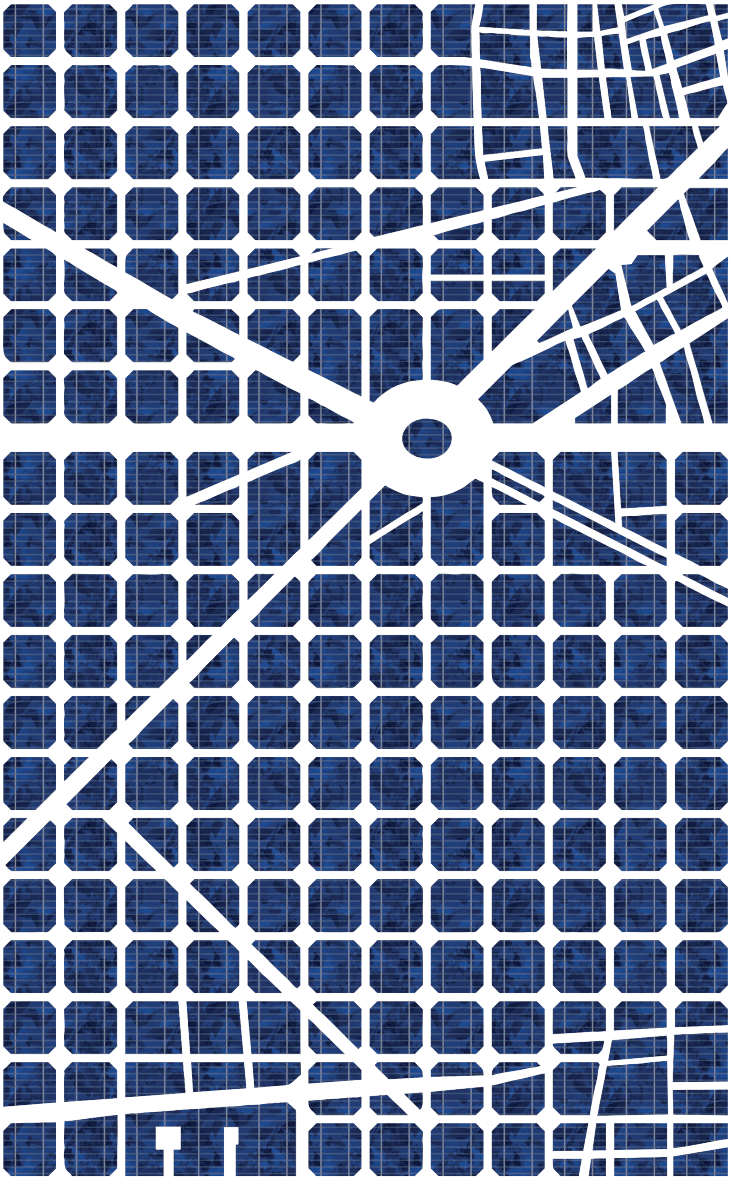
Driving solar

Integrating photovoltaic systems, electric vehicles, and consumer behaviour in models of smart energy systems

Mart van der Kam



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Integratie van fotovoltaïsche systemen, elektrische voertuigen, en consumentengedrag in modellen van slimme energiesystemen

(met een samenvatting in het Nederlands)

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Contents

Chapter 1

Introduction

On September 2nd 2019, the Dutch government announced to invest 5 million Euro in the placement of 472 *smart* charging stations in 21 municipalities (Rijksoverheid, 2019a). These charging stations are considered smart because they are bidirectional, enabling electric vehicles (EVs) to store renewable energy, for instance from photovoltaic (PV) solar panels, which can be fed back to the grid during peak electricity demand. This is also known as vehicle-to-grid (V2G). One of the earliest applications of V2G was to use EVs as a source of emergency power supply after the 2011 earthquake in Japan (Corchero & Sanmarti, 2018). This earthquake caused the Fukushima nuclear disaster, which led to an increased attention to integration of stabilizing mechanisms in the electricity infrastructure in Japan (Weiller & Neely, 2015). In contrast, the Netherlands has one of the most stable electricity grids in the world (Oirsouw, 2012). Furthermore, Japanese EV models can charge as well as discharge, but out of all European EV models only the Renault Zoë has the ability to discharge (Hofs, 2019). Hence, it begs the question whether it makes sense to adopt V2G technology in the Netherlands, or in other countries with a reliable electricity grid and a low number of EVs that can discharge.

