Utrecht University
Copernicus Institute of Sustainable Development

Master Thesis Energy Science

GEO4-2510

30 ECT

Stimulation of grid-aware electric vehicle charging

A price-based linear programming model and practical implications to stimulate grid-aware charging in the Netherlands

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30/06/2023

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Word count: 15801

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Summary

While the expanding electric vehicle (EV) fleet shows great environmental advantages, it also creates an increase in electricity demand that is causing pressures on the electricity grid. The concept of controlled charging, i.e. coordinating the moment and capacity of EV charging, has the potential to reduce or mitigate these pressures, especially when charging is constraint to the physical and technical boundaries of the electricity grid. This concept is known as grid-aware charging. While there are several studies that focus on applying controlled charging for grid provision, the literature is lacking a study that focusses on stimulating these grid-charging services. This study aims to fill this gap with the following research question:

How can the adoption of grid-aware charging strategies be stimulated in the Netherlands?

To answer this research question, desk research is performed to identify typical Dutch driving profiles, Linear Programming models are proposed that coordinate charging based on price, using on hourly electricity prices, to minimize charging costs, a quantitative analysis is performed to identify the influence of the driving behavior on these profiles and costs, and nine expert interviews are conducted to identify concrete roles and tasks for involved stakeholders to stimulate grid-aware charging.

The results show that charging costs reductions for a delayed, smart, and V2G strategy are 37%, 62%, and 137%, respectively. All three controlled charging profiles show significant peak reductions in electricity extraction in the evening, and charge during hours where the electricity prices are lower, i.e. night, morning, and afternoon. The V2G strategy discharges the battery during the evening. It was observed that mileage has a linear effect on the absolute charging costs but does not strongly influence average charging costs. Furthermore, the height and volatility of electricity prices influence both charging costs and discharging profits. The expert interviews show that for a successful scale up of grid-aware charging, market parties should function as aggregator, coordinating the charging for consumers. Governments should focus on stimulating the market, creating market boundaries, and creating consumers awareness on the advantages of grid-aware charging. Furthermore, transparent collaboration based between the market, DSO, and government is crucial for the effective stimulation of grid-aware charging in the Netherlands.

The proposed LP model contributes to the body of literature that simulates charging behavior based on a minimization of costs. Further research could focus on the environmental benefits of the proposed charging profiles by the increased consumption of renewable electricity.

1. Introduction

The consequences of global greenhouse gas emissions become more and more visible in daily life, which stresses the need for the reduction of CO2 emissions across all sectors. The electrification of all sectors can contribute to this reduction, since electricity can be generated carbon-free (Sugiyama, 2012). An example is the electrification of the transportation sector, which still largely depends on fossil fuels and accounts for 23% of global emissions (IEA, 2022b). The largest contributor within this sector is road transport, and a transition towards electric vehicles (EVs) proposes great potential to reduce the sectors' emissions (Chen et al., 2015). The rapid growing stock of EVs shows that this transition is already moving fast (IEA, 2022a).

While the expanding EV fleet shows promise for environmental targets, it also created challenges due to the increased electricity demand required to charge these vehicles. If this charging happens uncontrolled, i.e. charging at full capacity the moment an EV is connected to the grid, charging usually occurs at hours that already have demand peaks, which leads to increased pressure on the power grid and transmission lines (García-Villalobos et al., 2014; Staudt et al., 2018). This pressure can result in increased peak loads, net congestion, power loss, reduced load factor, harmonic distortion, and other undesired effects (Sadeghian et al., 2022; Verhoog et al., 2020). To prevent these negative grid impacts, large and expensive power grid reinforcements are required (Rizvi et al., 2018; Ucer et al., 2018).

Controlled charging strategies, such as delayed charging, smart charging, and Vehicle-to-Grid (V2G), offer the possibility to reduce these negative impacts by coordinating the moment and power of charging (Crozier et al., 2020). Delayed charging refers to shifting the charging moment to off-peak hours, reducing the increase of demand peaks (Nour et al., 2019). Smart charging refers to a more coordinated charging strategy, where charging is optimized to achieve a certain goal, e.g. to mitigate congestion (Fachrizal & Munkhammar, 2020; Sadeghian et al., 2022). Lastly, V2G allows a bidirectional power flow between the EV's battery and the grid, increasing the load flexibility by allowing the EV to operate as a distributed energy source (Eid et al., 2016; Tan et al., 2016). These strategies allow the EV batteries to be used for several grid-services, such as ancillary services, integration of renewable energy sources (RES), or reducing charging costs.

The objectives or goals of these different controlled charging strategies can be divided into two main categories: to maximize the benefit of the EV driver, or to provide grid support (Cardona et al., 2018). The first category coordinates the charging to minimize the charging costs, while respecting the user's preferences and driving behavior (Delmonte et al., 2020). While this might be desirable from the user's point of view, it can also create higher peak demands and local congestion when a high number of EVs start charging simultaneously due to e.g. low electricity prices (Islam et al., 2021). The second category coordinates the charging to minimize negative grid impacts and provide flexibility to the grid when required, which leads to better grid performance, but generally also results in lower financial benefits for the EV driver (Prakash et al., 2022).

The rapid growing EV stock combined with the increasing grid pressure calls for an increase in adoption of controlled charging strategies, especially strategies that consider the technical and physical boundaries of the electricity grid. Such a strategy is also referred to as *grid-aware* *charging* (Fahmy et al., 2020). Since this strategy does not focus on maximizing consumers' benefits, consumer acceptance is expected to be relatively low (Delmonte et al., 2020). To increase this acceptance, the consumers that adopt these strategies can be compensated financially, as this is argued to be one of the most important drivers in the adoption of controlled charging strategies (Ghotge et al., 2022; van Heuveln et al., 2021).

To determine how consumers can be compensated, it is relevant to know what the maximum financial benefits of implementing a controlled charging strategy are. There is a large body of literature that focusses on the coordination of charging to provide grid flexibility. Recent literature focused on the financial benefits of applying a V2G strategy to provide ancillary services (Amamra & Marco, 2019; Huda et al., 2020; Sarabi et al., 2016). Other studies focused on optimizing the integration of RES into the electricity grid (Shang et al., 2020; Taljegard et al., 2019) or minimizing system losses (Singh & Tiwari, 2020). These studies, however, identified charging strategies that did not focus primarily on reducing charging costs, but rather on multiple objectives, and therefore do not quantify a minimization of charging costs, but rather a reduction.

Only a few studies focused on this minimization; Datta et al. (2019) studied the reduction in charging costs if an EV is combined with a home energy management system. However, they only quantified charging costs for a Vehicle-to-Home (V2H) strategy, neglecting delayed charging, smart charging, and V2G strategies. Fan & Chen (2019) compared charging costs of a delayed charging and a V2G strategy. While they do make a comparison between the strategies, they use four electricity tariffs and simulate only one charging session, which provides very limited information for the financial potential for a longer period and does not include hour-based electricity prices. in this study. Similarly, Jian et al. (2018) show charging cost reductions when charging is coordinated based on Shanghai electricity tariffs, but do not use hour-based prices and only use a limited time scope, therefore providing no insight in annual cost reductions. López et al. (2015) quantify charging costs based on hour-based electricity prices for a smart charging and a V2G strategy for multiple EVs in a particular system. While they include the hour-based prices, they only simulate one charging sessions, and therefore do not provide insight in annual charging costs. Lastly, all the above mentioned studies do not include the influence of driving behavior on the charging costs, while driving is the EVs' primary function.

What the literature is largely lacking, are studies that simulate controlled charging profiles that focus solely on minimizing the EV's charging costs, while charging is coordinated based on hour-based electricity prices. Additionally, there are no studies found that includes the influence of driving behavior on the controlled charging costs, therefore neglecting the influence of the EVs primary function. Furthermore, none of the above studies quantifies charging costs for one entire year, but rather focus on one charging session. Lastly, none of the abovementioned studies provide any insights in how the simulated charging profile and quantified costs can contribute to stimulate the adoption of controlled charging strategies.

This study aims to fill this gap by simulating charging profiles that aim to minimize charging costs, based on hour-based electricity prices. To do so, the Netherlands is used as a case study. This has two reasons; first, the Netherlands is a European frontrunner in EV penetration, as well as in their charging infrastructure (ANWB, 2023). Secondly, as the Netherlands currently experiences increasing grid pressure, there is a great urge for an increase in grid-aware charging throughout the country (Netbeheer Nederland, 2023).

This study aims to identify how grid-aware charging can be stimulated in the Netherlands. It does so by identifying five driving profiles that represent typical Dutch EV drivers. The charging behavior of these five driving profiles is simulated by Linear Programming (LP) technique, that aims to minimize the charging costs based on hour-based electricity prices. Four LP models are created in this research, one for each of the following charging strategies: uncontrolled charging (functioning as a reference case), delayed charging, smart charging, and V2G. These models will result in a charging profile and charging costs for all driving profiles and charging strategies. These results are aggregated to form the charging profile and costs of the average Dutch EV driver per charging strategy. Hereafter, this research focusses on the influence of the driving behavior on this profile and the costs. Lastly, to identify how these results can result in an increase in adoption of grid-aware charging in the Netherlands, nine expert interviews are conducted with multiple stakeholders. This translates into the following main research question:

How can the adoption of grid-aware charging strategies be stimulated in the Netherlands?

To answer this research question, the following sub questions are composed:

1. What are driving profiles for typical Dutch electric vehicle drivers?
2. What are the charging profiles and charging costs for electric vehicles in the Netherlands?
3. How do the driving profiles influence the charging profile and charging costs of electric vehicles in the Netherlands?
4. What factors can influence the consumer adoption of grid-aware charging in the Netherlands?

The time scope of this study is 2030. This is chosen because while the implementation of delayed and smart charging strategies might be in a relatively advanced stadium, the V2G strategy is still not widely commercially available (Ghotge et al., 2022). The scope is set to 2030, to obtain results that are closer to the time of implementation of V2G.

Lastly, the study focusses on private charging points, as the adoption of controlled charging strategies pose a large challenge here. While currently 67% of the EV drivers has a private charging point (Rijksdienst voor Ondernemend Nederland, 2022). While this is expected to reduce to approximately 40% by 2050, it is still a large share of the total charging points, stressing the urge to stimulate controlled charging strategies here (Refa et al., 2021).

2. Theoretical background

In this section, the theoretical background of this research is discussed. The section starts with a brief literature review on controlled charging, then EV trends in the Netherlands are discussed. Furthermore, this section elaborates on controlled charging in the Netherlands, and ends with a section on electricity pricing.

2.1. Brief literature review

Controlled charging refers to coordinating the EV's charging moment and power. This is usually done by communication between the power grid and the EV, where the power grid gives out signals to increase, decrease, or postpone charging, which can be done for several reasons (Tan et al., 2016). This section elaborates on the technical requirements of the different charging strategies, the services they can provide, possible system architectures, and challenges.

2.1.1 Technical requirements

To control the power flow from grid to vehicle, an active controller of the power flow and a simple communication system is required (Habib et al., 2015). Both components are rather simple and bring limited additional costs. A V2G strategy, however, requires more extensive software and hardware. This includes a more extensive communication system, a bidirectional charger, and hardware in the EV to make it 'V2G ready' (Sharifi et al., 2019; Yilmaz & Krein, 2013). Most new EVs in the Netherlands will be V2G-ready by 2030 (Refa et al., 2021).

2.1.2 System architecture

The architecture of a controlled charging system can be either centralized or decentralized. In a centralized architecture, an aggregator is responsible for charging and discharging a certain number of EVs (Ravi & Aziz, 2022). Aggregators are usually profit-oriented parties that operate between the power system and EV drivers to coordinate charging to improve power grid flexibility (Sadeghian et al., 2022). An example of such a structure is shown in Figure 1. Aggregators aim to maximize their profit by charging at lower demand hours, and participating on e.g. frequency markets, while considering driver's preferences. A challenge they face is the large amount of data they need to process and optimize (Ravi & Aziz, 2022).

In a decentralized architecture, a local system is responsible for managing the charging and discharging of one of more EVs. It consists of smaller and simpler communication systems, but also has lower revenue due to limited available services (Ravi & Aziz, 2022). Typical systems are the combinations of one of more EVs and a building, neighborhood, or one household (Tan et al., 2016).

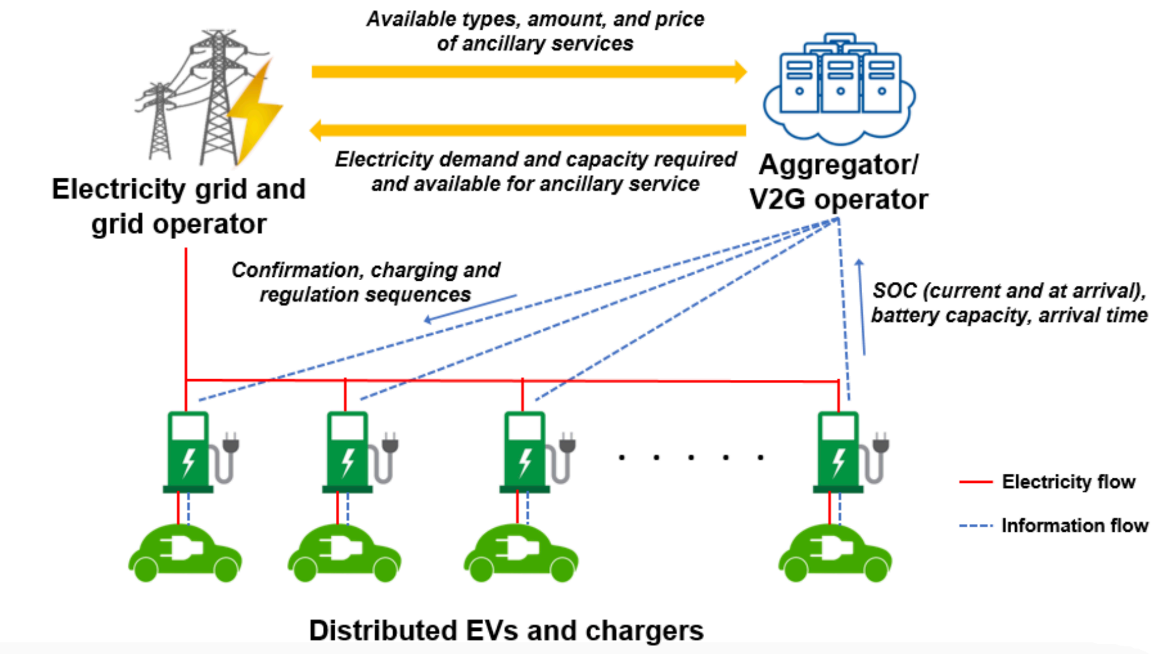

Figure 1: Architecture example of a centralized controlled charging system. From Ravi & Aziz (2022).

2.1.3 Grid-support services

The flexibility that the controlled charging services offer can be used for several services that provide grid support. Delayed and smart charging can be used for load only services, which means that it can only increase or decrease its load, and not provide active power support (Yilmaz & Krein, 2013). A V2G strategy does allow active power support due to the bidirectional power flow, which increases the available potential services it can offer (Ravi & Aziz, 2022). This section discusses these services for the controlled charging strategies.

Frequency support

Frequency regulation is required when demand and supply are out of balance, and therefore cause a frequency deviation (Yilmaz & Krein, 2013). This regulation is provided on three levels: primary, secondary, and tertiary regulation, which differ on response time and function. EVs are mainly suitable for providing primary and secondary support (Liu et al., 2019; Mu et al., 2013; Wang & Chen, 2019).

Voltage regulation

To balance supply and demand for reactive power, voltage regulation is required (Sharifi et al., 2019). The battery charger is used to select a proper phase angle, which helps to compensate capacitive and inductive reactive power (Habib et al., 2015). This service is only available for V2G technology, as it requires the controlling of the switching of the AC/DC converter (Choi & Sarlioglu, 2018; Hu et al., 2022).

Load flexibility

Load flexibility refers to flexibility on the demand side to obtain a more desired load shape. Controlled charging can offer solutions in load shifting by delaying the moment of charging until after peak hours, while only V2G can provide more active support with peak shaving and load leveling (Tan et al., 2016). Load flexibility can be coordinated by a price incentive, availability of RES, or available grid capacity (Jian et al., 2018; López et al., 2013).

Spinning reserve

Spinning reserve are backup generators that can be activated immediately to provide grid support during e.g. sudden frequency drops or power outages (Rebours & Kirschen, 2005). It requires relatively low total available energy, but a quick response time, which is ideal for EV batteries (Ravi & Aziz, 2022). All controlled charging strategies can be effectively used for spinning reserve (Pavić et al., 2015; Sortomme, 2012; Yilmaz & Krein, 2013).

Congestion mitigation

Grid congestion occurs when high electricity demand or supply causes grid components to overload (Verhoog et al., 2020). Grid congestion can be solved by upgrading grid infrastructure or by increasing demand or supply locally to compensate for the high supply or demand (Ravi & Aziz, 2022). The flexible character of EV batteries combined with a controlled charging strategy is suitable for mitigation congestion (Deb et al., 2018; Staudt et al., 2018).

Integration of renewable energy sources

The integration of the intermittent RES in the remains a challenge (Ravi & Aziz, 2022). Coordinating charging based on RES generation can increase the grid's efficiency as well as the RES utilization share, especially for solar PV and wind generation (Fachrizal & Munkhammar, 2020; Pilpola & Lund, 2019; Raoofat et al., 2018; Tarroja & Hittinger, 2021).

2.1.4 Challenges

While the implementation of controlled charging strategies can have several advantages for the grid, it also faces some challenges that hinder adoption. The main challenges are social barriers, high investment costs, energy loss, and battery degradation (Tan et al., 2016; Yilmaz & Krein, 2013). The social barriers are mainly focused on the availability of battery capacity at any given time, which is a barrier for all controlled charging strategies. The other challenges are mainly for the V2G strategy, as this strategy is associated with higher investment costs, energy loss due to the charging and discharging efficiency, and the increased degradation of the EV's battery due to the increased number of charging and discharging cycles (Han et al., 2019; Shariff et al., 2019).

2.1.5 Controlled charging simulations

Several studies in the literature included EV driving behavior, where most studies used a stochastic driving pattern in their analysis. Nour et al. (2019) and Singh & Tiwari (2020) chooses a charging start time by using a gaussian distribution. Schuller et al. (2015) based their driving behavior on 1000 real German driving profiles from 2008 for one week. Sachan et al. (2020) focused on parking behavior based on real data from a Danish travel survey. All these studies use aggregated or stochastic methods to determine the starting moment of one charging sessions, or one week of charging. However, none of the above studies focuses on the influence of the driving behavior on the charging profile or costs.

There are several studies that used a LP or Mixed-Integer Linear Programming (MILP) approach to simulate charging behavior based on an objective. Richardson et al. (2012) proposed a LP to maximize charging output to several EVs, while remaining within limits of the local grid. Franco et al. (2015) showed that a MILP model can coordinate EV charging within an unbalanced electricity grid. Schuller et al. (2015) proposed a MILP model that doubles the consumption of variable RES. Fan & Chen (2019) showed with a MILP model that charging costs can be reduced with smart charging, and a profit can be made with a V2G strategy. These studies show that LP is a good technique to simulate EV charging profiles.

Fan & Chen (2019) simulated charging profiles when charging was coordinated based on electricity price. The profiles are shown in Figure 2. What can be observed, is that the delayed charging profile shifts the charging load to the late evening and night hours, when off-peak pricing starts. The V2G strategy discharges the remaining electricity of the battery first, before recharging during the night. The costs were \$0.97 and \$-1.14 for the delayed charging and V2G strategy, respectively.

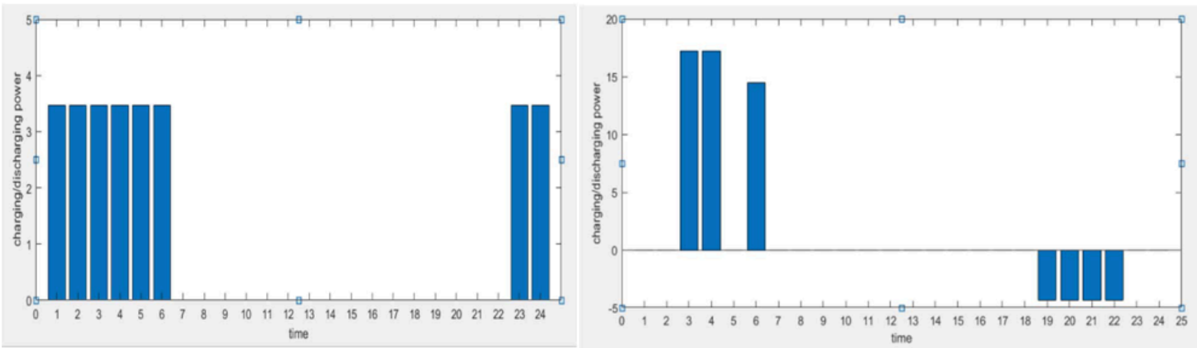

Figure 2: Charging profiles of a delayed charging strategy (left) and a V2G strategy (right). From Fan & Chen (2019)

López et al. (2015) proposed a charging strategy that aims to maximize EV drivers benefits by relying on demand side management strategies. In respond to hourly prices, the smart charging and V2G strategy shift the peak load from the evening to the night, shown in Figure 3. The results show a cost reduction of 55% and 58% for a smart charging and V2G strategy, respectively. While the figure shows the charging profile of one EV, the cost reduction represents the average reductions of several EVs, explaining the mismatch.

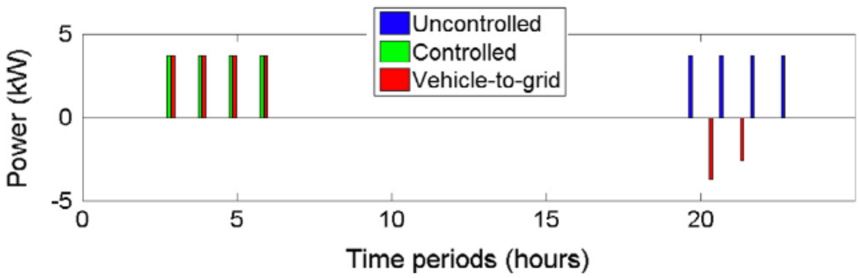

Figure 3: Charging profile of an uncontrolled, controlled, and V2G strategy. The controlled strategy is comparable to the smart charging strategy in this study. From López et al. (2015)

Jian et al. (2018) simulated charging profiles based on Shanghai charging behavior, while charging with a smart charging strategy, coordinated based on electricity price. The charging profile is shown in Figure 4 and shows a clear shift of the demand peak from the evening to the night. They observed a cost reduction of 65% with respect to the random charging strategy.

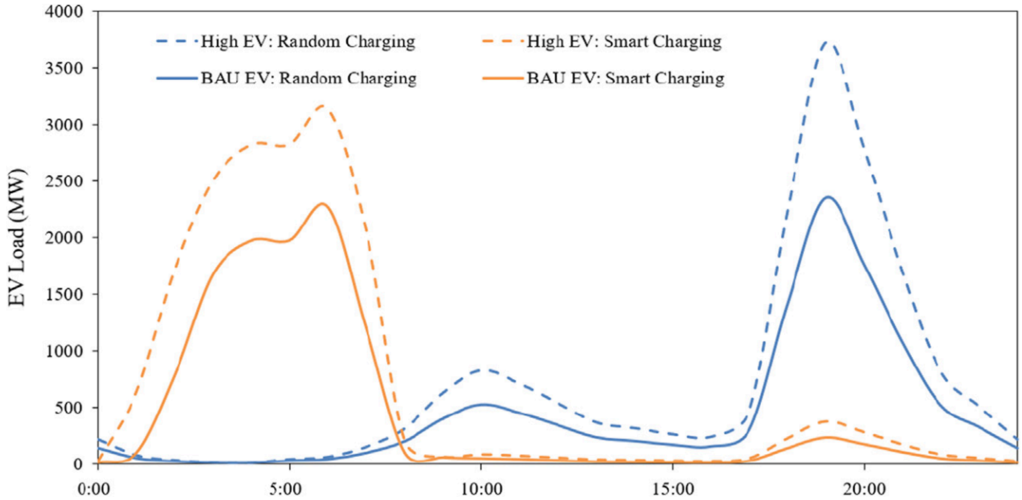

Figure 4: Charging profile of an uncontrolled and a smart charging strategy. The dotted and full line indicate different EV growth scenarios. From Jian et al. (2018)

2.2 Electric vehicle charging trends in the Netherlands

It is expected that in 2030, there will be over 2 million EVs in the Netherlands (Refa et al., 2021). This increase from approximately 330 thousand EVs in 2022, shows that the Dutch EV fleet is growing fast (ANWB, 2023). Currently, most EV drivers have a private charging point: approximately 67% (Rijksdienst voor Ondernemend Nederland, 2022). As the diversity of EV drivers increases, the number of EV drivers with a private parking place will decrease, which will result in an expected decrease of private charging points to 41% (Refa et al., 2021). Nevertheless, this share is still larger compared to public and workplace charging, which are both expected to account for approximately 30% of the Dutch charging points.

The standard charging capacity of a private charging point is 11 kW (ElaadNL, 2023). This is allowed by the typical grid connection of Dutch households, which is a 3-phase 25A connection that results in a maximum capacity of 17.3 kW (Zweistra et al., 2020). However, the low voltage grid was built for a maximum capacity of 4 kW per household, with a maximum average household peak capacity of approximately 1 kW, and the standard charging capacity strongly exceeds this. The influence of the large charging capacities on the low voltage grid can be observed in Figure 5. When charging is uncontrolled, the maximum grid capacity is exceeded every day. The expectation that this will be the case for half of the Dutch neighborhoods in 2030 emphasizes the urge for a large uptake of controlled charging in the Netherlands (Rijksdienst voor Ondernemend Nederland, 2022).

