	Alternating Current
ACC	Achievable Cycle Count
ANN	Artificial Neural Network
CC-CV	Constant Current - Constant Voltage
CE	Charge Event
CS	Current Shift
DC	Direct Current
DOD	Depth Of Discharge
EFV-CSP	Electric Freight Vehicle - Charge Scheduling Problem
EV	Electric Vehicle
EVSP	Electric Vehicle Scheduling Problem
FRD	Facility Related Demand
FS	Fictive Shift
GVRP	Green Vehicle Routing Problem
MIP	Mixed Integer Programming
MS	Morning Shift
MSE	Mean Square Error
ICE	Internal Combustion Engine
PDF	Probability Density Function
SOC	State Of Charge
SOH	State Of Health
TCO	Total Cost of Ownership
UCS	Unidirectional Charge Scheduling
V2G	Vechicle to Grid
WDF	Wear Density Function

Chapter 1

Introduction

1-1 Electric Vehicles in Transportation

Freight transportation, currently dominated by fossil fuelled vehicles, contributes largely to sustainability problems, including noise and air pollution, global warming and oil dependency [4]. The adoption of electric vehicles (EVs) could solve these problems by enabling much cleaner and efficient transport [1]. Local and national governments try to discourage the use of diesel trucks by introducing more stringent regulations which limit the allowed CO_2 and NO_x emissions for internal combustion engine (ICE) vehicles. Additional diesel bans in congested, urban areas will further contribute to an accelerated adoption of electric trucks. Recently, some of the major Dutch cities including Amsterdam, Rotterdam and Utrecht introduced measures that restrict the use of ICE vehicles in environmental zones. On top of that, Utrecht has announced a full ban of all ICE vehicles from its inner city in 2025 [5]. Aside from environmental aspects, other drivers contributing to the attractiveness of adopting EVs in transportation are technology readiness and total cost of ownership (TCO) [6]. Technology readiness comprises the ability of the EV manufacturers to develop a variety of EV models and to achieve sufficient production capacity. In the coming years, it is likely that these factors will lag behind the demand [6]. A few drivers can be associated with the TCO difference between traditional diesel trucks and EVs which include battery size and cost, daily driving distances, electricity consumption and the fuel price differential. Cost competitiveness of EVs is achieved when the reduced operational costs outweigh the high initial investment costs. Especially in the light commercial vehicle (LCV) segment, cost parity with diesel fuelled trucks seems near, due to relatively low battery investment costs.

However, substituting conventional ICE vehicles with EVs within the transportation and logistics sector is not straightforward. In contrast to ICE vehicles, EVs have to refuel frequently due to the relatively low energy content of their batteries. Moreover, the recharging process of an EV with the current battery and recharging technologies is a lot more time consuming than refuelling a conventional ICE vehicle. Both the lower range and long recharging times are characteristics that reduce the availability and flexibility of EVs. This poses some additional challenges when using EVs from strategic, planning, and operational perspectives [7].

From the perspective of the fleet owner, the influence of the reduced availability and flexibility of EVs can be problematic as these factors might ultimately lead to larger required fleets to perform operations. Larger fleets are associated with higher investment and operational costs and will result in an increase of TCO of the electric fleet.

1-2 Incorporating EVs in Logistics Operations

To optimise the use of EVs in the transportation sector, the EV limitations regarding charging and range should be taken into account during at least one of the following processes:

- Routing of vehicles: this relates to the assignment of a sequence of destinations to vehicles, while also determining where and how long to charge [8].
- Scheduling of vehicles: in contrast to routing, the scheduling of vehicles comprises the assignment of vehicles to a set of trips with fixed time constraints instead of destinations [9].
- Charge scheduling: decisions regarding charge scheduling are related to where and when to charge a specific vehicle. Note that during this process it is not decided on the assignment of vehicles to trips.

This thesis focuses on the charge scheduling for a fleet of EVs. Much research has been devoted to the routing of EVs, especially in the context of en-route recharging of vehicles. The issues related to limited range of alternative fuelled vehicles were first considered by Erdougan et al. (2012) [10] who proposed the Green Vehicle Routing Problem (GVRP). More recent studies have been dedicated to analysing the effect of charging station location and capacity, non-linear charging curves, time windows, variable electricity pricing and partial charging [11]. An interesting problem in the context of scheduling EVs is the Electric Vehicle Scheduling Problem (EVSP) (e.g. [9],[12],[13],[12]). This problem is mainly used in order to evaluate the financial feasibility of electrifying a fixed schedule of trips, such as in a bus network, by comparing the TCO of different technical concepts at the system level. In its most general form, the EVSP has the goal to find an optimal vehicle schedule by minimising the number of vehicles and operational cost related to driving distance. In contrast to both the routing and scheduling of EVs, the charge scheduling for EVs is covered less in literature.

This thesis will use online grocer Picnic as a case study to optimise the charge schedule in the context of a last-mile distribution system. Currently, the company has a fully electric fleet of LCVs that is responsible for the final delivery trip to customers. This provides the opportunity to analyse the current use of EVs in a last-mile delivery context. In the next section, an introduction of the company is given and the use of EVs in their last-mile is analysed.

1-3 EVs in Last-mile Distribution at Picnic

Picnic is an e-grocer that started operation in September 2015 after two years of research and development behind the scenes. Picnic's stores can be accessed exclusively online using a mobile application, which means that there are no physical stores that can be visited. An order can be placed until 10:00PM on the day before delivery, and has a minimum billing amount of €25. The assortment of Picnic contains over 10.000 different products ranging from ambient, chilled and frozen products. In contrast to competitors, Picnic offers a lowest price guarantee on their products and charges no delivery costs, which reduces the margin that remains for the distribution of the goods. This puts pressure on the cost effectiveness of the supply chain of Picnic. An overview and description of the entire supply chain of Picnic is given in Figure 1-1. The next section will elaborate on how the EVs are currently used to cover the final trip to the customers.

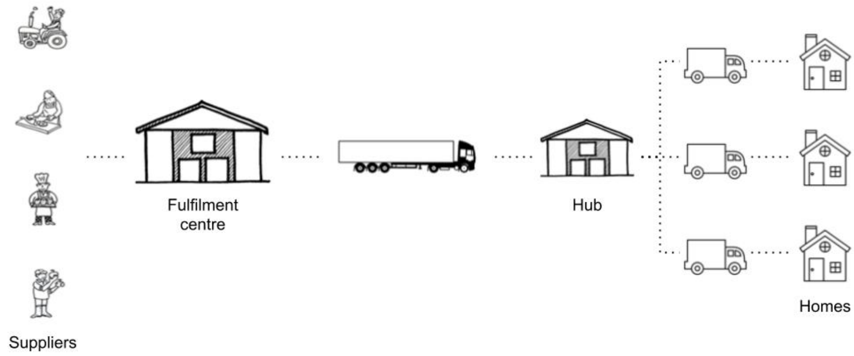


Figure 1-1: The Supply Chain of Picnic: a schematic overview from left to right. Different suppliers deliver products at one of the fulfilment centres. Here, individual customer orders are collected and combined in frames. Subsequently, the frames are transported to the regional hubs using trucks where they are cross docked to the electric delivery vehicles. These EVs are responsible for the last-mile delivery trip to the customers' homes.

Picnic has an electric fleet of roughly 700 Goupil G4 LCVs that is responsible for the last-mile distribution of the groceries [2]. These vehicles combine a small footprint (outer dimensions: 1.4 x 2.96m) with a high payload capacity (6m^3) and a relatively low top speed (50km/h). As indicated before, the use of EVs in the transporting sector goes hand in hand with several strategic and operational challenges. Nevertheless, there are some characteristics of the last-mile distribution model of Picnic that are favourable for the adoption of EVs:

- Urban hubs: the location of the hubs are an important aspect of the last-mile delivery distribution model that was selected at Picnic. The hubs are all located relatively close and centred with respect to the delivery areas that they serve. As a result, they reduce the distance travelled in last-mile delivery trips. Another consequence is that the last-mile delivery routes are driven at a low average speed; only the urban road network is used.

- Payload characteristics: grocery delivery can be characterised by a relatively high weight and volume per customer order. The amount of customers that can be served in one delivery trip is constrained by the vehicle payload capacity. Consequently, a relatively low number of customers can be served in one delivery trip when comparing grocery deliver with for example parcel delivery.

The urban hub model and payload characteristics both limit the amount of distance that is driven in Picnic's last-mile delivery trips. An analysis that is presented in Section 4-1-2 shows that individual last-mile delivery trips at Picnic are never constrained by the vehicle range. Consequently, charging outside of the depot is not needed. Many fleet owners prefer depot charging over charging at public locations due to a combination of factors including the scarcity of available charging infrastructure, cargo security concerns during charging and inefficient use of the drivers' time [14]. Furthermore, financial benefits could be obtained by charging in off-peak hours at the depot. For these reasons, only depot charging will be considered in this work.

The schedule of trips for every vehicle, or vehicle rotations, determine the energy demand of the vehicles over time, as well as the available time for charging. Therefore, the entire trip schedule should be taken into account in order to properly address the range constraints of each vehicle when a charge schedule is made. At Picnic, the last-mile distribution trips are scheduled in a multi-shift context. A shift contains a set of trips that is driven in the same time interval, and therefore impose time constraints on the maximum duration of trips. A shift schedule is built up by multiple shifts that are strictly separated in time. From a planning perspective, this means that when ignoring energy constraints, trips from consecutive shifts can always be executed by the same vehicle. The shift schedule that is performed during the week at most hubs comprises three shifts which are all scheduled in the afternoon. In practise, the battery capacity of the vehicles is often sufficient to perform three consecutive trips without recharging. At the moment, there are no supporting systems in place that help to make a charge schedule in any way because energy related issues rarely occur.

A recent expansion of Picnic's services has added two morning shifts next to the three existing afternoon shifts, summing up to a total of five shifts per day. As a consequence of this, individual vehicle use should be intensified to prevent an unacceptable growth of the fleet. This means that vehicles cover more distance on a daily basis, require more energy and are away from the home depot longer, which leaves less time for charging. It can be said that the increase in energy requirement and the decrease in available time for charging leads to a decrease in charging flexibility, which is defined as the idle time spent not charging [15]. Higher daily energy demands and the decrease in charging flexibility could lead to a higher peak energy consumption at the depot. Grid capacity constraints limit the peak power that can be drawn from the grid on a specific depot location. These grid capacity constraints are imposed by grid operators and are meant to counteract overloading of the grid. However, they pose a threat for achieving charge feasibility for all vehicle rotations during the day. Therefore, the capacity of the grid should be taken into account during the construction of the charge schedule.

1-4 Charge Scheduling

High daily energy demands and limited charging infrastructure availability may lead to energy infeasibility of the vehicle schedule or impractical charging schemes, consisting of many charge events. Since the execution of a charge schedule requires manual labour, for example when driving EVs to charger locations and (un)plugging vehicles from the charger, there is a motive to minimise the number of charge events and thereby to reduce the labour cost that is associated with the execution of the charge schedule. Another component that influences the cost to execute a charge schedule is energy cost. For businesses operating on a larger scale and consequently consuming a lot of energy, the option of having a time variable energy pricing contract becomes an attractive alternative. These variable energy contracts can be leveraged in order to decrease energy cost, by charging during times of low energy prices. One last, and less covered, aspect that contributes to the cost of a charge schedule are battery wear costs, which are inherently related to the use of an EV battery. EV batteries constitute a large part of vehicles costs. Lithium-ion batteries are subject to deterioration of the electro-chemical properties over time, ultimately leading to a reduction of the available power and battery capacity, resulting in a performance and range deterioration of the vehicle [16]. In order to preserve the long term flexibility of EVs, it is necessary to prevent battery degradation as much as possible [17]. This can be done by taking into account the factors that have a known negative effect on battery deterioration in charging problems. One of these known effects is the state of charge (SOC) range in which the battery is cycled. Therefore, adapting a charge schedule of a vehicle in such a way that it is cycled in less harmful SOC ranges, contributes to the cost effectiveness of a charge schedule. All these factors emphasise the necessity to investigate the cost related to the charging schedule.

1-5 Aim of the Thesis

The aim of this work is threefold: (1) to develop a model to optimise the charge schedule for a fleet of EVs while considering labour, battery degradation and energy cost and taking into account constraints related to the vehicle, charging infrastructure and grid, (2) to investigate the impact of the three different shift schedules on charging cost and (3) to study the impact of adapting the configuration of both the vehicle and charging infrastructure on charging cost. The impact of charge scheduling optimisation on charging cost is investigated in a real-life case study for Dutch e-grocer Picnic, that currently operates a last-mile delivery process with over 700 EVs [2]. The charging cost of optimised charge schedules are compared with cost of the current charging process obtained with operational data. Moreover, the impact of the three different shift schedules on charging cost is investigated, which are based on two actual shift schedules and one fictive schedule for Picnic. Lastly, we study the impact of adapting the configuration of both the vehicle and charging infrastructure referring to the vehicle battery size, charge rate and charge type. The latter refers to the amount of possible coordination during the charging process in which we consider two types: uncoordinated and coordinated charging. Uncoordinated charging resembles the use of basic chargers, and coordinated charging corresponds to the use of smart chargers.

1-6 Research Questions

Based on the previously stated research aim, the main research question can be defined:

How can the charge schedule for a fleet of electric vehicles be optimised during day-to-day operations?

In order to answer this question, several sub-questions need to be answered:

1. What charge scheduling optimisation models and algorithms have been proposed in literature?
2. How can the charge schedule optimisation problem be formulated in a mathematical model?

There are several sub-questions that are answered in the context of the case study at Picnic.

3. What is the energy demand of the electric fleet of Picnic?
4. What charge scheduling process is currently used at Picnic?
5. What are the characteristics of Picnic's current vehicle and surrounding charging infrastructure?
6. How can an experimental study be set up that uses the proposed model to study the impact of charge schedule optimisation on charging cost?
7. What is the impact of charge schedule optimisation on charging cost?
8. What is the impact of vehicle and charging infrastructure configurations on charging cost?

1-7 Research Approach

In order to answer the main and sub research questions the following research approach is used. A review considering the most recent literature in the area of charge scheduling optimisation is performed to assess the state of art, to learn how existing models are defined in literature and to derive what contributions can be done to the field. Based on this literature review, a new model will be formulated for the charge scheduling problem, which is specifically designed for the case of Picnic. Several aspects of case study are analysed in order to (1) asses the performance of the current charging process of Picnic with quantitative operational data and (2) to derive the necessary information for the design of experiments. These experiments are performed to compare the performance of the charge scheduling model to the performance of the current charging process. Furthermore, additional experiments are proposed to investigate the impact of vehicle and charging infrastructure configurations. The used research approach is schematically visualised in Figure 1-2.

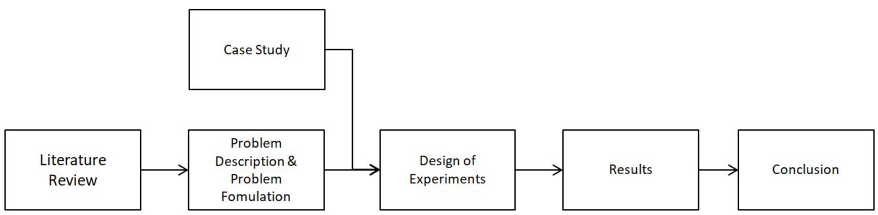


Figure 1-2: The research approach

1-8 Structure

This thesis is organised as follows. First, an overview of the relevant literature with respect to charge scheduling optimisation is presented in Chapter 2. Subsequently, the problem will be defined in Chapter 3. Moreover, a mathematical formulation for the charge schedule optimisation is formulated. Sub-questions 3-5 are all discussed in Chapter 4. The aim of these questions is to analyse the specific characteristics of the charge scheduling problem at Picnic. Subsequently, in Chapter 5, the experimental study is set up. The results of the experimental study are given in Chapter 6. Having stated the answers to all sub questions, the answer to the main research question is given in the concluding Chapter 7.

Chapter 2

Charge Scheduling Optimisation

This chapter will review relevant literature with respect to charge scheduling optimisation and thereby provides an answer to the first research question:

- What charge scheduling optimisation models and algorithms have been proposed in literature?

First, in Section 2-1 the subject of charge scheduling optimisation is classified into two main groups: vehicle to grid charge scheduling and unidirectional charge scheduling. Subsequently, the relevant literature within these groups is discussed in Section 2-2 and 2-3. Section 2-4 elaborates on the unidirectional charge scheduling for fleet owners. Section 2-5 covers literature with respect to battery degradation models that can be incorporated in the charge scheduling problem. Finally, Section 2-6 discusses the contributions of this work in the view of the existing literature.

2-1 Types of Charge Optimisation Problems

Within the general topic of charge scheduling optimisation problems, two main groups are subdivided:

- Vehicle to Grid (V2G) charge scheduling: V2G systems use EV batteries to temporarily store energy which can be provided back to the grid. V2G systems,- "could help carbonise transportation, support load balancing, integrate renewable energy into the grid, increase revenues for electricity companies, and create new revenue streams for automobile owners" [18]. The main goal of V2G charge scheduling optimisation problems is to determine when EV batteries should be charged, discharged or used for frequency regulation [19].
- Unidirectional charge scheduling (UCS): these types of problems consider only the unidirectional flow of energy from the grid to the vehicle.

The two different types of charging optimisation problems that were identified will be discussed more elaborately in the next two sections.

2-2 V2G Charge Scheduling

Although V2G capability is not considered to be a part of this thesis, elements of V2G charge scheduling models could be useful input for UCS models. Especially within the topic of battery degradation, many recent contributions have focused on incorporating wear cost during the optimisation of a V2G charge schedule (i.e. [20], [21], [22]). Since battery cost constitute a large part of EV cost, determining the contribution of battery degradation is an important aspect when assessing the financial feasibility of EVs in V2G systems [22]. Farzin et al (2016) [20] propose a practical battery wear model that can be incorporated in V2G charge scheduling problems. Other aspects of work related to V2G charge scheduling focuses on addressing the uncertainties regarding future energy prices, vehicles use and grid load to optimise the integration of EVs into power systems. Moving time window optimisation is a much used approach to determine the charge schedule for vehicles in these uncertain environments.

2-3 Unidirectional Charge Scheduling

The perspective from which the charging problem is addressed determines the objectives of the optimisation. Three perspectives are identified:

- Power system level
- Owner of charging infrastructure
- Vehicle/fleet owner

Power System Owner and EV Aggregators

The first group is the one of the power system level. Examples of actors that operate on this level are EV aggregators and grid operators. The benefits that EVs can offer to power systems are voltage support, frequency regulation, reserve and demand response capabilities [23]. EV aggragation comprises the joint operation of the charging process of a large number of EVs to ensure system impact (i.e. [24], [25],[26]). This can be achieved by regulating the charge rate of individual vehicles [27].

Owner of Charging Infrastructure

The owner of charging infrastructure offers charging services to fleet or vehicle owners. The main objective for charge scheduling from the perspective of the charging infrastructure owner is to maximise profit while ensuring the mobility objectives of the customers [28]. Sometimes the objective is to minimise waiting time (i.e. [29], [30]). Zhang et al. (2017) [31] propose a charging optimisation method for EVs at commercial parking lots with extended charging times. Arrival and departure behaviour of vehicles is modelled as a Poisson process. A two stage dynamic programming optimisation framework is used that includes a short and long term prediction of electricity prices. Also the operators of battery swapping stations can be assigned to this group. Some recent contributions focus on the profit maximisation of battery swapping station under uncertain demand and energy prices by scheduling the charging of batteries (i.e. [23], [32]).

Vehicle/fleet Owner

The last class covers the subject of charge scheduling optimisation from the perspective of the fleet owner. For the fleet owner the most important goal is to minimise the cost related to charging. As was mentioned in the introduction, many fleet owners prefer depot charging over charging at public locations due to a combination of factors. Therefore, in this work, charge scheduling for fleet owners is limited to depot charging. All relevant literature that was found covers charge scheduling from a single location. In the next section, a more elaborate survey of the literature in this subject is given.

2-4 Unidirectional Charge Scheduling for Fleet Owners

This section covers the literature within the subject of UCS from the perspective of the fleet owner. Up to our knowledge, only three contributions cover the subject from this perspective. Firstly, Pelletier et al. (2018) [14] introduce the Electric Freight Vehicle Charge Scheduling Problem (EFV-CSP). This contribution focuses on optimising the depot charge planning over the course of multiple days for a given set of routes for electric freight vehicles. The objective function is build up of multiple components including time-dependent energy costs, battery degradation and facility-related demand charges. A realistic non-linear charging process is modelled. A mixed integer programming (MIP) formulation is proposed and solved using an exact solver. Small scale test instances are generated that have fleet sizes of 3 to 9 vehicles, each performing two trips a day with a time horizon of three days. Secondly, Sundstrom et al. (2010) [33] propose a charge scheduling optimisation model with the goal of minimising charging costs, achieving satisfactory state-of-energy levels and optimal power balancing. The problem includes variable electricity prices over time and also variable available wind power over time. Both a linear and quadratic approximation of battery behaviour is used to take into account the relationship between applied, external, charging power and the rate of change of the battery SOC. The optimisation model is based on a MIP formulation and solved using an exact CPLEX algorithm. The test instances contain a mix of 50 commuter and taxi vehicles performing a series of trips over the course of one day. A different type of problem that covers the subject of unidirectional depot charge scheduling for fleet owners is the Simultaneous Electric Vehicle Scheduling and Optimal Charging Problem, which considers a joint optimisation of vehicle scheduling and charge scheduling. This problem is discussed by Sassi et al. in three contributions (2014a) [34], (2014b) [35], and (2017) [19]). In these studies it is the goal to optimise both the allocation of a fleet of ICE vehicles and EVs to trips and the charge schedule while satisfying constraints related to the grid, chargers and EVs battery capacities. Optimisation objectives consists of both maximising the use of EVs and to minimise the costs related to charging. Only depot charging with time dependent charging costs is considered. In Sassi et al (2014a) [34] a mixed integer formulation is given and real test small and medium sized instances are solved using CPLEX. In Sassi et al. (2014b) [35], a two phase sequential heuristic is developed to solve large instances. In Sassi et al (2017) [19], it is proven that the Electric Vehicle Scheduling and Charging Problem is NP-hard in the ordinary sense. Furthermore, two heuristics, a Sequential Heuristic and a Global Heuristic, are proposed to solve large instances.

2-4-1 Deterministic nature of UCS for Fleet Owners

When analysing the characteristics of the discussed unidirectional optimisation problems for fleet owners, it should be noted that the problem characteristics are of deterministic nature. Namely, the vehicle arrival and departure times as well as the energy demands are assumed to be known beforehand. This makes the problem solution method suitable for linear programming, which means that a global optimum can be found. In the contribution of Pelletier et al (2018) [14], non-linear charge curves are discretised in linear segments in order to incorporate this behaviour in the linear model. The energy demand of the EVs can either be modelled to be deterministic or stochastic. Deterministic models can be used whenever the arrival times at charging stations and energy requirements of trips are known, while stochastic models are used to represent these factors when these are uncertain.

2-4-2 Objectives of UCS for Fleet Owners

A couple of objectives are identified with respect to UCS for fleet owners, which are reducing energy cost, battery wear, facility related demand charges and labour cost. First, the goal of balancing power generation and consumption can become financially beneficial from the perspective of the fleet operator, due to price incentives in the form of variable energy prices. By charging the vehicles during periods of low energy prices, the variable energy prices can be leveraged to reduce overall costs related to energy. A second objective, as was introduced by Pelletier et al. (2018) [14], is the minimisation of facility related demand (FRD) charges, which depend on the maximum power demand during an entire billing period. This means there is a incentive for spreading out the energy demand to keep FRD charges low. It should be noted that not all energy contracts involve FRD charges. As mentioned in the introduction of this thesis, another objective of charge schedule optimisation for a fleet owner might be to reduce the costs related to performing the charge events. Up to our knowledge, there have not been any contributions that take this cost component into account. A last objective comes in the form of preventing battery degradation. EV batteries constitute a large part of vehicles costs. The cost of lithium-ion battery packs are expected to remain above €300/kWh for the next 10 years [36]. Lithium-ion batteries are subject to deterioration of the electrochemical properties over time, with degradation occurring during charging and discharging corresponding to cyclic ageing, and the degradation during storage corresponding to calendar ageing [36]. The involved chemical and mechanical processes ultimately lead to a reduction of the available power and battery capacity, resulting in a performance and range deterioration of the vehicle. The decreased battery capacity, or state of health (SOH), can be measured as a percentage of the original battery capacity. Equation 2-1 is used to determine the battery SOH in percent.

$$SOH = \frac{C_m}{C_{rated}} \cdot 100 \tag{2-1}$$

C_m represents the current maximum releasable capacity in Ah and C_{rated} represents the original capacity rated by the manufacturer. Battery degradation effects origin from multiple and complex mechanisms, which depend on the specific cell type and operating conditions [16]. Due to the correlation and cross-dependency of these mechanisms, it is rather challenging to quantify the contribution of the different mechanisms to battery ageing [37]. However, some factors can still be related to an accelerated ageing of batteries, -" such as overcharging, overdischarging, high and low temperatures, high SOC during storage, large DOD, and high charging or discharging rates." [36]. In order to preserve the long term flexibility of EVs, it is necessary to prevent battery degradation as much as possible. This can be done by taking into account the factors that have a known negative effect on battery deterioration in charging problems. Therefore, some practical battery wear models have been proposed to address these issues. Han et al. (2014) [3] and Farzin et al. (2016) [20] propose a battery wear model that is based on experimental cycle life data and directly indicates wear cost, which makes it very suitable for charging optimisation. These models will be more elaborately discussed in the next section.