This thesis addresses this question. More specifically, I investigate the potential of V2G and smart charging of EVs, i.e. shifting of charging demand, to support the integration of intermittent renewables in the electricity grid. Providing a realistic estimate of this potential can help to assess how much smart charging stations can contribute to load balancing, and whether additional solutions to support the integration of renewable energy sources are necessary.

Smart charging and V2G are systemic innovations that are expected to have a large impact on energy and transport systems. Energy and transport systems can be characterized as socio-technical systems (Auvinen & Tuominen, 2014; Hughes, 1983). The concept of socio-technical systems emphasizes the interrelatedness of social and technical aspects of a system. For example, social factors such as economic structures, societal values, and power relations between actors shape energy and transport systems. At the same time, the technical structure of these systems influence societies, for instance the availability and costs of electricity and transportation, which depend on power sources and infrastructures. Changes in one component of the system can have impact on other components in the system. Socio-technical systems have a mix of linear and non-linear relations between different components in the system, making it difficult to predict how such systems evolve in time. Hence, studying the potential functioning of smart charging and V2G requires a systems perspective, taking technical as well as social aspects into account.

Simulation models are a valuable tool in assessing future socio-technical systems, as they allow for explorations of these systems that would be costly, impractical, or unethical to do with real-life experimentation. However, social aspects of EV charging are insufficiently addressed in simulation models of smart energy systems. In particular, consumers are often represented either as passive participants in automated charging schemes, see e.g. Hu, Morais, Lind, & Bindner (2016), Nunes, Farias, & Brito (2015), Škugor & Deur (2015), and

Waraich et al., 2013, or as being driven only by driving needs and costs of charging, see e.g. Lee, Lukszo, & Herder, (2018), Olivella-rosell, Villafafila-robles, & Sumper (2015), and Waraich et al. (2013). This view of consumers is too simplistic, as it ignores the social and moral dimensions of pro-environmental behaviour which have been shown to be important (Axsen & Kurani, 2013; Noppers, Keizer, Milovanovic, & Steg, 2016). Consumers play a vital role in realizing smart charging and V2G systems, as they must be willing to *adopt* technologies such as PV solar panels and EVs, and *change their behaviour* in line with these technologies. The behaviour of early EV adopters is *not aligned* with optimal system functioning. While PV solar panels deliver most of their energy during the day, EVs are mostly charged in the early morning and early evening, thereby adding to existing peak demand (E-Laad, 2013). Consumer adoption and willingness to change energy behaviour are major sources of uncertainty in assessing the development and future performance of smart charging and V2G. Reducing these uncertainties requires a more realistic view of consumer behaviour in simulation models.

This thesis addresses this by integrating theories of consumer behaviour from innovation science and environmental psychology in simulation models of energy systems. Furthermore, the thesis provides various empirical contributions on user behaviour by analyzing PV solar panel diffusion, EV diffusion, and EV charging behaviour. With these simulation models and analyses, I provide new evidence in how consumers shape energy system, and contribute to the larger effort of integrating insights from social sciences with energy science (Geels, Berkhout, & van Vuuren, 2016; Kastner & Stern, 2015; Stern, Sovacool, & Dietz, 2016).

The rest of this chapter first discusses the technologies, concepts, theories and general modelling approach used in this thesis. Section 1.1 discusses solar energy and EVs in the context of the energy transition. Section 1.2 presents a short history of the electricity grid and explains why it needs to be modernized to accommodate *smart energy systems*. Section 1.3 elaborates on the role of consumers and behavioural change in realizing smart energy systems. Section 1.4 discusses the role of simulation models to inform energy policy design, and to what purpose simulation models are used in this thesis. Then, Section 1.5 formulates the main research objective, and Section 1.6 provides an outline of the remaining chapters.