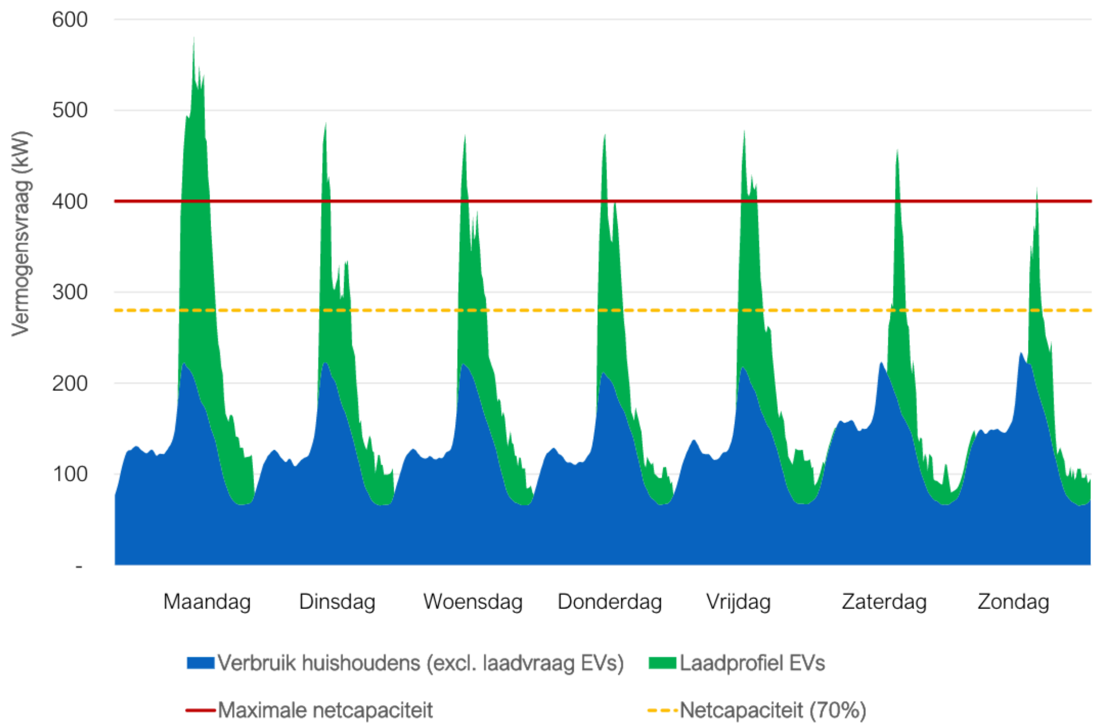

Figure 5: Simulation of an electricity demand profile of a Dutch neighborhood with 250 households with 100 EVs, for one week. The blue graph indicates the electricity demand of the households without the EVs, the green graph indicates the electricity demand of the EVs, the yellow dotted line indicates 70% of the total grid capacity, and the red line indicates the maximum grid capacity. From Refa et al. (2021).

The average Dutch EV driver starts charging its battery when the State-of-Charge (SoC) is around 30%, and they charge it up to approximately 90% (Rijksdienst voor Ondernemend Nederland, 2022). More than 60% of Dutch EV drivers follow a fixed charging pattern, where charging mainly starts and stops at the same time. Figure 6 shows the start and end times of Dutch EV drivers. The starting peaks at 9 PM and 11 PM can be explained by the start of the off-peak electricity tariffs in Noord-Brabant and Limburg, and the rest of the Netherlands, respectively. Most EV drivers leave their EV connected to the grid until they leave home again the next day. Furthermore, what can be observed is that Dutch EV drivers leave their EV connected until the morning after a charging event.

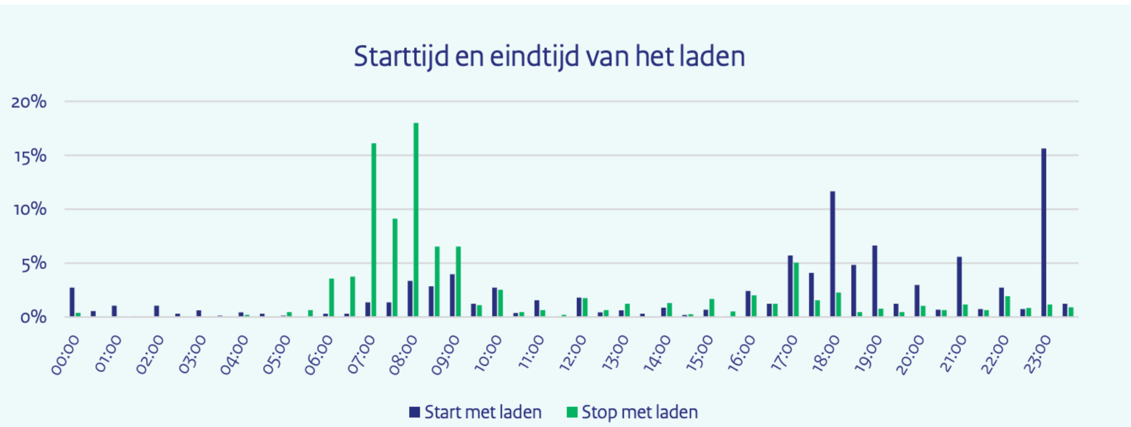

Figure 6: Start time and end time of Dutch chargers, per hour of the day. The blue bars indicate the start times, and the green bars indicate the end times. From Rijksdienst voor Ondernemend Nederland (2022)

This fixed pattern can also be observed in Figure 7, which represents a quantification of the charging power demand of 100 EVs for private charging points (ElaadNL, 2023). What can be observed, is that charging power slowly increases from 9 AM to 4 PM, whereafter the charging power increases more rapidly. There are two peaks, at 9 PM and at 11 PM, which can be explained by the peak in starting times from figure 6. The charging gradually reduces and is close to zero at 6 AM.

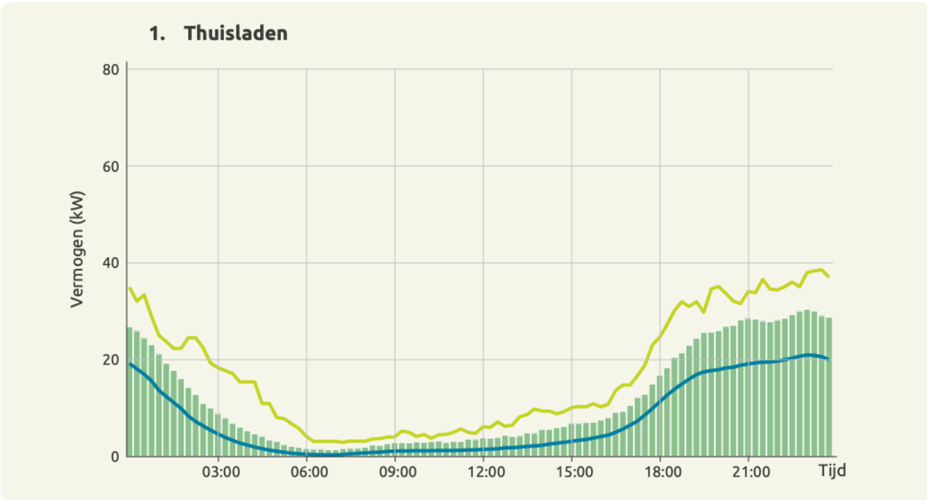

Figure 7: Simulation of charging power demand of 100 EVs on private charging points. The green bars indicate the 95th percentile, the blue line the average demand, and the green line the maximum demand. From ElaadNL (2023)

2.3 Controlled charging in the Netherlands

While more than 40% of Dutch charging infrastructure possesses some form of controlled charging functionality, only 5% of the charging sessions in the Netherlands happens controlled (ElaadNL, 2023; Nationale Agenda Laadinfrastructuur, 2022). To increase this, the National Agenda Charging Infrastructure (NAL), a policy program that connects TSOs, DSOs, governments, and market parties, have set clear ambitions to increase the number of grid-aware controlled charging sessions to 60% by 2025 (Nationale Agenda Laadinfrastructuur, 2022). In their action plan Smart Charging for Everyone (SLVI), they established five activities to stimulate grid-aware charging. These activities are listed below, whereafter a brief description is provided.

1. Ensuring and enhancing attractiveness of controlled charging availability
    a. By market concessions and permits
    b. By agreements with employers' organizations
    c. Forming a leading coalition of providers
    d. Development of a certification mark
2. Stimulating adoption of controlled charging infrastructure
3. Enabling grid-aware charging
4. Inspiring consumers to embrace smart charging
    a. Creation of an up-to-date information base
    b. Educate and inspire
    c. Support during the purchasing process
5. Knowledge development

The first activity focuses on shaping the market and increasing the availability of grid-aware charging services. This activity focuses on availability of grid-aware charging for public and workplace charging, and on stimulating the market. The certification mark will function as a quality label on the provided controlled charging services. The second activity focuses on financially stimulating the adoption of controlled charging infrastructure, since they argue that the price of smart charging infrastructure can form an adoption barrier for consumers. The condition of a potential subsidy is that the consumer charges grid-aware, using a service with a certification mark. The third activity focuses on formulating a charging profile that indicates the maximum available capacity at any moment. The fourth activity aims to create consumer awareness on grid-aware charging, and convincing and supporting consumers in the entire process of the adoption of grid-aware charging services. The fifth activity aims to stimulate knowledge development on several topics.

2.4 Electricity pricing

There are several electricity markets, which mainly differ on timespan before the moment of delivery. There is the Forward and Futures Market, where electricity exchanges for longer periods of time are made. Another market is the Day-Ahead Market (DAM), which is an auction-style market where electricity is bought and sold for every hour of the following day. Lastly, there are Intraday Markets. Buyers and sellers can adjust their demand or supply and make power exchanges for periods of 15 minutes or longer, which must be completed at least 5 minutes before delivery. This section elaborates on how DAM prices are determined, and how this price will change in the future.

Every day when the electricity market opens and producers of electricity enter their price-volume bid for every hour of the next day (Nord Pool, 2020). The price of these bids equals the marginal costs of production for the specified volume. The bids are placed in a so-called merit order, where all bids get lined up based on price, as shown in Figure 8. Buyers also place their volume bids, and when the market closes at noon, the electricity price for that hour is determined by the electricity costs of the generator that is required to meet total demand (Cludius et al., 2014; TenneT, n.d.).

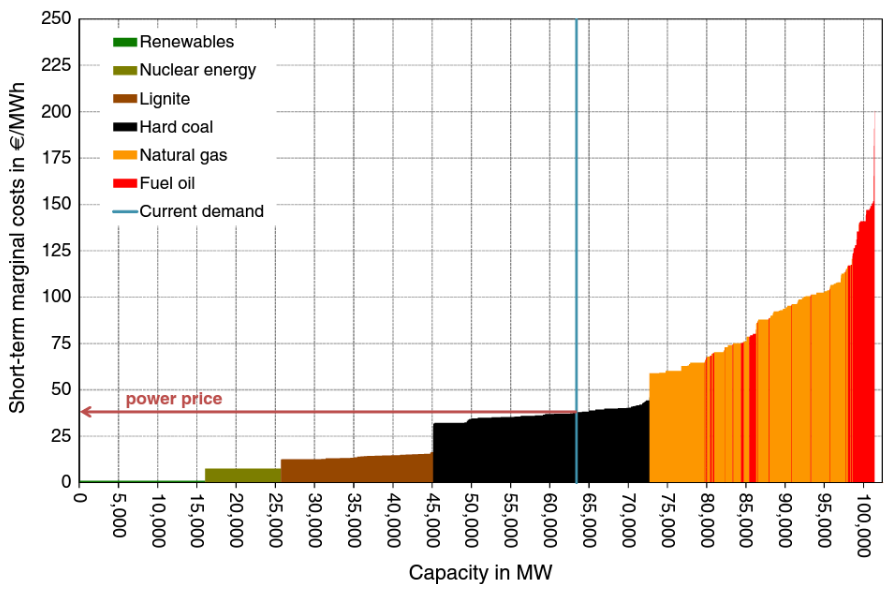

Figure 8: Example of a German merit order curve, from Cludius et al. (2014).

Since marginal costs are mainly determined by fuel costs and CO2 prices, RES have marginal costs close to zero. The increased integration of these RES causes the merit order to shift to the right, also referred to as the merit order effect (MOE), resulting in lower overall electricity prices (Figueiredo & Silva, 2019). This effect is the strongest in hours when demand is lower, and/or when RES supply is highest, e.g. during sunny or windy days, but during periods of high demand and low RES generation, conventional power plants will mainly determine the electricity price (Benhmad & Percebois, 2018). This results in a more volatile electricity market, with large price differences within a day or between days, especially with the expected increase of RES in the future.

3. Methodology

To answer the main research question, this research uses a mixed methods approach. The first research question is answered using qualitative desk research, the second research question is answered by the creation of four quantitative charging behavior models, the third research approach is answer by a quantitative driving profile analysis, and the last research question is answered by conducting qualitative expert interviews. The methods, the (sub)results, and the interrelations are shown in Figure 9. This section discusses these methods per sub question in more detail.

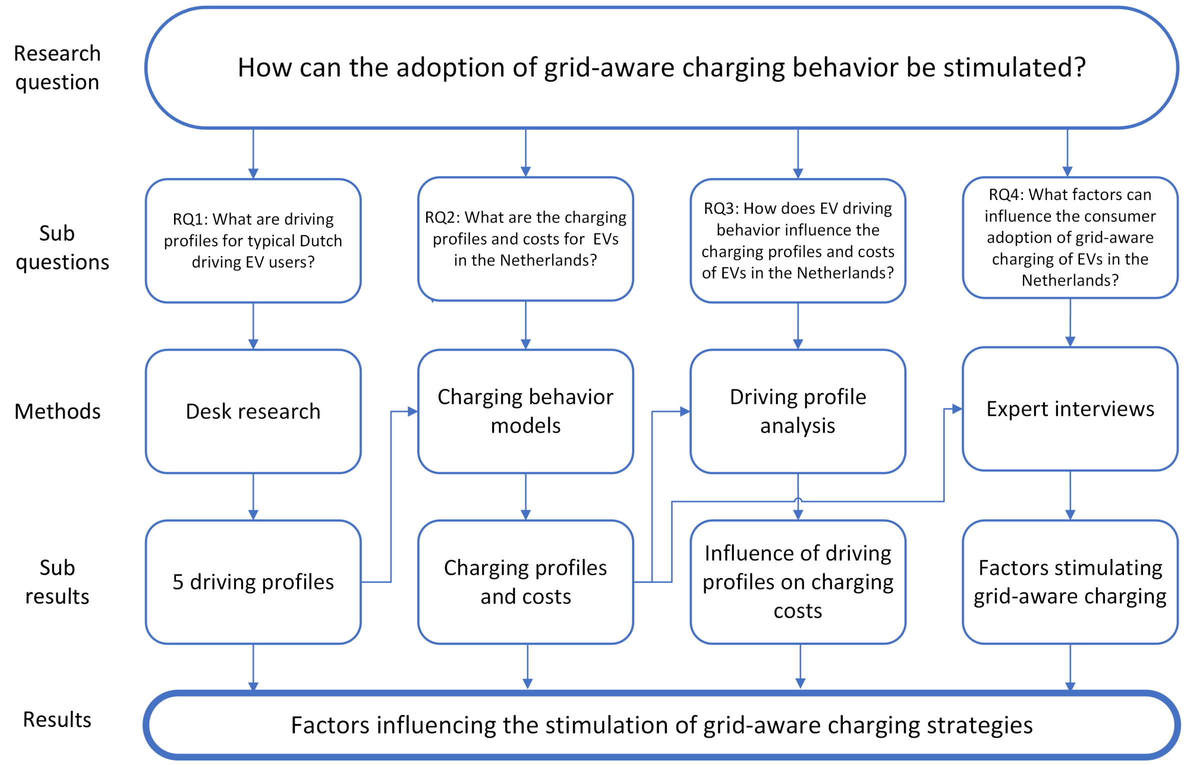

Figure 9: Schematic overview of the research methods

3.1 Driving profiles

EV charging behavior is largely influenced by the driving behavior. Therefore, to simulate charging profiles, this study first identifies driving behavior of typical Dutch EV drivers. This driving behavior is translated into five driving profiles. This section elaborates on the identification and composition of these driving profiles.

3.1.1 Identification of driving profiles

According to Central Bureau of Statistics (CBS), Dutch EV drivers can best be divided into five categories, mainly based on age and phase of life (CBS, 2017). These categories differ in driving intensity, but also include other factors such as goal of driving activities. The categories are described below.

- Age 18 to 30, or ‘young adults’: people in this group are finishing their education or recently started a full-time job. They are moving out of their parent’s house and might start a new family. They travel mostly by public transport and do not own a car.

- Age 30 to 50, or 'rush hour generation': people in this group are employed, focused on their career, and usually have a family with children which need to be picked up and dropped off at school, social, and sports activities.
- Age 50 to 65, or 'semi-retirees': people in this group are still employed, but they are working towards their retirement. They start working less, and their children are usually moved out already.
- Age 65 to 75, or 'recent retirees': people in this group are almost, or recently retired. The car is not used for commuting anymore, and the trips are shorter and less frequent.
- Age 75+, or 'elderly'. At age 75, people must be re-examined to use their drivers' license and drive significantly less.

The driving profiles used in this study are largely based on these profiles but are modified slightly for two reasons. First, as CBS argues, most people in the group aged 18 to 30 do not own a vehicle but instead use public transport to travel. It was deemed not relevant to include that part of the group in this study. Second, what is lacking in the categories is a group that uses their vehicle more occasionally, e.g. only for groceries or picking up children for school, instead of a more regular driving schedule, e.g. a driver that uses its EV to go to work daily. The driving profiles in this study are defined below.

- **Young Professional (YP):** people in this group are typically aged 25 to 35, are employed, but do not yet have kids.
- **Working Parent (WP):** people in this group are typically aged 30 to 50, are employed, and have a family with children that need to be picked up and dropped off at school, social, and sports activities.
- **Semi-retiree (SR):** people in this group are typically aged 50 to 65, are employed, but work less since they are approaching their retirement age. Their children are moved out already, or at an age where they do not have to be picked up and dropped off regularly.
- **Retiree (R):** people in this group are typically aged 65 to 80 and are in their retirement. They have more spare time during the day and are still capable to drive.
- **Occasional Driver (OD):** people in this group do not have a typical age or typical driving schedule.

The following section elaborates on how the driving behavior per profile is determined.

3.1.2 Mileage of the driving profiles

In this section, the process of determining the main characteristics of the driving profiles is shown. First, the time scope for a driving profile was determined. This scope is set for one week, meaning that the driving profile is repeated throughout the simulation of one year. While this is not an accurate presentation of an annual driving pattern, it is deemed a good approximation given the general weekly stability of driving patterns (Schuller et al., 2015). Holidays and weekly deviations in driving behavior are therefore neglected in this study.

Then, the mileage per driving profile was determined. The annual mileage differs significantly between the driving profiles, to allow the identification of the influence of the annual mileage on the charging costs. Figure 10 shows the annual mileage per CBS (2017) category per capita in the Netherlands. Since the data is rather outdated, the absolute mileages are not used in this study. However, it is assumed that the ratios between the categories have remained approximately the same.

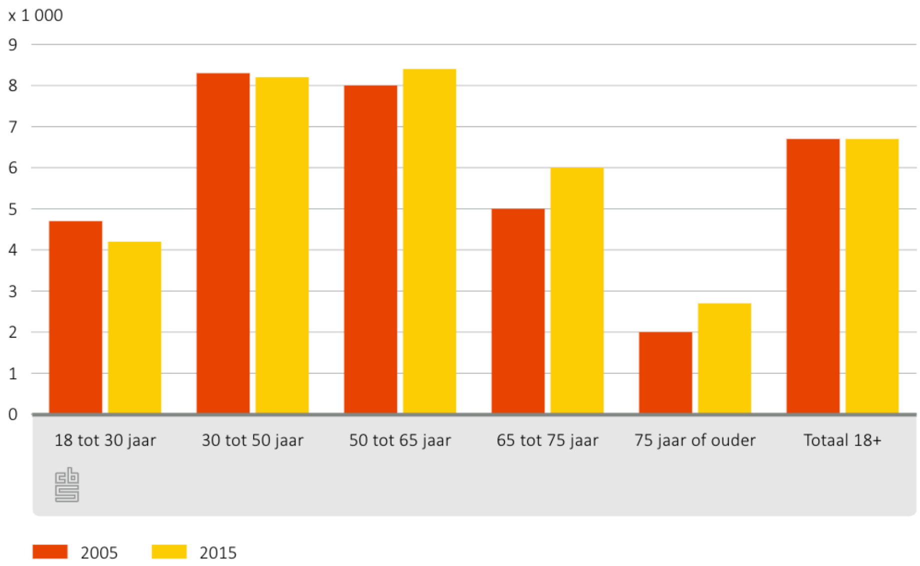

Figure 10: Different annual mileages of the CBS driving profiles per Dutch capita. From CBS (2017).

As these five profiles represent typical Dutch EV drivers, the average mileage of these profiles should equal the mileage of the average Dutch EV driver. However, car ownership is not equally distributed amongst age groups in the Netherlands. The mileage is therefore determined by the weighted average, as shown in equation 3.1, where X indicates the driving profile, and λ_X the contribution of the driving profile to the average. Table 1 shows the distribution of car ownership amongst age groups in the Netherlands. Due to the mismatches in age groups between the driving profiles and CBS (2021), the ownership share of the 75+ group is divided between the SR and R profiles, and the aged 18 to 25 group is allocated to the OD profile.

$$(3.1).\ \ average\ mileage\ = \sum_{X=1}^{5} mileage_X * \lambda_X$$

Table 1: Contribution of the driving profiles to average Dutch EV driver. The age groups and their share in car ownership in the Netherlands is obtained from CBS (2021).

Driving profile	Age group	Share in car ownership	Contribution to combined profile (λ_X)
YP	25 to 35	14.6%	14.6%
WP	35 to 45 & 45 to 55	15.9% + 20.7%	36.6%
SR	55 to 65 & 0.5 * 75+	19.8% + 5%	24.8%
R	65 to 75 & 0.5 * 75+	15.8% + 4.5%	20.3%
OD	18 to 25	3.7%	3.7%

The mileage was determined by providing the driving profiles with some context, which relates to real driving behavior. Each driving profile got allocated several activities where

Dutch people travel to by car, shown in Table 2. The average distance to these activities is provided by CBS (2021). The mileage per driving profile was determined, and by trial and error activities were added and removed to reach the mileage of the average Dutch EV driver, which is estimated at 16890 km/year in 2030 (ElaadNL, 2023).

Table 2: Activities where Dutch people drive to and the average distance when travelled to by car, both obtained from CBS (2021). Last five columns show the frequency the activities occur in the driving profiles.

Activity	Distance [km]	YP	WP	SR	R	OD
To and from work	22.81	8	8	6	0	2
Business trips	30.28	1	2	2	0	0
Service and care	12.21	0	2	3	2	1
Shopping and groceries	6.75	2	3	2	3	2
Education	26.27	0	0	0	0	2
Visiting	23.91	1	2	1	4	1
Spare time activities (sports, hobbies, etc)	17.07	1	3	2	3	1
Touring, hiking	23.83	0	0	1	1	0
Other	11.72	1	1	1	1	1

These mileages are shown in Figure 11. What can be observed, is that each profile differs significantly in mileage, and the average mileage approximates the mileage for the average Dutch EV driver. Furthermore, the differences between the driving profiles resembles the differences of the CBS profiles in Figure 10, except for the difference between the WP and SR profiles. This difference is introduced to include more variety between the driving profiles. The next section elaborates on the composition of the driving profiles.

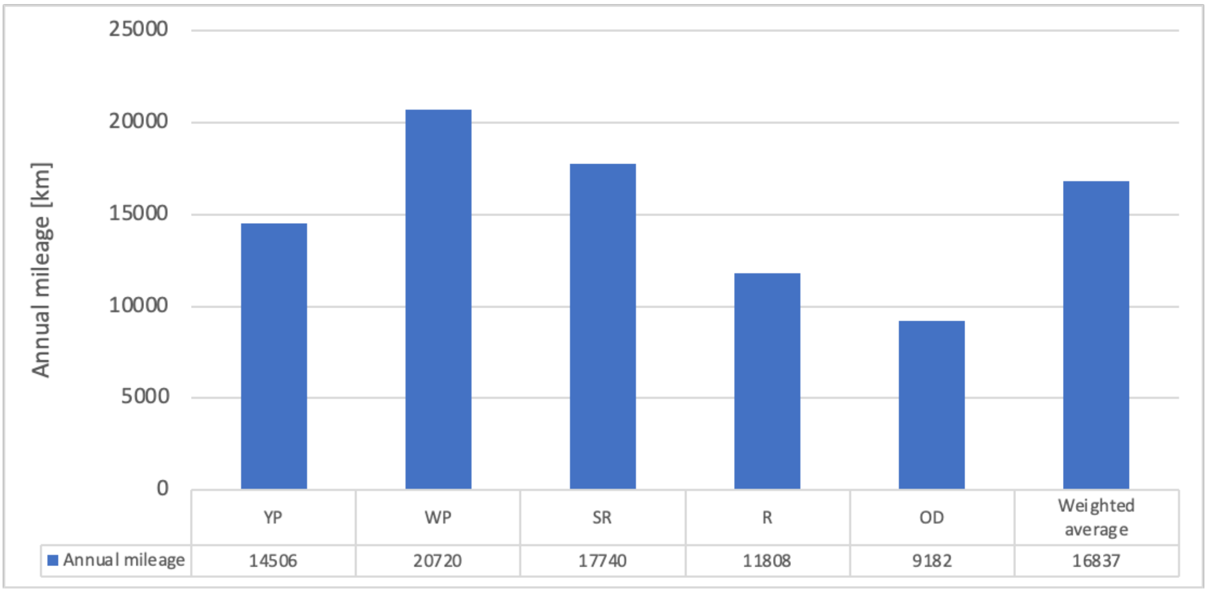

Figure 11: Annual mileage of the different driving profiles, and the weighted average mileage

3.1.3 Composition of the driving profiles

This study aims to identify what the influence of driving behavior is on the charging profile and costs. Due to the limited availability on weekly, monthly, or annual driving schedules of the typical Dutch EV drivers, the composition of the activities is done anecdotal, i.e. based on a brief story rather than on comprehensive data. The placement of the activities in the weekly driving schedules is done arbitrarily. This section provides the composition of one driving profile, the YP profile, to provide some insights in this process. The composition of the other profiles can be found in appendix A.

