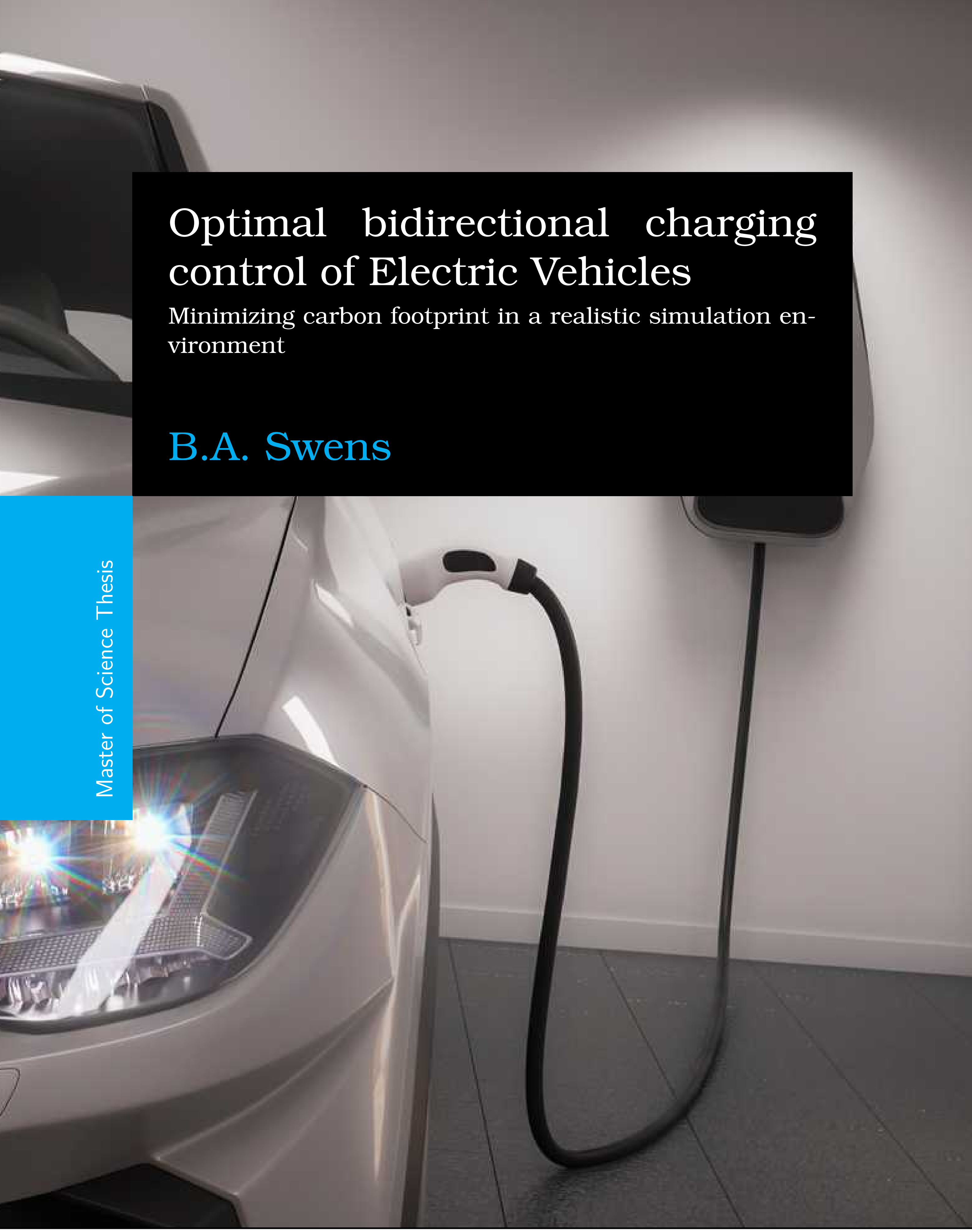

Optimal bidirectional charging control of Electric Vehicles

Minimizing carbon footprint in a realistic simulation environment

B.A. Swens

Master of Science Thesis

Delft University of Technology

Delft Center for Systems and Control

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Master of Science Thesis

For the degree of Master of Science in Systems and Control at Delft University of Technology

B.A. Swens

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Abstract

Electricity grids worldwide are experiencing increased peak demands and decreasing simultaneity due to higher shares of Renewable Energy Sources (RES). It is expected that many grids will soon reach their limits. One solution to mitigate these issues is exploiting flexibility in e.g. electric vehicles. In this work, a shrinking horizon model predictive controller is constructed to optimally charge and discharge EVs with respect to the day ahead electricity price or grid carbon intensity. The model takes into account that users with a dual rate electricity plan only want to charge during their off-peak hours. A feature to implement a household PV setup in the optimization is included. The possible consequences in terms of associated carbon emissions, utility costs and user costs are analysed using a simulation based on data from 4279 charging sessions that took place between June 23, 2021 and June 23, 2022. The sessions are split in 2855 weekday sessions (duration between 4 and 24 hours) and 1424 weekend sessions (duration between 4 and 60 hours). It is found that using current circumstances, minimizing the carbon emissions using bidirectional charging results in a higher price (5.5 %) for the utility than using the current state of the art, unidirectional charging minimizing the wholesale electricity cost. Bidirectional charging minimizing the wholesale electricity cost results in higher emissions compared to unidirectional charging (2.8 %), and even compared to uncontrolled charging (0.9 – 3.6 %). The reason for this seems to be a negative correlation between carbon intensity and wholesale price during the times that vehicles are typically connected although this needs further investigation to be confirmed.

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Preface and acknowledgements

This document is the result of 9 months of research, to obtain a Master of Science degree in Systems and Control at the Delft University of Technology. As a son of a sustainability consultant, I grew up with the consciousness of the biggest challenge we're facing today as humanity. Engineering to boost environmental sustainability has become my 'north star' and the moment that I chose Systems and Control I already knew that I wanted to focus my thesis on sustainability.

One of the sectors in which huge leaps can be taken towards a sustainable future is mobility. In the current day people are accustomed to the freedom that personal vehicles provide. Although the most effective way to tackle unsustainable transport is taking away the personal vehicle, this is socially infeasible at this moment. Therefore, within the boundaries of what people accept, we need to accelerate sustainable transport as quickly as possible.

With the world accelerating towards fully electric transportation, people tend to forget that just using an EV may be better than using an ICE vehicle, yet it still is far from sustainable. As long as gas and coal plants generate the electricity, the EV is more efficient, but ultimately also uses fossil fuels for transportation. The two main factors that make an EV still unsustainable are the production of the vehicle (with the battery pack as main driver) and the production of the electricity.

We are already producing a lot of renewable electricity, sometimes even more than we can consume. If we can use this electricity, especially during times of excess, to charge our EVs this would be a big step towards truly sustainable mobility. Therefore, this project came to me as the perfect opportunity to combine Systems and Control with sustainability and my third passion, e-mobility.

I want to thank specifically my good friend Bas Lottman for providing me this opportunity. I also want to express my gratitude to Huib Keemink who, as a Systems and Control alumnus, was always available to brainstorm and help out whenever i was stuck. Moreover, I want to thank Sergio Grammatico and Peyman Mohajerin Esfahani who made time to sit and discuss my progress with me whenever I needed some guidance from the Universities perspective.

I also want to thank all my colleagues at *Jedlix* for making me feel welcome and included, and for providing such an inspiring and positive environment to carry out my thesis research.

Lastly, I want to give credit to my girlfriend Floor for helping me out with my planning, which remains to be my weak spot, and my parents and brother for their unconditional support and understanding whenever their schedule needed to adapt to mine because of my thesis.

I'm happy with the result of the thesis, and I hope that Jedlix will reap the fruits of the research I did as soon as V2G steering becomes available in vehicles.

Delft, University of Technology B.A. Swens
August 25, 2022

"We are the first generation to feel the impact of climate change and the last generation that can do something about it"

— *Barack Obama*

Chapter 1

Introduction

1-1 Flexibility and its importance

Our societies biggest challenge today is indubitably climate change. One of the key pillars in tackling climate change is electrification of almost every aspect in our lives in combination with renewable electricity production. From heating buildings to cooking, from transport to industry. At the same time, a shift needs to take place from fossil-based electricity generation to renewable electricity generation. This gives rise to a new challenge; how to deal with vastly increasing electricity demand and with more volatile electricity supply, due to less predictable and intermittent electricity sources such as solar and wind? Until now, grids were designed to have enough capacity to provide electricity to connected parties, even during the highest peaks. But with increasing peaks and decreasing simultaneity (the synchronization of supply and demand) on the grid, the current system will soon reach its limit if the way of using it remains the same. One option would be to drastically increase grid capacity, but this would require investments in the order of €90 billion for The Netherlands alone [4]. But there is another, much smarter solution at hand: using flexibility, or in short *flex*.

Flexibility is found in many electrical appliances, such as heat pumps, boilers, tumble dryers and electric vehicles. This is easily explained using the example of a boiler. By default a boiler tries to keep the water temperature constant, so as soon as hot tap water is used, the boiler switches on and brings the temperature back to the set temperature as quickly as possible, and then switches off again. However, the same level of comfort can be reached while also exploiting the flexibility. Using forecasting methods, the next moment of hot water consumption can be predicted with reasonable accuracy. The only requirement is then that the boiler temperature is sufficiently high at the moment of tap water consumption. Note that it may also be higher, thus storing the excess energy in the form of heat for later use. This way the boilers electricity consumption can be steered in a way that is beneficial for one or preferably multiple stakeholders. For example, the consumer pays less and the peak load in the grid decreases, bringing value to both the end consumer and the grid operator. Similar strategies can be exploited with heat pumps, such as explored by Hong et al. [5].

Time shifts of up to 6 hours were achievable after adding rigorous thermal buffering to the heating system, providing a great deal of flexibility.

Another example of a *flexible load*, is an Electric Vehicle (EV). EVs are often plugged in to the charging station for approximately 14 consecutive hours, while they only need around 4 hours to obtain the required state of charge [6]. This means that there is freedom to choose when to charge the vehicle. By default, an EV will start charging immediately upon plugging in. Because users often plug in upon coming home from work, this is often the time that people also start cooking, washing and heating the house, so-called peak time. To relieve grid pressure, it is therefore beneficial to postpone charging to a later time when electricity demand is less, so-called off-peak time. This measure also comes with a financial incentive since energy prices are generally lower during the night. Moreover, with increasing amounts of renewable energy sources, the imbalance on the grid increases too. EVs can play a significant role in mitigating imbalance issues, as they can ramp up or down their charge speeds almost instantaneously. But there is more. Electric vehicles are not only a flexible load, they are potentially also storage batteries on wheels. They can not only postpone their charging to a more beneficial time, but theoretically they can also store renewable energy during the day, and use this energy later during the night to e.g. to power the washing machine or electric hob. This way, the EV contributes not only to shaving the peak in electricity demand, but also to increase the utilization of Renewable Energy Sources (RES). To this end, the International Organization for Standardization (ISO) is developing the *ISO15118-20* standard to enable Vehicle-to-Grid (V2G), which is expected to be implemented in virtually all future EVs on the market.

1-2 Large and small scale applications

1-2-1 Current practice

Today, the flexibility provided by electric vehicles is already being utilized by aggregators such as *Jedlix*. Jedlix aggregates electric vehicles into different pools. A pool of vehicles is called a Virtual Power Plant (VPP). The total consumption of these VPPs can be increased or decreased based on steering signals from VPP owners. Using unidirectional smart charging (erroneously called *V1G* in industry), either upward or downward flexibility can be provided. Providing upward flexibility means in this application that the total charging power must be turned down (analogous to ramping **up** a power plant, hence the name upward flexibility). Downward flexibility thus means increasing the total charging power. A VPP can therefore be configured to deliver either upward or downward flexibility.

In the scenario of an upward pool, vehicles in the pool start charging upon connection, and pause charging when the VPP owner requests upward regulation. Charging stops as soon as the desired state of charge is reached. In a downward pool, vehicles postpone charging until either a downward regulation signal is received or they need to start charging in order to meet their charging needs in time.

On a small, single household scale, people install so-called 'smart chargers' at home, to make sure their consumption never exceeds their contracted power. This means that the charger will automatically reduce power when other household appliances draw too much current (e.g.

the washing machine is turned on). Furthermore, some smart chargers can be connected to the owner's Photo Voltaic (PV) installation, allowing for charging on PV production, if the vehicle is connected and not fully charged at the time of solar electricity generation. This way, a consumer exploits the flexibility of his EV by shifting the charging to the time of PV production. Other household appliances can be used to optimize so-called self-consumption too. An example of the effects can be seen in Figure 1-1, where the yellow line indicates the solar energy production.

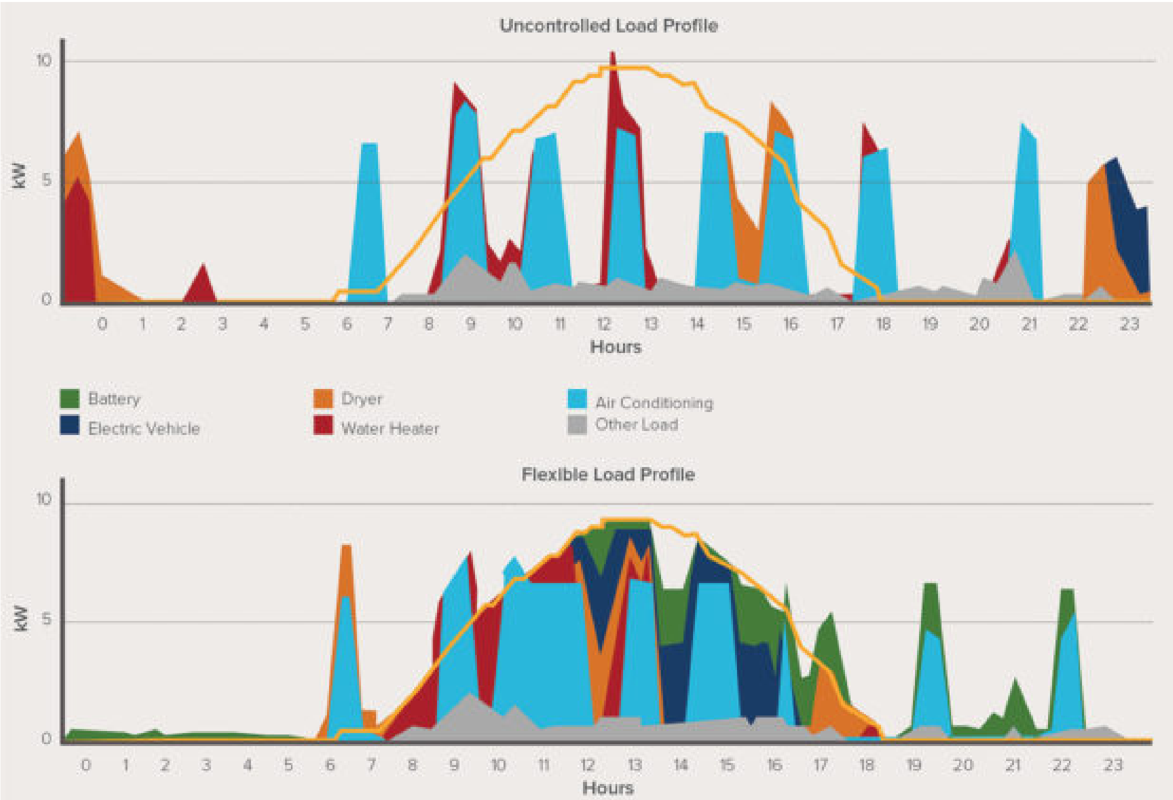

Figure 1-1: Example of exploiting flexibility on a small scale [1]

1-2-2 Future possibilities

Currently, many more methods with regard to smart charging are being developed. Some examples are smart charging for energy autonomy [7], smart charging for micro grid optimization [8] and smart charging for frequency regulation [9].

1-3 Research outline

Following the literature research preceding this thesis and in collaboration with Jedlix, the research gap was identified which forms the basis for this thesis.

> Optimal steering of EV charging and discharging to ensure minimal carbon emissions from both a single household and an aggregator's perspective, using real user data.

To develop this optimal steering method, three subtasks are identified:

- Build a Model Predictive Controller to control the charging of the vehicle
- Identify a suitable cost function that effectively minimizes the associated carbon emissions
- Simulate a representative set of charging sessions and analyse performance of model

1-4 Approach

To successfully develop and implement the proposed method, the following approach was used:

1. Data acquisition, to get a better understanding of the available data and steering parameters.
2. Strategy development, to identify viable optimization parameters
3. Cost function development, translating the strategy into a mathematical equation to be minimized
4. Baseline and alternative strategies development, to benchmark the proposed methods to
5. Data processing, combining several sources and modifying and filtering data to be used
6. Simulation, to generate results of all available strategies

1-5 How to read this thesis

This section will briefly explain which topics are covered where to help the reader navigate through this thesis.

Ch 2 covers a brief overview of the potential of Vehicle-to-Grid technology, how it can be used, and how it is used in this thesis.

Ch 3 starts with a general explanation of Model Predictive Control, followed by a section on Shrinking Horizon Control. Subsequently some existing applications of MPC in smart charging are discussed. The chapter ends with an elaboration on the model used in this thesis.

Ch 4 introduces the challenges of carbon minimization in EV charging, followed by the various used cost functions and constraints. Next, the assumptions are laid out, and the working principle of the used toolboxes is explained. Finally the used data, data processing and results evaluation is discussed.

Ch 5 shows the working of the model and elaborately discusses the results.

Ch 6 gives a summary of the conclusions and some recommendations for future research and policies.

Chapter 2

V2G Potential

As mentioned in chapter 1, many parties are focusing on exploiting the possibilities associated with Vehicle-to-Grid (V2G) technology. In this chapter, the potential of V2G technology will be discussed and a framework for application of V2G within this paper will be set.

In 2021, Di Natale et al. [10] published a case study of the Swiss energy system, investigating the potential impact of V2G operation on energy systems with a high share of renewable energy production. It was then compared to using reservoirs and pumped-hydro storage facilities in terms of ability to decrease amount of Greenhouse Gas (GHG) intensive electricity imports from connected grids.

As stated before, controlled charging of EVs can shift their electricity demand to maximize self-consumption of generated PV electricity during the day. With V2G operation, additional surpluses can be captured in EV batteries and fed back to the grid at times of high demand to reduce GHG-imports.

In a scenario with a high share of Renewable Energy Sources (RES), V2G shows the ability to reduce the imported GHG emissions by around 35% in the year 2050, which is similar to the potential of reservoirs and pumped hydro storage. By combining the storage technologies, a reduction of 60% could be obtained.

2-1 Short-term storage

Vehicle-to-grid technology is very much suited for short-term storage. That is, storing small amounts of excess electricity during times of high RES generation and low demand, to be used during times of low RES generation and high demand. For this technology to become interesting, EVs need to reach a significant aggregated capacity, and an increased share in the production of renewable energy can further increase the impact.

The prognosis is that in 2030, 140-240 million electric vehicles will be on the road globally [11]. Even in the most conservative scenario this will result in an aggregated capacity of approximately 7 TWh. Looking at The Netherlands alone, the expectation is that 2.3 million registered passenger cars will be fully electric by 2030, which accounts for 115 GWh of aggregated storage capacity (this is still only 25% of all passenger cars in The Netherlands) [4]. Comparing this to the (current) average daily electricity consumption of 298 GWh, this is a significant amount.

2-2 Long-term storage

On the other hand, V2G will not be useful for seasonal storage for two main reasons. Firstly, due to the fact that lithium-ion batteries lose their charge over time. This phenomenon is called battery drain, and is not taken into account in this thesis. This is justified because the battery drain during charging sessions is negligible, but during extended periods of several weeks of idle time, the drain is not negligible anymore, and for seasonal storage this becomes a real burden. This could potentially be solved with better battery technology in the future. The second reason, which is harder to solve with new technology, is the fact that a lot of excess storage capacity would be needed for seasonal storage. Not only is this extra storage very expensive, but since the main function for EVs will still be transportation, all the extra weight and volume of the extra capacity must be transported as well, resulting in much higher energy consumption. To enable seasonal storage in EVs, there are three main aspects of batteries that need to improve enormously, namely energy density (the battery capacity per unit mass), the marginal costs of capacity (the price per unit energy), and the drain. Since these are very unrealistic to happen within the near and even not-so-near future, it can be stated that EVs will not be suitable for seasonal storage for the foreseeable future. Moreover, it is inherently unsustainable to transport all this energy that doesn't need to be transported. This view is shared by Kempton and Tomić [12], who argue that V2G is well equipped for storage of up to 4 days.

2-3 Grid balancing

Another interesting use case for V2G technology is grid balancing. This means exploiting the storage capacity of EVs for mitigating the imbalance on the grid. Currently, this grid balancing typically happens by means of gas plants that can be ramped up or down quickly whenever grid imbalance occurs. EVs have the ability to ramp up charging or discharging to full power within seconds, making them applicable in all stages of frequency regulation. An added benefit of using it in this manner is that the volumes are limited, since the imbalances are usually only for a short period of time. This results in limited battery degradation [13]. Moreover, since assets that can ramp up or down on such short notice are often very expensive, the compensations from Transmission System Operator (TSO)s for providing these services are generous. This is a very interesting use case to further explore, but it focuses mainly on forecasting. To adequately bid on the frequency regulation market, an aggregator or Balance Responsible Party (BRP) managing a fleet of vehicles, must accurately forecast the amount of balancing power available during 4-hour consecutive blocks. This means that throughout one 4-hour block, this capacity must be available on the instant. The proceedings of this use case are investigated by Schuller and Rieger [9] for the German regulation energy markets.

Based on price data from 2011 and 2012, they concluded that a maximum profit of €730.31 per vehicle was possible.

2-4 Cost-efficiency

Utilizing Electric Vehicle (EV) batteries is by far the most cost-efficient form of energy storage, since zero additional investments are necessary. The only costs that need to be taken into account are the additional degradation costs. Since there is little empirical data available with regards to V2G operation, it is hard to quantify this degradation. Nevertheless, if a storage battery was to be bought specifically for storing excess renewable energy, degradation would take place too, on top of the large initial investment.

When charging and discharging an electric vehicle, power losses occur in various places. Most losses occur in the transformer. Interpolating the results of Apostolaki-Iosifidou et al. [14] a charging efficiency of 90% and discharging efficiency of 85% is assumed. This results in a round trip efficiency of 76.5%.

2-5 V2G application in this thesis

In this thesis, the possibilities for V2G operation will be explored for optimally charging EVs with respect to day ahead price or carbon emissions. Using either of these metrics, will help overcome the simultaneity issues, as an excess of renewable electricity is likely to result in both low prices and low carbon emissions, as further explained in section 4-4. Moreover, a controller will be developed that optimally uses V2G in combination with domestic solar Photo Voltaic (PV) installations, to maximize the self-consumption of residential RES systems.

Chapter 3

MPC Design

3-1 Model Predictive Control

To control the charging of the electric vehicle, a Model Predictive Controller (MPC) is designed. A model predictive controller is a controller that uses a model of the system at hand, in this case the charging/discharging of a vehicle battery, to predict its future output signal. It then solves an online optimization problem to select the optimal control sequence. In other words, using the model, a prediction can be made of the state evolution if any set of inputs is given to the system. Typically, five important items are part of the design procedure:

1. Process model
2. Cost function (or performance index)
3. Constraints
4. Optimization
5. Receding horizon principle

There are several reasons to choose for Model Predictive Control over another type of controller. First of all, MPC can handle constraints. In practice, all systems are subject to constraints of various natures. This can be hardware constraints (for example the maximum acceleration of a vehicle), regulatory constraints (for example the maximum noise of a wind turbine), safety constraints (the maximum speed on a specific road), and so on. In more traditional control methods such as PID control, the tuning parameters are used to keep the signals within bounds, or more advanced setups are used to mitigate the negative results such as integrator windup. Usually the optimal control strategy touches one or more of the constraints. MPC uses a direct approach by modifying the unconstrained solution in such a way that the constraints are respected.

Two types of constraints can be identified. The *inequality* constraints, are typically bounds on the control inputs or states of the system. The *equality* constraints can be user requirements such as a specific state at the end of the prediction horizon, or a fixed constant control signal after the control horizon.

Furthermore, MPC can handle Multi-input Multi-output (MIMO) systems, making it much easier to use in systems where outputs are affected by multiple inputs, and it can incorporate future reference information into the problem because it has so-called 'preview capability' (it essentially predicts its future states).

In this thesis, the system is MIMO, with charging and discharging power as inputs, and state of charge and battery power as outputs. A cost function to-be-minimized is constructed, indicating the performance of the system with respect to some future control sequence. This cost function is discussed in chapter 4. Model predictive control is sometimes referred to as Receding Horizon Control, due to its receding nature.

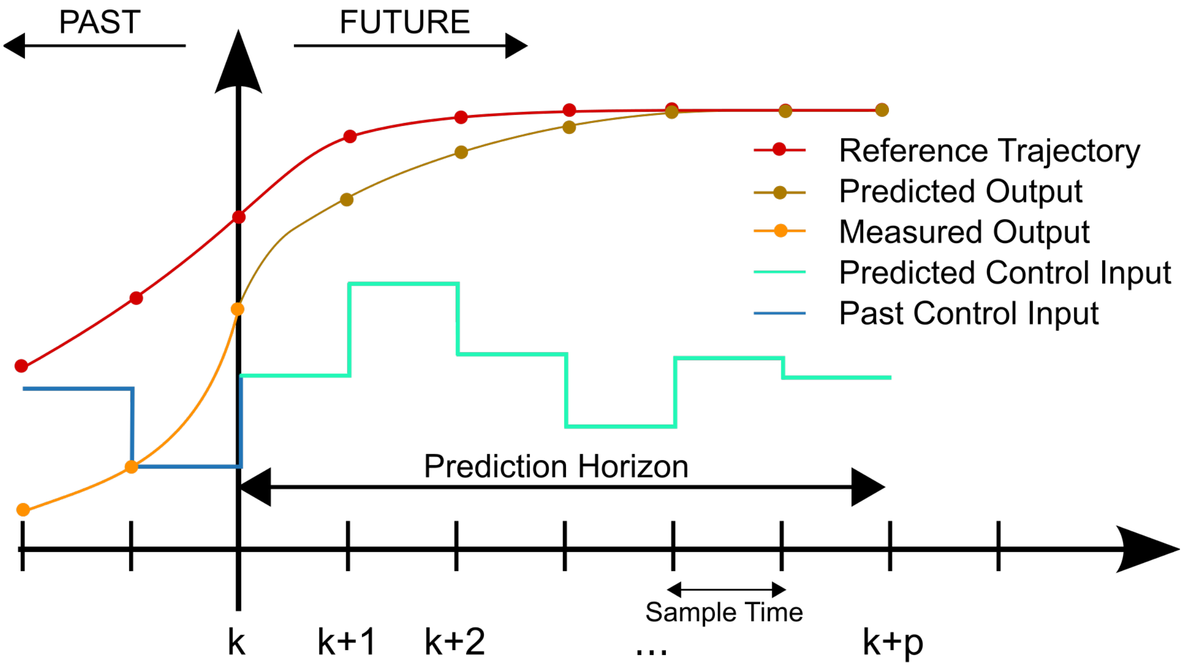

Figure 3-1: Basic working principle of MPC [2]

At each time step, an optimal control sequence is calculated that minimizes the cost function over a predetermined control horizon while respecting the constraints. The first control action of this calculated control sequence is then applied to the system, and the rest of the calculated actions are discarded. The system then provides an output which is usually not exactly the output predicted by the MPC beforehand. This is due to the fact that a model is by definition a simplification of reality. Therefore in reality there are always external factors playing a role. In the case of charging this could be a delay in the signal, or unforeseen losses due to battery temperature regulation. This new measured output is used as initial state for the next calculation of the optimal control sequence over the same horizon length. The first control action of this new control sequence is implemented again, and the other actions are discarded. In other words, the system keeps predicting the same number of steps into the future, hence the name Receding Horizon Control. One iteration is shown in Figure 3-1.

3-2 Cost function

The most common type of cost function is the linear quadratic cost function which has the following form

$$J(x(0), \mathbf{u}) = \frac{1}{2} \sum_{k=0}^{N-1} x^T(k)Qx(k) + u^T(k)Ru(k) + \frac{1}{2}x^T(N)P_f x(N) \tag{3-1}$$

with Q, R and P_f being the tuning parameters. The Q-matrix defines the penalty on the state and R defines the penalty on the inputs. P_f is the penalty on the final state. To guarantee existence and uniqueness of the solution, Q and P_f must be chosen real, symmetric and positive semidefinite, and R must be real, symmetric and positive definite. The reason that R must be positive definite is that setting R to zero would imply a free pass for the input to go to infinity. This exact function steers the input and the states to zero, but by replacing for example $x(k)$ by $a - x(k)$ the states are steered towards a.

By varying the weight on the terms relative to each other, the controller can be set to steer the system to its desired state quickly using large control actions, or more slowly using smaller control actions. By a large Q relative to R, the states are contributing more towards the total cost than the inputs. This means that it makes sense to use large inputs in order to push the states towards the reference more quickly. Note that the contribution of Q, R and P_f depend on their value relative to one another. Setting them all to $1000 \times I$ results in a different cost, but the exact same optimal input sequence $\mathbf{u}$, compared to setting them all to $0.1 \times I$.

3-3 Horizons

In MPC, two horizons can be distinguished. The prediction horizon, N_p and the control horizon N_c. For this thesis, they are assumed to be the same and will therefore be referred to as the horizon. This is, however, not necessarily the case. The prediction horizon determines how many time steps in the future the state is predicted. The control horizon indicates how many future control actions are computed. After the control horizon, it is assumed that the control signal does not change anymore (it is kept constant at the last value, $u(N_c)$), and with that assumption the total cost function (which is calculated over the prediction horizon) is minimized.

3-4 Shrinking horizon control

A specific type of model predictive control is Shrinking Horizon Model Predictive Control (SHMPC). SHMPC uses a prediction horizon that shrinks at each time step. For the use case at hand, this is a very useful feature, because the leaving time is static, and does not move forward every time step. SHMPC limits the number of time steps that the system needs to predict the future and calculate future inputs for, to the leaving time of the vehicle. This saves half of the computational load because the average horizon is exactly half of the number of time steps between the start and the end of the session (since the horizon decreases linearly from the initial horizon to 0). This is significant, especially if this system is to be implemented on a large scale, while being centrally computed. Moreover, if a receding horizon is used, many control actions are calculated for after the set departure time. This is a waste of computational power. Since model predictive control solves an online optimization problem in each time step, it is important to be cautious about the computational load. This computational intensity is also the largest drawback of MPC. In EV charging, the horizon is not receding. The departure time stays the same and comes closer every time step. Therefore a shrinking horizon control method makes sense in this case. Furthermore, since the goal is not one reference value, but the lowest cost based on a varying curve, it does not make sense to have a control horizon that is smaller than the prediction horizon. Therefore the control horizon and prediction horizon are always equal to the amount of time steps left until the set departure time.

3-5 MPC for smart EV Charging

Some research has already been done into MPC for EV charging. Yamaguchi et al. [15] proposed a method using MPC with a MILP objective function to optimize EV charging in a Home Energy Management System (HEMS). This paper focused on price optimization with different purchasing and selling price. An AR model was used to predict the energy consumption in future time steps. Later this research was appended with a particle swarm optimization. By using Particle Swarm Optimization (PSO), Yoshimura et al. [16] enabled the use of non-linear cost functions and non-linear constraints. The cost of charging at the office is also incorporated. The simulated scenario only accounts for vehicles traveling about 5 km to work and back, and only a few driving profiles and only one vehicle type is used. Therefore the results are not representative for the real world.

In 2017, Janjic et al. [17] proposed a predictive control approach to maximize profits from secondary frequency control for a commercial fleet. This was an interesting approach as it no longer puts the transportation function of EVs at the first place. The main objective is to maximize the total revenue gerenated by the fleet. To do so, the connection times are fixed and mandatory, taking away the freedom to use the vehicle at any time. Given the fixed connection times, the fleet owner tries to minimize customer waiting time. This is a very interesting and novel approach, but it is not applicable to personal vehicles which form the majority of vehicles on the road.

3-6 The battery model

As explained above, model predictive control requires a model of the system to be controlled. In this case, a model of the charging and discharging of a battery is needed. To this end, a simple, second order, discrete time direct input-output model was created:

$$x_{k+1} = \begin{bmatrix} E_{k+1} \\ P_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & dt \\ 0 & 0 \end{bmatrix} \begin{bmatrix} E_k \\ P_k \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \frac{1}{60} & -\frac{1}{60} \end{bmatrix} \begin{bmatrix} u_k^c \\ u_k^d \end{bmatrix} \tag{3-2}$$

$$y_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} x_k \tag{3-3}$$

where E denotes the electric energy stored in the battery, and P is the charging power in kWh per minute. u^c and u^d denote the charging and discharging power in kW respectively. Subscript k indicates the time step.

It is easy to see that this system is controllable. The controllability matrix, defined for a 2-dimensional system by

$$\mathcal{C} = \begin{bmatrix} B & AB \end{bmatrix} = \begin{bmatrix} 0 & 0 & {}^{dt}\!/_{60} & -{}^{dt}\!/_{60} \\ {}^{1}\!/_{60} & -{}^{1}\!/_{60} & 0 & 0 \end{bmatrix} \tag{3-4}$$

is clearly full row rank, hence the system is controllable.

Chapter 4

Methodology

In this chapter, the cost function and the constraints will be explained. As some of the constraints are soft, these will be incorporated in the cost function. The hard constraints are mostly physical limitations of the system, such as the maximum charging power and the grid connection capacity.

4-1 Minimizing carbon emissions

The first objective is singular and relatively straight-forward; minimize carbon emissions related to a households total electricity consumption. This is achieved by making sure the energy that needs to be drawn from the grid has an as low as possible carbon intensity. To minimize the carbon emissions related to a households electricity usage, some background knowledge is required.

Throughout every day, the energy mix of the grid electricity varies. On a sunny day around noon, a large part of the electricity may be generated by solar panels, pushing down the average carbon emissions for one kWh of electricity at that moment. During a windless winter evening on the other hand, the electricity will mostly be generated by gas and coal plants, resulting in high average carbon emissions per kWh. The real-time and historic carbon intensity are modeled and monitored by a firm called electricityMap.org.

4-1-1 Efficiency losses

While charging an EV, electric energy is converted from alternating current (AC) from the grid-side to direct current (DC), as the battery stores energy in DC. In this conversion, some of the energy is dissipated as heat, resulting in energy losses. When discharging, the DC electricity needs to be converted back to AC, which again induces some conversion losses. Other components such as the components and cables of the charge post, circuit breakers and the battery itself impose energy losses too, but the lion's share of the energy losses is due to the AC/DC transformer. The efficiency of these processes are dependent on several factors such as charging current, amount of phases used, state of charge of the battery and whether the vehicle is charging or discharging [14].

During charging, a Kia e-Niro for example scores an efficiency of 79.58% for 10A on one phase and 80.32% when the current is increased to 16A. Much larger differences are observed by switching to three-phase charging, resulting in 86.98% efficiency at 10A and 87.21% at 16A. The influence of charging current on the efficiency is minimal, meaning that PV-owners can easily scale the charging current depending on the PV output without noticeable difference in efficiency. Note that the low efficiency on single-phase charging is due to the fact that the on-board charger (which is essentially an AC/DC converter) is designed for three phase charging and is hence inefficient for single-phase charging [18]. For linearity purposes, it is assumed in this thesis that there is one constant charging efficiency and one constant discharging efficiency. For future studies it would be very interesting to investigate a method with a minimum charge and discharge speed, to prevent (dis)charging at a very low rate, as this often results in higher losses.

4-1-2 Battery degradation

There is one more factor that needs to be taken into account. Repeatedly charging and discharging results in battery degradation. Lots of research has been done in battery degradation and it depends on many factors. These factors can be split up in two categories; cyclic ageing and calendric ageing. Cyclic ageing is the degradation of the battery due to repeatedly charging and discharging the battery. Factors that play a role in cyclic ageing are C-rate (charging/discharging power in kW as fraction of the total capacity in kWh) and Depth of Discharge (DOD). Calendric ageing is the degradation of the battery due to time passing. Important factors for calendric ageing besides time are temperature and State of Charge (SOC) [19] [20]. Since most of the factors for calendric ageing are not influenced by charging, this is mostly left out of the equation. Interestingly, according to Ahmadian et al. [19], a (sustained) high SOC results in higher calendric ageing, and a low SOC (equivalent to a high DOD) results in increased cyclic ageing. This means that a high DOD increases degradation on a cycle basis, and high SOC increases degradation on a time basis. To limit the cyclic ageing, the ISO15118-20 protocol will likely support discharging up to a rate of 3.7 kW, which is usually less than 0.1C and for large batteries even less than 0.05C. As explained in section 4-3, soft constraints will be imposed on the state of charge to limit both the calendric ageing and cyclic ageing.

4-2 Single vehicle/HEMS model

The first use case explored in this thesis is the optimal charging using Vehicle-to-Grid (V2G) of an Electric Vehicle (EV) in a Home Energy Management System (HEMS). For the case at hand, the carbon intensity of the Dutch electricity grid will be used. It is assumed that the carbon emissions of electricity generated by a household Photo Voltaic (PV) system are zero, neglecting the emissions associated with the production of the PV system and the end-of-life related emissions. Therefore, the total carbon emissions related to the household electricity consumption is the volume drawn from the grid during each time step multiplied by the carbon intensity at that time step.

Since this model assumes a single household, it is assumed that the contribution on the grid carbon intensity of feeding electricity back to the grid is negligible. Consequently, it is undesirable to feed electricity back to the grid. This is an acceptable strategy since the Dutch government announced that the net-metering rule is being phased out, rendering feeding electricity back into the grid significantly less attractive, compared to directly consuming or storing this electricity within the household. For this method we will assume that perfect forecasts for electricity production, grid carbon intensity and household demand are available. The cost function then becomes

$$V_N(\mathbf{u}) = \sum_{k=1}^{N} e_k^+(u_k)c_k \tag{4-1}$$

where $\mathbf{u} = \begin{bmatrix} u_1 & \cdots & u_N \end{bmatrix} = \begin{bmatrix} u_1^c & \cdots & u_N^c \\ u_1^d & \cdots & u_N^d \end{bmatrix}$ denotes the vector of the decision variables, charging speed and discharging speed respectively, at each time step. N is the amount of time steps before departure, and is therefore also the horizon. c_k denotes the grid carbon intensity at time step k, in gr CO_2eq/kWh. e_k^+ denotes $\max(e_k, 0)$ with e_k the energy taken from/delivered to the grid, defined as

$$e_k(u_k) = e_{d,k} + e_{b,k}(u_k) - e_{p,k} \tag{4-2}$$

where $e_{d,k}$ denotes the domestic electricity demand at time step k, excluding the vehicle demand. $e_{b,k}$ is the electric energy delivered to the vehicle at time step k, and $e_{p,k}$ represents the energy production by a domestic solar PV or wind turbine. Note that $e_{g,k}$ and $e_{b,k}$ can also take negative values, indicating that energy is fed back into the grid or into the home respectively.

The most interesting part, and the only part we can influence, is the battery energy $e_{b,k}(u_k)$. The input u_k is defined as the effective electric power going into and out of the battery in kW. This means the power that is left after conversion for charging, and before conversion for discharging. This way, the battery model can stay simple, as discussed in chapter 3:

$$x_{k+1} = \begin{bmatrix} E_{k+1} \\ P_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & dt \\ 0 & 0 \end{bmatrix} \begin{bmatrix} E_k \\ P_k \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \frac{1}{60} & -\frac{1}{60} \end{bmatrix} \begin{bmatrix} u_k^c \\ u_k^d \end{bmatrix} \tag{4-3}$$

The battery energy is defined as follows:

$$e_{b,k}(u_k) = \begin{bmatrix} \frac{dt}{60} & -\frac{dt}{60} \end{bmatrix} \begin{bmatrix} u_k^c \frac{1}{\eta_c} \\ u_k^d \eta_d \end{bmatrix} \tag{4-4}$$

where η_c and η_d denote the charging and discharging efficiencies respectively. Different from the method used by Yamaguchi et al. [15], using this method, no auxiliary variables are needed and the problem is linear as is. Due to the efficiency losses, it will never be optimal to charge and discharge at the same time.

4-2-1 Constraints

Furthermore, we need several intuitive constraints to ensure satisfactory state of charge at departure time, a specific minimum state of charge throughout to conserve battery health and for emergency trips, and a specific maximum state of charge. Note that the minimum SOC is to limit the depth of discharge, which increases the cyclic ageing, while the maximum SOC is to limit the calendric ageing, which increases at high SOC.

The full objective function can now be rewritten as

$$V_N(\mathbf{u}) = \sum_{k=1}^{N} \max \left(e_{d,k} + \underbrace{\begin{bmatrix} \frac{dt}{60\eta_c} & -\frac{dt}{60}\eta_d \end{bmatrix} \begin{bmatrix} u_k^c \\ u_k^d \end{bmatrix}}_{e_{b,k}(u_k)} - e_{p,k},\ 0 \right) c_k \tag{4-5}$$

$$\text{s.t.}\ \ u_k^c, u_k^d \geq 0 \tag{4-6}$$

$$u_k^c \leq \text{ecs} \tag{4-7}$$

$$u_k^d \leq \text{eds} \tag{4-8}$$

$$E_k \geq \text{minSOC} * B \tag{4-9}$$

$$E_k \leq \text{maxSOC} * B \tag{4-10}$$

$$E_N \geq \text{dSOC} * B \tag{4-11}$$

where E denotes the first state from Equation 4-3, representing the battery energy, ecs and eds denote the estimated (max) charge and discharge speed respecitvely. minSOC and maxSOC denote the state of charge boundaries set by user preferences for battery health conservation and emergency trip reserves. B denotes the battery capacity of the EV, ans dSOC denotes the desired state of charge.

4-3 Soft SOC boundaries

The cost function as described above has one major drawback: when a vehicle has a SOC that is lower than the minimum SOC or higher than the maximum SOC at the moment of connection, the problem becomes infeasible and the program stops. This is solved by implementing constraints 4-9 and 4-10 in the cost function as soft constraints by adding two terms to the cost function:

$$C_l \max \left(\frac{\text{minSOC}}{100} * B - E_k,\ 0 \right) \tag{4-12}$$

$$C_u \max \left(E_k - \frac{\text{maxSOC}}{100} * B,\ 0 \right) \tag{4-13}$$

where C_l and C_u denote weights for violating the lower bound and upper bound respectively. This way the SOC is allowed to violate the bounds at a cost. A high value for C_l and C_u will result in direct charging/discharging until the SOC is within bounds, regardless of the current carbon intensity. A low value on the other hand, will result in a slight preference to

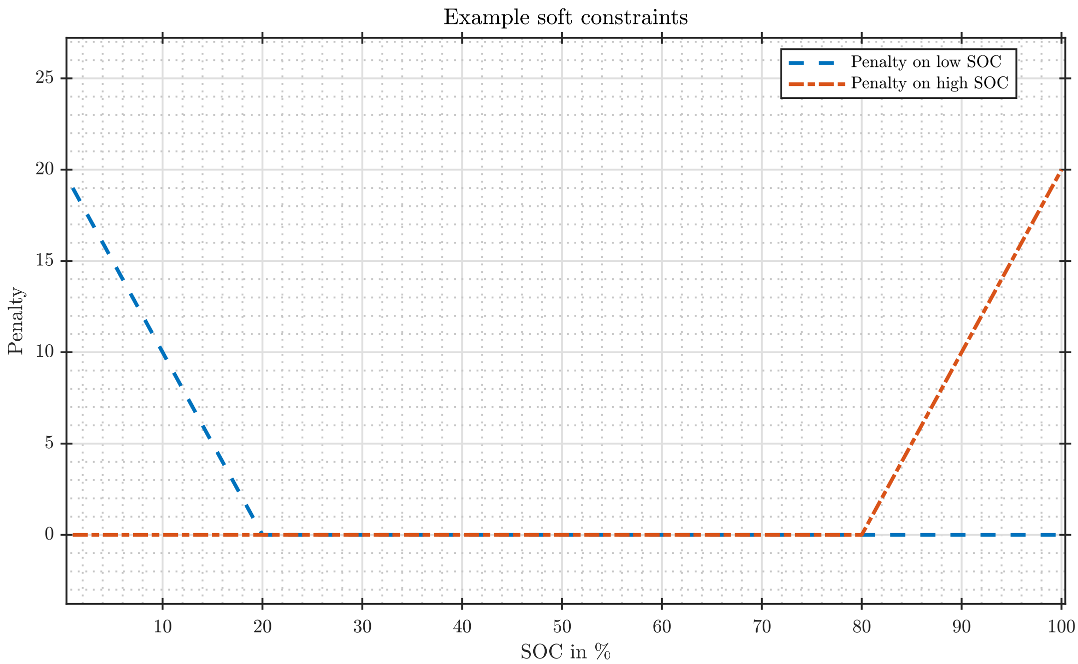

Figure 4-1: Penalty for a being at an SOC below minSOC or above maxSOC

stay within bounds, but if a high profit in terms of emissions can be made, these bounds can be violated. A big violation will always result in a higher penalty than a small violation. An example of these expressions is shown in Figure 4-1. In this example minSOC and maxSOC are taken to be 20% and 80% respectively, and C_l and C_u are both equal to 1. Moreover, if the dSOC is higher than the maxSOC, the charging above maxSOC will happen only at the very end of the charging session, regardless of the carbon intensity at that time. This is due to the fact that a penalty is observed for every time step that the SOC is above the maxSOC. The model will violate this maxSOC for a minimal number of time steps, hence this only happens at the very end of the session. This is a fair policy since sustaining a high SOC for extended periods of time increases the calendric battery degradation heavily [19]. If a user wants a SOC of 100% at the end of his session, for example because the user has a road trip planned, it is wise to fill up the SOC only just before leaving. This is in line the advise that OEMs give to their customers buying their first EV. Since the trade-off between violating the maxSOC for a longer period of time and having to charge at the end of the session regardless of the carbon intensity is a personal choice, it could be considered to make these weights user inputs. Users typically won't have a great understanding of the meaning of these weights, so they could be advised by the supplier of the controller. Another option would be to further research the cost of degradation, and base the weights on this cost. This would, however, result in a dynamic weight which could significantly increase the complexity of the model.

The total cost function now becomes

$$
\begin{aligned}
V_N(\mathbf{u}) = \sum_{k=1}^{N} \max & \left(e_{d,k} + \underbrace{\begin{bmatrix} \frac{dt}{60\eta_c} & -\frac{dt}{60}\eta_d \end{bmatrix} \begin{bmatrix} u_k^c \\ u_k^d \end{bmatrix}}_{e_{b,k}(u_k)} - e_{p,k},\ 0 \right) c_k \\
& + C_l \max\left(\frac{\text{minSOC}}{100} * B - E_k,\ 0 \right) \\
& + C_u \max\left(E_k - \frac{\text{maxSOC}}{100} * B,\ 0 \right)
\end{aligned} \tag{4-14}
$$

$$
\text{s.t. } u_k^c, u_k^d \geq 0 \tag{4-15}
$$

$$
u_k^c \leq \text{ecs} \tag{4-16}
$$

$$
u_k^d \leq \text{eds} \tag{4-17}
$$

$$
E_N \geq \text{dSOC} * B \tag{4-18}
$$

4-4 Carbon versus price optimization

As can be seen in chapter 5, using only carbon optimization oftentimes results in no discharging, as the volatility of the carbon intensity is not high enough to make it worth discharging and incurring the associated conversion losses. However, if the price is chosen as optimization parameter, discharging is very often desirable. Moreover, the business model with carbon optimization is unfortunately quite weak as it often results in more expensive charging compared to unidirectional, price optimized charging, which is the current state of the art. Ultimately most consumers want to minimize their electricity bill. This could, also from an environmental perspective, still be a reasonable approach.

In the current energy market, the cheapest sources are always put into operation first. The cheapest sources are always renewable, since they have no marginal operation costs and are therefore considered free, whereas gas and coal have a price tag since they consume resources and require labourers to produce electricity. This means that consuming more electricity can, and at certain volumes surely will, result in making use of a more expensive and therefore often dirtier energy source. This way, when electricity is cheap this usually means it is relatively clean too, and choosing to charge at this point often results in more renewable or nuclear power to be put into operation. This principle is shown in Figure 4-2. Note that this regards the wholesale energy prices, which is often not what consumers pay. However, for this case it is assumed that the user is on a dynamic rate, which represents the day-ahead hourly wholesale price.

The negative side of this approach is that currently, the marginal price of electricity from a coal plant is lower than electricity from a gas plant. This means that optimizing over price will sometimes prefer staying at the coal plant electricity rather than moving up to gas plant electricity, while moving up may decrease the average carbon intensity.

To do this, a very small alteration to the cost function was made by replacing the carbon

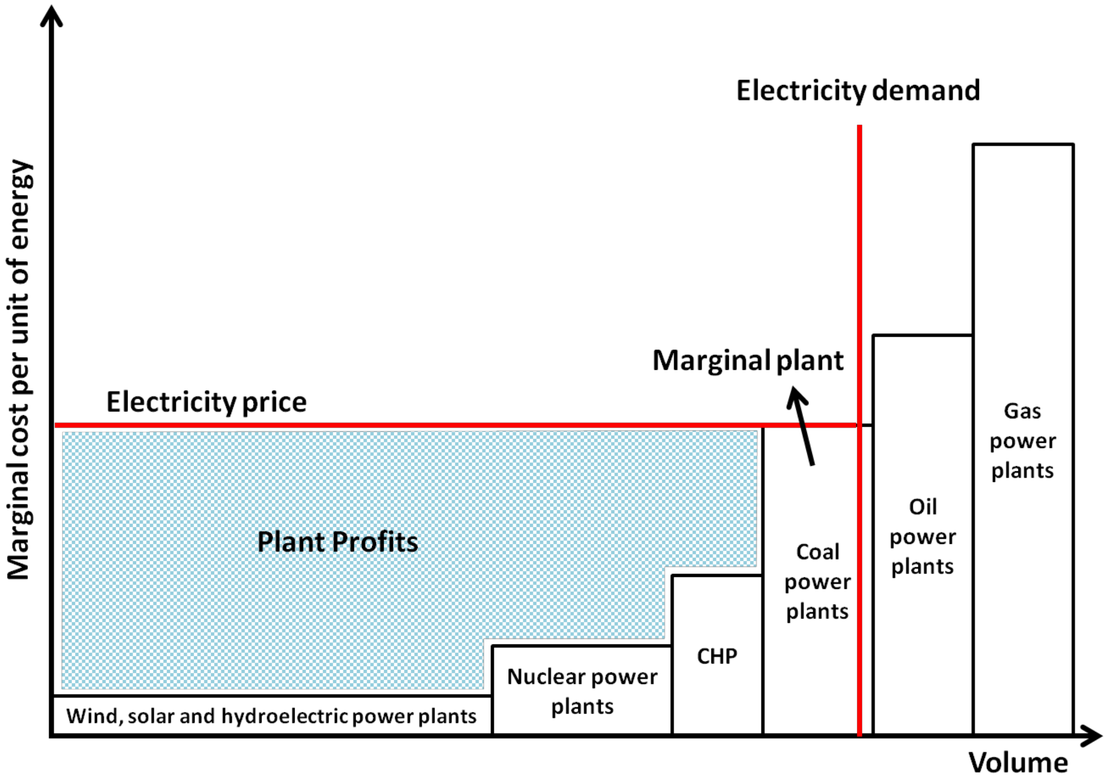

Figure 4-2: Merit order dispatch in electricity markets [3]

intensity for the day-ahead price, resulting in the following:

$$\begin{aligned} V_N(\mathbf{u}) = \sum_{k=1}^{N} \max & \left(e_{d,k} + \underbrace{\begin{bmatrix} \frac{dt}{60\eta_c} & -\frac{dt}{60}\eta_d \end{bmatrix} \begin{bmatrix} u_k^c \\ u_k^d \end{bmatrix}}_{e_{b,k}(u_k)} - e_{p,k},\ 0 \right) p_k \\ & + C_l \max\left(\frac{\text{minSOC}}{100} * B - E_k,\ 0 \right) \\ & + C_u \max\left(E_k - \frac{\text{maxSOC}}{100} * B,\ 0 \right) \end{aligned} \tag{4-19}$$

$$\text{s.t. } u_k^c, u_k^d \geq 0 \tag{4-20}$$

$$u_k^c \leq \text{ecs} \tag{4-21}$$

$$u_k^d \leq \text{eds} \tag{4-22}$$

$$E_k \geq \text{minSOC} * B \tag{4-23}$$

$$E_k \leq \text{maxSOC} * B \tag{4-24}$$

$$E_N \geq \text{dSOC} * B \tag{4-25}$$

where p_k denotes the day-ahead electricity price per kWh at time step k.

4-4-1 Penalty on changing charge speed

As can be seen in chapter 5, the cost function optimizing over electricity price resulted in some undesirable behaviour, since this price is constant for a full hour. Clearly, the model will use the cheapest hours possible for charging. Since it is very unlikely (and theoretically impossible) that the most expensive hour needed, is needed for the full hour, it will only need a part of this hour, giving some flexibility in when to charge during this hour. Without any incentive to charge in a specific way during this hour, it could switch on and off infinitely many times without the total cost changing. Therefore a very small penalty was added to the derivative of the charge speed as follows:

$$\begin{aligned} V_N(\mathbf{u}) = \sum_{k=1}^{N} \max \left(e_{d,k} + \underbrace{\begin{bmatrix} \frac{dt}{60\eta_c} & -\frac{dt}{60}\eta_d \end{bmatrix} \begin{bmatrix} u_k^c \\ u_k^d \end{bmatrix}}_{e_{b,k}(u_k)} - e_{p,k},\ 0 \right) p_k \\ + C_l \max\left(\frac{\text{minSOC}}{100} * B - E_k,\ 0\right) \\ + C_u \max\left(E_k - \frac{\text{maxSOC}}{100} * B,\ 0\right) \\ + \varepsilon \left|\Delta u_k\right| \end{aligned} \tag{4-26}$$

$$\text{s.t. } u_k^c, u_k^d \geq 0 \tag{4-27}$$

$$u_k^c \leq \text{ecs} \tag{4-28}$$

$$u_k^d \leq \text{eds} \tag{4-29}$$

$$E_k \geq \text{minSOC} * B \tag{4-30}$$

$$E_k \leq \text{maxSOC} * B \tag{4-31}$$

$$E_N \geq \text{dSOC} * B \tag{4-32}$$

where ε denotes an arbitrary small number.

4-5 Multi-vehicle scenario

To create a method that is more feasible to be implemented on a large scale, a multi-vehicle optimization model was built in a way that an aggregator such as Jedlix is able to monetize the flex provided by users. For the business model to hold, the main focus in this model is optimization on price, although carbon optimization is explored too. Moreover, the results in terms of carbon of both models are extensively analysed in chapter 5.

For an aggregator it is infeasible to incorporate household demand into the equation, hence this is not taken into account. Moreover, with a view on the future of net-metering, it is very much possible that the price received for feeding back electricity will be simply the day-ahead price or the imbalance price. This is one of the scenarios that is assessed for the multi-vehicle models.

To this end, a new cost-function was constructed, not only summing over the time steps but also over the vehicles. The household consumption and production are not taken into account, because especially household consumption is almost impossible to predict and generally not in the scope of an aggregator. Solar production will be taken into account later in subsection 4-5-1. The new cost function then becomes:

$$\begin{aligned} V_{N,W}(\mathbf{u}) = \sum_{k=1}^{N} \sum_{m=1}^{W} & \underbrace{\begin{bmatrix} \frac{dt}{60\eta_m^c} & -\frac{dt}{60}\eta_m^d \end{bmatrix} \begin{bmatrix} u_{k,m}^c \\ u_{k,m}^d \end{bmatrix}}_{e_{k,m}(u_{k,m})} \quad p_k \\ & + C_l \max(\text{minSOC}_m/100 * B_m - E_{k,m},\ 0) \\ & + C_u \max(E_{k,m} - \text{maxSOC}_m/100 * B_m,\ 0) \\ & + \varepsilon \left|\Delta u_{k,m}\right| \end{aligned} \tag{4-33}$$

$$\text{s.t.}\ \ u_{k,m}^c, u_{k,m}^d \geq 0 \tag{4-34}$$

$$u_{k,m}^c \leq \text{ecs}_m \tag{4-35}$$

$$u_{k,m}^d \leq \text{eds}_m \tag{4-36}$$

$$u_{k,m}^c = u_{k,m}^d = 0 \qquad \text{if } k > N_m \tag{4-37}$$

$$E_{N_m} \geq \text{dSOC}_m * B_m \tag{4-38}$$

where W denotes the total number of active sessions and m is the session/vehicle index. $k = 1$ for the current time step, and $k = N$ for the time step where the last vehicle disconnects. N_m is the final time step for session m, and $N = \max_m(N_m)$. Note that this cost function is optimized again at every time step, where N and W are updated to include all the sessions active at that very time step. This means that both N and W are time-varying. This was not indicated in the equation for brevity.

This model does not take in to account that most EV users don't pay the day-ahead price for their electricity. In stead, in The Netherlands, about 80% of people still have a dual tariff energy plan. This means that during the day (usually between 07:00 and 23:00), users pay a peak rate for their electricity, and during the night (23:00 to 07:00) they pay a lower off-peak rate. Current practice is that users will always charge during their off-peak rate as much as possible, a so-called 'user-first' strategy. This means that if a vehicle can fulfill its charging needs during off-peak hours, this must happen. If a vehicle needs all the available off-peak hours, and additionally needs for example 5 kWh of peak hour charging, the system must ensure that no more than 5 kWh is charged during peak hours, and the vehicle is charging throughout the available off-peak hours. This way it is ensured that the user always pays the lowest possible price for charging the EV.

This feature is implemented in the model too, by adding a large penalty for charging during a users peak hours. For each session, the corresponding type of contract is examined and an array is created with zero's during off-peak hours and high values during peak hours. If the user is on a dynamic rate or on single tariff, the array contains only zero's. This array is multiplied with the charging power per time step resulting in the following cost function:

$$
\begin{aligned}
V_{N,W}(\mathbf{u}) = \sum_{k=1}^{N} \sum_{m=1}^{W} & \underbrace{\begin{bmatrix} \frac{dt}{60\eta_m^c} & -\frac{dt}{60}\eta_m^d \end{bmatrix} \begin{bmatrix} u_{k,m}^c \\ u_{k,m}^d \end{bmatrix}}_{e_{k,m}(u_{k,m})} \; p_k \\
& + C_l \max(\text{minSOC}_m/100 * B_m - E_{k,m},\ 0) \\
& + C_u \max(E_{k,m} - \text{maxSOC}_m/100 * B_m,\ 0) \\
& + \varepsilon \, |\Delta u_{k,m}| \\
& + \text{TP}_{k,m} \ \frac{dt}{60\eta_m^c} \ u_{k,m}^c
\end{aligned}
\tag{4-39}
$$

$$
\text{s.t.} \quad u_{k,m}^c, u_{k,m}^d \geq 0 \tag{4-40}
$$

$$
u_{k,m}^c \leq \text{ecs}_m \tag{4-41}
$$

$$
u_{k,m}^d \leq \text{eds}_m \tag{4-42}
$$

$$
u_{k,m}^c = u_{k,m}^d = 0 \qquad \text{if } k > N_m \tag{4-43}
$$

$$
E_{N_m} \geq \text{dSOC}_m * B_m \tag{4-44}
$$

where $\text{TP}_{k,m}$ denotes the tariff penalty for session m at time step k, which - as stated above - will be a high number if the respective user is in peak-rate at k.

The way of handling user tariff differences as implemented, is the way Jedlix currently tackles this situation. As stated before, the most important objective is to keep the user cost for charging at a minimum. This limits the possibilities for the aggregator severely. Especially in summer during daytime, low-carbon and cheap electricity is often available during the day, but the aggregator is not allowed to charge most of the vehicles because users are in peak rates during these hours. A possible solution to this problem could be to overrule the user preferences, and compensate the user for any excess electricity charged during peak hours. With increasingly volatile energy prices, it may very well be beneficial for an aggregator to overrule the user's tariffs and charge during user peak hours, and compensate the user for the more expensive session. Clearly this compensation is necessary since otherwise users would simply stop using the service since it does not provide the cheapest possible charging. This is a small step from the current model, as the only thing that needs to change is the magnitude of the penalty for charging at peak hours. In stead of an arbitrary high number, this can be changed into the price difference between a users peak and off-peak rate. This represents exactly the amount that an aggregator would need to compensate the user for. If the high number in TP_m is replaced by $(g_m^{\text{peak}} - g_m^{\text{off-peak}})$, where g_m^{peak} and $g_m^{\text{off-peak}}$ denote the user's peak and off-peak tariff respectively, this is problem is solved. This way, charging during user peak hours only happens if it is profitable for Jedlix to do so, taking into account that the user needs to be compensated. An example of this tariff penalty is shown in Figure 4-3

What is not yet taken into account here, is that energy is lost when providing V2G services. As explained in subsection 4-1-1, charging and discharging an electric vehicle comes with efficiency losses. Taking 10 kWh from a battery is good for feeding 10 $\eta_d \approx 8.5$ kWh back into the grid. To then fill up the battery to the initial SOC, ${}^{10}/_{\eta_c} \approx 11.11$ kWh is needed from the grid. Assuming that the two happen during the same rate period, this means that the user is paying for 2.61 kWh more than if no V2G operation would have taken place. This damage could be limited if the discharging happens at a price that is not only cheaper for the utility

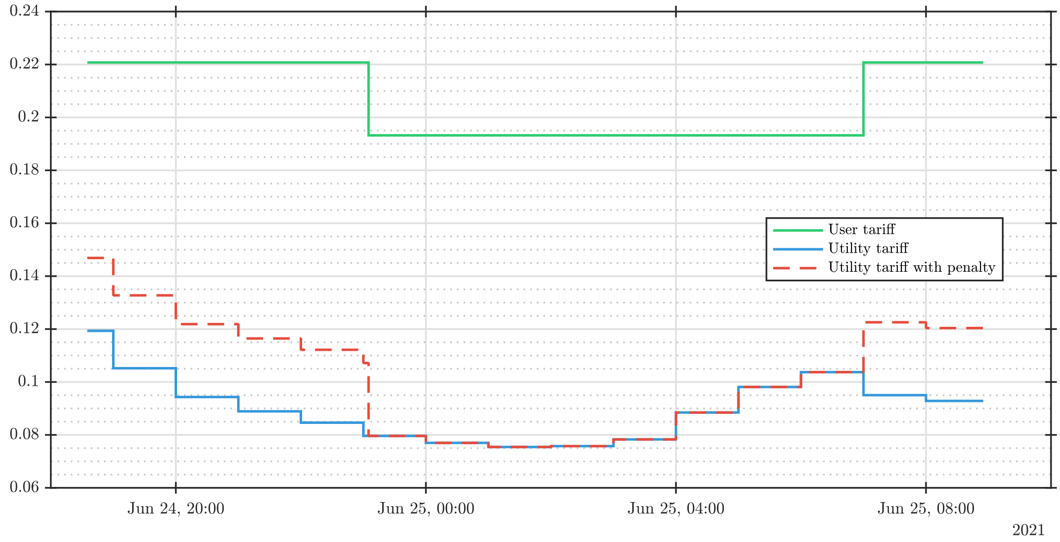

Figure 4-3: Example of tariff compensation penalty

or aggregator but also for the user. Either way, the user needs to be compensated for any additional loss, if a business case needs to be built. This could be incorporated in the cost function by an extra term $\left(\frac{dt}{60\eta_m^c} - \frac{dt}{60}\eta_m^d\right) u_k^d g_m^{\text{peak}}$. This way the user is compensated at the users peak tariff for the extra electricity that is consumed. Due to time restrictions this is considered outside of the scope of this research. Therefore the "V1G" smart charging model was used to compute the lowest possible session price for the user, and this was compared to the cost of the V2G optimized charging policy.

4-5-1 Solar implementation

As mentioned before, net metering will be phased out over the upcoming years. Assuming once again that grid feedback will only yield the day-ahead price in the future, it becomes much more interesting to make sure generated electricity is consumed within the household. Therefore, an effort was made to incorporate PV production in the equation. By providing details on the location, azimuth, tilt and capacity of a PV set-up, the *Solcast* platform is able to accurately predict the PV production.

The expression for $e_{k,m}(u_{k,m})$ is transformed to include solar production, and the tariff penalty is now imposed whenever the sum of PV production and charging power results in grid power consumption. The reason that household usage is not taken into account in this optimization is that it is, especially from an aggregators perspective, unrealistic to assume this information is available.

Household usage predictions would be inaccurate. This results in undesired feeding back solar electricity whenever the household consumes less than predicted, or undesired grid consumption whenever the household consumes more than predicted. In the last case, flexibility is lost, since solar electricity could have been used for the household, leaving more flexibility in the battery charging. The unwanted feedback of generated solar is assumed to be more expensive than the loss of flexibility. For the solar model, price-optimization is used. The cost function then becomes:

$$
\begin{aligned}
V_{N,W}(\mathbf{u}) = \sum_{k=1}^{N} \sum_{m=1}^{W} & \left(\underbrace{\begin{bmatrix} \frac{dt}{60\eta_m^c} & -\frac{dt}{60}\eta_m^d \end{bmatrix} \begin{bmatrix} u_{k,m}^c \\ u_{k,m}^d \end{bmatrix} - \frac{dt}{60}\ e_{p,k,m}}_{e_{k,m}(u_{k,m})} \right) \ p_k \\
& + C_l \max(\text{minSOC}_m/100 * B_m - E_{k,m},\ 0) \\
& + C_u \max(E_{k,m} - \text{maxSOC}_m/100 * B_m,\ 0) \\
& + \varepsilon \left|\Delta u_{k,m}\right| \\
& + \text{TP}_{k,m}\ \max\left(e_{k,m},\ 0\right)
\end{aligned} \tag{4-45}
$$

$$
\text{s.t.}\ \ u_{k,m}^c, u_{k,m}^d \geq 0 \tag{4-46}
$$

$$
u_{k,m}^c \leq \text{ecs}_m \tag{4-47}
$$

$$
u_{k,m}^d \leq \text{eds}_m \tag{4-48}
$$

$$
u_{k,m}^c = u_{k,m}^d = 0 \qquad \text{if } k > N_m \tag{4-49}
$$

$$
E_{N_m} \geq \text{dSOC}_m * B_m \tag{4-50}
$$

Note that the tariff penalty is now imposed on any electricity consumed from the grid, not on electricity charged to the vehicle. This is pivotal for the system to work, because otherwise charging during peak tariff would be penalized, while solar generation exclusively happens during peak tariff. Therefore, self-consumption by means of EV charging would be penalized, which is counterproductive. Note that generated solar may very well still be fed back to the grid, if the grid price is attractive. As can be seen in chapter 5, currently the solar charging feature often results in a higher price for the consumer. This is due to the fact that many consumers are on a tariff plan that is cheaper than the cheapest moments on the day-ahead market. Using the possible future scenario, where electricity feedback yields the day-ahead price, and electricity consumption is subject to the user tariff, it will always make sense to sell as much as possible, since it can always be bought back for less.

Therefore, the scenario where everyone uses tariffs as they were offered on august 12, 2022, was also investigated. At this day, prices as obtained from Dutch utility Oxxio were as follows:

- Dual rate: Peak: €0.75162/kWh, Off-peak: €0.58214/kWh
- Single rate: €0.66541/kWh

4-6 Assumptions

In this section, an overview is presented of all the assumptions that are made in the models.

4-6-1 Single Vehicle/HEMS scenario

- There are no disturbances in the system
- Feeding back electricity to the grid yields no benefit in terms of carbon
- Perfect information is available on future household demand and production
- No delays are apparent in the communication between controller and EV
- The charge speed and discharge speed can be precisely controlled between -3.7 and 11 kW
- The vehicle has a 50 kWh battery
- The startSOC is 40 % and the dSOC is 80 %, resulting in a session of 20 kWh

4-6-2 Multi-vehicle scenario

- There are no disturbances in the system
- Feeding back electricity to the grid yields either negative carbon emissions at the intensity of that moment or the day-ahead price, depending on the optimization curve
- The charge speed and discharge speed can be precisely controlled between -3.7 and 11 kW
- The minSOC and maxSOC are fixed at 20 % and 90 % respectively
- Peak rate hours are 07:00 - 23:00
- Accurate information is available regarding the current SOC of the vehicle
- Solar electricity is assumed to be free in terms of both money and emissions
- Household usage is assumed to be unpredictable and is left out of the equation

4-7 Optimization

For implementing the MPC, the `YALMIP` toolbox was used. If no specific solver is assigned, `YALMIP` automatically chooses a suitable solver. All cost functions have been formulated in a way that the MATLAB solver '`linprog`' can solve them efficiently. This way, `YALMIP` automatically chooses `linprog` as solver. However, it can be seen that a non-linear term is present in Equation 4-5 and 4-45:

$$\max\Big(e_{d,k} + e_{b,k}(u_k) - e_{p,k},\ 0\Big) \text{ and } \max\Big(e_{k,m},\ 0\Big) \tag{4-51}$$

Luckily, the solver recognizes this and automatically translates this non-linear term into linear terms by introducing an auxiliary variable. If this variable is called α, Equation 4-51 is replaced by α and the constraints $e_{d,k} + e_{b,k}(u_k) - e_{p,k} \leq \alpha$ and $0 \leq \alpha$ are added. Now the problem is linear. Linprog only solves the solver-based optimization problem (see here) By default, the `linprog` function uses the dual simplex algorithm. If this algorithm fails, `linprog` can be forced to use the interior point algorithm. As the dual simplex performed well, I will only explain this option. For further information please refer to the MATLAB documentation [21]. Regardless of the chosen algorithm, `linprog` will first preprocess the problem in an attempt to simplify it. This is done by the following steps [21]:

- Check if there are variables with the same upper and lower bound. If so, fix and remove the variable
- Check if any linear constraint involves only one variable. If so, change constraint to bound (in case of an inequality constraint) or fix and remove the variable (in case of an equality constraint)
- Check if bounds and linear constraints are consistent
- Check if all variables are bounded by constraints. If not, check for boundedness and fix variables at their bound.
- Convert linear inequalities to equalities using slack variables

4-7-1 Dual simplex algorithm

The `linprog` dual simplex algorithm performs a simplex algorithm on the dual problem. By preprocessing as described above, the original problem is reduced to the primal problem in the form

$$\begin{aligned} &\min_x f^T x \\ &\text{s.t. } \begin{cases} A \cdot x = b \\ \quad 0 \leq x \leq u. \end{cases} \end{aligned} \tag{4-52}$$

where A and b are the constraint matrices.

These are subsequently translated into the dual problem:

$$\begin{aligned} &\max b^T y - u^T w \\ &\text{s.t. } \begin{cases} A^T \cdot y - w + z = f \\ \qquad\qquad z \geq 0, w \geq 0. \end{cases} \end{aligned} \tag{4-53}$$

where y and w denote the vectors of Lagrange multipliers associated with the equality and inequality constraints respectively, and z denotes a slack variable vector.

Now that the dual problem is constructed, the dual simplex algorithm starts the first phase. In phase 1, the algorithm looks for an initial feasible solution by solving an auxiliary problem, with the objective function being the linear penalty function

$$P = \sum_j P_j(x_j)$$

where $P_j(x_j)$ takes a positive value whenever one of the bounds of the original problem is violated. That is:

$$P_j\left(x_j\right) = \begin{cases} x_j - u_j & \text{if } x_j > u_j \\ 0 & \text{if } l_j \leq x_j \leq u_j \\ l_j - x_j & \text{if } l_j > x_j \end{cases} \tag{4-54}$$

with l_j and u_j the lower and upper bounds of variable x_j respectively. This way, at any point where the value of P equals zero, the original problem has a feasible point.

This feasible point is then used as initial point for phase 2. In phase 2, the simplex algorithm is applied, starting at the initial point obtained in phase 1. To explain what happens during phase 2, a definition of basic and nonbasic variables is needed. Assuming the problem is given in the standard form of Equation 4-52, and A is an m-by-n matrix of rank $m < n$, then the basic variables are the m variables of which the column is contained in the basis for the column space of A. The complement of these basic variables, the variables that are *not* contained in the basis for the column space of A, are called the nonbasic variables.

The vector of basic variables is denoted as x_B, and the vector of nonbasic variables is denoted as x_N. At each iteration, the algorithm checks the solution for optimality according to the optimality conditions defined as:

$$\begin{gathered} F(x, y, z, s, w) = \begin{pmatrix} A \cdot x - b \\ x + s - u \\ A^T \cdot y - w + z - f \\ x_i z_i \\ s_i w_i \end{pmatrix} = 0, \\ x \geq 0, z \geq 0, s \geq 0, w \geq 0 \end{gathered} \tag{4-55}$$

if the solution is not optimal, the algorithm continues with the following steps:

1. Pick one variable, the *entering variable*, from x_N, and add corresponding column of the nonbasis to the basis
2. Pick one variable, the *leaving variable*, from x_B and add corresponding column of the basis to the nonbasis (removing it from the basis)
3. Update solution and objective value
4. Check optimality conditions
5. If optimal: terminate, if not optimal: start from 1.

This way, the algorithm checks all the vertices for optimality until it finds the optimal one.

4-8 Data processing

For the single vehicle scenario, household consumption and production data was obtained from the UCI Machine Learning Repository [22], and was recorded at a house in Sceaux (7 km south of Paris). As very little specific household data was available, only one households data was used to show the working of the model. In this data set the average power was transformed to energy per time step and interpolated to fit the 5 minute step size. Carbon intensity data was a courtesy of Electricitymap.org and day-ahead prices were obtained from the publicly available Entsoe transparency platform. The day-ahead prices were retimed to 5 minute intervals and forward filled. The carbon intensity data was linearly interpolated to 5 minute intervals. No statistically significant results could be obtained due to the lack of representative data.

For the simulations of the multi-vehicle scenario, in addition to carbon data from Electricitymap.org and day-ahead prices from Entsoe, data provided by Jedlix was used. Jedlix provided access to their database, making it possible to combine several tables to obtain comprehensive session data, consisting of i.a.:

- start time
- stop time
- start SOC
- desired SOC
- battery capacity
- tariff type
- tariffs

The set was then filtered, to delete all faulty or very short sessions. As the user tariffs are manually entered by the users, there is uncertainty regarding the reliability of these tariffs. For example, some users put their tariffs in euro cents per kWh in stead of euro per kWh. The system then thinks that the user pays about €25/kWh, in stead of €0.25/kWh. Therefore, all sessions with single tariffs higher than €0.75/kWh and all sessions with peak tariffs higher than €1.00/kWh were removed from the set.

Furthermore, the start times were rounded up to the following 5-minute interval and the stop times were rounded down to the previous 5-minute interval. This does cost a tiny bit of flexibility but ensures that every session is optimized synchronously.

The user price for users with dynamic rates is calculated according to the taxation as in place in august 2022. This means that on top of the day-ahead price the energy tax (€0.04010/kWh) and ODE (surcharge for sustainable energy- and climate transition, €0.03325/kWh) are added, and subsequently 9% VAT is added to the gross sum.

Now a set was created for weekday sessions and another set for weekend sessions. Weekday sessions start and end on a weekday, and have a duration of between 4 and 24 hours. Weekend sessions start on friday, saturday or sunday and are between 4 and 60 hours. The complete data sets consist of 2855 weekday sessions and 1424 weekend sessions summing to a total of 4279 sessions that took place between June 23, 2021 and June 23, 2022.

4-8-1 Solar

For the solar feature, a different set of sessions was used. This is due to the availability of the solar data. This feature was added later in the process of this thesis, and the source for solar data, Solcast, only allows for historic data queries up to one week ago. Therefore, the data was captured for a period of 3 weeks, between July 21, 2022 and August 11, 2022. Clearly, this is summer data and the results are therefore by no means representative for yearly numbers, but they do show the workings of the model. In total, 314 sessions of users with a solar PV set-up were simulated. The PV generation data was generated by Solcast, and the carbon intensity, day-ahead prices and session details were used from Elecricitymap, Entsoe and Jedlix respectively.

4-9 Comparison

Results of the main models are compared with a baseline strategy where no smart charging happens. The vehicle starts charging immediately at its maximum charging speed, and stops when it reaches the desired state of charge. Another strategy is also created, in which a unidirectional algorithm decides the optimal times to charge, without utilizing V2G capabilities. This strategy is called 'V1G'. Basically, the only change that needs to be made is that the discharging speed is fixed to 0. Moreover, the minimization of carbon emissions is compared to the minimization of electricity costs, in terms of average carbon intensity, as it is expected that these will show a certain correlation.

Chapter 5

Numerical results

5-1 Single-vehicle/HEMS scenario

For the single vehicle scenario, it is assumed that the user has a dynamic rate electricity plan, as this is the scenario in which the steering of EV charging is most lucrative for the user, and therefore most demand for a system like this will come from consumers with this type of plan. In a dynamic rate plan, the user has a different kWh price each hour, based on the day-ahead price. As very little specific household data was available, only one households data was used to show the working of the model. Therefore no statistically significant results could be obtained at this time. The first scenario that was analysed assumes that the EV arrives at 18:30 on a Tuesday and leaves the next morning at 07:00.

In Figure 5-1 can be seen that the carbon optimization results in no discharging at all. This can be explained by the fact that the grid carbon intensity fluctuates between 383 and 319 gr/kWh. This is not enough to justify charging and discharging, where the round-trip efficiency is 76.5% percent. In order to justify V2G operation while optimizing on total carbon emissions in the shown scenario, the moments of charging must be less than 76.5% of the moments of discharging. It is important to note that the least carbon intensive times of a session can not be used for V2G as they will be used regardless to fulfill the charging demand.

The day-ahead price, on the other hand, fluctuates between €219.09/MWh and €108.91/MWh. Since less than two hours is needed to fulfill the charging demand, it is possible to charge extra during the second cheapest hour and the third cheapest hour, at €111.52/MWh and €112.88/MWh. This is significantly less than 76.5% of €219.09/MWh, making it profitable to discharge at the beginning as shown in Figure 5-2.

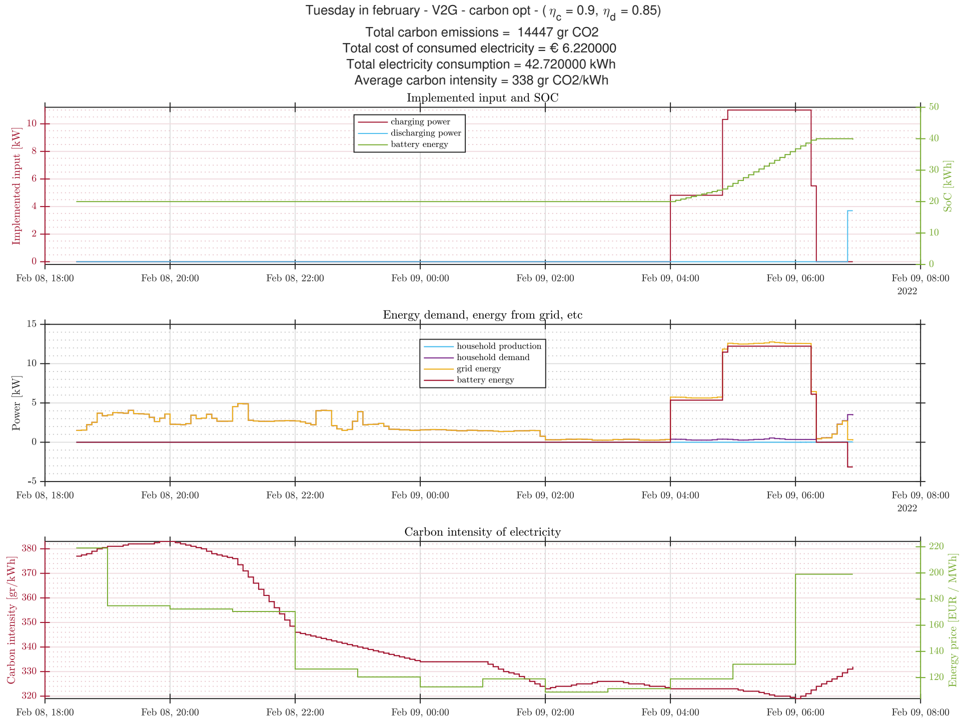

Figure 5-1: First scenario - V2G Carbon optimized

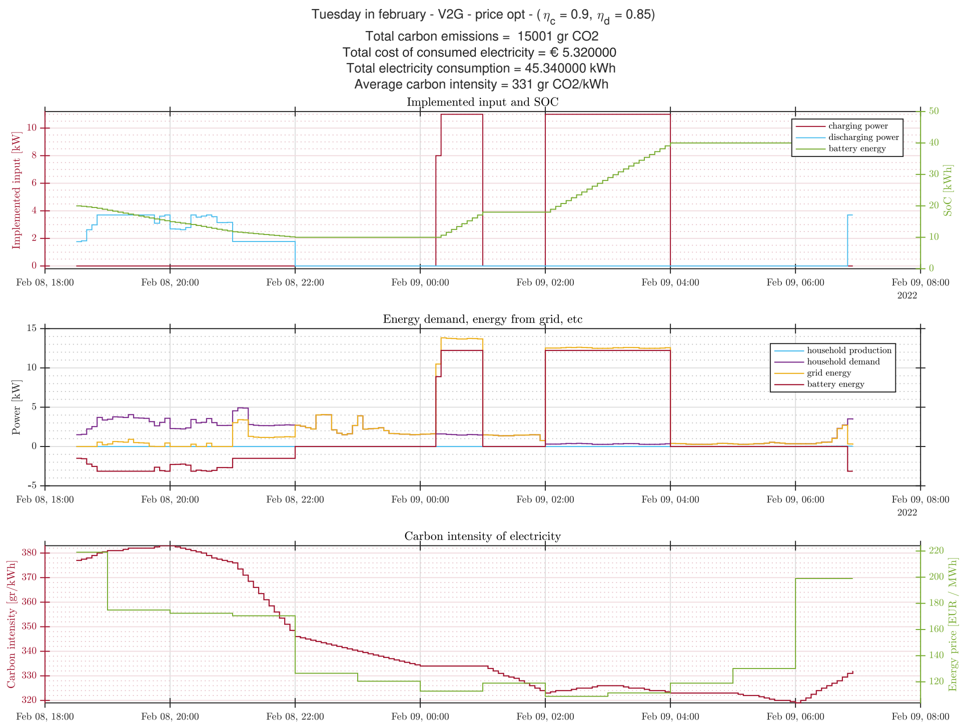

Figure 5-2: First scenario - V2G Price optimized

The second scenario shown assumes that the EV arrives at 18:00 on a Friday in April, and leaves the next evening at 18:00 on Saturday.

The first baseline strategy shown in Figure 5-3, named 'Direct charging', simulates a baseline strategy using uncontrolled charging. This means that the vehicle starts charging at its maximum charge speed upon connection, and stops when the desired SOC is reached. The associated *bought* electricity had total associated emissions of 15654 grams of CO_2, averaging at 403 gr/kWh.

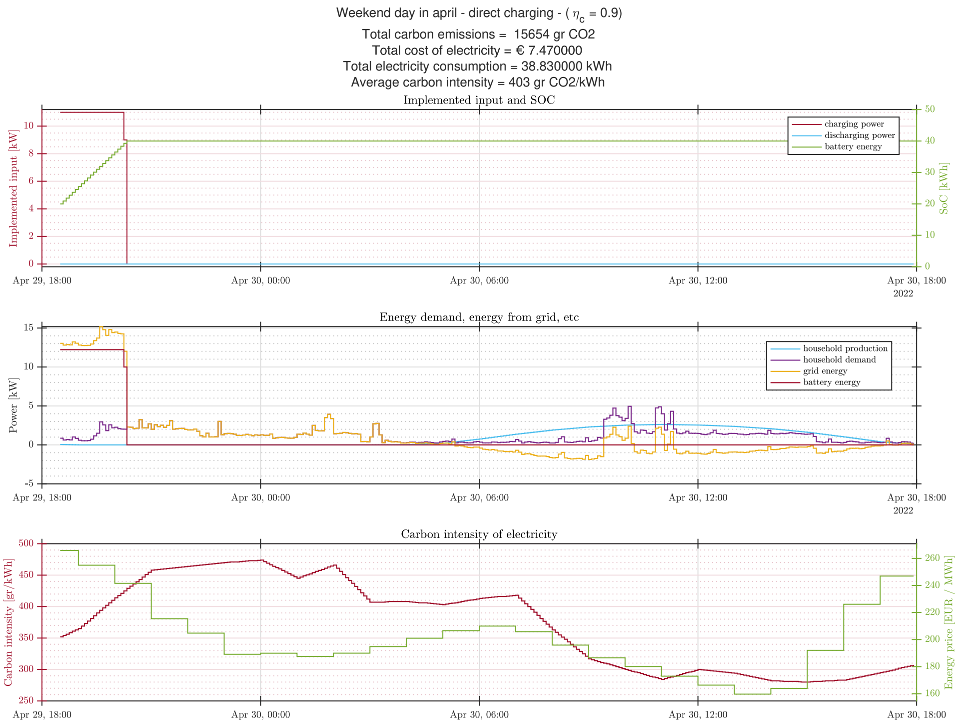

Figure 5-3: Second scenario - Direct Charging

The second baseline strategy shown in Figure 5-4, named 'V1G charging', simulates a baseline strategy representing the current state of the art of smart charging, including solar optimization. Optimizing unidirectional smart charging based on day-ahead price. A price benefit of 25% (€1.78) is obtained, while saving 32% (almost 5 kg) on CO_2 emissions, averaging at 366 gr/kWh. It is important to note that significantly less electricity (29.86 vs 38.83 kWh) is drawn from the grid, since all the produced solar is self-consumed in stead of fed back into the grid, which is considered to be wasted in terms of emissions in this analysis. The electricity flowing through the grid connection is shown by the yellow line in the middle graph of each figure. Whenever this line is below zero, electricity is fed back into the grid.

The strategy representing the main objective of minimizing the emissions of carbon dioxide associated with a households total electricity usage is shown in Figure 5-5. With 10018 gr CO_2, another 8.3% carbon emission savings are achieved compared to the unidirectional smart charging. On the other hand the session is 8.9% more expensive.

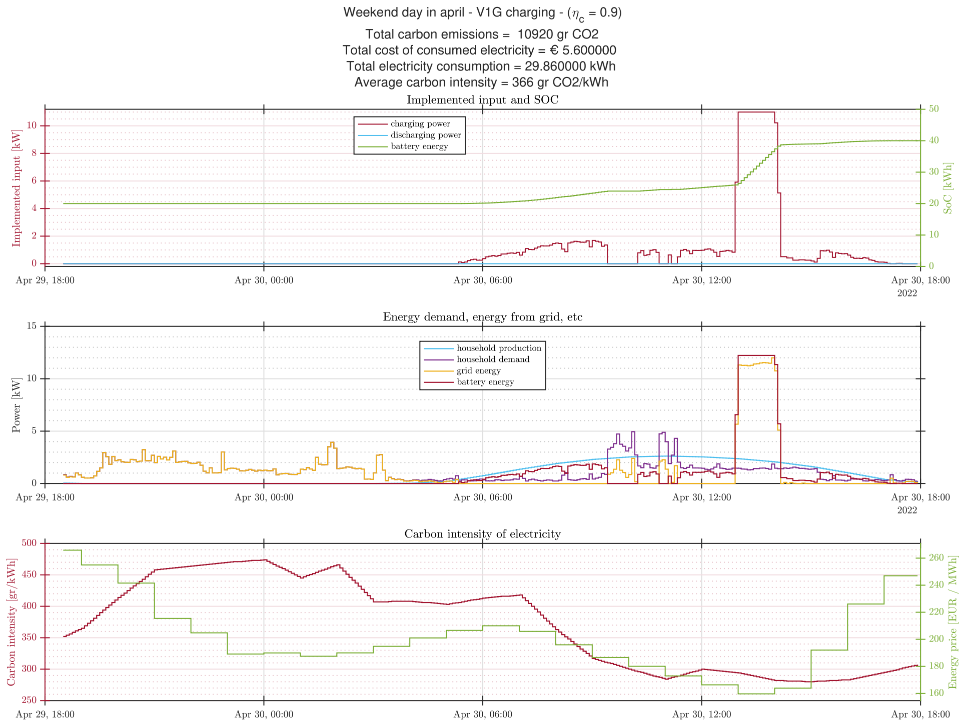

Figure 5-4: Second scenario - V1G Price optimized

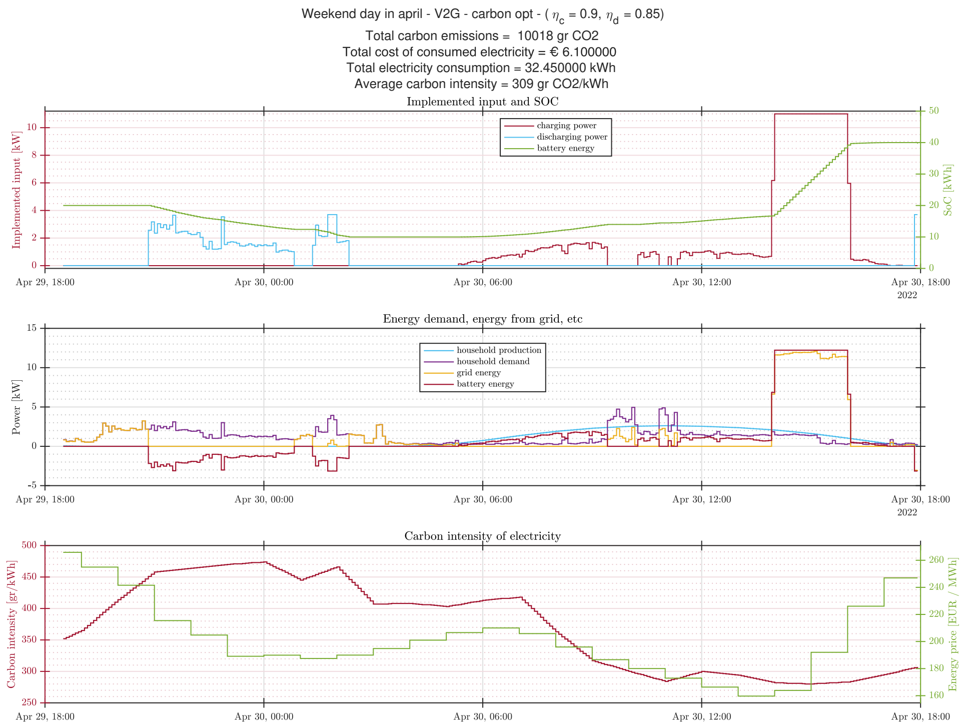

Figure 5-5: Second scenario - V2G CO_2 optimized

As explained in section 4-4, a potentially good alternative to overcome the fact that the session discussed above is significantly more expensive is to optimize over price, while using vehicle-to-grid technology. This strategy is shown in Figure 5-6 and results in both lower emissions and a (slightly) lower price compared to the baseline unidirectional smart charging optimization. The consumed electricity is about 2 kWh extra due to the conversion losses associated with discharging the vehicle.

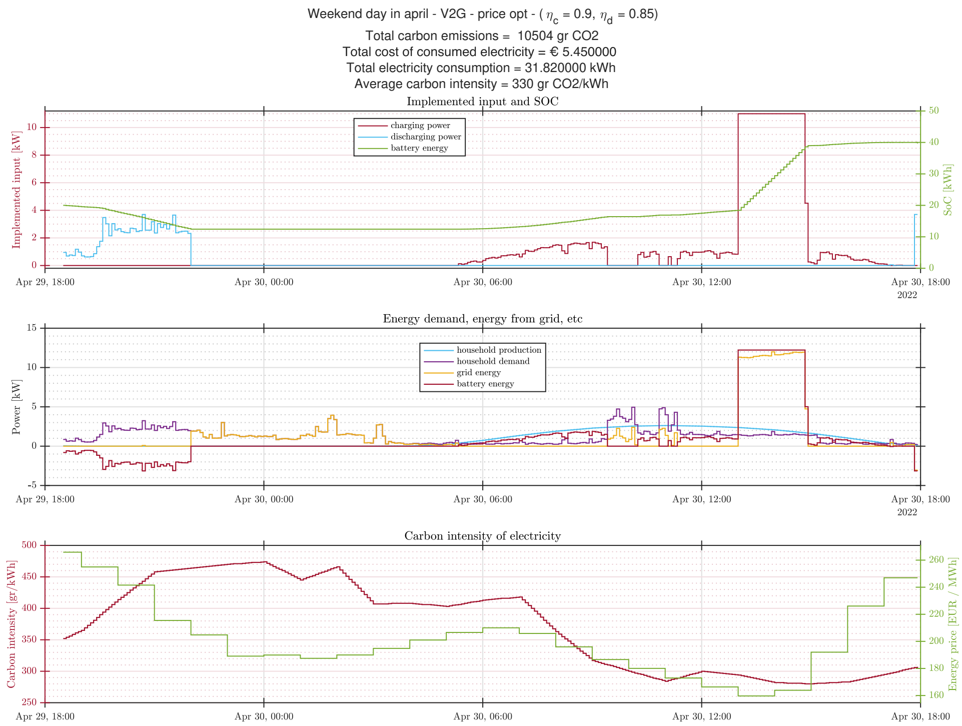

Figure 5-6: Second scenario - V2G Price optimized

Once again, these values are based on a single optimization and are therefore by no means representative of large scale benefits, but it does give a good understanding of the factors influencing the system.

5-2 Aggregated vehicle scenario

To simulate the aggregated vehicle scenario models, a larger set of 4279 sessions in total was used. Details on this set can be found in section 4-8. To analyse the performance of the models, a number of metrics was used:

Table 5-1: Metrics overview

Carbon emissions	The average carbon emissions per session, where feeding back can be seen as negative emissions, since the carbon emitted during charging is already accounted for, and carbon is saved during discharging since another asset is now using low carbon electricity in stead of high carbon electricity
Utility cost	The cost of the sessions for the utility, i.e. the cost based on day-ahead prices for both providing and taking electricity to/from the grid
User cost net	The cost of the sessions for the users, based on the current net metering principle, where kWh's taken from and delivered to the grid in the same rate period are canceled out
User cost day-ahead	The cost of the sessions for the users, based on the plausible future scenario, where delivering electricity back to the grid yields the day-ahead price, while taking electricity from the grid is based on consumer rates (single or dual tariff)

As mentioned before, various models were assessed to compare performance of the proposed models:

Table 5-2: Model overview

Direct	Charging starts at max power from the moment the vehicle is connected until the desired SOC is reached
V1G	Unidirectional smart charging, optimizing over day-ahead price for maximum utility profits while respecting users peak/off-peak rates
V2G Pen	Bidirectional smart charging, optimizing over day-ahead price for maximum utility profits while respecting users peak/off-peak rates
V2G Comp	Bidirectional smart charging, optimizing over day-ahead price for maximum utility profits while compensating for any additional peak hours charging
CO_2 V1G	Unidirectional smart charging, optimizing over carbon intensity for minimum emissions while respecting users peak/off-peak rates
CO_2 V2G	Bidirectional smart charging, optimizing over carbon intensity for minimum emissions while respecting users peak/off-peak rates
V2G No Pen	Bidirectional smart charging, optimizing over day-ahead price for maximum utility profits, assuming every user is on a dynamic rate (note that many users are in fact on old plans with rates that are lower than the actual costs, and are therefore often cheaper off)

5-2-1 Weekdays

The session results are split up in weekend sessions and weekday sessions. In this section the results for the weekday sessions are discussed. The results are shown in Table 5-3 and Figure 5-7. In Figure 5-7, the data labels indicate the percentage-difference compared to the uncontrolled charging baseline. As can be seen in the figure, the differences between the used models in price for the utility are significant.

Table 5-3: Results weekdays - mean costs and emissions

	Direct	V1G	V2G Pen	V2G Comp	CO_2 V1G	CO_2 V2G
Utility [€]	5.1225	4.1704	3.8389	3.8388	4.5342	4.3971
User Net [€]	6.1739	5.5758	5.4705	5.4562	5.7083	5.5023
User DA [€]	6.1739	5.5758	5.4505	5.4285	5.7038	5.5000
Emissions [kg CO_2]	9.6929	9.7669	10.0426	9.9401	9.3787	9.1015

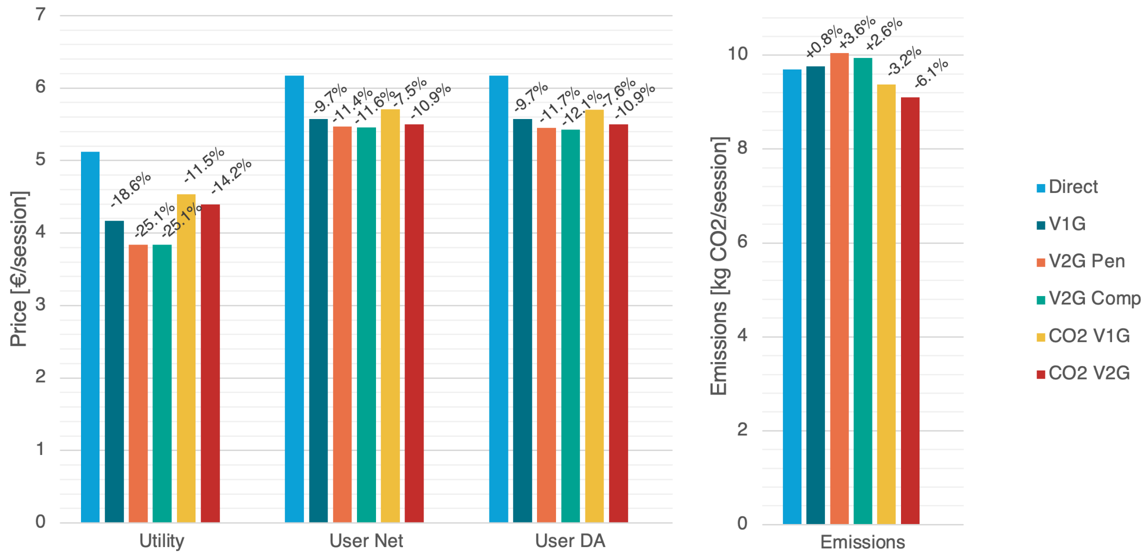

Figure 5-7: Weekdays - mean price and emissions per session - %-difference vs. Direct charging

Optimizing the associated carbon emissions results in 6.1% less emissions compared to the direct charging base line, while also saving 14.2% in costs for the utility and 10.9% in costs for the end user. This sounds very promising, however, comparing to the current state of the art - unidirectional, price optimized smart charging - an increase in utility cost of 5.4% is observed.

Unfortunately, the emissions are higher than the direct charging baseline model in every scenario where CO_2 minimization is not the main objective. This means that using V2G optimizing over day-ahead price is on average worse in terms of carbon dioxide emissions than not using smart charging at all. One hypothesis is that this happens because many users are still on a dual rate plan. This forces the program to only charge during off-peak hours, which is between 23:00 and 07:00. As there is little to no solar generation between these hours, the carbon intensity is typically higher during the night.

However, two extra simulations were run where the tariff penalty was left out of the cost function, one using price optimization and one using carbon optimization. This results in complete freedom to choose when to charge, as if every user was on a dynamic rate plan. To this end, all user tariffs were also overwritten to represent a dynamic rate plan. To prevent a distorted image of the user costs, for the direct charging baseline scenario it was also assumed that every user has a dynamic rate plan. Although in the price optimization the emissions decreased slightly (by 1.5%) compared to the scenario with tariff penalty, the associated emissions are still higher than in the uncontrolled charging scenario.

Another hypothesis is that the higher emissions are due to the fact that the maxSOC is fixed at 90% while about 30% of all sessions have a dSOC above 90%. All these sessions will fulfill the last few percentage points at the very end of the session, regardless of the carbon intensity at that moment, to minimize the penalty for having a high SOC. This hypothesis was tested by filtering out all sessions where this was the case. This resulted in 1901 weekday sessions. Even now, the associated emissions using direct charging were lower compared to the V2G scenario without tariff penalties. The results of both tests are shown in Table 5-4, where

Price price optimization, and Carbon indicates carbon optimization, both using V2G and without the tariff penalty. As all users are assumed to be on a dynamic rate plan, there is no difference between a scenario with and without net metering, hence only one user cost is shown.

Table 5-4: Weekdays - Hypothesis testing - No penalty on peak tariff

	All sessions			Sessions with dSOC ≤ 0.9		
	Direct	Price	Carbon	Direct	Price	Carbon
Utility [€]	5.1225	3.7632	4.4376	4.7604	3.3156	4.0835
User [€]	7.4939	6.0122	6.7473	6.9732	5.0726	6.2353
Emissions [kg CO_2]	9.6929	9.8961	8.7265	9.1408	9.3552	8.2027

A third hypothesis is that the correlation between day-ahead price and grid carbon intensity, during the times where users typically charge, is less than anticipated. Unfortunately there was not enough time to thoroughly test this hypothesis. A start at testing this hypothesis was made and can be found in Appendix A.

The impact of the compensation strategy compared to the strategy with a high penalty on peak-tariff charging was small, but beneficial for all parties. The biggest benefit was in the emissions, saving about 1% on average.

5-2-2 Weekends

The weekend simulations, consisting of 1424 sessions, show slightly different results. In Table 5-5 and Figure 5-8 can be seen that the emissions of the models optimizing over day-ahead price are much closer to the uncontrolled, direct charging baseline than during weekdays. The unidirectional price-optimized strategy even shows slightly less emissions, and the bidirectional, price optimized strategies both have less than 1% extra emissions. The CO_2 V2G strategy shows 13.4% less emissions compared to the direct charging scenario, while showing the lowest user costs according to current tariff structures. For the utility it is 5.5% more expensive than unidirectional, price optimized smart charging. Another result that is perhaps not very surprising, yet important to realize, is that the weekend sessions are significantly less carbon intense and cheaper than weekday sessions, regardless of the strategy. Specifically for the emissions this is shown in the bottom row of Table 5-5.

Table 5-5: Results weekends - mean costs and emissions

	Direct	V1G	V2G Pen	V2G Comp	CO_2 V1G	CO_2 V2G
Utility [€]	4.7388	3.5536	3.0795	3.0770	3.9463	3.7475
User Net [€]	5.9309	5.5783	5.5819	5.5845	5.655	5.5248
User DA [€]	5.9309	5.5783	5.6848	5.6865	5.655	5.6007
Emissions [kg CO_2]	9.1235	8.9602	9.2083	9.1750	8.3948	7.9016
Emissions vs weekday	−5.9%	−8.3%	−8.3%	−7.7%	−10.5%	−13.2%

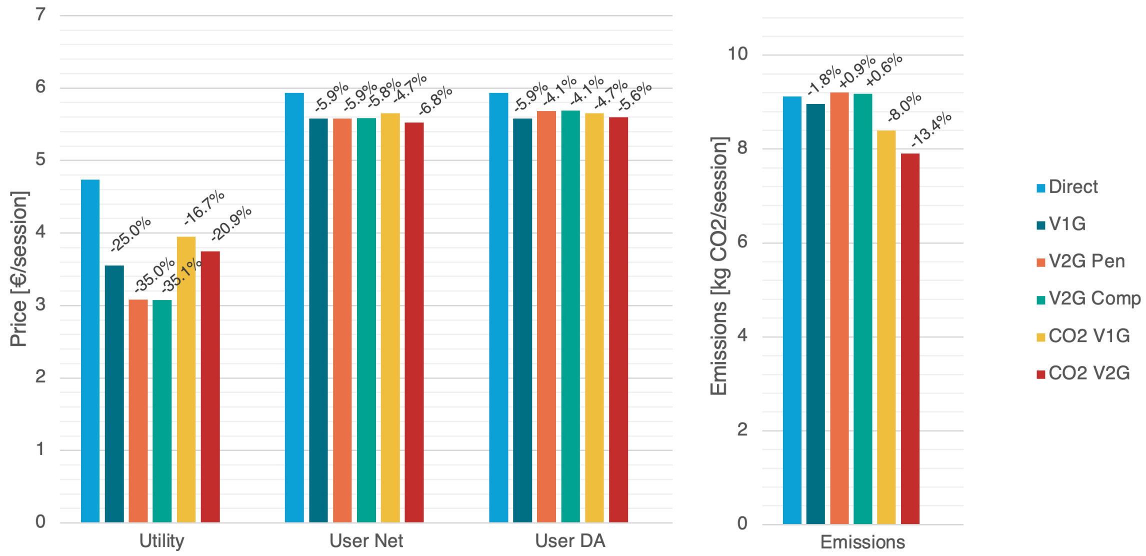

Figure 5-8: Weekends - mean price and emissions per session - %-difference vs. Direct charging

5-2-3 Solar implementation

The model with PV production included is compared to the model without solar included. Both models use price optimization with V2G. Again the possible future scenario where electricity consumption is subject to the user tariffs, and electricity feedback is subject to the day-ahead price is used. Moreover, a tariff penalty is active, forcing the system to consume only during off-peak hours if possible. Similar to the other models in the multi-vehicle optimization, feeding back electricity accounts for negative carbon emissions corresponding to the grid carbon intensity at that time. This is reasonable since another user will now consume the user's solar power in stead of the (more carbon intense) grid power. Solar power is here assumed to have zero carbon intensity, neglecting the production and end-of-life related emissions.