1.1 Solar energy, electric vehicles, and the energy transition

PV solar panels as well as EVs have experienced significant growth over the last years. One of the reasons these technologies are increasingly popular are concerns for human-induced climate change of citizens and governments. In 2015, 195 nations committed to the 2015 Paris Climate Agreement aiming to limit global temperature rise below 2 degrees Celsius above pre-industrial levels, and pursue efforts to limit it to 1.5 degrees Celsius (UNFCCC, 2015), According to the Intergovernmental Panel on Climate Change (IPCC), CO_2 emissions should reach net zero by 2040 to have a high probability of reaching the 1.5 degree target

(IPCC, 2018). The main cause of human-induced climate change are the CO_2 emissions from our fossil fuel based economies, and drastic decarbonisation is needed to reach the targets of the agreement. Both the electricity production sector and the transport sector rely heavily on fossil fuels, 64% (IEA, 2019a) and 93% respectively (IEA, 2019c), and account for a large share of global CO_2 emissions, 42%[1] and 24% respectively (IEA, 2018).

CO_2 emissions can be reduced through a combination of limiting energy use, increasing energy efficiency, and producing energy from non-CO_2 emitting sources, such as solar energy, wind energy, thermal energy, hydraulic energy, and nuclear energy. Large scale structural changes in energy systems are called energy transitions. A historical example of an energy transition is the move from biomass-based to fossil fuel-based economies. This transition has had a deep impact, as it enabled the development of modern societies. We can expect the energy transition to clean energy to have large societal impacts as well, on matters ranging from geopolitics to industrial processes and to end-consumers.

PV solar panels are a promising technology to contribute to the decarbonisation of our energy supply (Creutzig et al., 2017). PV solar panels consist of cells that convert solar irradiation to electricity, and do not emit CO_2 during this process. The first silicon solar cell was introduced in 1954 by Bell Labs, with an efficiency of 6% (Chapin, Fuller, & Pearson, 1954). Early use of PV solar panels was limited to experiments and space exploration due to high costs. The costs of PV solar panels have decreased rapidly over the last years (Louwen, Van Sark, Faaij, & Schropp, 2016), and PV systems have become increasingly popular amongst households. PV solar panels are modular, and can therefore be produced at a size suitable for household rooftops, enabling consumers to be closely involved in greening the energy system. Though the total electricity produced by PV solar panels was only 1.8% of global electricity production in 2017 (IEA, 2019a), the global installed PV capacity has shown large annual growth rates of at least 24% in the last decade (IRENA, 2019).

Fossil-fuel based processes can become more sustainable by using electricity as an energy source, because many of the viable clean energy sources produce electricity. This is a key reason why the electrification of transportation is a major target in greening our economies. EVs and hydrogen vehicles both use electricity as an energy source. Electricity can be used to charge EV batteries, and to produce hydrogen through electrolysis. Of these two technologies, especially EVs have increased in popularity. Like PV solar panels, EVs are actually a quite old technology. The first electric vehicle was developed in 1890, and EVs were a serious competitor for market dominance for internal combustion engine (ICE) vehicles (Kirsch, 2000). ICE vehicles won this battle, but EVs have seen a resurgence recently. While only 0.6% of the global passenger car fleet were EVs in 2018, global sales increased by 68% (IEA, 2019b), and the costs of EV battery have declined rapidly (Nykvist & Nilsson, 2015).

[1] Including heat production

1.2 The electricity grid

Unlike fossil fuels, electricity cannot be stored, but it can be converted to other forms of energy, such as electrochemical energy in batteries and mechanical energy in flywheels, and later reconverted to electricity. In the conversion processes exergy, i.e. thermodynamically usable energy, is lost, which is why transportation of electricity is preferred to storage in many cases. Early use of electricity for lighting was local and based on batteries and dynamos, but large scale electrification of societies only took off with the development of electricity grids (Hughes, 1983). While early direct current (DC) electricity grids spanned a maximum of 2.5 km, the advent of alternating current (AC) supported more efficient transportation over longer distances (Oirsouw, 2012). Nowadays, grids transport electricity between countries and are among the biggest and most complicated infrastructures.

Electricity grids are usually divided in three levels classified by voltage (Oirsouw, 2012). High voltage transportation networks transport electricity across countries and large regions, and are connected to large power plants and wind farms, heavy industry, and medium voltage distribution networks. Medium voltage distribution networks distribute electricity through smaller regions, and are connected to medium sized distributed energy sources, medium heavy industry, and high and low voltage distribution networks. Low voltage distribution networks distribute electricity locally, and are connected to residential buildings, offices, local distributed energy sources, and the medium voltage distribution network.