Young Professionals (YP)

The YP is typically aged 25 to 35 and is in the beginning of its career. The YP has no kids, or kids that are too young to encounter in any activities out of the house. The YP commutes to work 4 days a week, leaving home early, and returning late in the afternoon or beginning of the evening. The YP does shopping/groceries twice a week, has one business meeting and one unspecified meeting in the evening. The YP barely uses the EV in the weekend, except for one spare time activity and one visitation. The YP profile is shown in Figure 12.

YP							
Hour	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
1							
2							
3							
4							
5							
6							
7							
8	*Work*		*Work*				
9		*Work*		*Work*			
10							
11						*Spare time*	
12							
13				*Business*			*Visiting*
14							
15							
16							
17					*Shopping*		
18	*Work*		*Work*				
19	*Shopping*	*Work*		*Work*			
20							
21							
22			*Other*				
23							
24							

Figure 12: The Young Professional driving profile. The white squares indicate that the EV is parked at home and the grey squares that the EV is driving or parked elsewhere.

3.2 Charging behavior model

The second part of this research focusses on simulating charging profiles and quantifying charging costs for the different charging strategies. Figure 13 schematically shows the inputs and outputs of the charging behavior model. This section discusses the inputs of the model, the model design, and how the outputs are translated into one charging profile and cost per charging strategy.

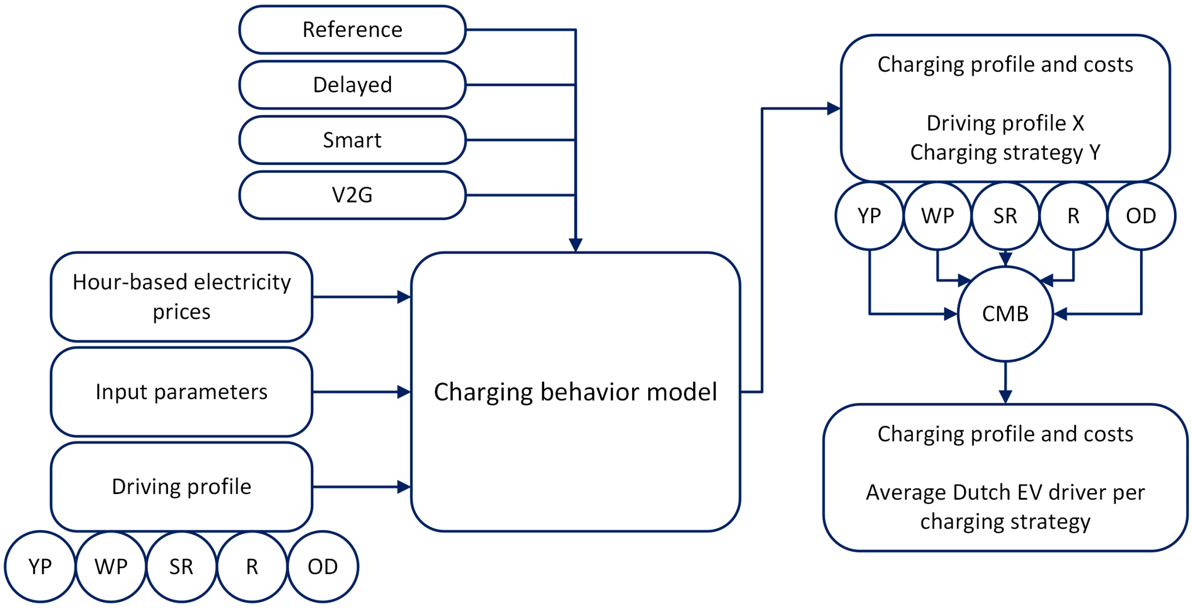

Figure 13: Schematic overview of the inputs and outputs of the charging behavior model

3.2.1 Inputs

The input of the model consists of three main components: the hour-based electricity prices, the parameters, variable bounds and system limits, and the driving profiles. This section discusses these inputs in more detail.

3.2.1.1 Hour-based electricity prices

The simulation coordinates charging based on the hour-based electricity prices. These prices are provided by The Netherlands Environmental Assessment Agency (PBL) and are a part of their Climate and Energy Exploration (KEV), a study that calculates and estimates the effects of Dutch national policies on the climate. The prices are the result of the COMPETES model, which simulates DAM electricity prices based on several inputs (PBL, n.d.). There are three scenarios provided by PBL: a low, mid, and high price scenario. This research uses the mid scenario. Furthermore, the assumption is made that electricity can be bought and sold for the hour-based prices, which therefore excludes taxes.

The distribution of electricity prices per hour of the day is shown in Figure 14. What can be observed, is that during the night, the electricity price is relatively low, especially at 5 and 6 AM. During the start of the morning, the prices increase, and at the end of the morning they start declining again. At noon, general electricity prices are the lowest. During the afternoon, the prices increase again, with a peak at 6 and 7 PM, after which they slowly decreasing again.

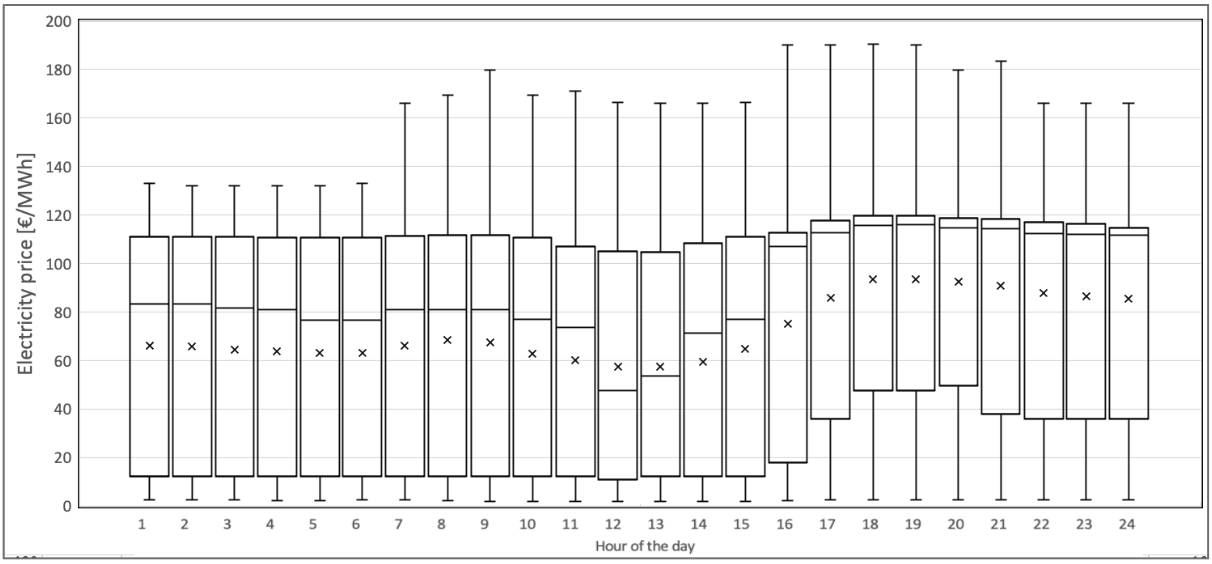

Figure 14: Distribution of the predicted hour-based electricity prices for 2030 per hour of the day, provided by PBL. The cross inside the box indicates the average electricity price, and the bar inside the box indicates the median electricity price.

Figure 15 shows a heatmap of the distribution of the average electricity price per hour throughout one week. What can be observed here, is that on Monday to Friday evenings, the electricity prices are the highest, mainly between 5 and 9 PM. Furthermore, there is a small morning peak around 8 AM. Electricity is on weekdays the cheapest during the nights, and during the afternoons. During the weekend the electricity prices are overall lower, especially on during the morning and afternoon.

Mid - 2030 predictions by PBL							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	72	70	71	73	80	56	41
2	71	68	72	73	80	57	40
3	71	64	72	70	79	55	40
4	71	65	72	69	78	51	41
5	69	65	71	70	76	50	41
6	71	65	69	70	78	49	40
7	74	71	74	75	86	44	38
8	76	76	81	82	91	42	32
9	76	76	79	81	87	40	31
10	71	71	73	74	81	40	29
11	68	66	69	69	77	41	30
12	66	66	68	66	71	35	30
13	65	66	67	66	73	36	30
14	68	66	69	68	78	37	29
15	73	69	76	75	81	45	34
16	83	81	85	82	92	57	45
17	98	90	94	95	102	64	57
18	105	96	100	104	106	76	69
19	104	97	99	104	107	76	69
20	102	97	97	104	105	74	69
21	100	95	95	102	104	70	68
22	95	92	93	98	101	69	67
23	92	91	91	96	101	68	65
24	89	91	91	96	100	68	65

Figure 15: Heatmap indicating the distribution of the predicted average hour-based electricity prices for 2030 throughout the week, provided by PBL. Higher prices are indicated by deeper red colors.

3.2.1.2 Input parameters

In this section, the parameters that are used in the charging behavior model are discussed. Table 3 gives an overview of these parameters. Below, a description of the parameters is provided, together with how the value is obtained.

Table 3: Input parameters used in the charging behavior models.

Notation	Parameter	Unit	Value
$\boldsymbol{E_{battery}}$	Battery capacity	kWh	72.2
$\boldsymbol{e_{consumption}}$	Specific electricity consumption	kWh/km	0.2
$\boldsymbol{E_{MAX,from\ grid}}$	Maximum charging capacity from grid	kWh	11
$\boldsymbol{E_{MAX,into\ grid}}$	Maximum discharging capacity into grid	kWh	8.9
$\boldsymbol{\eta_{charge}}$	Charging efficiency	%	90
$\boldsymbol{\eta_{discharge}}$	Discharging efficiency	%	90
$\boldsymbol{SoC_{MIN}}$	Minimum State-of-Charge	%	30
$\boldsymbol{SoC_{MAX}}$	Maximum State-of-Charge	%	90
$\boldsymbol{SoC_{threshold}}$	Threshold State-of-Charge	%	50
$\boldsymbol{SoC_{start}}$	Starting State-of-Charge	%	90
$\boldsymbol{c_{degradation}}$	Battery degradation costs	€/kWh$_{\text{discharged}}$	0.0201

Battery capacity

The total capacity of the EVs battery, expressed in kWh. The value used in this study is the weighted average battery capacity of the 10 most sold EVs in The Netherlands in 2022 (Autoweek, 2023; EV-database, n.d.). This weighted average is calculated by equation 3.2, where the *i* represents the type of EV.

$$(3.2).\quad E_{battery} = \frac{\sum_{i=1}^{10} EVs\ sold_i * E_{battery,i}}{\sum_{i=1}^{10} EVs\ sold_i}$$

Specific electricity consumption

The amount of electricity that the EV consumes while driving, expressed in kWh/km. The current accepted average electricity consumption is 0.2 kWh/km (ElaadNL, 2023).

Maximum charging capacity

The maximum amount of electricity that the charger can extract from the grid during one hour, expressed in kWh. For private charging, 11 kWh is the standard in the Netherlands (ElaadNL, 2023; Refa et al., 2021).

Maximum discharging capacity

The maximum amount of electricity that the charger can inject into the grid during one hour, expressed in kWh. This value is set at 8.9 kWh (Schram et al., 2020), which equals the maximum charging capacity minus the charging losses for charging and discharging.

Charging efficiency

The combined efficiency of the charger and battery pack, that causes a loss in electricity from the grid to the EV (Datta et al., 2019). The efficiency is assumed linear and therefore not dependent on charging power. A typical EV charging efficiency is 90% (Crozier et al., 2020; Datta et al., 2019; Sachan et al., 2020).

Discharging efficiency
Identical to the charging efficiency, but only in the reverse direction, i.e. EV to grid. A typical EV discharging efficiency is 90% (Datta et al., 2019).

Minimum State-of-Charge and maximum State-of-Charge
Bounds set on the SoC of the EV's battery that aim to extent the batteries lifetime, expressed in percentages of total battery capacity. The battery's lifetime increases significantly if the SoC remains between 20% and 90% of the total battery capacity (Amamra & Marco, 2019; Beyazıt et al., 2022; Fan & Chen, 2019).

Threshold State-of-Charge
The threshold value at which the EV will start to charge in the reference simulation, expressed as percentage of total battery capacity. According to Delmonte et al. (2020), most people charge their EV when it is still above 40% SoC, while (Deb et al., 2018) argue that this value is around 55%. The used value here is 50%.

Starting State-of-Charge
The SoC at the beginning of the simulation, expressed in percentage of total battery capacity. The SoC at the start of the simulation is assumed to be 90%.

Battery degradation costs
Irreversible chemical reactions in the battery that occur due to the charging and discharging cause the total available battery capacity to decrease (Tan et al., 2016). The total battery costs are divided by the reduced available capacity to express this in monetary terms, in $€/kWh_{discharged}$.

The costs are determined by equation 3.3 (Beyazıt et al., 2022), where C_{unit} represents the costs of the battery pack per kWh, C_{labor} the cost of labor, SV the salvage value, N_{cycle} the number of cycles the battery can run before the capacity drops below an acceptable level, and DoD the maximum depth of discharge, which is the inverse of SoC_{MIN}.C_{unit} & C_{labor} are €127 and €156 (Beyazıt et al., 2022), respectively, SV is 60% of the capital costs of the battery (Kolawole & Al-Anbagi, 2019), and N_{cycle} equals 3221 cycles at 80% DoD (Han et al., 2019). This comes down to $0.0201\ €/kWh_{discharged}$

$$(3.3).\quad c_{degradation} = \frac{C_{unit} * E_{battery} + C_{labor} - SV}{N_{cycle} * E_{battery} * DoD}$$

3.2.1.3 Driving profiles

The driving profiles provide the input for the driving behavior in the charging behavior model. For every timestep, the model determines whether the EV is driving, parked at home, or parked elsewhere. When the EV is driving, the model determines the activity and the corresponding distance, as provided in Table 2. The distance in km is multiplied with $e_{consumption}$ to obtain the consumed electricity required for the driving activity. This is shown in equation 3.4, where $E_{consumed}$ represents the electricity consumed due to the driving activity, and $d_{activity}$ represents the distance for this driving activity.

$$(3.4). \quad E_{consumed} = d_{activity} * e_{consumption}$$

3.2.2 Model design

This study includes the creation of four models, each describing a different charging strategy. These models are made in Excel, and the simulation is performed by OpenSolver. In this section, the design of these models is discussed. The equations and variables mentioned in this section are based on the controlled charging simulations of Richardson et al. (2012), Franco et al. (2015), Schuller et al. (2015), López et al. (2015), Fan & Chen (2019), Jian et al. (2018), and Datta et al. (2019), and modified where required to fit the model. This section starts with the general model design, whereafter the four models are discussed separately.

3.2.2.1 General model design

Each simulation aims to identify the charging profile of one EV for one year, according to one charging strategy, including the driving behavior as described in one driving profile. The timestep in all models is one hour, which is denoted from here on with index *i*.

Table 4 gives an overview of the variables that are used to present and describe the model. It should be noted that $E_{discharge,i}$ and $E_{into\ grid,i}$ are only applicable for the V2G strategy, as this is the only model that allows electricity to flow out of the EV's battery.

Table 4: Variables used in the charging behavior models.

Notation	Variable	Unit	Variable description
$\boldsymbol{SoC_i}$	State-of-Charge	kWh	The amount of energy that is available in the battery at timestep *i.*
$\boldsymbol{E_{charge,i}}$	Charged electricity	kWh	The amount of electricity that is charged into the battery at timestep *i.*
$\boldsymbol{E_{discharge,i}}$	Discharged electricity	kWh	The electricity that is discharged from the battery at timestep *i.*
$\boldsymbol{E_{from\ grid,i}}$	Extracted electricity	kWh	The electricity that is extracted from the grid at timestep *i.*
$\boldsymbol{E_{into\ grid,i}}$	Injected electricity	kWh	The electricity that is injected into the grid at timestep *i.*

Each simulation starts with the same starting conditions, where $SoC_0 = SoC_{start}$. Hereafter, for every timestep, the simulation calculates the SoC by using equation 3.5, where $E_{consumed,i}$ represents the consumed electricity due to a driving activity. It should be noted that the last term is only applicable to the V2G simulation, since this is the only simulation that can discharge electricity into the grid.

$$(3.5). \quad SoC_i = SoC_{i-1} - E_{consumed,i} + E_{charge,i} - E_{discharge,i}$$

The following section elaborates on the characteristics of the four models separately.

3.2.2.2 Reference charging strategy

The reference charging strategy represents an EV that is charged uncontrolled, i.e. it is charged at full capacity the moment the EV is connected to the grid. The EV starts charging when it arrives at home and the SoC is below the $SoC_{threshold}$. From this moment, the EV charges at full capacity until either the SoC reaches SoC_{MAX}, or the EV is disconnected from the grid for a driving activity. When the SoC reaches SoC_{MAX}, the EV stays connected to the grid until the next driving activity. This is important for the delayed charging simulation, as this model can only charge after a charging activity in the reference charging simulation. This is discussed in more detail in the next section.

3.2.2.3 Delayed charging strategy

The delayed charging simulation aims to minimize charging costs by postponing the charging moment towards hours with lower electricity prices. This means that the EV is only allowed to charge during the timesteps in which the EV was connected to the grid in the reference charging simulation. To illustrate, when the EV arrives at home at 7 PM with an SoC of 40%, It starts to charge in the reference charging simulation. It disconnects the next morning at 8 AM for a driving activity. The delayed charging strategy is therefore allowed to charge between 7 PM and 8 AM on this day.

To coordinate the based on a minimization of charging costs, a LP is formulated. The objective function F(x) is shown in equation 3.6, where P_i represents the electricity price at timestep *i*.

$$(3.6).\quad F(x) = min. \sum_{i=1}^{8760} E_{from\ grid,i} * P_i$$

This minimization of charging costs is obtained by finding the optimal value for the decision variables:

$$E_{from\ grid,i}$$

To constrain the simulation to the allowed charging moments. The binary variable $\alpha_{delayed,i}$ is introduced. This variable has a value of 1 for the timesteps when there was a grid connection in the reference simulation, and 0 when there was no connection, as shown in equation 3.7. The electricity that is charged into the EV can be calculated by equation 3.8.

$$(3.7).\quad \alpha_{delayed,i} = \begin{cases} 1, & grid\ connection\ in\ referece\ simulation \\ 0, & else \end{cases}$$

$$(3.8).\quad E_{charge,i} = E_{from\ grid,i} * \eta_{charge} * \alpha_{delayed,i}$$

The decision variables are bounded by zero and the maximum charging capacity, as shown in equation 3.9.

$$(3.9).\quad 0 \leq E_{from\ grid,i} \leq E_{MAX,from\ grid}$$

Lastly, there are two constraints that bound the simulation, which are shown in equation 3.10 and 3.11. Equation 3.10 ensures that the SoC always stays within the boundaries that minimize the increased degradation of the battery.

$$(3.10). \quad SoC_{MIN} \leq SoC_{\mathrm{i}} \leq SoC_{MAX}$$

Equation 3.11 was implemented in this model to increase the realism of charging behavior. The $SOC_{full,i}$ equals SoC_{MAX} at the timestep when, in the reference charging simulation, the EV leaves the house with an SoC equal to SoC_{MAX}, and equals 0 otherwise. These constraints the delayed charging simulation to have a fully charged battery at certain moments, rather than optimizing the charging behavior based purely on the driving profile. Without this constraint, the simulation will sometimes charge the EV just enough to satisfy the daily driving activities. As EV drivers usually do not know their exact daily mileage in advance, and therefore to have a more realistic model, this constraint was introduced.

$$(3.11). \quad SoC_i \geq SOC_{full,i}$$

3.2.2.4 Smart charging strategy

The smart charging simulation coordinates charging based on a minimization of costs, while assuming the EV is always connected to the grid when it is parked at home. This increases the flexibility in choosing the charging moment compared to the delayed charging simulation.

This constraint is denoted in the binary variable $\alpha_{smart,i}$, which has a value of 1 for the timesteps when there was a grid connection in the reference simulation, and 0 when there was no connection, as shown in equation 3.12.

$$(3.12). \quad \alpha_{smart,i} = \begin{cases} 1, & parked\ at\ home \\ 0, & else \end{cases}$$

The objective function, decision variables, variable bounds, and constraints are identical as in the delayed charging strategy. These elements can therefore be found in section 3.2.2.3 in equation 3.6 to 3.11, where $\alpha_{smart,i}$ replaces $\alpha_{delayed,i}$.

3.2.2.5 Vehicle-to-Grid strategy

The V2G strategy aims to minimize charging costs by not only charging the EV at the timesteps with the lowest energy prices, but also by discharging the EV to generate revenue. The EV is assumed to be connected to the grid whenever it is parked at home.

To coordinate charging according to the V2G strategy, again, a LP is formulated. Again, the objective function aims to minimize charging costs, and is shown in equation 3.13. This function now includes the revenue generated by the injection of electricity back into the grid, as well as the costs of the increased battery degradation.

$$(3.13). \quad F(x) = min. \sum_{i=1}^{8760} (E_{from\ grid,i} * P_i - E_{into\ grid,i} * P_i + E_{discharge,i} * \ c_{degradation})$$

The charging profile is obtained by finding the optimal values for the decision variables:

$$E_{from\ grid,i} \text{ and } E_{into\ grid,i}$$

Since the battery is only allowed to charge and discharge when the EV is connected to the grid, the charged and discharged electricity are calculated by equation 3.14 and 3.15, and $\alpha_{V2G,i}$ by equation 3.16.

$$(3.14).\quad E_{charge,i} = E_{from\ grid,i} * \eta_{charge} * \alpha_{V2G,i}$$

$$(3.15).\quad E_{discharge,i} = \frac{E_{from\ grid,i}}{\eta_{discharge}} * \alpha_{V2G,i}$$

$$(3.16).\quad \alpha_{V2G,i} = \begin{cases} 1, & parked\ at\ home \\ 0, & else \end{cases}$$

The decision variables are bounded by zero, and the maximum charging and discharging capacities, as is shown in 3.17 and 3.18.

$$(3.17).\quad 0 \leq E_{from\ grid,i} \leq E_{MAX,from\ grid}$$

$$(3.18).\quad 0 \leq E_{into\ grid,i} \leq E_{MAX,into\ grid}$$

Lastly, there are two constraints that bound the simulation, shown in equation 3.19 and 3.20. As these constraints are identical to equation 3.8 and 3.9, more details on these constraints can be found in section 3.3.2.3.

$$(3.19).\quad SoC_{MIN} \leq SoC_{\mathrm{i}} \leq SoC_{MAX}$$

$$(3.20).\quad SoC_i \geq SOC_{full,i}$$

It should be noted that the EV is not allowed to charge and discharge simultaneously. However, the charging and discharging efficiencies cause this to be unprofitable, since the electricity price for extraction and injection are identical. An additional constraint was therefore not required.

3.3.3 Combined profile

The charging profile of the five driving profiles are aggregated into the combined (CMB) profile, which represents the charging profile of the average Dutch EV driver. This is done by equation 3.22, where $E^{CMB}_{from\ grid,i}$ indicates the electricity extraction for the combined profile at timestep *i*, $E^{X}_{from\ grid,i}$ indicates the amount of electricity that is extracted from the grid at timestep *i* for driving profile *X*, λ_X indicates the contribution to the combined profile for driving profile X as shown in Table 1.

$$(3.22).\quad E^{CMB}_{from\ grid,i} = \sum_{X=1}^{5} E^{X}_{from\ grid,i} * \lambda_X$$

3.3 Driving profile analysis

In this section, the methods of the driving profile analysis are discussed. This analysis focused on the influence of the driving profiles on the charging profile and costs. This is done by comparing the charging profiles and costs of the separate driving profiles, not the combined profile. Differences in these results are explained by differences in the driving profiles. The differences between the profiles that this analysis focused on are the annual mileage and the hours that the EV is parked at home, which are shown in Table 5.

Table 5: Mileage and time the EV is not parked at home, per driving profile.

Characteristic	Unit	YP	WP	SR	R	OD
Annual mileage	[km]	14506	20720	17740	11808	9182
Time not parked at home	[h]	49	56	49	19	28

3.4 Sensitivity and uncertainty analysis

In this section, the sensitivity and uncertainty analyses are discussed. The sensitivity analysis focused on the influence of the electricity prices on the results, and the uncertainty analysis focused on the influence of the anecdotal composition of the driving profiles on the results.

3.4.1 Sensitivity analysis

As mentioned in section 3.2.1.1, PBL has provided three scenarios for the electricity prices: a low, mid, and high scenario. In the sensitivity analysis, the influence of the electricity scenarios on the charging profile and costs are determined. The simulations are therefore also run with the low and high electricity price scenarios, to identify what the influence of the electricity price is. The rest of this section elaborates on the differences between the low, mid, and high electricity price scenario.

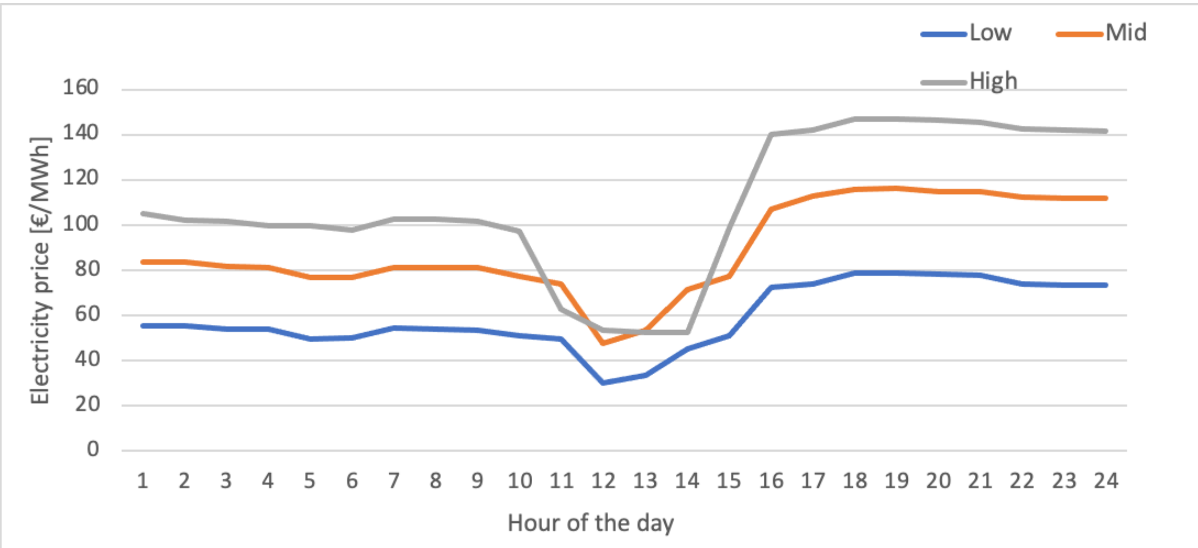

Figure 16: Median electricity price distribution of the three electricity scenarios from PBL throughout the day.

Figure 16 shows the median electricity price per hour of the day for the three price scenarios. The median is used here, since the median is less sensitive to outliers and therefore shows a good representation of distribution of the electricity prices. What can be observed here, is that the three scenarios have a similar flow in the graph throughout the day; prices start in the night at a medium height, they are at a lowest in the beginning of the afternoon, rise in the late afternoon, to reach their peak in the evening. The main difference between the three scenarios in the drop in the afternoon in the high price scenario compared to the other scenarios. The electricity prices are relatively lower in the afternoon, and this price drops takes several hours longer than in the other price scenarios.

The heatmaps indicating the distribution of the average electricity prices throughout the week are provided in Appendix B. These heatmaps show a similar distribution of the electricity prices throughout the week. The absolute values for the electricity prices do differ significantly, however.

3.4.2 Uncertainty analysis

The uncertainty analysis aims to identify the influence of the assumptions made in the composition of the driving profiles. To analyze the influence of these assumptions, the composition of one driving profile was radically changed twice, to form two new driving profiles. these new driving profiles have an identical mileage and number of hours parked at home but differ in the moment they drive and are parked elsewhere. These profiles do not represent a typical Dutch driving profile but are rather used as an extreme opposite to the regular driving profile identify what the differences in charging profile and costs are.

As most driving profiles have rather similar driving behavior, i.e. drive mostly during the morning, afternoon, and a little during the evening, it was expected that this analysis would create similar results for all profiles. Therefore, it was deemed appropriate to do this analysis only on one driving profile. The YP profile is chosen due to the average mileage compared to the other profiles, and since it includes several hours weekly where it is parked elsewhere, which is not included in the R and OD profiles. The two new driving profiles are shown in Appendix C.

3.5 Expert interviews

The charging profiles and costs for the different charging strategies, as well as the influence of the driving profiles do not provide any guidance of how it can be implemented in practice to stimulate the adoption of grid-aware charging behavior. To establish how this adoption can be stimulated, it is important to understand the current market mechanisms, the stakeholders, their interests and expectations, and emerging future trends.

To create a better understanding of this, nine expert interviews were conducted. The experts were chosen based on their area of expertise and their relationship towards controlled charging. The experts can be divided into four groups: DSOs (D), market parties (M), policy experts (P), and process facilitators (F). This divergent mix allows the understanding of market mechanisms and stakeholders from multiple perspective, which reduces stakeholder biases and therefore increases the validity of the results from the expert interviews. An overview of the interviewees, their expert code, and their relationship with controlled charging is provided in Table 6.

The nine experts are selected via the network of the Dutch Association of Renewable Energy (NVDE). The interviews are conducted using a semi-structured approach, and all interviews followed a similar structure. Since the interviewees all had different knowledge levels and a different area of expertise, the discussed topics initiated many follow-up questions, which led to new insights and ideas. All interviewees gave consent for the interview to be used in this study, and the results of the interviews are anonymized. The interviews were conducted in

Dutch, by preference of the interviewees. A general interview guide is provided in Appendix E.

Table 6: Overview of interviewees and their relation to controlled charging, per expert code.

Expert code	Relation with controlled charging
D.1	Project manager Smart Charging at a knowledge institution funded by DSOs, focusing on formulating and analyzing Smart Charging concepts and pilots
D.2	Representative at a DSO
M.1	Product owner Smart Charging at a company that produces and supplies energy
M.2	Representative at a company that produces and supplies energy and energy efficient technologies and solutions
M.3	Business developer smart energy systems at a company that produces and supplies energy and energy efficient technologies and solutions
P.1	Policy developer at a Dutch ministry in the field of Smart Charging and V2G
P.2	Policy expert and former member of the Dutch House of Representatives
F.1	Member of an organization that connects DSOs, the government, and market parties to identify ambitions and actions required to ensure a smooth and safe integration of EVs into the electricity grid
F.2	Facilitator that guided and formulated smart charging concepts with DSOs, the government, and market parties

4. Results

In this section, the results of the research are discussed. The section starts with the results of the charging behavior models, whereafter the influence of the driving profiles on these results are analyzed. The section continues with the sensitivity and uncertainty analyses and ends with the results of the expert interviews. For readability reasons, some sections discuss the results V2G strategy separate from the other results, as this includes a different type of results.

4.1 Simulation results

The results of the charging simulations are shown in Table 7. What can be observed, is that all controlled charging simulations show cost reductions compared to the reference scenario. There are significant differences in reduction between the strategies. The results show that the V2G simulation shows the largest cost reductions, followed by the smart charging simulation, and then the delayed charging simulation. The rest of this section discusses the charging profiles and costs per charging simulation.

Table 7: Charging costs of the four simulations, per charging strategy

Result	Unit	Reference	Delayed	Smart	V2G
Annual charging costs	[€]	319.0	202.3	121.4	-117.3
Reduction in annual charging costs	[%]	-	37%	62%	137%
Average charging costs	[€/100 km]	1.89	1.20	0.72	-0.70
Average charging costs reduction	[€/100 km]	-	0.69	1.17	2.59

4.1.1 Reference charging strategy

The reference simulations show annual charging costs of €319.0, and an average charging costs of € 1.89 per 100 km. These relatively high costs can be explained by the charging profile, shown in Figure 17. What can be observed, is that most of the electricity is extracted during hours where the electricity prices are relatively high, i.e. during the late afternoon and evening. There is only a little charging during the hours where electricity prices are relatively lower.

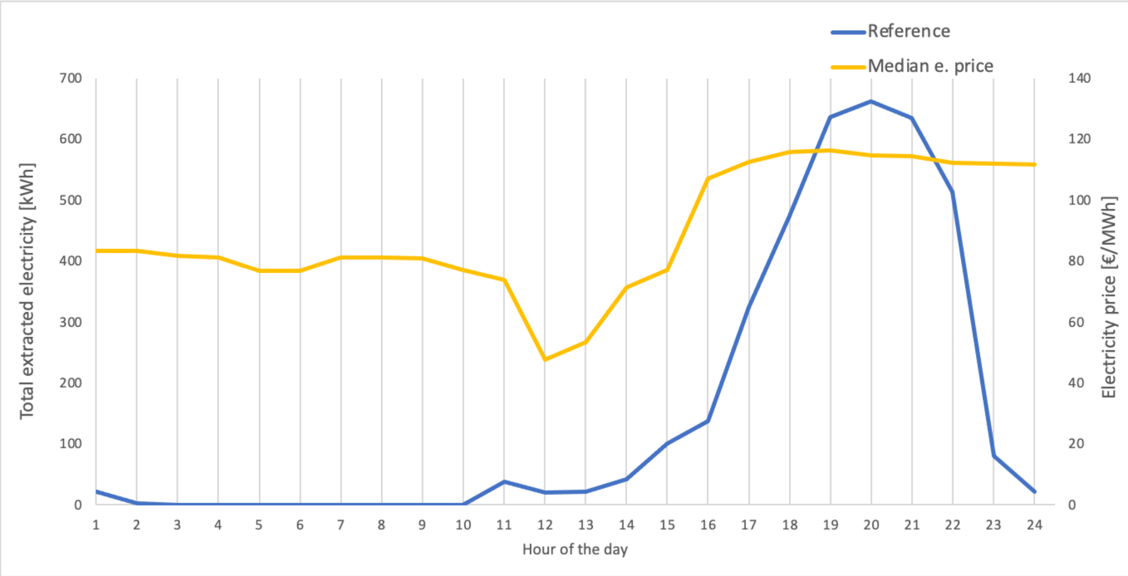

Figure 17: Charging profile of the reference simulation (left-hand axis) together with the median electricity price (right-hand axis)

What comparing the charging profile of the reference simulation with Figure 7, it can be observed that the same evening peak occurs in both profiles. The main differences are two charging peaks in the ElaadNL (2023) profile at 9 and 11 PM. These two peaks are caused by the increase in charging sessions at 9 and 11 PM, observed in Figure 6. As these peaks represent EV drivers that start charging at off-peak hours, rather than when they arrive at home, this can be considered a form of delayed charging. Since the reference strategy represents no form of controlled charging, these peaks are excluded, and the charging profile of ElaadNL is expected to resemble the profile of the reference simulation.

4.1.2 Delayed charging strategy

The delayed charging simulation show annual charging costs of €202.3, which is reduction of 37% compared to the reference simulation. The reduction in costs can be explained by the charging profile of the delayed charging simulation, as shown in Figure 18. What can be observed, is that the large charging peak in the evening is significantly reduced and shifted towards the night and morning. The peak in electricity extraction in the night is around 5 AM, simultaneously with a small dip in electricity prices, which shows that the model is charging at moments when the prices are most favorable, thus explaining the charging cost reductions.

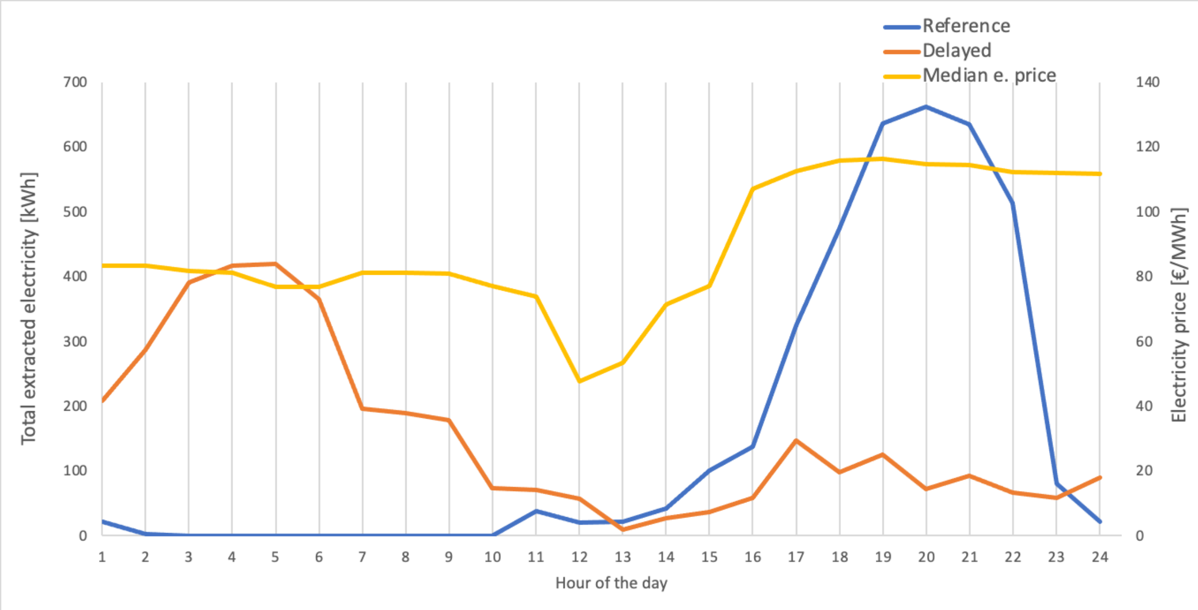

Figure 18: Charging profile of the delayed charging and reference simulation (left-hand axis) together with the median electricity price (right-hand axis)

What is remarkable here, is that there is still some charging during the evening, where the electricity prices are relatively high. This can be explained by Figure D.1 in appendix D, which shows the distribution of the electricity extraction throughout the week. What can be observed here, is most evening charging is done on Sunday. When looking at Figure 15, it can be observed that Sunday evening has relatively low electricity prices compared to Monday night. The simulation sometimes charges at Sunday evening rather than Monday night due to lower electricity prices. The model succeeds postponing the charging moment to later hours, which validates the model.

4.1.3 Smart charging strategy

The smart charging simulation show annual charging costs of €121.4, which is a reduction of 62%, compared to the reference simulation. This reduction in costs can be explained by the charging profile of the smart charging simulation, shown in Figure 19. What can be observed, is that there is almost no charging activity in the evening. Instead, the charging activity is shifted towards the night, morning, and afternoon, where the electricity prices are relatively low. There is a charging peak at noon, where prices are usually at a lowest. The main differences of this profile and the delayed charging profile is that the smart charging simulation has no more charging activity during the evening and less during the night, but instead charges significantly more during the morning and afternoon. This explains the additional cost reductions compared to the delayed charging simulation.

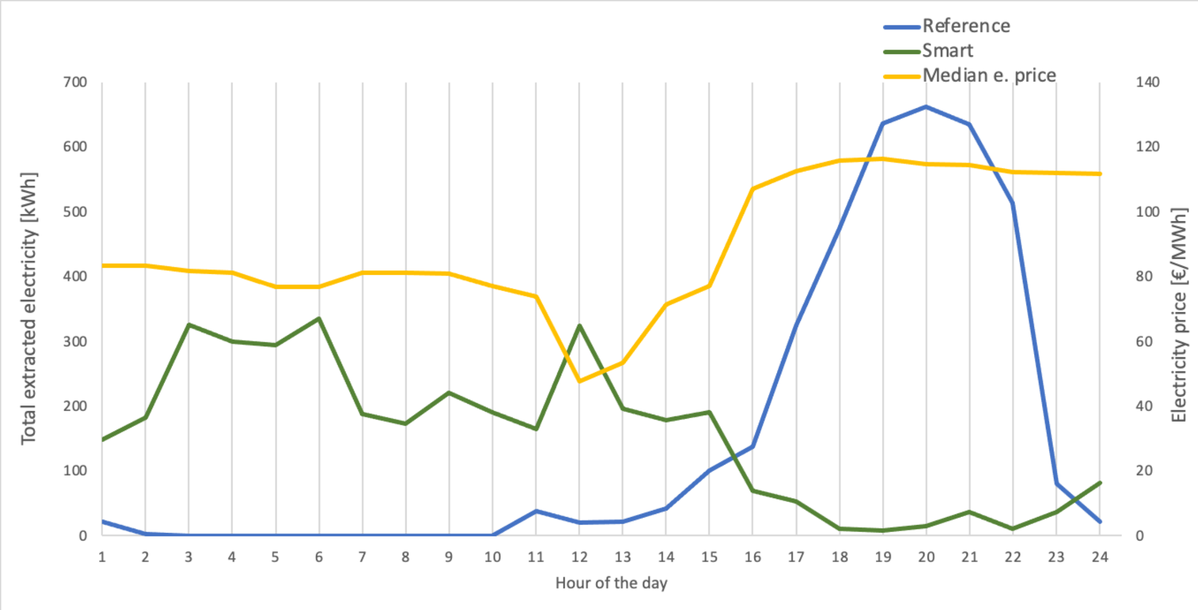

Figure 19: Charging profile of the smart charging and reference simulation (left-hand axis) together with the median electricity price (right-hand axis)

The same is observed in Figure D.1 in appendix D. The electricity extraction throughout the week shows a distributed pattern, where charging is centered at moments with low electricity prices. The EV mainly charges during the weekends and recharges during the middle of the week, preferably on Wednesday night, when prices are lower compared to surrounding weekdays. This shows that the simulation succeeds in finding the cheapest hours to charge the EV, which validates the model.

4.1.4 V2G strategy

The V2G simulation show net charging costs of - €117.3, which is a reduction of 137%, compared to the reference simulation. This means that the V2G simulation can make profits, while satisfying the driving behavior. Table 8 shows a breakdown of the charging costs, as well as the annual electricity interaction between the EV and grid. What can be observed, is that the discharging profits exceed the charging costs by almost €200. However, the net charging costs are increased by the battery degradation costs of €79.4. This is a share of approximately 16.5% of the total discharging profits, which shows that the costs of battery degradation significantly reduce the discharging profits.

What can also be observed, is that the electricity extraction from the grid is more than 9 MWh, which is almost 250% of the electricity required to satisfy the driving profile. Almost 4.4 MWh of this electricity is injected back into the grid; to put this into context, this is approximately the same as the average annual electricity consumption of a Dutch five person household (Nibud, 2023). The charging efficiencies cause an electricity loss of more than 1 MWh.

Table 8: Breakdown of the charging cost and electricity interaction with the grid of the V2G simulation.

Result	Unit	V2G
Annual charging costs	[€]	283.5
Annual discharging profits	[€]	480.2
Annual battery degradation costs	[€]	79.4
Annual net charging costs	[€]	-117.3
Total electricity extracted	[kWh]	9138
Total electricity used for driving	[kWh]	3732
Total electricity injected into grid	[kWh]	4392
Total electricity lost	[kWh]	1014

Figure 20 shows the charging and discharging profiles of the V2G strategy. Most electricity is extracted in the night, morning, and afternoon, with peaks at 5 AM and at noon. The EV is usually discharged in the evening, with a peak at 7 PM, when electricity prices are high. This shows that the model succeeds in charging when electricity prices are low, and discharging when the prices are high, while satisfying the driving profile, which validates the model.

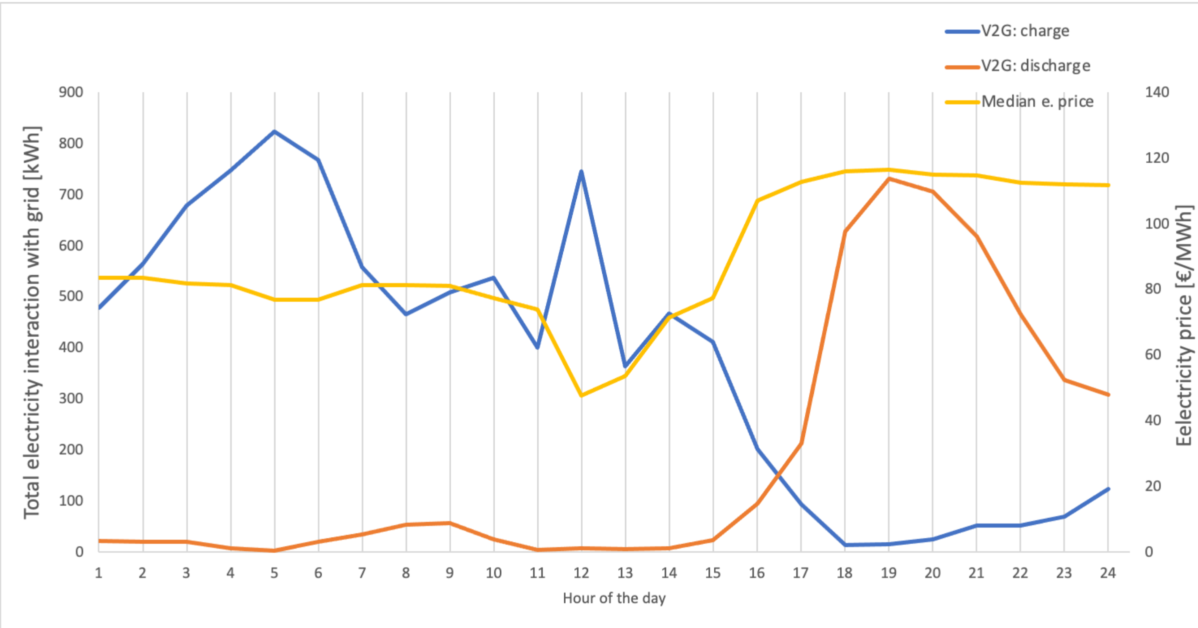

Figure 20: Charging and discharging profile of the V2G simulation (left-hand axis) together with the median electricity price (right-hand axis)

The same charging and discharging behavior is also shown in Figure D.1 in appendix D. The EV charges mostly during the night on weekdays and discharges the battery in the evening. This is financially viable, since it can recharge during night, when electricity prices are low again. It can be observed that most electricity is discharged on Friday evening, since electricity prices are generally high at that moment. Furthermore, similar as in the smart charging strategy, due to the low prices in the weekend, there is a lot of charging activity there. Discharging activity in the weekend focusses mainly on Saturday. Since the prices of Sunday evening and Monday night are rather similar, it is not financially viable to discharge and charge the EV during these times.

4.2 Driving profile analysis

In this section, the results of the driving profile analysis are discussed. This section is divided in two; the first part contains the reference, delayed, and smart charging strategy, and the second part the V2G strategy. The heatmaps indicating the distribution of the electricity extraction throughout the week, together with a visualization of the SoC throughout the simulation are shown in appendix E.

4.2.1 Reference, delayed, and smart charging strategy

The annual charging costs of the three simulations are shown per driving profile in Figure 21, together with the annual mileage. What can be observed, is that the charging costs differ significantly between the profiles. It can be observed that for each charging simulation, it holds that a higher mileage leads to higher annual charging costs. This can be explained by the increased costs due to the increase in required electricity for driving activities.

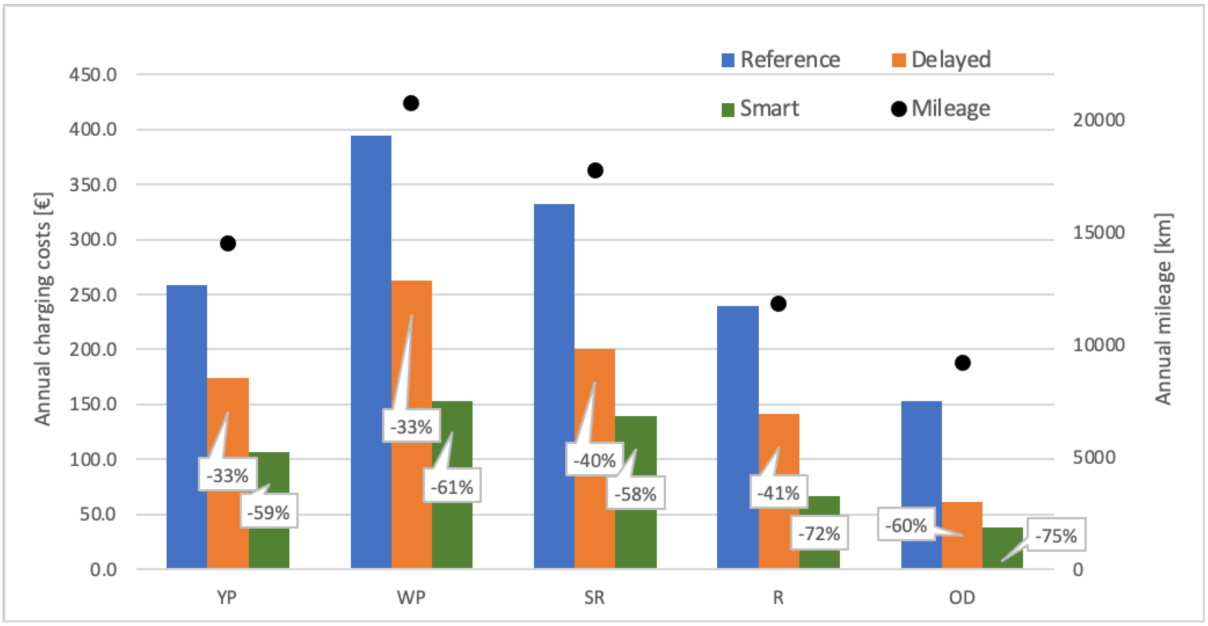

Figure 21: Annual charging costs of the five driving profiles for the reference, delayed charging, and smart charging simulations (left-hand axis). The labels indicate the cost reduction compared to the reference simulation, and the black dot indicates the annual mileage (right-hand axis)

What is remarkable here, is the significant higher cost reductions of the OD for both the delayed and smart charging simulations, which are also observed for the smart charging simulation in the R profile. This can be explained by the mileage of these profiles. Since the mileage of these profiles allow the EV to only be charged once a week, the simulation charges only during the hours when the electricity prices are at a weekly minimum, explaining the large cost reductions. Furthermore, both profiles are parked more often at home compared to the other profiles, especially during the afternoon on weekdays, which increases the flexibility to charge at hours where electricity prices are low.