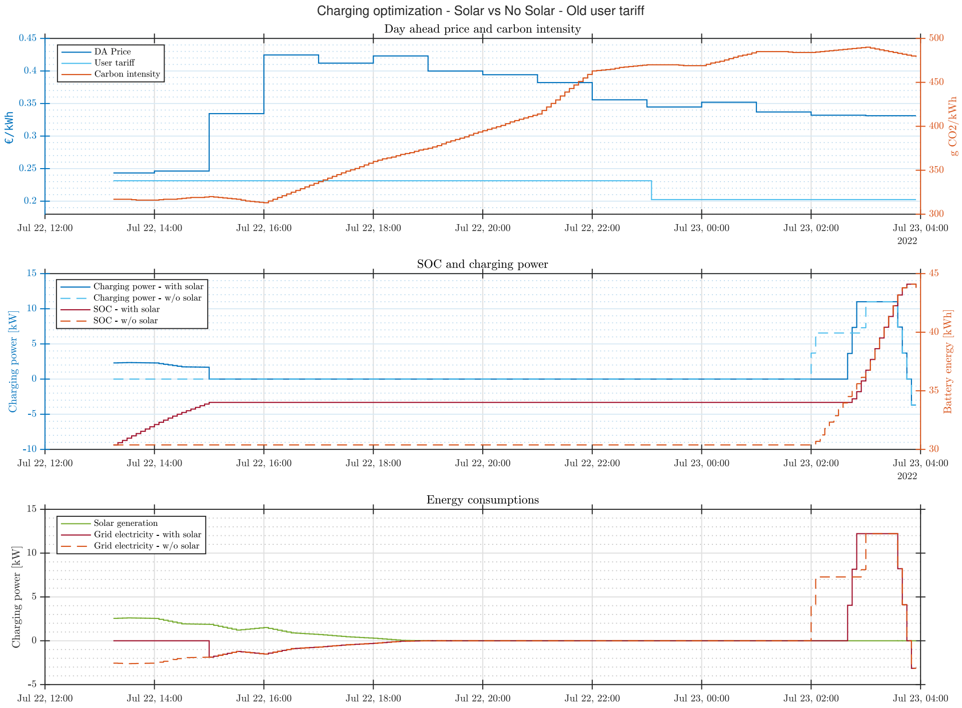

Figure 5-9: V2G price optimization including solar generation

As can be seen in Figure 5-9, the model is working as intended. Solar generated while the day-ahead price is low is self-consumed, while solar generated while the day-ahead price is high is fed back to the grid. As shown in Table 5-6 on average, the profit for the utility is 11 cents per session, which is fairly good as this feature is mainly aimed at the consumer. Moreover, on average 186 grams of carbon is saved per session, by just using the produced electricity smarter. However, the average profit for the user is less than 1 cent per session, and in some scenario's, such as the one shown in Figure 5-9, the optimization including the solar production is more expensive for the user.

In this specific scenario the user tariffs per kWh are €0.2314 at peak hours and €0.2024 at off-peak hours. Without solar optimization, the net cost of his session (including the profits from feeding back the produced electricity) is €0.7414, while the net cost with solar optimization is €0.9127. The reason for this is that the user rate for consuming electricity is lower than the day-ahead price (which the user receives for feeding back) throughout the day. Therefore, at the moment of production, theoretically the user could sell the electricity and directly buy the same electricity back and make a profit. If the user only buys back the electricity later during off-peak hours, which happens in the default strategy, the profit is even bigger. Therefore, the default strategy of postponing charging until the cheapest moment during off-peak tariff and directly selling all generated electricity is more profitable for the user than self-consuming solar electricity.

Clearly these tariffs are not sustainable, since the utility is making huge losses on these customers. Therefore the same simulations are done assuming tariffs that are offered currently, as explained in subsection 4-5-1. To make the difference between the two clearer, the simulated sessions are split up in sessions that are subject to dynamic rates and sessions that are subject to fixed rates (single or dual). Using the new rates, the business case is much more attractive, and the results are shown in Table 5-6 in the rows indicating 'new rates'.

Table 5-6: Results solar addition

		All (341)		Dynamic (29)		Non-Dynamic (285)	
		Session	kWh	Session	kWh	Session	kWh
User price [€]	No solar - old rates	2.2389	0.10163	7.4235	0.27812	1.7113	0.07939
	Solar - old rates	2.2303	0.10124	7.4235	0.27812	1.7019	0.07895
	No solar - new rates	12.3040	0.55851	7.4235	0.27812	12.8006	0.59384
	Solar - new rates	11.9846	0.54401	7.4235	0.27812	12.4487	0.57751
Utility price [€]	No solar	3.6101	0.16387	4.8527	0.18180	3.4837	0.16161
	Solar	3.4969	0.15873	4.8527	0.18180	3.3590	0.15583
Emissions [kg CO_2]	No solar	7.8836	0.35786	8.3474	0.31273	7.8364	0.36354
	Solar	7.6971	0.34939	8.3474	0.31273	7.6309	0.35401

It can be seen that, using dynamic rates, there is no difference between incorporating the solar production and neglecting the solar production. This is due to the fact that on a dynamic rate plan, buying and selling electricity always happens at the same price. Therefore, high prices result in discharging and low prices result in charging regardless of the origin of the electricity. For example, when prices are low, it is desirable to self-consume solar since feeding it back doesn't do much. At the same time, it is desirable to charge the vehicle since it is cheap at that time, regardless of whether solar electricity is produced at the same time. The other way round, if prices are high while solar electricity is produced, it is desirable to feed that energy back to the grid, while it is equally desirable to discharge the vehicle if possible. Using the new rates, users can save on average 205 grams of emissions (2.6 %) per session, while at the same time saving €0.45 (2.8 %) per session, or 1.7 cents per kWh. The utility profits too, with average savings of 12.5 cents (3.6 %) per session. Do note that these numbers are based on a small set of sessions, concentrated in three weeks in July and August. Therefore no conclusions can be drawn based on these numbers.

Chapter 6

Conclusions and recommendations

6-1 Conclusions

The goal of this research was to create a controller to optimally charge and discharge EVs with minimum carbon emissions.

First, a method to control a single vehicle was constructed. As mentioned in chapter 4, it is assumed that perfect forecasts for grid carbon intensity, household (PV) production and household demand are available. For the grid carbon intensity and the household production this is a reasonable assumption since they are well predictable. The household demand is difficult to predict with reasonable accuracy. This could be tackled by implementing smart household appliances, home batteries, or other measures. This way, the household demand can somewhat be steered and therefore more easily predicted.

The single vehicle model could still very well be used without the household demand and is easy to implement. It can reduce carbon emissions and make better use of produced solar electricity. Financially, the greatest benefit lies with users on a dynamic rate, because they are exposed to the largest and most frequent price fluctuations. The model can be implemented by a somewhat skilled hobbyist but it requires a microcomputer with internet access, an API connection to the vehicle and access to a solar production forecast for the households PV setup, the electricity prices until the end of the session (either known day-ahead prices or a forecast) and a grid carbon intensity forecast. These forecasts can either be built by the user or taken from other platforms such as Solcast, Entsoe and electricityMap.org through their APIs. However, these are typically not free.

More meaningful results were obtained by the multi-vehicle model, where an aggregated fleet of vehicles can be steered by a central party such as an aggregator.

To make the scenario realistic, there are many factors that need to be taken into account, such as the price for the utility, the price for the user and battery degradation. A model was built to minimize carbon emissions while taking all these factors into account.

To examine the impact of price optimization on emissions, a price optimizing model was developed as well, using both unidirectional and bidirectional charging. One important takeaway is that the current structure of dual tariffs works counterproductive in terms of carbon emissions, as the lowest carbon intensity is usually observed during the day, but a typical off-peak tariff is only active during the night.

Optimizing over carbon emissions is obviously beneficial in terms of carbon emissions. Compared to uncontrolled charging, it is also cheaper for both the user and the utility. However, for the utility it is still more expensive than unidirectional price-optimized charging, which is available today.

The main conclusion that can be drawn from this thesis is the following: At this moment, V2G optimization to minimize carbon emissions is 5.5 % more expensive for the utility than the current state of the art; unidirectional, price optimized smart charging. Moreover, V2G optimization to minimize the cost for the utility results in 2.8 % higher emissions than the current state of the art and even 0.9–3.6 % higher emissions than using uncontrolled charging.

To find the reason for these higher emissions, the tariff penalty was taken out of the cost function that optimizes over price, allowing the model to charge at any time regardless of the user tariff at that moment. Although this resulted in even lower costs for the utility and lower emissions than with the tariff penalty in place, they remained higher than with the direct charging strategy.

In a preliminary investigation, to be found in Appendix A, the correlation between day ahead price and carbon intensity on a smaller timescale and around the times that users typically start their sessions is lower than anticipated. This correlation seems to be negative, which would indeed explain why postponing the charging is beneficial in terms of price but results in higher emissions.

Lastly, a feature was built to implement user solar production in the optimization. Based on summer time simulations, this seems to be beneficial in terms of emissions (2.6 %) and price, both for the user (2.8 %) and the utility (3.6 %). As these results are based on a small set of sessions in summer time, they are by no means representative for yearly results.

6-2 Recommendations for future research and policy

For future research, it is recommended to look into compensation for the conversion losses incurred by the consumer, due to V2G operation on behalf of the utility. To better account for and minimize battery degradation, this subject should also be further researched.

Another interesting direction would be to optimize over carbon emissions, with a constraint forcing the utility cost to be less than or equal to the cost under unidirectional price optimization. This way, the benefits of V2G operation can be granted to carbon emissions, while maintaining the price benefits of current-day price optimization.

More fundamentally, a study to combine the associated CO_2 emissions and the day ahead price in the cost function would be logical. By putting a price on emissions, an optimal balance between price and emissions can be determined.

On a policy level, it has become clear that the dual tariff structure is hurting the environment, the utilities and the users. As most users are on a dual tariff, they are incentivised to consume electricity during the night, when the carbon intensity is generally higher than during most of the day. Large-scale adoption of dynamic rates would certainly help in optimizing EV charging, as it enables more flexibility. Another option would be to activate off-peak rates during the middle of the day, for example between 10:00 and 15:00. Lastly, an emissions-based energy tax would push low-carbon energy prices down further. This way, the cost and emissions objectives would be artificially aligned.

The fact that optimization on carbon intensity is slightly more expensive for the utility compared to the current unidirectional is not necessarily a problem. At this moment, about 90% of EV drivers use uncontrolled charging, so on a large scale even V2G carbon optimization results in a significant price benefit over the current practice. As many companies are investing in becoming net zero, it is not unthinkable that utilities and aggregators will sacrifice a portion of their possible smart charging benefits in favor of significant carbon savings. Additionally, with consumers being increasingly environmentally conscious, a strong marketing campaign could very well draw new customers to the utility if they ensure smart charging for minimal emissions, compensating for the sacrificed benefits per session.

Appendix A

Hypothesis - negative correlation carbon intensity and price

It is often assumed that there is a strong correlation between the grid carbon intensity and the wholesale market price, due to the merit order as explained in section 4-4 [?]. However, it seems that this does not hold for the specific times where users are plugged in. Often, on windy and sunny days, both the average energy price and the average carbon intensity are low, however, within this day there might be a negative correlation.

After looking into the average hourly price and carbon intensity over the course of the same time period as the sessions data set (June 23, 2021 until June 23, 2022) the hypothesis seems to be confirmed, as shown in Figure A-1

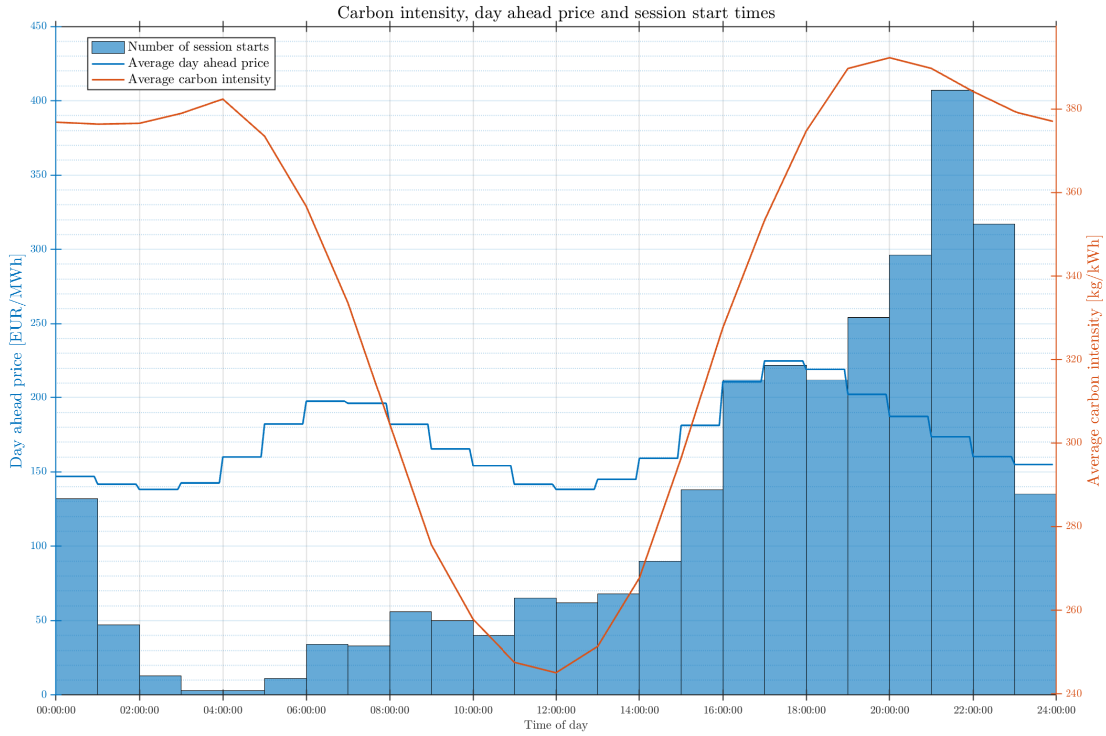

Figure A-1: Histogram of session start times with overlay of day ahead prices and carbon intensities

It can be seen that between 17:00 and 18:00 the price has reached its peak, while the carbon intensity is still relatively low. After 17:00, the average carbon intensity stays at a higher point until roughly 07:00 in the morning. Therefore, from a price perspective it makes sense to postpone charging to after the evening peak, during the night. From a emissions perspective, on the other hand, it is desirable to start charging straight away.

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Glossary

List of Acronyms

BRP	Balance Responsible Party
EV	Electric Vehicle
PSO	Particle Swarm Optimization
DOD	Depth of Discharge
GHG	Greenhouse Gas
HEMS	Home Energy Management System
ISO	International Organization for Standardization
MIMO	Multi-input Multi-output
MPC	Model Predictive Controller
PV	Photo Voltaic
RES	Renewable Energy Sources
SHMPC	Shrinking Horizon Model Predictive Control
SOC	State of Charge
TSO	Transmission System Operator
V2G	Vehicle-to-Grid
VPP	Virtual Power Plant

List of Symbols

η_c	Charging efficiency
η_d	Discharging efficiency
ε	Arbitrary small number

$\mathbf{u}$	$\begin{bmatrix} u_1 & \cdots & u_N \end{bmatrix} = \begin{bmatrix} u_1^c & \cdots & u_N^c \\ u_1^d & \cdots & u_N^d \end{bmatrix}$
ecs	Max charge speed
eds	Max discharge speed
maxSOC	Maximum state of charge
minSOC	Minimum state of charge
B	Battery capacity of EV
c_k	Grid carbon intensity at time step k [gr CO_2eq/kWh]
C_l	Weight on lower SOC bound
C_u	Weight on upper SOC bound
E	Electric energy stored in battery [kWh]
e_k	$e_k(u_k) = e_{d,k} + e_{b,k}(u_k) - e_{p,k}$
e_k^+	$\max(e_k, 0)$
$e_{b,k}$	Electric energy delivered to the vehicle at time step k
$e_{d,k}$	Domestic electricity demand at time step k
$e_{p,k}$	Domestic electricity production at time step k
$g_m^{\text{off-peak}}$	Off-peak tariff for user m
g_m^{peak}	Peak tariff for user m
P	Charging power [kWh/min]
p_k	Day-ahead electricity price at time step k [€/kWh]
u^c	Charging power [kW]
u^d	Discharging power [kW]
dSOC	Desired state of charge
k	Time index