2-5 Battery Degradation Models

In this section, two practical battery degradation models will be discussed. Typically, battery manufacturers specify the cycle lifetime of batteries with the *achievable cycle count* (ACC) for different *depth of discharge* (DOD) points, which indicates how many times a battery can be charged or discharged before it reaches the end of its lifetime. This relation can then be visualised in a ACC-DOD curve, of which an example is given in Figure 2-1. For clarity, for the ACC-DOD curves it is assumed that the battery is always discharged from a 100% SOC, which represents the situation in which a battery is always cycled from full charge. However, in reality batteries are cycled in different SOC ranges, which limits the usability of the ACC-DOD curve. To overcome these issues, some steps are required to transform the ACC-DOD characteristics into a practical battery wear model. The models of Han et al. (2014) [3] and Farzin et al. (2016) [20] do exactly this and will be discussed in the Subsections 2-5-1 and 2-5-2.

2-5-1 Practical Wear Model of Han et al.

Han et al. (2014) [3] propose a new index called the *wear density function* (WDF). This function represents the unit wear costs at a specific DOD value. A continuous and discrete time battery wear function are derived using both the battery price and ACC-DOD data. Since this work models in discrete timesteps, the discrete model will be presented. The $W_d(s)$ represents the battery degradation cost as a function of cycled energy within a certain SOC interval $(s + \Delta s)$ and satisfies the following equation:

$$BatteryPrice = 2 \cdot ACC(DOD) \cdot \sum_{s=1-D}^{1-\Delta s} (W_d(s) \cdot \Delta q) \tag{2-2}$$

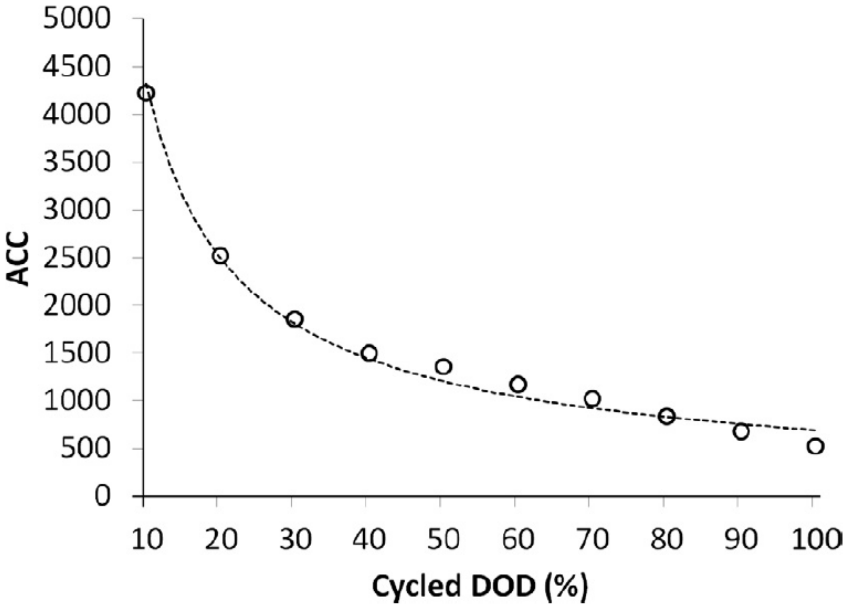


Figure 2-1: ACC-DOD curve. Each marker represents a sample point where the achievable cycle life is known. The continuous line shows the best fit curve of the ACC data. [38]

Δq is the quantity of energy that corresponds to a SOC interval $(s + \Delta s)$. This function can be used to derive the degradation cost for different SOC intervals. For example, using a step size of 10% yields ten different equations:

$$W_d(0.9) = \frac{BatteryPrice}{ACC(0.1) \cdot 2 \cdot 0.1 \cdot BatterySize \cdot \mu^2} \tag{2-3}$$

$$W_d(0.8 + 0.9) = \frac{BatteryPrice}{ACC(0.2) \cdot 2 \cdot 0.2 \cdot BatterySize \cdot \mu^2} \tag{2-4}$$

$$W_d(0 + ... + 0.9) = \frac{BatteryPrice}{ACC(1.0) \cdot 2 \cdot 1.0 \cdot BatterySize \cdot \mu^2} \tag{2-5}$$

The resulting values of the wear density function can be used to incorporate wear cost in a discrete manner. Figure 2-2 shows both an example of a continuous wear cost function derived from the best curve fit of ACC data, and a discrete wear cost function corresponding to the original data measured at ten DOD points. These functions are derived by using the data from Figure 2-1.

2-5-2 Practical Wear Model of Farzin et al.

Farzin et al. (2016) [20] propose a model that is derived using a similar approach as Han et al. (2014) [3]. The discharge coefficient K_d is derived from the ACC-DOD characteristics and describes the lost capacity in terms of total processed energy. When calculating the lost capacity between two arbitrary DOD values, the following formula can be used:

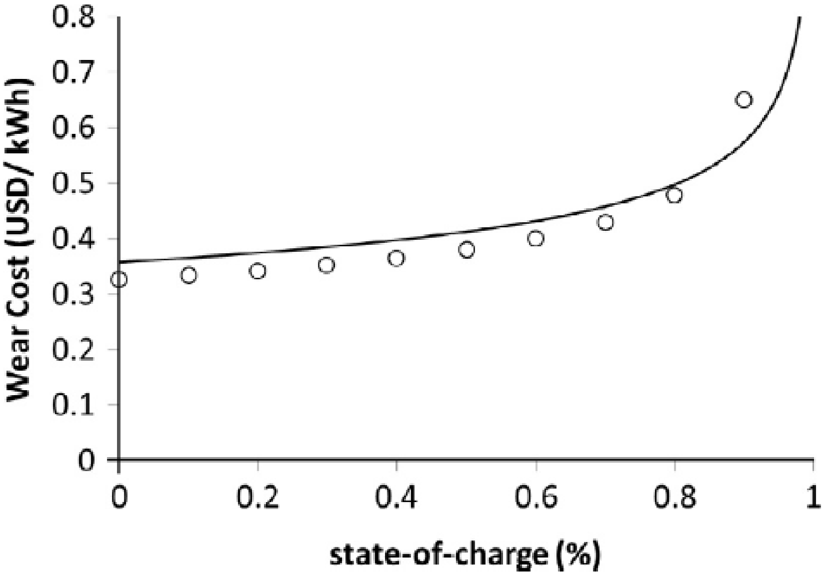


Figure 2-2: Discrete and continuous wear costs functions derived by using the ACC-DOD data from Figure 2-1

$$\Delta E = E|D_{ini}K_{Dini} - D_{fin}K_{Dfin}| \tag{2-6}$$

With ΔE representing the battery wear in kWh corresponding to one charge/discharge action. E denotes the battery capacity before the charge/discharge action. D_{ini} and D_{fin} are the initial and final DOD and K_{Dini} and K_{Dfin}

2-6 Contributions

In this contribution, the original EFV-CSP that was proposed by Pelletier et al (2018) [14] is extended in several ways. Firstly, the labour cost related to the manual handling of charging events will be taken into account. A fixed penalty for each charging event that has to be performed is implemented. The charged energy is presumed to be a linear function of time, which decreases the problem complexity and makes it more suitable for the optimisation of large scale problems. Related to the charged energy, a corresponding SOC dependent battery degradation model that was proposed by Han et al. (2014) [3] is implemented. Secondly, two slightly different models are presented in order to study the effect of coordinated charging versus uncoordinated charging, which compares traditional 'dumb' charging versus the use of smart chargers. In contrast to the model of Pelletier et al (2018) [14], peak charge costs are eliminated as cost component since they are not a part of the energy pricing model. The goal of the EFV-CSP is to optimise the depot-charging costs for a given set of vehicle rotations, where the charging cost consists of energy costs, labour costs and battery degradation costs.

2-7 Summary

What charge scheduling optimisation models and algorithms have been proposed in literature?

Charge scheduling optimisation problems can be roughly divided into two different classes: Vehicle to Grid problems and unidirectional charging problems. Unidirectional charge scheduling problems consider only the unidirectional flow of energy from the grid to the vehicle and can be addressed from different perspectives including the power system level, charge infrastructure owner and the vehicle/fleet owner. This thesis focuses on charge scheduling from the perspective of the fleet owner and in this area three relevant contributions were found. Pelletier et al [14] introduce the Electric Freight Vehicle Charge Scheduling Problem. This contribution focuses on optimising the depot charge planning over the course of multiple days for a given set of routes for electric freight vehicles. Sundstrom et al. (2010) [33] propose a charge scheduling optimisation model with the goal of minimising charging costs, while ensuring satisfactory state-of-energy levels for the vehicles and not exceeding the amount of available wind power. A different type of problem discussed by Sassi et al (2014a) [34], (2014b) [35], and (2017) [19]) that covers the subject of unidirectional depot charge scheduling for fleet owners is the Simultaneous Electric Vehicle Scheduling and Optimal Charging Problem, which considers a joint optimisation of vehicle scheduling and charge scheduling. The objectives of charge scheduling optimisation for fleet owners include the reduction of energy cost, facility related demand charges, labour cost and battery degradation. In order to preserve the long term flexibility of EVs, it is necessary to prevent battery degradation as much as possible. This can be done by taking into account the factors that have a known negative effect on battery deterioration in charging problems. Therefore, some practical battery wear models have been proposed to address these issues. Han et al. (2014) [3] and Farzin et al. (2016) [20] propose a battery wear model that is based on experimental cycle life data and directly indicates wear cost, which makes it very suitable for charging optimisation. Both models use ACC-DOD battery data to incorporate SOC dependency of battery degradation. Lastly, the contributions of this work are discussed in Section 2-6.

Chapter 3

Modelling

In this chapter the model is presented that is used to optimise the charging costs during day-to-day operations. By fulfilling this task, the following research question can be answered:

- How can the charge schedule optimisation problem be formulated in a mathematical model?

In this chapter, an extension of the EFV-CSP is proposed that takes into account time dependent energy costs, battery degradation costs and labour costs. First, a mathematical formulation for the charge schedule optimisation problem without the consideration of battery degradation is formulated in Section 3-1. This model is extended in Section 3-2 to incorporate the effects of battery degradation. In Section 3-3, model adjustments are presented that enable the use of coordinated charging. Finally, in Section 3-4 the implementation and formulation of the model is verified.

3-1 Basic Model Formulation

This section presents a charge scheduling model without considering battery degradation cost. The assignment of vehicles to trips is determined preceding to the charge schedule optimisation. This significantly reduces the problem complexity compared to the case where the vehicle trip allocation and charge scheduling are determined in a joint process. Moreover, the energy requirements of all trips are known. In a real-life context, this would mean that the energy requirement of trips should be predicted using certain trip characteristics. The focus of the EFV-CSP is on the depot charging of EVs, which means that the only opportunity to charge the EVs is when they are located at the depot. The entire time horizon is discretised into a number of fixed time periods $p \in P$. The hub opening and closing periods are defined as O_p and C_p. The set of uniform vehicles $k \in K$ is characterised by maximum and minimum allowable battery SOC: soc_{max} and soc_{min} and battery energy capacity E (kWh). Moreover, the SOC at the beginning of an operational day is specified as soc_{start}. Every vehicle has to

Table 3-1: Variables and parameters that are used in the charge scheduling problem formulation.

P	The set of periods
K	The set of vehicles
S	The set of charger types
D	The set of discretised SOC intervals
R	The set of trips
A_k	The set of arrival periods that belong to vehicle k
α_r	Arrival period of trip r
β_r	Departure period of trip r
O_p, C_p	Hub opening and closing periods
c_p	The energy cost per period in €
cec	Fixed cost per charge event in €
t	The duration of one period in hours
E	Battery energy capacity in kWh
Δsoc_r	Energy requirement of trip r as SOC differential
v_r	vehicle that executes trip r
μ_r	Trip preceding trip r
κ_s	Amount of available chargers of type s
γ_s	The charged SOC per period for a charger of type s in %
P_s	The charge rate for a charger of type s in kWh
G	Grid peak capacity in kWh
soc_{min}	Minimum SOC
soc_{max}	Maximum SOC
soc_{start}	SOC at the start of a operational day
$\mathrm{soc}_{p,k}$	Continuous variable indicating the SOC of vehicle k at period p
$\mathrm{soc}^+_{d,r}$	Continuous variable indicating SOC differential in charge interval d for route r
$\mathrm{u}_{d,r}$	Binary variable that equals one if charge interval d is used before trip r
N	Integer variable indicating the number of charge events during uncoordinated charging
$\mathrm{Ns}_{r,s}$	Binary variable that equals 1 if a charge event is used before trip r during coordinated charging
$\mathrm{x}_{p,k,s}$	Binary variable that equals one if vehicle k at period p uses charger of type s
y	Continuous variable indicating the maximum power drawn from the grid
$\mathrm{z}_{p,k,s}$	Binary variable that equals one if vehicle k is plugged in a charger of type s at period p

execute a known sequence of trips from the set $r \in R$. Trips can be further defined by their departure period β_r, arrival period α_r and energy requirement Δsoc_r (%). The vehicle that executes a certain trip r, is denoted by V_r and the preceding trip is defined as μ_r. Moreover, let the set A_k contain the arrival periods of all trips that belong to vehicle k. The charger types from the set $s \in S$ can be characterised by their charge rate P_s (kW), the SOC differential that can be charged in one period λ_s (%) and amount of available chargers per type $\mathcal{K}_s$. Let the binary decision variable $x_{p,k,s}$ be 1, if a charger of type s is charging vehicle k during period p, and 0 otherwise. A continuous variable $soc_{p,k}$ denotes the SOC of vehicle k at the start of period p. y keeps track of the peak charging power that is drawn from the grid during the entire time horizon. Binary variable $z_{p,k}$ equals 1 if a charge event starts for vehicle k in period p, and 0 otherwise. To count the number of charge events, an integer variable N is introduced. The peak power demand is constrained by the grid capacity G.

Objective Function

The objective for the charge scheduling model is to minimise costs related to charging and is given as follows:

$$\sum_{p\in P}\sum_{k\in K}\sum_{s\in S} x_{p,k,s}P_s t c_p + Ncec \tag{3-1}$$

The first term represents the energy costs of charging, which is calculated by multiplying the total charged energy during a charging period by the time-dependent energy costs c_p (€/kWh) to derive the cost of the charged energy. The second term accounts for the labour costs related to performing charge events through multiplication of the number of charge events by a fixed cost per charge event *cec*.

Charge Scheduling Constraints

$$\sum_{p=\beta_r}^{\alpha_r}\sum_{s\in S} x_{p,V_r,s} = 0 \qquad \forall r \in R \tag{3-2}$$

$$\sum_{k\in K} x_{p,k,s} \leq \mathcal{K}_s \qquad \forall p \in P, s \in S \setminus \{1\} \tag{3-3}$$

$$\sum_{s\in S} x_{p,k,s} \leq 1 \qquad \forall p \in P, k \in K \tag{3-4}$$

$$\sum_{k\in K}\sum_{s\in S} P_s x_{p,k,s} \leq y \qquad \forall k \in K, p \in P \tag{3-5}$$

$$0 \leq y \leq G \tag{3-6}$$

$$z_{p,k} \geq x_{p,k,s} - x_{p-1,k,s} \qquad \forall k \in K, p \in P \setminus \{1\}, s \in S \tag{3-7}$$

$$z_{1,k} \geq x_{1,k,s} \qquad \forall k \in K, s \in S \tag{3-8}$$

$$x_{p,k,s} \in \{0,1\} \qquad \forall p \in P, k \in K, s \in S \tag{3-9}$$

$$z_{p,k} \in \{0,1\} \qquad \forall p \in P, k \in K \tag{3-10}$$

Constraints 3-2 prevent a vehicle from being charged during trips. Constraints 3-3 limit the amount of chargers of type s that can be used during every period to $\mathcal{K}_s$, while constraints

3-4 enforce that each vehicle can be charged by only one charger at the same time. Constraints 3-5 keep track of the peak charging power that is drawn from the grid during the entire time horizon and constraint 3-6 limits this peak charging power to the grid capacity. Lastly, constraints 3-7 and 3-8 are used to identify the period that corresponds to the start of a charging event.

Energy Constraints

$$soc_{\alpha_r,V_r} = soc_{\beta_r,V_r} - \Delta soc_r \qquad \forall r \in R \tag{3-11}$$

$$soc_{p,k} = soc_{p-1,k} + \sum_{s \in S} \lambda_s x_{p-1,k,s} \qquad \forall k \in K, p \in P \setminus \{1,\}, p \notin A_k \tag{3-12}$$

$$soc_{min} \leq soc_{p,k} \leq soc_{max} \qquad \forall k \in K, p \in P \tag{3-13}$$

$$soc_{1,k} = soc_{start} \qquad \forall k \in K \tag{3-14}$$

Constraints 3-11 relate the SOC of the vehicle at trip departure to the SOC at trip arrival by reducing it with the trip energy requirement Δsoc_r. During charging, constraints 3-12 enforce the increase of the SOC of a vehicle with the SOC differential that corresponds to a certain charge rate λ_s. Constraints 3-13 ensure that the SOC of a vehicle always stays between the minimum and maximum allowable SOC. Constraints 3-14 set the SOC of the vehicle at the start of the time horizon.

Charge Event Constraints

$$\sum_{p \in P} \sum_{k \in K} z_{p,k} = N \tag{3-15}$$

$$\sum_{p=Op}^{Cp} z_{p,k} = 0 \qquad \forall k \in K \tag{3-16}$$

These constraints are required to count the number of charge events that are used in a charge schedule. Constraints 3-15 count the number of charge events. Constraints 3-16 prevent charging events from starting during night hours when there is no one present at the hub.

3-2 Model Extension I: Battery Degradation

The practical battery wear model proposed by Han et al. (2014) [3] that is discussed in Section 2-5-1 is implemented in order to incorporate the costs related to battery degradation during charging and discharging. The next subsection describes the formulation that extends the original MIP formulation proposed in Section 3-1 with a discrete wear cost function.

3-2-1 Problem Formulation

The following problem formulation is applicable for the case when the wear cost function is increasing with respect to SOC, which resembles the situation in which more battery degradation occurs during cycling at higher SOC values. The SOC of the batteries is split into a number of intervals $d \in D$ of equal size L (%), with the upper SOC value of an interval corresponding to S_d. The battery wear cost is represented by W_d in €/kWh for every SOC interval d. A new continuous variable is introduced $soc^+_{d,r}$ that keeps track of the quantity of every SOC interval that is used to charge vehicle k between arrival of trip μ_r and departure of trip r. To clarify this variable, an example is visualised in Figure 3-1. In this example the entire SOC range is divided into ten equal intervals of 10% SOC. The example visualises a charging event between trip μ_r and r from 10% to 25% SOC. The corresponding used SOC intervals will become $soc^+_{1,r} = 10\%$ and $soc^+_{2,r} = 5\%$ respectively. Lastly, let a binary decision variable $u_{d,r}$ equal 1, if the corresponding SOC interval is used during charging before trip r and after μ_r, and 0 otherwise

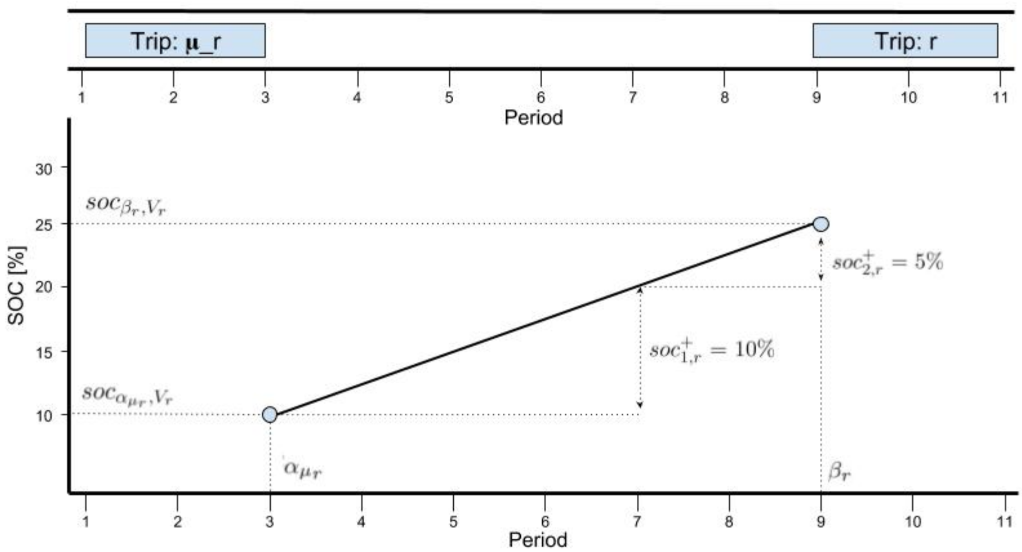


Figure 3-1: An example to clarify the $soc^+_{d,r}$ variable. A charge event charges a vehicle between 10% and 25% SOC, which results that the associated SOC interval become $soc^+_{1,r} = 10\%$ and $soc^+_{2,r} = 5\%$. All other SOC charge intervals are equal to zero.

Objective Function

$$\sum_{p\in P}\sum_{k\in K}\sum_{s\in S} x_{p,k,s}P_s tc_p + Ncec + \sum_{r\in R}\sum_{d\in D} 2W_d soc^{+}_{d,r}E \tag{3-17}$$

The objective function now comprises three terms, of which the first two represent the energy costs and labour costs and are identical to equation 3-1. In addition, the third term is used to take into account the costs related to battery degradation. The total charged amount of energy per interval is derived by multiplying the SOC variation in every interval $soc^{+}_{d,r}$ with the battery energy capacity E (kWh), and then the corresponding degradation cost is determined by multiplying those factors with the interval dependent degradation cost W_d. Because cyclic ageing affects the battery health during charging and discharging, a final multiplication by a factor of two is required to calculate the total battery degradation.

Battery Degradation Constraints

$$\sum_{d\in D} soc^{+}_{d,r} = soc_{\beta_r,V_r} - soc_{\alpha_{\mu_r},V_r} \qquad \forall r \in R \tag{3-18}$$

$$0 \leq soc^{+}_{d,r} \leq Lu_{d,r} \qquad \forall d \in D, r \in R \tag{3-19}$$

$$soc^{+}_{d,r} \leq S_d - soc_{\alpha_{\mu_r},V_r} + 100 - u_{d,r}100 \quad \forall d \in D, r \in R \tag{3-20}$$

Constraints 3-2-3-16 are still valid for this model extension. In addition, constraints 3-18 limit the sum of all $soc^{+}_{d,r}$ intervals to the difference in energy of vehicle k between the departure time of trip r and the arrival period the preceding trip. Constraints 3-19 limit the SOC differential that can charged in a SOC interval between zero and the maximum amount that can be charged in one interval. Constraints 3-20 limit the amount that can be charged in interval $soc^{+}_{d,r}$ based on the upper SOC value of that interval and the SOC of the vehicle after the last trip. Note that this constraint is only valid in the case of non-decreasing wear cost with respect to SOC.

3-3 Coordinated Charging

In this section additional constraints are introduced to model a coordinated charging process. When considering the coordination during the charging process of a fleet of EV two different types of charging can be distinguished: uncoordinated and coordinated charging. This section first discusses the difference between these concepts after which the problem definition for coordinated charging is presented.

3-3-1 Coordinated vs Uncoordinated Charging

Uncoordinated charging is when the vehicle charging starts immediately after plugging in a vehicle or after a fixed start delay and continues until the vehicle battery is fully charged or disconnected [39]. Uncoordinated charging of EV fleets may lead to high peak demands and thereby to overloading of the grid [40]. Coordinated smart charging optimises time and power demand with the objectives of minimising charging cost, valley filling and peak shaving [39]. However, these objectives may never interfere with the mobility objectives of the EVs [41]. To be able to leverage on the possible benefits of coordinated charging, a smart charging infrastructure is required. This comprises smart chargers, connected vehicles and a energy management systems that controls the charging of the vehicles. When comparing the behaviour of coordinated charging with uncoordinated charging, two major differences can be identified:

1. Charge events can stop and start at any moment in time, including the hub closing times.
2. The interruption of a charge event is possible without imposing additional cost.

3-3-2 Problem Definition

During uncoordinated charging, every interruption of a charge event corresponds to operational cost. Coordinated charging events may be frequently interrupted by the smart charger without imposing additional cost. To take into account the charging event cost in coordinated charging, not the number of charge events should be counted, but the number of used *charge opportunity intervals*. A charge opportunity interval is defined as time between the arrival of the preceding trip α_{μ_r} and departure of a trip β_r. Note that the number of charge opportunity intervals is equal to the number of trips. The binary decision variable $Ns_{r,s}$ equals 1 if the charge opportunity interval corresponding to trip r is used, and 0 otherwise.

Objective Function

$$\sum_{p\in P}\sum_{k\in K}\sum_{s\in S} x_{p,k,s}P_s tc_p + \sum_{r\in R} Ns_{r,s}cec + \sum_{r\in R}\sum_{d\in D} 2W_d soc^{+}_{d,r}E \tag{3-21}$$

In order to take into account the impact of operating with smart chargers, the second term of the objective function now calculates labour cost by multiplying $Ns_{r,s}$ with cec.