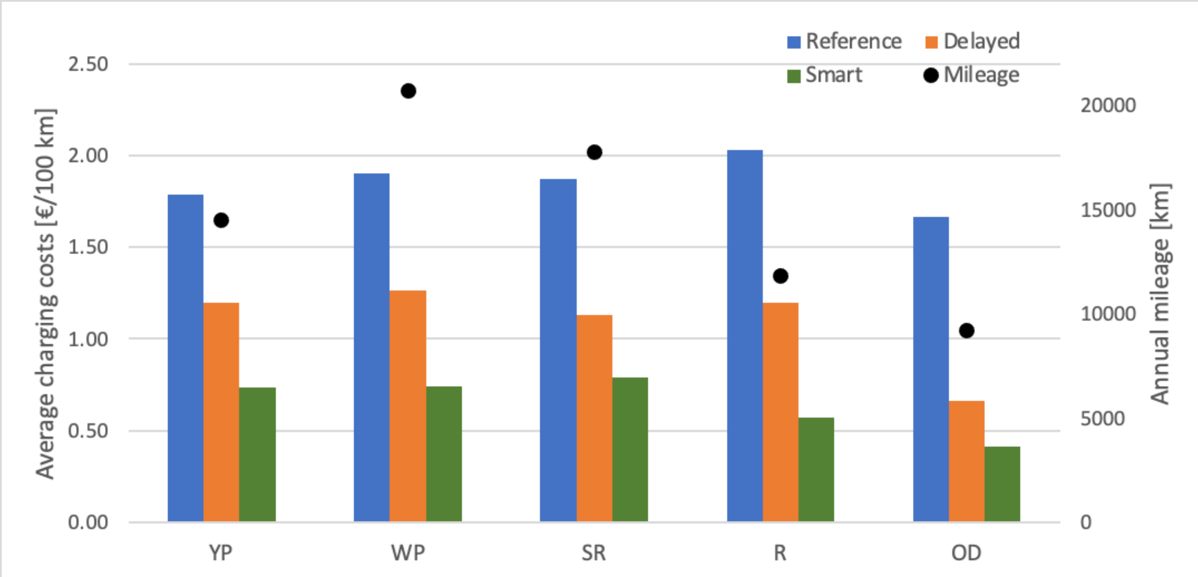

Figure 22: Average charging costs of the five driving profiles for the reference, delayed charging, and smart charging simulations (left-hand axis). The black dot indicates the annual mileage (right-hand axis).

Figure 22 shows the average charging costs for the charging simulations, per driving profile. What can be observed, is that for all profiles except the OD profile, the delayed charging simulation shows relatively equal average charging costs. This shows that the average charging costs are not (strongly) influenced by the annual mileage. Furthermore, the smart charging simulations show relatively equal average charging costs for the YP, WP, and SR profile, which differ from the results of the R and OD profile. The largest difference between these profiles is the time that the EV is parked at home. This suggests that the average charging costs of the smart charging strategy are influenced by the time that the is parked at home.

In Appendix E, the distribution of the SoC throughout the simulation for all driving profiles and charging strategies is shown. What can be observed, is that the SoC for the smart charging simulation is more often on a higher level compared to the delayed charging and reference simulations. Between the reference and the delayed charging simulations, the SoC in the latter simulation seems to have a less favorable SoC distribution, but the differences are small. Furthermore, it can be observed that the driving profiles with a higher mileage seem to have a less favorable distribution compared to the lower mileage profiles. This is explained by the increased distance travelled and the less time parked at home, which increases the SoC reduction and decreases the time to charge it, respectively.

4.2.2 V2G strategy

The annual charging costs of the V2G simulation are shown per driving profile in Figure 23, together with the annual mileage. What can be observed here, is that a higher mileage leads to higher net charging costs. Since there is more electricity required for driving, there is less available battery capacity to discharge the EV and generate a profit when the EV returns to home. Furthermore, what is remarkable here, is that the R profile has more discharging profits compared to the OD profile, while having a lower mileage. This can be explained by the time the EV is parked at home. Since the EV is parked at home more often in the R profile, the simulation has more time to buy and sell electricity to generate profit. This shows that the time the EV is parked at home influences the net charging costs for the V2G strategy.

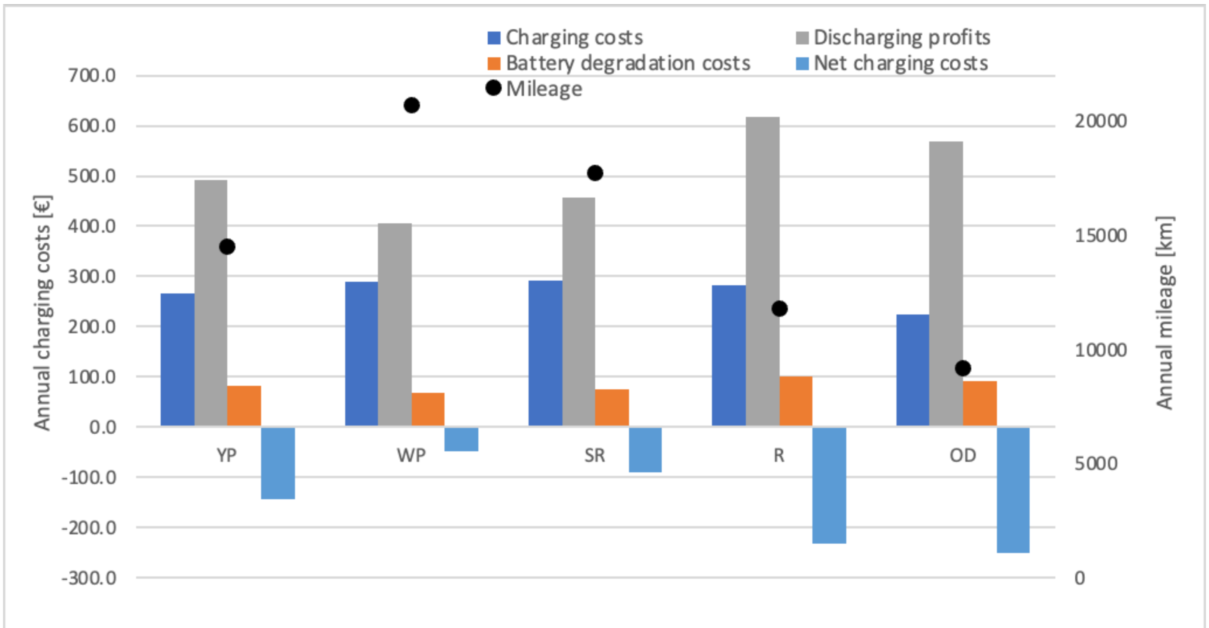

Figure 23: Breakdown of the annual net charging costs of the five driving profiles for the V2G simulation (left-hand axis). The black dot indicates the annual mileage (right-hand axis).

Figure 24 shows the annual and the average charging cost as function of the annual mileage for the V2G simulations. What can be observed here, is that while it is not a perfect fit, the results do suggest a negative linear correlation between annual charging costs and mileage for the V2G simulation. Furthermore, the results suggest a negative exponential correlation between the average charging costs and the annual mileage. The exact role of the time that the EV is parked at home cannot be distinguished here.

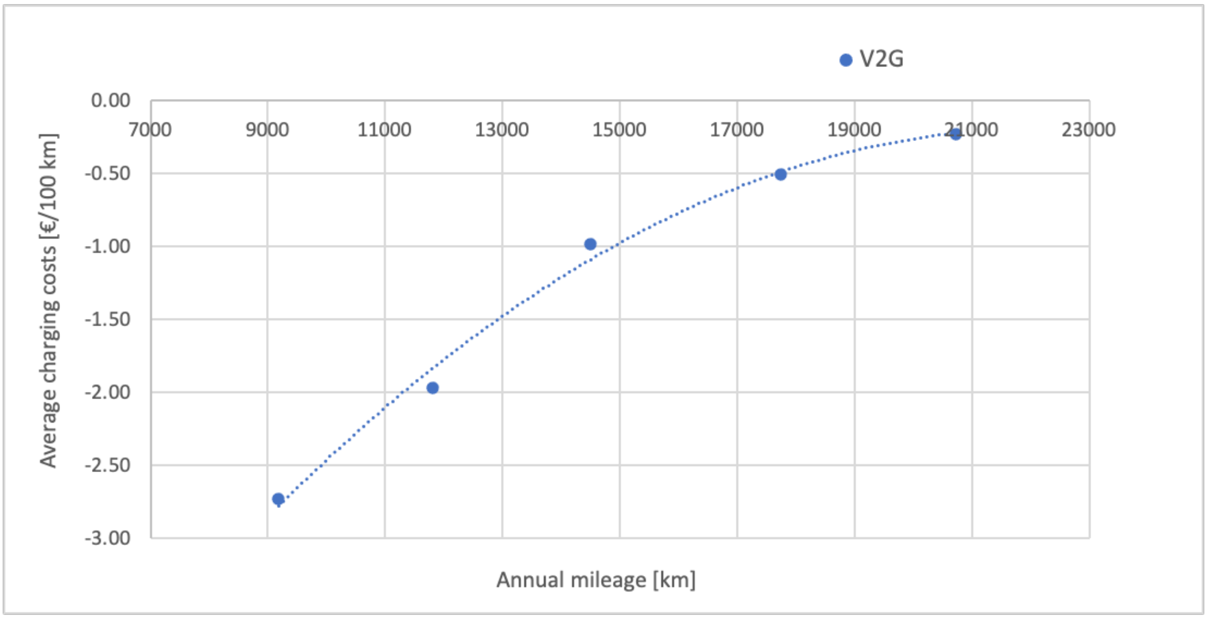

Figure 24: Graph indicating the relation between average charging costs and annual mileage of the V2G simulation.

In Appendix E, the distribution graphs of the SoC of the different driving profiles and charging strategies are shown. What can be observed, is that the SoC is more often at a lower level for the V2G simulation compared to the other simulations, for all driving profiles. The ability to discharge the EV has a negative effect on the SoC, resulting in a SoC that is more often less charged. Furthermore. between the profiles with the different mileages, there does not seem to be a significant difference in distribution of the SoC.

4.3 Sensitivity and uncertainty analyses

In this section, the results of the sensitivity and uncertainty analysis are discussed. The section starts with the sensitivity analysis and ends with the uncertainty analysis.

4.3.1 Sensitivity analysis

Table 9 shows the results of the sensitivity analysis for the reference, delayed, and smart charging strategy. What can be observed, is that while the different electricity price scenarios show different absolute charging costs, the relative reductions between the electricity price scenarios are the same for both controlled charging simulations. This shows that higher electricity prices result in higher absolute cost reductions, but not in higher relative cost reductions for the delayed and smart charging simulations.

Table 9: Results of the sensitivity analysis for the reference, delayed, and smart charging simulations.

Results		Strategy	High	Mid	Low
Annual charging costs	[€]	Reference	401.0	319.0	221.3
		Delayed	257.9	202.3	141.0
		Smart	152.1	121.4	85.5
Average charging costs	[€/100km]	Reference	2.38	1.895	1.31
		Delayed	1.53	1.201	0.84
		Smart	0.90	0.721	0.51
Reduction in charging costs	[%]	Delayed	-36%	-37%	-36%
		Smart	-62%	-62%	-61%

Figure 25 shows the charging profiles of the sensitivity analysis. What can be observed, is that the charging profiles are almost identical, regardless of the electricity price scenario. This shows that the electricity price scenarios do not influence the charging profile for the delayed and smart charging simulations.

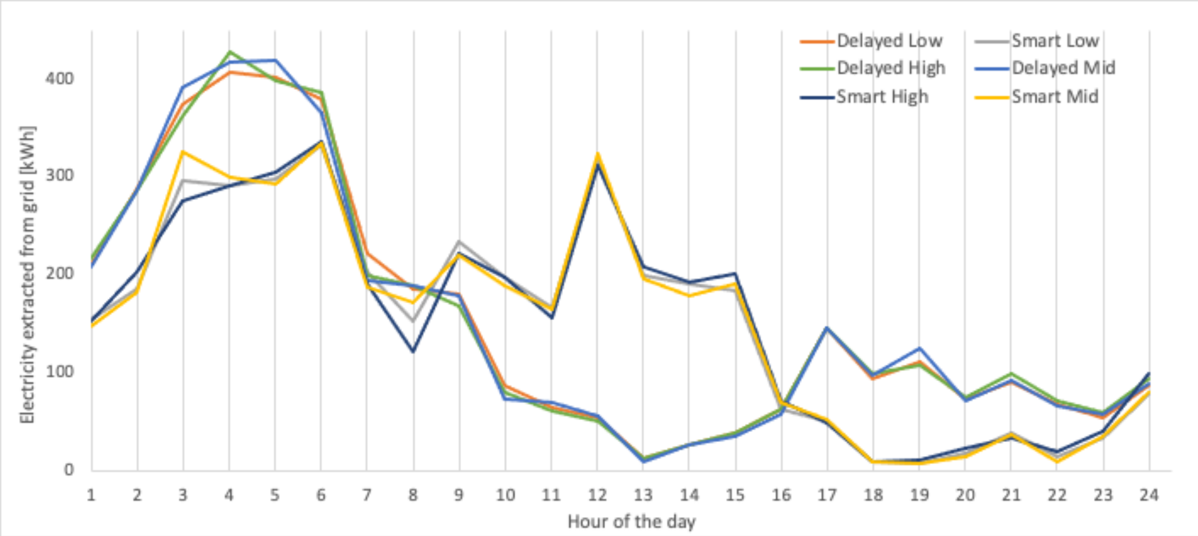

Figure 25: Charging profile of the sensitivity analysis of the delayed and smart charging simulation for the different electricity price scenarios from PBL

Table 10 shows the results of the sensitivity analysis of the V2G simulation. What can be observed here, is that in the high electricity price scenario, the charging costs are lower compared to the low electricity price scenario. This can be explained by two factors. First, a relative increase in electricity prices cause an increase in both the charging costs and discharging profits. This relative increase causes an unequal absolute increase between electricity price at charging and discharging moments, as the charging price is generally lower than the discharging price. This causes the absolute discharging profits to increase more than the absolute charging costs, therefore decreasing the charging costs.

The other reason is the increase in discharged electricity for the high scenario compared to the mid and low scenario. This increase is caused by two effects: the battery degradation costs, and relative differences in intraday electricity prices. First, the battery degradation costs are fixed per kWh of discharged electricity. The simulation considers these costs when it decides whether it is financially viable to charge and discharge the EV's battery. Since these costs are fixed, they are relatively larger when electricity prices are lower, and therefore result in less financially viable moments to charge and discharge the EV. Second, an increase in relative differences in intraday electricity prices can result in more financially viable moments to charge and discharge the EV. As the high scenario has higher relative intraday differences, mainly due to the longer afternoon price decrease, there is more electricity extracted and injected.

Table 10: Results of the sensitivity analysis for the V2G simulation.

Result	Unit	High	Mid	Low
Annual charging costs	[€]	-185.80	-117.3	-48.90
Reduction in charging costs	[%]	146%	137%	122%
Total electricity injected in the grid	[kWh]	4965	4392	3949

Figure 26 shows the charging profiles of the sensitivity analysis for the V2G strategy. What can be observed, is that while all scenarios have a similar flow of the graph, the high scenario generally extracts and injects more electricity compared to the mid and low scenario. This indicates that an increase in electricity price does influence the charging profile of the V2G simulation.

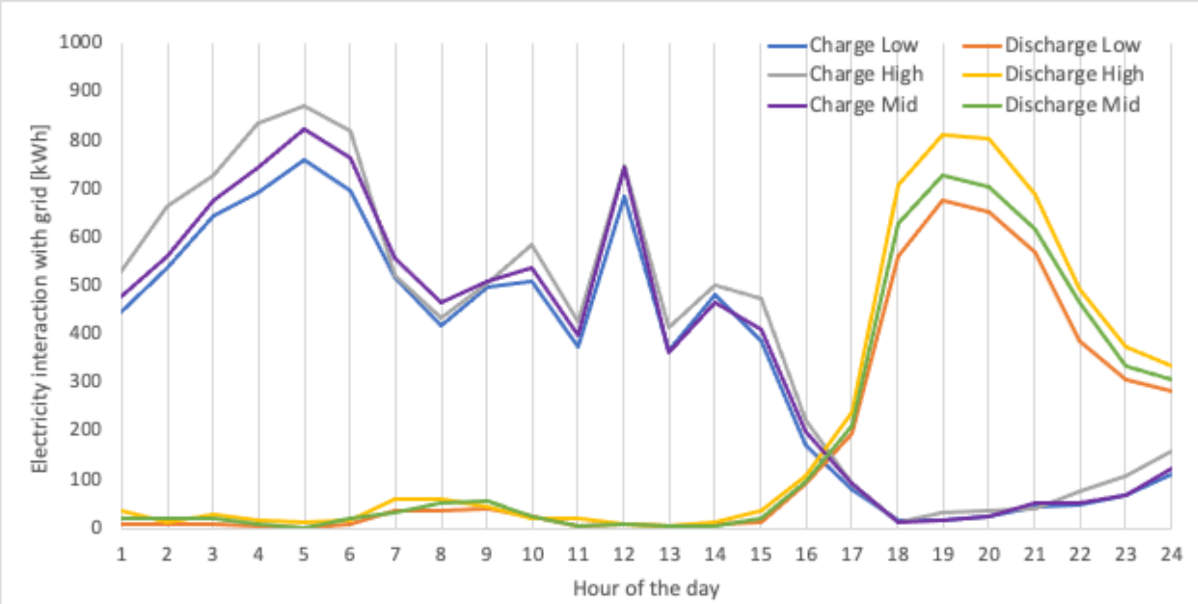

Figure 26: Charging and discharging profile of the sensitivity analysis of the V2G simulation for the different electricity price scenarios from PBL

4.3.2 Uncertainty analysis

The results of the uncertainty analysis for the reference, delayed, and smart charging simulations are shown in Figure 27. What can be observed here, is that the UNC1 has the lowest charging costs of all three simulations, while the UNC2 and the YP profile have similar costs. This shows that when the EV is intensively used during the weekend, and less on weekdays, the charging costs are lower.

Furthermore, what can be observed, is that while there are significant differences in charging costs between the reference and delayed charging simulations, the smart charging simulation has relatively equal costs for all three driving profiles. This shows that the assumptions made in the composition of the driving profiles do influence the results of the reference and delayed charging simulation, while the results of the smart charging simulations are not strongly influenced by the assumptions.

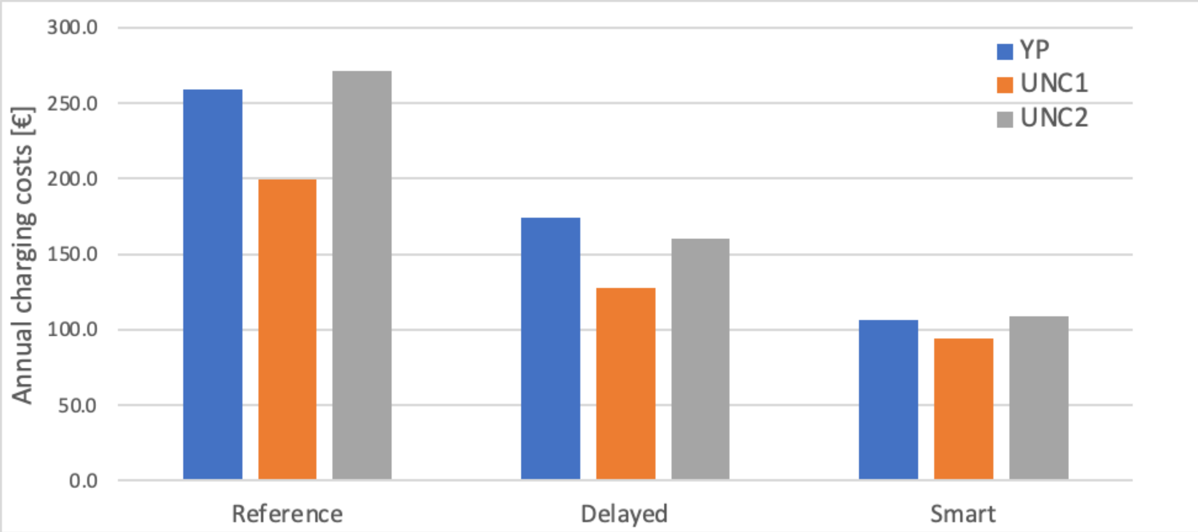

Figure 27: Results of the uncertainty analysis

The results of the uncertainty analysis of the V2G simulation are shown in Table 11. What can be observed here, is that the net charging costs are the lowest for the YP profile. This can be explained by Figure E.1, E.11, and E.13 in appendix E. The main difference between the YP profile and the uncertainty profiles is that the YP can charge during weekends, where electricity has the lowest price, and discharge during weekday evenings, when it has the highest price. The combination of these moments shows the largest reductions in charging costs.

Table 11: Results of the uncertainty analysis for the V2G simulation

Result	Unit	YP	UNC1	UNC2
Annual charging costs	[€]	-142.8	-112.1	-94.6
Reduction in charging costs	[%]	155%	120%	141%
Total electricity injected in the grid	[kWh]	5636	4654	4610

It can therefore be argued that the assumptions made in the composition of the driving profiles influence the V2G charging and discharging behavior. It shows that the driving profile that drives on weekdays during the morning and afternoon and is parked at home a lot during the weekends is able to reduce charging costs the most.

4.4 Factors stimulating grid-aware charging

The goal of the interviews was to identify the key stakeholders, their interests, their interrelations, and their role in the stimulation of grid-aware charging. This is presented in a schematic overview in Figure 28. What can be observed here, is that there is a collaboration required between the government, DSO, and the market, to effectively stimulate the consumer adoption of grid-aware charging. An effective functioning of this collaboration requires goodwill, mutual trust, and transparency from all involved stakeholders. The rest of this section provides a more detailed explanation of the individual roles, and the importance of the collaboration.

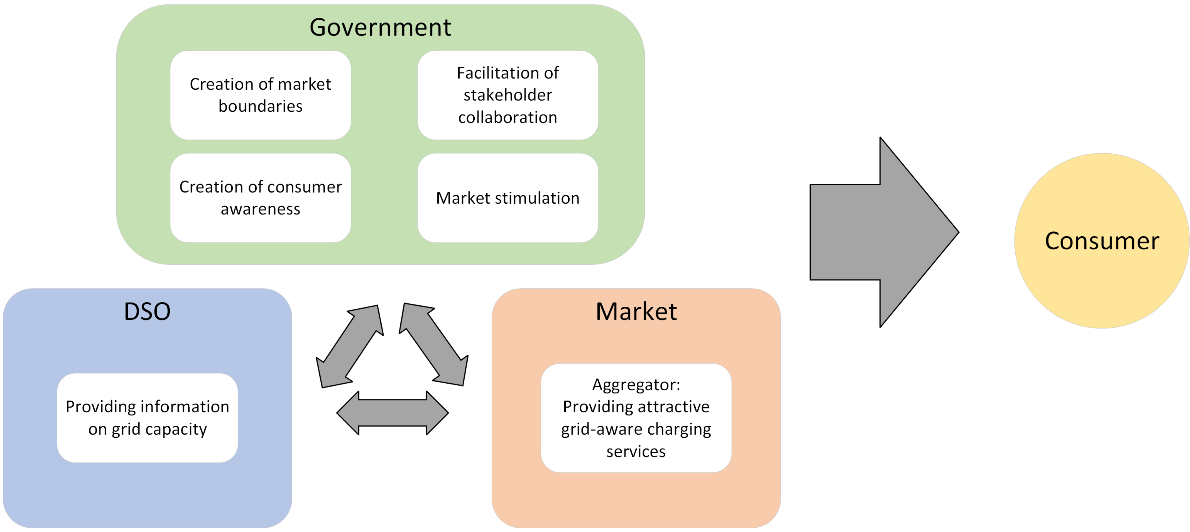

Figure 28: Schematic overview of involved stakeholders, their roles, and their relation to each other and to the consumer.

4.4.1 Key messages

The first important outcome of the interviews is that it is difficult to mandate certain charging behavior at private charging points. Current household connections allow consumers to extract up to 17.3 kW of power at any given time. The implementation of new tariff structures can limit the electricity extraction of households, but these new tariffs are still in legislative process and not expected to be implemented in the next couple of years (P.1; P.2). It is therefore important to persuade consumers into engaging in controlled charging (F.2).

Aggregator

The main driver for consumers to engage in any controlled charging strategy is a financial compensation. The results of this study show great cost reduction for different type of EV drivers, but the adoption of controlled charging is still lacking. One of the main barriers is lack of interest, combined with complexity. As M.3 mentioned:

"Consumers are not interested in optimizing their charging behavior themselves, to safe 100 euro per year. They are not reluctant to engage, but someone needs to facilitate this for them, to reduce the complexity and effort, in exchange for a fixed reduction in costs."

Market parties are considered a good fit for the role of aggregator here, since they are consumer-oriented and therefore have experience with fulfilling consumer preferences. Furthermore, both D.2 and F.2 mentioned that as market parties have the knowledge and capabilities to effectively scale up technologies, they could prove crucial in the scale up of grid-aware charging. A proposed aggregator structure by F.1 is an energy supplier that operates between DSO and end-user and minimizes charging costs within the boundaries provided by both the DSO and consumer.

Providing grid-aware charging strategies instead of a strategy that aims to maximize financial benefits is in the interest of the market here. As the grid capacity is used more efficiently, there is more capacity available for the market to grow, i.e. to increase the EV penetration. To create and optimize these grid-aware charging strategies, they require transparent information sharing of the DSOs on the available grid capacity, possible moments of congestion, and moments of abundant capacity.

Market stimulation

However, the current limited availability of such services show that the market is underdeveloped. The market needs to be stimulated to create momentum. Three factors are mentioned to stimulate the market, which should be developed in close collaboration with all stakeholders, to ensure an effective implementation. The three factors are mentioned below, whereafter they are discussed in more detail.

5. Standardization of prerequisites
6. Ensuring interoperability
7. Creation of a certification mark.

The prerequisites of controlled charging include smart charging infrastructure, such as smart charging points and communication systems. The availability of these systems is essential for the increase of controlled charging adoption, while the placement of ‘dumb’ charging infrastructure would hinder this adoption. Therefore, all new placed infrastructure should be ‘smart charging ready’. As the increase in costs for the smart infrastructure is likely to be compensated by the reduction in charging costs within several years, subsidies are not necessary here. To quote P.2:

“Providing subsidies for a proven technology is pointless, and a waste of money. If the technology is proven, and there is a healthy business case, the market will step in.”

The importance of interoperability is stated by F.1, M.1, M.2, and M.3. Hardware, software, communication systems; all equipment should be able to communicate with each other. This creates an open, fair, and competitive market, which increases the incentive to innovate. M.3 clearly states the wish to put this in European legislation, and have European wide standards for technology, to increase the number of potential clients for market parties.

Lastly, the creation of a certification mark could enhance this interoperability. This mark could be used to indicate that a particular charging service lives up to certain standards, or it could be used to indicate that infrastructure contains certain communication services or technology. Besides increasing the operability, it could also be a useful tool to provide clear technology standards for producers and service provides, and it could provide product assurances to customers, which are all important for the uptake in grid-aware charging.

Creation of market boundaries

This new and emerging market should also have clear boundaries, to protect the market parties, DSOs, and the consumers. It is important to clearly state everyone’s responsibilities here and what happens when parties disagree on certain matters. It is important that all stakeholders are actively involved in this process. Furthermore, it is important to understand that when boundaries are too strict, it can hinder innovation in the market, but when they are too loose, it can lead to unnecessary grid reinforcements or uneven distribution of expenses and costs.

Creation of consumer awareness
Another important barrier that was discussed in the interviews, was a general lack of awareness on controlled charging, how it works, its advantages, and its disadvantages. Consumers need to be informed and they need to have a trustworthy place to go to with any questions. Nationwide awareness campaigns could stress the urge and the benefits of controlled charging and take away uncertainties and complexity (D.1; F.1; F.2). To quote M.1:

“The willingness to adopt increases significantly, when controlled charging is attached to a goal that appeals to consumers.”

Furthermore, consumers require an easily accessible online information base where they can turn to with any questions. This should be a governmental website, or something equally trustworthy for consumers, such as the Royal Dutch Touring Club (ANWB) (P.1; F.1). It is important to design the awareness campaigns and information base with all stakeholders involved, including consumers. Furthermore, the communication should be clear and easy.

Facilitate and sustain stakeholder collaboration
As can be observed, there are a lot of areas where interests of the stakeholders intersect. To ensure a smooth and effective scale up of controlled charging, it is essential that there is active collaboration between stakeholders, based on trust, transparency, and goodwill. The government needs to play a facilitating role, where it guides conversations and acts as decision maker when interests are not aligned. It is argued that while this might lead to difficult decisions, it is important to act and decide fast to maintain momentum (P.1; P.2; D.1; D.2).

This scale up is new for everyone, and there are a lot of lessons to be learned and mistakes to be made. It is important that there are regular feedback moments with all stakeholders, where choices and processes are evaluated, and adapted where required. Questions like: are the set market boundaries still working for all stakeholders, is everyone still participating as agreed upon, is the stimulation working, are there new opportunities emerging, how do we react? It will be a complicated process, and since all stakeholders have significant benefits from it, a good functioning collaboration is essential.

Vehicle-to-Grid
One final key message that emerged from the interviews, was on V2G. It was identified that injecting electricity back into the grid is too complex for now. While the technology might be available, not enough EVs and charging points are V2G ready and there are many legislative and administrative barriers that hinder the adoption of V2G strategies. Most interviewees doubt the coordinated discharging of EVs to provide grid support, but rather foresee a more decentralized role, where the electricity is mostly used to supply electricity to the EVs own household, or in the neighborhood. All interviewees argue that the scale up of delayed and smart charging will provide many practical lessons that can be applied in the scale up of V2G. To quote D.1:

“*V2G is complex and requires much more collaboration and communication between stakeholders. Let’s wait and see what we can learn while scaling up smart charging. When smart charging has become the standard, we will see how much flexibility we still require to* *balance the grid. Then we can with certainty estimate its potential and its role in our power system."*

4.4.2 Roles and actions

Table 12 summarizes the roles and specific action points that emerged from the expert interviews. As can be observed, all roles and action points require active contribution of multiple stakeholders to ensure a successful scale up.

Table 12: Stakeholder roles and actions that stimulate grid-aware charging.

Stakeholder role	Action	Lead stakeholder	Involved stakeholders
Aggregator	Creation of attractive variety of controlled charging services	Market	DSO, government
Creation of market boundaries	Creation of clear market boundaries	Government	Market, DSO
Creating consumer awareness	Awareness campaigns, creation of trustworthy information base	Government	Market, DSO
Market stimulation	Standardization of prerequisites, ensuring interoperability, creation of certification mark	Government	Market, DSO
Facilitation of stakeholder collaboration	Facilitate and sustain stakeholder collaboration, create feedback loops on scale up process	Government	Market, DSO
Provide clear and transparent information on grid capacities	Supporting the market in optimizing grid-aware charging strategies	DSO	Market

5. Conclusion

In this section, the main research question is answered. This research was divided into four parts: the driving profiles, the charging costs and profiles, the influence of the driving profiles, and the factors than can stimulate the adoption of grid-aware charging. The main research question is repeated below:

How can the adoption of grid-aware charging strategies be stimulated in the Netherlands?

The first part of the research has identified driving profiles for typical Dutch EV drivers. Dutch drivers can be divided into five categories, which are a young professional, working parent, semi-retiree, retiree, and occasional driver. These profiles differ in age, phase of life, demographics, and on driving behavior.

The second part of the research resulted in the charging costs and profiles for the three different controlled charging strategies. What was observed, is that when charging is coordinated to minimize charging costs, that a delayed charging strategy shows a 37% cost reduction, a smart charging strategy shows a 62% cost reduction. Evening charging peaks are largely reduced, and charging is shifted to the night, morning, and afternoon. Furthermore, it was shown that higher electricity prices lead to higher absolute charging costs, but that it did not strongly affect the relative cost reductions or the charging profiles.

The V2G strategy showed charging during the night, morning, and afternoon, and the battery was discharged during the evening. This resulted in a 137% cost reduction compared to the reference strategy, therefore generating a profit. A total of 4.4 MWh of electricity was injected back into the grid. Furthermore, an increase in electricity prices and price volatility lead to lower charging costs due to increased discharging profits. Lower electricity prices will, on the contrary, result in higher charging costs when charging with the V2G strategy.

The third part of the research focused on the influence of the driving behavior on the charging costs. What was observed, is that for the delayed and smart charging strategy, there is a linear correlation between annual charging costs and annual mileage. However, the average charging costs are not strongly influenced by the annual mileage. When an EV is parked at home more often, the average charging costs can be reduced. Additionally, it was observed that the moment of driving does influence the charging costs for the delayed charging strategy but has less effect on the charging costs of the smart charging strategy.

The net charging costs for a V2G strategy are more strongly influenced by mileage. The discharging profits increase when the mileage decreases. These profits also increase when the EV is parked at home more often. Furthermore, the average charging costs showed a negative exponential relation with the annual mileage for the V2G strategy. Lastly, it was also observed that the moment of driving influences the charging costs for the delayed charging and V2G strategy, but not for the smart charging strategy.

The fourth part of the research aimed to identify the stakeholders and their roles in the stimulation of grid-aware charging. What was observed, is that since grid-aware charging cannot be mandated for private charging points, consumers need to be convinced. The market seems designated to take on the role of aggregator here, facilitating the grid-aware charging for the consumers, while compensating them financially. The results of this research show significant cost reductions for the charging strategies, what seems enough for a market party to build a business case on. The government should take on a directive role and focus on stimulating the market by standardizing prerequisites for controlled charging, ensuring interoperability, preferably Europe-wide, and create a certification mark. Furthermore, they should shape market boundaries and create consumer awareness by awareness campaigns and an information base. To succeed in the upscaling of grid-aware charging, a close collaboration between the stakeholders that is based on mutual trust and transparency is crucial for the success of the stimulation of grid-aware charging in the Netherlands.

Lastly, this research has shown that while V2G holds the largest potential in cost reduction, and can provide more extensive services to the grid, there are several administrative and legislative barriers that hinder the upscaling of V2G. What was observed, is that it is more likely that V2G will take on a more decentralized role in the electricity system, where the discharged electricity is used at a consumers' household, or in the neighborhood, instead of the electricity being injected into the grid.

6. Discussion

In this section, the methodological considerations, theoretical embedding, and implications and recommendations that emerged from this research are discussed.

6.1 Methodological considerations

This section discusses the considerations of the research methods. One point of consideration is the composition of the driving profiles. The idea behind the composition of the driving profiles was to simulate a charging profile and quantify the costs that could be generalized for the typical Dutch EV drivers described in the different profiles, e.g. “a typical working parent can reduce €130 in charging costs when charging with a delayed strategy”. However, the driving profiles contain assumptions and biases due to the anecdotal part in the composition. A stochastic composition process could have reduced these assumptions and biases. However, there was not enough data available of driving behavior of these typical Dutch drivers to create an academically valid method to compose five different driving profiles. Main conclusions on cost reductions are therefore not drawn from the individual driving profiles, but from the combined profile, which showed valid charging behavior, as discussed in section 4.1.1.

A second methodological consideration was the selection of software used to create the model. While excel is more user friendly, and the researcher had more experience with Excel, a programming language with higher computational power would have significantly reduced the time required to run simulations. This would have given the possibility to perform more analyses on the data, to acquire a better understanding of the results.

A third methodological consideration was the use of the hour-based electricity price predictions from PBL. It was deemed relevant to include the 2030 prices, since the technologies discussed in this study are not widely applied at this moment, while it is more likely that they will be in 2030. However, what became evident in the past several years, is that electricity prices can very quickly change drastically, e.g. the Russian invasion in Ukraine has caused large increases in electricity prices. The use of predicted electricity prices therefore will always add a certain level of uncertainty. The absolute charging costs for the different strategies should therefore be considered as a cost indication, while the relative cost reductions are shown to be less prone to change due to electricity price changes.

Another methodological that is relevant to mention consideration was the exclusion of taxes on electricity. Due to this exclusion, the electricity price used to determine the charging costs and discharging profits, does not represent the actual costs or profits for an EV driver. However, with the exclusion of taxes, the results are more generalizable. Taxes differ between the type of user, the amount of electricity that is extracted annually, and it differs between nations. This study presents the generic cost reductions, based on the hour-based electricity prices, which can be used for any type of user that simply adds its own taxes.

6.2 Theoretical embedding

The results of this study are aligned with quantifications of charging costs of previous studies. Jian et al. (2018) show a cost reduction of 65% when using a smart charging strategy, which is comparable to the 62% reduction shown in this study. López et al. (2015) show cost reductions of 55% for a controlled charging strategy, and 59% for a V2G strategy. While the 55% is comparable to the 62% reduction in this study, the V2G shows a different result. However, Fan & Chen (2019) show much higher V2G cost reductions, as this strategy reduces charging costs from \$0.97 to -\$1.14, thus generating profit, which is more in line with the results of this study. While Tarroja & Hittinger (2021) do not quantify charging costs, they do argue that the V2G strategy can significantly increase the economic benefits compared to delayed and smart charging strategies.

The simulated charging profiles also show similarities to the existing literature. As discussed in section 4.1.1, the reference charging profile shows similarities with the average Dutch charging profiles for private charging from ElaadNL (2023), shown in Figure 7. Furthermore, the delayed charging model shows a similar profile as simulated by Jian et al (2018), where charging peaks are shifted to the night. This profile is shown in Figure 4. Fan & Chen (2019) simulated V2G profile shows charging in the night, and discharging in the evening, shown in Figure 2, which comparable to the simulated profile from this study. This shows that while the cost reductions might not be identical to cost reductions found in other studies, the charging profiles show the same charging behavior for the different charging strategies.

Since the literature is lacking studies that focus on the influence of driving behavior on controlled charging cost reductions and profiles, a comparison with current literature was not possible. To the best of the authors knowledge, this study is the first study that made a start to identify what factors in driving behavior influence the controlled charging profile and costs.

Lastly, the results from the expert interviews showed some similarities with the action points from the SLVI action plan (Nationale Agenda Laadinfrastructuur, 2022). The identified similarities are the stimulation of the prerequisites, the development of a certification mark, the creation of consumer awareness, creation of market boundaries, and a close collaboration between all involved stakeholders. The results of this research contribute to this action plan by quantifying potential financial benefits of controlled charging and placing more focus on private charging points.

The factors stimulating grid-aware charging deviate from the SLVI action plan by highlighting the role of market parties as aggregator, as there are crucial in the upscaling of grid-aware charging for private charging points. Furthermore, there is more attention on the importance of interoperability in this study, to create a larger incentive for the market to innovate. Lastly, the SLVI action plan aims to financially stimulate smart charging infrastructure, while this study argues that the increased costs for this infrastructure is quickly compensated by the charging cost reductions.

6.3 Implications and recommendations

The current tariffs and structures for household connections make it difficult to mandate grid-aware charging for private charging points. Consumers therefore must be convinced to adopt a grid-aware charging strategy. Consumers are not reluctant here; they want to engage in grid-aware charging, but they need someone to facilitate this for them, and require a financial compensation. Market parties should fulfill the role of facilitator, or aggregator, and operate between consumers and DSOs to provide the flexibility that the grid requires, while optimizing the charging to reduce charging costs. The potential revenue that can be generated per EV is quantified by this research.

The smart charging simulation shows a reduction in costs of 62%. What should be noted, is that this simulation can see the electricity prices of the coming days and can therefore decide whether to charge or not. However, DAM prices are only available for the current and following day. The model therefore has a ‘perfect’ foresight ability, and the charging behavior is therefore ‘too optimized’ in some regard. However, it should be noted that if an aggregator coordinates the charging and makes accurate electricity price predictions based on e.g. weather forecasts, the actual cost reductions will resemble the cost reductions found in this study.

Furthermore, the V2G simulations show that the average Dutch EV driver can satisfy its annual mileage of more than 16000 km, while also injecting 4.4 MWh back into the grid. While there were some serious doubts on the administrative, technical, and jurisdictional feasibility of discharging the EV into the grid, this research did highlight the decentralized potential of V2G. If this electricity was not injected into the grid, but rather used in a household, this amount of electricity could satisfy an average five person household in the Netherlands. While this does not mean that household demand and the available supply from the EV match, it does show that a V2G strategy shows potential to significantly reduce grid-dependency of households.

Additionally, the electricity market mechanisms are based on balancing supply and demand. The increase in flexibility of demand could influence the electricity pricing mechanisms. When the demand is shifted from the hours with a high electricity price, to hours with a low electricity price, the difference in price between these hours will reduce, therefore changing the results of the simulations. Further studies could investigate what the effect of this increased flexibility is on future electricity prices, and what the influence of this effect would be on the charging profile and costs.

The simulated charging profiles have shown that charging is concentrated at hours where electricity prices are low. As these prices tend to be low when there is a high penetration of renewable electricity in the grid, it could mean that this charging strategy causes a large increase in RES consumption. Further research could investigate what the increase in RES consumption due to the simulated charging profiles, and how this is translated in terms of environmental benefits.

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Appendix A. Driving profiles

Young Professionals (YP)

The YP is typically aged 25 to 35 and is in the beginning of its career. The YP has no kids, or kids that are too young to encounter in any activities out of the house. The YP commutes to work 4 days a week, from Monday to Thursday, leaving home between 7 and 9 AM, while returning 9 hours later. The YP does shopping/groceries on Monday and Friday, has an unspecified meeting on Wednesday, and a business meeting on Thursday. During the weekends, the EV is barely used, only for one spare time activity on Saturday and a visit on Sunday. This is schematically shown in Figure XX.

YP							
Hour	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
1							
2							
3							
4							
5							
6							
7							
8	*Work*		*Work*				
9		*Work*		*Work*			
10							
11						*Spare time*	
12							
13				*Business*			*Visiting*
14							
15							
16							
17					*Shopping*		
18	*Work*		*Work*				
19	*Shopping*	*Work*		*Work*			
20							
21							
22			*Other*				
23							
24							

Figure A. 1: The Young Professional driving profile. The white squares indicate that the EV is parked at home and the grey squares that the EV is driving or parked elsewhere.

Working Parent (WP)

The WP is typically aged 30 to 50 and is in the middle of its career. The WP started a family, and the kids are at an age where they need to be picked up and dropped off at school, social, or sports activities. The WP commutes to work four days a week and has two weekly business trips. It drives to three spare time activities, which are for the WP himself, or for its kids. Groceries are done three times per week, and the EV is used for two weekly services, two visitations, and one spare time activity. This driving profile is shown in Figure XX.

WP							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1							
2							
3							
4							
5							
6							
7	*Work*				*Work*		
8		*Work*	*Work*				
9							
10							
11						*Shopping*	
12							
13	*Business*			*Business*		*Spare time*	
14							*Visiting*
15							
16							*Service*
17	*Work*				*Work*	*Other*	
18		*Work*	*Work*	*Service*			
19		*Shopping*		*Shopping*			
20					*Visiting*		
21	*Spare time*		*Spare time*				
22							
23							
24							

Figure A. 2: The Working Parent driving profile. The white squares indicate that the EV is parked at home and the grey squares that the EV is driving or parked elsewhere.

Semi-Retirees (SR)

The SR is typically aged 50 to 65, is still employed, but works reduced hours as the SR is approaching the retirement age. The SR works less, and its kids are moved out of the house, or at an age where they do not require to be picked up or dropped off anymore. The SR commutes to work three times a week, and still does two business trips weekly. It provides service/takes care of close ones, has several spare time activities, and uses the EV for shopping/groceries, visiting friends, a weekly day trip during the weekend, and one undefined activity. This driving profile is shown in figure XX.

SR							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1							
2							
3							
4							
5							
6							
7							
8	*Work*		*Work*				
9				*Service*	*Work*		
10							*Day trip*
11						*Spare time*	
12				*Shopping*			
13		*Business*		*Other*			
14					*Business*	*Service*	
15							
16		*Service*					
17							
18	*Work*		*Work*				
19	*Shopping*				*Work*	*Visiting*	
20		*Spare time*					
21							
22							
23							
24							

Figure A. 3: The Semi-Retiree driving profile. The white squares indicate that the EV is parked at home and the grey squares that the EV is driving or parked elsewhere.

Retirees (R)

This group consist of people that are aged 65-80 and have started their retirement. They do not have to commute to work anymore, and therefore drive less regular. They visit friends and family more often, have more spare time activities, take care for close ones, go on a weekly hiking/touring trip, and have one unidentified activity. Their travel behavior occurs mainly during the day.

R							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1							
2							
3							
4							
5							
6							
7							
8							
9							
10				*Shopping*			
11	*Other*		*Service*				*Visiting*
12				*Spare time*			
13		*Shopping*		*Service*		*Day trip*	
14			*Visiting*		*Visiting*		
15	*Visiting*	*Spare time*					*Shopping*
16							
17							
18							
19							
20	*Spare time*						
21							
22							
23							
24							

Figure A. 4: The Retiree driving profile. The white squares indicate that the EV is parked at home and the grey squares that the EV is driving or parked elsewhere.

Occasional Drivers (OD)

This group consists of people that do not have a regular weekly driving schedule. Example of people in this group are stay-at-home parents, students, people that work during the evening, or people aged 80+. They make smaller trips typically once or twice a day to do groceries, spare time activities or to pick someone up, and sometimes they use it for larger trips with friends or family. They drive during less regular times and include more evening and weekend trips. This profile does not represent a specific group, but rather functions as a diversification profile in this study. The activities chosen are therefore not specifically representative for the group members. This driving profile is shown in figure XX.

OD							
Hour	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
1							
2							
3							
4							
5							
6							
7							
8						*Work*	
9					*Education*		
10							
11		*Shopping*					
12			*Education*				*Spare time*
13							
14							
15		*Other*			*Shopping*		
16							
17							
18						*Work*	
19							
20							
21							
22		*Visiting*	*Other*				
23							
24							

Figure A. 5: The Occasional Driver driving profile. The white squares indicate that the EV is parked at home and the grey squares that the EV is driving or parked elsewhere.

Appendix B. Sensitivity analysis

Low - 2030 predictions by PBL							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	50	48	49	50	55	40	30
2	48	47	50	50	55	41	29
3	48	43	50	47	54	39	30
4	48	44	49	47	53	37	31
5	47	44	49	48	51	35	30
6	48	44	47	48	52	35	30
7	51	49	51	51	57	32	28
8	52	52	55	56	61	29	24
9	53	52	54	55	59	29	22
10	49	49	50	50	54	28	21
11	47	45	47	47	52	29	21
12	45	45	46	45	48	25	21
13	45	44	45	45	49	26	22
14	46	45	46	46	52	26	21
15	50	47	51	51	54	32	24
16	57	55	58	57	62	40	33
17	68	62	65	65	69	45	41
18	72	67	70	72	73	53	49
19	73	68	69	72	74	53	49
20	70	67	68	72	72	52	49
21	70	66	66	71	71	49	48
22	65	64	64	67	69	48	47
23	63	62	63	66	68	48	46
24	61	62	62	65	68	48	46

Figure B. 1: Heatmap indicating the distribution of the low electricity price scenario from PBL. Higher prices are indicated by deeper red colors.

High - 2030 predictions by PBL							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	91	90	93	96	102	66	52
2	90	87	91	91	101	66	53
3	88	85	92	87	101	65	54
4	87	84	94	86	98	63	52
5	89	84	92	89	95	63	54
6	88	85	89	90	99	61	52
7	95	92	98	99	104	58	49
8	98	99	104	103	108	56	42
9	98	99	101	103	108	52	40
10	90	91	96	95	97	48	38
11	86	85	87	89	93	46	38
12	84	85	86	86	91	42	38
13	82	84	84	83	86	44	39
14	87	85	86	84	92	47	38
15	93	88	97	94	101	58	44
16	105	103	108	102	117	70	60
17	122	117	119	115	129	80	71
18	128	124	125	132	134	95	86
19	127	126	124	131	133	97	87
20	124	124	122	130	132	89	89
21	123	123	120	127	131	86	86
22	118	119	116	123	129	84	86
23	113	117	113	123	127	84	84
24	112	116	112	123	127	83	84

Figure B. 2: Heatmap indicating the distribution of the high electricity price scenario from PBL. Higher prices are indicated by deeper red colors.

Appendix C. Uncertainty analysis

Figure XX and Figure XX show the driving profiles for the uncertainty analysis. which are from here on referred to as UNC1 and UNC2. The UNC1 profile concentrates its activities from Friday to Sunday during the morning, afternoon, and evening. This is a large alteration in driving behavior compared to the YP profile, where the driving activities are concentrated on Monday to Thursday morning, afternoon, and evening. The UNC2 profile concentrates its driving activities in the evening and early night during weekdays. This profile also includes one evening where a lot of activities are concentrated, to increase the diversity between the uncertainty profiles and the YP profile.

UNC1							
Hour	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
1							
2							
3							
4							
5							
6							
7							
8					Work	Work	Work
9							
10							
11							
12							Business
13							
14							
15							
16							
17							
18					Work	Work	Work
19				Work	Shopping		
20						Shopping	Spare time
21				Work			
22					Visiting	Other	
23							
24							

Figure C. 1: The first Uncertainty driving profile. The white squares indicate that the EV is parked at home and the grey squares that the EV is driving or parked elsewhere.

UNC2							
Hour	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
1							
2							
3		Work		Work			
4			Work		Work		
5							
6							
7							
8							
9							
10							
11							
12							
13							
14							
15							
16							
17	Work		Work		Shopping		
18		Work		Work	Visiting		
19					Spare time		
20					Other		
21					Shopping		
22				Business			
23							
24							

Figure C. 2: The second Uncertainty driving profile. The white squares indicate that the EV is parked at home and the grey squares that the EV is driving or parked elsewhere.

Appendix D. Weekly charging profiles: combined profile

Reference

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	21	0	0	0
2	0	0	0	3	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0
11	0	0	0	38	0	0	0
12	0	0	0	0	0	21	0
13	0	0	0	0	0	21	0
14	0	0	0	0	0	21	21
15	0	0	38	0	38	4	21
16	40	0	38	0	38	0	21
17	40	0	38	0	38	0	208
18	40	0	15	0	209	4	205
19	1	0	163	0	205	62	205
20	21	230	163	21	0	203	23
21	21	230	163	21	0	200	0
22	21	216	94	21	0	162	0
23	12	3	21	13	0	32	0
24	0	0	21	0	0	0	0

Delayed

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	72	5	39	57	4	4	28
2	92	3	64	74	3	0	51
3	122	9	100	123	5	0	31
4	111	9	120	125	6	1	45
5	126	12	107	123	6	9	36
6	92	10	119	81	0	9	55
7	3	7	68	45	3	5	64
8	0	5	0	34	1	16	134
9	0	0	0	4	2	23	150
10	0	0	0	0	2	19	52
11	0	0	0	9	10	27	25
12	0	0	0	0	11	36	10
13	0	0	0	0	8	2	0
14	0	0	0	0	8	2	18
15	0	0	11	0	9	0	16
16	34	0	10	0	3	0	11
17	36	0	5	0	0	0	105
18	19	0	0	0	25	0	54
19	34	0	4	0	22	0	67
20	1	18	7	0	0	5	41
21	1	20	17	0	0	10	46
22	3	4	8	0	0	12	40
23	3	8	5	0	0	4	38
24	6	16	5	0	0	7	54

Smart

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	19	17	23	29	13	9	36
2	26	32	10	58	2	14	41
3	16	67	92	70	17	15	49
4	15	57	88	72	12	29	27
5	40	58	78	58	9	36	16
6	28	70	126	51	1	9	50
7	2	34	80	18	2	18	34
8	2	12	0	21	5	38	94
9	0	2	0	7	3	40	169
10	0	8	2	1	2	57	121
11	0	6	1	14	7	20	116
12	6	21	6	10	16	159	106
13	9	0	16	1	17	59	94
14	2	50	0	39	4	39	44
15	0	18	6	18	10	48	90
16	15	1	3	7	3	14	27
17	1	4	1	0	0	5	42
18	3	0	0	0	0	2	6
19	3	1	0	0	0	0	4
20	0	4	0	0	0	6	4
21	2	8	0	2	0	13	13
22	0	2	3	1	0	5	0
23	11	8	2	6	4	5	1
24	25	14	12	3	1	16	10

V2G: charge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	40	67	77	102	70	43	78
2	49	101	98	108	76	37	94
3	51	131	107	170	87	47	83
4	51	126	121	210	115	64	58
5	70	138	135	175	150	78	77
6	58	115	132	159	132	82	88
7	18	75	91	96	33	101	143
8	11	33	7	36	18	154	207
9	5	23	8	16	13	151	291
10	12	35	29	25	26	193	216
11	2	65	5	75	41	63	150
12	32	88	33	98	60	255	179
13	25	6	37	4	61	99	130
14	21	79	0	154	22	106	83
15	2	40	24	53	36	130	124
16	28	21	10	39	5	50	48
17	2	21	8	1	2	6	53
18	1	4	0	0	4	0	5
19	7	0	0	0	2	1	5
20	5	8	4	2	2	3	0
21	0	20	1	6	3	17	4
22	4	3	7	8	15	12	3
23	8	10	3	21	2	12	11
24	25	25	14	26	0	14	19

V2G: discharge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	4	0	8	0	9	0	1
2	1	0	7	0	9	3	0
3	2	0	2	0	9	5	1
4	3	0	2	0	0	0	2
5	1	0	2	0	0	0	0
6	7	0	7	0	3	0	2
7	17	5	6	1	5	0	0
8	6	8	2	19	15	0	3
9	6	5	1	24	12	4	3
10	0	0	0	9	6	7	2
11	0	0	0	0	0	4	0
12	0	0	0	0	2	2	3
13	0	0	0	0	0	0	4
14	0	0	0	3	0	1	2
15	1	0	0	7	3	6	4
16	6	4	5	40	15	12	11
17	17	42	19	73	19	17	25
18	105	65	37	90	187	93	51
19	97	76	105	99	190	118	42
20	122	91	81	139	114	117	40
21	102	78	32	97	185	94	30
22	98	41	37	59	117	88	26
23	60	45	29	44	62	77	18
24	54	35	24	43	72	70	9

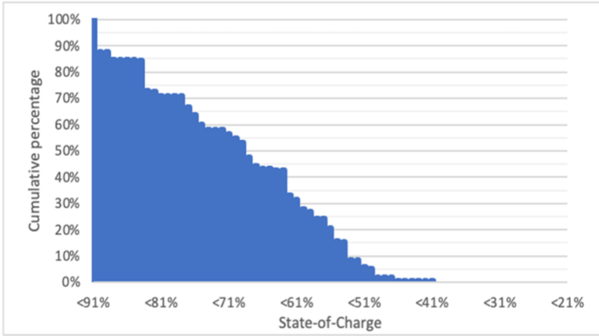
Figure D. 1: Heatmaps indicating the weekly distribution of annual extracted electricity of the reference, delayed charging, smart charging and V2G strategy of the combined profile.

Appendix E. Weekly charging profiles: five driving profiles

E.1 Young Professional

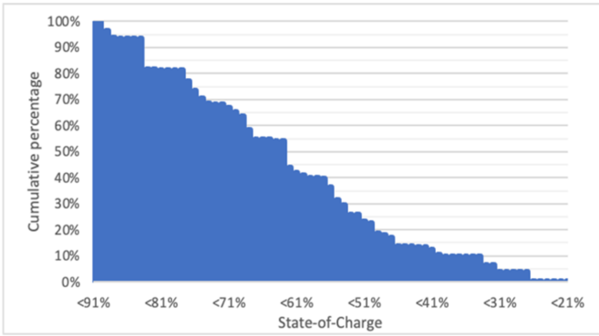
Reference

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	143	0	0	0
2	0	0	0	20	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0
8		0		0	0	0	0
9					0	0	0
10					0	0	0
11					0		0
12					0	143	0
13					0	143	
14					0	143	143
15					0	25	143
16					0	0	143
17						0	17
18					0	0	0
19			143		0	0	0
20	143	143	143	143	0	0	0
21	143	143	143	143	0	0	0
22	143	135		143	0	0	0
23	79	0	143	88	0	0	0
24	0	0	143	0	0	0	0



Delayed

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	1	34	22	57	29	0	0
2	34	17	64	38	22	0	13
3	56	61	65	101	33	0	13
4	56	62	64	72	40	0	22
5	56	84	64	69	40	0	33
6	34	66	76	68	0	0	22
7	23	50	55	35	22	0	22
8		33		11	7	0	26
9					11	0	15
10					13	0	59
11					66		79
12					73	44	70
13					55	13	
14					53	11	121
15					46	2	110
16					7	0	77
17						0	56
18					0	0	24
19			23		0	0	12
20	6	10	45	0	0	0	23
21	6	0	99	0	0	11	0
22	22	0		0	0	0	12
23	22	0	0	0	0	0	0
24	44	0	0	0	0	0	11



Smart

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	22	1	11	59	19	0	11
2	39	17	22	49	11	4	11
3	22	56	42	77	33	18	5
4	11	56	65	90	45	24	24
5	13	47	64	50	22	31	15
6	33	46	83	63	0	0	24
7	5	34	65	32	11	11	11
8		51		22	0	22	13
9					6	33	102
10					14	25	143
11					47		156
12					72	98	139
13					74	78	
14					23	44	195
15					55	6	62
16					0	0	33
17						0	22
18					0	11	5
19			0		0	0	0
20	0	0	0	0	0	0	11
21	11	20	0	11	0	0	0
22	0	10		6	0	0	0
23	1	0	3	0	7	4	0
24	33	0	33	11	0	7	0

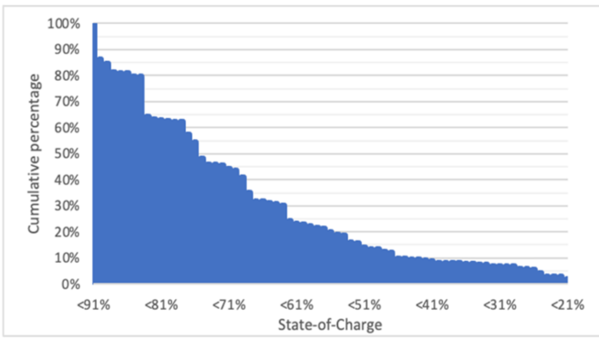
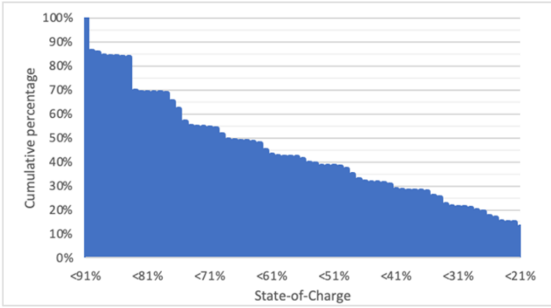


Figure E. 1: Heatmaps indicating the weekly distribution of the annual extracted electricity of the reference, delayed charging, and smart charging strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). From top to bottom: reference, delayed charging, and smart charging simulation. Figure shows the results of the Young Professional simulation.

V2G: charge							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	56	47	90	103	34	36	53
2	36	129	78	134	61	22	66
3	56	146	103	187	89	38	74
4	50	117	166	199	63	64	67
5	66	155	176	163	115	79	50
6	66	171	227	185	45	47	66
7	45	99	133	100	39	60	76
8		89		52	6	121	163
9					44	100	250
10					79	169	242
11					142		324
12					184	213	293
13					204	192	
14					120	183	318
15					100	136	140
16					11	33	38
17						22	28
18					2	0	11
19			0		0	0	0
20	11	0	2	11	0	0	0
21	0	10	4	11	0	11	0
22	0	20		11	11	11	11
23	12	21	3	22	0	11	12
24	23	10	22	39	0	11	11



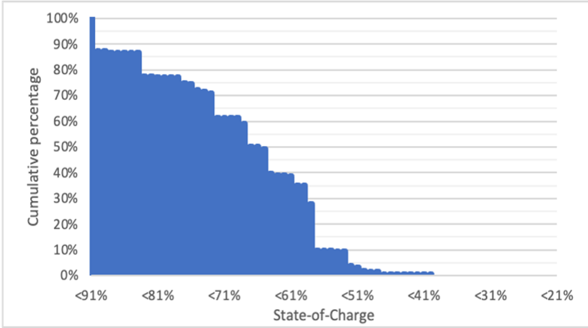
V2G: discharge							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	9	0	9	0	9	0	6
2	0	0	0	0	9	0	0
3	9	0	0	0	9	9	9
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	9	0	0	0	8	0	0
7	27	9	18	9	0	0	0
8		24		34	18	0	9
9					35	9	0
10					18	9	0
11					0		0
12					0	0	9
13					0	0	
14					0	0	0
15					9	7	6
16					45	19	18
17						36	15
18					266	158	45
19			160		271	153	36
20	171	142	115	192	205	118	27
21	187	107	78	147	172	72	18
22	126	56		89	114	98	27
23	73	49	38	83	98	71	14
24	63	32	26	52	89	82	0

Figure E. 2: Heatmaps indicating the weekly distribution of the annual extracted electricity of the V2G strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). Figure shows the results of the Young Professional simulation.

E.2 Working Parent

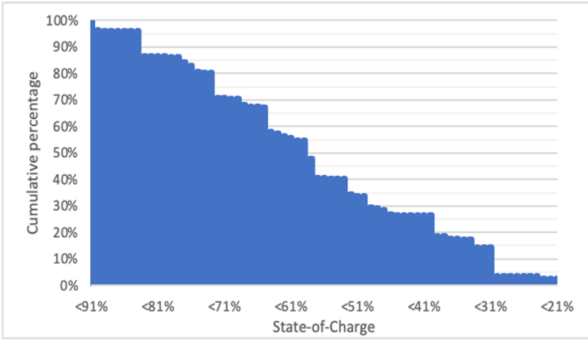
Reference

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7		0	0	0		0	0
8				0		0	0
9				0		0	0
10				0		0	0
11				0			0
12				0		0	0
13							0
14				0		0	
15				0		0	0
16				0		0	
17				0			561
18	0				561	11	561
19	0		0		561	11	561
20	0	572	0	0		11	64
21		572		0	0	1	0
22	0	536	0	0	0	0	0
23	0	7	0	0	0	0	0
24	0	0	0	0	0	0	0



Delayed

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	195	0	97	0	0	0	0
2	237	0	148	0	0	0	11
3	311	0	246	0	0	0	11
4	281	0	301	0	0	0	0
5	320	0	268	0	0	0	0
6	238	0	293	0	0	0	1
7		0	163	0		0	0
8				0		0	11
9				0		0	0
10				0		0	0
11				0			0
12				0		0	0
13							0
14				0		0	
15				0		0	0
16				0		0	
17				0			265
18	0				68	0	139
19	0		0		59	0	177
20	0	43	0	0		0	103
21		54		0	0	0	124
22	0	10	0	0	0	0	105
23	0	21	0	0	0	0	102
24	0	43	0	0	0	0	144



Smart

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	38	32	55	0	22	11	33
2	49	74	15	14	0	11	45
3	34	144	219	3	22	12	70
4	36	80	143	22	11	35	28
5	80	103	143	14	8	44	17
6	44	138	232	14	0	0	40
7		51	144	0		29	33
8				3		50	63
9				11		32	157
10				0		70	169
11				22			230
12				22		142	191
13							199
14				39		89	
15				16		77	223
16				13		15	
17				0			84
18	0				0	0	14
19	0		0		0	0	11
20	0	12	0	0		11	3
21		12		0	0	22	25
22	0	1	0	0	0	11	0
23	21	12	3	11	0	1	1
24	32	21	11	0	0	22	24

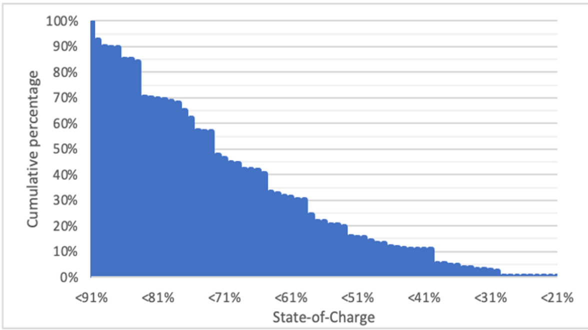
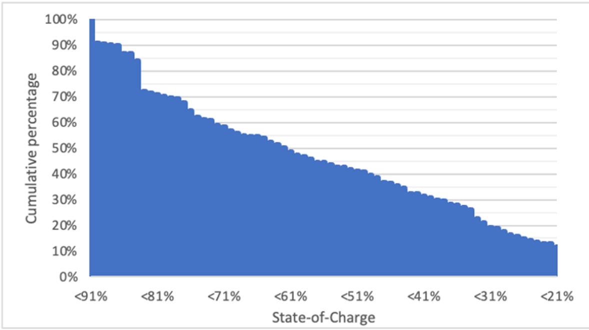


Figure E. 3: Heatmaps indicating the weekly distribution of the annual extracted electricity of the reference, delayed charging, and smart charging strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). From top to bottom: reference, delayed charging, and smart charging simulation. Figure shows the results of the Working Parent simulation.

V2G: charge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	56	100	88	100	112	44	74
2	56	135	143	68	142	33	77
3	57	168	144	133	122	39	53
4	66	173	158	182	189	56	23
5	91	183	143	136	195	50	35
6	67	166	138	130	214	85	44
7		132	72	85		85	100
8				11		152	121
9				19		125	259
10				55		176	296
11				152			239
12				255		240	258
13							250
14				269		217	
15				89		146	281
16				77		50	
17				0			82
18	0				10	0	3
19	11		0		5	0	11
20	10	23	11	0		0	0
21		33		12	0	11	5
22	11	1	11	4	22	13	3
23	11	1	3	33	0	11	11
24	33	33	14	41	0	11	27



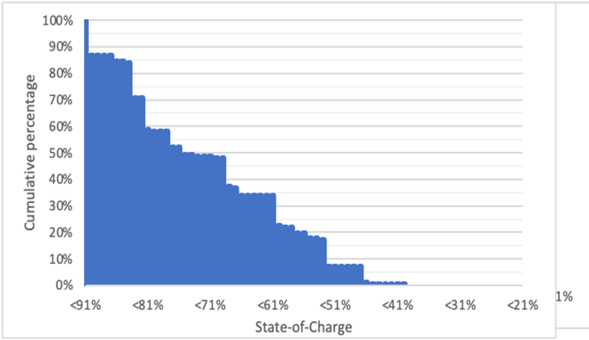
V2G: discharge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	7	0	9	0	0
2	0	0	9	0	9	9	0
3	0	0	0	0	9	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	9	0	9	0	0	0	0
7		9	0	0		0	0
8				25		0	0
9				45		5	9
10				9		9	3
11				0			0
12				0		0	0
13							9
14				0		3	
15				10		9	9
16				45		18	
17				80			18
18	190				284	121	41
19	188		104		280	141	18
20	119	98	79	82		99	25
21		66		61	248	102	18
22	35	45	69	27	168	67	18
23	11	45	49	22	54	73	1
24	22	36	40	24	84	78	0

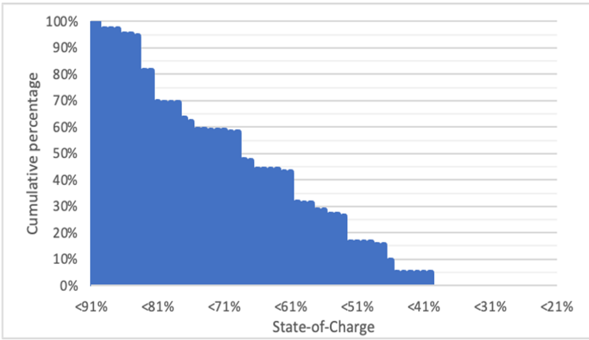
Figure E. 4: Heatmaps indicating the weekly distribution of charged electricity of the V2G strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). Figure shows the results of the Working Parent simulation.

E.3 Semi-Retiree

Reference							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0
8		0		0	0	0	0
9		0				0	0
10		0		0		0	
11		0		0			
12		0				0	
13						0	
14		0		0			
15		0		0		0	
16				0		0	0
17		0		0		0	0
18		0		0		0	0
19		0	572	0			0
20	0		572	0	0	572	0
21	0	0	572	0	0	572	0
22	0	0	380	0	0	572	0
23	0	0	0	0	0	130	0
24	0	0	0	0	0	0	0



Delayed							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	147	0	0	87
2	0	0	0	242	0	0	156
3	0	0	0	374	0	0	68
4	0	0	0	381	0	0	137
5	0	0	0	374	0	0	96
6	0	0	0	245	0	0	171
7	0	0	0	150	0	0	216
8		0		110	0	0	370
9		0				0	426
10		0		0		0	
11		0		0			
12		0				0	
13						0	
14		0		0			
15		0		0		0	
16				0		0	0
17		0		0		0	0
18		0		0		0	0
19		0	0	0			0
20	0		0	0	0	22	0
21	0	0	7	0	0	30	0
22	0	0	22	0	0	36	0
23	0	0	22	0	0	14	0
24	0	0	22	0	0	22	0



Smart							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	22	7	65	7	3	83
2	0	1	7	140	0	11	67
3	0	23	17	191	7	13	49
4	0	69	91	174	2	22	34
5	11	25	57	146	0	33	28
6	21	28	98	122	0	16	97
7	0	35	59	52	0	11	58
8		12		63	14	25	231
9		8				30	274
10		22		3		51	
11		20		3			
12		67				222	
13						191	
14		161		38			
15		73		14		76	
16				7		36	69
17		16		0		22	23
18		0		0		0	0
19		5	0	0			0
20	0		0	0	0	0	5
21	0	4	0	0	0	11	0
22	0	0	10	0	0	3	0
23	13	7	0	0	11	14	0
24	28	21	10	7	6	22	0

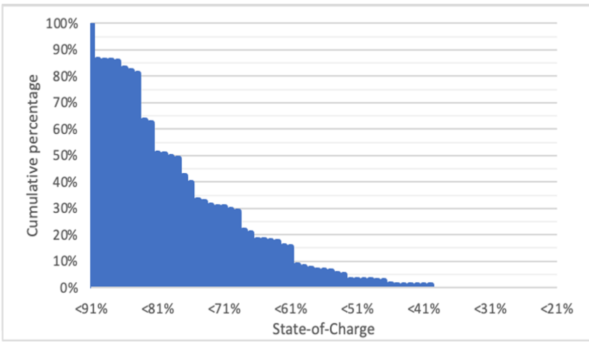


Figure E. 5: Heatmaps indicating the weekly distribution of the annual extracted electricity of the reference, delayed charging, and smart charging strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). From top to bottom: reference, delayed charging, and smart charging simulation. Figure shows the results of the Semi-Retiree simulation.

V2G: charge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	23	53	84	129	55	23	127
2	50	55	110	175	41	50	148
3	66	102	100	263	74	49	144
4	45	102	93	302	88	66	95
5	55	88	153	238	140	79	153
6	61	78	133	233	107	77	166
7	33	33	118	115	77	112	253
8		52		75	55	164	351
9		60				161	396
10		68		11		208	
11		152		8			
12		195				281	
13						286	
14		188		111			
15		163		11		229	
16				11		110	111
17		53		0		11	32
18		15		0		0	0
19		0	0	0			5
20	0		0	0	0	8	0
21	0	15	0	0	11	22	5
22	0	0	12	7	11	11	0
23	12	18	0	11	8	22	11
24	23	21	20	11	0	24	16

V2G: discharge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	9	0	9	0	9	0	0
2	1	0	9	0	9	0	0
3	0	0	0	0	9	9	0
4	9	0	0	0	0	0	0
5	1	0	0	0	0	0	0
6	9	0	7	0	0	0	0
7	27	0	9	0	18	0	0
8		9		0	32	0	0
9		12				6	0
10		0		21		9	
11		0		0			
12		0				0	
13						0	
14		0		9			
15		0		9		9	
16				45		12	23
17		84		99		49	45
18		122		195		102	76
19		151	72	223			81
20	194		65	194	186	94	53
21	149	66	45	130	176	71	37
22	143	34	27	79	118	84	23
23	93	45	2	59	59	60	19
24	63	31	11	42	52	53	9

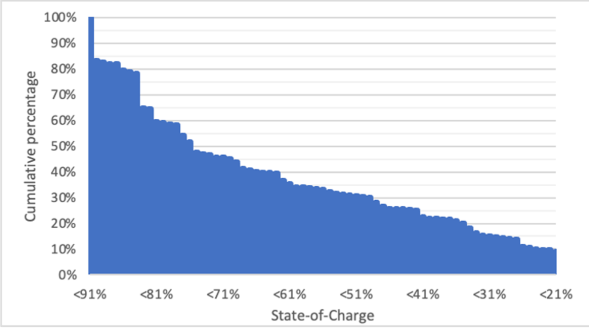
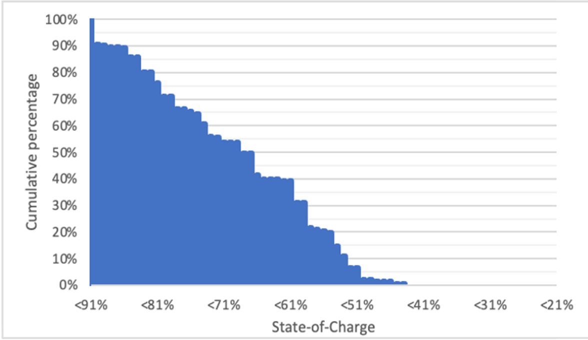


Figure E. 6: Heatmaps indicating the weekly distribution of the annual extracted electricity of the V2G strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). Figure shows the results of the Semi-Retiree simulation.

E.4 Retiree

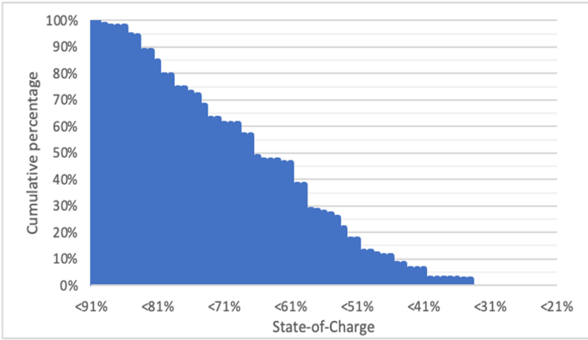
Reference

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0
10	0	0	0		0	0	0
11		0		187	0	0	
12	0	0	0		0	0	0
13	0		0		0		0
14	0	0		0			0
15			187	0	187		
16	198	0	187	0	187		0
17	198	0	187	0	187		0
18	198	0	70	0	20		0
19	6	0	0	0	0	187	0
20		0	0	0	0	187	0
21	0	0	0	0	0	187	0
22	0	0	0	0	0	46	0
23	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0



Delayed

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	59	0	22	22
2	0	0	0	43	0	0	22
3	0	0	0	78	0	1	25
4	0	0	0	99	0	3	27
5	0	0	0	100	0	45	25
6	0	0	0	48	0	44	33
7	0	0	0	15	0	23	25
8	0	0	0	26	0	78	124
9	0	0	0	22	0	113	143
10	0	0	0		0	94	146
11		0		44	0	133	
12	0	0	0		0	144	0
13	0		0		0		0
14	0	0		0			0
15			55	0	11		
16	166	0	48	0	11		0
17	177	0	26	0	0		0
18	91	0	0	0	0		0
19	166	0	0	0	0	0	0
20		0	0	0	0	0	0
21	0	0	0	0	0	3	0
22	0	0	11	0	0	11	0
23	0	0	0	0	0	0	0
24	0	0	0	0	0	3	0



Smart

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	11	0	0	19	0	23	5
2	11	11	0	52	0	33	16
3	0	0	9	49	11	22	38
4	0	11	15	33	5	30	16
5	27	33	11	44	11	24	0
6	11	27	23	33	3	18	28
7	6	11	16	0	0	3	22
8	11	8	0	4	8	51	38
9	0	0	0	16	11	78	90
10	0	11	9		0	73	137
11		6		25	0	100	
12	29	22	32		26	186	81
13	44		81		31		92
14	12	49		73			69
15			29	41	11		
16	72	4	16	0	14		23
17	5	0	4	0	0		9
18	16	0	0	0	0		0
19	13	0	0	0	0	0	0
20		0	0	0	0	11	0
21	0	0	0	0	0	5	18
22	0	0	0	0	0	0	0
23	0	11	0	8	0	0	3
24	9	4	0	0	0	5	3

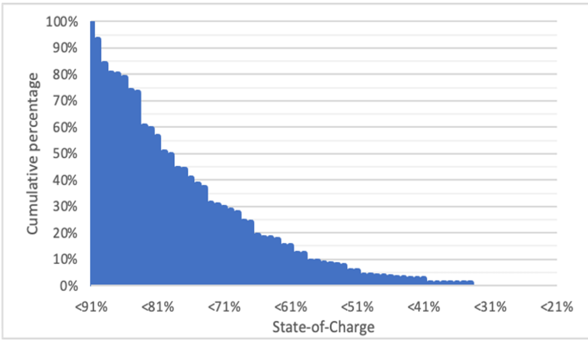


Figure E. 7: Heatmaps indicating the weekly distribution of the annual extracted electricity of the reference, delayed charging, and smart charging strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). From top to bottom: reference, delayed charging, and smart charging simulation. Figure shows the results of the Retiree simulation.

V2G: charge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	23	42	46	77	44	63	46
2	51	81	23	81	13	33	83
3	23	101	60	127	46	56	67
4	40	82	67	180	60	57	61
5	57	109	80	185	110	115	69
6	35	33	59	120	80	89	89
7	13	17	68	93	33	111	118
8	44	30	29	22	11	197	202
9	22	33	31	44	33	248	231
10	51	76	121		72	258	282
11		132		72	99	309	
12	142	165	164		165	327	207
13	113		183		154		178
14	95	136		121			166
15			120	79	106		
16	132	89	47	38	11		70
17	11	31	39	3	6		52
18	5	0	0	0	0		11
19	13	0	0	0	0	5	0
20		0	0	0	11	2	0
21	0	11	0	0	0	22	2
22	0	0	0	9	11	11	0
23	0	11	9	11	0	0	11
24	18	26	0	11	0	6	12

V2G: discharge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	9	0	9	0	0
2	0	0	9	0	9	0	0
3	0	0	7	0	9	9	0
4	2	0	9	0	0	0	9
5	0	0	9	0	0	0	0
6	0	0	9	0	8	0	8
7	27	0	3	0	0	0	0
8	27	9	9	18	18	0	9
9	25	9	5	27	36	0	0
10	0	0	0		18	0	4
11		0		0	0	18	
12	0	0	0		9	9	9
13	0		0		0		0
14	0	0		0			9
15			0	7	9		
16	23	18	27	53	36		9
17	62	89	92	80	85		18
18	127	147	148	174	197		45
19	107	165	101	188	201	202	35
20		150	75	141	164	187	52
21	171	86	33	88	112	127	45
22	137	38	24	72	36	127	43
23	98	42	21	38	58	115	44
24	100	36	9	76	63	72	27

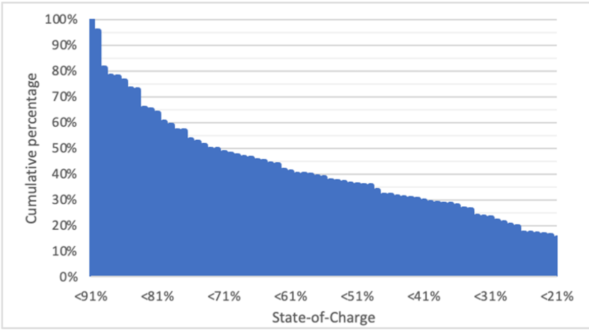
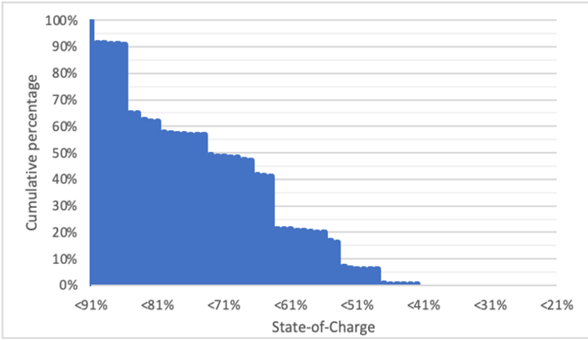


Figure E. 8: Heatmaps indicating the weekly distribution of the annual extracted electricity of the V2G strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). Figure shows the results of the Retiree simulation

E.5 Occasional Driver

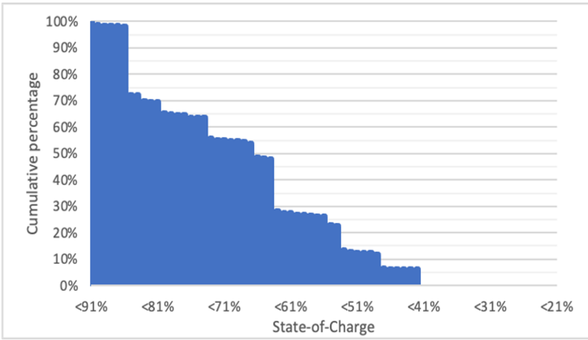
Reference

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	11	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0
8	0	0	0	0	0		0
9	0	0	0	0			0
10	0	0	0	0			0
11	0		0	0			0
12	0	0		0			
13	0	0		0			11
14	0	0		0	0		11
15	0			0			11
16	0	11		0	0		2
17	0	11		0	0		0
18	0	11	11	0	0		0
19	0	1	11	0	0	528	0
20	0	0	11	0	0	528	0
21	0	0	4	0	0	528	0
22	0			0	0	290	0
23	0	11	0	0	0	0	0
24	0	11	0	0	0	0	0



Delayed

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	0	0	0	61
2	0	2	11	0	0	0	67
3	0	11	11	0	0	0	94
4	0	0	0	0	0	0	72
5	11	0	0	0	0	0	67
6	11	0	11	0	0	0	50
7	0	0	0	0	0	0	56
8	0	0	0	0	0		244
9	0	0	0	0			355
10	0	0	0	0			377
11	0		0	0			352
12	0	0		0			
13	0	0		0			0
14	0	0		0	0		0
15	0			0			0
16	0	1		0	0		0
17	0	0		0	0		0
18	0	11	4	0	0		0
19	0	0	11	0	0	0	0
20	0	11	11	0	0	0	0
21	0	11	11	0	0	6	0
22	0			0	0	17	0
23	0	0	0	0	0	28	0
24	0	0	0	0	0	28	0



Smart

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0	0	0	11	11	0	28
2	0	0	0	0	0	11	72
3	0	11	0	5	0	14	63
4	0	0	0	18	11	25	54
5	8	4	9	11	0	54	11
6	3	4	10	7	0	26	58
7	0	0	0	0	3	60	33
8	4	4	0	11	11		114
9	0	0	0	0			286
10	0	4	11	0			274
11	0		37	0			261
12	0	2		43			
13	4	8		28			53
14	0	9		24	16		27
15	0			11			0
16	0	9		0	13		0
17	0	0		0	3		0
18	0	0	0	0	0		0
19	0	4	0	0	0	10	4
20	0	0	0	0	0	2	0
21	0	3	6	0	0	22	0
22	0			0	0	11	0
23	0	0	0	8	0	23	0
24	0	0	8	0	0	11	0

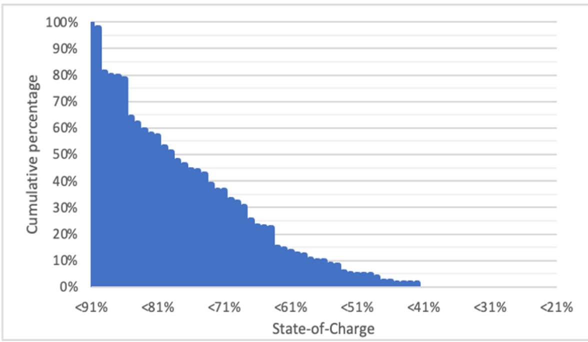


Figure E. 9: Heatmaps indicating the weekly distribution of the annual extracted electricity of the reference, delayed charging, and smart charging strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). From top to bottom: reference, delayed charging, and smart charging simulation. Figure shows the results of the Occasional Driver simulation.

V2G: charge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	22	56	44	68	36	83	77
2	22	74	50	109	70	56	79
3	33	59	69	82	45	110	94
4	6	108	61	94	89	164	91
5	59	124	76	121	128	143	122
6	48	75	96	67	122	174	85
7	12	23	55	66	52	283	241
8	44	22	33	33	22		280
9	22	44	50	11			405
10	33	80	110	54			410
11	49		139	71			399
12	77	160		110			
13	60	172		109			69
14	58	128		88	117		79
15	55			35			19
16	22	71		1	43		11
17	0	36		1	11		0
18	0	0	0	0	0		4
19	0	0	3	0	0	0	0
20	0	0	3	0	0	11	0
21	0	14	8	11	0	34	0
22	0			22	11	11	0
23	0	15	0	19	7	33	11
24	1	13	28	12	0	34	15

V2G: discharge

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	1	0	9	0	9	0	0
2	9	0	0	0	9	0	0
3	18	0	9	0	9	0	0
4	0	0	9	0	0	0	0
5	9	0	0	0	0	0	0
6	18	0	9	0	0	0	0
7	27	0	0	0	9	0	0
8	19	8	8	45	13		0
9	37	0	12	53			0
10	0	0	0	10			0
11	0		0	0			0
12	9	0		0			
13	9	0		0			24
14	0	0		9	9		16
15	18			9			9
16	46	9		40	43		27
17	126	77		71	57		36
18	252	133	176	161	118		52
19	187	145	149	159	185	91	94
20	145	119	110	108	127	75	89
21	91	106	65	75	73	69	60
22	81			64	53	56	21
23	55	47	18	45	50	57	45
24	20	50	38	36	62	55	45

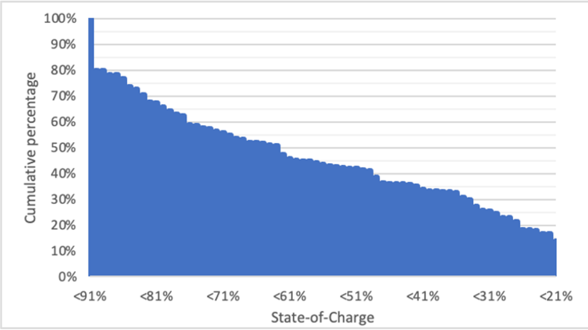
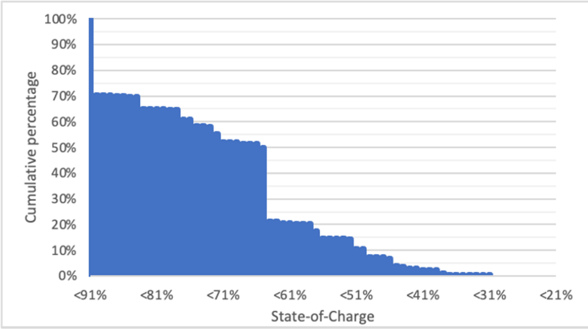


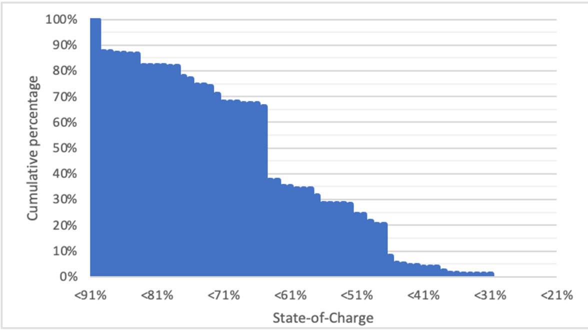
Figure E. 10: Heatmaps indicating the weekly distribution of the annual extracted electricity of the V2G strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). Figure shows the results of the Occasional Driver simulation.

E.6 Uncertainty 1

Reference							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	49	0	0	0	0	286	286
2	0	0	0	0	0	286	286
3	0	0	0	0	0	97	286
4	0	0	0	0	0	0	217
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0
8	0	0	0	0			
9	0	0	0	0			
10	0	0	0	0			
11	0	0	0	0			
12	0	0	0	0			
13	0	0	0	0			
14	0	0	0	0			
15	0	0	0	0			
16	0	0	0	0			
17	0	0	0	0			
18	0	0	0	0			
19	0	0	0				
20	0	0	0				
21	0	0	0				
22	0	0	0	0			286
23	0	0	0	0	286		286
24	0	0	0	0	286		286



Delayed							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	4	0	0	22	0	136	132
2	11	2	0	33	0	63	165
3	11	11	4	22	0	114	111
4	2	0	22	22	0	216	154
5	11	2	11	35	0	209	141
6	11	0	22	35	0	227	179
7	11	0	11	2	0	264	193
8	13	11	11	0			
9	11	0	11	11			
10	0	0	0	0			
11	11	15	48	13			
12	13	11	44	22			
13	11	24	26	13			
14	4	11	35	22			
15	11	24	11	13			
16	11	0	0	0			
17	0	0	0	0			
18	0	0	0	0			
19	0	0	0				
20	0	0	0				
21	0	0	0				
22	0	0	0	0			55
23	0	0	0	0	0		44
24	0	0	0	0	11		33



Smart							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	11	0	0	21	21	70	135
2	12	11	0	4	21	62	121
3	22	2	13	33	0	72	53
4	22	10	10	44	30	156	125
5	21	0	11	20	10	146	83
6	0	11	22	32	30	198	162
7	13	11	11	0	20	295	187
8	21	0	0	0			
9	0	0	11	0			
10	2	32	22	0			
11	30	24	22	13			
12	10	32	39	52			
13	46	23	30	33			
14	32	33	22	54			
15	0	33	33	2			
16	2	0	2	0			
17	0	0	0	0			
18	0	0	0	0			
19	0	0	0				
20	0	0	0				
21	0	0	0				
22	0	0	0	10			63
23	0	0	0	10	0		63
24	0	11	0	0	22		29

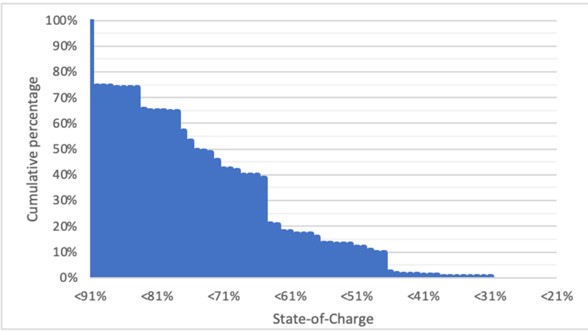
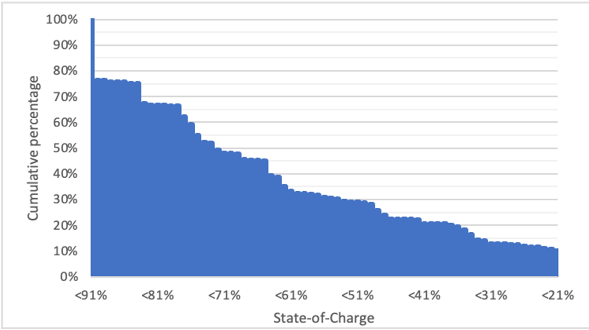


Figure E. 11: Heatmaps indicating the weekly distribution of the annual extracted electricity of the reference, delayed charging, and smart charging strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). From top to bottom: reference, delayed charging, and smart charging simulation. Figure shows the results of the first Uncertainty simulation.

V2G: charge							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	30	33	34	56	33	120	149
2	43	55	35	110	55	135	155
3	43	89	55	144	69	139	134
4	31	76	45	113	93	254	112
5	87	77	44	121	148	263	133
6	55	68	65	111	97	350	195
7	11	12	22	55	100	367	285
8	23	22	11	23			
9	23	33	12	11			
10	22	55	46	33			
11	98	111	121	66			
12	85	165	132	101			
13	77	144	131	111			
14	55	132	110	69			
15	44	112	68	35			
16	23	24	2	14			
17	0	1	0	11			
18	2	0	0	0			
19	0	0	0				
20	0	0	0				
21	0	11	0				
22	0	0	0	21			83
23	11	0	0	22	0		127
24	0	0	0	21	0		112

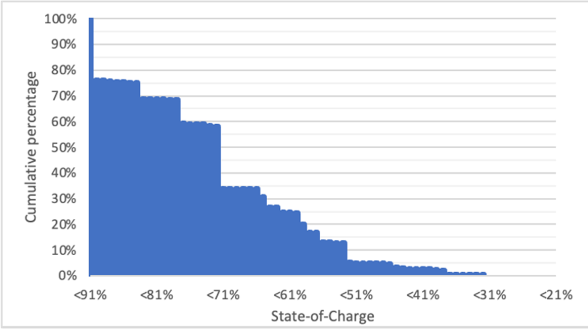


V2G: discharge							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	18	0	9	0	9	5	6
2	9	0	9	0	14	4	9
3	2	0	9	0	9	9	0
4	2	0	9	0	0	0	8
5	11	0	9	0	0	0	0
6	9	0	9	0	0	0	0
7	18	0	9	9	45	0	0
8	18	9	0	25			
9	29	9	1	27			
10	9	0	0	9			
11	0	0	0	0			
12	0	0	0	9			
13	9	0	0	0			
14	9	0	0	9			
15	27	1	0	9			
16	55	20	19	27			
17	115	98	96	59			
18	205	143	151	87			
19	206	162	122				
20	131	108	100				
21	85	91	54				
22	62	55	12	171			62
23	45	71	10	124	114		63
24	46	38	18	121	113		71

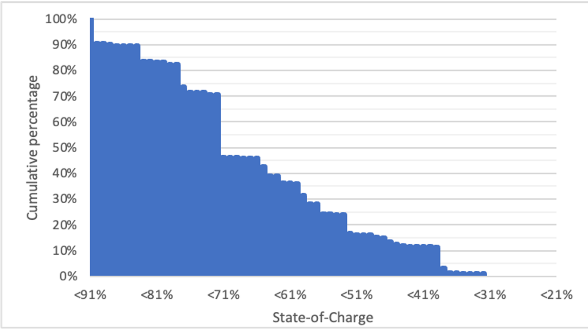
Figure E. 12: Heatmaps indicating the weekly distribution of the annual extracted electricity of the V2G strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). Figure shows the results of the first uncertainty simulation.

E.7 Uncertainty 2

Reference							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0					222	0
2	0					0	0
3	0					0	0
4	0	0		0		0	0
5	0	0	286	0	286	0	0
6	0	0	286	0	286	0	0
7	0	0	286	0	286	0	0
8	0	0	52	0	286	0	0
9	0	0	0	0	85	0	0
10	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0
17		0		0		0	0
18						0	0
19						0	0
20						0	0
21						0	0
22					286	0	0
23					286	0	0
24					286	0	0



Delayed							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	0					11	31
2	22					9	11
3	11					22	33
4	11	0		0		11	17
5	22	0	99	0	124	15	22
6	11	0	101	0	99	0	22
7	9	0	66	0	47	0	42
8	11	0	0	0	11	0	22
9	0	0	11	0	18	0	39
10	0	0	13	0	87	44	61
11	11	0	85	0	130	9	66
12	20	0	120	0	223	61	72
13	22	0	175	0	234	20	75
14	9	0	155	0	167	44	72
15	0	0	41	0	67	20	42
16	0	0	44	0	22	0	0
17		0		0		0	0
18						0	0
19						0	0
20						0	0
21						11	0
22					0	0	0
23					0	0	0
24					0	9	9



Smart							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	9					11	22
2	11					4	22
3	22					20	4
4	26	30		56		33	15
5	11	61	52	20	120	18	9
6	11	30	92	10	72	0	22
7	11	11	40	0	27	11	20
8	10	2	10	11	0	0	21
9	0	10	0	11	11	4	87
10	0	0	10	10	15	11	70
11	33	41	39	11	49	4	71
12	11	41	49	47	132	97	92
13	11	51	157	56	165	78	109
14	9	30	93	41	83	47	82
15	0	10	22	21	58	22	33
16	0	12	2	10	0	22	15
17		0		0		0	11
18						0	0
19						0	0
20						0	0
21						4	0
22					0	0	11
23					0	0	0
24					0	12	0

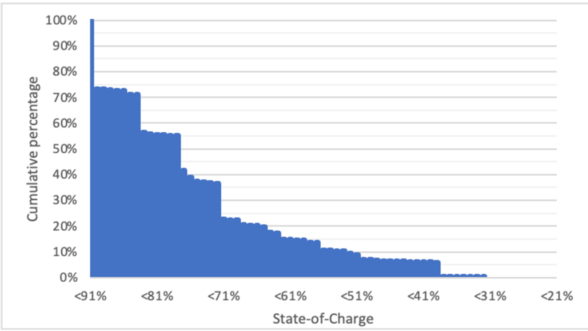


Figure E. 13: Heatmaps indicating the weekly distribution of the annual extracted electricity of the reference, delayed charging, and smart charging strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). From top to bottom: reference, delayed charging, and smart charging simulation. Figure shows the results of the second uncertainty simulation.

V2G: charge							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	34					15	55
2	33					22	55
3	35					37	56
4	44	112		107		48	34
5	45	52	117	97	160	45	33
6	44	73	129	61	140	64	13
7	22	44	55	44	33	64	24
8	44	11	11	11	22	45	89
9	11	0	11	0	22	52	132
10	11	12	77	0	39	110	226
11	55	76	99	44	95	133	237
12	88	97	144	108	223	202	263
13	88	77	222	118	265	170	238
14	67	98	204	87	125	159	225
15	66	87	76	22	115	79	90
16	45	22	22	12	22	12	34
17		0		0		11	23
18						0	0
19						0	0
20						0	0
21						11	0
22					11	11	11
23					0	22	12
24					0	11	11

V2G: discharge							
Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
1	9					21	0
2	11					23	0
3	0					14	0
4	19	38		24		0	9
5	19	29	36	16	18	0	0
6	9	9	3	0	17	0	0
7	18	18	12	27	9	0	0
8	36	49	46	76	27	0	0
9	45	56	47	56	39	9	9
10	9	9	3	9	18	9	0
11	0	0	0	9	2	9	0
12	0	0	0	0	0	0	0
13	9	9	0	0	0	0	9
14	9	0	9	9	0	1	9
15	18	27	15	27	0	9	0
16	45	84	53	72	59	9	0
17		168		163		61	19
18						142	40
19						175	45
20						124	63
21						127	53
22					281	77	30
23					247	72	45
24					239	78	53

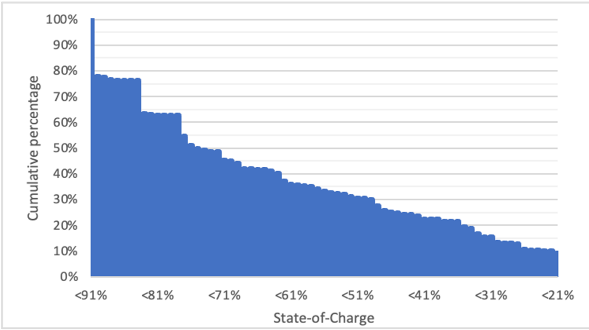


Figure E. 14: Heatmaps indicating the weekly distribution of the annual extracted electricity of the V2G strategy (left-hand side) and the distribution of the SoC throughout the entire simulation (right-hand side). Figure shows the results of the second uncertainty simulation.

Appendix F.

Interview guide for the identification of factors that stimulate grid aware charging. The interviews start with an introduction of this research, the focus of and system boundaries (i.e. the Netherlands, private charging), and a short discussion on the results. What does the interviewee think of the results? Are they higher/lower than expected? Then, each interview starts with a general question:

Can you explain in simple words what controlled charging is, and what the most important advantages of controlled charging are? How does grid-aware charging fit in here?

From here on, the interview usually followed a natural flow, where more in-depth questions were asked when interesting topics were discussed, leading to new and undiscovered topics. When a discussion on a certain topic ended, one of the following questions was used to restart the conversation.

- Wat is your vision on the role of the government for the implementation of controlled charging?
- What are according to you the most important factors that stimulate grid-aware charging?
- What are the most important barriers for the adoption of grid-aware charging?
- How can these barriers be reduced?
- How can the relevant stakeholders collaborate to increase grid-aware charging adoption?
- Which stakeholders need to be involved in the creation of policy on grid-aware charging?
- How can policy makers deal with uncertainties and risks during the development of policy for new technologies, such as controlled charging?
- How can policy makers include future developments and innovations in their policy?
- How can the results of this study contribute to simulation of grid-aware charging?
- What role do the different stakeholders have in stimulating knowledge development on grid-aware charging?
- What role do you specifically see for V2G in the near future? And later?