The electricity grid has been designed to transport electricity from large power plants through high voltage networks to medium and low voltage networks to end-costumers. There are two main differences between large power plants and decentralized renewable energy sources relevant for grid design. Firstly, many decentralized renewable energy sources such as rooftop solar panels are connected to the low voltage grid, which were not designed to handle the voltage rise and increased power flows resulting from high penetration of these energy sources (Bayer, Matschoss, Thomas, & Marian, 2018; Oirsouw, 2012). The capacities of low voltage grids pose limits to how much PV solar panels can be installed. This was illustrated recently when a Dutch football club wanted to install PV solar panels on their canteen building, but the local distribution grid operator (DSO) did not approve their request, because the grid capacity was too low to handle the additional power flows (Van den Berg, 2019). Secondly, while power plants can be controlled to increase or decrease production to match demand, decentralized renewable energy sources such as PV solar panels and wind turbines produce energy depending on weather conditions. If there is more demand for electricity than there is supply, the 50 Hz grid frequency falls, while the grid frequency rises if there is more supply than demand. Electricity grids need to operate at a stable frequency to prevent outages (ETSO-E, 2014). The grid is designed in such a way that generating units respond automatically to changes in frequency. Introducing large numbers of decentralized weather dependent energy sources will make it harder to maintain this balance.

There are several solutions for these issues. Firstly, while it is not possible to make the sun shine brighter or the wind blow harder, it is possible to turn PV solar panels and wind turbines off, known as curtailment (C. Li et al., 2015). Secondly, the grid can be strengthened in order to enable balancing energy demand and supply across large regions (Elliott, 2016). This solution, also known as a super-grid, takes advantage of the fact that, for large areas, there are large variations in energy balances at any point in time. Thirdly, electricity storage can be used to match (local) demand and supply (Dunn, Kamath, & Tarascon, 2011; Luthander, Widén, Nilsson, & Palm, 2015). Fourthly, electricity demand can be aligned with local energy production automatically in so-called *smart grids* (Luthander et al., 2015).

The term "smart grid" is an umbrella term catching many ideas about modernizing the grid with ICT technologies. The European Technology Platform Smart Grids defined a smart grid as "an electricity network that can intelligently integrate the actions of all users connected to it - generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies" (ETP, 2010). I refer to the combination of smart grids connected to generators and consumers as *smart energy systems* (SES). In SES, ICT-enhanced appliances can adjust their electricity demand according to grid conditions and local energy generation. Currently, grid operators can already have agreements with factories on electricity demand for economic use of the electricity grid (Shoreh, Siano, Shafie-khah, Loia, & Catalão, 2016), but ICT technologies can enable a diverse set of household appliances to shift their demand automatically. For example, a *smart* washing machine can start its cycle when PV solar panels are producing energy, pause when production is low because of a passing cloud, and continue when the sky is clear again. Not every electrical appliance is suitable for shifting its demand depending on grid conditions, the electricity demand of appliances such as lightning and television can largely be considered non-shiftable. For technologies such as heating and cooling systems and wet appliances the exact timing of demand is less important, as heating, cooling, and washing cycles can be shifted within a certain margin (Abi Ghanem & Mander, 2014; Staats, De Boer-Meulman, & Van Sark, 2017; Widén, 2014). Demand shifting can also reduce the impact of clean energy technologies on the demand side, by alleviating peaks in electricity demand of technologies such as heat pumps and EVs.

EVs can play a key role in SES, and have high potential to shift their charging demand. EVs typically have a high energy use compared to other household appliances (Van Vliet, Brouwer, Kuramochi, Van den Broek, & Faaij, 2011), and there is thus a lot of energy demand to be shifted. Also, many cars are stationary for long periods, 95% of the time according to Cogill et al. (2014), which offers a time-frame in between trips to shift demand. Furthermore, current charging demand of EVs peaks in the evening, coinciding with peaks in the electricity demands of households (E-Laad, 2013). If this pattern does not change, high EV penetration levels will require grid investments to prevent overloads (Eising, Van Onna, & Alkemade, 2014). Charging EVs in the night instead of the evening will significantly reduce the pressure on the grid caused by large EV fleets. Finally, energy could also be

extracted from the EV battery via V2G technology (Lund & Kempton, 2008) in order to provide balance to the local grid.

1.3 The role of consumers in smart energy systems

In SES, consumers play a more active role than in current energy systems, where they have a mostly passive role (Verbong, Beemsterboer, & Sengers, 2013). To make SES a success, consumers, as energy users, but also as energy producers (prosumers), must be willing to *adopt* innovative, smart energy technologies and *change their energy behaviour* in line with the innovative technology. The behaviour and preferences of individual consumers are thus an important determinant of SES performance, but also a major source of uncertainty, and SES may greatly increase heterogeneity in consumers' energy behaviour. Technology adoption and behavioural change are thoroughly studied topics in innovation science and environmental psychology respectively, and I use theories from both fields to investigate the role of consumers in SES.

As mentioned above, technology adoption is a key factor in realizing SES. The process by which innovations are adopted by a population is called technology diffusion. The diffusion of new technologies usually follows an S-shaped pattern, with a slow start, followed by a take-off and rapid market diffusion, and finally the rate of diffusion decreases when the market moves towards saturation (Rogers, 2003). This pattern follows from social structures, in which consumers with different characteristics adopt a new technology at different points in time. Rogers (2003) classifies adopters in five categories depending at which point in the diffusion process they adopt the technology: innovators, early adopters, early majority, late majority, and laggards. The characteristics of these groups can differ per technology, e.g. the early adopters of one technology are not necessarily the early adopters of another technology.

To study how consumer adoption influences the formation of SES, we need to investigate multiple diffusion processes. SES consist of multiple types of smart energy technologies (SETs), e.g. metering systems, smart appliances, distributed generation, and energy storage, which do not necessarily follow similar diffusion patterns (Rai, Reeves, & Margolis, 2016). How these different SETs diffuse through society will shape the future energy system in several ways. As grid issues can arise locally, the spatial and temporal diffusion patterns determine where and when grid issues arise and whether local solutions for these issues are available. If the same consumers adopt multiple types of SETs, demand and supply can be balanced behind the electricity meter, or consumers can even go off-grid (Palensky & Kupzog, 2013). If this is not the case, consumers should be enabled to supply (PV) energy to the grid and could participate in peer-2-peer trade systems for economic benefits.

The second important aspect of consumer behaviour is their willingness to change their energy behaviour, of which load shifting and energy saving are most relevant in the context of SES. Currently, consumers are used to a very high degree of availability of electricity.

Consumers will have to be incentivized to hand over control of their appliances to provide grid services to either the smart appliance itself or to DSOs, as they are often reluctant to engage in such programs due to privacy and autonomy concerns (Sintov & Schultz, 2015). Furthermore, offering grid services with EVs may increase battery degradation (Ahmadian, Sedghi, Elkamel, Fowler, & Aliakbar Golkar, 2018; Bishop, Axon, Bonilla, & Banister, 2016). Consumers can be motivated to engage in load shifting or electricity saving behaviour when they perceive higher benefits than costs (Steg, 2016; Steg & Vlek, 2009). One can distinguish instrumental, affective, and social costs and benefits, i.e. consequences with regard to respectively money and time, pleasure and comfort, and or social status (Steg, 2016; Steg & Vlek, 2009; Van der Werff, Perlaviciute, & Steg, 2016). Another important motivational factor affecting the likelihood to engage in load shifting and energy saving behaviour is environmental self-identity, which is the extent to which one sees oneself as an environmentally friendly person (Van der Werff, Steg, & Keizer, 2013). Environmental self-identity can be strengthened by past sustainable behaviour (Van der Werff, Steg, & Keizer, 2014b). A strong environmental self-identity in turn is related to the interest in participation in SES (Van der Werff & Steg, 2016), load shifting, and energy saving behaviour (Peters, Van der Werff, & Steg, 2018).

In environmental psychology, two ways to promote load shifting and energy saving behaviour are distinguished: via structural and via psychological strategies. Structural strategies change the instrumental costs and benefits of the desired behaviour or the costs and benefits of the behaviour alternatives, while psychological strategies aim to promote the desired behaviour without changing the actual costs and benefits (Steg, Perlaviciute, & Van der Werff, 2015; Van der Werff et al., 2016). Energy saving behaviour seems more strongly related to individual variables, such as identity, than to sociodemographic variables, such as income (Abrahamse & Shwom, 2018). Recent smart grid pilot projects have used this insight. Where early projects focussed mainly on technical and financial considerations (Geelen, Reinders, & Keyson, 2013; Verbong et al., 2013), psychological strategies for consumer engagement are increasingly used (Mengolini, Gangale, & Vasiljevska, 2016). A better understanding of how these strategies affect consumer behaviour can help to design better policies for SES.

1.4 The role of simulation models in energy policy design

I incorporate the discussed theories from innovation sciences and environmental psychology in simulation models of the energy system. Simulation models are simplifications of real-world phenomena that can be described based on mathematical equations. Empirical data can be used for calibration and validation of simulation models. Energy policy makers and practitioners rely on simulation models as an important tool to inform intelligent policy design and investment decisions. The energy system is one of the biggest infrastructures in

the world, and structural changes require high investments and can take decades to realize (Sovacool, 2016). Furthermore, the complex relations between different components of socio-technical systems such as the energy system lead to many uncertainties regarding system development (Verbong & Geels, 2010). However, there is great urgency to implement policies stimulating the transition to a sustainable global energy system to limit climate change. Experimentation and pilot projects can help in determining the functioning of new technologies and policies, but the results of these projects can be hard to generalize. On the other hand, large-scale experimentation with innovative technologies is expensive and impractical to realize. Simulation models can be used for *ex ante* policy evaluation through explorations of systems and scenarios, thereby supporting the identification of robust policies for the energy transition (Holtz et al., 2015; Pfenninger, Hawkes, & Keirstead, 2014; Rai & Henry, 2016). In this thesis, I use various simulation models to study the *potential* functioning of a set of smart energy technologies in a social context, and explore which *key uncertainties* influence this functioning.

An important application of energy models, including those in this thesis, is to determine the *potential* of a certain technology or set of technologies to contribute to a certain goal, e.g. generate energy, reduce greenhouse gas emissions, or load balancing. There are different types of potentials for energy technologies. Blok (2007) distinguishes the following: the *theoretical potential*, the *technical potential*, the *economic potential*, the *profitable potential*, the *market potential*, and the *enhanced market potential*. The *theoretical potential* describes what can be achieved according to thermodynamic theory, e.g. how much of the energy available in solar irradiation can in principle be harvested (the Carnot limit). The *technical potential* takes the limitations of a certain technology into account, e.g. how much solar energy can be converted into usable energy by PV solar panels given current efficiencies. The *economic potential* looks at the economic attractiveness of technologies from a societal perspective, e.g. how much solar energy can be harvested by PV solar panels that show a positive net present value taking into account the interests of all societal stakeholders. The *profitable potential* looks at the attractiveness of technologies for private investors from a financial perspective, e.g. how much solar energy can be harvested by PV solar panels that have a positive net present value for households given current subsidy schemes. The *market potential* looks at how likely it is that technologies are adopted by society taking into account all barriers and stimuli, e.g. how much energy can be harvested by PV solar panels adopted by people that are likely to invest in PV solar panels. Finally, the *enhanced market potential* takes the market potential into account together with policies directed to stimulate technology adoption, e.g. how much energy can be harvested by PV solar panels when a policy is implemented making it easier for renters to invest in PV solar panels. The models in this thesis incorporate technical specifications and theories of adoption and behaviour, but do not take economic considerations into account. The focus is thus on the technical potential, market potential, and enhanced market potential.

A second application of models is to explore *key uncertainties* in systems. As stated earlier, socio-technical systems have a mix of linear and non-linear relations between different components of the system, leading to high uncertainty in how systems develop. Furthermore, models of future energy systems have to rely on historical data for parameterization, which can lead to overestimation and underestimation of key factors in a model. Methods such as factorial exploration and sensitivity analysis can be used to investigate system boundaries and explore which uncertainties have a high impact on outcomes at a system level (Kwakkel & Pruyt, 2013). Such analyses can point to new directions for research in order to reduce critical uncertainties.

Simulation models can be classified as top-down and bottom-up. Top-down models rely on descriptions and data of system behaviours at an aggregate level, such as equilibrium equations, system dynamics, and macro-economic data. Bottom-up models describe the behaviour of its components and can be used to study the behaviour *emerging* from its components and their interaction. Models can also be a hybrid of top-down and bottom-up. The best modelling approach is usually determined by the type of problem the model is intended to study. Currently, many energy models rely on top-down equilibrium models (Hoekstra, Steinbuch, & Verbong, 2017). However, such models are unsuitable for incorporating non-linear relations and can therefore underestimate exponential growth of new technologies resulting from positive feedback loops. Top-down models based on system dynamics can incorporate non-linear relations, and can be a suitable tool for modelling energy systems if relations between aggregate components are known (Hoekstra et al., 2017). The strength of bottom-up models is that they offer a high level of flexibility and are therefore well-suited to handle locality, high time resolutions, and heterogeneity of system components, all of which are highly relevant for studying SES development. Therefore, I apply bottom-up and hybrid models in this thesis.

1.5 Research objective

This thesis explores the benefits and limits of using EVs as a source of flexible demand and/or storage in smart energy systems with a high level of intermittent renewable energy sources. The central research question is as follows:

What is the potential contribution of EVs to the integration of intermittent renewable energy sources taking into account constraints posed by technology and consumer behaviour?

I focus on the technical potential, market potential, and enhanced market potential of EVs to contribute to load balancing. Furthermore, I explore the impact of uncertainties for specific factors on this potential. I investigate the influence of smart charging and V2G algorithms,

renewable energy capacity, technology diffusion patterns, policy interventions, charging infrastructure, EV use and charging behaviour. These factors are explored in separate chapters, and I use different simulation and data analysis techniques depending on which is best suited for the specific sub-problem of that chapter. Theories and concepts from energy science, innovation studies, and environmental psychology inform the simulation models. Furthermore, I analyse rich micro-level datasets of PV solar panel diffusion, EV diffusion, and EV charging behaviour.

Each chapter considers the combination of PV solar panels and electric passenger vehicles (Chapter 4 also includes wind energy). PV solar panels and EVs are technologies of high interest to investigate the role of consumers in smart grids for several reasons: (1) The specific combination of PV solar panels and EVs can enhance the sustainability of both technologies, as EVs can be used to store excess PV power and charging EVs with PV solar power enables their potential as a highly clean mode of transportation. (2) Both technologies can be adopted and used by a large share of households, as opposed to for instance wind turbines. (3) Both technologies are envisioned to play key roles in future energy systems, but have different functions in that system: PV solar panels can supply electricity, while EVs can use and store electricity. (4) Adoption levels for both technologies are relatively high as compared to for instance home batteries and hydrogen vehicles, meaning that large datasets of actual diffusion and usage can inform this study.

This research focusses on the Netherlands, and uses mainly Dutch data sources. The installed PV capacity in the Netherlands is 4.2 GW and covered 3.3% of total electricity production in 2019 (Dutch New Energy, 2019), making the Netherlands the 14th ranking country with highest PV capacity per capita in the world (IRENA, 2019). The installed PV capacity is growing rapidly, with 46% in 2018 compared to 25% worldwide (Dutch New Energy, 2019)), and the Dutch government has set a target of having 35 TWh of installed renewables on land, which includes PV solar panels, in 2030 (Rijksoverheid, 2011). The Netherlands is a front-runner country in EV deployment. EVs make up about 1% of the Dutch vehicle fleet, making the Netherlands the country with the second highest EV ownership per capita in the world after Norway (ACEA, 2018b). Furthermore, growth rates are high: the total number of EVs doubled in 2018. We can expect the growth to continue as the Dutch government has the ambition that by 2030 all new vehicles sold in the Netherlands are zero-emission vehicles (Rijksoverheid, 2019b). Several on-going Dutch projects are experimenting with and developing smart charging of EVs and V2G.[2] One of these projects takes place in the area of Lombok in Utrecht, the Netherlands, where the first European bi-directional charge points were installed by the company LomboXnet. LomboXnet is a case study in Chapter 2.

[2] For an overview of projects, see https://www.livinglabsmartcharging.nl/en/

1.6 Thesis outline

This thesis presents four research chapters and a conclusion, as outlined below. Three of the research chapters are based on works which have been published in a variety of journals, the fourth chapter has been submitted, see Table 1.1. Various co-authors have contributed to these chapters, for which I am grateful. Table 1.2 presents an overview for each of the research chapters.

Chapter 2 focusses on the effect of different smart charging and V2G algorithms on the increase in PV self-consumption (the amount of locally PV generated energy that can be used to directly meet local energy demand), PV generated electricity that gets send to the grid, and peak reduction for the case study of LomboXnet. LomboXnet manages a microgrid, consisting of PV installation, an office, internet servers, three households, and two EVs. We simulate one real-time smart charging algorithm, one real-time V2G charging algorithm, and an optimisation V2G algorithm which determines EV charging profiles based on predictions for PV solar power supply. For the latter, we also evaluate the effect of uncertainties in PV solar power prediction. We compare the results to a baseline scenario in which the EVs always charge at maximum charging capacity. Additionally, we investigate what effect these algorithms could have on EV battery degradation. Furthermore, we perform a sensitivity analysis investigating the effect of upscaling of the microgrid, and variations in EV use and EV models.

Chapter 3 focusses on the effect of diffusion of PV solar panels and EV on annual PV yield, annual energy demand, and regional PV self-consumption. Based on micro-level diffusion data, we characterize and contrast the adopter groups of PV solar panels and EVs by linking adoption levels to neighbourhood characteristics. Furthermore, we apply the Bass model of diffusion (Bass, 1969) to project future diffusion of these technologies for NUTS-3 regions (Eurostat, 2018), and show what the impact could be on regional energy systems. We investigate the effect on total PV self-consumption of variations in total market potential of both technologies, the average PV system size, and the average EV battery capacity available for V2G services

Chapter 4 focusses on the effect of policy interventions, renewable energy capacity, and charging infrastructure on energy self-sufficiency, self-consumption, peaks in energy demand and supply, and EV user comfort. We present an agent-based model of a fictional area in which agents drive EVs to go to work, shopping, and their house. When the EVs are parked at a charge point, agents can decide to charge at the maximum charging rate, or only when excess renewable energy from PV solar panels and wind energy is available. Agents decide how they charge based on policy interventions, their environmental self-identity, and their range anxiety. The policy interventions we model are (1) *no intervention*, (2) *dual tariff scheme*, (3) *automated smart charging*, and (4) *information and feedback*. Furthermore, we perform a sensitivity analysis exploring the key uncertainties in our model parameters.

Chapter 5 focusses on how EV charging behaviour can inform policy related to public charging infrastructure roll-out. This chapter takes a wider perspective to evaluate policy measures stimulating smart charging and V2G next to policy measures that aim to support large EV fleets by increasing the availability of charge points. We identify five policy measures related to charging infrastructure, and formulate what sort of charging behaviours are optimal to implement these. The policy measures are related to enabling increased EV adoption, cost-effectiveness of charging infrastructure, and sustainability of e-mobility. The policy measures are: (1) *increase the number of charge points*, (2) *reduce hogging*, (3) *overnight charging*, (4) *solar charging*, and (5) *vehicle-to-grid*. We analyse a large dataset of charging sessions and link these to the policy measures through a multi-criteria analysis. We compare charging behaviour between neighbourhoods, link specific behaviours to neighbourhood characteristics, and identify coherent policy mixes for public charging infrastructure roll-out.

Chapter 6 summarizes the findings and provides two main conclusions. Furthermore, I formulate recommendations for policy makers and identify directions for further research.

Table 1.1 Publication status of the research chapters

Chapter	**2**	**3**	**4**	**5**
Article title	Smart charging of electric vehicles with photovoltaic power and vehicle-to-grid technology in a microgrid; a case study	Diffusion of solar photovoltaic systems and electric vehicles among Dutch consumers: Implications for the energy transition	Agent-based modelling of charging behaviour of electric vehicle drivers	Multiple roads ahead: How charging behaviour can guide policy for charging infrastructure roll-out
Co-authors	Wilfried van Sark	Toon Meelen Wilfried van Sark Floor Alkemade	Annemijn Peters Wilfried van Sark Floor Alkemade	Wilfried van Sark Floor Alkemade
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Table 1.2 Overview of the research chapters

Chapter title	**2. Smart charging and vehicle-to-grid algorithms in a microgrid**	**3. Diffusion of photovoltaic systems and electric vehicles**	**4. An agent-based model of sustainable charging**	**5. Charging behaviour and charging infrastructure roll-out**
Technologies	● EVs (Smart charging & V2G) ● PV solar panels	● EVs (V2G) ● PV solar panels	● EVs (smart charging) ● PV solar panels ● Wind energy	● EVs (smart charging & V2G)
Comparison of:	● Smart charging algorithms ● Microgrid composition ● EV use	● Adopters EV & PV (at neighbourhood level) ● NUTS-3 regions	● