Simulating smart charging optimization for electric vehicles

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A quantification and statistical analysis of the cost reduction and emission reduction potential of an aggregated Dutch EV fleet

by

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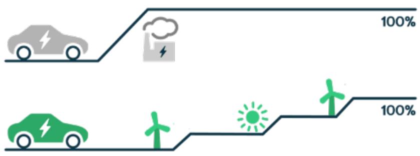

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This thesis is confidential and cannot be made public until September, 2023.

♪ What I love most about rivers is
you can't step into the same river twice,
the water is always changing,
always flowing ♪

♪ What I dream the day might send,
just around the river bend ♪

Pocahontas

Preface

The uncertainty of the future both intrigues and vexes me. To consider what impact trends in technology and innovation are going to have on our future society is something I like to study. In the field of renewable energy, the energy transition is demanding a re-design of the structure and handling of the electricity grid. When I was introduced to this project over a year ago, I knew this was the opportunity I was looking for to execute academic research, while sticking close to implementation within the industry. I am grateful for the opportunity I received to wonder about the long term future in the electricity system, and the guidance I received to connect it to everyday business. I want to thanks Leaseplan and all colleagues at the Faraday Keys office, for their support the past year and all new skills they taught me during my graduation internship. This project showed me to constantly change my perspective and try to understand the incentives of other stakeholders. In the end, to develop an idea to the next phase, the real challenge is getting the right people on board.

This thesis is the final step to complete my academic education and to finish the master Sustainable Energy Technology at the TU Delft. During this research project, I was able to show a learned to deal with large amounts of data, and improved my skills in Excel, Python, Latex, and SPSS.

I would like to thanks my supervisor Rishabh Ghotge for the freedom I received to structure my own project trough out the first phase. And at the same time, the close collaboration and steering towards the end. I want to thank you for the encouragement to learn Python and the tips and tricks how to improve my code. Very little is left from the project proposal we defined together over a year ago. However, the possibility to steer the project, based on data availability and agreements with external parties, was key to make this research a success. It is strange to realise the biggest challenge was to develop a workable research design to create useful simulation output from the data, and most of my time went into phase one.

Fred and Frank, the strongest encouragement I received is the feeling of a team in this challenge they call thesis writing. The feedback while struggling with our thesis process together, was often the support that helped me to continue in the right direction. Froenk, now is the time, choose something and go for it. Besides that, your level of expertise on the topic made you a perfect partner to discuss my progress with.

Looking back to the steps I took the past year, I am happy with the result of this thesis. The results have both scientific as commercial relevance, and I am happy to receive the opportunity to continue to work on a smart charging service for an EV aggregator in the future.

Marnix Paanakker
Amsterdam, August 2019

Executive Summary

Stakeholders from different levels of the government, the industry, universities and non-governmental organisations in The Netherlands all pledge for a faster transition from internal combustion engines toward electric driving. Electric vehicles (EVs) are considered effective to reduce carbon emissions in the transportation sector. Besides that, EVs could be the catalyst to enable more renewable energy to the electricity mix, if smartly integrated with the current electricity grid.

To ensure robustness and security of supply, continuous balancing between supply and demand in the electricity grid is needed. Electrification of mobility is one of the trends in our changing electricity system that demands an increase of flexibility. Flexibility is defined as the means that enable the electricity system to transit to a different state of equilibrium between generation and consumption. To safeguard the stability and security of supply in the future, with increasing renewable electricity in the energy mix, new flexibility options have to be unlocked. While the mobility transition to electric driving could cause serious problems in increasing peak demands, opportunities arise to deliver flexibility with EV smart charging at the same time.

To ensure that the potential of EVs could be fully realised, new types of cooperation between the automotive sector and the electricity sector is necessary. One could conclude there is a strong synergy between the energy transition the mobility transition. That synergy is positioned central in this research and smart charging of EVs is the designated tool to act as an enabler to integrate the two sectors.

The objective of this research is to understand what smart charging can bring business and society at large. In close collaboration with the largest fleet operator in the world and a commercial aggregator, the impact of smart charging on both cost reduction and carbon reduction was simulated for an EV fleet in 2018. The simulation is designed to quantify the cost reduction of EV smart charging in The Netherlands as realistic as possible. Besides cost reduction quantification, the objective is to create a better understanding of what variables influence smart charging cost reduction. This is done via a statistical analysis of the smart charging simulations output. Where the financial incentive is the key driver to commercialise smart charging, a decrease of the carbon footprint could create positive externalities at the same time. Furthermore, this research also has the objective find the direct impact of smart charging on carbon intensity of the electricity used for personal transport.

In this research, an EV aggregators perspective is leading. The EV aggregators could utilizing available flexibility in an EV fleet to deliver flexibility services. The strategy chosen to simulate is based on day ahead market optimization and passive balancing on the imbalance market. The EV fleet is assumed to be an isolated portfolio handled by the balance responsible party (BRP). The average synthetic load profile over 2018 was €41,56 per MWh and this is used as benchmark to quantify the smart charging savings in the simulations. Different smart charging simulation set-up scenarios are designed and executed. Simulation A shows the losses in a worst case smart charging scenario. Simulation B is optimizing smart charging on the day ahead market only and is not able to reach any savings compared to the benchmark. Simulation C is integrating the imbalance market and shows a significant drop in average prices, indicating the smart charging algorithms are able to utilize the fluctuations in the imbalance market prices. Simulation D integrates forecasting tools for both the EV charging demand and price forecasting into the smart charging algorithms. This makes the latter the most realistic simulation to use to calculate the cost reduction potential for smart charging. In all simulations a real-world charging data set with 300.000 historic charging sessions was used. For each session, a new smart charging profile is determined by the optimization algorithms. The session price and session carbon intensity is calculated for both the smart charging scenarios as the business-as-usual scenarios. To compare the results of the different smart charging set-up scenarios, the average session price of all session in that simulations is used. At the same time, the smart charging savings is calculated based on the defined benchmark.

The findings within this thesis support the conclusion that the used smart charging algorithms work properly and could decrease the electricity purchase price in The Netherlands. Additionally we found that the carbon intensity of the charged electricity during the smart charging schedule decreases compared to a business as usual scenario. This is a direct result of a correlation between the carbon intensity in the grid and day ahead prices in The Netherlands.

EV aggregators are able to add flexibility to the demand side of the electricity system by means of smart charging, if a strong price incentive is provided. If stakeholders across the mobility and the energy sector work together, a real-world commercial implementation based on the price incentives on day ahead market and imbalance market in The Netherlands is possible. In the statistical analysis, multiple regression models show a linear relation between three independent variables (the session duration, session volume and maximum power of the charge point) and two dependent variables (the average session purchase price and savings per session). The key insights from the models empowered three main recommendations to EV aggregators to optimize the smart charging savings in the future:

1. Encourage longer session lengths
2. Encourage regular overnight charging sessions behaviour, independent from the charging needs
3. Stimulate access to high charging power

The data showed compelling differences between the ~ 20% BEVs and the ~ 80% PHEVs and their results were separated accordingly in this research. In all simulation set-up scenarios are the PHEVs outperforming the BEVs in terms of a lower average session price and higher cost reduction.

If the smart charging strategy is executed as proposed in this thesis, the EV aggregator is exposed to the day ahead market and imbalance settlements for its portfolio. The EV aggregator is able to decrease the electricity purchase price, while acting as BRP. The exposure to the markets brings significant risk. Collaboration with an electricity supplier or BRP could potentially increase the smart charging savings for the EV aggregator. Furthermore, other revenue streams to utilize flexibility could be investigated. If stacking different flexibility strategies is possible, it could increase the smart charging value in the future.

Contents

1

Introduction

In this opening chapter, the entanglement of energy and mobility is discussed. First, the role of the electric vehicle in the energy transition is described. After that, the difficulties and opportunities regarding electric vehicles in the electricity system are discussed. This is used as framework to introduce smart charging of electric vehicles as service. In section 1.3 the research problem, research objective and research questions are described. Last part of this chapter explains the structure of this thesis and elaborates on the industrial collaboration during this research project.

1.1. The role of electric vehicles in the energy transition

Climate change is often referred to as one of the biggest challenges of our generation. Human kind has been late in acknowledging this danger and has so far done too little about it. Global warming and climate change is discussed on all levels, but decision makers continue to choose economic growth over ecologic stability [12]. Aligning decarbonisation with economic growth, without extreme political or economic sacrifices, could be an effective strategy to decrease greenhouse gas emission.

PARIS AGREEMENT

Article 2

1. This Agreement, in enhancing the implementation of the Convention, including its objective, aims to strengthen the global response to the threat of climate change, in the context of sustainable development and efforts to eradicate poverty, including by:
   - (a) Holding the increase in the global average temperature to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change;
   - (b) Increasing the ability to adapt to the adverse impacts of climate change and foster climate resilience and low greenhouse gas emissions development, in a manner that does not threaten food production;
   - (c) Making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development.
2. This Agreement will be implemented to reflect equity and the principle of common but differentiated responsibilities and respective capabilities, in the light of different national circumstances.

Figure 1.1: United Nations Paris Agreement[37]

As formulated in figure 1.1, late 2015 during the United Nations Conference on Climate Change (COP21), 195 countries came together in Paris to agree on ambitions and terms to decrease greenhouse gas emission. The overall goal is to restrain global warming to below 2 degrees (and pursue efforts to remain below 1,5) above pre-industrial levels [37].

The transportation sector contributes significantly to the global greenhouse gas emissions. The sector is responsible for 14% of the anthropogenic greenhouse gas emissions in 2014[15]. Only true zero-emission innovations in the electrification of transport can solve emission challenges [16]. The long term decrease of CO2 emissions in the transportation sector should be achieved by technological innovation, like EVs, instead of changing behaviour to lower transport volumes [27]. To fulfill the emission reduction ambitions within the transportation sector, replacing fossil fuelled engines with electric engines, power by renewable produced energy carriers is needed [39].

In The Netherlands, the government pushed its agenda on electric vehicles (EVs) in passenger road transport via the 'Green deal elektrisch Vervoer 2016-2020' [11]. In this document, all involved stakeholders, including the government, car manufacturers, environmental organisations, transportation companies, car leasing companies, provinces, municipalities, universities and more, agreed on the ambition to reach 50% EVs in new sales in 2025. In 2035, all new sold vehicles have no exhaust pipe emissions, according to the ambitions [11].

EVs has already existed since the 1800s, but its inferior technology compared to Internal Combustion Engine (ICE) vehicles restrained the market penetration [14]. Since EVs are considered very effective technologies to reduce CO2 in the transportation sector, sustainability reasons provided recently new incentives to invest in R&D, to improve the technology and implement EVs on a large scale [40]. This transition is associated with both global climate change and fossil fuel usage, but also addresses a lot of other aspects, like air quality and noise pollution [34].

Prior research indicates that to ensure that the potential of EVs could be fully realised, new types of cooperation between the automotive sector and the electricity sector are necessary[18, 34]. This cooperation is new and little can be found about automotive industries going into the electricity sector or vice versa.

EVs have a high potential to minimize carbon dioxide emissions, and could be a catalyst to enable more renewable energy into the electricity mix, if smartly integrated with the current electricity grid [40]. One could conclude there is a strong synergy between the energy transition and the mobility transition from ICE vehicles to EVs.

That synergy is positioned central in this research and smart charging (SC) of EVs is the designated tool to act as an enabler to integrate the two sectors.

> ''full environmental potential of electric vehicles will only be realized if they are not simply used as a substitute for conventional ICE vehicles, but also as a tool for load management in the electricity grid, and as one component in an integrated network of different transport modes in an urban setting'' [34].

1.2. Smart charging as tool to balance the grid

1.2.1. Stabilizing the electricity grid

The Netherlands has one of the most robust electricity systems in the world with a security of supply over 99,99% [36]. The inherent characteristic of electricity requires a constant and continuous balance between supply and demand. The power system is designed with a certain deviation allowance, but has strict boundaries to prevent power outages. The responsibility of this balance lies with the transmission system operators (TSOs) and the power balance is maintained by the different European markets. In The Netherlands, the responsibility of balancing the grid lies with TenneT, the Dutch TSO. In figure 1.2, a graphical representation of the power grid shows how generation and consumption can be seen as the supply and demand that need to be in balance.

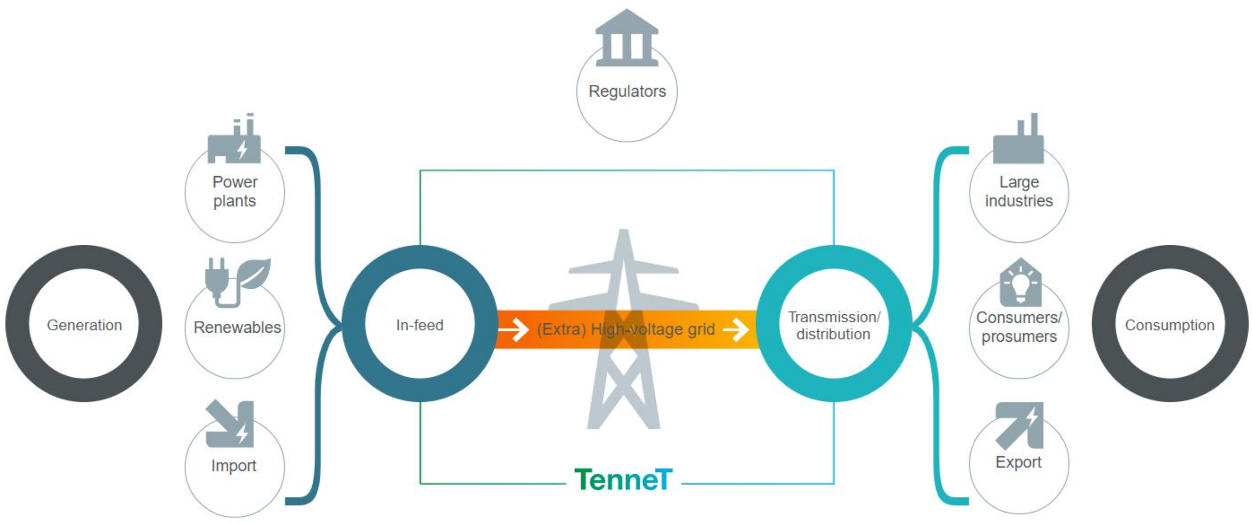

Figure 1.2: graphical representation of balancing the grid by TenneT

The resilience of the system depends on the ability to respond correctly to variability in supply or demand of power to maintain the balance, which is referred to as flexibility.

> "Flexibility in the electricity system are the means that enable it to transition from one state of equilibrium between generation and consumption to another." [36]

Three key forms of flexibility are important to distinguish for this research[21]:

- Supply-side flexibility, e.g. power plant response or power curtailment
- Energy storage, e.g. pumped hydro, battery storage or hydrogen storage
- Demand-side flexibility, e.g. peak-shaving or load shifting

The electricity demand is changing both predictable and unpredictable in time. In a traditional fossil fuel based power system, a portfolio of power plants deliver the needed flexibility by changing their production power on the supply side [21].

1.2.2. The energy transition is changing growing the need for flexibility in the electricity grid

In the energy transition towards a low-carbon power system, both the supply side and demand side of the electricity system is changing significantly. Variable renewable electricity production like wind and solar is substituting the fossil electricity production and this causes serious challenges to the flexibility in the system.

1. The intermittent character of solar and wind energy increases the need for flexibility
2. Phasing out fossil electricity production decreases the available flexibility

On top of that, more flexibility is needed due to changes on the demand side as well. Electrification in heating and electrification of mobility increases the local peak demand, as well as local electricity production with rooftop solar system. This is resulting in an increase of local congestion in the grid [24, 29, 43]. Accordingly, extra flexibility is needed not only on a national level, but also on a local level to deal with peak demand and local congestion. Currently no commercial markets are available to handle this problem and grid reinforcement is used as a solution, but this is not a sustainable solution if the described trends are taken into account [4, 8, 32]. The distribution system operators could decrease the investments in infrastructure significantly if demand side flexibility is delivered by EVs, but a price incentive should be provided[42]. The high complexity of designing a local flexibility markets, slows down the emerging of new markets.

> `‘‘To Realise a renewable electricity future a mix of new flexibility options has to be unlocked’’` [36].

TenneT states that there is no single solution to solve the challenges rising in the changing energy system. Instead a combination of different options are investigated, where in the end the markets will find the cheapest way to structure the system. One of the solutions often mentioned in literature, is creating flexibility with EVs[21]. Nowadays, demand response based on price incentives is applied commercially to large industries but not to the residential sector. Literature shows there is significant value in the flexibility of the batteries of EVs, that could be used to stabilize the electricity grid with smart charging[6, 17, 19, 20, 25]. With integration of digitalization, opportunities arise to utilize the flexibility in residential assets such as EVs. However, this is this not a commercial activity at the moment, the question is why.

1.2.3. Price incentive as bare necessity for EV aggregator

If there are price incentives in place for demand response with EVs, aggregators can build a smart charging platform to optimize the EV charging demand in time. If EV aggregators will be able to utilize smart charging while responding to price incentives, it will flatten the peak demand and it will decrease the price fluctuations[42]. To optimize the economic reward of EV flexibility, two conditions are key:

1. Maximize the economic value with the given flexibility

2. Maximize the available flexibility within an EV fleet

The first maximization of the economic value with the given flexibility is the main task of technical aggregators, using complex dispatch algorithms. The second maximization could be depending on the driving and driver behaviour and therefore the incentives towards the driver. The available flexibility could increase if driver behaviour is better forecasted or simply by creating restrictions for the EV driver, like capping the battery capacity.

Extensive research has been conducted about the deployment of EV smart charging as a demand response strategy [2, 31, 43], but real world implementation lacks behind [30]. Expert futurologist, researchers and policy makers are eager to describe the trends that smart charging of EVs is inevitable in a future energy smart grid [8, 11, 32, 39]. But, how could it be integrated in the current state-of-the art system and markets?

In an earlier study, the value of SC of EVs is determined in three set-up possibilities [23]:

- Use local office solar production to charge EVs
- Charge EVs based on dynamic pricing
- Use available flexibility of EVs to provide demand response ancillary services

The researchers used a single mixed integer linear programming formulation to decide the charging logic for the EV fleet. According to their research, using only 1 of the above strategies, the economic reward is too little. [23].

The goal of this research is to simulate smart charging of an EV fleet in The Netherlands and quantify the cost reduction for an EV aggregator.

1.3. Research Approach

1.3.1. Research problem definition: uncertainty of economic reward of smart charging

The role of EVs in the energy transition is described in section 1.1. EVs are powered by potentially renewable produced electricity instead of fossil fuels and EVs have no tailpipe emissions. This inherent characteristics results in the conclusion that the impact of the mobility transition on the energy transition is inevitable.

The opportunity to use the available flexibility of EVs to stabilize the grid to a future ready electricity system allows more intermittent renewable energy in the grid and accelerates the energy transition. But, where the first effect is realised by the decision to drive electric and the second effect is long term and complex to quantify, a third potential impact on the energy transition could be imagined. In an electricity market in the middle of the energy transition, the electricity in the grid is a mix of renewable and fossil energy. The fossil energy power plants deliver constant power for a stable price and are able to scale up or down. The renewable energy has a variable production, little flexibility and has to deal with forecasting errors, which results in an unstable price. These differences in electricity production create the expectation that the electricity price will fall if abundant renewable energy is available and the price will rise if little renewable energy is available. Smart charging services will optimize the charging schedule of an EV with the target to decrease the charging costs. The correlation between renewable energy presence and price, could result in a lower carbon intensity for the electricity molecules going physically into the EV.

Several environmental and economic advantages of large scale integration of smart charging services into the electricity system are described in section 1.2. A smart charging service could be seen as the catalyst to the synergy between the energy transition from fossil to renewable energy and the mobility transition from ICE vehicles to EVs. Nevertheless, smart charging as an innovative tool is far away from common practice.

A running smart charging platform will be controlled by computers and algorithms running on servers, without interference of humans. However, to commercially roll out a smart charging service, a significant upfront investment is needed. A significant upfront investment is needed for among other things; forecasting tools, smart charging algorithms, integration with charging infrastructure and hardware, testing, marketing, overhead and more. EV aggregators forbear those investments, since the economic reward is uncertain and expected difficulties a fast scale up brings significant risks.

1.3.2. Research objective and research questions

The objective in this research is to quantify the cost reduction and create better understanding of the potential of smart charging an EV fleet in The Netherlands. This could take away the uncertainty of the economic rewards for EV aggregators. If significant economic rewards could be expected, the results could convince potential EV aggregators to invest into the commercialisation of EV smart charging. Besides the cost reduction, this research also has the objective to find the direct impact of smart charging on carbon intensity of the electricity used for personal transport.

This motivates the following main research question:

`What is the effect of smart charging an aggregated EV fleet on the costs and carbon intensity of the charged electricity?`

Accompanied by the following sub questions:

1. `How much cost reduction per EV could be realised with smart charging for different smart charging set-up scenarios in 2018?`
2. `What is the difference in smart charging cost reduction for BEVs and PHEVs?`
3. `What effect has the duration, the volume and the maximum power on the achieved smart charging cost reduction and how could they predict future cost reduction?`
4. `What strategies could be used to improve the smart charging cost reduction in the future?`
5. `How is the carbon intensity of the electricity changing if comparing smart charging to a business-as-usual scenario?`

1.3.3. Structure of the report

To quantify the economic and environmental upside of smart charging, this research proposes a smart charging simulation design for The Netherlands. Historic EV charging data from 2018 is provided by LeasePlan. To achieve the objective, this research is structured into three phases:

1. Define a realistic algorithmic smart charging set-up
2. Run the smart charging simulations
3. Statistical analysis of the simulation results

Figure 1.3: The three phases of this research

In chapter 2, theories and context precursory to the rest of this research are described to understand the following chapters. Chapter 3 is an extensive description of the research method and analysis design. In section 3.6 of the first phase, an essential question for the rest of this research is answered:

> What is the most realistic smart charging simulation set-up in The Netherlands and how does it differ from a real-world situation?

To determine the effect of smart charging an EV fleet on the carbon intensity of the charged electricity, in phase two the carbon intensity in the grid at charging time is calculated for all sessions. Positive externalities of smart charging are tested during the simulations in this research. The results of the carbon intensity analysis is presented in chapter 5, answering the first sub-question. In the following sections of chapter 5, the financial results are presented and discussed. After all results are presented and the sub-questions are answered, a summary of the results and answers is presented in chapter 6, where the main research question will be answered.

1.3.4. Industrial collaboration

This research was initiated in collaboration with LeasePlan. The company has interest in its outcome, since a smart charging service provided by an EV aggregator could potentially be a service to add to there business. This research is part of an exploratory project, where besides the economic value, the technology readiness is also tested. During this project, a partnership with both a charge point operator and a aggregator was made to build and test the infrastructure for applying smart charging on a small amount of test cars. The partnership with the commercial aggregator was key in this research, since their forecasting and dispatching algorithms are used in the simulations as described in chapter 3.

2

Landscape & context

2.1. Drivers and barriers for electric vehicle adoption

High efficiencies and zero tail pipe emissions are currently the most important drivers for EV adoption [3]. EVs are seen as promising innovation within the transportation sector for years, but large scale adoption lacks behind on the expectations [34]. Fast adoption of EV driving is lacking behind due to different barriers. Besides the technical difficulties, also environmental, social and political barriers are important [33]. Many different technical barriers for EVs are mentioned in the literature; high-performance batteries, new components, interface to the grid, IT based applications to manage loads efficiently, fragmented infrastructure and privacy of charging data [7, 33, 34, 40]. Even if technical problems in for example battery capacity, charging speed, and social problems like driving distance and charging infrastructure availability are solved, there is still a financial barrier compared to ICE vehicles to overcome [34]. As discussed by [34] there are two steps towards large scale implementation of EVs. First, technical barriers in vehicle technology should be improved. Second, new business models which makes EV driving economically viable for industry and consumers should be developed.

A study in Norway showed that for a high percentage of EV drivers, the economic benefits created by governmental incentives, were the most important drivers to buy an EV. Most drivers are not willing to pay significantly more for EVs compared to ICE vehicles [13]. The most successful incentives include zero import tax, zero VAT on purchase, zero VAT on EV leasing and free toll roads for EV drivers. This is an extra indicator that removing the financial barrier for EV driving will be extremely important in accelerating the adoption rates within leasing customers.

Both the car manufacturing sector as well as the car leasing services are changing with the rise of EVs and this brings challenges and opportunities. Even though regulations already have promoted and increased the use of EVs, their leasing costs have remained higher than that of ICE vehicles in The Netherlands. If new business opportunities could be exploited to lower the costs of EV leasing within The Netherlands, adaptation of EVs could accelerate exponentially. According to literature, the reduction for EV leasing costs would allow a higher market penetration rate that would consequently push the energy transition towards a carbon neutral society [7][13][40].

The fact that the leasing costs of EVs is higher than ICE vehicles, is one of the main reasons for slow growth of EV sales in many countries[40]. The literature mentioned could be summarised as a two sided adaption problem. Firstly the technical barriers should be taken away, resulting in EVs becoming the superior technology instead of inferior. This step is already set in motion and some current EV models are considered not inferior but comparable with or superior to ICE vehicles [1]. Secondly, the price of EVs and EV driving or leasing must compete with ICE vehicles. Despite favourable policies and regulations, leasing an electric vehicle remains an expensive choice compared to comparable ICE vehicles. If new services for EVs could gain extra revenue, it could potentially decrease the cost and therefore stimulate EV adoption.

2.2. The smart charging ecosystem in The Dutch electricity sector

To understand the cost reduction potential of smart charging in The Netherlands, an introduction in the Dutch electricity sector is provided. First, the roles and corresponding responsibilities in a smart charging ecosystem are described. Subsequently, the structure of a Dutch residential electricity bill is discussed. This is used as framework to find the possibilities to decrease the electricity costs with smart charging. Eventually, this will result in the chosen smart charging strategy in The Netherlands for the simulation design in this research.

2.2.1. Roles and responsibilities

The 1998 Electricity Act was the beginning of the liberalization of the Dutch electricity market and thereby the start of energy supplier freedom of choice. In The Netherlands, it is by law forbidden since 2004 to group activities in transmission or distribution system operation with electricity production or electricity trading [26]. In figure 2.1 a simple schematic representation of a liberalised electricity system is shown. The involved stakeholders control the physical system together.

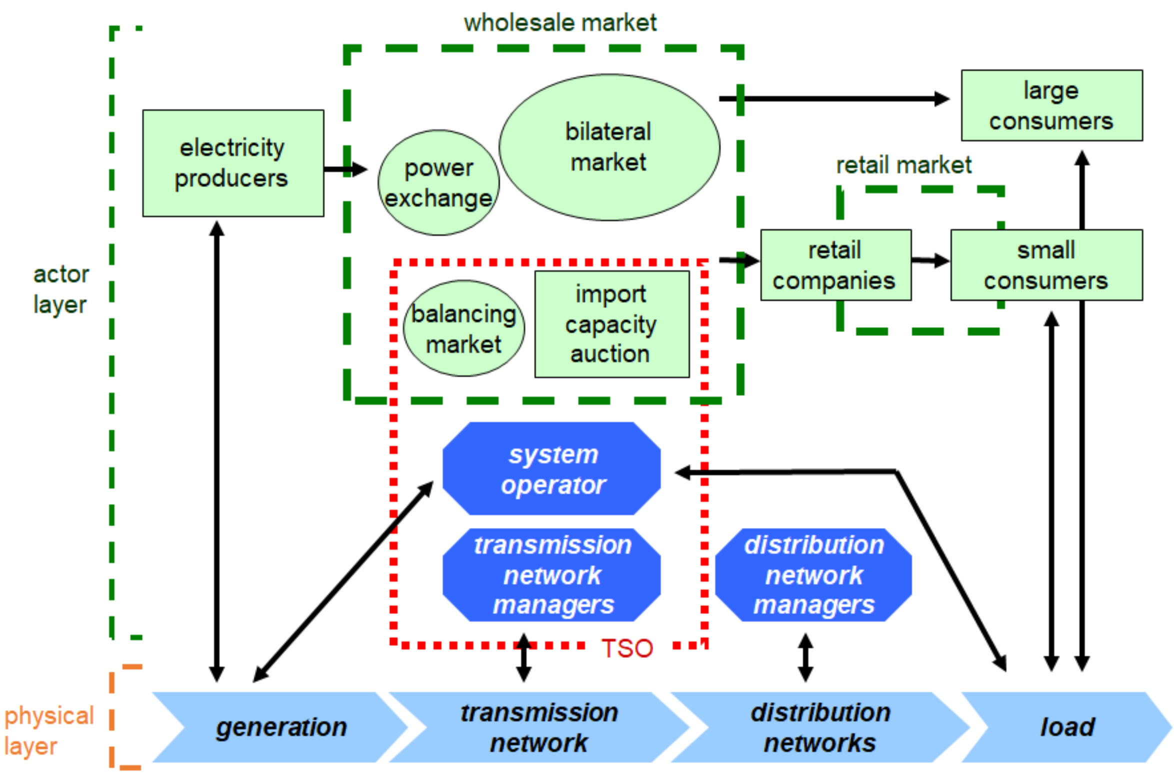

Figure 2.1: A simple schemetic representation of the Dutch electricity system [10]

The transmission system operator (TSO) TenneT is state-owned and responsible for the high voltage electricity grid (220 kV and 380 kV)[35]. Several distribution system operators (DSOs, referred to as distribution network managers in figure 2.1) are controlling the medium and lower voltage grid locally. Table 2.1 shows an overview of the different roles and their responsibilities. The energy producer, balance responsible party and energy supplier is often referred to as supplier for simplicity [38]. The combination of the three is a useful simplicity, since large energy suppliers in The Netherlands deliver those three services grouped in the same company. However, they have three separated roles in the electricity supply chain and should be separated to see there relation with an aggregator. To be able to use EVs for smart charging, data communication infrastructure is needed between the aggregator and the charge point operator.

Role	Responsibility
Transmission system operator	High voltage grid Electricity market regulation
Distribution system operator	Medium and low voltage grid
Energy Producer	Physical generation of electricity
Balance responsible party	Balance supply and demand within portfolio
Energy supplier	source, supply and invoice electricity to customer
EV Aggregator	Optimize EV charging schedule Optimize electricity purchase bids Provide electricity market entry
Charge point operator	Deliver electricity to EV Operate and invoice charging infrastructure Data communication with aggregator
EV Driver	Data communication charging preferences

Table 2.1: Roles and responsibilities involved in smart charging operation

2.2.2. The structure of a Dutch electricity bill

For a residential consumer in The Netherlands, the legal split in the energy sector mentioned in section 2.2.1 could be found in the invoice as well. Level 1 of figure 2.2 shows a schematic representation of the structure of a Dutch residential electricity bill. The network costs are fixed costs and shown in yellow in figure 2.2. The yearly costs are divided over the TSO and the DSO for their services. The electricity costs in the invoice are shown in blue in the figure and are payed to the energy supplier. The electricity costs contain both fixed costs and variable costs. Depending on commercial choices, the ratio between the two blue blocks in level 1 of figure 2.2 is changing. The electricity tax and costs for renewable energy storage are displayed in orange. For both the fixed costs and the variable costs a 21% VAT is charged. This means that 21% VAT tax is payed over the all blocks in level 1, including the electricity tax.

In level 2 of figure 2.2, we zoom in on the electricity costs payed to the energy supplier. After deduction of the VAT in orange and the electricity purchase price in green the margin for energy supplier is left in blue. The energy supplier uses the blue margin to cover overhead, customer service, billing services and other operational costs. The energy supplier strives to purchase the electricity as cheap as possible to decrease the green block and increase the blue block, resulting in profit.

The green block in level 2 could be seen as the costs the electricity supplier makes to supply the physical electricity. The costs per MWh for an energy supplier is a complex aggregation of all purchased energy in the suppliers portfolio. The portfolio contains power purchase agreements, where large amounts of electricity is purchased long term for a fixed fee. Long term contracts are traded on forward or future whole sale markets, weeks, months or years ahead. Closer to the delivery moment $t = 0$, different markets play a role. The ENDEX day ahead market auction closes a bid ladder every day for the next day. During the day intra-day trading is still possible as well to change your portfolio based on your demand forecast. In the end, the balance responsible party is contracted by the supplier and aims to perfectly match the purchased electricity and supplied electricity, to avoid imbalance charges. The average price of all long term and short term trades the energy supplier made, combined with the balance responsible party costs could be allocated to a specific moment in time. The objective of the aggregator is to use the flexibility in electricity demand to decrease the overall electricity purchase price. In figure 2.2 the potential smart charging saving is visualized as a grey block in level 3.

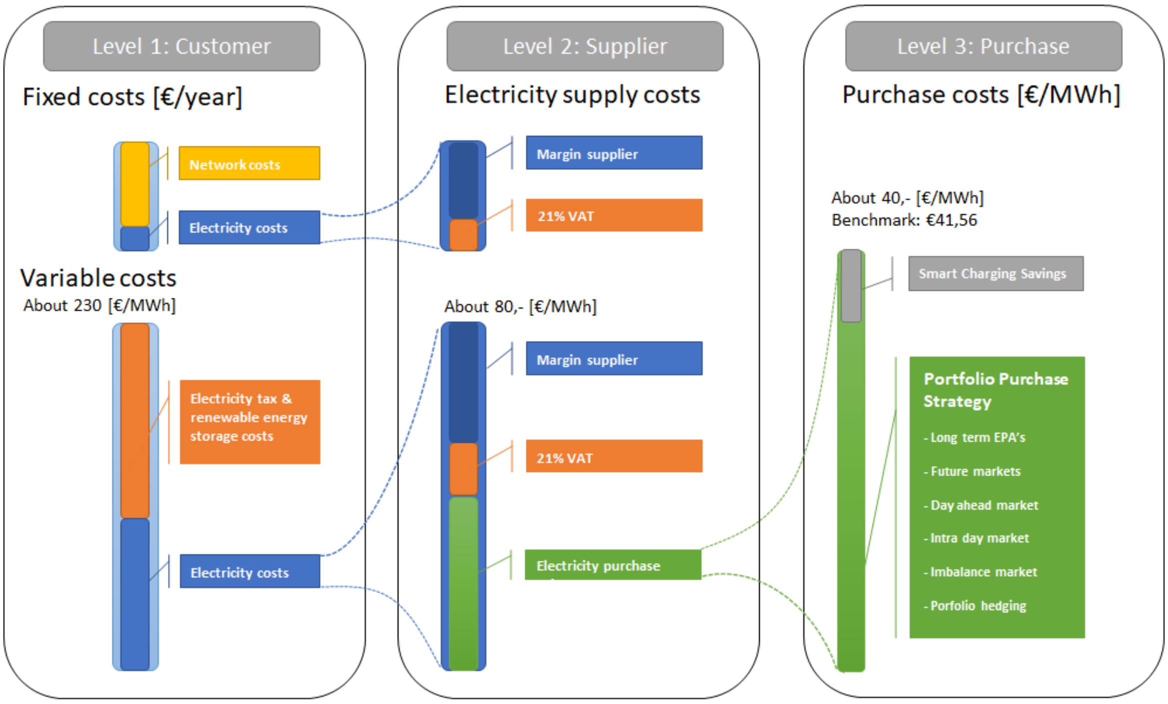

Figure 2.2: A simplification of the structure of a Dutch residential electricity bill

2.2.3. Defining the smart charging strategy and benchmark

EV aggregators could use different strategies to utilize EV flexibility and create value. This could be defined in three basic categories, with different stakeholders to create the price incentive as showed in figure 2.3. The first option for an EV aggregator is to deliver flexibility to the DSO. Congestion management, Voltage control, power quality support or grid capacity management, all could be seen as different flexibility services which could be delivered to the DSO [38]. Nevertheless, none of these defined value streams for flexibility are commercially applicable in The Netherlands yet. The possibility deliver flexibility services to the DSO is therefore not taken into account in this research. However, it could be an interesting opportunity in the future and an EV aggregator should keep the developments in this area in mind.

> "In electricity markets, spot and future contracts only function as a preliminary schedule since the demand and supply of electricity cannot be predicted perfectly; hence another market is needed for ancillary services" [35]

The second option to utilize the EVs flexibility is to deliver ancillary services to the TSO. Again, commercial

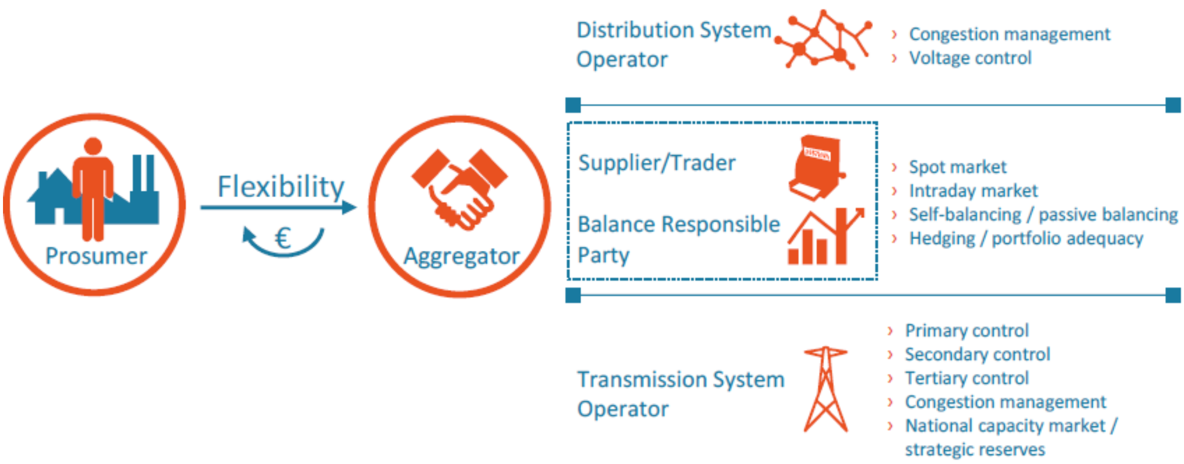

Figure 2.3: The potential customers for the flexibility services of an EV aggregator according to the USEF [5]

access to this value stream is not applicable yet. The Dutch TSO started with pilots in both primary and secondary reserves to allow EV aggregators to enter the market under special conditions. The tertiary reserve market should technically be accessible for EV aggregators. However, the entry bid in that market is 20 MW and therefore far out of scope for current EV aggregators in The Netherlands. If the pilots running in primary and secondary reserve market are successful for EVs and the quantification shows significant value, EV aggregators could potentially utilize EV flexibility in ancillary services in the future. Still, the ancillary service markets are capped and if market entry will be easy for aggregators in the future it could be saturated at one point. This results in a decrease of value for flexibility until the reward is approaching zero.

The third option to utilize the EVs flexibility is to deliver services to the electricity supplier or BRP. This is a revenue stream that is accessible in the current market set-up for EV aggregators. Four different flexibility service could be provided to the BRP according to USEF [38]:

- Day ahead optimization
- Intraday optimization
- Self balancing or passive balancing
- Generation optimization

Generation optimization is referring to demand side flexibility needed to overcome start ramping up or ramping down periods of large production units and is not taken into account in this research. Intra day optimization is also not taken into account, since the prices are less volatile and little opportunities arise in the intra day market. If the ratio renewable energy in the electricity mix is increasing, the intra day market could get more volatile in the future.

Day ahead portfolio optimization is aiming to reduce the overall electricity purchase costs for the next day by shifting loads as much as possible to hours with lower prices. A self balancing service refers to shift loads last minute based on the load of the rest of the portfolio, trying to match the energy program demand as purchased. If the aggregated metering data of the connections in the BRPs portfolio measured the energy program is not matched, imbalance is created. Tennet is calculating all imbalance in the total market and settles the imbalance market by invoicing the BRPs. If a BRP creates imbalance in the opposite direction of the market average, the imbalance created is actually helping the TSO to keep the balance. Depending on the direction of the deviation from the energy program compared to the rest of the market a BRP could get fined or compensated. Passive balancing is the service to deliberately create imbalance, expecting to get compensated for the effort. This requires complex imbalance price forecasting tools, but could potentially add significant value to the BRP.

Since the actual portfolios of electricity supplier and BRPs will always be confidential, it is difficult to quantify what the value of flexible loads is in Day ahead and imbalance portfolios of a large BRP. However, some EV aggregators became registered BRPs in the TSOs BRP register. In this research, we decided to investigate the value of smart charging, while combining day ahead optimization with passive balancing on the imbalance market. The EV fleet is assumed to be an isolated BRP portfolio.

To be able to quantify the smart charging savings, a benchmark of electricity purchase price is needed. Since the height of the average electricity purchase price is the main indicator of the success of an BRP, there is no information available about it. To be able to define a benchmark for the electricity purchase price in 2018, the average was taken from the synthetic load profiles from that year. The average synthetic load profile over 2018 was €45,56 per MWh [28], and this is used as benchmark in this research.

3

Simulation method and analysis design

In this chapter, the research design of phase 2 from figure 1.3 is described. Four smart charging simulations are performed for every unique charging session in the dataset. The four different simulations are referred to as simulation A, B, C and D. In the first section, an explanation of the general simulation approach could be found. Next, the performed simulations A, B, C and D are thoroughly discussed. The simulation all differ in strategy or market choices. Figure 3.1 shows graphical representation of the simulation design on the next page.

3.1. Models: the commercial algorithms and solver

While defining the simulation set-up, the algorithms are build to run real-time in the pilot project conducted in the same period as the simulations. In this section, a description is made from the algorithms used in the real world. Later the changes made to the algorithm in the simulation are described. The energy purchase and the profile optimization block as shown in figure 3.1 is described.

3.1.1. Energy purchase algorithm

The first step is to define the nominated energy purchase day ahead. This nomination is based on a forecast of the day ahead market electricity prices and a forecast of the energy demand by the fleet. The estimated energy demand for one specific car is purchased in the cheapest hours the car is expected to be connected.

- Timeframe: daily before gate close time day ahead market

Input session data:

- Forecasted energy demand [kWh]
- Forecasted start time session
- Forecasted end time session
- Forecasted maximum capacity charge point [kW]

Input market data

- Forecasted day ahead prices

Output energy purchase algorithm:

- Day ahead bid in kWh for every our the next day

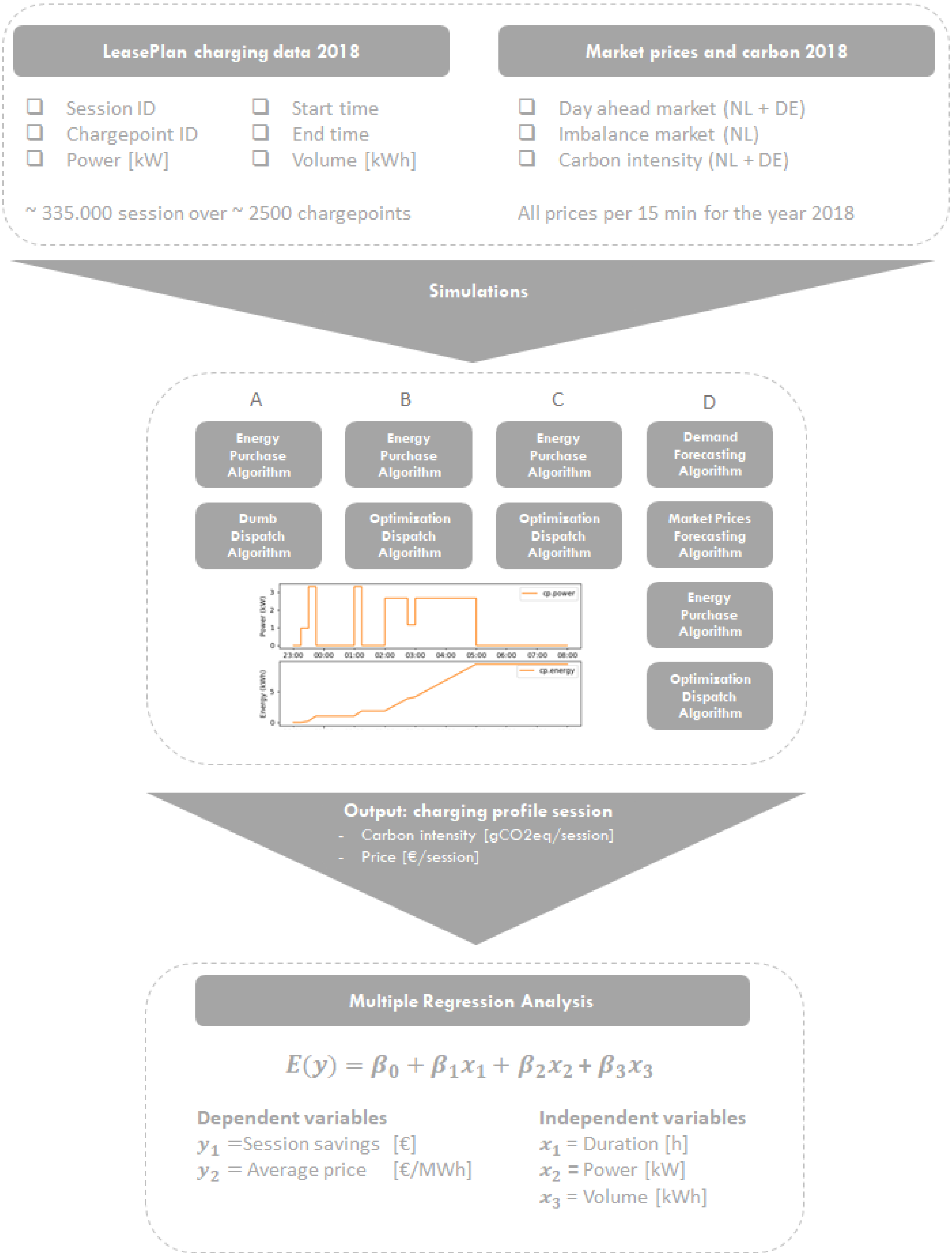

Figure 3.1: Graphic representation of the research design

3.1.2. Profile update optimization algorithm

The second step is to define the smart charging profile during the day based on the imbalance markets and the EV fleet presence. Based on new opportunities, the initial day ahead charging schedule for a specific car could be changed. The charging schedule will also change if a forecasting error occurs in the energy demand. So the flexibility of car A could be used to charge the (cheap) energy bought for car B, if car B is not at home and connected to the charge point as expected. The larger the EV fleet, the better this system works.

- Timeframe: continuously with timesteps of 15 min for decision variable for every active session

Input session data:

- The day ahead bid from the energy purchase algorithm
- Forecasted energy demand [kWh]
- Start time session
- Expected end time session
- The maximum power of the charge point [kW]

Input market data

- Forecasted imbalance market prices

Output:

- Continuously updated charging profile and send to each car with active charging session

3.2. General approach of the simulations

All the input data for the simulations is described in chapter 4. For each row in the EV charging dataset, a new dataframe is generated and solved in each simulation to find the price and carbon intensity if smart charging was applied during the time of that session in 2018. The newly generated dataframe is filled from the session data and market data, except for the last column. Table 3.1 shows an example visualisation of the newly generated dataframe.

Data Frame	Min_Energy	Max_Power	Price	Carbon Intensity	Power
Start	**0**	**Max Power**	**Price**	**Carbon Intensity**	-
Next PTU	**0**	**Max Power**	**Price**	**Carbon Intensity**	-
Next PTU	**0**	**Max Power**	**Price**	**Carbon Intensity**	-
Next PTU	**0**	**Max Power**	**Price**	**Carbon Intensity**	-
End	**Volume**	**Max Power**	**Price**	**Carbon Intensity**	-

Table 3.1: Example of a generated data frame build for each unique charging session in a simulation

The first column is a time based index. The index is starting at the start of session timestamp, and stretches down to the end of session timestamp. All rows in between represent a PTU of 15 minutes. For the first and last PTU, the maximum power of the charge point is multiplied with ratio active time over full PTU. This compensates for the partial presence of the car during that first and last PTU.

The second column describes the minimum amount of kWh that needs to be charged at the end of every PTU. By placing the total volume of the session in the last row, the algorithm recognises this as the constraint that the total volume should be charged at departure. The other rows are kept empty.

The third column is filled with the maximum power of the charge point and the fourth and fifth are filled with the prices and carbon intensity of that PTU. The last column represents the power charged and is kept empty.

The objective of the simulations is to minimize the electricity purchase cost of every charging sessions utilizing the available flexibility. If the dataframe is filled, the solver takes all information in the frame into account to solve the last column. The total power needed to charge the car is distributed over the span with of the time frame, will picking the cheapest moments. The filled data frame results in the charging schedule, an example is shown in table 3.2. Figure 3.4 and figure 3.5 are examples of such a solved charging schedule.

Data Frame	Min_Energy	MaxPower	Price	Carbon	Power	Costs	Emission
New_Start	0	3.7	€27,21	519,96	0	-	-
Next PTU	0	3.7	€27,31	519,96	0	-	-
Next PTU	0	3.7	€30,17	506,18	0	-	-
Next PTU	0	3.7	€20,87	506,18	3.7	0,0193	468,21
New_End	1.25	3.7	€25,58	506,18	1.3	0,0068	164,51
Total						€ 0,026	632,73 [gCO2eq/kWh]

Table 3.2: Example of a solved and filed data frame

When the solver is finished, the price is multiplied with the power to calculate the costs in € per PTU. The carbon emission per PTU is calculated by multiplying the carbon intensity with the power. Both are summed for the full data frame and stored in the results in the session row.

$$Costs: C_{session j} = \sum_{n=1}^{i} \frac{1}{4} \cdot DV_i \cdot P_i \cdot \lambda_i \tag{3.1}$$

$$Emission: E_{session j} = \sum_{n=1}^{i} \frac{1}{4} \cdot DV_i \cdot P_i \cdot I_i \tag{3.2}$$

DV_i = the decision in domain [0,1]
P_i = power
λ_i the price for that PTU
I_i = the carbon intensity for that PTU

3.3. Simulation A: Worst case simulation

In simulation A, a dumb charging profile is applied, where the session is charging full power until the demand is met. We assume this profile is what actually happened during the charging period in 2018. Two different financial outputs are generated in this simulation. The first is based on a set benchmark electricity price, to compare the results with not executing smart charging, as showed in figure 3.2. Notice the constant benchmark price in this figure.

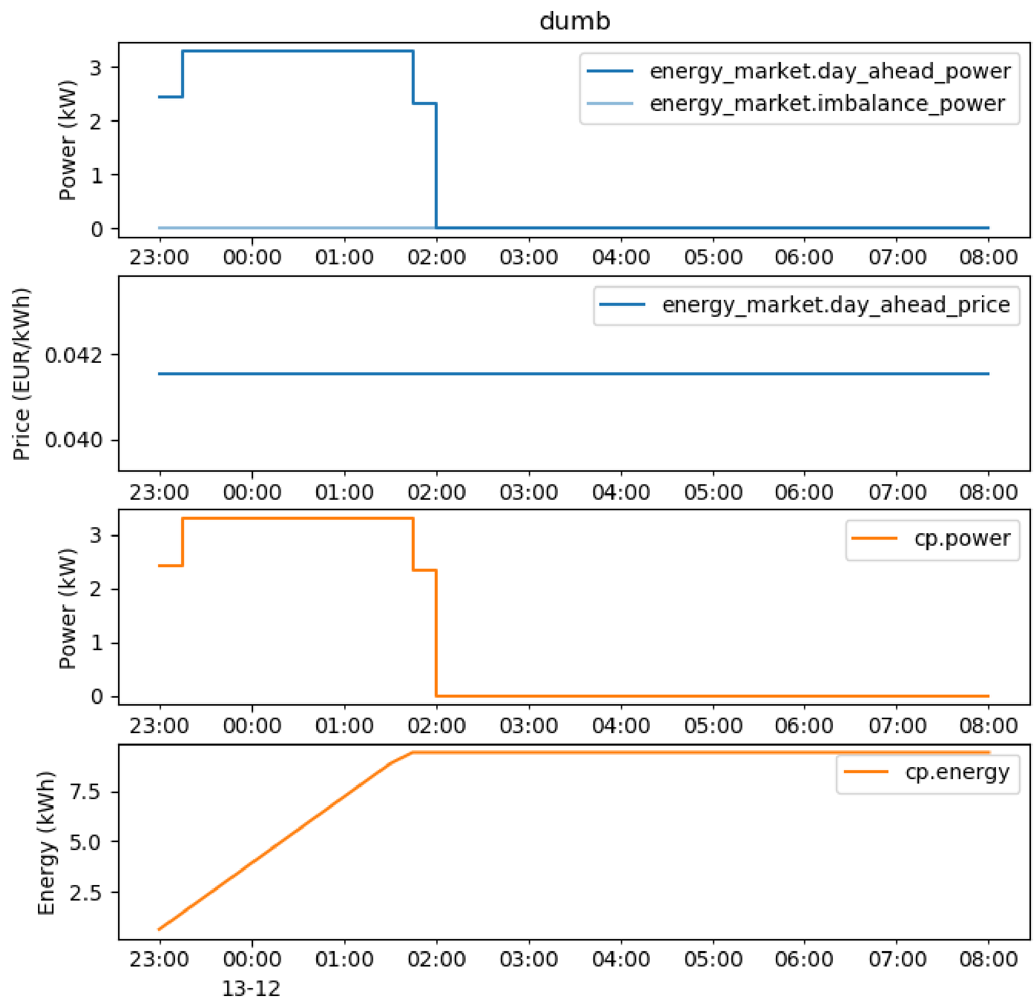

Figure 3.2: Example of dumb dataframe solved on in simulation A

The second output is based on a dumb charging profile, while exposed to the day ahead market. This shows the worst case scenario of a failing smart charging service. The energy profile purchased the day ahead based on the energy purchase algorithm described in section 3.1.1 could not be followed, since dumb charging profile is applied. This means the imbalance price is payed during the hours the car was charged, while the energy was not purchased. Besides that, a compensation is received for the energy purchased day ahead, but not consumed. This compensation is also based on the imbalance price. If a driver does not allow smart charging when the session starts, but overrules the system and demands full power directly, simulation A is applied. Since the energy purchase algorithm uses the full connection time to purchase energy, but the session was charged as fast as possible, the financial results of this simulation shows a worst case scenario for bad forecasting tools. Since the charging session is exposed to the imbalance market for its price, this will indicate the amount of risk present in the system. This simulation is not build only to define a financial benchmark, but to find the benchmark for the carbon intensity based on dumb charging. In figure 3.2 an example is shown of a profile for a session based on simulation A exposed to the imbalance market.

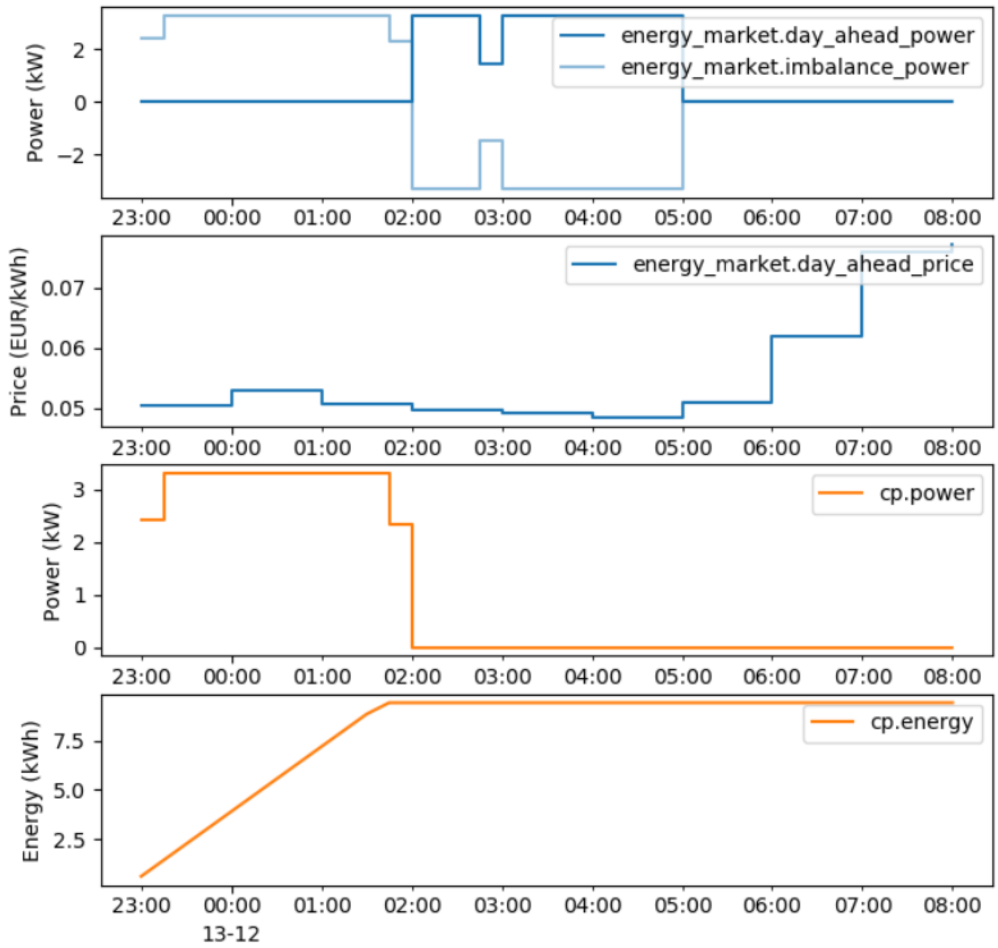

Figure 3.3: Example of boost dataframe solved on in simulation A

3.4. Simulation B: The day ahead market simulation

Simulation B is based on the day ahead market. In this simulation, the day ahead market prices are filled in the dataframe as illustrated in table 3.1. The imbalance price is neglected in this simulation. Since the more fluctuating imbalance price is expected to bring favourable opportunities for smart charging, the value of smart charging based on only the day ahead market is expected to be lower. However, simulation B is still of high value for this research, since it sets a new benchmark for the next simulations.

Besides that, the carbon intensity results in this simulation are of significant value. The expectation is that the day ahead market is more influenced by renewable energy penetration in the grid compared to the imbalance market, so the carbon emission savings while smart charging based on the day ahead market only, is expected to be higher. Since the renewable energy penetration is still low in The Netherlands, simulation A is also executed with the German data. The Germany simulation is an exact copy of simulation A, with both the German day ahead market as the German carbon intensity in the grid as substitution of the Dutch data.

If this simulation strategy would be applied to a real-time situation, the day ahead price would not be know and only a forecast could be fed into the solver. Since historic data is fed into the simulation, no forecasting error is assumed, so the model simulates the situation where every session follows exactly the profile as day ahead purchased as describe in section 3.1.1. The cost of this smart charging simulation is due to forecasting error higher in a real-time scenario compared to the simulation results. In figure 3.4 an example is shown of a smart charging profile for a session based on simulation B. The figure shows that the power to charge the car is scheduled during the lowest prices in the time frame. The prices on the day ahead market in this particular time frame peak between 07:00 and 08:00 with prices above €0,07 per kWh. The lower prices in the time frame are close to €0,05 per kWh, which corresponds to €50 per MWh. One should realise, that even if the smart charging systems works perfectly, the result is heavily depending on the prices during the time interval. €50 per MWh is well above the €41,56 benchmark and this specific charging session would be a pain for an EV aggregator, increasing the overall costs.

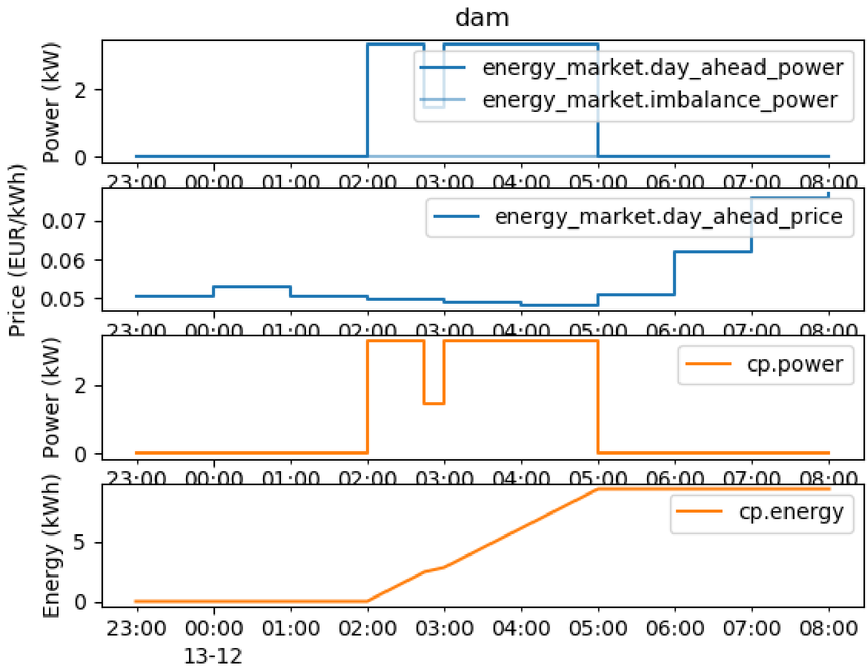

Figure 3.4: Example of dataframe solved on in simulation B

3.5. Simulation C: The imbalance simulation

Simulation C is a copy of simulation B, with the addition of self balancing on the imbalance market. If the solver would be allowed to trade freely on the perfectly predicted imbalance market, gaming will occur in the shape of a large amount of trades to decrease costs. Due to the inherent impossibility to predict the imbalance price perfectly, the solver could not be allowed to trade freely on the imbalance market. To allow a realistic amount of imbalance trading, the solver is bound to 80% commitment of the day the ahead nomination purchased on the day ahead market. This results in a 20% energy purchase on the cheapest moment of the imbalance market. The decision for this ratio in the simulation design was made together with the commercial aggregator. The imbalance market is very difficult to predict in advance, but the stronger the deviation of the outliers, the higher the change of correctly predicting them.
In figure 3.5 an example is shown of a smart charging profile for a session based on simulation C.

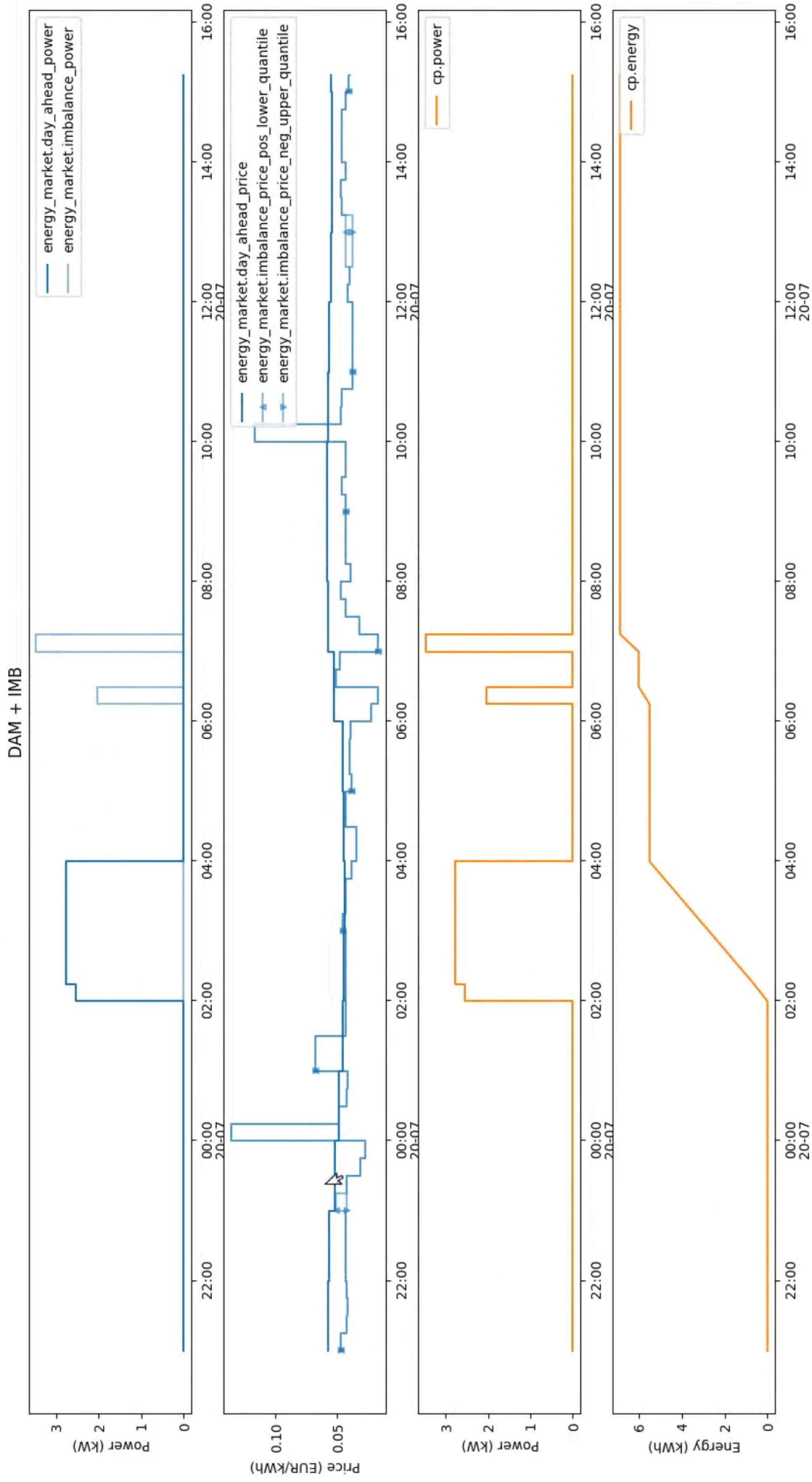

Figure 3.5: Example of dataframe solved in simulation C

3.6. Simulation D: The forecast simulation

In the set-up of the simulations B and C, we assume zero demand and price forecasting error. Since no forecasting error is assumed, every EV could be charged exactly as planned day ahead, or changed based on perfectly known imbalance opportunities (price incentives) during the day. In a real world situation, both demand and price could not be known exactly.

In this research, one of the key targets is to simulate smart charging as closely to a real world scenario as possible. To find a more realistic result, forecasting tools are added in simulation D. Both the charging session data as the price data of the first 6 months of 2018 is provided to self-learning algorithms to forecast both the demand and the prices. After the learning process, the second half of the data is fed into the smart charging simulation. This decreases the size of the simulation output significantly, but gives a more realistic result. Including the forecasting changes the process, compared to the previous simulations. The steps taken are described in two phases, similar as the two algorithms described in section 3.1.

3.6.1. Phase 1: day ahead situation

In the first phase, the day ahead situation is mimicked. The system is aware of the fact that a session is going to take place the next day, but has no information about it. Besides that, no information is available about the day ahead market prices and the imbalance market prices. The reference data is fed into the algorithms to create the forecasting. As described in chapter 4, each session is coupled to a specific car and driver with an ID. With all historic data from the session from that specific ID, the demand forecast is made. Next to the demand information also the prices need to be estimated. The day ahead price is estimated for all hours the next two days based on the historic prices, without feeding the real day ahead prices. This could be summarised in four input variables that are estimated in phase 1:

- The volume
- The start time
- The duration
- The day ahead prices

The maximum power of the charge point is known per ID, which means that now all information is known for the energy purchase algorithm as described in section 3.1.1 to run.

3.6.2. Phase 2: near real-time situation

In the real time situation mimic, different input are needed for the profile update optimization algorithm as described in section 3.1.2:

- The day ahead bid based on forecasting in phase 1
- The actual energy demand [kWh]
- The actual start time session
- The actual duration of the session
- The maximum power of the charge point [kW]
- The imbalance market prices

In a real world situation, the profile update optimization algorithm will update the charge profile every couple of minutes, based on updated forecasting. In phase 2 of simulation D, the profile is updated only once. The actual data from the dataset replaces the estimated data from phase 1 and the day ahead bid and maximum power is also known. The imbalance market prices is the only input which is not calculated or fed in yet. Ideally, the imbalance price forecast is calculated during the start of the session and updated every couple of minutes. If done so, the algorithm could change the charging profile every couple of minutes, like it would have done in a real world scenario. Unfortunately, it was too complex to integrate the imbalance forecasting in such a way. The simulation set-up design is build to handle 2 phases, but adding extra forecasting and optimization calculations for all steps in every session was too complex to design during this research. Besides that, the run time of the simulation would exponentially rise towards a calculation impossible to run on a ordinary computer.

To realistically quantify the smart charging savings, it is crucial to add the imbalance market to simulation D, yet it should be restricted to prevent gaming and produce results that are realistic and trustworthy. If ambitious assumptions are made in the choice to add the imbalance market, the result could be theoretically outstanding, while practically not feasible.

To deal with this problem, in simulation D the imbalance market is added in a cautious and deligate matter. The assumption is made that algorithm is able to predict the 5% highest and 5% lowest imbalance price moments, but has no information about the rest of the imbalance prices. The reasoning behind this choice is that the stronger the deviation, the higher the probability the forecasting algorithm will recognise the outlier and label it as opportunity. The choice to feed 5% is totally arbitrary, but expected to be cautious enough to confidentially mark as reachable.

After feeding the 5% highest and lowest imbalance prices to the system, the solver will dispatch the actual charging profile. After that, the real historic day ahead prices and imbalance prices are fed in to calculate the actual prices payed.

3.7. The output of the simulations

For simulation A, B and C, an output data file contained 292.924 rows of charging session from 2.366 unique cars containing columns itemized below.

The first columns is identical to the charging session input data:

- index number
- Session ID
- Charge Point ID
- Car type
- Car brand
- Car Model
- Start session [timestamp]
- End session [timestamp]
- Volume charged [kWh]
- Duration of session [h]
- Maximum power of charge point [kW]

The next columns are the output of the simulations as displayed by figure 3.1 and calculated as described in formula 5.1 and 5.2:

- Simulation A: session costs [€]
- Simulation A: carbon intensity [g CO2 eq]
- Simulation B: session costs [€]
- Simulation B: carbon intensity [g CO2 eq]

- Simulation C: session costs [€]
- Simulation C: carbon intensity [g CO2 eq]

Simulation A was repeated for the German market resulting is a slightly smaller dataset. Simulation D was the last simulation done, only focusing on price and not on carbon intensity. This resulted in the following output:

- Simulation D: session costs [€]

3.8. Metrics to compare the results

To compare the results of the different simulations with each other, the total session savings in euros and the total session savings in carbon emission are calculated. After that, the average price as well as the average carbon intensity is calculated.

Total session savings in €:

$$S_{session j} = V_j * \lambda_b \cdot C_{\text{session j}} \tag{3.3}$$

Total session emission savings in gCO2eq/kWh:

$$E_{session j} = \text{Session carbon}_j - \text{Dumb session carbon}_j \tag{3.4}$$

Average session price:

$$\lambda_j = \frac{C_{\text{session j}}}{V_j} \tag{3.5}$$

Average Session Carbon [gCO2eq/kWh]

$$e_j = \frac{\text{Session carbon}_j}{V_j} \tag{3.6}$$

This results in the following columns for the charging sessions from 2018:

- Average session price [€/kWh]
- Average session carbon intensity [g CO2 eq/kWh]
- Total session savings [€]
- Total session savings [g CO2 eq/kWh]

The average price per session is a useful metric, since every single charging session could be compared to the benchmark very intuitively. Nevertheless, taking the average of a large dataset does not always show the best insights. The total session in € is an interesting number to find per session. The amount of kWh charged is an important factor in the differences between the two metrics. For example, one could expect PHEVs to reach lower average prices, since the demand per session is lower on average. A BEV with a higher demand could not reach a similar low average price in the same time interval. However, if the average price is still below the benchmark and the volume high, the savings in € could be larger for the BEV. For this reason, both metrics are calculated for every session in the data set and discussed in chapter 5.

To calculate the result of the total fleet, the total cost is used instead of the average price. Dividing the total costs in € over the total charged energy in MWh by the full fleet gives the result in €/MWh more accurate than taken the mean of all average session prices.

3.9. Multiple regression analysis

In this section, the research design of phase 3 in figure 1.3 is described. The simulations as described earlier in this chapter results in information on the price and carbon intensity for every session in the initial dataset. This chapter gives a description of the statistical analysis conducted to transfer the results of the simulations into models and insights. The results of the simulations are described in terms of independent and dependent variables. After that, the steps performed in the analysis and multiple regression are described. To conclude, an overview of the different tests executed is given.

Multiple regression is an extension of simple linear regression where two or more independent variables are used to predict the variance of one dependent variable. Before multiple regression could be performed, the data should be checked for sources of bias. A normality bias is not possible in this research, since the size of the dataset is of significant size. A linearity bias should be checked. In a multiple regression analysis, two problems may arise; overfitting and multicollinearity. Overfitting is caused by adding too many independent variables. Due to the small amount of independent variables in this research there is no risk of overfitting. Multicollinearity occurs when variables are correlating with each other, this should be checked during when analysing all the correlations in this research.

3.9.1. Multiple regression model

In multiple regression, the regression coefficents, denoted as β, describe the linear relationship between the dependent variable (x) and independent variable (y). For a multiple regression with three independent variables, equation 3.7 and 3.8 describes the general model.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon \tag{3.7}$$

$$E(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \tag{3.8}$$

Due to the available dataset as shown in section 4, in this research is chosen to take three main independent variables into account:

- x_1 = Duration in hours
- x_2 = Power in kW
- x_3 = Volume in kWh

The model could potentially improve if extra independent variables are added. For example, information about the temperature during the session or the battery size of the car. However, there is no trustworthy information available, apart from what was provided in the initial data set. The data distribution of the independent variables are displayed in section 4.

Different dependent variables y_i are tested in the statistical analysis. In section 3.7 the average session price in [€/MWh] and session savings in [€] are mentioned as important output from the simulations and consequently those results are used as dependent variables in the analysis. Besides the financial results, similar independent variables are used to perform multiple regression on the carbon intensity output.

- y_1 = price[€/MWh]
- y_2 = Session_Savings[€]
- y_3 = Emission[gCO2eq/kWh]
- y_4 = Session_Savings[gCO2eq]

3.9.2. The bivariate correlation

To understand the linear correlation between different variables in a dataset, the standard deviation and covariance are standardized to find the Pearson product-moment correlation coefficient, correlation coefficient in short[9]. The coefficient is calculated as follows:

$$r = \frac{COV_{x_1 x2}}{S_{x_1} S_{x2}} = \frac{\sum_{i=1}^{n}(x_{i_1} - \bar{x_1})(x_{i_2} - \bar{x_2})}{(N-1)(S_{x_1} S_{x_2})} \tag{3.9}$$

The correlation coefficient is a number between -1 and 1, where an increase in r indicates a stronger correlation, and 1 shows a 100% correlation [9].

- ±0.1 small effect
- ±0.3 medium effect
- ±0.5 large effect
- ±0.8 very large effect

3.9.3. Linearity and multicollinearity

While performing multiple regression analysis, the assumption is that the outcome variable is linear related to the predictors, but this assumption should be checked. If this assumption is not true, a linearity bias makes the model invalid.

Multicollinearity could impact the regression output if there is a strong correlation between the independent variables. Minor collinearity pose little threat to the outcome of the regresion analysis. To spot multicollinearity, the variance inflation factor (VIF) is taken into account. The tolerance of the relationship between two variables is the inverse of the VIF.

$$Tolerance = \frac{1}{VIF} \tag{3.10}$$

Some general guidlines about multicollinearity [9]:

- If the largest VIF is greater than 10 then there is cause for concern
- If the average VIF is substantially greater than 1 then the regression may be biased
- Tolerance below 0.1 indicates a serious problem
- Tolerance below 0.2 indicates a potential problem

In all regressions, the VIF and Tolerance are checked in this research, if potential problems are found, it will be discussed in the results.

3.9.4. overview of the performed tests

The multivariate regression is carried out for the different dependent variables as defined above in the different simulations. All test are repeated for three different inputs:

- All data
- Only BEVs
- Only PHEVs

The split between BEVs and PHEVs is important, since the data is significant different as seen in section 4.

test	Dataset	Simulation	Dependent_Variable
y1	All	A (NL)	price[€/MWh]
y2	All	A (NL)	Session_Savings[€]
y3	All	A (NL)	Emission[gCO2eq/kWh]
y4	All	A (NL)	Session_Savings[gCO2eq]
y5	All	B	price[€/MWh]
y6	All	B	Session_Savings[€]
y7	All	B	Emission[gCO2eq/kWh]
y8	All	B	Session_Savings[gCO2eq]
y9	All	A (DE)	price[€/MWh]
y10	All	A (DE)	Session_Savings[€]
y11	All	A (DE)	Emission[gCO2eq/kWh]
y12	All	A (DE)	Session_Savings[gCO2eq]
y13	All	D	price[€/MWh]
y14	All	D	Session_Savings[€]
y15	BEV	A (NL)	price[€/MWh]
y16	BEV	A (NL)	Session_Savings[€]
y17	BEV	A (NL)	Emission[gCO2eq/kWh]
y18	BEV	A (NL)	Session_Savings[gCO2eq]
y19	BEV	B	price[€/MWh]
y20	BEV	B	Session_Savings[€]
y21	BEV	B	Emission[gCO2eq/kWh]
y22	BEV	B	Session_Savings[gCO2eq]
y23	BEV	A (DE)	price[€/MWh]
y24	BEV	A (DE)	Session_Savings[€]
y25	BEV	A (DE)	Emission[gCO2eq/kWh]
y26	BEV	A (DE)	Session_Savings[gCO2eq]
y27	BEV	D	price[€/MWh]
y28	BEV	D	Session_Savings[€]
y29	PHEV	A (NL)	price[€/MWh]
y30	PHEV	A (NL)	Session_Savings[€]
y31	PHEV	A (NL)	Emission[gCO2eq/kWh]
y32	PHEV	A (NL)	Session_Savings[gCO2eq]
y33	PHEV	B	price[€/MWh]
y34	PHEV	B	Session_Savings[€]
y35	PHEV	B	Emission[gCO2eq/kWh]
y36	PHEV	B	Session_Savings[gCO2eq]
y37	PHEV	A (DE)	price[€/MWh]
y38	PHEV	A (DE)	Session_Savings[€]
y39	PHEV	A (DE)	Emission[gCO2eq/kWh]
y40	PHEV	A (DE)	Session_Savings[gCO2eq]
y41	PHEV	D	price[€/MWh]
y42	PHEV	D	Session_Savings[€]

4 The simulation input data

To be able to run the simulations and create results to answer the main research question, different datasets are combined and analysed. A real world EV charging dataset provided by LeasePlan created the opportunity to design a data driven research approach. Since understanding of the data is key to both the research set-up and results, this chapter gives an comprehensive description of the EV charging data used in the project.

Before the data could be fed into the simulations, some cleaning and data preparation was needed and those steps are also described. After that, the other datasets used in this research are mentioned. For the simulation the day ahead and imbalance markets prices from the year 2018, as well as the carbon intensity in the grid of that year is used. To run the simulations several other dataset were used:

- Day ahead market prices from The Netherlands in 2018
- Imbalance prices from The Netherlands in 2018
- The carbon intensity in the grid in The Netherlands in 2018
- Day ahead market prices in Germany in 2018
- The carbon intensity in the grid in Germany in 2018

4.1. The EV charging dataset and preparation steps

The EV charging dataset is a merge of a first file containing initially 412.709 home charging sessions and a second file with descriptive information about the cars involved. The two files are merged on identification and used as one dataset. The charging sessions date from 11 months from 2018 (August is missing). From the approximately 2500 unique cars about 80% are PHEVs and 20% are BEVs. After deletion of the unnecessary columns 8 columns are present:

- Session ID
- Charge Point ID
- Car type
- Car brand
- Car Model
- Start session [timestamp]
- End session [timestamp]
- Volume charged [kWh]

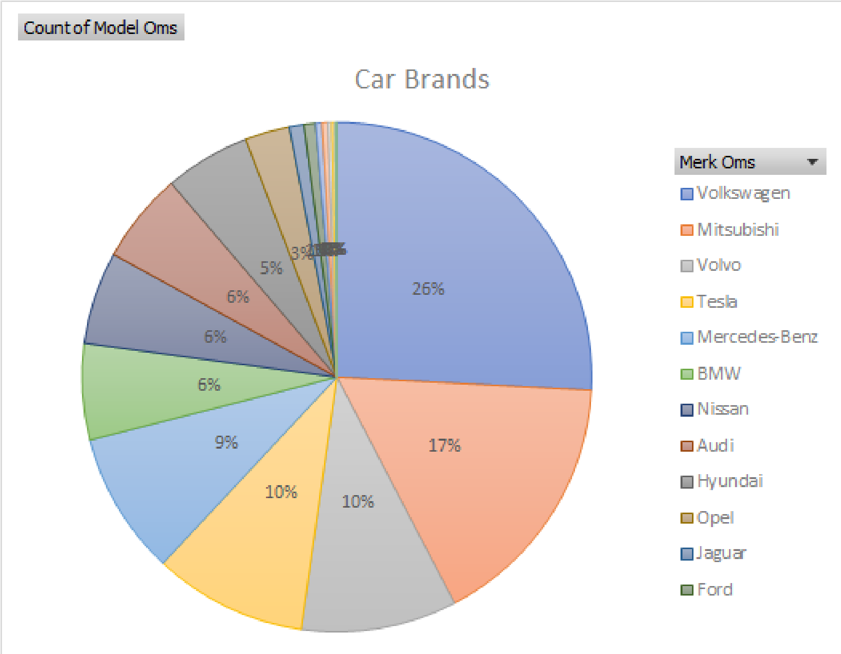

Figure 4.1: Pie chart of car brands in dataset

In figure 4.1 the distribution of the different car brands is shown in a pie chart. Due to the large size of the real world dataset, manipulation of data is avoided if possible. Unfortunately one important variable in this dataset is missing; the maximum power of the charge point. Since one of the expectations is the maximum charging power has a strong influence on the flexibility and correlates with the revenue, this variable is key. If opportunities arise on the energy markets, the algorithm will charge as much as possible to utilize the opportunity. The maximum power of the charge point will be a important constraint to the algorithm and the simulations could not run without it.

To approach the real maximum power per charge point and car, the average power over each session is calculated. For each unique home charge point, recognised by the unique charge point ID, the maximum average power of all session is expected to be the maximum power. This is expected to be adequate, since all unique charge point have significant amount of sessions. The maximum power will be found at one of the short sessions where the car was charging at maximum power for the full time of the session, without idle connection time.

Another inevitable manipulation in the data is the removal of missing or misleading data points. The rows containing sessions from 2017 or with missing values are deleted. Sessions with volumes charged below 1 kWh and above 100 kWh are deleted.

In the initial dataset, sessions where found with a duration of several days, several weeks or even several months. Those sessions where also found in the live session data coming in during that period and the cause was known. Some drivers prefer to disconnect the charging cable from the car, but leave the cable in the charge point at home instead of bringing it with them in the car. This results in a continuous active session and makes the handling of swiping the card to start the next session redundant. The data from charge sessions with this behaviour shows misleading high flexibility and should be removed from the dataset. It was not possible to label this specific behaviour in the data in hindsight. To delete the majority of the data representing those apparent flexible sessions, the choice was made to delete all session with volume above 100 kWh or a duration above 24 hours.

The results was a clean dataset consisting of 292.785 home charging sessions usable for the smart charging simulations.

To properly understand what the data looks like, different data distribution figures are shown. Firstly, the distribution of the session duration in hours is shown in figure 4.2. Figure 4.3 shows the data distribution of the maximum power of the charge point, found as described above. The third figure 4.4 shows the distribution of the volume charge in kWh per session.

After the data distribution figures of the full dataset, the same figures are shown for both the BEV and PHEV part of the dataset.

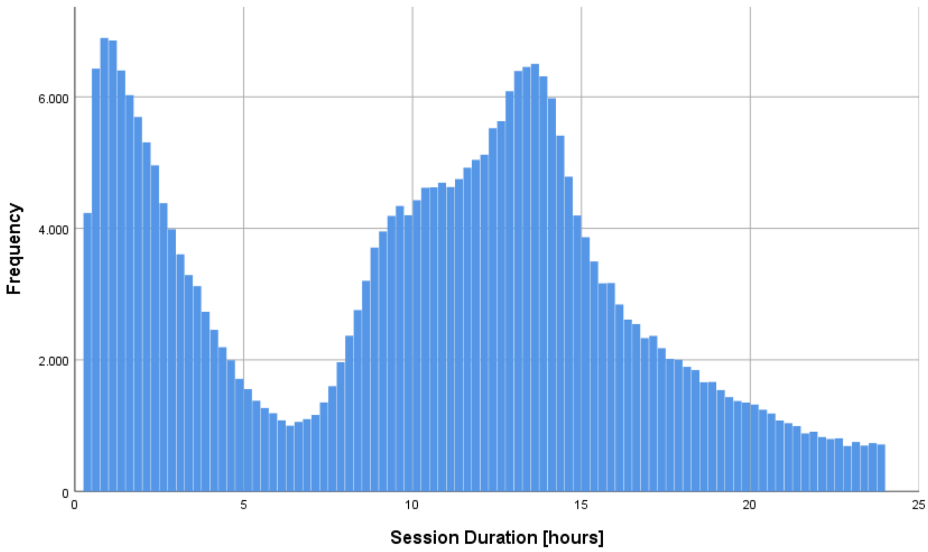

Figure 4.2: Session duration data distribution

Figure 4.2 has a range from 0.25 hours to 24 hours and clearly shows two peaks. The first bulk between 0.25 and 5 hours reflects the short sessions. The data shows that those session are mostly during the day. The second peak has a bit wider range between 8 and 16 hours and reflects mostly overnight charging session. Over 65% of the session are longer than 8 hours, which could have a positive impact on the simulation results.

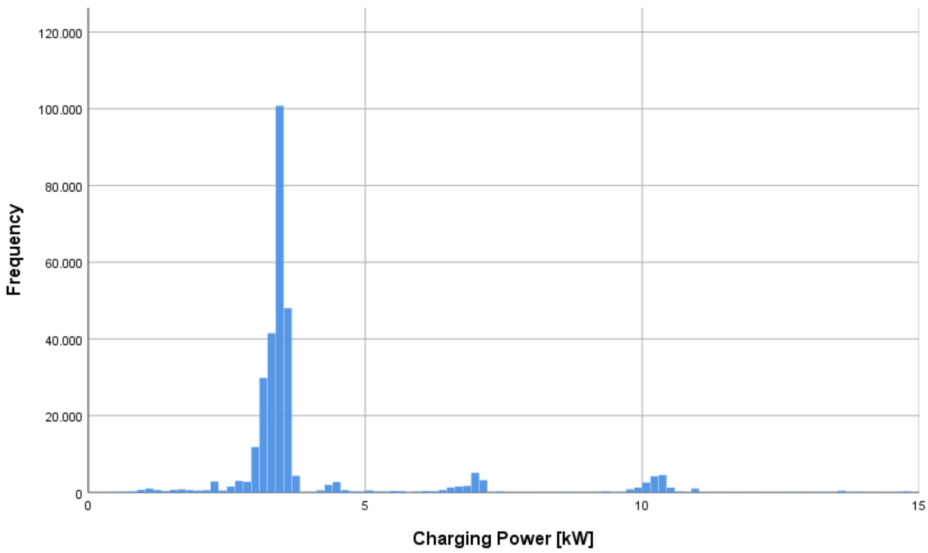

Figure 4.3: Max power data distribution

Figure 4.3 shows the calculated maximum power of the charge points multiplied with the amount of sessions per charge point. We can see the strongest peak up to 3.7 kW rated power, which is the standard power output for a one phase 16 ampere home charge point. It emphasises that most sessions have slow charging power. Over 86% of the charge sessions contains a maximum power below 4 kW.

For larger batteries, single phase 32 ampere shows a peak up to a rated power of 7.4 kW and three phase 16 ampere shows a peak up to 11 kW. The data displays the peaks, where theoretically expected, which gives confidence in the strategy chosen to calculate the maximum power of the charge points.

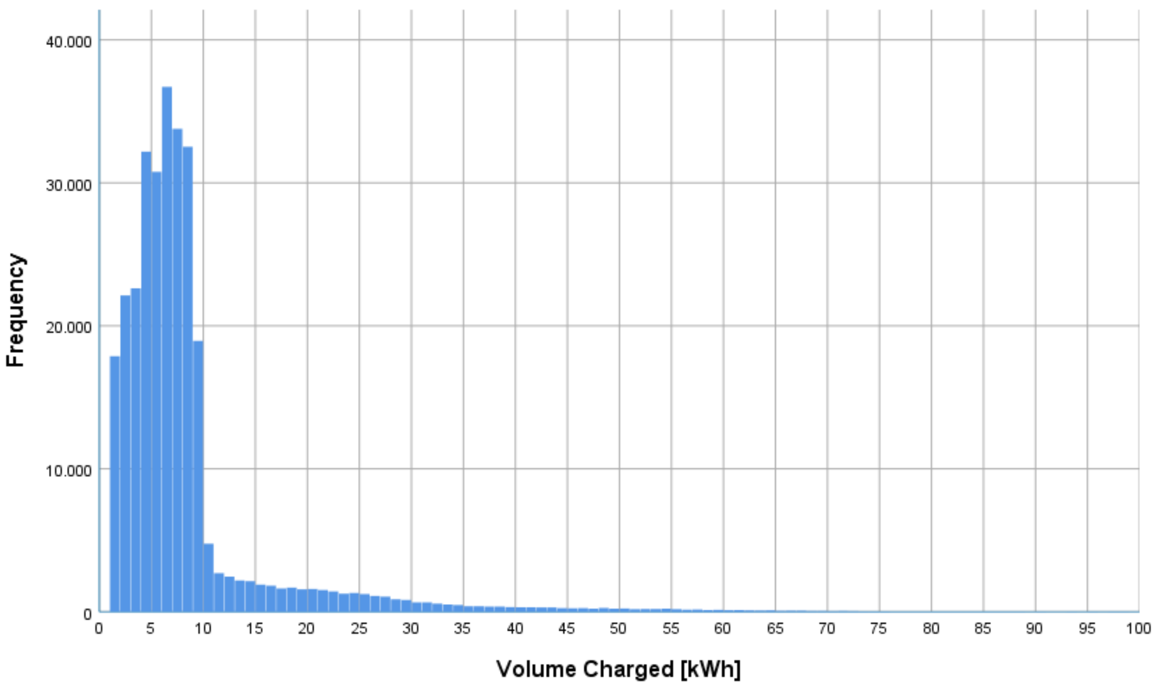

Figure 4.4: Volume data distribution

Figure 4.4 shows the distribution of the amount of kWh charged per session. This looks a normal distribution with a tail to the right. The graph could be explained by the fact that over 80% of the data is from PHEVs and there battery capacity is rather small. this gets clear when the data is split in BEVs and PHEVs in figure 4.9 and figure 4.10.

Where the full dataset was shown in blue above, the next figures show the a split for BEVs in green and PHEVs in light brown.

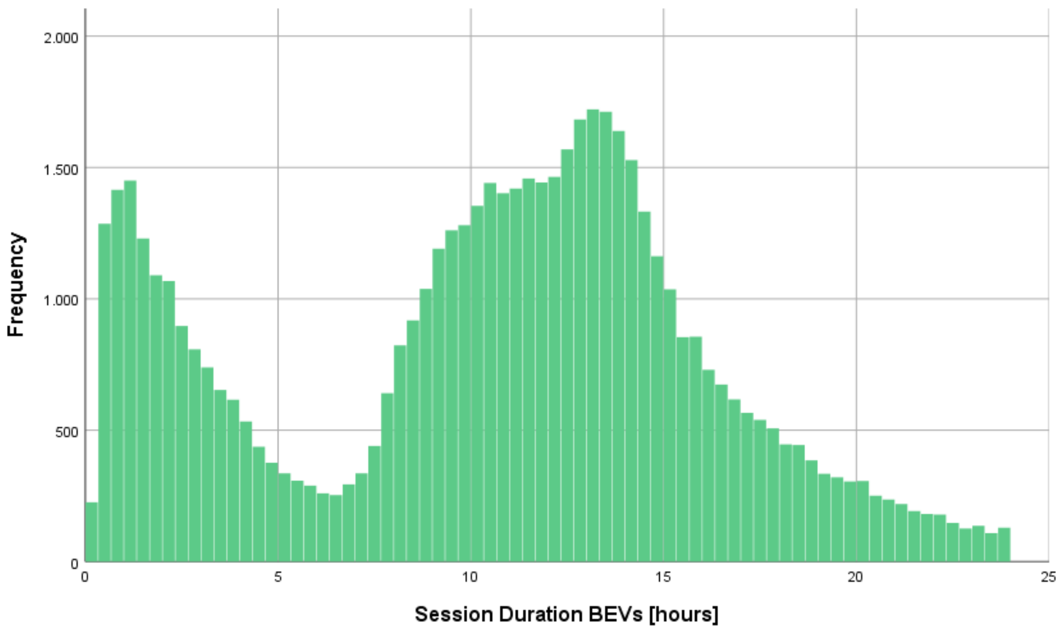

Figure 4.5: Session duration data distribution of the BEVs in the dataset

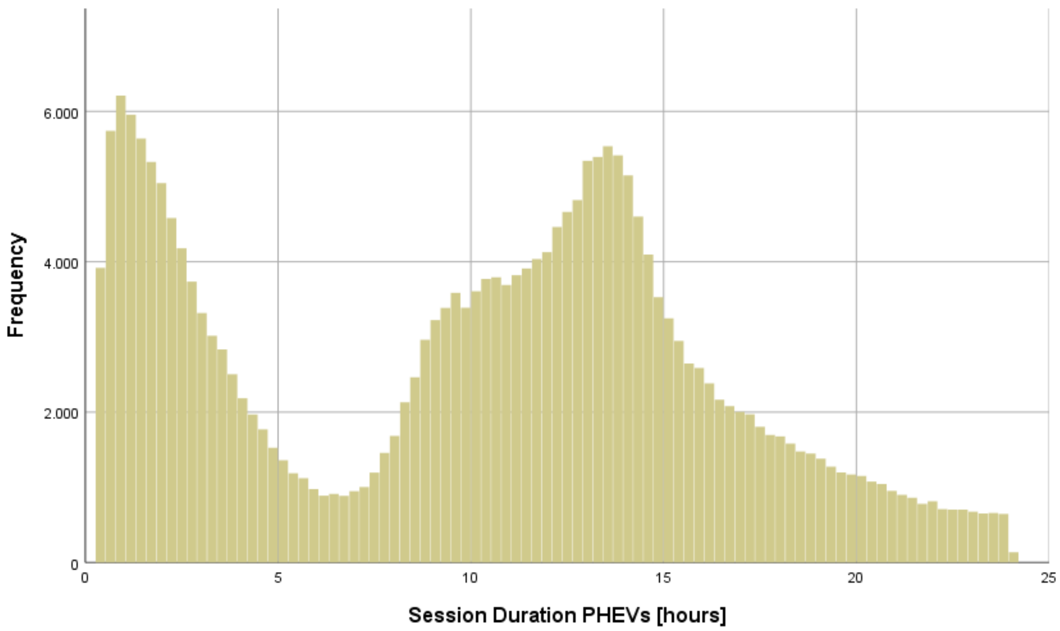

Figure 4.6: Session duration data distribution of the PHEVs in the dataset

Figure 4.5 and figure 4.6 are similar distributed. This points out that the charging behaviour in terms of connecting hours per session is not significant different for PHEV drivers and BEV drivers.

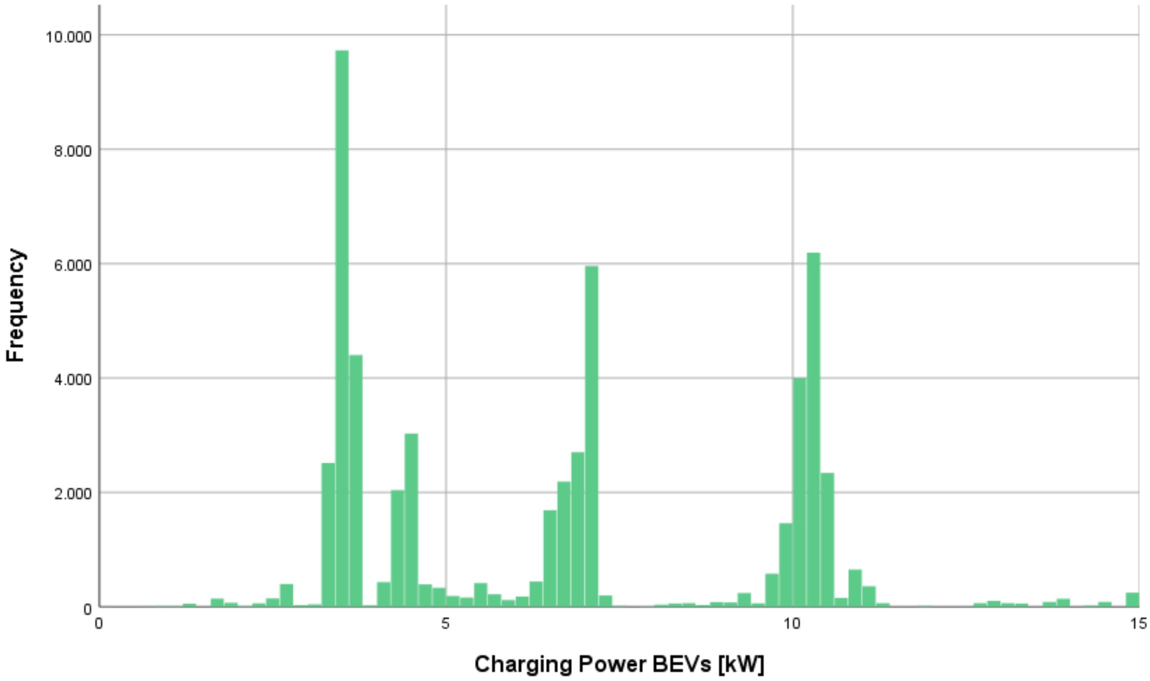

Figure 4.7: Max power data distribution of the BEVs in the dataset

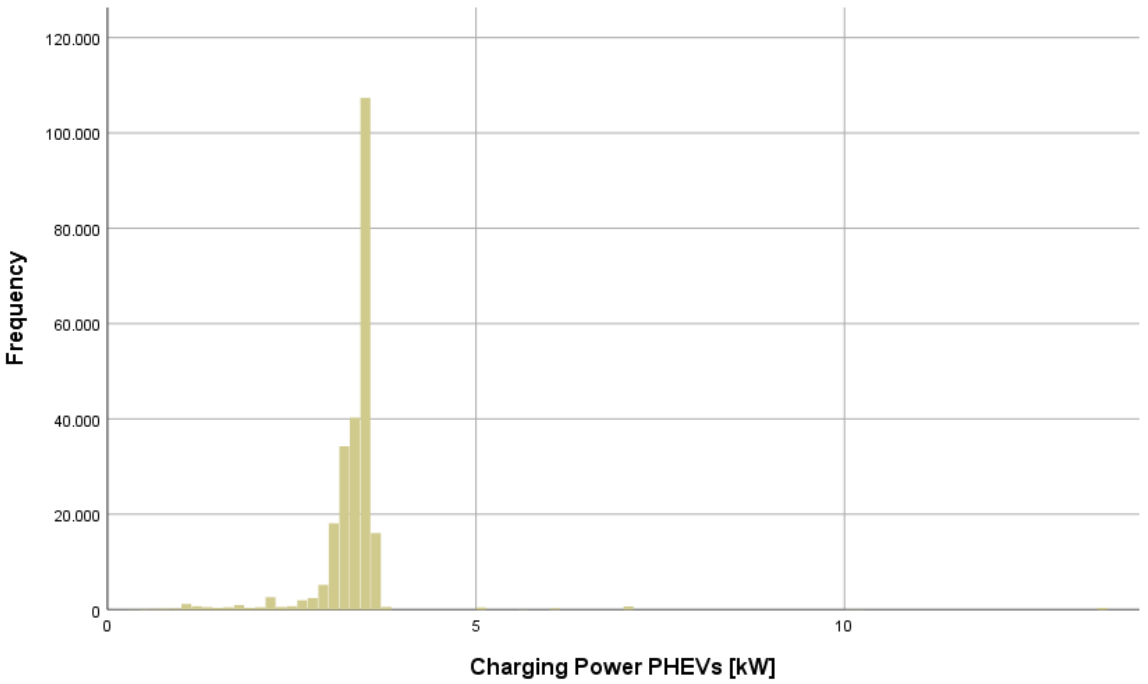

Figure 4.8: Max power data distribution of the PHEVs in the dataset

Figure 4.7 and figure 4.8 differ significantly. The PHEVs have a rather small battery size, which does not need high power to charge, even when the battery is fully empty. Since a charger with more power is an extra investment, a distribution with rated peak on 3.7 kW could be expected. The BEVs have significantly larger batteries and with a large battery a more powerful charger gives security the battery will have a desired state of charge at departure.

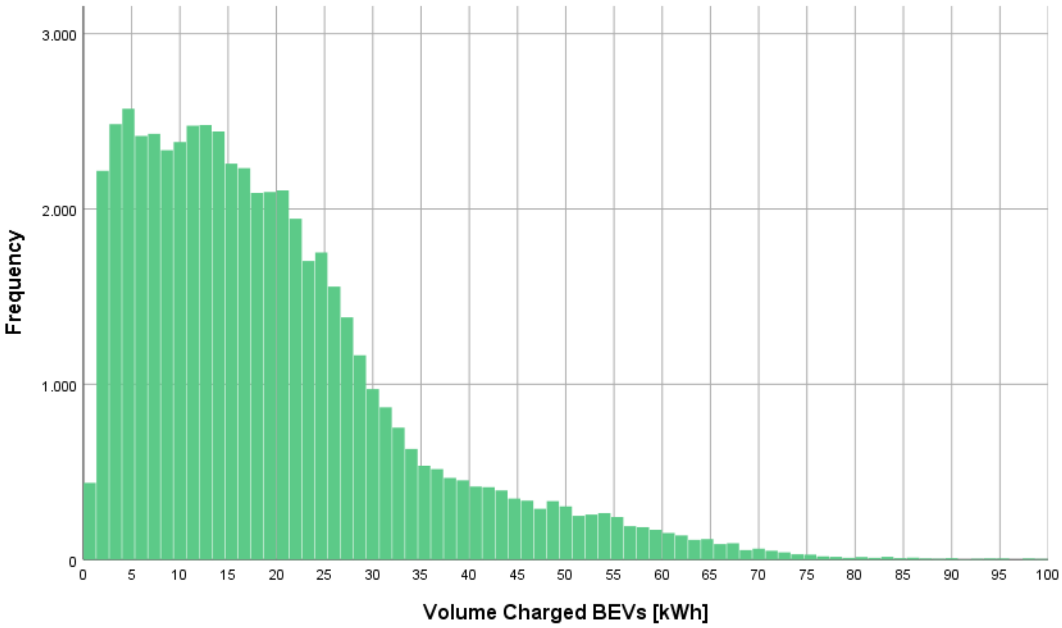

Figure 4.9: Volume data distribution of the BEVs in the dataset

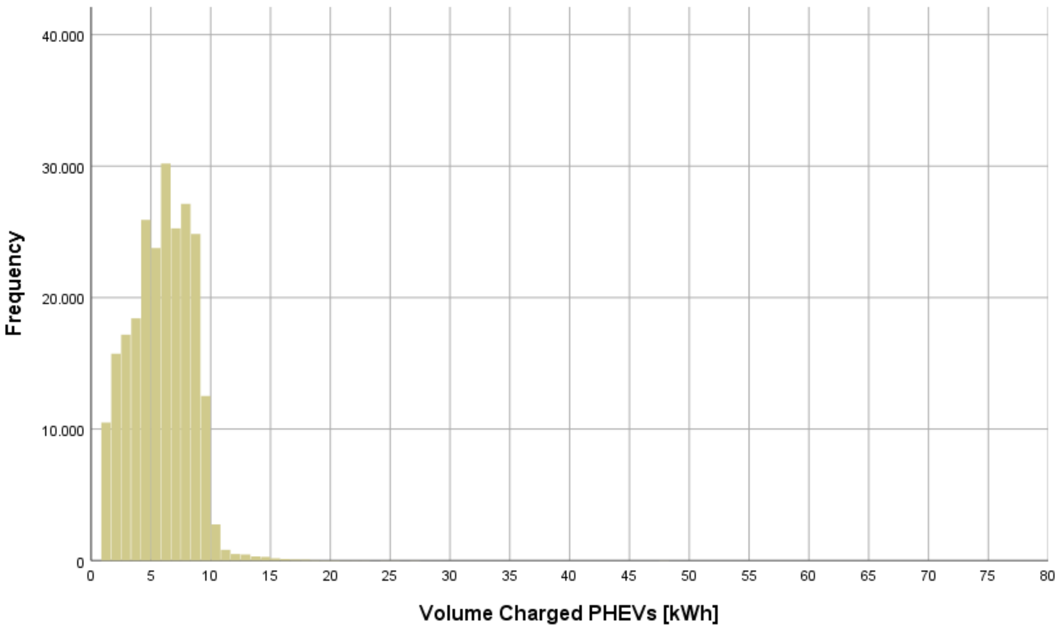

Figure 4.10: Volume data distribution of the PHEVs in the dataset

Figure 4.9 containing the BEVs is very different compared to the full data set in figure 4.4. One could notice the volumes above 10 kWh (which is 70%) disappears to a small tail in figure 4.4 due presence of the abundant PHEV data. figure 4.10 seems normal distributed from 0 to 10 kWh, which is the maximum battery size of the most PHEVs. The average volume charged for BEVs is 19,6 kWh, while for PHEVs the average is 5,9 kWh.

4.2. The day ahead market and imbalance prices

The historic day ahead market prices and imbalance market prices from 2018 are available on the website of the transparency platform of the European Network of Transmission System Operators Europe (ENTSO-E). The data frame of the both the day ahead and imbalances prices need an index based on all PTUs in 2018. The hourly day ahead prices are redistributed over 4 PTUs to fit the needed data frame.

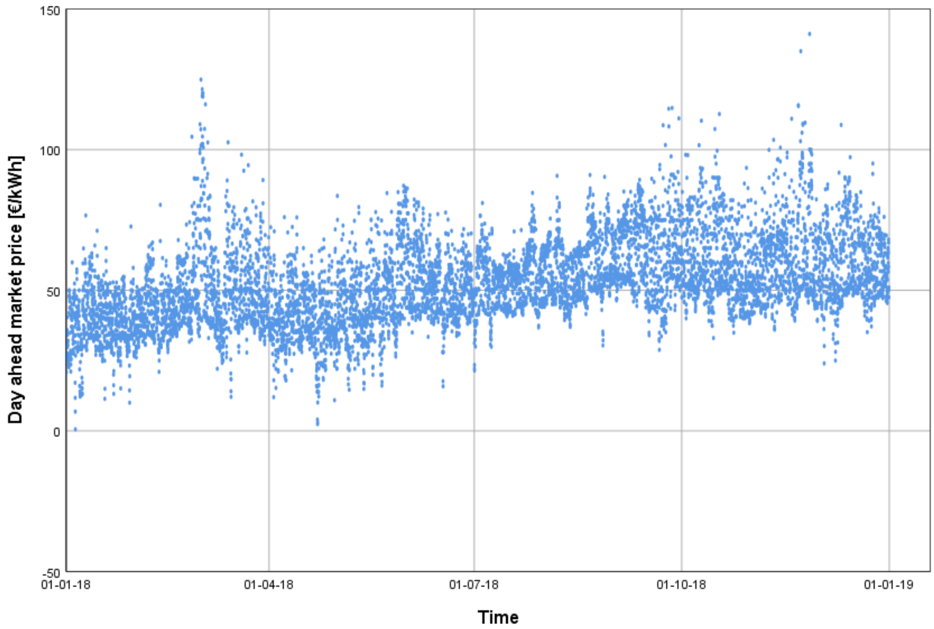

Figure 4.11: The day ahead market prices in The Netherlands

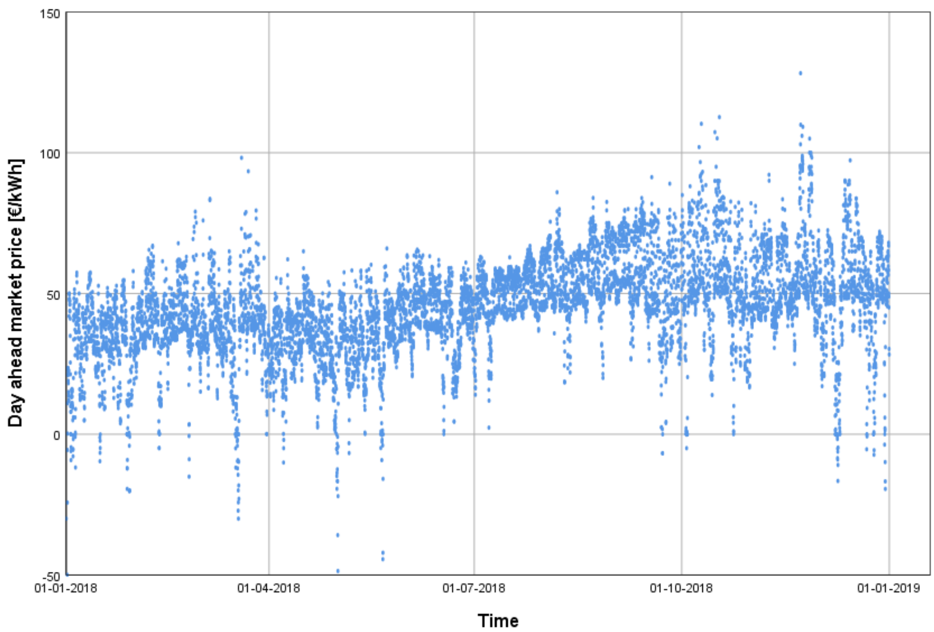

Figure 4.12: The day ahead market prices in Germany

4.3. Carbon intensity in The Netherlands and Germany

To test the hypothesis on the real carbon reduction of smart charging, the data from www.electricitymap.org is used for this research. the ElectricityMap is calculation the average carbon intensity in the grid in The Netherlands by accounting for all internal production units. Also the electricity in and outflow of the country is taken into account.

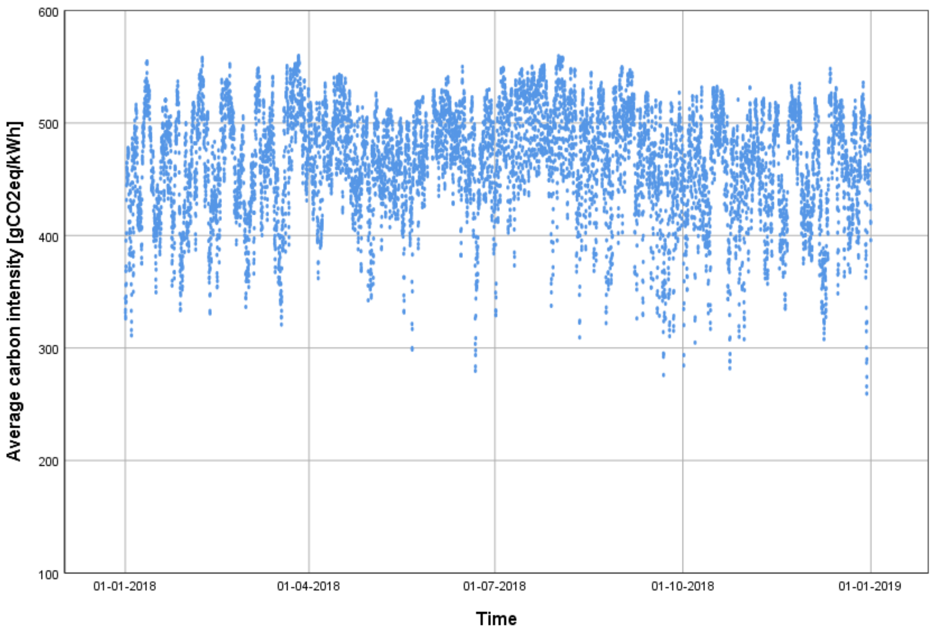

Figure 4.13: The carbon intensity of 2018 in The Netherlands

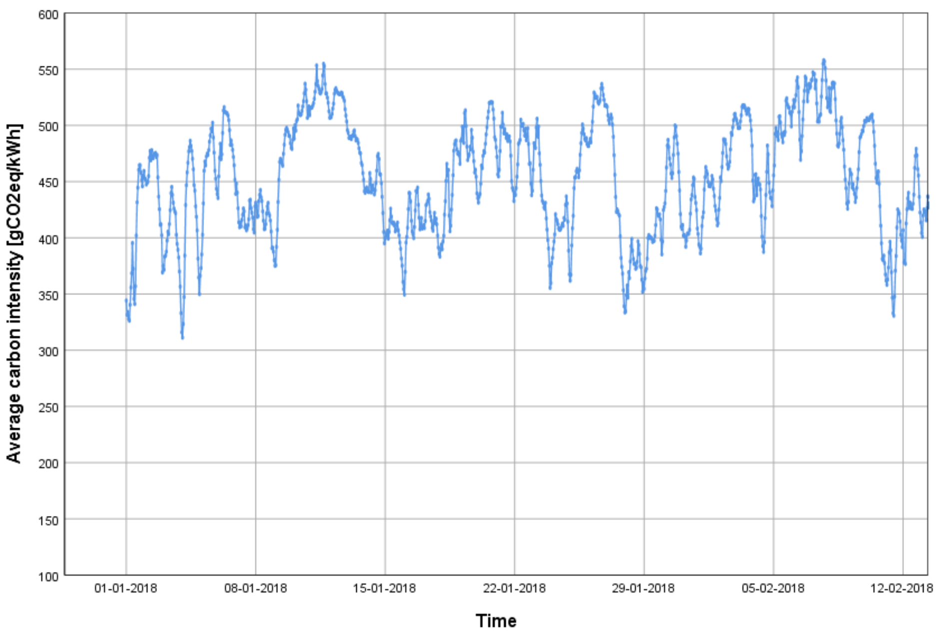

Figure 4.14: The carbon intensity of the first two months in 2018 in The Netherlands

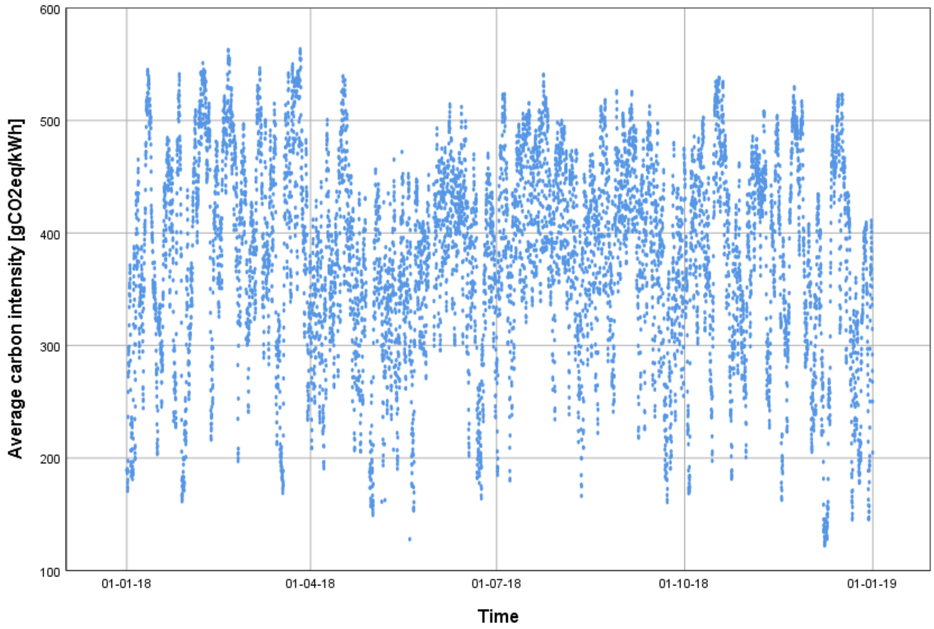

Figure 4.15: The carbon intensity of 2018 in Germany

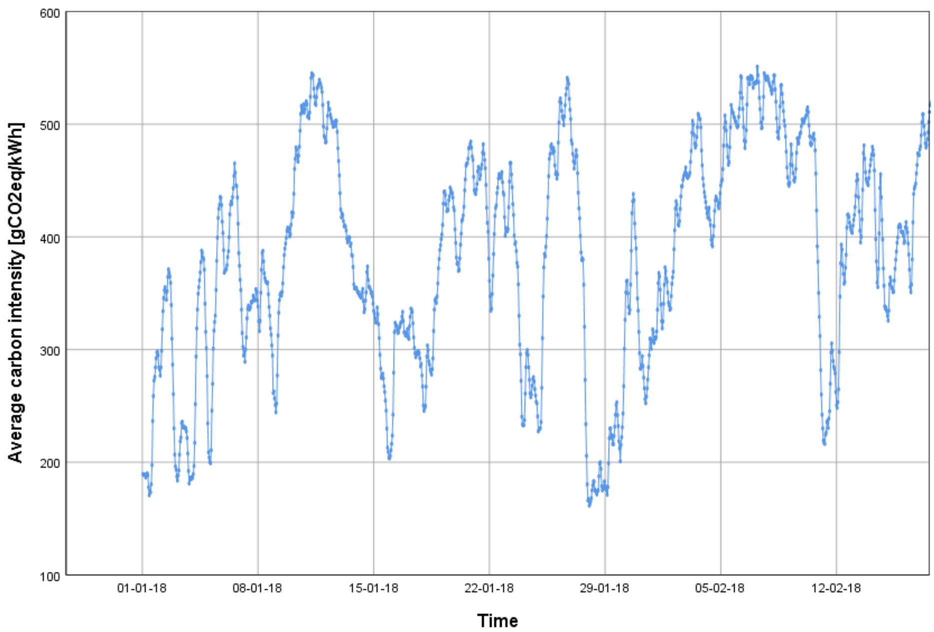

Figure 4.16: The carbon intensity of the first two months in 2018 in Germany

To compare the smart charging savings on carbon intensity with a country with more renewable energy penetration and thus more price fluctuation based on renewable energy availability, both the day ahead market price 2018 and the carbon intensity in the grid for 2018 from Germany is used.

5

Results and discussion

In this chapter, the results of the simulation and analysis are presented. The sub-questions are used to structure this chapter and provide all insights needed to answer the main research question. Different simulations set-up scenarios are executed and analysed, all exposing the EV charging demand to variable prices instead of paying a fixed cost per kWh. Simulation A shows the losses in a worst case smart charging scenario. Simulation B is optimizing smart charging on the day ahead market only and is not able to reach any savings compared to the benchmark. Simulation C is integrating the imbalance market and shows a significant drop in average prices, indicating the smart charging algorithms are able to utilize the fluctuations in the imbalance market prices. Simulation D integrates forecasting tools for both the EV charging demand and price forecasting into the smart charging algorithms. This makes the latter the most realistic simulation to use to calculate the cost reduction potential for smart charging. To compare the results of the different smart charging set-up scenarios, the average session price of all session in that simulations is used.

5.1. The average price per session for the smart charging simulations

In this section, the average price per session of the smart charging simulations will be discussed. As described in section 3.7, the average price found in each simulation is an important finding, since this will be used to calculate the cost reductions. In table 5.1 an overview of the findings is presented. The different simulation set-up scenarios as discussed below.

The Netherlands	price [€/MWh]	compared to dumb charging	compared to benchmark
Benchmark	41,56	-28,0%	
Simulation A	57,75		+39,0%
Simulation B	43,21	-25,2%	+4,0%
Simulation C	31,44	-45,6%	-24,4%
Simulation D	36,46	-36,9%	-12,3%

Germany	price [€/MWh]	compared to dumb charging	compared to benchmark
Simulation A	47,09		
Simulation B	35,88	-23,8%	`No benchmark defined`

Table 5.1: Overview of mean of average session price per simulation set up and relating savings in percentages

5.1.1. Simulation A: The worst case scenario

The benchmark to compare the average price with is set on 41,56 €/MWh based on the 2018 prices. The smart charging cost reduction will be calculated relatively to this benchmark. However, to understand the effect of the smart charging algorithms, the financial results of simulation A shows a different perspective.

While exposing EV charging to variable prices, opportunities arise to decrease the electricity purchase price by smart charging. At the same time, a risk is taken to end up with increased electricity purchase prices. The distribution of the average session price of simulation A as described in section 3.3 is shown in figure 5.1. In this scenario, the energy is purchased day ahead based on a smart charging profile, while the charging is executed in a dumb profile charging full power until demand is met. This scenario describes a failing smart charging system, while exposed to variable prices of the imbalance market, thus could be seen as a worst case scenario. The black line in figure 5.1 show the average session price of €57,75 per MWh for this simulation. This price is well above the chosen benchmark, but gives an indication of size of the risk if the system would be failing. Besides that, this number shows a different benchmark perspective. Comparing the other simulation against simulation A will show the impact of the algorithms between smart charging and the worst case scenario.

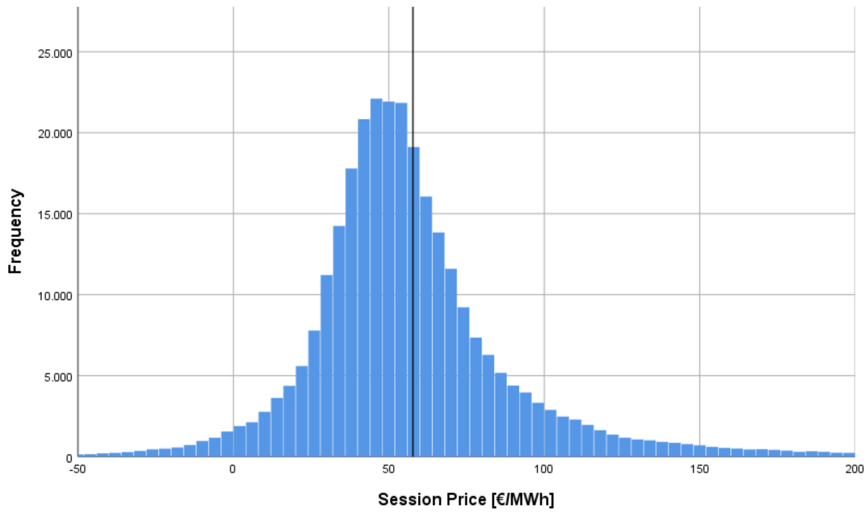

Figure 5.1: Distribution of the average session price for simulation A

5.1.2. Simulation B: smart charging with day ahead prices

Simulation B depends merely on the day ahead market and is not taking the opportunities in the imbalance market into account. Since no negative prices occurred in the day ahead market in 2018, the the electricity purchase price could not drop below zero for any hour for that year. This scenarios assumes every EV will follow exactly the charging schedules as planned the day ahead. This results in a portfolio with no imbalance, since there is an exact overlap with purchased and used electricity.

Figure 5.2 shows the result data distribution of the average session price for simulation A. The average session price for this simulation set-up is €43,21. Compared to the defined benchmark of 41,56 €/MWh, simulation A shows no savings, but a loss. The real world results will be even worse, due to forecasting errors. This results into a conclusion that smart charging exclusively on the day ahead market brings high risks and do not bring any cost reduction for an EV aggregator.

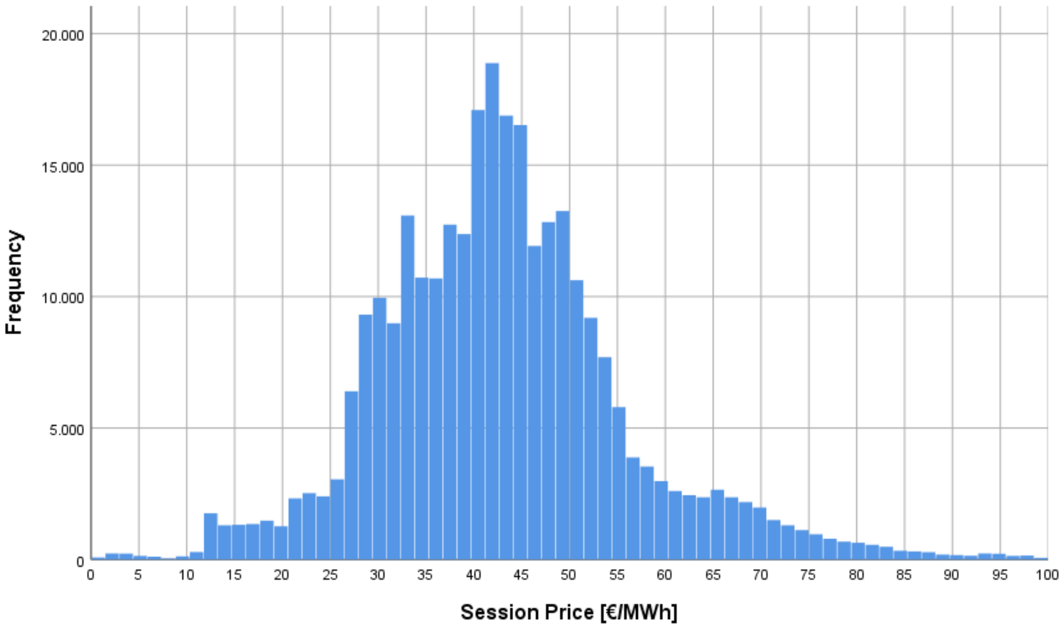

Figure 5.2: Distribution of the average session price for Simulation B in The Netherlands

Nevertheless, when comparing figure 5.2 to figure 5.1, it is clear the smart charging algorithms as a system decrease the costs significantly from €57,75 on average to €43,22 on average. This decrease in costs is explained by the utilization of the available flexibility in the smart charging session. To show the effect of the volume, duration and maximum power on the average session price, a multiple regression is applied to the simulation A results. The analysis shows a significant linear model:

$$E(y_1) = 53,82 - 1,11 \cdot x_1 - 0,05 \cdot x_2 + 0,09 \cdot x_3 \tag{5.1}$$

- $E(y_1)$ = Expected average session price in €/MWh based on x_1, x_2 and x_3
- x_1 = Duration in hours
- x_2 = Power in kW
- x_3 = Volume in kWh

Simulation B is performed a second time, while feeding the German day ahead market prices. The German day ahead market prices are fluctuating stronger as shown in figure 4.12. This results in a lower average price over 2018 and a lower mean of the average session price of simulation B. The data distribution of simulation B in Germany is shown in figure 5.3 and the correlation multiple regression model is shown below.

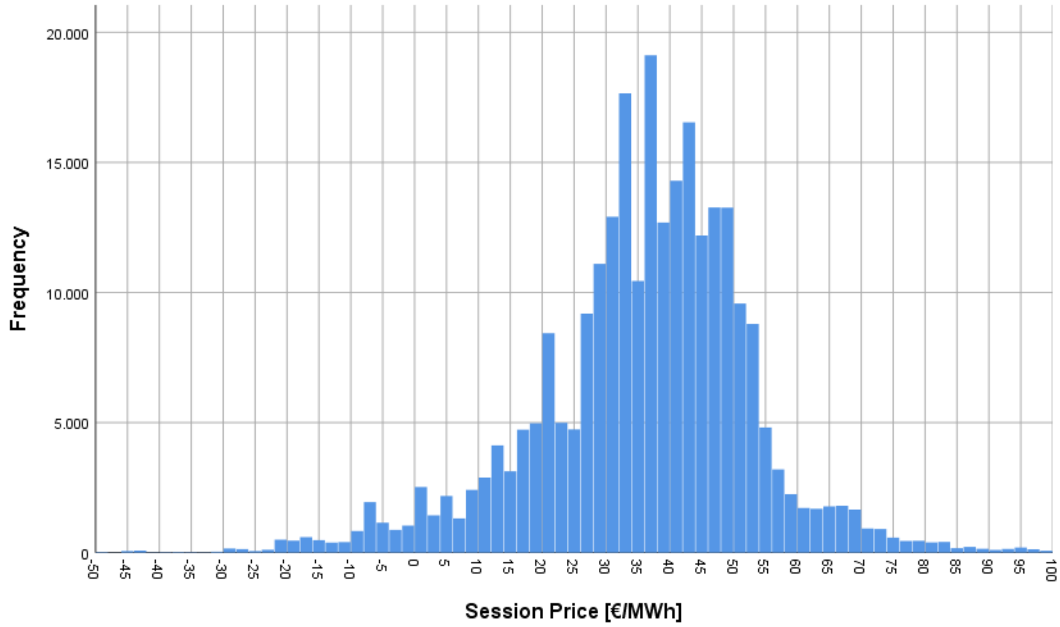

Figure 5.3: Distribution of the average session price for Simulation B in Germany

The multiple regression model for the results in the simulation with the German data is shown in formula 5.2.

$$E(y_9) = 46,04 - 1,07 \cdot x_1 - 0,09 \cdot x_2 + 0,12 \cdot x_3 \tag{5.2}$$

- $E(y_9)$ = Expected average session price in €/MWh based on x_1, x_2 and x_3
- x_1 = Duration in hours
- x_2 = Power in kW
- x_3 = Volume in kWh

The market prices fed into the simulation in Germany and The Netherlands are different, but the algorithms used and the charging session data input is exactly the same. As a result, the found correlation with the predictors in the multiple regression analysis is expected to be similar.

Fortunately, the beta coefficient found in The Netherlands and Germany are very similar. For every hour added to a charging session, the expected price is decreasing €1,11 and €1,07 respectively. The fact that the data shows that longer sessions are expected to have a lower session price, proves the theory that increasing flexibility in terms of session duration has a positive impact on the value of smart charging. The second term x_2 also shows an negative effect on the average price. While increasing the power with 1 kW, the average price in simulation B will decrease with €0,05 and €0,09 respectively. For x_3, a small in increase in price of €0,09 or €0,12 is expected per extra kWh of volume charged.

5.1.3. Simulation C: combining day ahead and imbalance prices

In simulation C, the imbalance prices are added to the simulation and a passive balancing strategy is performed. Figure 5.4 shows the results have a wider spread due to the negative prices occurring in the imbalance market. The average price of the smart charging sessions drops to 31,44 €/MWh, while adding the imbalance market opportunities.

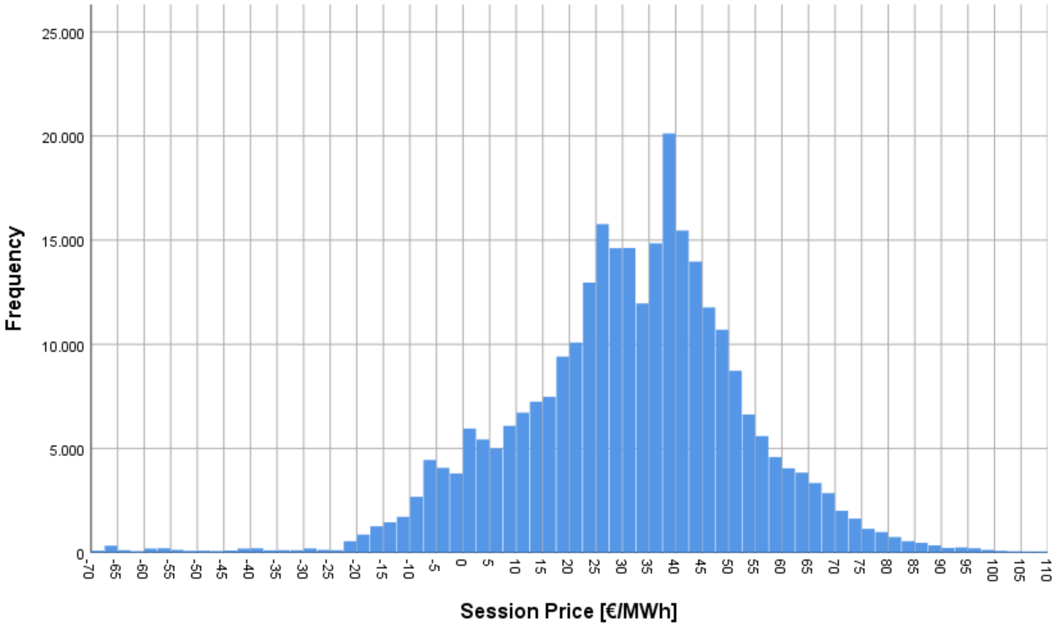

Figure 5.4: Distribution of the average session price for Simulation C

When performing a multiple regression analysis on the results of simulation C, the starting points is higher and the influence of x_1, x_2 and x_3 grows:

$$E(y_5) = 52,78 - 2,14 \cdot x_1 - 0,82 \cdot x_2 + 0,42 \cdot x_3 \tag{5.3}$$

- $E(y_5)$ = Expected average session price in €/MWh based on x_1, x_2 and x_3
- x_1 = Duration in hours
- x_2 = Power in kW
- x_3 = Volume in kWh

5.1.4. Simulation D: smart charging simulation with integration of forecasting errors

In section 3.6, simulation D is described as most realistic smart charging simulation set-up of this research. This implies that the smart charging results of simulation D are the best simulation to describe cost reduction in The Netherlands in reality. The distribution of the average price per session for simulation D is presented in figure 5.5. The result is with a 36,46 €/MWh average session price an improvement on simulation B, due to the incorporation of the imbalance market. Nonetheless, the results could not reach the optimum of simulation C. Where simulation C assumed the day ahead price and the EV charging demand to be known, simulation D integrated their forecasting. This resulted in a higher average session price, since the algorithms had to deal with the forecasting errors.

The average session price in €/MWh is calculated to both compare the simulation with each other and calculate the potential of smart charging if extrapolated to a total fleet. In the distribution of the average session price results of simulation D in figure 5.3, the average result is indicated with a red line.

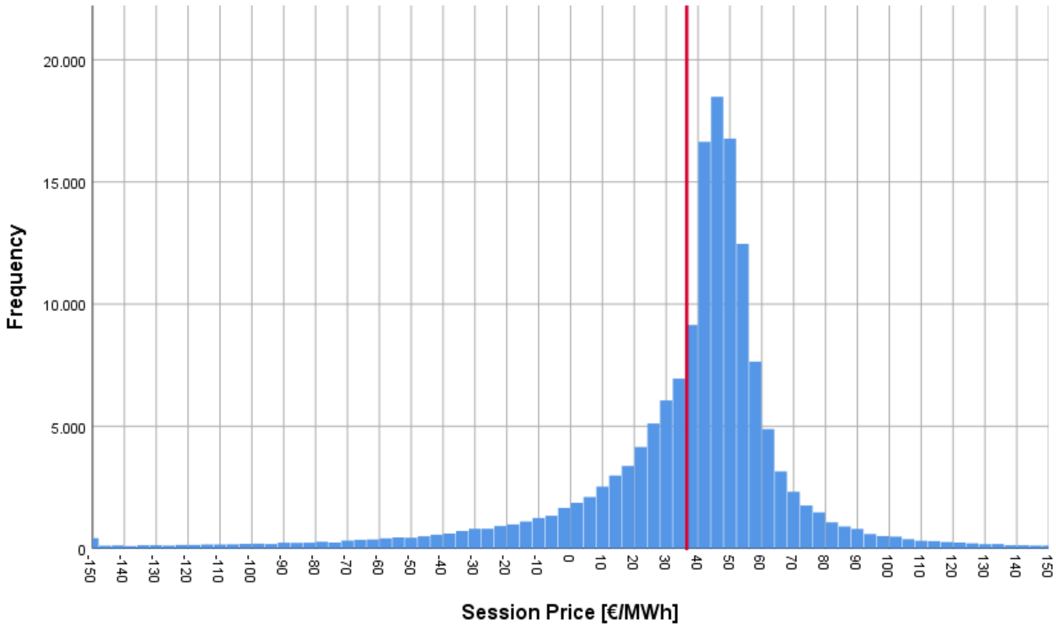

Figure 5.5: Distribution of the average session price for Simulation D

The figure shows that the average price is clearly not corresponding with the peak of the result distribution. This indicates that the average is strongly influence by the long tail on the left side, with session prices below -100 €/MWh. If in reality turns out that it is difficult to reach the low prices as simulated for those sessions, the average price could quickly rise from 36,5 to 45 €/MWh. This would significantly decrease the value of smart charging found earlier and this risk should be taken into account.

A multiple regression analysis for the average price results of simulation D is showing again a linear relationship between the average price and the variables duration (x_1), power (x_2) and volume (x_3).

$$E(y_{13}) = 60,05 - 2,15 \cdot x_1 - 1,91 \cdot x_2 + 0,66 \cdot x_3 \tag{5.4}$$

- $E(y_{13})$ = Expected average session price in €/MWh based on x_1, x_2 and x_3
- x_1 = Duration in hours
- x_2 = Power in kW
- x_3 = Volume in kWh

5.2. The smart charging cost reduction per car per year

Chapter 4 clearly shows there is a significant difference in the data of the BEVs and the PHEVs. Due to this difference, the data results are split based on the car type and analysed in this section separately as well. For all calculations of the cost reduction per EV per year in this section, the results from simulation D are used, since the integration of the forecasting tools in simulation D gives the most realistic results.

In table 5.2 the simulation results are split in BEVs and PHEVs to calculate the average price in €/MWh. The PHEVs show a lower average price in every simulation. A possible explanation for the decrease in price is the difference in volume. The regression model of formula 5.10 shows an increase of €0,66 to the average session price for every kWh extra volume charged. Since the PHEVs have a small battery and therefore mostly charge small volume below 10 kWh in a similar overnight charging sessions, the average session price could expected to be lower.

	All data (100%)	BEVs (~ 20%)	PHEVs (~ 80%)
The Netherlands	price [€/MWh]	price [€/MWh]	price [€/MWh]
Simulation A	57,75	59,08	57,43
Simulation B	43,21	45,12	42,77
Simulation C	31,44	35,64	30,45
Simulation D	36,46	39,62	35,51
Germany	price [€/MWh]	price [€/MWh]	price [€/MWh]
Simulation A	47,09	48,51	46,73
Simulation B	35,88	37,92	35,35

Table 5.2: Splitting the average session price results in BEVs and PHEVs

The average prices in table 5.2 could be used to calculate the yearly cost reduction per car:

$$S = D_{year} \cdot (P_{average} - P_{benchmark}) \tag{5.5}$$

- S = savings [€/car/year]
- D_{year} = Energy demand per car per year
- $P_{average}$ The average session price [€/MWh]
- $P_{benchmark}$ The benchmark session price [€/MWh]

For this calculation, the assumption is made a BEV is charging 4 MWh per year and a PHEV 1,5 MWh per year.

$$S_{BEVs} = D_{year} \cdot (P_{average} - P_{benchmark}) = 4 \cdot (41,56 - 39,62) = €7,76 \tag{5.6}$$

$$S_{PHEVs} = D_{year} \cdot (P_{average} - P_{benchmark}) = 1,5 \cdot (41,56 - 35,51) = €9,08 \tag{5.7}$$

The PHEVs charge on average for a lower price compared to the BEVs. The BEVs use with 4 MWh/year significant more electricity compared to 1,5 MWh for PHEVs, but the yearly savings is still found to be higher for the PHEVs, due to the lower average price. One should realise that both the assumption of the yearly electricity demand and the chosen benchmark have a high impact on the result in this calculation. To find the smart charging cost reduction per car per year for forecasting D based on the simulation output, the savings were calculated for each session specifically.

$$S_{session} = D_{session} \cdot (P_{session} - P_{benchmark}) \tag{5.8}$$

The savings per car is found by the sum of all session savings with the same car ID:

$$S_{EV} = \sum_{i=1}^{n} S_{session\ i} \tag{5.9}$$

Now the cost reduction is calculated for every EV in the dataset. There were 780 BEVs present in simulation D. The distribution of the results is shown in figure 5.6. The maximum savings reached by one specific car is €39,23 and maximum loss was €-39,15. The mean of all savings is €1,01. Since simulation D calculated the savings for only 6 months in 2018, the average total saving for BEVs in 2018 is calculated as follow: $S_{Average\ BEV} = 1,01 \cdot 2 = €2,02$

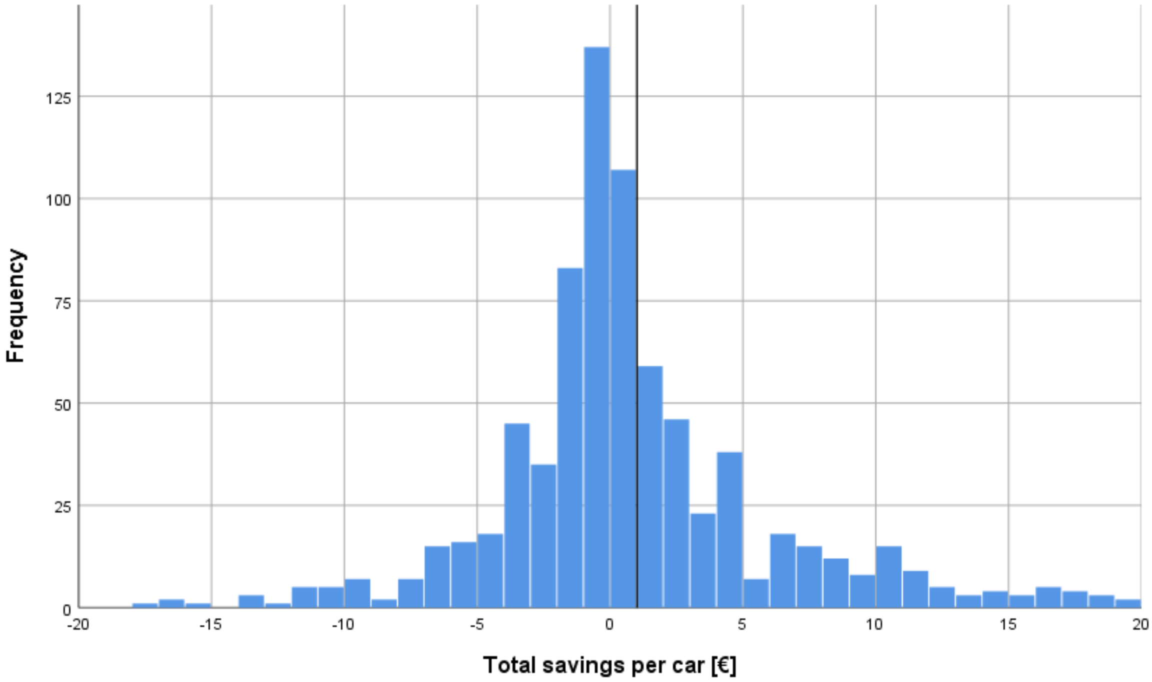

Figure 5.6: Distribution of the session savings for the BEVs

If all PHEVs in simulation D are separated, 1350 unique cars were used. The total cost reduction is variating between €-23,19 and €32,11 per PHEV. The mean of the PHEVs is a saving of €3,13. This gives a average yearly saving: $S_{Average\ PHEV} = 3,13 \cdot 2 = €6,26$

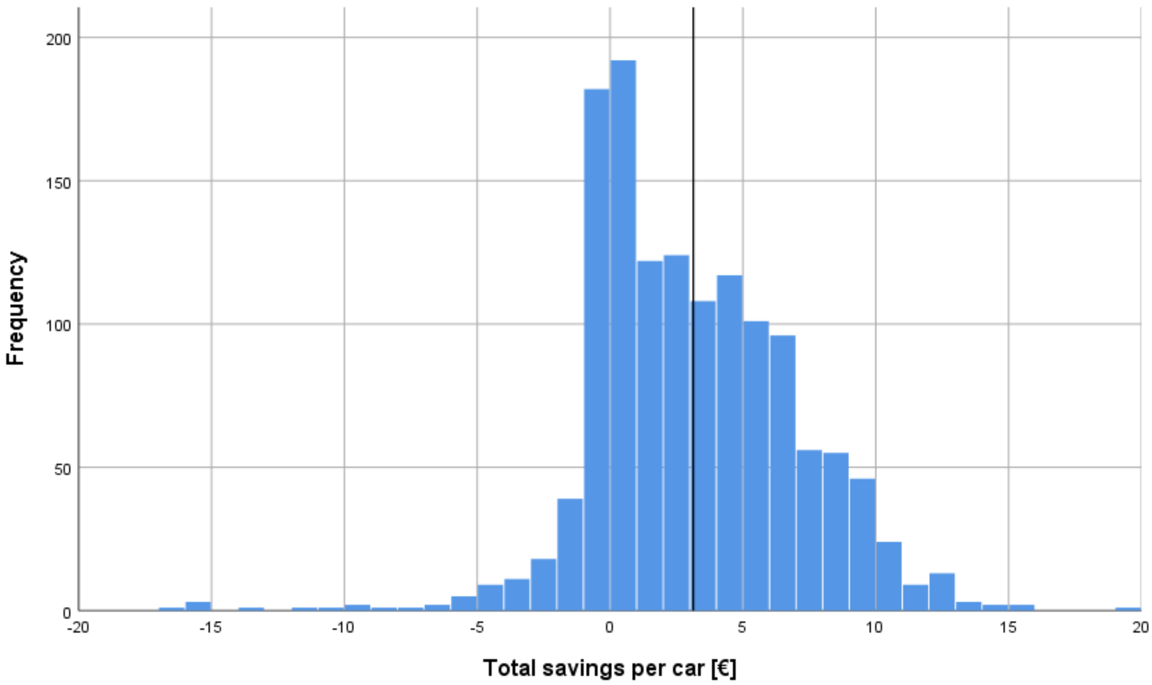

Figure 5.7: Distribution of the session savings for the PHEVs

Table 5.3 gives an overview of the extreme outliers in figure 5.6 and 5.7.

Highest saving BEVs	EV Model	Total savings [€]	Volume charged [kWh]	Power [kW]
1	Mercedes B-klasse	39,23	2489	10,43
2	BMW i3	34,53	2056	10,54
3	Tesla model x	34,37	4164	14,83
Lowest saving BEVs	EV Model	Total savings [€]	Volume charged [kWh]	Power [kW]
778	Tesla model x	-17,05	5163	10,34
779	Tesla model x	-24,77	2540	3,37
780	Opel ampera-e	-39,15	2877	3,62
Highest saving PHEVs	EV Model	Total savings [€]	Volume charged [kWh]	Power [kW]
1	Volkswagen Golf	32,10	941	13,56
2	Audi A3	19,28	753	6,06
3	Audi A3	15,45	1070	3,47
Lowest saving PHEVs	EV Model	Total savings [€]	Volume charged [kWh]	Power [kW]
1348	Mitsubishi Outlander	-17,05	1596	3,31
1349	Mitsubishi Outlander	-24,77	562	3,21
1350	Mitsubishi Outlander	-39,15	1200	3,28

Table 5.3: Overview of best and worst performing vehicles

If the sum is taken for all session savings of all EVs in the 2018 dataset, the potential of smart charging for the 2018 dataset could be found.

The savings in € per vehicle is an important results to understand the spread of results based on the proposed smart charging strategy. In table 5.4, the sum of savings of all session is shown per simulation set-up scenario.

	Months of smart charging	Total savings all EVs [€]
Simulation B	12	-2.701
Simulation C	12	24.762
Simulation D	6	5.018

Table 5.4: Overview savings in the total fleet for each simulation

It could be seen that the overall savings of the total fleet based on simulation D is €5.018,- for half a year of smart charging. Before this number is interpreted to define the potential financial upside of smart charging, one important remarks about the benchmark should be taken into account. The benchmark is chosen to mimic the situation where the EV aggregator is responsible for its EV load in an isolated BRP portfolio, which makes it vulnerable. The business case for an energy supplier is a numbers game. A growing portfolio increases the large scale and long term deals one could make, which could decrease the average purchase price substantially. A potential EV aggregator could potentially increase the value of its fleet by cooperation with an energy supplier and/or an BRP. If figure 2.2 is taken into account, the margin for the supplier is substantial. This margin exists in this business, since the supplier takes significant risk, by exposing to long term contracts. Both on the purchase side as the selling side of a suppliers portfolio, the commitments are not always hedged.

If the smart charging strategy is executed as proposed in this thesis, the EV aggregator is exposed to the day ahead market and imbalance settlements for its portfolio, while the BRP is not at risk. Basically, the EV aggregator act as BRP for its own fleet, to be able to optimize it. If this risk is carried by the EV aggregator, the marging normally payed for this risk should flow toward the EV aggregator as well.

We could conclude the potential value of smart charging for an EV aggregator could be significant higher, if both level 2 and level 3 of figure 2.2 is taken into account.

Furthermore, other revenue streams mentioned in figure 2.3 could increase the smart charging value in the future.

5.3. Predicting the smart charging value with multiple regression models

Splitting the BEVs and PHEVs improves the reliability of the multiple regression model, since the different trends between BEVs and PHEVs do create noise for each other. There are two different dependent variables analysed in this research. First the average session costs per session is discussed. Subsequently, the total session savings as independent variable is analysed.

The average costs per session

The average cost per session is the calculated for every session in dataset in 2018. The result in average session is independent from the chosen benchmark and reflects the electricity purchase price expected based on smart charging.

- x_1 = Duration in hours
- x_2 = Power in kW
- x_3 = Volume in kWh

$$E(y_{13}) = E(P_{All}) = 60,05 - 2,15 \cdot x_1 - 1,91 \cdot x_2 + 0,66 \cdot x_3 \tag{5.10}$$

$$E(y_{27}) = E(P_{BEVs}) = 63,63 - 2,03 \cdot x_1 - 1,79 \cdot x_2 + 0,45 \cdot x_3 \tag{5.11}$$

$$E(y_{41}) = E(P_{PHEVs}) = 58,42 - 2,30 \cdot x_1 - 3,13 \cdot x_2 + 1,85 \cdot x_3 \tag{5.12}$$

Where $E(y)$ is the expected average session price in €/MWh based on x_1, x_2 and x_3

The total savings per session

The second independent variable in the regression analysis is the session savings in €.

$$E(y_{14}) = E(P_{All}) = -0,125 + 0,012 \cdot x_1 + 0,018 \cdot x_2 - 0,004 \cdot x_3 \tag{5.13}$$

$$E(y_{28}) = E(P_{BEVs}) = -0,249 + 0,020 \cdot x_1 + 0,024 \cdot x_2 - 0,005 \cdot x_3 \tag{5.14}$$

$$E(y_{42}) = E(P_{PHEVs}) = -0,104 + 0,010 \cdot x_1 + 0,017 \cdot x_2 - 0,003 \cdot x_3 \tag{5.15}$$

Where $E(y)$ is the expected session savings in € based on x_1, x_2 and x_3

5.3.1. The impact of the session duration

In the multiple regression models, the duration of the session is denoted as x_1 and shows a negative linear relationship with the price, where longer sessions have a lower average price in the smart charging simulations. For simulation D, a decrease of €2,15 per extra hour is found in the linear regression.

$$E(P_{All}) = 60,05 - 2,15 \cdot x_1 - 1,91 \cdot x_2 + 0,66 \cdot x_3$$

The simulation input data in chapter 4 shows that the duration of the sessions is rather similar for both BEVs and PHEVs. The multiple regression analysis of simulation D is repeated twice for the BEVs and PHEVs respectively:

$$E(P_{BEVs}) = 63,63 - 2,03 \cdot x_1 - 1,79 \cdot x_2 + 0,45 \cdot x_3$$

$$E(P_{PHEVs}) = 58,42 - 2,30 \cdot x_1 - 3,13 \cdot x_2 + 1,85 \cdot x_3$$

The weight of the x_1 variable became stronger, the difference is small, especially if compared to x_2 and x_3.

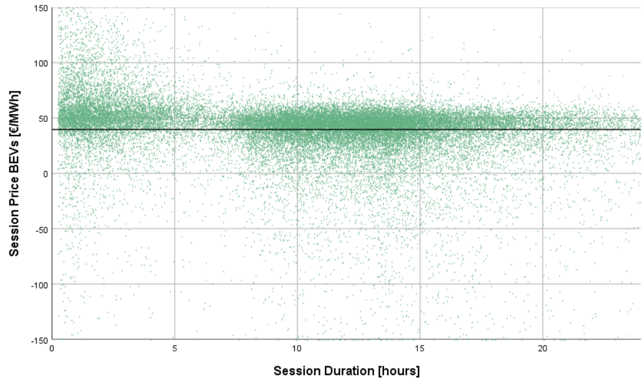

Figure 5.8: BEVs

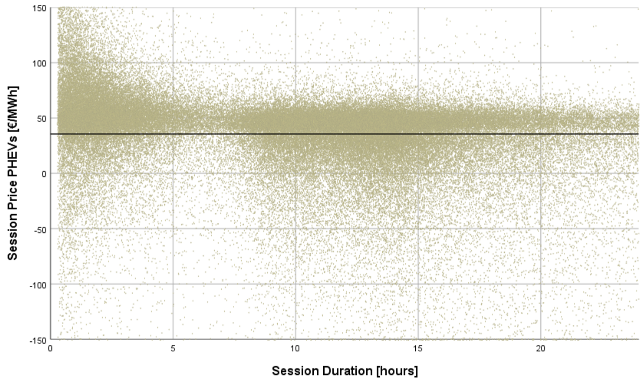

Figure 5.9: PHEVs

Figures 5.8 and 5.9 show the relationship between the session duration and the session price for BEVs and PHEVs. The average price is marked as a black line in the graphs. To help visualize both the average and the centre point with the highest density of sessions, figure 5.10 and 5.11 display the same graph zoomed in. The structural mismatch between the highest density of points and the average line eye-catching in these figures. In the PHEV graphs, the denser area in the left upper corner shows that the smart charging system has a more outliers towards expensive prices for very short sessions. The average price calculated for all session under

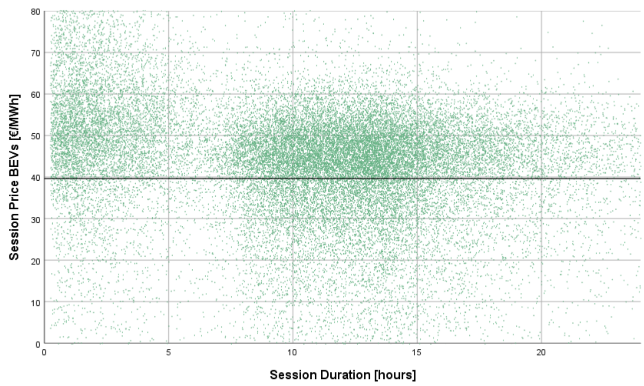

Figure 5.10: BEVs

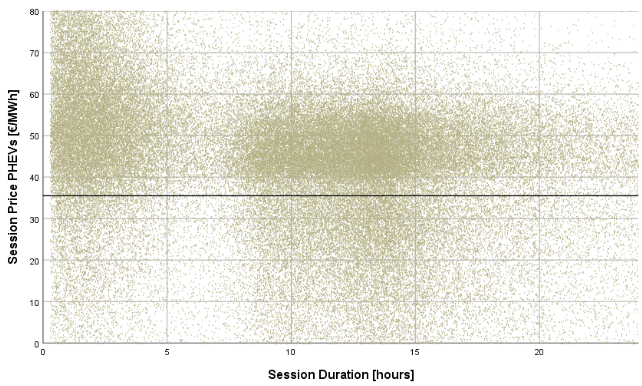

Figure 5.11: PHEVs

To emphasis the strong influence of x_1 on the average price, table 5.5 shows the price drop for data chunks with rising x_1. We can conclude that the duration is an important indicator for the expected average price and increasing session duration will have a positive effect on the smart charging savings potential.

Simulation D Duration [hours]	All data (100%) price [€/MWh]	BEVs (~ 20%) price [€/MWh]	PHEVs (~ 80%) price [€/MWh]
$\frac{1}{4} \leq x_1 < 24$	36,46	39,62	35,51
$\frac{1}{4} \leq x_1 < 1$	57,24	56,23	57,67
$1 < x_1 < 5$	52,20	54,69	50,85
$5 < x_1 < 10$	37,32	39,46	34,73
$10 < x_1 < 24$	33,23	37,15	28,78

Table 5.5: The average session price split based on the session duration for both BEVs and PHEVs

5.3.2. The impact of the maximum power of the charge point

Figure 5.12 and 5.13 show the relationship between the maximum power of the charge point and the average session price. Similar peaks are found as in graphs 4.7 and 4.8.

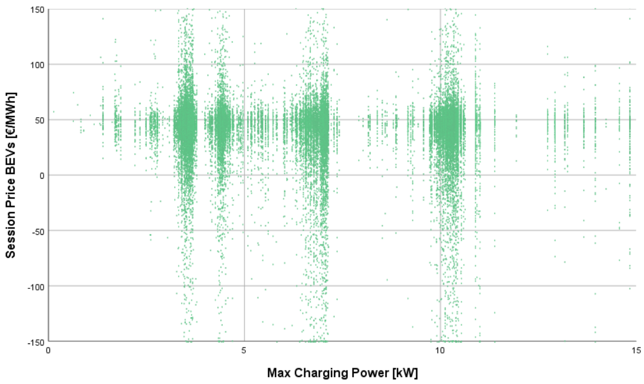

Figure 5.12: BEVs

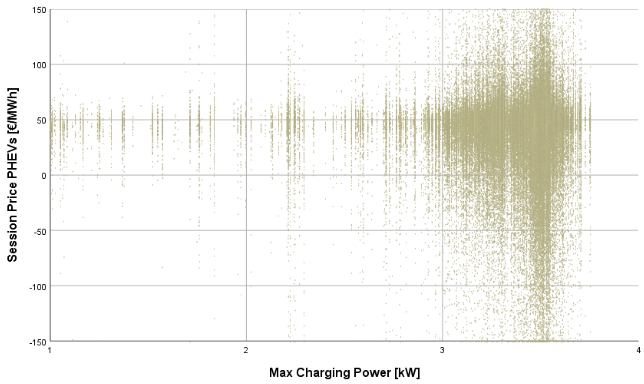

Figure 5.13: PHEVs

In the multiple regression models, the power of the charge point is denoted as x_2 and shows a negative linear relationship with the price. More power available in the charge point allows the smart charging algorithms to better utilize the low price market opportunities.

$$E(P_{All}) = 60,05 - 2,15 \cdot x_1 - 1,91 \cdot x_2 + 0,66 \cdot x_3$$

$$E(P_{BEVs}) = 63,63 - 2,03 \cdot x_1 - 1,79 \cdot x_2 + 0,45 \cdot x_3$$

$$E(P_{PHEVs}) = 58,42 - 2,30 \cdot x_1 - 3,13 \cdot x_2 + 1,85 \cdot x_3$$

Simulation D Max Power [kW]	All data (100%) price [€/MWh]	BEVs (~ 20%) price [€/MWh]	PHEVs (~ 80%) price [€/MWh]
all	36,46	39,62	35,51
$0 < x_2 < 1$	42,81	50,86	41,23
$2 < x_2 < 4$	36,03	41,47	34,71
$4 < x_2 < 8$	39,50	39,69	28,88
$8 < x_2$	38,39	38,50	7,68

Table 5.6: The average session price split based on the max power for both BEVs and PHEVs

A remarkable result is the average price of €7,68 per MWh for PHEVs with a connection over 8kW. This are only 241 sessions from 1 car with a unrealistic high connection for a PHEVs. Nevertheless, it shows that if this was possible in reality, the increased charging power give the algorithm the change to really utilize the low prices.

5.3.3. The impact of volume of the charging session

In the multiple regression models, the session volume is denoted as x_3 and shows a positive linear relationship with the price. More kWh demand decreases the flexibility of the session and increases the average session price accordingly.

$$E(P_{All}) = 60,05 - 2,15 \cdot x_1 - 1,91 \cdot x_2 + 0,66 \cdot x_3$$

$$E(P_{BEVs}) = 63,63 - 2,03 \cdot x_1 - 1,79 \cdot x_2 + 0,45 \cdot x_3$$

$$E(P_{PHEVs}) = 58,42 - 2,30 \cdot x_1 - 3,13 \cdot x_2 + 1,85 \cdot x_3$$

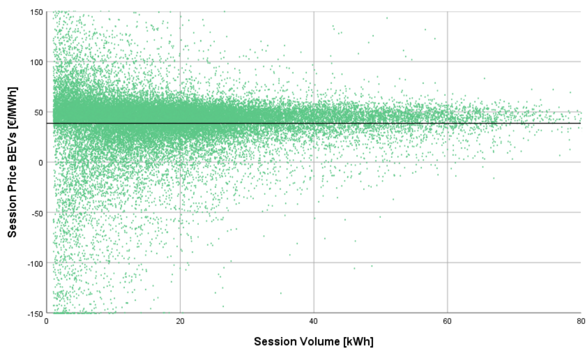

Figure 5.14: BEVs

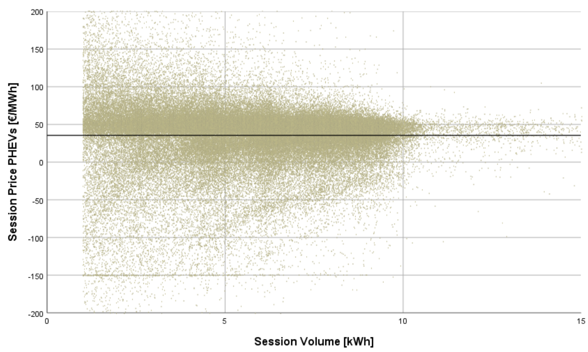

Figure 5.15: PHEVs

Simulation D Volume[kWh]	All data (100%) price [€/MWh]	BEVs (~ 20%) price [€/MWh]	PHEVs (~ 80%) price [€/MWh]
all	36,46	39,62	35,51
$0 < x_3 < 3$	34,58	33,86	34,66
$3 < x_3 < 6$	34,83	38,44	34,52
$6 < x_3 < 9$	34,98	38,12	34,75
$9 < x_3 < 15$	36,29	37,43	35,25
$15 < x_3$	40,08	40,09	39,03

Table 5.7: The average session price split based on the session volume for both BEVs and PHEVs

5.4. The effect of smart charging on the carbon intensity

In this section the results are shown to find the answer to sub-question 2: How is the carbon intensity of the electricity changing if comparing smart charging with dumb charging? First, the correlation between the day ahead price and the carbon intensity is checked in both The Netherlands and Germany. Subsequently, the effect of smart charging on the carbon intensity is discussed based on the results of the simulations and analysis.

5.4.1. The correlation between the day ahead price and the carbon intensity in the grid

The idea that smart charging based on price incentives has an effect on the carbon intensity of the charged electricity, is based on the assumption that a correlation exists between prices and carbon intensity. Before the effect of smart charging on the carbon intensity in the grid is analysed, the simulation input data could be visualized and analysed to test this assumption. Since the correlation is expected to be stronger in a electricity markets with more renewable energy in the mix, data from the day ahead market and the carbon intensity from Germany is used to compare the results with The Netherlands. Germany has a significant higher percentage of renewable energy in the mix, as well as more heavy polluting lignite power plants, which raises the expectation of the correlation.

In figure 5.16, both the Dutch carbon intensity and the day ahead prices are shown for the first week of January in 2018. A correlation between the two is clearly visible, but the Pearson correlation coefficient for the carbon intensity and the day ahead market in The Netherlands is only 0,22, which is a small effect as described in section 3.9.2.

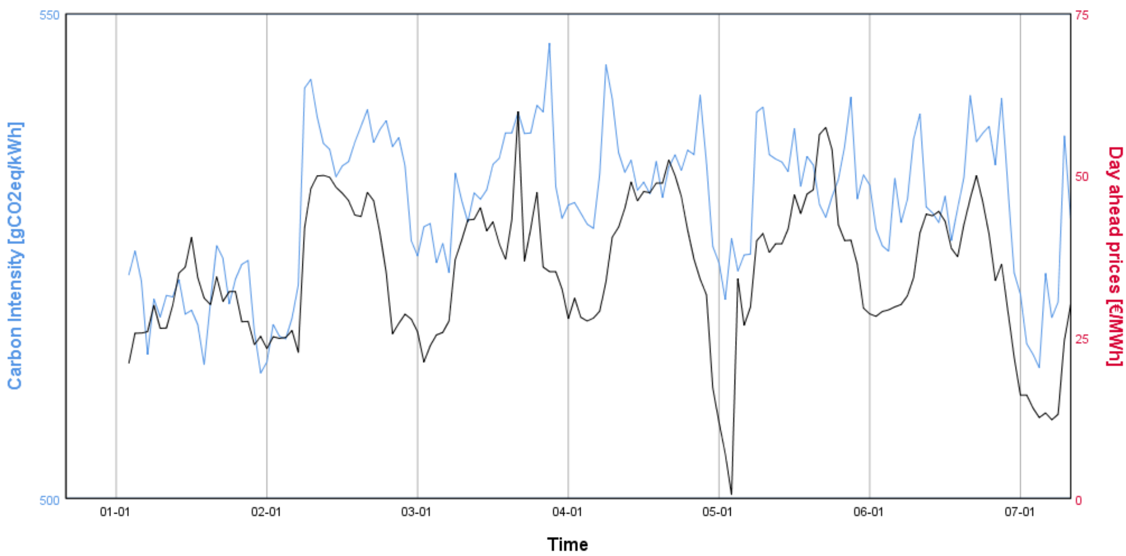

Figure 5.16: The Carbon Intensity and day ahead prices for January 2018 in The Netherlands

Figure 5.16 could be misleading, since the axes are adjusted to show the fluctuations on a similar scale. In figure 5.17 and figure 5.18, the carbon intensity and day ahead prices are shown for both The Netherlands and Germany on a scale adjusted to to visualize the overlap in Germany. This comparison shows that the correlation is expected to be much stronger in Germany due to a stronger fluctuating carbon intensity, as expected.

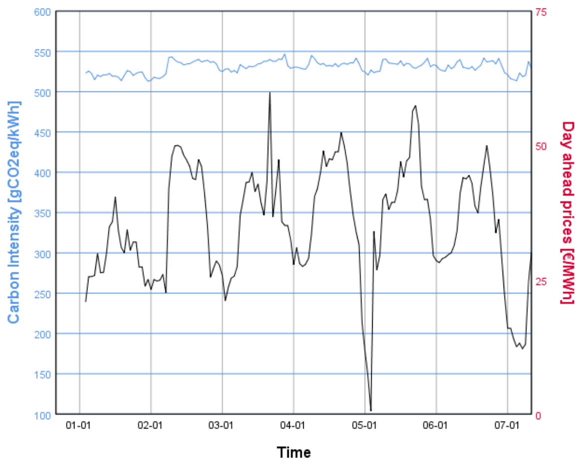

Figure 5.17: The Netherlands

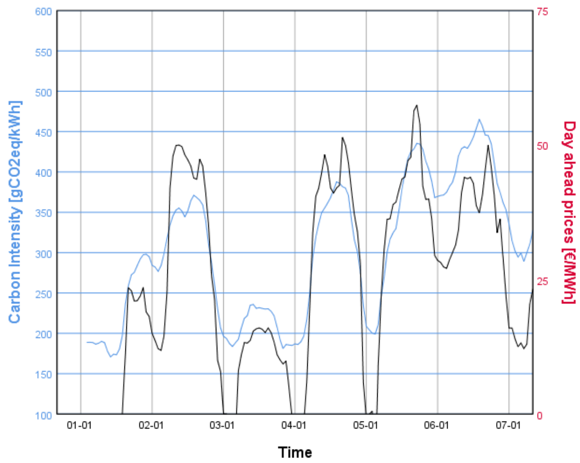

Figure 5.18: Germany

The Pearson correlation coefficient for the carbon intensity and the day ahead market in Germany is 0,64, which shows a large effect and is indeed stronger than the 0,22 found in The Netherlands. Where figures 5.16, 5.17 and 5.18 show only the first week of January, figure 5.19 and 5.20 shows the full year in a scatter.

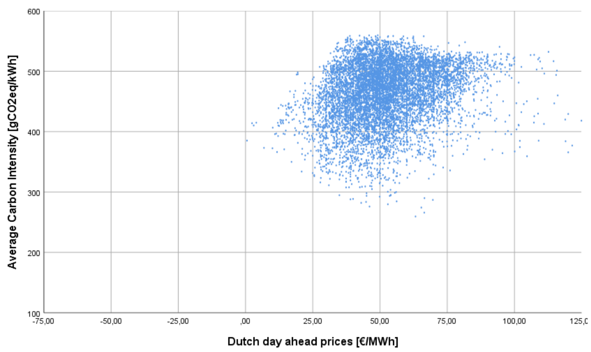

Figure 5.19: Scatter of carbon intensity in The Netherlands

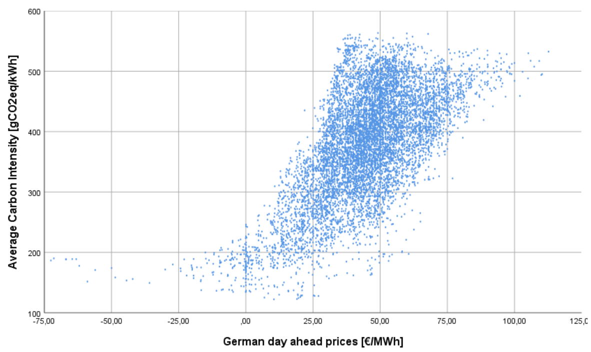

Figure 5.20: Scatter of carbon intensity in Germany

In The Netherlands the carbon intensity could be referred to as a scatter cloud, where no correlation could be seen with the eye. However, in Germany a clear linear correlation could be seen in figure 5.20.

The graphs and correlations coefficients show that there is indeed a correlation between the day ahead price and the carbon intensity in the grid and it will get stronger if more renewable energy will be added to the electricity markets. Based on this correlation, an lower average carbon intensity could be expected if comparing the smart charging schedule to the dumb schedule.

5.4.2. How is the average carbon intensity per session changing if comparing smart charging with dumb charging in The Netherlands and Germany?

Above the correlation is described between the carbon intensity and the day ahead prices. In the smart charging simulations different set-up scenarios are executed, based on different market choices. in figure 5.8 the mean is taken from the average carbon intensity of all sessions for simulation A, B and C in The Netherlands and simulation A and B in Germany.

	The Netherlands [gCO2eq/kWh]	Germany [gCO2eq/kWh]		The Netherlands [gCO2eq/kWh]
Simulation A	465,1	386,0	Simulation A	465,1
Simulation B	458,8	369,5	Simulation C	461,0
Savings	1.4%	4.3%	Savings	0.5%

Table 5.8: Comparing the average carbon intensity

The correlation found in the input data resulted indeed in a decrease of carbon intensity on average during charging times for smart charging compared to a dumb charging schedule. In The Netherlands, the results savings of 1,4% while optimizing on the day ahead market is rather small. Figures 5.21 and 5.22 show a scatter plot of the average carbon intensity per session to compare the dumb charging and smart charging. Figures 5.23 and 5.24 shows similar plots for the simulations performed with the data for Germany.

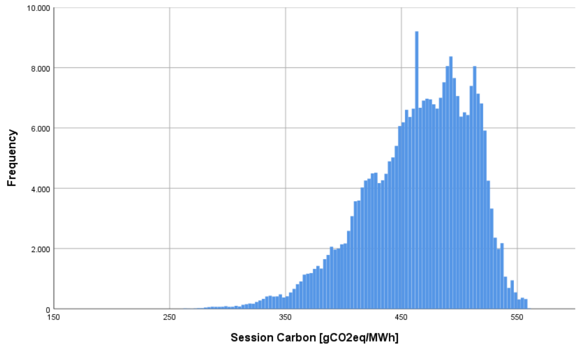

Figure 5.21: Dumb charging in The Netherlands

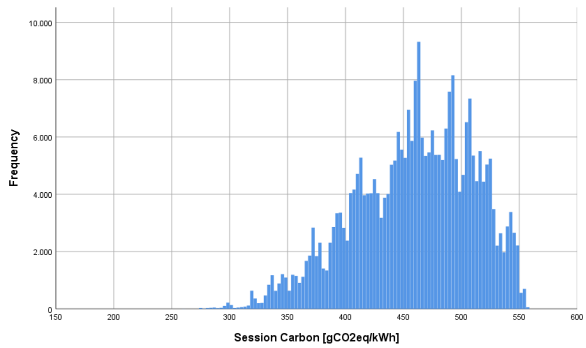

Figure 5.22: Smart charging in The Netherlands

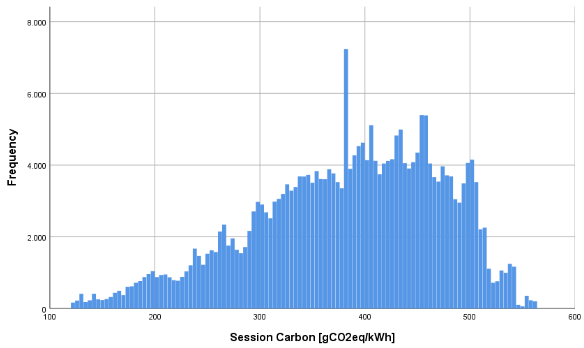

Figure 5.23: Dumb charging in Germany

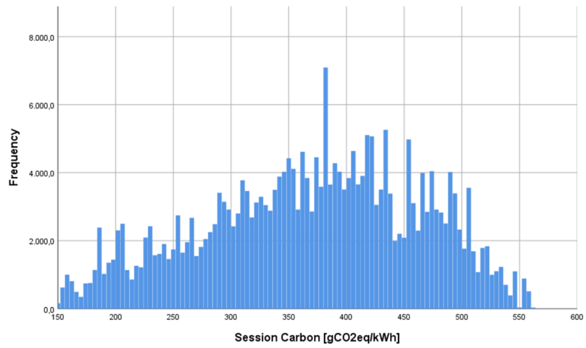

Figure 5.24: Smart charging in Germany

Changes are high that in reality smart charging will not be based on the day ahead market only, but imbalance market optimization will be added to increase the financial result. As shown in table 5.8, the result will decrease to a saving of mere 0,5% in simulation C. The expectation that the savings would improve in the German market was found in the results, with a 4,3% savings. This improvement could be explained by the stronger correlation found in the previous section.

The results of the simulations is showing a decrease in the carbon intensity in the grid at charging if smart charging is applied. However, the significance of the impact of the decreased carbon intensity is debatable.

According to Verzijlbergh, using the carbon intensity in the grid to estimate emission savings for smart charging leads to imprecise outcomes [41]. Reduction of CO_2 emissions is depending strongly of the system set-up. Fore example, when combining smart charging locally with renewable produced electricity from a wind turbine, research found the CO_2 emissions reduction potential to be $\sim 50\%$ [22].

6 Conclusions and Recommendations

For most experts, it is an obvious and inevitable trend that smart charging of electric vehicles will be common practice in a future electricity smart grid. This thesis strives to close the gap between a futuristic electricity system design and the current situation in The Netherlands. A smart charging simulation set up is designed in close collaboration with the worldwide largest leasing company and an aggregator active in The Netherlands. To start of this chapter, the key insights of this research are presented. Successively the sub-questions are answered and reflected on one by one. Ultimately, the sum of all the answers together form the answer to the main and research question of this thesis.

6.1. Key insights

The findings within this thesis support the conclusion that the used smart charging algorithms work properly and could decrease the electricity purchase price in The Netherlands below the chose benchmark. Additionally we found that the carbon intensity of the charged electricity during the smart charging schedule decreases compared to a business-as-usual scenario. This is a direct result of a correlation between the carbon intensity in the grid and day ahead prices in The Netherlands.

EV aggregators are able to add flexibility to the demand side of the electricity system by means of smart charging, if a strong price incentive is provided. If stakeholders across the mobility and the energy sector work together, a real-world commercial implementation based on the price incentives on day ahead market and imbalance market in The Netherlands is possible.

A dataset of 300.000 real-world home charging session from 2018 enabled not only the quantification of the effect of smart charging on the electricity purchase price, but also a statistical analysis of the simulation results. In this analysis, multiple regression models show a linear relation between three independent variables (the session duration, session volume and maximum power of the charge point) and two dependent variables (the average session purchase price and savings per session). The key insights from the models empowered three main recommendations to EV aggregators to optimize the smart charging savings in the future:

1. Encourage longer session lengths
2. Encourage regular overnight charging sessions behaviour, independent of the charging needs
3. Stimulate access to high charging power

The data showed compelling differences between the ~ 20% BEVs and the ~ 80% PHEVs and their results were separated accordingly in this research. In all simulation set-up scenarios, the PHEVs are outperforming the BEVs in terms of a lower average session price and higher cost reduction.

If the smart charging strategy is executed as proposed in this thesis, the EV aggregator is exposed to the day ahead market and imbalance settlements for its portfolio. The EV aggregator is able top decrease the electricity purchase price, while acting as BRP. The exposure to the markets brings significant risk. Collaboration with an electricity supplier or BRP could potentially increase the smart charging savings for the EV aggregator. Furthermore, other revenue streams to utilize flexibility could be investigated. If stacking different flexibility strategies is possible, it could increase the smart charging value in the future.

6.2. Quantification of the smart charging costs reduction

The first and second sub-questions request a quantification of the cost reduction for BEVs and PHEVs. The cost reduction is quantified in two metrics. Firstly in an average price per session in € per MWh. Secondly the session savings in € based on the defined benchmark. Both are later used as dependent variable in the statistical analysis.

6.2.1. The average session price

One of the key outcomes in this research is the average electricity purchase price for a smart charging schedule on the day ahead and imbalance markets in 2018.

The worst case scenario points out a failing smart charging system will end up with an average purchase price only ~ 10% above the average day ahead market price. With the smart charging set-up, the average price is decreased to 39,62 and 35,51 for BEVs and PHEVs respectively. This leads to the conclusion that this smart charging set-up will decrease the average electricity purchase price below the chosen benchmark. The average prices achieved in the simulation are around 20% below the average day ahead market prices in 2018.

	Worst case scenario	Day ahead market	Benchmark	BEV simulation	PHEV simulation
Average price	57,75 [€/MWh]	52,53 [€/MWh]	42,56 [€/MWh]	39,62 [€/MWh]	35,51 [€/MWh]

6.2.2. The costs savings based on the benchmark

Based on the defined benchmark, the average session prices found in the simulation and the assumption of 4 MWh and 1,5 MWh charging demand for BEVs and PHEVs respectively, the yearly electricity purchase cost reduction savings is calculated. The calculations showed that with smart steering of the electricity consumption, approximately €8,- could be saved for BEVs and €9,- for PHEVs. If the demand assumption is not used, but the sum of the savings based on the real world data from 2018 is taken for every unique BEV or PHEV, simular numbers are found. The cost reduction for BEVs in the simulation varies between ±€40,-. This means our best BEV saved €40,- in 6 months of charging and the worst BEV lost around €40,- in the same period. The average saving per BEV per year is calculated to be around €2,50. For PHEVs the spread of results is less wide between a loss of €23 or saving of €32. The mean of the smart charging savings for PHEVs is calculated to be around €7,50.

6.3. Strategies to improve the cost reduction of smart charging

To deal with the third and fourth sub-question, multiple regression models are defined and a reflection on the simulation method is described. The smart charging simulation conducted resulted in an average session price for 156.254 historic sessions in 2018. The input session details contained information about the car type, the session start and end time, the session volume and the maximum power of the charge point. This was used to build a linear regression model to give the effect of those variables on the average price per session. Beside the average price, the total savings per session is directly calculated for each session using the benchmark price and are also used as dependent variables in the multiple regression analysis. The regression models found are shown below:

$$
\begin{aligned}
E(P_{BEVs}) &= 63{,}63 - 2{,}03 \cdot x_1 - 1{,}79 \cdot x_2 + 0{,}45 \cdot x_3 \\
E(P_{PHEVs}) &= 58{,}42 - 2{,}30 \cdot x_1 - 3{,}13 \cdot x_2 + 1{,}85 \cdot x_3 \\
E(S_{BEVs}) &= -0{,}249 + 0{,}020 \cdot x_1 + 0{,}024 \cdot x_2 - 0{,}005 \cdot x_3 \\
E(S_{PHEVs}) &= -0{,}104 + 0{,}010 \cdot x_1 + 0{,}017 \cdot x_2 - 0{,}003 \cdot x_3
\end{aligned}
$$

- $E(P)$ is the expected average session price in €/MWh based on x_1, x_2 and x_3
- $E(S)$ is the expected session savings in € based on x_1, x_2 and x_3
- x_1 = Duration in hours
- x_2 = Power in kW
- x_3 = Volume in kWh

The size of the dataset is large enough to find the models above with a significance below 0,000 and a colinearity tolerance above 0,76 and a VIF below 1,30. As explained in section 3.9.3, this means colinearity between variables in the models is not an issue and the linear relationships found are strongly backed up by the data. The average price per session and savings per session are calculated differently, but both represent the level of success of the smart charging simulation. The correlation between the two independent variables is large for BEVs with a Pearson correlation factor of -0.67 and very large for PHEVs with a Pearson correlation factor of -0,86. The effect of the duration, the volume and the maximum power of the session is shortly described to define different strategies for EV aggregators to improve the smart charging cost reduction in the future.

6.3.1. The session duration x_1

In theory, longer sessions give the smart charging optimization solver a wider range of possible charging moments, which in a fluctuating market should result in a lower average electricity purchase price. The regression model shows that the average price is expected to decrease with €2,03 and €2,30 respectively per extra hour added to a session. The expected session savings is increasing on average €0,02 and €0,01 for every hour added to the session.

The results show clearly that it is in an EV aggregator interest to increase the average duration of the controllable EV charging sessions to decrease the electricity purchase price. Since the session duration is a direct result of the connection to the charge point, the only way to increase the average session duration of an EV fleet is by influencing human behaviour. A first strategy could be to incentivize the driver to connect the EV to the charger as long as possible for overnight charging sessions, even if the state of charge is high enough already. Another possibility is to incentivize the EV drivers to skip short charging sessions during the day if charging is not needed or to communicate the fact that no extra charging is needed.

6.3.2. The maximum charging power of the session x_2

As with longer sessions, theory expects higher charging speeds in smart charging to result in a lower electricity purchase price, since more electricity could be consumed during the low price periods. The regression model shows indeed a decrease in price and an increase in savings for a higher maximum charging power x_2. For BEVs the average price is expected to decrease with €1,79/MWh per kW and the expected session savings increases on average with €0,024 per kW. For BEVs this is €3,13/MWh and €0,017 respectively.

The maximum capacity is depending on both the charge point and the EV, but the cars are generally not the bottleneck, since they are manufactured to handle fast charging if needed. An EV aggregator would benefit from access to high charging power at the installed home charge points. For PHEVs the charge point connection is standard 3,7 kW, since the smaller battery size does not demand higher power to charge the car overnight. With larger batteries in BEVs the data shows the charging power is increasing on average as well. Since a higher charging power demands an extra investment, the question arises whether the extra smart charging savings with higher power outweighs this investment. The answer to this question depends on which party has to do the investment and how the benefit of smart charging is distributed amongst the stakeholders. This could be an interesting question for further research.

6.3.3. The volume of the session x_3

There is a positive relationship between the electricity demand and the purchase price of €0,45 per kWh for BEVs and €1,85 per kWh for PHEVs. The expected session savings are decreasing with €0,005 per kWh for BEVs and with €0,003 per kWh for PHEVs.

The volume is an interesting variable. In theory, a high energy demand obligates smart charging solver to charge longer and decreases the idle time. This results in less freedom to schedule the demand in cheaper hours. On the other hand, the smart charging saving potential is calculated by multiplying savings per kWh with the expected demand, so low charging demand results inevitable in low rewards. Since the multiple regression model is build on session level, the first theoretical assumption is found. Still, the idea to incentivize drivers to charge less kWh per session to increase the smart charging value is very counter intuitive. A more sensible behaviour change that could benefit the EV aggregator is to stimulate repetitive overnight charging. If a driver connects the EV overnight to the charge point, even on days the state of charge is already sufficient at arrival, the overall average session volume will decrease, since more charge sessions and time is used to charge the same electricity demand.

6.4. The effect of the smart charging on the carbon intensity of the charged electricity

To answer the last and fifth sub-question, the effect of smart charging on the carbon intensity of the charged electricity is investigated. This is done by comparing the smart charging schedule with a business-as-usual scenario. The carbon intensity is measured in grams of CO_2 equivalent per kWh. We found that during the smart scheduled charging moments the carbon intensity was indeed lower, compared to a dumb charging profile. The strongest decrease was found when the smart charging algorithms react on day ahead prices only and do not take the imbalance market into account.

	The Netherlands Imbalance market	Germany Day ahead market	The Netherlands Day ahead market
Savings	0.5%	1.4%	4.3%

This means that if smart charging would have been performed for an EV fleet in 2018, the carbon intensity of the electricity physically flowing into the EV fleet would decrease. The EV fleet is assumed to react on price incentives, gaining this result. However, if one assumes the EV fleet is not changing the actual prices or behaviour of other players in the markets, the effect on the total system will be zero. If the enclosed EV fleet will decrease the carbon footprint of the charged electricity, without influencing the system as a whole, the carbon footprint of another player in the market will increase. This leads to the conclusion that smart charging of an EV fleet results in a decrease of the carbon footprint of the charged electricity of the EV fleet, but does not decrease the carbon footprint of the electricity consumed in the grid or the system.

However, the size of EV charging electricity demand is likely to increase, and growth of demand could change this effect in the future. If the smart charging profiles not only react on the market prices, but also influence the prices and behaviour of other players in the market, real effect on the carbon footprint could be realised. The effect of smart charging on the carbon intensity in the grid when the size influences the system would be an interesting scenario to investigate in further research. Another scenario worth investigating is the need for smart charging in a 100% renewable energy based electricity system.

6.5. Recommendations to improve smart charging for an EV aggregator

In section 6.3, recommendations for an EV aggregator are made based on the research results. Besides the strategies resulting from the multiple regression models, other strategies to improve the smart charging cost reduction were found during the course of this thesis. This results in the following recommendations for a EV aggregator:

- Increase the fleet size
- Integrate price incentives from the intra-day market
- Integrate price incentives from primary frequency containment reserves
- Fetch the state of charge data directly from the car
- Ask permission to drivers agenda to improve electricity demand forecasting
- Constantly update and improve forecasting tools
- Collaborate with balance responsible parties or become one to add extra value to smart charging
- Collaborate with energy suppliers with access to long term trading to hedge risk

The strategies mentioned above, are not based on the analysis performed in the simulation and therefore not conclusive. All strategies mentioned in this list require further research to support it with data.

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