Charge Event Constraints

$$\sum_{p=\mu_r}^{\beta_r} z_{p,v_r} \geq 0 - M(1 - Ns_{r,s}) \quad \forall r \in R \tag{3-22}$$

$$0 \geq \sum_{p=\mu_r}^{\beta_r} z_{p,v_r} - MNs_{r,s} \quad \forall r \in R \tag{3-23}$$

$$Ns_{r,s} \in \{0, 1\} \quad \forall r \in R \tag{3-24}$$

Constraints 3-22 and 3-23 ensure that the binary decision variable $Ns_{r,s}$ equals 1 if the term $\sum_{p=\mu_r}^{\beta_r} z_{p,v_r}$ is larger than 0. Both constraint 3-15 and 3-16 can be discarded in the case of coordinated charging, all other constraints remain valid (3-2-3-14, 3-18-3-20).

3-4 Model Verification

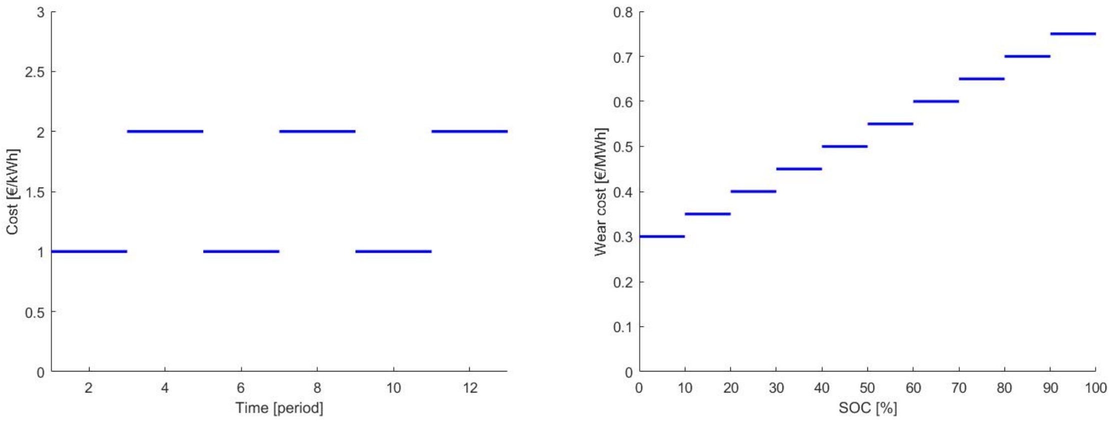
A small experimental study is set up in order to check whether the problem has been formulated and implemented correctly. This comprises some sanity checks that are performed with a simple instance that is solved using the MIP model. The problem is formulated using the Gurobi package in Python and solved on a machine with a Intel Core i7-4700MQ 2,4 GHZ processor with 8.0GB of RAM running on Windows 10. Three experiments are performed to verify whether the charge scheduling constraints are implemented correctly using a simple instance.

3-4-1 Instance and Cost Component Description

The time horizon is equal to 12 periods of one hour. Two vehicles are considered that both drive two trips during the day. The trip details for the simple instance are summarised in Table 3-2. The energy cost during the time horizon is visualised in Figure 3-2a. Labour cost is set at €2 for every charge event. The discrete wear cost function, considered for ten SOC intervals, is given in Figure 3-2b.

Table 3-2: A simple instance.

Trip	Vehicle	β	α	ΔSOC
1	1	3	4	10
2	2	8	9	30
3	2	6	7	20
4	2	11	12	20



(a) Energy price. **(b)** Discrete wear cost.

Figure 3-2: Energy cost and wear cost function.

3-4-2 Experiment 1

The SOC range of the vehicle is restricted to 10-100% SOC and the SOC at the start of the operational day is set at the lower bound of 10%. The battery capacity E of both vehicles is equal to 10kWh. One charger type is considered with a charge rate of 1kW. The number of chargers of this type κ_1 is equal to two. The peak power that can be drawn from the grid G is set at 2kW. Only uncoordinated charging is considered in this experiment. The charge scheduling model is used to solve the simple instance with these model settings. The optimal results are summarised in Table 3-7 and visualised in Figure 3-3 which shows the SOC of both vehicles during all periods. Table 3-4 shows the results for the SOC charge intervals that are used to determine the degradation cost. A red line indicates that the vehicle is being charged, while energy consumption represented by a step wise decrease of the SOC at the trip arrival period.

Table 3-3: Results for experiment 1.

Period	1	2	3	4	5	6	7	8	9	10	11	12	13
Vehicle 1													
$\mathrm{x}_{p,1,1}$	1	1	0	0	0	1	1	0	0	0	0	0	0
$\mathrm{z}_{p,1}$	1	0	0	0	0	1	0	0	0	0	0	0	0
$\mathrm{soc}_{p,1}$	10	20	30	30	20	20	30	40	40	10	10	10	10
Vehicle 2													
$\mathrm{x}_{p,2,1}$	1	1	1	1	1	0	0	0	0	0	0	0	0
$\mathrm{z}_{p,2}$	1	0	0	0	0	0	0	0	0	0	0	0	0
$\mathrm{soc}_{p,2}$	10	20	30	40	50	60	40	40	40	40	40	40	10
Power	2	2	1	1	1	0	1	1	0	0	0	0	0

As seen from Table 3-7, the variables $x_{p,k,s}$, $z_{p,k}$ and $soc_{p,k}$ work as intended. Binary variable $x_{p,k,s}$ equals 1 if a vehicle is charged during a period. Corresponding to $x_{p,k,s}$, $z_{p,k}$ becomes

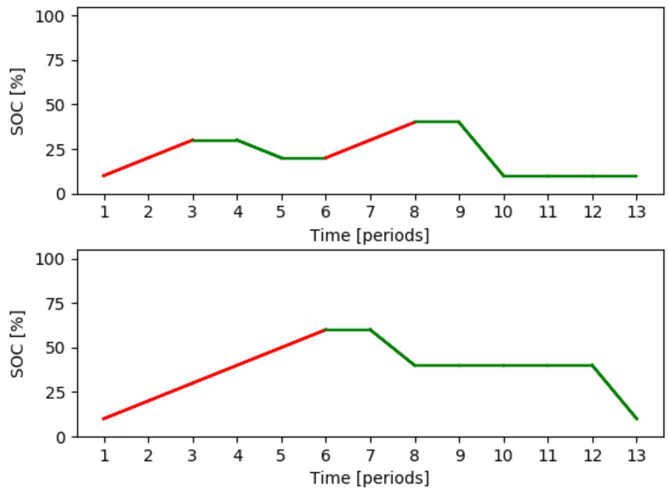


Figure 3-3: Visualised vehicle SOC for experiment 1: red lines indicate the periods in which the vehicle is being charged.

Table 3-4: Results for SOC charge intervals.

Trip	$soc^+_{1,r}$	$soc^+_{2,r}$	$soc^+_{3,r}$	$soc^+_{4,r}$	$soc^+_{5,r}$	$soc^+_{6,r}$	$soc^+_{7,r}$	$soc^+_{8,r}$	$soc^+_{9,r}$	$soc^+_{10,r}$
1	0	10	10	0	0	0	0	0	0	0
2	0	0	10	10	0	0	0	0	0	0
3	0	10	10	10	10	10	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0

one at the starting period of every charge event. The variable $soc_{p,k}$, increases with the right amount of energy in every charged period. It is seen that both vehicles executes two trips during the operational day as was planned, and that the SOC differential for every trip corresponds to the energy requirement of the trips. Furthermore, it is seen that the starting SOC is equal to 10% and that during the entire time horizon it stays between the imposed bound of 10-100%. In Table 3-4 it is seen that the SOC intervals that are used in every charge opportunity interval corresponding to a trip are equal to the charged SOC in that interval. Table 3-5 gives the results for every cost component. Since three charge events with a corresponding cost of €2 are used, the total labour cost are equal to €6. The energy costs can be checked by counting the number of charging periods for the two energy prices. There

Table 3-5: Cost components.

Component	Cost [€]
Degradation	3.85
Labour	6
Energy	12
Total	21.85

are six charged periods where $c_p = 1$ and three periods where $c_p = 2$, which sums up to a total of cost of €12. The degradation cost can be checked by multiplying every SOC interval that is larger than zero with the corresponding wear cost $2W_dE$.

3-4-3 Experiment 2

This experiment considers the same model settings, but now the grid capacity constraint is set at the value of 1kW, which means that only one charger can be used at the same time. The optimal results are summarised in Table 3-6 and visualised in Figure 3-4. It is clearly visible that, as intended, only one charger is used at the same time. This is enforced by variable y that is equal to the grid capacity constraint of 10kWh. This leads to higher energy cost since one vehicle is forced to charge during periods of higher energy prices.

Table 3-6: Results for experiment 2.

Period	1	2	3	4	5	6	7	8	9	10	11	12	13
Vehicle 1													
$x_{p,1,1}$	1	1	0	0	0	1	1	0	0	0	0	0	0
$z_{p,1}$	1	0	0	0	0	1	0	0	0	0	0	0	0
$soc_{p,1}$	10	20	30	30	20	20	30	40	40	10	10	10	10
Vehicle 2													
$x_{p,2,1}$	0	0	0	1	1	0	0	0	1	1	1	0	0
$z_{p,2}$	0	0	0	1	0	0	0	0	1	0	0	0	
$soc_{p,2}$	10	10	10	10	20	30	30	10	10	20	30	40	10
Power	1	1	0	1	1	1	1	0	1	1	1	0	0

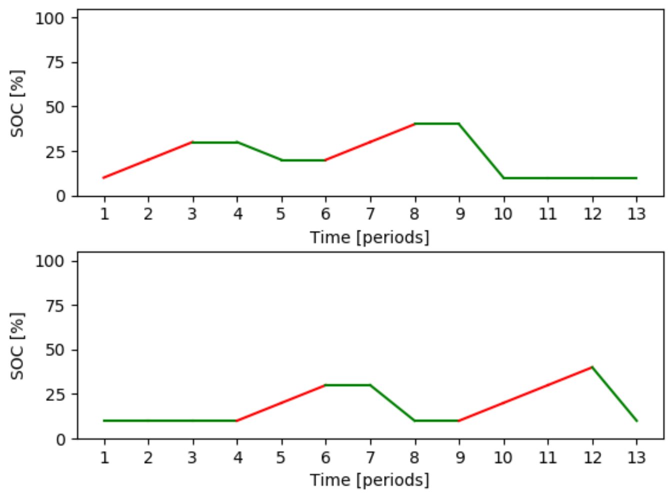


Figure 3-4: Visualised vehicle SOC for experiment 2.

3-4-4 Experiment 3

One last experiment is performed to check whether coordinated charging functionality was implemented correctly. The same instance is solved, now with the ability to use coordinated charging. The grid capacity constraint is again set at 2kW, just as in experiment 1. The SOC of both vehicles during all periods are visualised in Figure 3-5. Table 3-8 shows which charge opportunity intervals $Ns_{r,s}$ are used. It is seen that the charge event belonging to the first vehicle is shortly interrupted in order to benefit from lower energy prices.

Table 3-7: Results for experiment 3.

Period	1	2	3	4	5	6	7	8	9	10	11	12	13
Vehicle 1													
$x_{p,1,1}$	1	1	0	0	0	1	1	0	0	0	0	0	0
$z_{p,1}$	1	0	0	0	0	1	0	0	0	0	0	0	0
$soc_{p,1}$	10	20	30	30	20	20	30	40	40	10	10	10	10
Vehicle 2													
$x_{p,2,1}$	1	1	0	1	1	1	0	0	0	0	0	0	0
$z_{p,2}$	1	0	0	0	0	0	0	0	0	0	0	0	0
$soc_{p,2}$	10	20	30	30	40	50	60	40	40	40	40	40	10
Power	2	2	0	1	1	1	1	1	0	0	0	0	0

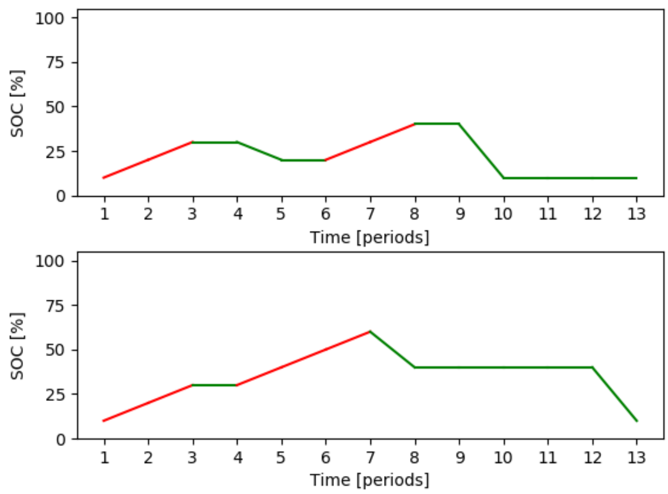


Figure 3-5: Visualised vehicle SOC for experiment 3

Table 3-8: The used charge opportunity intervals

$Ns_{1,1}$	$Ns_{2,1}$	$Ns_{3,1}$	$Ns_{4,1}$
1	1	1	0

3-4-5 Conclusion

It can be concluded that the model works as intended. As shown in the tables, the variables $x_{p,k,s}$, $z_{p,k}$, $soc_{p,k}$, $soc^{+}_{d,r}$ and $Ns_{r,s}$ all behave as expected. In experiment 2, the correct implementation of the grid capacity constraint G was checked. Experiment 3 showed that model adjustments enabling coordinated charging work as intended.

3-5 Summary

How can the charge schedule optimisation problem be formulated in a mathematical model?

In this chapter a MIP model for the charge scheduling problem was proposed. Two important conditions related to the problem are that (1) the assignment of vehicles to trips is determined preceding to the charge schedule optimisation and (2) the energy requirements of all trips are known. A step wise approach was used to introduce the model. First, the problem formulation for the charge scheduling problem without the incorporation of battery degradation cost is given in Section 3-1. Subsequently, the model is extended in Section to be able to account for battery degradation cost in Section 3-2, using a discrete battery wear model from Han et al (2014) [3]. Model adjustments that enable coordinated charging, which resembles the use of smart chargers, are presented in Section 3-3. Lastly, the implementation of the proposed model is verified in Section 3-4.

Chapter 4

Case Study

This chapter consists of three parts, in which different aspects of the case study of e-grocer Picnic are analysed. This will outline the necessary information to set up the experimental study in Chapter 5. The following questions are answered in consecutive order:

- What is the energy demand of the electric fleet of Picnic?
- What charge scheduling process is currently used at Picnic?
- What are the characteristics of Picnic's current vehicle battery and surrounding charging infrastructure?

In Section 4-1 the energy demand of the fleet is analysed. Subsequently, the current charge scheduling process of Picnic is discussed in Section 4-2. Finally, the vehicle and charging infrastructure characteristics are discussed in Section 4-3.

4-1 The Energy Demand of the Fleet

The energy requirement of Picnic's EVs over time is important input for the charge scheduling problem and sets the basis for the experimental study. The input of the charge scheduling problem, as proposed in Chapter 3, consists of three important parts of information: the trip departure and arrival times (β_r, α_r) and the energy requirement of trips (Δsoc_r). This input can be derived by analysing the trip planning of Picnic and the characteristics of typical Picnic trips, which is done in this section. It thereby gives an answer to the first sub-question of this chapter:

- What is the energy demand of the electric fleet of Picnic?

4-1-1 Shift Schedule Analysis

Trip departure and arrival times determine when the assigned vehicle should contain a certain amount of energy and what time remains for charging. At Picnic, departure and arrival times of trips are planned on the basis of the shift schedule. A shift sets the ultimate departure and arrival time for trips that are driven in that shift. The combination of all shifts during the day is called the shift schedule. The current shift schedule of Picnic is build up in such a way that different shifts do not overlap in time, which means that trips from different shifts are also strictly separated. This has multiple advantages: the same delivery driver, also known as Runner, can execute multiple trips in sequence. Furthermore, the same vehicle can be used in succeeding shifts. Figure 4-1a shows the current shift (CS) schedule that is performed at most hubs. Figure 4-1b shows the morning shift (MS) schedule that was first performed in august 2018 in Leiden. Compared to the traditional schedule, this MS schedule contains two additional shifts in the morning. These shift are 15 minutes shorter than the afternoon shifts to ensure that the second morning shift ends at noon. The number of trips that are driven in every shift is determined by demand and capacity. The demand is determined by the number and size of customer orders throughout the day. The capacity of Picnic is constrained by the component in the supply chain with the lowest capacity, such as production capacity at fulfilment centres, the number of EVs, the available runners, etc. The demand and available capacity can differ largely for specific days of the week and hub locations over the country. An analysis was performed to get an idea of the scale of operations in the last-mile process of Picnic. This is done using a data set containing the number of trips for every shift for different hubs over a period of 37 weeks. The average shift sizes for two hubs is given in Figure 4-2.

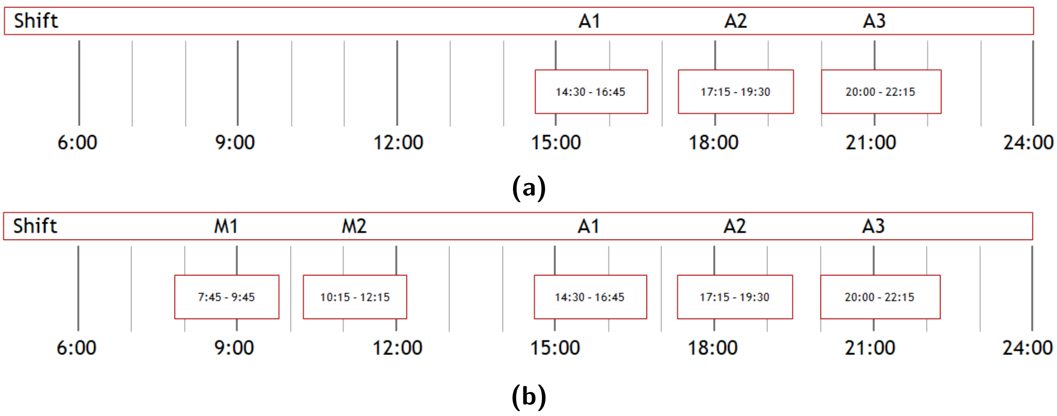
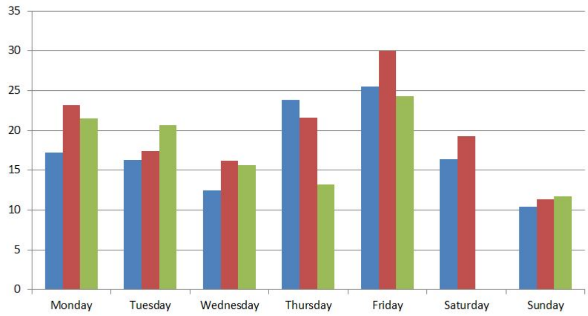


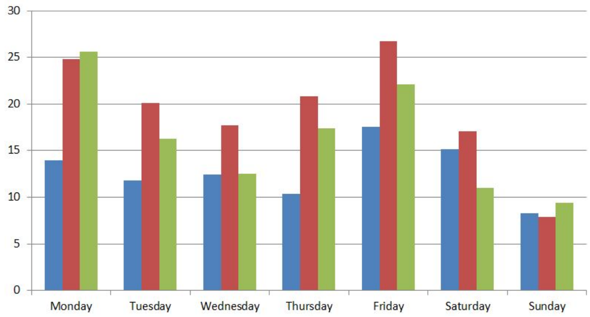
Figure 4-1: (a) CS schedule: composed of three shifts (A1-A3) in the afternoon that are all of equal length. Note that all shifts are strictly separated in time. (b) MS schedule: in addition to the three afternoon shifts, two morning shifts are performed (M1-M2), which are 15 minutes shorter than the afternoon shifts.

4-1-2 Trip Energy Analysis

In addition the departure and arrival times of trips, the quantity of energy that is required for the trips is needed as input for the charge scheduling problem. This is dependent on



(a) Average shift sizes for hub Amersfoort



(b) Average shift sizes for hub Ypenburg

Figure 4-2: Average shift sizes for two hubs

certain trip characteristics that influence power consumption. To be able to understand what drives the energy demand of trips it is important to know the breakdown of a typical trip at Picnic, which is given in the next subsection. Subsequently, Picnic's last-mile delivery trips are characterised using operational trip data. Since the trip energy requirements are required preceding the construction of the charge schedule, it is necessary to get high quality predictions of trip energy requirements. At Picnic, there are no such trip energy predictions yet. Therefore, it is interesting to investigate the usability of different trip characteristics for the prediction of trip energy requirements. A predictive trip energy requirement model is presented in the final part of this section.

Breakdown of a Trip

Every trip consists of five main parts: loading, stem time (start), delivery drive time, stem time (end) and unloading time. Two schematic overviews of a trip are depicted in Figure 4-3 and 4-4. Figure 4-3 shows a trip from a geographical perspective, while Figure 4-4 shows the different parts of a trip in a block diagram. Every trips starts with the loading of the frames with groceries into a delivery vehicle for which a certain amount of loading time is reserved. Next, the actual driving of the trip can commence. This starts with the stem time, which is the time that is required to drive to the delivery area. After reaching the delivery area, the actual delivery of groceries is performed during the delivery drive time. In this part of the trip, a sequence of activities is repeated for the number of customers that are served within the trip. This sequence consists of delivery drive time, parking time and drop time. After the final delivery, the stem time from the delivery area towards the hub has to be taken into account. Finally, after each trip some time is allocated for the unloading of frames and sorting of deposit items.

Trip Data

In order to characterise the last-mile delivery trips of Picnic, a data set containing several features of 16980 Picnic delivery trips is used, all originating from the CS schedule. An overview of the data is given in Table 4-1. The data is obtained from multiple sources. The SOC differential and trip distance data were collected by performing a survey with delivery drivers in which they were asked to specify the SOC and mileage before and after every trip.

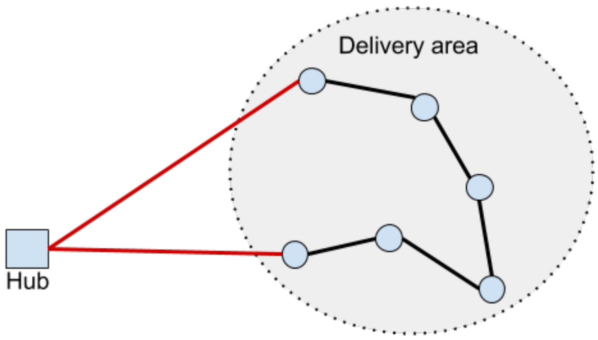


Figure 4-3: Overview of a trip: the red lines indicate the drive time to the delivery area, also known as stem time. When arrived in the delivery area, a set of customers is served after which the vehicle returns to the hub

Table 4-1: Trip data: overview of trip characteristics from 16980 trips

Feature		Min	Max	Average
ΔSoC	%	6	60	24,0
Date	-	03/07/17	19/05/18	-
Trip start time	min	-	-	-
Trip end time	min	-	-	-
Payload weight	kg	10,1	552,7	190,6
Number of deliveries	#	1	19	11,15
Trip distance	km	6	42	17,7
Trip duration	min	23,9	165,0	114,7
Total stem time	min	6,3	61,7	27,5
Delivery drive time	min	5,3	112,6	87,3
Total drop time	min	5,3	99,6	68,3
Ambient temperature	C	-8,3	28,1	11,9

The SOC differential is used to get a measure of the energy requirement for a trip. However, it should be noted this is not a pure measure for the trip energy consumption. The vehicle SOC is defined as a fraction of the energy content divided by the current maximum energy capacity of the battery. As the battery capacity is subject to degradation over time, equal trip energy requirements will not lead to equal SOC requirements for batteries with different SOH. However, it is assumed that all batteries have a 100% SOH and therefore, that all SOC differentials are comparable. This is a reasonable assumption since all vehicles from the data set are relatively new (average mileage = 3414km). The outside temperature was extracted from the database of the KNMI and merged with the other data. This data is added since it is expected that it plays a role in the energy efficiency of EVs. The remaining features were extracted from the planning software of Picnic.

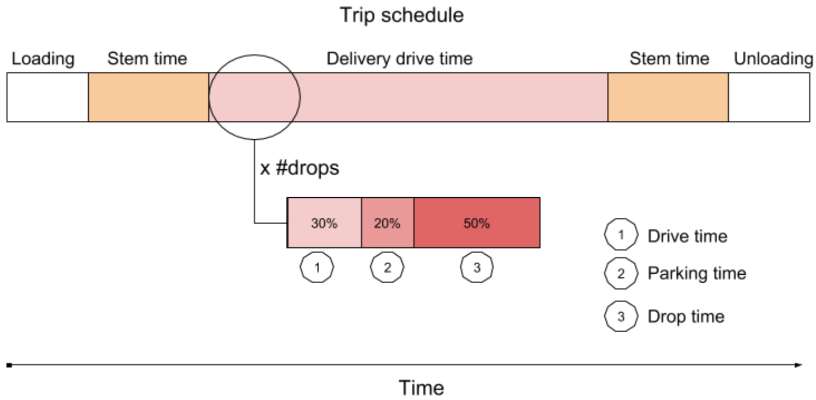


Figure 4-4: Schematic breakdown of a trip: the white parts indicate the (un)loading time of the frames, orange parts are the stem time to and from the delivery area, and the red part is the delivery drive time. The delivery drive time consists of a repetitive sequence for every customer with: drive time, parking time and drop time.

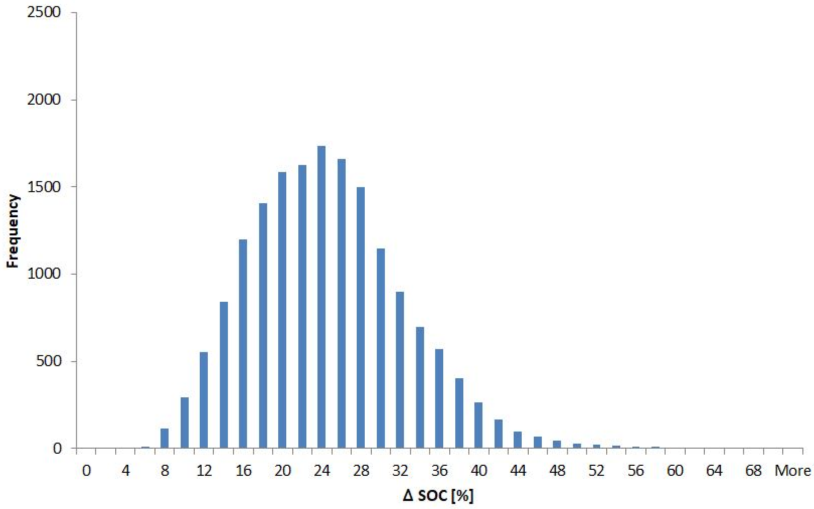
Trip Data Analysis

Using the trip data that was presented in the previous section, histograms are made of some of the main characteristics of trips like the SOC requirement, trip distance and trip duration. These histograms are visualised in Figure 4-5. Figure 4-5a shows the distribution of the SOC differential trips. It is seen the last-mile trips at Picnic require a small part of the battery capacity. Just 3% of all trips requires more than 40% SOC, which indicates that vehicles can be used to drive multiple trips on one battery charge per day in most cases. Figure 4-5b visualises the distribution of trip distance. The resemblance of this distribution with the SOC differential distribution is clear, indicating that trip distance is an important factor for the determination of the energy requirements of trips. Lastly, Figure 4-5c depicts the distribution of the duration of trips.

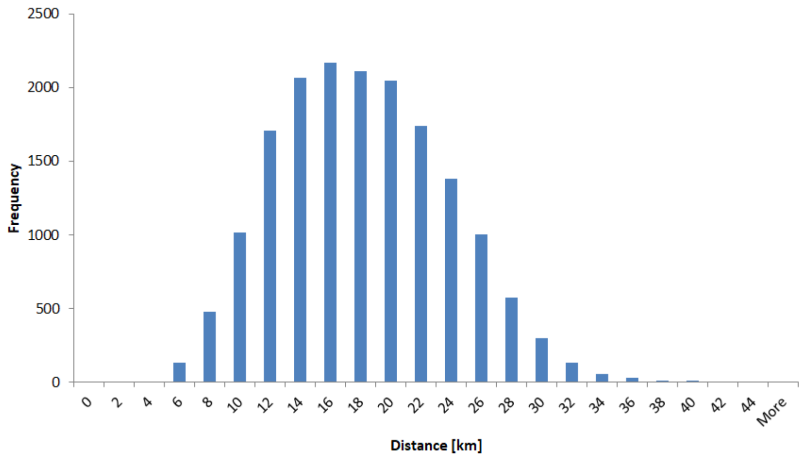
Trip Energy Requirement Prediction Model

A crucial part of information for setting up the charge scheduling problem is the energy requirement of trips, which should be based on trip energy predictions. The availability of this information is an important precondition to be able to set up the problem, while the quality of the information determines the quality of the output schedule. Therefore, the ability to predict the energy requirements of trips with certain trip characteristics is investigated in this section. It should be noted that development of this model is not considered to be a main objective of this Thesis, but rather a side step to check whether this important information for the charge scheduling model can be adequately predicted. Therefore, this part will not contain an elaborate discussion and comparison of multiple energy prediction models, but the development and discussion of a single model. There are multiple types of models that can be built:

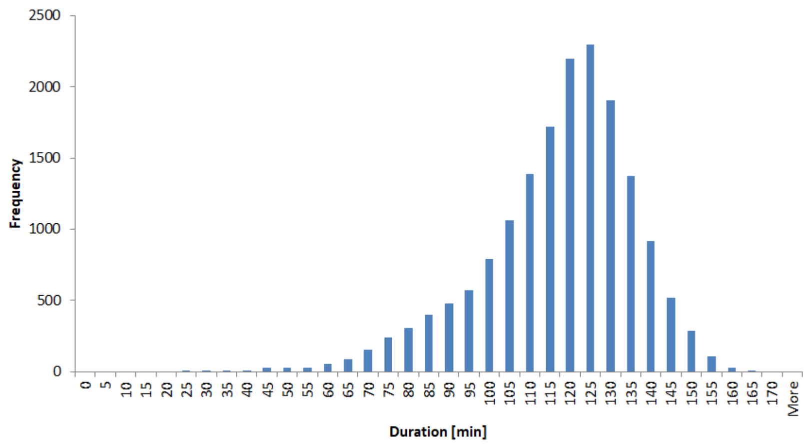
- Data driven model: historic data consisting of trip characteristics and corresponding energy related output can be used to model the energy requirement of a trip.



(a)



(b)



(c)

Figure 4-5: (a) Trip delta SoC histogram. (b) Trip distance histogram (c) Trip duration histogram

- Physical prediction model: an understanding of underlying physical principals behind the power consumption and regeneration of the vehicle can be modelled. Factors related to energy consumption, such as acceleration, aerodynamic and rolling resistance, grading,etc and energy regeneration should be incorporated.

In the case of Picnic, a physical model would be unnecessary complex and most likely add computational time when compared to a data driven model. Moreover, sufficient trip data is available. Therefore, the most logical choice is to develop a data driven model. Within this category, there is a large amount of different models that can be used, such as regression models, genetic algorithms, support vector machines and artificial neural networks (ANN). An ANN was selected, because it is easy to implement and it automatically weighs the features that are important for the model. An ANN is a nature inspired model based on the central nervous systems of animals. An elaborate description of the development of this model is presented in Appendix 7-2-2. The model is built in Matlab and has goal to predict the SOC differential target value using the features from the dataset presented in Table 4-1. The performance of the model is measured as the average mean square (MSE) error and correlation coefficient, which are equal to 12,4 and 0,89 respectively. These outcomes show a high correlation between the used features and the target value, and therefore model can be used to accurately predict the energy requirement of trips. It should be noted that there would always exist a certain uncertainty in the trip energy prediction model with the current available data. This is due to several influences that can not be determined such as mechanical factors, driving behaviour and environmental factors. Examples of mechanical factors are drivetrain and powertrain efficiency and tire pressure. Driving behaviour is mainly relevant due to driving speed and accelerations. Driving at high speeds is more energy demanding. Moreover, high accelerations are usually associated with higher energy requirements. Also hard braking can have a negative influence on energy efficiency due to lower energy regeneration. Environmental factors include wind speed and slopes.

4-2 Current Charge Scheduling Process

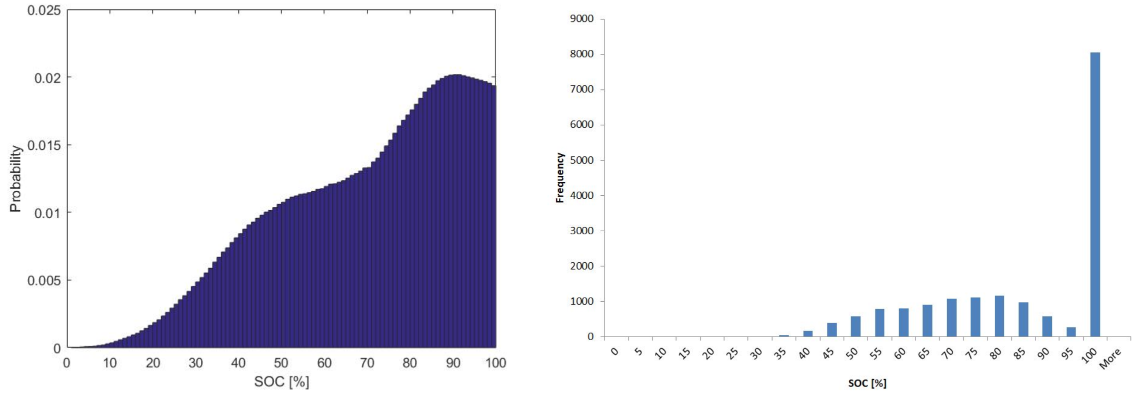
The current charge scheduling process is relevant in order to get an insight how much time is available for making the generation of the charge schedule and to understand what considerations currently play a role in this process. This can be used to derive the current operational performance of the charge scheduling process. The charge scheduling process was analysed by conducting several interviews with the involved schedulers and performing data analysis. By doing this, the following sub-question can be answered:

- What charging planning process is currently used at Picnic?

First, an analysis of the current charging scheduling process is presented in Section 4-2-1, and secondly, an overview of the entire planning timeline is discussed in Section 4-2-2.

4-2-1 Rules During Scheduling

At the moment, no charge schedule is made at the hubs. Instead, some general rules are followed which are designed to minimise the risk of having less than fully charged vehicles



(a) The discrete PDF for driving in a certain SOC interval

(b) SOC distribution at trip departure

Figure 4-6: SOC cycling ranges and SOC at trip departure

at the start of the an operational day. In order to reduce this risk, runners are asked to plug in their vehicle after arriving at the hub from the final trip of their working day. This ensures that vehicles are always charged after they have been used. Unless a vehicle is used for another trip later on the same day, the vehicle is fully charged to 100%. Furthermore, a vehicle is charged when the energy content of its battery is presumed to be too low to cover a new trip. This is done to prevent vehicles from running out of energy while they are on the road. A replacement vehicle is then used to drive the trip. Since there are no energy requirement predictions for trips, the SOC value at which vehicles are withheld from operation is prescribed by the hub management. SOC values between 30-50% are used for different hubs. In some cases, the hub management assesses if the energy level of a vehicle is sufficient to cover a specific trip on the basis of some trip characteristics, such as delivery area and number of orders. It should be noted that these general rules related to charging on one hand minimise the risk of having not fully charged vehicles but on the other hand tend to result in driving in higher than required SOC ranges. As explained in Section 3-2, this can be harmful for vehicle batteries. In order to get a detailed understanding of the effects of the rules that are followed during the charging process, an analysis is done with the data presented in Table 4-1 in the previous section. First of all, Figure 4-6a shows a discrete PDF of the SOC during driving. Secondly, a histogram of the SOC values at the beginning of trips is shown in Figure 4-6b. What is seen from these figures, is that the vehicles are currently predominantly cycled in the higher SOC ranges of the battery. Furthermore, it is seen that vehicles are frequently recharged to 100% SOC, which causes the vehicles to be fully charged at trip departure in 47.4% of all cases.

4-2-2 Picnic's Planning Timeline

In Figure 4-7, an overview of the planning timeline is given. This figure indicates the important events during the planning, such as order slot closings, completion of routing and the shift start time.

From this planning timeline can be derived how much time is available for charging between

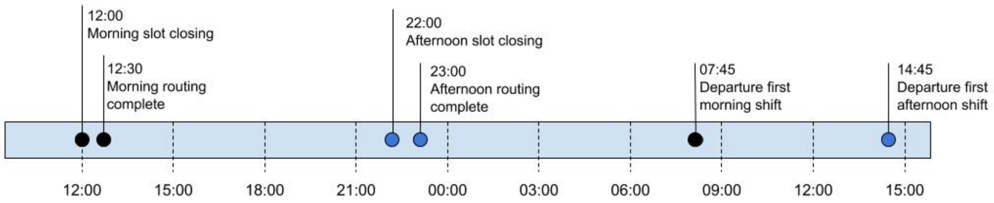


Figure 4-7: Planning timeline: this figure indicates the most important events in the planning.

the arrival of the last shift on one operational day and the departure of the first shift on the next operational day. Furthermore, the time that is reserved for the generation of the charge schedule can be determined using this timeline. It can be seen that the complete set of routes for the next operational day is known at 23:00. This leaves not much time for the calculation of the charge schedule, since the hub closing time at 23:30 restricts the start of new charge events, in the case of uncoordinated charging. This constraint should be taken into account for the operational implementation of a charge scheduling algorithm.

4-3 Vehicle and Charging Infrastructure Characteristics

There are a number of factors related to the EV and charging infrastructure that need to be identified so that the charging optimisation problem can be set up. First, there is the vehicle charging curve. This curve gives the relation to the amount of energy that can be charged into the battery over time. Secondly, other battery characteristics like battery capacity, topology and cell chemistry type are important. These battery characteristics determine in large part what battery wear behaviour can be expected [16]. In order to cover this subject, first some general information about charge curves and charge currents is given. Subsequently, the charging characteristics of the vehicle under consideration, the Goupil G4, are given. By discussing these subjects, the answer to the following sub-question is given:

- What are the characteristics of Picnic's current vehicle battery and surrounding charging infrastructure?

4-3-1 Vehicle Charging Characteristics

The vehicle that is used by Picnic is the Goupil G4. The charging characteristics of this vehicle need to be characterised in order to set up the charging problem. This relates to the vehicle charging curve and general battery specifications.

General characteristics Goupil G4

The Goupil G4 is classified in the so called light commercial vehicle (LCV) segment. The narrow width of the vehicle of 1.4 meters provides benefits when navigating through congested inner cities. The energy consumption of the vehicle is relatively low because of its low top speed of 50km/hr. Due to this, a respectable operational range of 70km can still be achieved with this vehicle considering its limited battery capacity of 12kWh. The Goupil G4 contains a Li-ion battery pack with LiFePO4 chemistry cells. This cell chemistry offers a higher security and longer cycle lifetime compared to other Li-ion cell chemistries, at higher cell costs [42]. An on-board AC charger is installed that transforms 230V AC source, to the 48V DC battery level. Table 4-3 and 4-4 show the characteristics of the cell type and battery pack that is used in the Goupil G4.

Table 4-2: Vehicle characteristics

Vehicle Characteristics	Unit	Value
Length	m	2.96
Width	m	1.40
Weight	kg	921
Top speed	km/hr	50
Range	km	70

Table 4-3: Battery characteristics

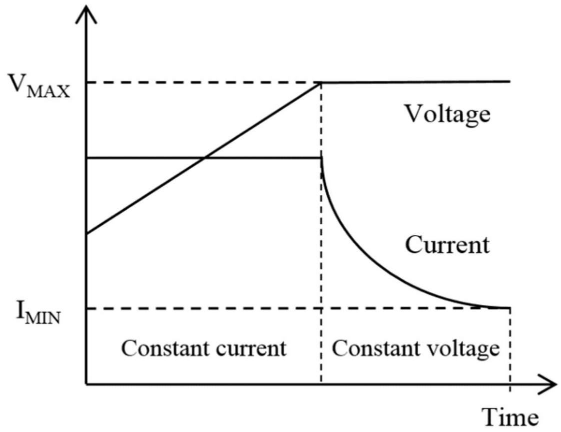
Battery Characteristics	Unit	Value
Pack nominal voltage	V	48
Pack capacity	kWh	12
Modules in parallel	#	5
Cells in series	#	15
Operating temperature	C	-20 to 45

Table 4-4: Cell characteristics

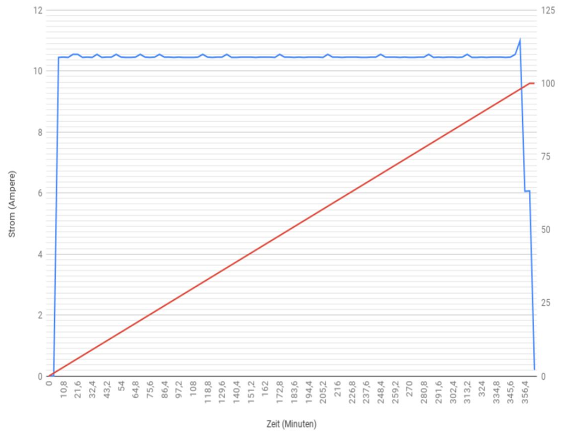
Cell Characteristic	Unit	Value
Cell chemistry		LiFePO4
Cell type		Prismatic
Nominal voltage	V	3.3
Nominal capacity	Ah	50
C-rate	C	5

Charge Curve

The charging process of the Goupil G4 needs to be analysed in order to derive the rate of change of the battery SOC. The charging process of an EV is typically associated with a constant current constant voltage (CC-CV) technique to enable a quick, safe and efficient charging of a EV battery [43]. In this scheme, visualised in Figure 4-8a, the constant current is applied until the maximum cell voltage is reached. During this CC phase the SOC will increase linear with time. Subsequently, in the CV phase the battery voltage is held constant



(a) Constant current - constant voltage charging [44]



(b) Charge curve for the Goupil G4

Figure 4-8: Charging curves

and the current is reduced exponentially with time until the battery is fully charged. This phase is associated with a continuously decreasing SOC rate. The charge curve of the Goupil G4 was measured by Picnic Germany and the result is depicted in Figure 4-8b. It is apparent from Figure 4-8b that the charged energy can be seen as a linear function of time for the largest part of the charge curve. Only in the final part of the charge curve, the charge rate is reduced. This means that the proposed linear charging model in the charge scheduling model is a good approximation of the actual charging behaviour. The linear charge rate of the vehicle is equal to 2.0kW. This means that with an average trip energy requirement of 2.9kWh, the amount of trips that can be driven on one full hour of charging is equal to 0,70.

4-3-2 Charging Infrastructure Characteristics

The second part of this section relates to the characteristics of the surrounding charging infrastructure at Picnic. For the charge scheduling problem there are several aspects that need to considered consisting of the charger type, grid capacity, and energy contracts and markets.

Chargers

The amount and type of chargers is important information for the charge scheduling problem. The electrical grid supplies alternating-current (AC) and vehicle batteries work on direct current (DC). In order to allow vehicle batteries to charge, the charger has the function to transform the AC source in the required DC charging profile. There are two options regarding the placement of the vehicle charger: on-board and off-board. While the function of the charger remains the same, on-board chargers are generally designed for lower power ranges while off-board chargers are used for supplying the higher power ranges. It is beneficial to place high power chargers outside of the vehicle, since the charger volume and weight size with increasing charging power. The charging type that is associated with the use of off-board chargers is also called DC charging, because the power supply to the vehicle is already in DC. When an on-board charger is used, the charging type is called AC charging, since the AC is converted to DC inside the vehicle. Every Goupil G4 is fitted with a small on-board charger that can be connected to the grid through a regular 230V socket. The chargers do not communicate with the outside network and are not able to interrupt charging or to decrease/increase the charge rate. Since the amount of wall sockets can be easily extended without high capital investments, the amount of vehicles that can be charged at the same time is mainly constrained by the grid capacity.

Grid

In the context of the charge scheduling problem, the grid is mainly important because the grid capacity constraint sets the maximum power that can be drawn from the grid. On a local level, the peak power load that can be drawn from the grid is constrained by the local grid infrastructure capacity. The installed fuses determine the maximum load that can be drawn from the grid. This capacity is included in the energy contract and can be upgraded (in most cases) against additional cost. At most Picnic hubs, there is a three phase connection of 80 Ampere, which equals a maximum power of 55.2kWh. Note that total energy consumption at hubs does not only consist of chargers, but there should also be sufficient capacity for a cool cell, machinery and other tools that are used in the operation. The large scale adoption of EV vehicles will bring challenges for the electrical distribution network as it will result in a significant increase in electricity consumption in residential areas. Uncoordinated charging of EVs may have negative effects on the electrical distribution network including increased peak load, transmission loss, and stress on distribution transformer [45]. Especially large load peaks are harmful since these would require adequate backup of expensive fast generators, increase power losses of transmission/distribution lines, and frequently overload grid components [46].

Energy Contracts and Markets

One other important aspect of the charge scheduling problem is the price of energy. This is determined by the energy contracts that are made with energy suppliers. At the moment a fixed energy price over time is obtained. However, this may change in the future. Energy markets have been created to promote a better balance between power generation and consumption. Different energy markets have been identified in which the flexibility of EVs could be leveraged for the purpose of grid balancing including the day ahead market, intra-day market and imbalance market [47]. By means of price incentives the end user may adapt its energy consumption to times of low energy prices. Figure 4-9 shows sorted hourly sampled day ahead, intra-day and imbalance prices for the time span of a year. It can be seen that the energy prices are much more volatile in the imbalance market with respect to the day ahead markets. This means that theoretically, more revenue could be generated by trading on this market. However, it should be noted that trading on this market is more complex [47]. The features of the different energy markets will be discussed below:

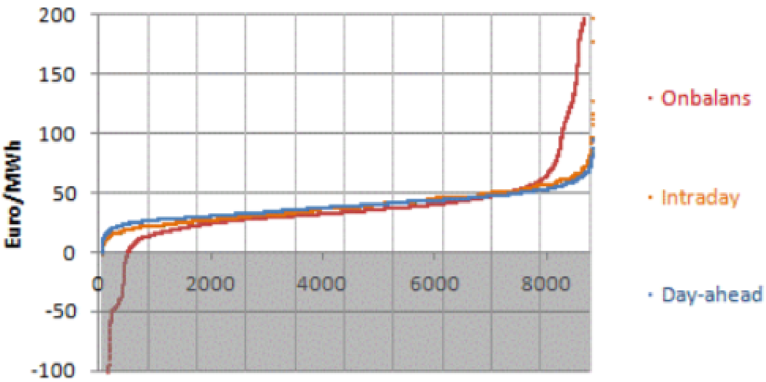


Figure 4-9: Volatility on different energy markets. The red, orange and blue line show sorted prices for the imbalance, intra-day and day-ahead market.

The day-ahead energy prices are traded on the APX. The principle of demand and supply determines an hourly variable energy price for the next day. A bidding process between large consumers and suppliers that is open until 12:00 AM on the day before delivery determines the hourly variable prices, which are published at 13:00 on the day before delivery. Access to the APX market could be obtained by participating in the bidding process. However, for smaller energy consumers, it would make more sense to get access through a APX energy contract. This requires no participation in the bidding process and still ensures access to the hourly variable energy price. Figure 4-10 depicts an example of hourly day ahead prices. In a research performed by Movares (2016) [47] it was concluded that a possible energy cost reduction of roughly 35% can be achieved by adjusting the charge profile to the day ahead prices.

Figure 4-10: Sampled hourly energy prices APX [48]

On the intra-day market, energy is traded on until five minutes before delivery. Energy trading on the intra-day market is also done on the APX market. Given the low short time resolution, both the day ahead and intra-day markets are called spot markets. In contrast to the day ahead and intra-day market, the imbalance market is not a tool for a better planning of energy generation and demand, but it is used for balancing disturbances that have occurred between supply and demand and last longer than 15 minutes. The research of Movaris (2016) [47] reports that a cost reduction of 60% can be achieved when the smart charging is adjusted to both the day-ahead and imbalance market. This can be done by stopping the charging process whenever the price differential between the day ahead and imbalance prices crosses a certain threshold. Although this energy market shows huge potential for the decrease in charging cost, the energy prices on the imbalance market are very hard to predict on a day ahead basis as required for the charge scheduling problem. Therefore, only the day ahead energy prices are used in this work.

4-4 Summary

Three different aspects of the case study of e-grocer Picnic are analysed. This will outline the necessary information to set up the experimental study in Chapter 5. The following subjects were be discussed in consecutive order: the energy demand of the fleet, the current charge scheduling process of Picnic and characteristics of the vehicle charging characteristics and charging infrastructure

What is the current energy demand of the electric fleet of Picnic?

The total energy consumption of the fleet over time is composed of the energy requirements of all individual trips, which can be characterised by the time of use and the quantity of energy that is required. By considering both factors for all trips, the entire energy requirement of the fleet over time can be derived. Trips at Picnic are scheduled on the basis of to different shift schedules. These schedules sets the ultimate departure and arrival time for trips that are driven different shifts. Demand and capacity determine the number of trips in every shift. The energy requirement of trips is determined. The predictive value of these trip characteristics was investigated by building a artificial neural network. This model proved to be capable of predicting trip energy requirements on the basis of some known trip characteristics.

What charging planning process is currently used at Picnic?

The current charge scheduling process was analysed by conducting several interviews with the involved schedulers and by performing data analysis. This is relevant in order to get an insight how much time is available for making the charge planning and to understand what considerations currently play a role in this process. It turns out that a main objective during the current charging process is ensuring that vehicles are at a 100% SOC at the start of an operation day. This reduces the risk of not achieving the mobility objectives of the vehicles, but on the other hand results in cycling in high SOC ranges which can be harmful for vehicle batteries.

What are the characteristics of Picnic's current vehicle battery and surrounding charging infrastructure and how can these change in the future?

Following the analysis of the current charging process, the characteristics of the vehicle and the charging infrastructure were presented.

- The charge energy can be represented by a linear function of time
- The charge rate is equal to 2.0kW
- An on board charger is responsible for the charging and is plugged into a regular wall socket
- The amount of vehicles that can be charged at the same time is predominantly constrained by the grid capacity of 55.2kW
- At the moment, no time variable energy prices are obtained
- Hourly variable energy prices from the day ahead energy can be incorporated into the charge scheduling problem

Chapter 5

Design of Experiments

An experimental study is performed to investigate the impact of charge schedule optimisation on charging cost. This chapter will discuss the required steps to set up the experimental study and thereby gives an answer to the following sub-question:

- How can an experimental study be set up that uses the proposed model to study the impact of charge schedule optimisation on charging cost?

The proposed experimental study comprises of two parts. First, the charge scheduling model is used to optimise the charge schedule for three different shift schedules. In a later experiment, some of the vehicle and charging characteristics are altered in order to investigate their influence on charging cost. Section 5-1 explains which shift schedules are considered and how corresponding instances are generated. Subsequently, in Section 5-2 the vehicle and charging infrastructure configurations that are investigated are presented. Next, in Section 5-3, the relevant model settings are discussed. Finally, the establishment of the different cost components is discussed in Section 5-4.

5-1 Instances

The EFV-CSP is solved for different instances that are based on a three shift schedule types. These schedules are presented in the Subsection 5-1-1. Subsequently, the methodology for generating the instances is explained in Subsection 5-1-2.

5-1-1 Shift Schedules

Three different shift schedules form the basis of the instances that are used to perform the experimental study. A shift schedule can be characterised by its shift time windows, which set the ultimate scheduled departure and arrival times for trips. The shift schedules under consideration are explained below and visualised in Figure 5-1.

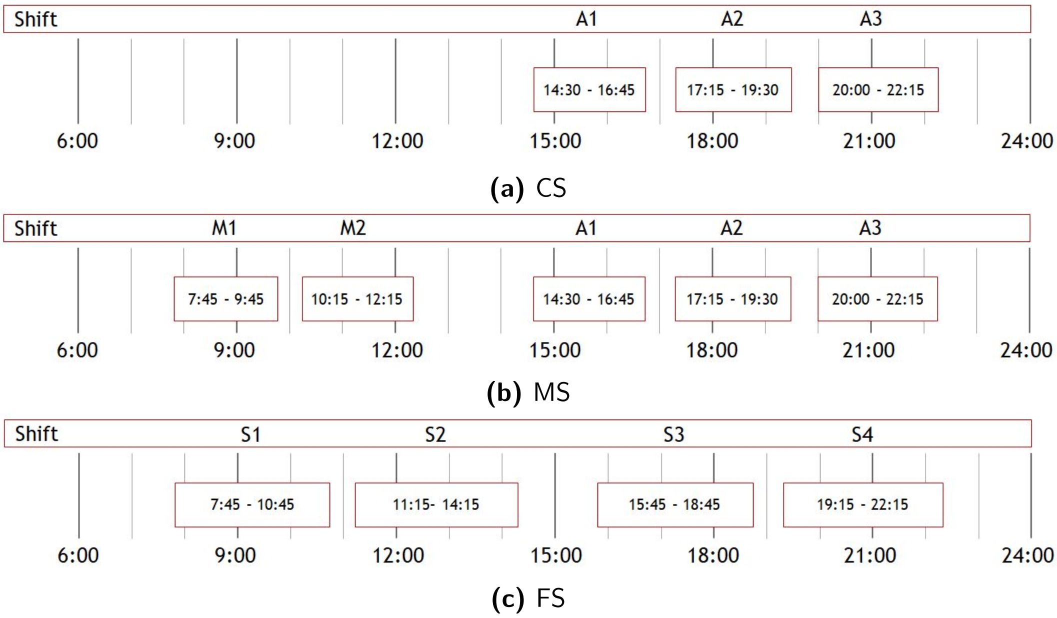


Figure 5-1: (a) Current shift schedule. (b) Morning shift schedule. (c) Fictive shift schedule.

- Current shift (CS) schedule: the shift schedule that is currently performed at the majority of the hubs. This schedule contains three shifts of equal duration that are driven in the afternoon. The average trip duration of 115 minutes is based on current trip data that was presented in 4-1-2.
- Current morning (CM) schedule: this is the current morning schedule that was first performed in august 2018 in Leiden (LID). In addition to the current afternoon shifts, this schedule is extended with two morning shifts which are slightly shorter (15 minutes) than the afternoon shifts. The average duration of the afternoon and morning trips are 115 minutes and 100 minutes respectively.
- Fictive shift (FS) schedule: this schedule was generated in order to determine the influence of performing longer and more energy demanding trips, which may be used after the introduction of a new vehicle. This shift schedule contains four shifts of equal duration with a longer break between shift two and three. The average duration of the trips is 180 minutes.

5-1-2 Generating Instances

An instance for the EFV-CSP is composed of a fixed set of vehicle rotations consisting of trips with corresponding energy requirements. For every shift schedule, seven instances are generated, resembling one entire operational week. The following steps should be performed in order to generate a usable instance for the EFV-CSP:

1. Shift size determination

2. Trip sampling process
3. Vehicle-trip allocation

Shift Size Determination

The first step of the instance generation process is to decide on the used shift sizes, which comprises the number of trips that are performed in each shift for every shift schedule and operational day. For the CS and CM schedule, the afternoon shift sizes originate from an actual operational week in hub Amersfoort. In addition, the additional morning shifts of the CM schedule are assigned a random shift size which is comparable to the day average. This is done because the current morning shift sizes at hub LID are still growing due to a scale-up of operations. The entire FS schedule will be filled with random shift sizes that are comparable to current average shift sizes.

Trip Sampling Process

The next step is the trip sampling process, which comprises the assignment of the required trip characteristics consisting of the trip distance, departure time, arrival time and energy requirement. In case of the CS and CM schedule, these features are sampled from a set of actual trips. For the FS schedule, the data from the set of actual trips is extrapolated to resemble the fictive trips, which are longer than current trips in terms of time and distance. Note that also the energy requirement is sampled using the SOC differential data and that the trip energy requirement prediction model was not used for this. The result of the trip sampling process is a trip schedule for an entire operational day. The trips in this trip schedule should be allocated to vehicles in order to generate a usable instance that can be solved by the EFV-CSP. One option is to manually assign vehicles to trips as in the current planning process. However, in this work a vehicle-trip allocation algorithm is used.

Vehicle-Trip Allocation

This vehicle-trip allocation is generated by solving a charge scheduling problem, which is explained in Appendix 7-2-2. Solving the problem generates a feasible vehicle-trip allocation, taking into account the battery range constraints, charge rate and grid capacity. The objective of the model is to minimise the number of vehicles that is required to perform a certain trip schedule. This can be especially useful when the fleet size is small compared to the maximum shift size in an instance. A safety margin is taken into account for the set values of the charge rate and minimum SOC. This is done to prevent the generation of very tightly constrained or even infeasible models during the dicretisation step of the EFV-CSP. Moreover, tightly energy constrained solutions are not preferable due to uncertainties related to energy consumption that occur during planning and operation. The characteristics of the resulting instances for the three shift schedules are given in Table 5-1. It is seen that the number of trips size with the amount of shifts in each schedule. Furthermore, the total energy requirement is a function of both number of trips and trip energy requirement, which in its turn is dependent on the trip duration. Even though the CM schedule contains more trips, the total energy requirement of the FS schedule is still higher due to the increase in trip energy requirement.

One interesting aspect of the FS schedule instances is that they are quite demanding in terms of energy, when compared to the vehicle battery capacity. The average daily energy consumption is approximately equal to the battery capacity of the current vehicles (12kWh). This means that, when taking into account a safety margin, multiple charge events for every vehicle rotation are required to ensure energy feasibility.

Table 5-1: The characteristics of the set of instances for the three shift schedules. The second column shows the summed amount of trips for the seven instances for every shift schedule. The third column indicates the summed amount of vehicle days that is required to perform each instance set, in which the use of one vehicle during one operational day counts for one vehicle day. The next column shows the total energy requirement of all trips. E_t represents the average energy requirement per trip, while E_v is the average energy requirement per vehicle day. Lastly, T_v indicates the average number of trips per vehicle day

Schedule	Trips	Vehicle days	Energy	E_t	E_v	T_v
	#	#	kWh	kWh	kWh	#
CC	415	164	1235.5	2,98	7,54	2,53
CM	615	164	1737.6	2,83	10,61	3,75
FS	481	164	1937.9	4,08	11,97	2,93

5-2 Vehicle and Charging Infrastructure Configurations

The second part of the experimental study comprises of the adaptation of some of the vehicle and charging infrastructure configurations. These configurations are generated by varying the following factors:

- Battery size
- Charge type
- Charge rate

The following subsections will discuss the different configurations and the expected implications for each factor. In Section 5-2-4 an overview of all configurations is given.

5-2-1 Battery Size

Battery degradation costs are dependent on the SOC range in which the batteries are cycled. In this work, we consider a battery subject to increased battery degradation effects at higher SOC. Therefore, the cost attributed to battery degradation can be influenced by changing the battery size. Over-sizing of the battery with respect to the required daily capacity can allow cycling in lower average SOC ranges and thereby reduce the effects of battery degradation. Moreover, larger batteries could reduce the operational cost related to charging, because the increased range could result in a reduction of the required charge events. These effects are investigated by solving the instances for a vehicle with two different battery capacities, which are:

1. A battery capacity that is equal to the current battery capacity of 12kWh.
2. A battery that has a capacity of 20 kWh.

5-2-2 Charging Type

The increased flexibility during the charging process that is enabled by smart chargers may help to reduce overall charging cost. The on and off switching during smart charging may help to achieve the desired SOC levels at the right moments in time without using many charge events, and thereby reduce degradation and labour cost. Moreover, the increased charging flexibility can be leveraged to charge during times of low energy prices. Two different types of charging are considered:

1. Uncoordinated charging: the characteristics of uncoordinated charging are described as follows. Firstly, the charging start and ending times are restricted to hub opening times. These opening times vary for the different shift schedules under consideration. Hub closing hours are between 23:10 - 10:10 for the CS schedule and between 23:10 and 7:10 for the MS and FS schedules. Secondly, interruptions of charge events are associated with additional operational costs.
2. Coordinated charging: coordinated charging does not have charge activity restrictions and related operational costs, because smart chargers are able to interrupt and continue charge events without human intervention. Coordinated charging is expected to provide more flexibility to charge during times of low energy cost, because there is no manual handling involved in switching.

5-2-3 Charge Rate

The charging cost could be influenced by the ability of fast chargers to quickly recharge between trips resulting in a lower average cycling SOC and thereby reduce battery degradation cost. Two charger configurations are considered:

1. Charger configuration 1: in this configuration the chargers will exclusively consist of the current slow chargers with a charge rate of 2 kW.
2. Charger configuration 2: in the second configuration, a limited number of additional chargers will be available that will have a charge rate of 5 kW. The number of fast chargers that is available is restricted to 8, which is related to the grid capacity constraint of 40 kWh.

5-2-4 Overview of Configurations

For each factor two different configurations are considered. Varying and combining all factors yields a total of eight different configurations that can be made. An overview of the different configurations is given in Figure 5-2 and the numbering of the different configurations can be seen in Table 5-2. The influence of all eight configurations are investigated separately for every shift schedule.

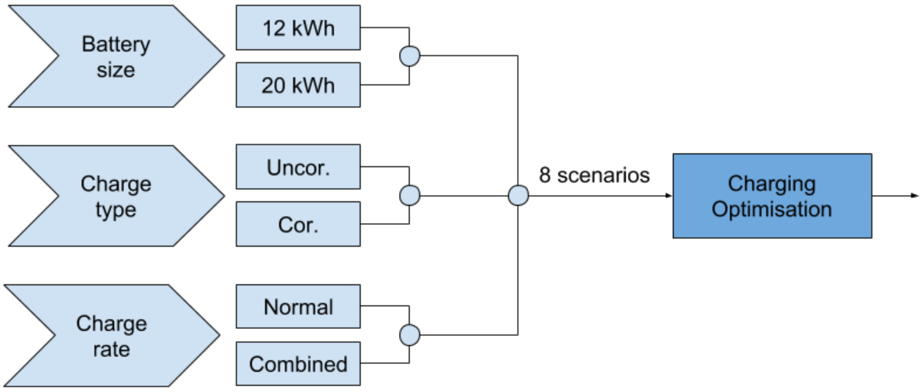


Figure 5-2: Overview of the different configurations

Table 5-2: Overview of configurations

Configuration	Charge config.	Charge type	Bat. size [kWh]
1.	C.Config. 1	Uncoordinated	12
2.	C.Config. 2	Uncoordinated	12
3.	C.Config. 1	Coordinated	12
4.	C.Config. 2	Coordinated	12
5.	C.Config. 1	Uncoordinated	20
6.	C.Config. 2	Uncoordinated	20
7.	C.Config. 1	Coordinated	20
8.	C.Config. 2	Coordinated	20

5-3 Model Settings

The problem was formulated using the Gurobi package in Python and solved on a machine with a Intel Core i7-4700MQ 2,4 GHZ processor with 8.0GB of RAM running on Windows 10. The maximum computational time is set at 3600 seconds, with a gap tolerance of 1.0%. The time horizon runs from 23:00 of the previous operational day until 23:00 of the current operational day and is discretised in steps of 10 minutes. Hub closing hours are between 23:10 - 10:10 for the CA schedules and between 23:10 and 7:10 for the CM and FS schedule. A uniform fleet of vehicles of the type Goupil G4 are considered. The battery size of this vehicle is equal to 12kWh and the charging curve is represented by a linear charge rate of 2kW, which sets the λ_s to 2.78%. The SOC range of the vehicles is restricted to 10-100% SOC. This bound is introduced in order to have an extra safety margin to take into account the uncertainties in the predicted energy requirement of trips. The SOC at the start of an operational day is set at the lower bound of 10%. This ensures that the resulting battery degradation and energy costs for different battery size scenarios will be comparable. Most current hubs have a 3x80A grid connection, which sets the peak power consumption at 55.2kWh. A margin is held for the power requirement of other tools and machinery by limiting the power consumption to 40kWh.

5-4 Cost Components

This section discusses the determination of the different cost components that are used during the charging optimisation, which comprise energy cost, battery degradation cost and labour cost.

5-4-1 Energy Cost

The time variable energy cost is based on a sampled day of hourly APX prices. Because the planning horizon runs from 23:00 on the previous day until 23:00 on the next day, 24 hourly energy prices are considered. A graph with the used hourly prices is given in 5-3. The hourly energy prices are denoted as c_p.

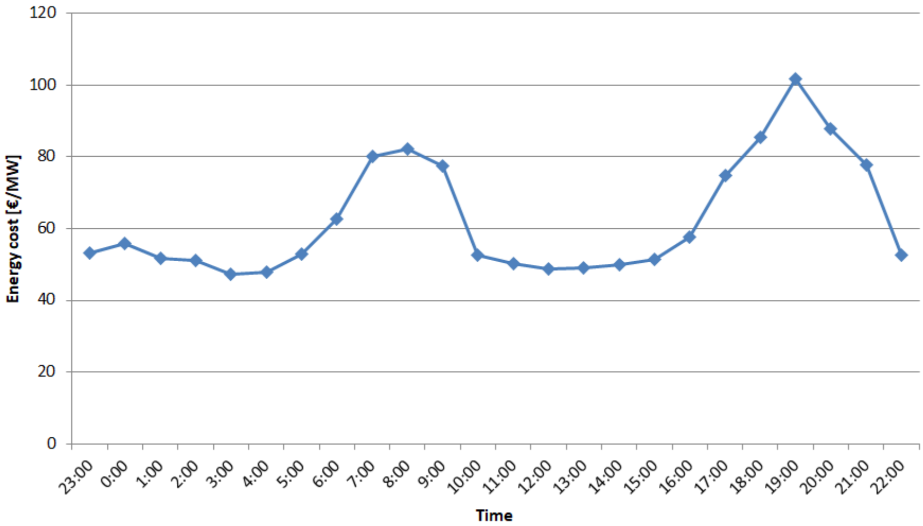


Figure 5-3: Hourly energy prices

5-4-2 Degradation Costs

The discrete wear density function for the battery under consideration is determined using the ACC-DOD curve from Han et al. (2014) [3]. This is a comparable battery to the Goupil G4, since it has the same battery chemistry LiFePO4 and the battery sizes are in the same range (12kWh vs 16kWh). The entire SOC range is divided into ten intervals of 10% SOC. Using equations 2-3 - 2-5 the wear cost for every interval can be determined. The battery capacity equals 12 kWh at a price of €10000. The wear costs $W_d(s)$ are defined as $cost/\Delta q$. By dividing the wear cost by q (the quantity of energy of one SOC interval), the average wear cost per unit of energy (€/kWh) can be derived, which is more convenient since the battery intervals are not of consistent for different battery capacities. The resulting discrete wear cost per SOC interval are given in Table 5-3

Table 5-3: Discrete wear cost per SOC interval

SoC interval [%]	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
$W_d(s)$ [€/kWh]	0.32	0.33	0.34	0.36	0.37	0.38	0.4	0.425	0.485	0.65

5-4-3 Charge Event Cost

Charging cost are based on operational cost related to the amount of time that is required to perform the activities associated with a certain charging event, which include the driving to the charger location, plugging and unplugging the vehicle and finally driving back to the loading dock where the operation can resume. It is estimated that each charge event requires four minutes of labour. At a wage of € 20/hr, this comes down to € 1,3 per charge event. These costs are denoted as *cec* in the objective function.

5-5 Summary

How can an experimental study be set up that uses the proposed model to study the impact of charge schedule optimisation on charging cost?

Three different shift schedules form the basis of the instances that are used to perform the computational study. Two schedules are actual schedules that are currently performed by Picnic, the third schedule is a fictive schedule. The fictive shift (FS) schedule was generated in order to determine the influence of performing longer and more energy demanding trips. For every shift schedule, seven instances are generated resembling the execution of one operational week. Each shift is filled with a number of real life trips that are randomly selected from a database of Picnic. The second part of the experimental study comprises of the adaptation of some of the vehicle and charging infrastructure configurations. These configurations are generated by varying the battery size, charge type and charge rate. For every factor one additional configuration with respect to the current situation will be considered. A larger battery size, the implementation of coordinated charging and fast chargers. The model settings that were used to perform the experiments are discussed in Section 5-3. Finally, this chapter closes off with a discussion of the cost components. An hourly variable energy price is used that is sampled from APX market data. The discrete wear density function for the battery under consideration is determined using the ACC-DOD curve from Han et al. (2014) [3]. The entire SOC range is divided into ten intervals of 10% SOC, yielding ten different wear cost intervals. For labour cost, a fixed cost for every performed charge event of €1.3 taken into account.

Chapter 6

Results

In this chapter the results from the experimental study are presented. The different experiments provide insights on the impact of charge schedule optimisation and vehicle and charging infrastructure configurations on charging cost. Thereby, this chapter will give an answer to the following research question:

- What is the impact of charge schedule optimisation on charging cost?
- What is the impact of vehicle and charging infrastructure configurations on charging cost?

In Section 6-1 the used metrics for the comparison of results are discussed. The performance of the current charging process is discussed in Section 6-2. The base case performance is compared to the results that are obtained by implementing charge schedule optimisation in Section 6-3. Subsequently, the impact of the shift schedule type, increasing the battery size, coordinated charging, fast charging and the variation of configurations is discussed in 6-3 - 6-8.

6-1 Metrics

The instance sets for different shift schedules yield a different number of trips and total energy requirement, as can be seen in Table 5-1. Logically, these differences will have a large effect on the total charging cost for every shift schedule. To enable a fair comparison between the results of the three shift schedules the results for all cost components are expressed as cost per consumed amount of energy, in €/kWh.

6-2 Base Case

The base case represents the charging process that is used at Picnic in which no charge schedule optimisation is used. The performance of the current charging process is considered in order to compare it to the results obtained when the proposed model is used to optimise the charge schedules. The charging cost for the base case is build up of the same cost components as the charge schedule optimisation and contains energy costs, battery degradation and labour costs. The values for the battery degradation and labour cost are derived using operational data and given in Table 6-1. The remainder of this section is used to explain how these values were derived.

Table 6-1: Cost components for the base case

Component	Unit	Value
Energy	€/kWh	0.063
Battery degradation	€/kWh	0.507
Charge events (CE)	€/kWh	0.30

Energy Cost

In the current situation, the price of energy is not variable over time. Therefore, a fixed energy price is considered for the base case. This fixed price is equal to the average of the variable hourly energy price that is used in the experiments. This is equal to 0.063 €/kWh.

Degradation Cost

In order to determine a realistic contribution of battery degradation in the base case, it is required to know in which typical SOC ranges the vehicles are currently cycled. A discrete probability density function (PDF) of the SOC during driving is made using the trip data originating from 16980 that was presented in Section 4-1-2. The result can be seen in Figure 4-6a, showing the probability of driving in a certain SOC interval of 1%. Using this PDF, the average wear cost during driving can be determined with the following equation:

$$AWC(d_{max}) = \int_{d_{min}}^{d_{max}} W(d) \cdot f(d) \cdot ds \tag{6-1}$$

Multiplying the discrete wear cost function $W(d)$, with the discrete PDF, denoted as $f(d)$, for all SOC intervals $d \in D$ yields the average wear cost contributed to driving in each SOC interval. Integrating this over all SOC intervals ($d_{min} \leq d \leq d_{max}$) gives the average wear cost (AWC) during driving, which is equal to 0.507 €/kWh for the current case at Picnic.

Labour Cost

The average cost per charged amount of energy is the metric that is used for comparing the results related to the labour cost. The following equation is used to calculate the average charge event cost per charged amount of energy C_{ch} in €/kWh:

$$C_{ch} = \frac{CC \cdot BatterySize}{cec} \tag{6-2}$$

Where CC represents the average charge cycle in %, $BatterySize$ is the battery size in kWh and cec is the cost for one charge event in €. Again, the trip data from Section 4-1-2 is used to derive the required data for the calculation of this metric in the base case. First, to derive a realistic value for the average charge cycle the average of the trip arrival SOC, which is equal to 64%, is used. The assumption is made that all vehicles are fully charged from this SOC. Subtracting the median of the arrival SOC from a 100% SOC yields the average charge cycle. Subsequently multiplying this with the battery capacity gives the quantity of charged energy that corresponds to this charge cycle. Lastly, this is divided by the cost related to one charge event to derive the cost per charged unit of energy, which results in a charge event cost of 0.30 €/kWh.

6-3 Impact of Charge Schedule Optimisation

The impact of charge schedule optimisation is determined by comparing the base case performance to the results of the experimental study. Since the base case performance is only determined for the CS schedule, the results are only directly compared for this schedule. The results are depicted in Figure 6-1. The results obtained for charge schedule optimisation consist of the average charging cost in €/kWh for the execution of seven operational days. It can be seen that a large overall reduction of charging cost of 25.2% is obtained. This reduction can be attributed to a reduction of degradation, labour and energy cost of 15.9%, 41.9% and 19.9% respectively. The potential benefits of charge schedule optimisation are high. For an average Picnic depot, performing 400 average trips per week, the overall cost reduction is roughly €260 per week. The reduction in battery wear, will lead to a extended lifetime of the batteries of 19.0% .

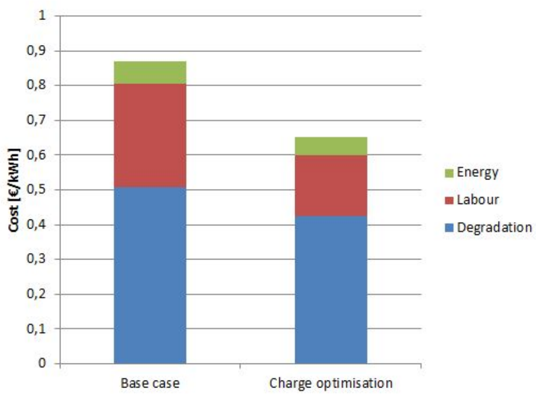


Figure 6-1: The benefit of charge schedule optimisation

6-4 Impact of Shift Schedule Type

The results for charge schedule optimisation for the different shift schedules are depicted in Figure 6-2. Again the results are based on the average results of all instances for the seven operational days. It can be seen that the charging costs for the MS and FS schedule are higher than for the CS schedule. For the MS schedule, an increase of charging cost of 7% is obtained, where the FS schedule yields an increase of 10%. This can be explained by the increase in energy demand for the MS and FS schedule. The intensified use of vehicles throughout the day results in an increase in energy requirement and the decrease in available time for charging. Higher daily vehicle energy demands result in a increase in the SOC cycling ranges and consequently increase battery degradation cost for the CM and FS schedule. Moreover, labour cost increase due to the increase in energy demand and the reduction in charging flexibility.

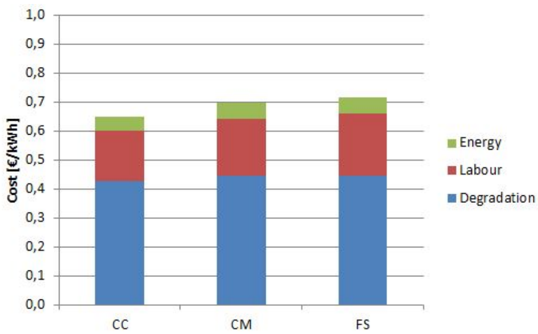


Figure 6-2: The charging cost under CS, MS and FS schedules

6-5 Impact of Increasing the Battery Size

The increase in battery size enables the possibility to cycle the battery in lower SOC ranges, because trip energy requirements are a lower fraction of the larger battery capacity. Since the battery degradation model is dependent on the cycled SOC ranges, a difference in charging cost can be expected. Therefore, the impact of increasing the battery size on charging cost is investigated. It should be noted that larger batteries are associated with higher initial investment costs. Nevertheless, this study could derive insights regarding the decrease in operational cost when using a larger battery. All instances for the CC, CM and FS schedule are solved for two different battery types:

1. A small battery capacity of 12kWh equal to the battery of the Goupil G4
2. A larger battery with a capacity of 20kWh.

The average of results for all shift schedules are depicted in Figure 6-3. It is seen that a large decrease of overall charging cost of 10% is obtained, due to the reduction in battery degradation cost (6%) and labour cost (23%).

6-6 Impact of Coordinated Charging

The increased flexibility during the charging process that is enabled by smart chargers may help to reduce overall charging cost. The on and off switching during smart charging may help

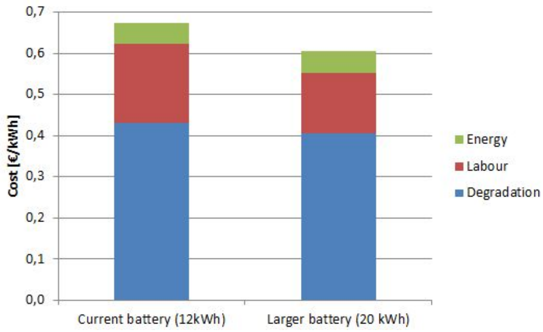


Figure 6-3: The impact of an increased battery size

to achieve the desired SOC levels at the right moments in time without using many charge event, and thereby reduce degradation and labour cost. Moreover, the increased charging flexibility can be leveraged to charge during times of low energy prices. All instances for the CC, CM and FS schedule are solved for two different battery types:

1. Uncoordinated charging: resembling the use of traditional 'dumb' chargers.
2. Coordinated charging: resembling the use of smart chargers.

The results are depicted in Figure 6-4. It can be seen that a large reduction of charging cost of 7% is achieved, due to a decrease of all battery degradation 4%, labour 15% and energy cost 11%.

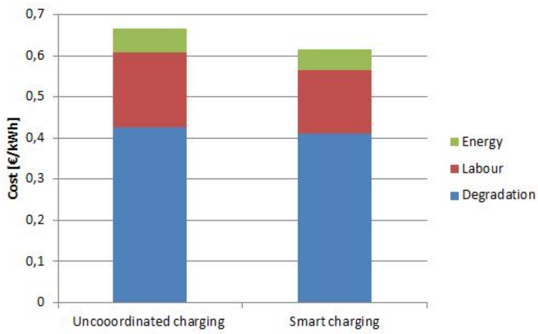


Figure 6-4: The impact of coordinated charging

6-7 Impact of Fast Charging

One last change in the charging infrastructure that is investigated is the addition of fast chargers. The charging cost could be influenced by the ability of fast chargers to quickly recharge between trips resulting in a lower average cycling SOC and thereby reduce battery degradation cost. All instances for the CC, CM and FS schedule are solved for two different charger configurations:

1. Charger configuration 1: an unlimited amount of slow chargers of 2kW is available.
2. Charger configuration 2: aside from the slow chargers, 8 additional chargers of 5kW are available.

It is seen from Figure 6-5 that the impact of the introduction of fast chargers is marginal. This can be explained by the small amount of fast chargers that is available in comparison with the number of vehicles in operation and grid capacity constraint. This limits the use of fast chargers, since the grid capacity has to be spread over more than 8 vehicles.

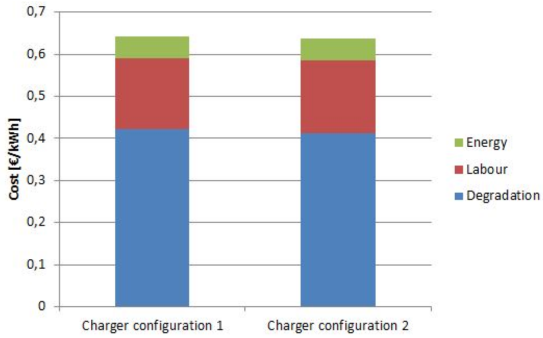


Figure 6-5: The impact of the introduction of fast chargers

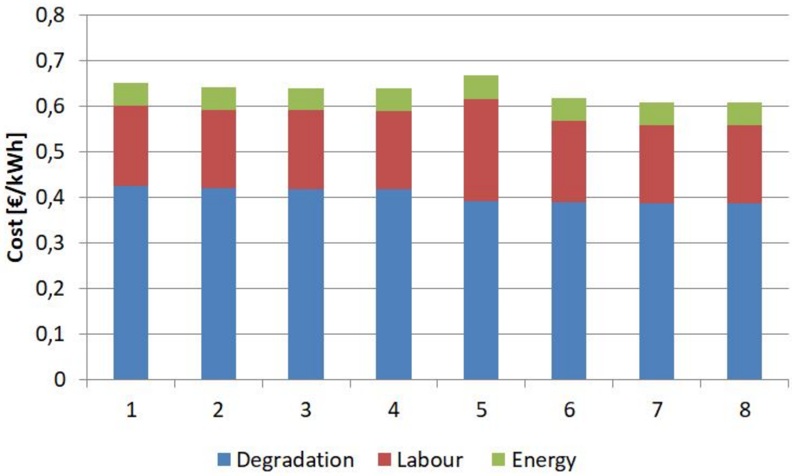
6-8 Variation of Configurations

The best of all tested configurations is determined by varying and combining all possible vehicle and charger configurations. This yields 8 different configurations that can be tested for the CC, CM and FS schedule. An overview of the possible combinations of configurations is given in Table 6-2.

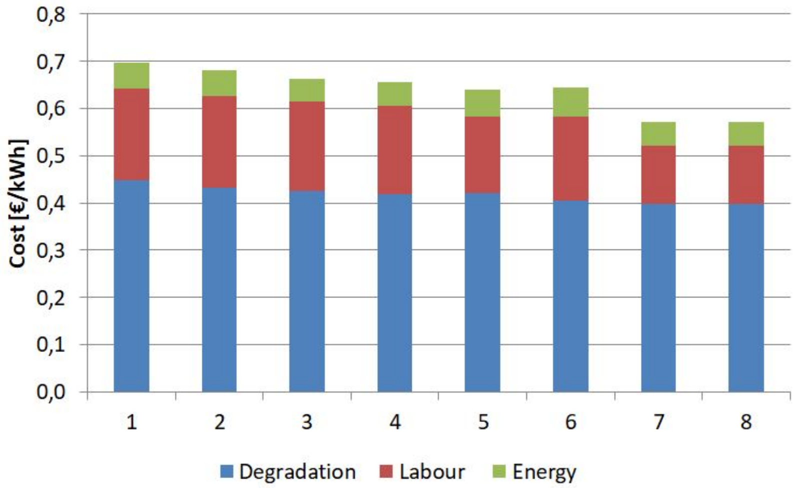
Table 6-2: Overview of configurations

Configuration	Charger config.	Charge type	Bat. size [kWh]
1.	C.Config. 1	Uncoordinated	12
2.	C.Config. 2	Uncoordinated	12
3.	C.Config. 1	Coordinated	12
4.	C.Config. 2	Coordinated	12
5.	C.Config. 1	Uncoordinated	20
6.	C.Config. 2	Uncoordinated	20
7.	C.Config. 1	Coordinated	20
8.	C.Config. 2	Coordinated	20

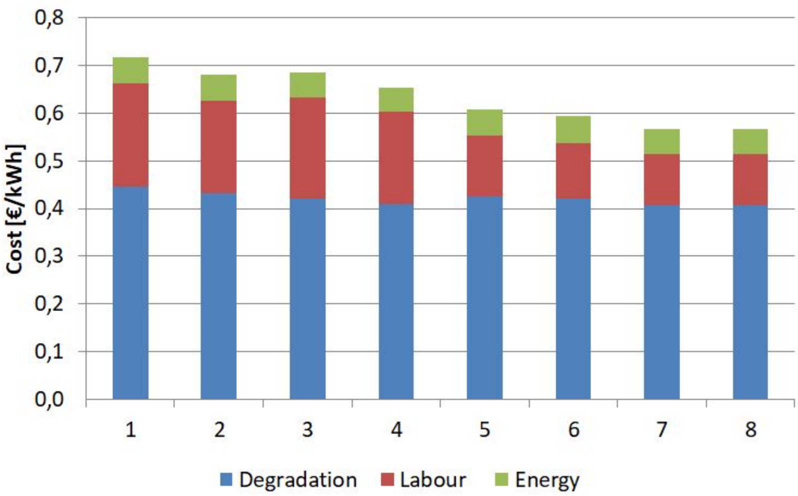
The results for all tested configurations and shift schedules are given in Figure 6-6. From these figures it is seen that the best tested configuration in all shift schedules combine coordinated charging and a larger battery size of 20kWh (configuration 7). When comparing this configuration to the basic configuration 1, a decrease of 6.6%, 12.7% and 15.1% is obtained for the CS, MS and FS schedule.



(a) CS schedule results



(b) MS schedule results



(c) FS schedule results

Figure 6-6: Results for all shift schedules and configurations

6-9 Summary

What is the impact of charge schedule optimisation on charging cost?

To enable a fair comparison between the results all cost components are expressed as cost per consumed amount of energy, in €/kWh. The base case represents the charging process that is used at Picnic in which no charge schedule optimisation is used. The performance of the current charging process is considered in order to compare it to the results obtained when the proposed model is used to optimise the charge schedules. The impact of charge schedule optimisation is determined by comparing the base case performance to the results of the experimental study. Since the base case performance is only determined for the CS schedule, the results are only directly compared for this schedule. A large overall reduction of charging cost of 25.2% is obtained, which can be attributed to a reduction of degradation, labour and energy cost. Furthermore, the impact of three different shift schedule types is investigated. It turns out that more energy demanding shift schedules result in higher average charging cost per charged amount of energy. Compared to the CS schedule, the charging cost of the MS and FS schedule increase by 7% and 10%. This can be explained by the increase in daily vehicle energy requirements and the decrease in charging flexibility in these shift schedules.

What is the impact of vehicle and charging infrastructure configurations on charging cost?

The impact of the increase in vehicle battery size, the addition of coordinated charging and the implementation of fast chargers is investigated. The introduction of a larger battery size, shows potential for decreasing cost related to charging (10%). Moreover, coordinated charging yields a large reduction of charging cost (7%), while the influence of fast chargers turns out to be marginal (1%). The best possible configuration combines larger battery size with coordinated charging and this yields a decrease in charging cost of 6.6%, 12.7% and 15.1% for the CS, MS and FS schedule.

Chapter 7

Conclusion and Future Work

This chapter presents the conclusions of this research and provides recommendations for Picnic and future work directions.

7-1 Conclusion

The main research question is: **How can the charge schedule for a fleet of electric vehicles be optimised during day-to-day operations?** The answer to this question can be given by answering all sub-questions.

What charge scheduling optimisation models and algorithms have been proposed in literature?
Charge scheduling problems for fleet owners is a relatively new field of research. Only three relevant contribution that cover this subject have been found. Pelletier et al (2018) [14] introduce the EFV-CSP. This contribution focuses on optimising the depot charge planning over the course of multiple days for a given set of routes for electric freight vehicles. Sundstrom et al. (2010) [33] propose a charge scheduling optimisation model with the goal of minimising charging costs, while ensuring satisfactory state-of-energy levels for the vehicles and not exceeding the amount of available wind power. A different type of problem discussed by Sassi et al (2014a) [34], (2014b) [35], and (2017) [19]) that covers the subject of unidirectional depot charge scheduling for fleet owners is the Simultaneous Electric Vehicle Scheduling and Optimal Charging Problem, which considers a joint optimisation of vehicle scheduling and charge scheduling. In this contribution, the original EFV-CSP that was proposed by Pelletier et al (2018) [14] is extended in several ways. Firstly, the labour cost related to the manual handling of charging events will be taken into account. A fixed penalty for each charging event that has to be performed is implemented. The charged energy is presumed to be a linear function of time, which decreases the problem complexity and makes it more suitable for the optimisation of large scale problems. Related to the charged energy, a corresponding SOC dependent battery degradation model that was proposed by Han et al. (2014) [3] is implemented. Secondly, two slightly different models are presented in order to study the effect

of coordinated charging versus uncoordinated charging. In contrast to the model of Pelletier et al (2018) [14], peak charge costs are eliminated as cost component since they are not a part of the energy pricing model.

How can the charge schedule optimisation problem be formulated in a mathematical model?
A MIP model for the charge scheduling problem was proposed. Two important conditions related to the problem are that (1) the assignment of vehicles to trips is determined preceding to the charge schedule optimisation and (2) the energy requirements of all trips are known. In a real-life context, this would mean that the energy requirement of trips should be predicted using certain trip characteristics. A step wise approach is used to introduce the problem. First, the problem formulation for the charge scheduling problem without the incorporation of battery degradation cost is given. Subsequently, the model is extended to be able to account for battery degradation cost, using a discrete battery wear model from Han et al (2014) [3]. Model adjustments that enable coordinated charging, which resembles the use of smart chargers are introduced last. The implementation of the proposed model is verified in order check whether the problem is formulated and implemented correctly.

The charge scheduling problem is considered for the case of Picnic, a Dutch e-grocer which already has a last-mile delivery process in place that uses EVs. The remaining sub-questions are all related to the case study that was performed at Picnic.

What is the energy demand of the electric fleet of Picnic?
The total energy consumption of the fleet over time is composed of the energy requirements of all individual trips, which can be characterised by the time of use and the quantity of energy that is required. By considering both factors for all trips, the entire energy requirement of the fleet over time can be derived. Trips at Picnic are scheduled on the basis of to different shift schedules. These schedules sets the ultimate departure and arrival time for trips that are driven different shifts. Demand and capacity determine the number of trips in every shift. The energy requirement of trips is determined. The predictive value of these trip characteristics was investigated by building a artificial neural network. This model proved to be capable of predicting trip energy requirements on the basis of some known trip characteristics.

What charge scheduling process is currently used at Picnic?
The current charge scheduling process was analysed by conducting several interviews with the involved schedulers and performing data analysis. This is relevant in order to get an insight how much time is available for making the charge planning and to understand what considerations currently play a role in this process. It turns out that a main objective during the current charging process is ensuring that vehicles are at a 100% SOC at the start of an operation day. This reduces the risk of not achieving the mobility objectives, but on the other hand results in cycling in high SOC ranges which can be harmful for vehicle batteries.

What are the characteristics of Picnic's current vehicle and surrounding charging infrastructure?
There are a number of factors related to the EV and charging infrastructure that need to be identified so that the charge scheduling problem for Picnic can be set up. The most important characteristics are listed below:

- The charge energy can be represented by a linear function of time
- The charge rate is equal to 2.0kW
- An on board charger is responsible for the charging and is plugged into a regular wall socket
- The amount of vehicles that can be charged at the same time is predominantly constrained by the grid capacity of 55.2kW
- At the moment, no time variable energy prices are obtained
- Hourly variable energy prices from the day ahead energy can be incorporated into the charge scheduling problem

How can an experimental study be set up that uses the proposed model to study the impact of charge schedule optimisation on charging cost?
In order to set up the experimental study a number of tasks need to be performed: instances need to be generated, the considered vehicle and charging infrastructure configurations need to be determined, the general model settings have to be set and the value for each cost component needs to be established. Three different shift schedules form the basis of the instances that are used to perform the computational study. Two schedules are actual schedules that are currently performed by Picnic, the third schedule is a fictive schedule. The fictive shift (FS) schedule was generated in order to determine the influence of performing longer and more energy demanding trips. For every shift schedule, seven instances are generated resembling the execution of one operational week. Each shift is filled with a number of real life trips that are randomly selected from a database of Picnic. The second part of the experimental study comprises of the adaptation of some of the vehicle and charging infrastructure configurations. These configurations are generated by varying the battery size, charge type and charge rate. For every factor one additional configuration with respect to the current situation will be considered. A larger battery size, the implementation of coordinated charging and fast chargers. The model settings that were used to perform the experiments are discussed in Section 5-3. Finally, this chapter closes off with a discussion of the cost components. An hourly variable energy price is used that is sampled from APX market data. The discrete wear density function for the battery under consideration is determined using the ACC-DOD curve from Han et al. (2014) [3]. The entire SOC range is divided into ten intervals of 10% SOC, yielding ten different wear cost intervals. For labour cost, a fixed cost for every performed charge event of €1.3 taken into account.

What is the impact of charge schedule optimisation on charging cost?
The base case represents the charging process that is used at Picnic in which no charge schedule optimisation is used. The performance of the current charging process is considered in order to compare it to the results obtained when the proposed model is used to optimise the charge schedules. The impact of charge schedule optimisation is determined by comparing the base case performance to the results of the experimental study. Since the base case performance is only determined for the CS schedule, the results are only directly compared for this schedule. A large overall reduction of charging cost of 25.2% is obtained, which can be attributed to a reduction of degradation, labour and energy cost. Furthermore, the impact of three different shift schedule types is investigated. It turns out that more energy demanding

shift schedules result in higher average charging cost per charged amount of energy. Compared to the CS schedule, the charging cost of the MS and FS schedule increase by 7% and 10%. This can be explained by the decrease in charging flexibility in these shift schedules.

What is the impact of vehicle and charging infrastructure configurations on charging cost?
The impact of the increase in vehicle battery size, the addition of coordinated charging and the implementation of fast chargers is investigated. The introduction of a larger battery size, shows potential for decreasing cost related to charging (10%). Moreover, coordinated charging yields a large reduction of charging cost (7%), while the influence of fast chargers turns out to be marginal (1%). The best tested configuration combines larger battery size with coordinated charging and this yields a decrease in charging cost of 6.6%, 12.7% and 15.1% for the CS, MS and FS schedule.

Finally, having stated the answer to all sub-questions, the answer to the main research question can be given:

How can the charge schedule for a fleet of electric vehicles be optimised during day-to-day operations?
A model is developed to minimise the cost related to the charge schedule for a fleet of EVs while considering labour, battery degradation and energy cost and taking into account constraints related to the vehicle, charging infrastructure and grid. This model is formulated as a MIP and implemented and solved by an exact solver in Gurobi. In order to assess the benefits of charge scheduling optimisation on charging cost, a real-life case study is performed for Dutch e-grocer Picnic, that currently operates a last-mile delivery process with over 700 EVs. In order to asses its performance, the proposed model was compared to the benchmark, which was determined using operational data. The proposed model outperforms the benchmark by 25.2% in total cost and all cost components are reduced individually. This confirms that the implementation of charge schedule optimisation provides high economical benefits in last-mile services using EVs. An immediate consequence of reduced battery wear cost is that expected lifetime of the vehicles batteries is extended (19.0%). Furthermore, the impact of three different shift schedule types, the increase in vehicle battery size, the addition of coordinated charging and the implementation of fast chargers is investigated. It turns out that more energy demanding shift schedules result in higher average charging cost per charged amount of energy. This can be explained by the decrease in charging flexibility in these shift schedules. The introduction of a larger battery size, shows potential for decreasing cost related to charging (10%). Moreover, coordinated charging yields a large reduction of charging cost (7%). The best tested configuration combines larger battery size with coordinated charging and this yields a decrease in charging cost of 6.6%, 12.7% and 15.1% for the CS, MS and FS schedule when compared to current configuration.

7-2 Recommendations and Future Research Directions

7-2-1 Recommendations to Picnic

Based on this research, some recommendations can be given to Picnic:

1. Picnic should evaluate whether the implementation of charge schedule optimisation is worth the additional investment costs. The algorithms and models should be implemented to predict energy requirements of trips and to optimise the charge schedule for the fleet.

2. Picnic should evaluate whether the additional investments to implement coordinated charging are worthwhile. More coordination during charging could be enabled by remotely controlled in-vehicle chargers that are capable of interrupting an ongoing charge event. Furthermore, vehicle monitoring devices are required since they facilitate real-time knowledge of the battery SOC, which are required to determine the charge commands. Implementing both systems could enable a centrally managed charging platform.

3. Picnic should consider the purchase of vehicles with a larger battery size in order to benefit from lower battery degradation effects and ensuring a longer lifetime of the batteries. A trade-off between initial investment costs and the increased operational lifetime of the batteries should be made. Note that the purchase of larger batteries would only have effect if it is done simultaneously with the implementation of charge schedule optimisation.

7-2-2 Recommendations for Future Research Directions

This work addresses the range and charging limitations of EVs during the charge scheduling of a fleet of EVs. An interesting new area of research would be to consider the scheduling of vehicles to trips and the scheduling of charge events in a joint process. This could generate improved results, due to the increased flexibility of the vehicle schemes. On the other hand, these types of problems are much more complex and therefore require efficient formulations and/or heuristics in order to derive high quality results efficiently. Another area of interest may lie in the implementation of more advanced battery degradation models, which take into account other operational factors other than cycling SOC or that incorporate degradation during storage.

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Scientific Paper

Charge Scheduling of Electric Vehicles in Last-mile Distribution

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***Abstract*—This paper proposes a model for charge scheduling of electric vehicles in last-mile distribution to investigate the impact of charge schedule optimisation on charging cost. A mixed integer problem formulation is proposed that considers labour, battery degradation and time-variable energy cost. The benefit of implementing charge schedule optimisation is assessed in a computational study for a real-life case at e-grocer Picnic. It turns out that the implementation of charging optimisation yields an overall reduction of charging costs by 25.2% when compared to the current operational charging performance. Furthermore, the impact of three different shift schedule types, the increase in vehicle battery size, the addition of coordinated charging and the implementation of fast chargers is investigated. It turns out that more energy demanding shift schedules result in higher average charging cost per charged amount of energy. The introduction of a larger battery size, shows potential for decreasing cost related to charging. Moreover, coordinated charging yields a large reduction of charging cost, while the influence of fast chargers turns out to be marginal.**

Keywords*—*Charge scheduling, Electric Vehicle, Last-mile Distribution

I. INTRODUCTION

Freight transportation, currently dominated by fossil fuelled vehicles, contributes largely to sustainability problems, including noise and air pollution, global warming and oil dependency [1]. The adoption of electric vehicles (EVs) could solve these problems by enabling much cleaner and efficient transport [2]. Three main drivers contribute to the attractiveness of EVs [3]: total cost of ownership (TCO), technology readiness and local and national regulations. However, substituting conventional internal combustion engine (ICE) vehicles with EVs within the transportation and logistics sector is not straightforward. In contrast to ICE vehicles, EVs have to refuel frequently due to the relatively low energy content of their batteries. Moreover, the recharging process of an EV is a lot more time consuming than refuelling a conventional ICE vehicle. Both the lower range and long recharging times are characteristics that reduce the availability and flexibility of EVs. This raises some additional challenges when using EVs from strategic, planning, and operational perspectives [4]. In order to successfully adopt EVs in last-mile distribution processes, the range and recharging limitations should be addressed adequately.

In this contribution, the range and recharging limitations of EVs are addressed during the depot charge scheduling of a fleet of EVs. The use of EVs is considered in the context of a last-mile delivery process while operating a multi-shift schedule, which means that vehicles can be used to execute multiple trips per day. It is assumed that individual trips, which span a number of customer orders, do not exceed vehicle range. Consequently, charging outside of the home depot is not needed. Many fleet owners prefer depot charging over charging at public locations due to a combination of factors including the scarcity of available charging infrastructure, cargo security concerns during charging and inefficient use of the drivers' time [5]. Many last-mile distribution service providers operate a large fleet of vehicles from one depot location. Due to the high investment cost that is associated with installing charging infrastructure, there are typically less chargers than vehicles. Moreover, grid capacity constraints limit the peak power that can be drawn from the grid on a specific depot location. These grid capacity constraints are imposed by grid operators and are meant to counteract overloading of the grid. Both factors should be taken into account during the construction of a charge schedule.

High daily energy demands and limited charging infrastructure availability may lead to energy infeasibility of the vehicle schedule or impractical charging schemes, consisting of many charge events. Since the execution of a charge schedule requires manual labour, for example when driving EVs to charger locations and (un)plugging vehicles from the charger, there is a motive to minimise the number of charge events and thereby to reduce the labour cost that is associated with the execution of the charge schedule. Another component that influences the cost to execute a charge schedule is energy cost. For businesses operating on a larger scale and consequently consuming a lot of energy, the option of having a time variable energy pricing contract becomes an attractive alternative. These variable energy contracts can be leveraged in order to decrease charging cost, by charging during times of low energy prices. One last, and less covered, aspect that contributes to the cost of a charge schedule is related to battery wear costs that depends on the use of an EV battery. EV batteries constitute a large part of vehicles costs. Lithium-ion batteries are subject to deterioration of the electro-chemical properties over time, ultimately leading to a reduction of the available power and battery capacity, resulting in a performance and range deterioration of the vehicle [6]. In order to preserve the long term flexibility of EVs, it is necessary to prevent battery degradation as much as possible. This can be done by taking into account the factors that have a known negative effect on battery deterioration in charging problems. One of these known effects is the state of charge (SOC) range in which the battery is cycled. To what extent the use of a battery contributes to battery wear is dependent on the SOC ranges in which the battery is cycled. Therefore, adapting a charge schedule of a vehicle in such a way that it is cycled in less harmful SOC ranges, contributes to the cost effectiveness of a charge schedule. All these factors emphasise the necessity to investigate the cost related to the charging schedule.

The aim of this work is threefold: (1) to develop a model to optimise the charge schedule for a fleet of EVs while considering labour, battery degradation and energy cost and taking into account constraints related to the vehicle, charging infrastructure and grid, (2) to investigate the impact of the three different shift schedules on charging cost and (3) to study the impact of adapting the configuration of both the vehicle and charging infrastructure on charging cost. The impact of charge scheduling optimisation on charging cost is investigated in a real-life case study for Dutch e-grocer Picnic, that currently operates a last-mile delivery process with over 700 EVs [7]. The charging cost of optimised charge schedules are compared with

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cost of the current charging process obtained with operational data. Moreover, the impact of the three different shift schedules on charging cost is investigated, which are based on two actual shift schedules and one fictive schedule for Picnic. Lastly, we study the impact of adapting the configuration of both the vehicle and charging infrastructure referring to the vehicle battery size, charge rate and charge type. The latter refers to the amount of possible coordination during the charging process in which we consider two types: uncoordinated and coordinated charging. Uncoordinated charging resembles the use of basic chargers, and coordinated charging corresponds to the use of smart chargers.

This paper is organised as follows. An overview of the relevant literature with respect to charge scheduling optimisation is presented in Section II. Subsequently, a mathematical formulation for the charge schedule optimisation problem without the consideration of battery degradation is formulated in Section III. This model is extended in Section IV to incorporate the effects of battery degradation. In Section V, model adjustments are presented that enable the use of coordinated charging. Subsequently, in Section VI, the details of the experimental study are given. The results of the experimental study are presented in Section VII. This paper ends with the conclusion in Section VIII.

II. Charge Scheduling Literature

Charge scheduling optimisation problems can be roughly divided into two different classes: Vehicle to Grid problems and unidirectional charging problems. Unidirectional charge scheduling problems consider only the unidirectional flow of energy from the grid to the vehicle and can be addressed from different perspectives including the power system level, charge infrastructure owner and the vehicle/fleet owner. This work focuses on the depot charge scheduling from the perspective of the fleet owner and in this area three relevant contributions were found. Pelletier et al (2018) [5] introduce the Electric Freight Vehicle Charge Scheduling Problem (EFV-CSP). This contribution focuses on optimising the depot charge planning over the course of multiple days for a given set of routes for a small fleet of electric freight vehicles. Sundstrom et al. (2010) [8] propose a charge scheduling optimisation model with the goal of minimising charging costs, while ensuring satisfactory state-of-energy levels for the vehicles and not exceeding the amount of available wind power. A different type of problem discussed by Sassi et al. in (2014a) [9], (2014b) [10] and (2017) [11] that covers the subject of unidirectional depot charge scheduling for fleet owners is the Simultaneous Electric Vehicle Scheduling and Optimal Charging Problem, which considers a joint optimisation of vehicle scheduling and charge scheduling. The objectives of charge scheduling optimisation for fleet owners include the reduction of energy cost, facility related demand charges, labour cost and battery degradation.

In this contribution, the original EFV-CSP that was proposed by Pelletier et al (2018) [5] is extended in several ways. Firstly, the labour cost related to the manual handling of charging events will be taken into account. A fixed penalty for each charging event that has to be performed is implemented. The charged energy is presumed to be a linear function of time, which decreases the problem complexity and makes it more suitable for the optimisation of large scale problems. Related to the charged energy, a corresponding SOC dependent battery degradation model that was proposed by Han et al. (2014) [12] is implemented. Secondly, two slightly different models are presented in order to study the effect of coordinated charging versus uncoordinated charging. In contrast to the model of Pelletier et al (2018) [5], peak charge costs are eliminated as cost component since they are not a part of the energy pricing model. The goal of the EFV-CSP is to optimise the depot-charging costs for a given set of vehicle rotations, where the charging cost consists of energy costs, labour costs and battery degradation costs. In the following sections a step wise approach is used to define the charge scheduling problem.

III. Basic Model Formulation

This section presents the basic charge scheduling model without considering battery degradation cost. The assignment of vehicles to trips is determined preceding to the charge schedule optimisation. Moreover, the energy requirements of all trips are known. In a real-life context, this would mean that the energy requirement of trips should be predicted using certain trip characteristics. The entire time horizon is discretised into a number of fixed time periods $p \in P$. The hub opening and closing periods are defined as O_p and C_p. The set of uniform vehicles $k \in K$ is characterised by maximum and minimum allowable battery SOC: soc_{max} and soc_{min} and battery energy capacity E (kWh). Moreover, the SOC at the beginning of an operational day is specified as soc_{start}. Every vehicle has to execute a known sequence of trips from the set $r \in R$. Trips can be further defined by their departure period β_r, arrival period α_r and energy requirement Δsoc_r (%). The vehicle that executes a certain trip r, is denoted by V_r and the preceding trip is defined as μ_r. Moreover, let the set A_k contain the arrival periods of all trips that belong to vehicle k. The charger types from the set $s \in S$ can be characterised by their charge rate P_s (kW), the SOC differential that can be charged in one period λ_s (%) and amount of available chargers per type $\mathcal{K}_s$. Let the binary decision variable $x_{p,k,s}$ be 1, if a charger of type s is charging vehicle k during period p, and 0 otherwise. A continuous variable $soc_{p,k}$ denotes the SOC of vehicle k at the start of period p. y keeps track of the peak charging power that is drawn from the grid during the entire time horizon. Binary variable $z_{p,k}$ equals 1 if a charge event starts for vehicle k in period p, and 0 otherwise. To count the number of charge events, an integer variable N is introduced. The peak power demand is constrained by the grid capacity G.

1) Objective Function: The objective for the charge scheduling model is to minimise costs related to charging and is given as follows:

$$\sum_{p \in P} \sum_{k \in K} \sum_{s \in S} x_{p,k,s} P_s c_p t + Ncec \tag{1}$$

The first term represents the energy costs of charging, which is calculated by multiplying the total charged energy during a charging period by the time-dependent energy costs c_p (€/kWh) to derive the cost of the charged energy. The second term accounts for the labour costs related to performing charge events through multiplication of the number of charge events by a fixed cost per charge event cec.

2) Charge Scheduling Constraints:

$$\sum_{p=\beta_r}^{\alpha_r} \sum_{s \in S} x_{p,V_r,s} = 0 \quad \forall r \in R \tag{2}$$

$$\sum_{k \in K} x_{p,k,s} \leq \mathcal{K}_s \quad \forall p \in P, s \in S \setminus \{1\} \tag{3}$$

$$\sum_{s\in S} x_{p,k,s} \leq 1 \quad \forall p \in P, k \in K \tag{4}$$

$$\sum_{k\in K}\sum_{s\in S} P_s x_{p,k,s} \leq y \quad \forall k \in K, p \in P \tag{5}$$

$$0 \leq y \leq G \tag{6}$$

$$z_{p,k} \geq x_{p,k,s} - x_{p-1,k,s} \quad \forall k \in K, p \in P \setminus \{1\}, s \in S \tag{7}$$

$$z_{1,k} \geq x_{1,k,s} \quad \forall k \in K, s \in S \tag{8}$$

$$x_{p,k,s} \in \{0,1\} \quad \forall p \in P, k \in K, s \in S \tag{9}$$

$$z_{p,k} \in \{0,1\} \quad \forall p \in P, k \in K \tag{10}$$

Constraints 2 prevent a vehicle from being charged during trips. Constraints 3 limit the amount of chargers of type s that can be used during every period to $\mathcal{K}_s$, while constraints 4 enforce that each vehicle can be charged by only one charger at the same time. Constraints 5 keep track of the peak charging power that is drawn from the grid during the entire time horizon and constraint 6 limits this peak charging power to the grid capacity. Lastly, constraints 7 and 8 are used to identify the period that corresponds to the start of a charging event.

3) Energy Constraints:

$$soc_{\alpha_r,V_r} = soc_{\beta_r,V_r} - \Delta soc_r \quad \forall r \in R \tag{11}$$

$$soc_{p,k} = soc_{p-1,k} + \sum_{s\in S} \lambda_s x_{p-1,k,s} \quad \forall k \in K,$$
$$p \in P \setminus \{1,\}, p \notin A_k \tag{12}$$

$$soc_{min} \leq soc_{p,k} \leq soc_{max} \quad \forall k \in K, p \in P \tag{13}$$

$$soc_{1,k} = soc_{start} \quad \forall k \in K \tag{14}$$

Constraints 11 relate the SOC of the vehicle at trip departure to the SOC at trip arrival by reducing it with the trip energy requirement Δsoc_r. During charging, constraints 12 enforce the increase of the SOC of a vehicle with the SOC differential that corresponds to a certain charge rate λ_s. Constraints 13 ensure that the SOC of a vehicle always stays between the minimum and maximum allowable SOC. Constraints 14 set the SOC of the vehicle at the start of the time horizon.

4) Charge Event Constraints:

$$\sum_{p\in P}\sum_{k\in K} z_{p,k} = N \tag{15}$$

$$\sum_{p=Op}^{Cp} z_{p,k} = 0 \qquad \forall k \in K \tag{16}$$

These constraints are required to count the number of charge events that are used in a charge schedule. Constraint 15 counts the number of charge events. Constraints 16 prevent charging events from starting during night hours when there is no one present at the hub.

IV. Model Extension I: Battery Degradation

This section introduces battery degradation and proposes a formulation to incorporate it in the charge scheduling model.

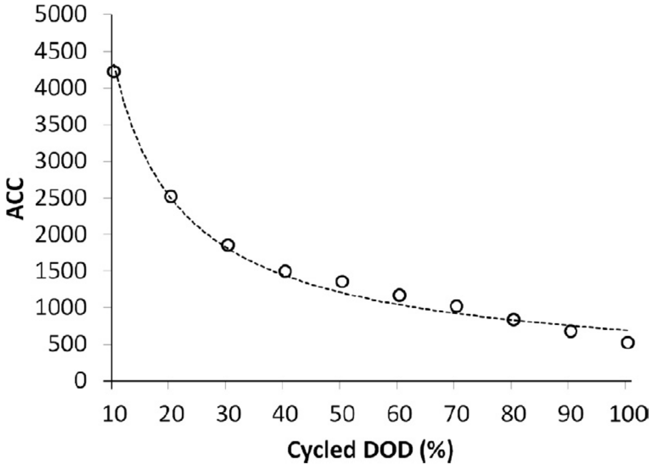

Fig. 1: ACC-DOD curve. Each marker represents a sample point where the achievable cycle life is known. The continuous line shows the best fit curve of the ACC data. [13]

Typically, battery manufacturers specify the cycle lifetime of batteries with the *achievable cycle count* (ACC) for different *depth of discharge* (DOD) points, which indicates how many times a battery can be charged or discharged before it reaches the end of its lifetime. This relation can then be visualised in a ACC-DOD curve, as given in Figure 1. For clarity, in ACC-DOD curves it is assumed that the battery is always discharged from 100% SOC, which represents the situation in which a battery is always cycled from full charge. However, in reality batteries are cycled in different SOC ranges, which limits the use of the ACC-DOD curve. To overcome these issues, some steps are required to transform the ACC-DOD characteristics into a practical battery wear model. The battery wear model that was proposed by Han et al. (2014) [12] does exactly this and we use this model to incorporate battery wear behaviour in the charge scheduling model. The model will be introduced in the next subsection.

A. Considered Wear Model

Han et al. (2014) [12] propose a new index called the *wear density function* (WDF). This function represents the unit wear costs at a specific DOD value. A continuous and discrete time battery wear function are derived using both the battery price and ACC-DOD data. Since this work models in discrete timesteps, the discrete model will be presented. The $W_d(s)$ represents the battery degradation cost as a function of cycled energy within a certain SOC interval $(s + \Delta s)$ and satisfies the following equation:

$$BatteryPrice = 2ACC(DOD) \sum_{s=1-D}^{1-\Delta s} (W_d(s)\Delta q) \tag{17}$$

Δq is the quantity of energy that corresponds to a SOC interval $(s + \Delta s)$. This function can be used to derive the degradation cost for different SOC intervals. For example, using a step size of 10% yields ten different equations:

$$W_d(0.9) = \frac{BatteryPrice}{ACC(0.1) \cdot 2 \cdot 0.1 \cdot BatterySize \cdot \mu^2} \tag{18}$$

$$W_d(0.8 + 0.9) = \frac{BatteryPrice}{ACC(0.2) \cdot 2 \cdot 0.2 \cdot BatterySize \cdot \mu^2} \tag{19}$$

$$W_d(0 + ... + 0.9) = \frac{BatteryPrice}{ACC(1.0) \cdot 2 \cdot 1.0 \cdot BatterySize \cdot \mu^2} \tag{20}$$

The resulting values of the wear density function can be used to incorporate wear cost in a discrete manner. Figure 2 shows both an example of a continuous wear cost function derived from the best curve fit of ACC data, and a discrete wear cost function corresponding to the original data measured at ten DOD points. These functions are derived by using the data from Figure 1.

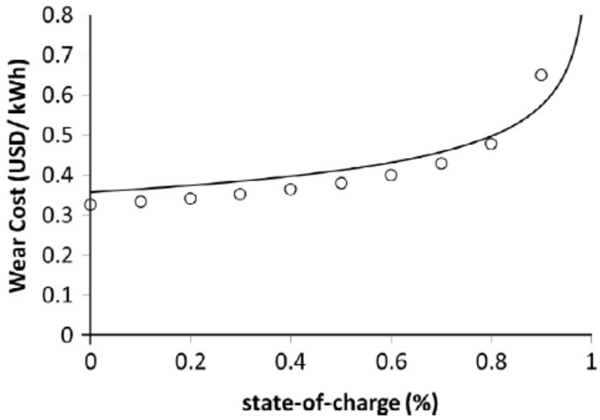

Fig. 2: Discrete and continuous wear costs functions derived by using the ACC-DOD data from Figure 1 [12]

The practical battery wear model proposed by Han et al. (2014) [12] is implemented in order to incorporate the costs related to battery degradation during charging and discharging. The next subsection describes the formulation that extends the original MIP formulation proposed in Section III with a discrete wear cost function.

B. Problem Formulation

The following problem formulation is applicable for the case when the wear cost function is increasing with respect to SOC, which resembles the situation in which more battery degradation occurs during cycling at higher SOC values. The SOC of the batteries is split into a number of intervals $d \in D$ of equal size L (%), with the upper SOC value of an interval corresponding to S_d. The battery wear cost is represented by W_d in €/kWh for every SOC interval d. A new continuous variable is introduced $soc^+_{d,r}$ that keeps track of the quantity of every SOC interval that is used to charge vehicle k between arrival of trip μ_r and departure of trip r. For example, if a vehicle is charged from 40% to 55% SOC between trip $r = \mu_x$ and $r = x$, the corresponding used SOC intervals become $soc^+_{3,x} = 10\%$ and $soc^+_{4,x} = 5\%$ respectively. Lastly, let a binary decision variable $u_{d,r}$ equal 1, if the corresponding SOC interval is used during charging before trip r and after μ_r, and 0 otherwise.

1) Objective Function:

$$\sum_{p \in P} \sum_{k \in K} \sum_{s \in S} x_{p,k,s} P_s c_p t + Ncec + \sum_{r \in R} \sum_{d \in D} 2 W_d soc^+_{d,r} E \tag{21}$$

The objective function now comprises three terms, of which the first two represent the energy costs and labour costs and are identical to equation 1. In addition, the third term is used to take into account the costs related to battery degradation. The total charged amount of energy per interval is derived by multiplying the SOC variation in every interval $soc^+_{d,r}$ with the battery energy capacity E (kWh), and then the corresponding degradation cost is determined by multiplying those factors with the interval dependent degradation cost W_d. Because cyclic ageing affects the battery health during charging and discharging, a final multiplication by a factor of two is required to calculate the total battery degradation.

2) Battery Degradation Constraints:

$$\sum_{d \in D} soc^+_{d,r} = soc_{\beta_r, V_r} - soc_{\alpha_{\mu_r}, V_r} \quad \forall r \in R \tag{22}$$

$$0 \leq soc^+_{d,r} \leq L u_{d,r} \quad \forall d \in D, r \in R \tag{23}$$

$$soc^+_{d,r} \leq S_d - soc_{\alpha_{\mu_r}, V_r} + 100 - u_{d,r} 100 \quad \forall d \in D \quad \forall r \in R \tag{24}$$

Constraints 2 - 16 are still valid for this model extension. In addition, constraints 22 limit the sum of all $soc^+_{d,r}$ intervals to the difference in energy of vehicle k between the departure time of trip r and the arrival period the preceding trip. Constraints 23 limit the SOC differential that can charged in a SOC interval between zero and the maximum amount that can be charged in one interval. Constraints 24 limit the amount that can be charged in interval $soc^+_{d,r}$ based on the upper SOC value of that interval and the SOC of the vehicle after the last trip. Note that this constraint is only valid in the case of non-decreasing wear cost with respect to SOC.

V. Model Extension II: Coordinated Charging

When considering the coordination during the charging process of a fleet of EV two different types of charging can be distinguished: uncoordinated and coordinated charging. This section first discusses the difference between these concepts after which the problem definition for coordinated charging is presented.

A. Uncoordinated vs Coordinated Charging

Uncoordinated charging is when the vehicle charging starts immediately after plugging in a vehicle or after a fixed start delay and continues until the vehicle battery is fully charged or disconnected [14]. Uncoordinated charging of EV fleets may lead to high peak demands and thereby to overloading of the grid [15]. Coordinated smart charging optimises time and power demand with the objectives of minimising charging cost, valley filling and peak shaving [14]. However, these objectives may never interfere with the scheduled vehicle use during the day [16]. To be able to leverage on the possible benefits of coordinated charging, a smart charging infrastructure is required. This comprises smart chargers, connected vehicles and a energy management systems that controls the charging of the vehicles. When comparing the behaviour of coordinated charging with uncoordinated charging, two major differences can be identified:

1) Charge events can stop and start at any moment in time, including the hub closing times.
2) The interruption of a charge event is possible without imposing additional cost.

B. Problem Definition

In order to consider the charging event cost in coordinated charging, not the number of charge events should be counted, but the number of used *charge opportunity intervals*. A charge opportunity interval is defined as the time between the arrival of the preceding trip α_{μ_r} and departure of a trip β_r. Note that the number of charge opportunity intervals is equal to the number of trips. The binary decision variable $Ns_{r,s}$ equals 1 if the charge opportunity interval corresponding to trip r is used, and 0 otherwise.

1) Objective Function:

$$\sum_{p\in P}\sum_{k\in K}\sum_{s\in S} x_{p,k,s}P_s c_p t + \sum_{r\in R} Ns_{r,s}cec + \sum_{r\in R}\sum_{d\in D} 2W_d soc^{+}_{d,r}E \tag{25}$$

In order to take into account the impact of operating with smart chargers, the second term of the objective function now calculates labour cost by multiplying $Ns_{r,s}$ with *cec*.

2) Charge Event Constraints:

$$\sum_{p=\alpha_{\mu_r}}^{\beta_r} z_{p,v_r} \geq 0 - M(1 - Ns_{r,s}) \quad \forall r \in R \tag{26}$$

$$0 \geq \sum_{p=\alpha_{\mu_r}}^{\beta_r} z_{p,v_r} - MNs_{r,s} \quad \forall r \in R \tag{27}$$

$$Ns_{r,s} \in \{0,1\} \quad \forall r \in R \tag{28}$$

Constraints 26 and 27 ensure that the binary decision variable $Ns_{r,s}$ equals 1 if the term $\sum_{p=\mu_r}^{\beta_r} z_{p,v_r}$ is larger than 0. Constraints 14 and 15 can be discarded in the case of coordinated charging, all other constraints remain valid (2 - 14, 22 - 24).

VI. Experimental Setup

The goal of this computational study is to evaluate the impact of charge schedule optimisation on charging cost. An exact solver will be used to solve a set of real-life instances that are derived from the operation of Dutch e-grocer Picnic. In the first part of this section an explanation of the used set of instances is given. Comparison of the base case cost with the results of the optimisation model provides insight in the performance of the optimisation model that was proposed in this paper. The impact of some minor adaptations in the vehicle and charging infrastructure are be investigated in a later experiment.

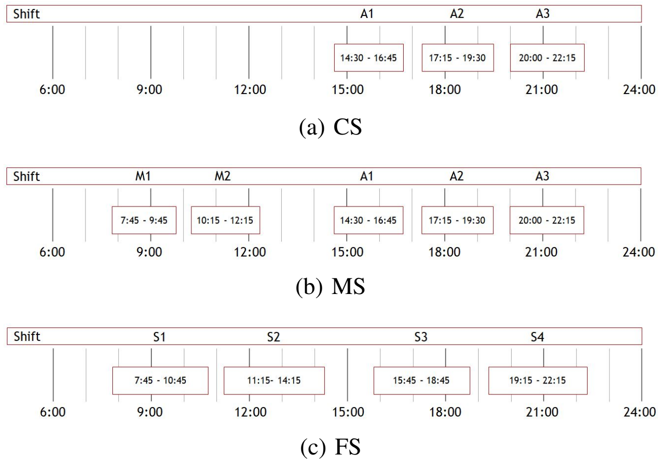

Fig. 3: (a) Current shift schedule, (b) Morning shift schedule, (c) Fictive shift schedule.

A. Instances

Three different shift schedules form the basis of the instances that are used to perform the computational study. A shift schedule is characterised by its shift time windows, which set the ultimate scheduled departure and arrival times for trips. The shift schedules that are used in this computational study are depicted in Figure 3. Note that all shifts in these schedules are strictly separated in time, which means trips from consecutive shifts can be executed by the same vehicle. The first two schedules are actual schedules that are currently performed by Picnic, the third schedule is a fictive schedule. The current shift (CS) schedule consists of three shifts of equal length that are all scheduled in the afternoon. Compared to the CC schedule, the morning shift (MS) schedule contains two additional shifts in the morning, which are both slightly shorter in duration. The fictive shift (FS) schedule was generated in order to determine the influence of performing longer and more energy demanding trips and contains four shifts of equal duration with a longer break between shift two and three. For every shift schedule, seven instances are generated resembling the execution of one operational week. Each shift is filled with a number of real-life trips that are randomly selected from a database of Picnic. A summary of the characteristics of all instances for every shift schedule is given in Table I.

TABLE I: Instance characteristics: the second column shows the total number of trips. The third column indicates the total of vehicle days that is required to perform each instance set, in which the use of one vehicle during one operational day counts for one vehicle day. The next column shows the total energy requirement. E_t represents the average energy requirement per trip, while E_v is the average energy requirement per vehicle day. Lastly, T_v indicates the average number of trips per vehicle day

Schedule	Trips	Vehicle days	Energy	E_t	E_v	T_v
	#	#	kWh	kWh	kWh	#
CC	415	164	1235.5	2,98	7,54	2,53
CM	615	164	1737.6	2,83	10,61	3,75
FS	481	164	1937.9	4,08	11,97	2,93

B. Experiments

The problem was formulated using the Gurobi package in Python and solved on a machine with a Intel Core i7-4700MQ 2,4 GHZ processor with 8.0GB of RAM running on Windows 10. The maximum computational time is set at 3600 seconds, with a gap tolerance of 1.0%. The time horizon runs from 23:00 of the previous operational day until 23:00 of the current operational day and is discretised in steps of 10 minutes. Hub closing hours are between 23:10 - 10:10 for the CS schedule and between 23:10 and 7:10 for the MS and FS schedule. A uniform fleet of vehicles of the type Goupil G4 is considered. The battery size of this vehicle is equal to 12kWh and the charging curve is represented by a linear charge rate of 2kW, which sets λ_s to 2.78%. The SOC range of the vehicles is restricted to 10-100% SOC. This bound is introduced in order to have an extra safety margin to take into account the uncertainties in the predicted energy requirement of trips. The SOC at the start of an operational day is set at the lower bound of 10%. This ensures that the all energy that is required has to be charged and therefore generates comparable results for battery degradation and energy costs. The peak power that can be drawn from the grid G is set at $40kWh$. The hourly variable energy prices c_p are based on a sampled day of hourly prices from the Dutch day-ahead energy market (APX), for the entire 24h period as seen in Figure 4. For every performed charge event a fixed cost of €1.3 is considered. The discrete wear density function for the battery under consideration is determined using the ACC-DOD curve from Zhou et al. (2011) [13]. The entire SOC range is divided into ten intervals of 10% SOC. Using equations 18 - 20 the wear cost for every interval is determined. The battery capacity equals $12kWh$ at a price of €10000. The wear costs $W_d(s)$ are defined as $cost/\Delta q$. By dividing the wear cost by q (the quantity of energy of one SOC interval), the average wear cost per unit of energy ($€/kWh$) can be derived, which is more convenient since the battery intervals are not of consistent for different battery capacities. The resulting discrete wear cost per SOC interval can be seen in Table II.

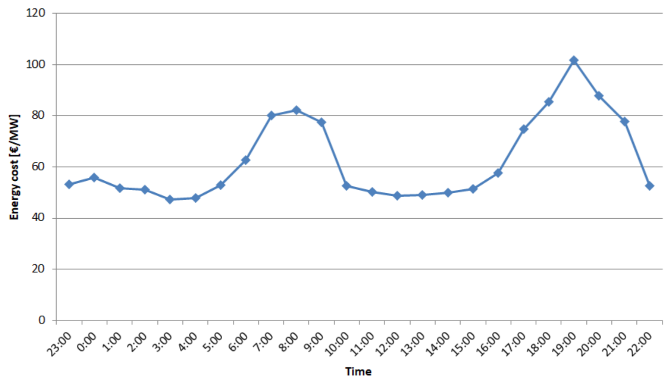

Fig. 4: Sampled hourly energy prices for the entire time horizon

TABLE II: The discrete wear cost per SOC interval.

SOC interval [%]	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
$W_d(s)$ [€/kWh]	0.32	0.33	0.34	0.36	0.37	0.38	0.4	0.425	0.485	0.65

The instance sets for different shift schedules yield a different number of trips and total energy requirement, as seen in Table I. Logically, these differences will have a large effect on the total charging cost for every shift schedule. To enable a fair comparison between the results of the three shift schedules, the results for all cost components are expressed as cost per consumed amount of energy, in €/kWh.

C. Base case performance

The base case represents the charging process that is used at Picnic in which no charge schedule optimisation is used. This is used as a benchmark to evaluate the proposed charge scheduling optimisation model. The charging cost for the base case consists of the same cost components as the charge schedule optimisation and contains energy costs, battery degradation and labour costs. The values for the battery degradation and labour cost are derived using operational data. Since the SOC dependency is taken into account in the battery wear cost model in this study, it is required to know in which SOC ranges the batteries are cycled during the current use of the vehicle to derive the current battery degradation cost. A discrete probability density function (PDF) of the SOC during driving is made using data originating from 16980 trips. The result can be seen in Figure 5, showing the probability of driving in a certain SOC interval of 1%. Using this PDF, and the battery wear cost function, the average wear cost during driving can be determined with the following formula:

$$AWC(d_{max}) = \int_{d_{min}}^{d_{max}} W(d)f(d)ds \tag{29}$$

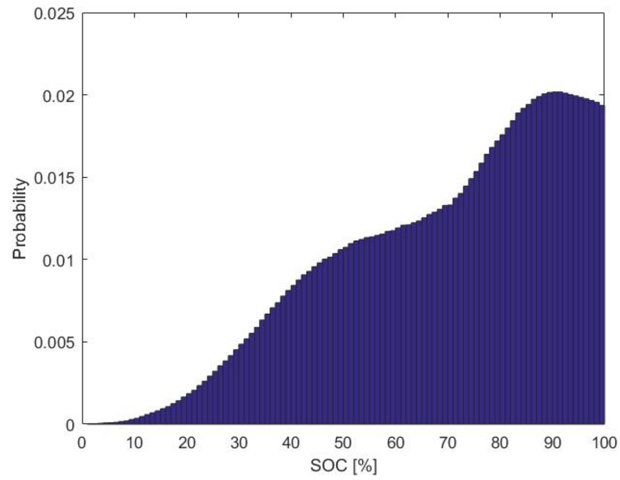

Fig. 5: The probability density function of driving in a certain SOC

For the determination of the current labour cost incurred with the performance of the charge events, we want to get an understanding of the typical charge cycle currently performed at Picnic. Using the average charge cycle, the labour cost corresponding to every charged kWh C_{ch} can be calculated using the following formula:

$$C_{ch} = \frac{CC \cdot BatterySize}{cec} \tag{30}$$

Where CC represents the average charge cycle in %, $BatterySize$ is the battery size in kWh and cec is the cost for one charge event in €. Again, the operational trip data is used to derive the required data for the calculation of this metric in the base case. First, to derive a realistic value for the average charge cycle the average of the trip arrival SOC, which is equal to 64%, is used. All vehicles are assumed to be fully charged from this SOC. Subtracting the average of the arrival SOC from a 100% SOC yields the average charge cycle. Subsequently multiplying this with the battery capacity gives the quantity of charged energy that corresponds to this charge cycle. Lastly, this is divided by the cost related to one charge event to derive the cost per charged unit of energy, which results in a charge event cost of 0.30 €/kWh.

It is assumed that for the base case, the average energy cost per charged amount of energy is equal to the average of the time dependent energy prices that are used in this study. The results for all cost components of the base case are listed in Table III.

TABLE III: The charging cost components for the base case

Component	Unit	Value
Energy	€/kWh	0.063
Battery degradation	€/kWh	0.507
Labour	€/kWh	0.30

VII. Experimental Results

This section presents the results of the experimental study and evaluates the impact of different phenomena on the charging cost.

A. Impact of Charge Schedule Optimisation

The impact of charge schedule optimisation is compared to the benchmark presented in Section VI-C. Since the base case performance is only determined for the CS schedule, the analysis is only carried out for this schedule. The results are depicted in Figure 6, where the presented cost corresponds to average charging cost in €/kWh for seven operational days. It is seen that an overall charging cost reduction of 25.2% is obtained. This reduction can be attributed to a decrease of degradation, labour and energy cost of 15.9%, 41.9% and 19.9% respectively. The potential benefits of charge schedule optimisation are high. For an average Picnic depot, performing 400 average trips per week, the overall cost reduction is roughly €260 per week. The reduction in battery wear, leads to an extended lifetime of the batteries of 19.0% .

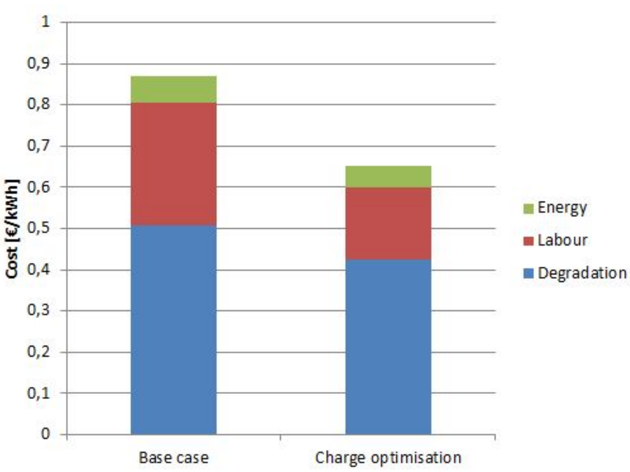

Fig. 6: The benefit of charge schedule optimisation

B. Impact of Shift Schedule Type

The results for charge schedule optimisation for the different shift schedules are depicted in Figure 7. Again the results are based on the average results of all instances for the seven operational days. It is seen that the charging costs for the MS and FS schedules are higher than the CS schedule. For the MS schedule, an increase of charging cost of 7% is obtained, whereas the FS schedule yields an increase of 10%. This is due to the increase in energy demand for both of the schedules. The intensified use of vehicles throughout the day results in an increase in energy requirement and the decrease in available time for charging. Consequently, there is a reduction of the charging flexibility, which is defined as the idle time spent not charging [17]. This results in higher SOC cycling ranges and a higher number of required charge events.

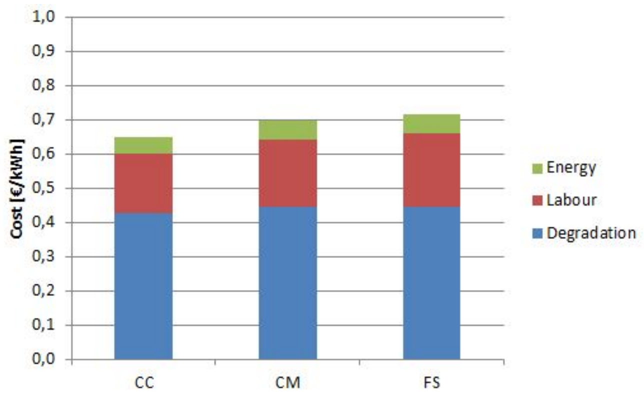

Fig. 7: The charging cost under CS, MS and FS schedules

C. Impact of Increasing the Battery Size

The increase in battery size enables the possibility to cycle the battery in lower SOC ranges because trip energy requirements become a lower fraction of the battery capacity. Since the battery degradation model is dependent on the cycled SOC ranges, a difference in charging cost is expected. Therefore, the impact of increasing the battery size on charging cost is investigated. It should be noted that larger batteries are associated with higher initial investment costs. Nevertheless, this study could derive insights regarding the decrease in operational cost when using a larger battery. In addition to the current battery of 12kWh, the experiments for all shift schedules are repeated for a battery of 20kWh. The average of results for all shift schedules are depicted in Figure 8. It is seen that a large decrease of overall charging cost of 10% is obtained. This decrease is a result of both the reduction in battery degradation cost (6%) and labour cost (23%).

D. Impact of Coordinated Charging

The increased flexibility during the charging process that is enabled by smart chargers may help to reduce overall charging cost. On and off switching during coordinated charging may help to achieve the desired SOC levels at the right moments in time without using many charge events, and thereby reduce degradation and labour costs. Moreover, the increased charging flexibility can be leveraged to charge during times of low energy prices. The results are depicted in Figure 9. It is seen that a large reduction of charging cost of 7% is achieved, due to a decrease of all battery degradation 4%, labour 15% and energy costs 11%.

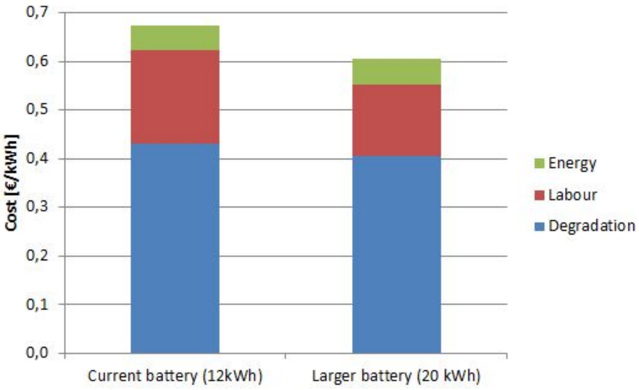

Fig. 8: The impact of an increased battery size

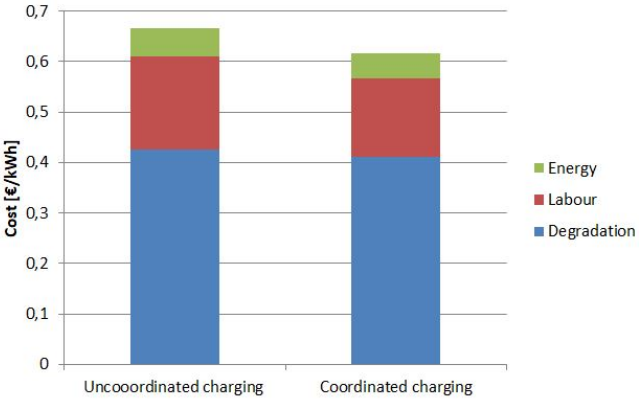

Fig. 9: The impact of coordinated charging

In addition, one last dimension in the charging infrastructure that is investigated is the introduction of fast chargers, whose impact turn out to be marginal.

VIII. Conclusion and Future Research Directions

This study aims to investigate the impact of charge schedule optimisation on overall charging cost, consisting of energy, labour and battery degradation. A model was introduced for this problem which was solved by an exact solver. The proposed model was tested with a set of instances derived from the real-life last-mile distribution system of Picnic. In order to asses its performance, the proposed model was compared to the benchmark, which was determined using operational data. The proposed model outperforms the benchmark by 25.2% in total cost and all cost components are reduced individually. This confirms that the implementation of charge schedule optimisation provides high economical benefits in last-mile services using EVs. An immediate consequence of reduced battery wear cost is that expected lifetime of the vehicles batteries is extended (19.0%). Furthermore, the impact of three different shift schedule types, the increase in vehicle battery size, the addition of coordinated charging and the implementation of fast chargers is investigated. It turns out that more energy demanding shift schedules result in higher average charging cost per charged amount of energy. This can be explained by the decrease in charging flexibility in these shift schedules. The introduction of a larger battery size, shows potential for decreasing cost related to charging (10%). Moreover, coordinated charging yields a large reduction of charging cost (7%).

This work addresses the range and charging limitations of EVs during the charge scheduling of a fleet of EVs. An interesting new area of research would be to consider the scheduling of vehicles to trips and the scheduling of charge events in a joint optimisation problem. This could generate improved results, due to the increased flexibility of the vehicle schemes. On the other hand, these types of problems are much more complex and therefore require efficient formulations and/or heuristics in order to derive high quality results efficiently. Another area of interest may lie in the implementation of more advanced battery degradation models, which take into account other operational factors other than cycling SOC or that incorporate degradation during storage.

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Trip Energy Prediction Model

A neural network is built in Matlab to predict the energy requirements of trips based on a set of trip characteristics. An elaborate description of the development of this model is presented this Appendix.

Architecture

ANNs are build up out of neurons and synapses:

- Neurons: have the function to sum the input synapses and then apply an activation function to this value. There are many activation functions that one could choose. Examples are the binary step, sigmoid and softmax function. Each activation function will process the input differently and therefore also give a different output of a neuron.
- Synapses: synapses interconnect individual neurons. They take an input value, multiply this by a weight and output the result to the next neuron. The synapses hold the weights that modify the output of one neuron to the input of another neuron. These weights are updated during the learning process of the neural network.

Three layers can be distinguished in neural networks: the input layer, the hidden layer(s) and the output layer. In the input layer the values of the used attributes are inserted. Synapses convert the models inputs to one or more hidden layers. More complex models tend to have more hidden layers. However, most problems can be sufficiently solved with a single hidden layer. Adding multiple hidden layers has the risk of over fitting the data.

Learning

In supervised learning the neural network is trained by minimising a selected cost function that compares the models predictions and targets. In case all the SoC differentials would be predicted correctly, the cost function would be equal to zero. Different learning algorithms can be used to search the solution space for the optimal solution. During the learning process the ANN's weights are iteratively updated to minimise the models cost function. Most learning algorithms look at what parameters have the highest influence in the results of the cost function. The derivative of the cost function over the models parameters will give the parameters that have the biggest influence on its result. Changing these parameters will decrease the cost function most. The algorithm will perform this procedure multiple times, until no further improvement is achieved.

A neural network was designed in Matlab. The next part shows the properties of the designed neural network.

- Input: the number of input neurons is dependent on the attributes of the data set. In our case 11, so the neural network has 11 input neurons.
- Output: the output of the model is dependent on the number of classes in the target data (the SOC differential).
- Hidden layers: the design of the hidden layers is a little less straight forward. First of all there is the question whether it would be smart to add a second hidden layer to the neural network. The choice here is made to stay in a one hidden layer configuration as this design is able to so . A rule of thumb concerning the number of neurons in the hidden layer is presented by Jeff Heaton: 'the optimal size of the hidden layer is usually between the size of the input and size of the output layers'. A small analysis was performed to check the influence of the number of hidden neurons (HN) on the performance of the model. The performance indicator is the mean absolute error of the targets vs predicted values in the test set. Each test was performed ten times. It can be seen that the initial decrease in MAE is small but significant. After HN = 3 the performance varies and does not improve significantly. Therefore, a hidden layer of three neurons is selected.

Activity Rule

The standard activation function in Matlab feedforward networks is the Tansig function.

Learning Rule

Supervised learning will be used to train the neural network. Because we have a vast amount of labeled observations this is the most logical choice. In supervised learning the neural network is trained by minimizing a selected cost function that compares the models predictions and targets. Scaled conjugate gradient back propagation is used as a training rule. Conjugate gradient propagation does not look directly in the steepest decent direction of the cost function. It turns out that this will not generally lead to the quickest convergence. Instead the algorithm will find and decent in the conjugate directions.

Error measures

A neural network is built in Matlab to predict the energy requirements of trips based on a set of trip characteristics. The features presented in table 4-1 are used as input of the model. 70% of the samples are used for training, 15% for validation and the remaining 15% is used for testing.

Table 1: Correlation coefficients for target features

Feature	Trip energy requirement [R^2]	Trip efficiency [R^2]
Distance [km]	0.72	0.041
Ambient temperature	0.036	0.24
Duration	0.31	0.0055
Total stem time	0.35	0.0093
Number of drops	0.046	0.015
Payload	0.034	0.011
Mileage	0.0012	0.0013

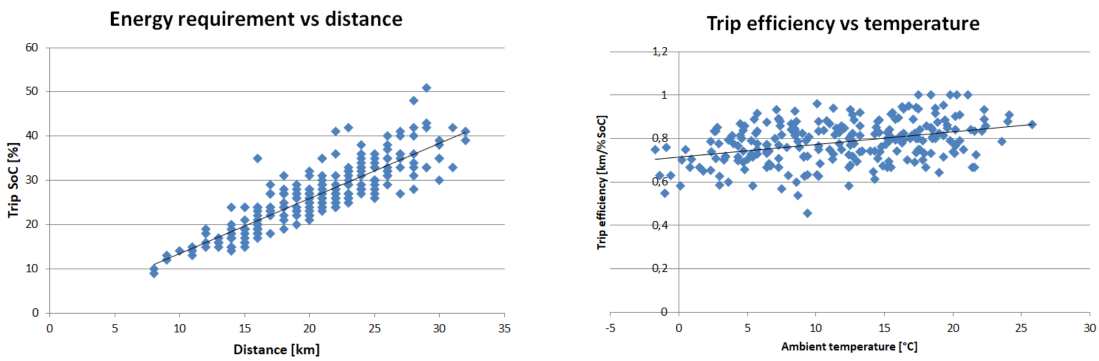
Model Performance

The average MSE and correlation coefficient of the final model are equal to 12,4 and 0,89 respectively. It should be noted that there would always exist a certain uncertainty in the trip energy prediction model with the current data set. This is due to several influences that can not be determined such as mechanical factors, driving behaviour and environmental factors. Mechanical factors can include drivetrain and powertrain efficiency but also tire pressure. Driving behaviour is mainly relevant due to driving speed and accelerations. Driving at high speeds is more energy demanding. Moreover, high accelerations are usually associated with higher energy requirements. Also hard braking can have a negative influence on energy efficiency due to lower energy regeneration. Environmental factors include wind speed and slopes.

Attribute Sensitivity

To provide insight in the features that are important for the prediction of the energy requirement of trips, a sensitivity analysis is performed. The correlation coefficient of individual features are determined using linear regression. Two different target features are being used: the trip energy requirement and the trip efficiency. The latter is defined as the trip distance divided by the trip energy requirement. Table 1 shows the correlation coefficients for both target features. It can be seen that the distance as well as the duration and the total stem time have a significant effect on the trip energy requirement. However, it should be noted that there is a high correlation between the trip distance and both the duration ($R^2 = 0.294$) and the total stem time ($R^2 = 0.439$). When looking at the trip efficiency, the ambient temperature seems to be a relevant feature. The number of drops, payload and mileage seem to have an insignificant effect on both the trip energy requirement and trip efficiency.

Figure 1a and 1b show the influence of the trip distance on the trip energy requirement and the influence of the ambient temperature on the energy efficiency. From 1a it can be seen that there is a strong correlation between trip distance and energy requirement ($R^2 = 0,72$). Figure 1b shows the trip efficiency defined as the amount of distance that can be driven on one percent SOC for the trip samples versus the ambient temperature. A trend can towards more efficient trips at higher ambient temperatures can be observed. However, this correlation is not that strong ($R^2 = 0,24$)



(a) Trip energy requirement vs trip distance

(b) Trp efficiency vs ambient temperature

Figure 1: Important energy related features

It can be concluded that a model can be made that has adequate predictive performance. Additional modelling efforts will most likely yield a model with increased performance.

Vehicle Trip Allocation

The vehicle trip allocation model is used to generate a set of feasible vehicle rotations that form the input of the charging optimisation model in Chapter 5. The analysis of the operation of Picnic has revealed some factors that should be taken into account during the scheduling of vehicles. The most important requirement is that the set of vehicle rotations should be charge feasible with respect to vehicle range and grid capacity. In this appendix a special type of EVSP will be proposed to solve the fleet minimisation problem.

Secondly, the amount of vehicles that is used during the operational day will be minimised, because a limited number of vehicles is available at every hub.

-0-3 Overview of the EVSP

The EVSP can be described as a multi-depot vehicle scheduling problem with EV charging and range constraints. In the EVSP, each trip has a specific start and end location and energy requirement. A vehicle can be charged fully or partially at one of the charging locations. The charged energy is a linear function of time. By focusing on logistical service provider operating from one depot, the traditional EVSP is simplified in several ways. Firstly, there is only a single depot from where the vehicles depart. Secondly, the start and end locations of service trips are fixed at the depot. This is in contrast to the majority of other EVSP problems, where start and end location of service trips are dispersed regionally. Lastly, the problem is simplified by restricting charging to only depot-charging. This means that charging can only occur at the single home-depot and not en-route. The goal is to minimise the size of the fleet that is required to perform a certain day schedule.

-0-4 Model Formulation

Let G(V,A) be a directed graph, where V represents a set of nodes and A a set of feasible arcs. The set of nodes V contains a node for each service trip $i \subseteq T$. Each trip has a certain starting time a_i, end time b_i, duration d_i and energy requirement e_i. Charging event nodes are represented by a set $R \subseteq V$. For each trip node $i \in I$ a corresponding charging node $r_i \in R$ is created that can be visited right after trip i. Each charge event node i has a earliest start time a_i which is equal to the end time of the preceding trip node: b_j. Also the set V contains a vehicle source node and sink node (o_v, w_v). Let $\delta^+(i)$ and $\delta^-(i)$ be the set of

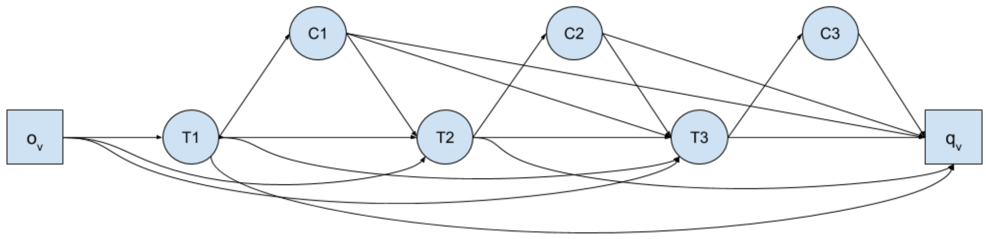


Figure 2: Graph of the EVSP

arcs that originate in node i and end in node i. Trip node i is connected to trip node j if the trip times do not overlap; $b_i < a_j$ or $a_i > b_j$. For the charge nodes $i \in R$ holds that they are connected to the corresponding preceding trip nodes $j \in T$ and all trip nodes after i for which: $a_j > a_i$. The charge node corresponding to node i is denoted as $r(i)$. Let the binary decision variable x_{ij} be equal to one if the service trip or charging event at node j is performed directly after node i. The variables y_i and z_i track the charge at arrival of node i and the time of arrival at node i. The variable h_i tracks the amount of charge that is added to a vehicle in the charge nodes. The battery capacity of a vehicle Q is given in kWh. The minimum battery capacity that should be available at all times is denoted as Q_{min} Let vc be the costs of a vehicle.

Objective Function

The objective for the charge scheduling model is to minimise the number of vehicles that is required to perform the trip schedule and is given as follows:

$$x(\delta^+(o_v)) * vc \tag{1}$$

Constraints

$$x(\delta^-(i)) - x(\delta^+(i)) = 0 \quad \forall i \in I \cup R \tag{2}$$

$$\sum_{(i,j)\in\delta^+(i)} x(\delta^+(i)) = 1 \qquad \forall i \in I \tag{3}$$

$$\sum_{(i,j)\in\delta^+(i)} x(\delta^+(i)) \leq 1 \qquad \forall i \in R \tag{4}$$

$$y_i - e_i + M_1(1 - x_{ij}) \geq y_j \qquad \forall i \in I, j \in V \tag{5}$$

$$y_{i+}h_i + M_1(1 - x_{ij}) \geq y_j \qquad \forall i \in R, j \in V \tag{6}$$

$$z_i + d_i - M_2(1 - x_{ij}) \leq z_j \qquad \forall i \in T, j \in V \tag{7}$$

$$z_i + g * h_i - M_2(1 - x_{ij}) \leq z_j \qquad \forall i \in R, j \in V \tag{8}$$

$$0 \leq h_i \leq Q - y_i \qquad \forall i \in R \tag{9}$$

$$0 \leq y_i \leq Q - Q_{min} \qquad \forall i \in V \tag{10}$$

$$z_i = a_i \qquad \forall i \in T \tag{11}$$

$$y_{o_v} = Q \tag{12}$$

$$x_{ij} \in \{0, 1\} \qquad \forall (i,j) \in A \tag{13}$$

$$M_1 = Q \tag{14}$$

$$M_2 = max(b) \tag{15}$$

Constraints 2 represent the flow conservation constraints. Constraints 3 ensure that every trip node will be visited exactly once and constraints 4 make sure that every charge event is performed maximally once. Constraints 5 and 6 keep track of the energy level before each node. Constraints 7 make sure that every node succeeding a trip node will start at a later time than the end time of the trip node. Constraints 8 keep time constraints for charge event nodes. Constraints 9 ensure that a battery can not be charged more than its maximum capacity. Constraints 10 impose the battery capacity limit. Constraints 11 set the arrival time at a trip node to the trip starting time. Constraints 12 set the battery SOC to its maximum capacity when leaving the vehicle source node. Constraint 12 defines the binary decision variable x_{ij}, meaning that node j is visited after i.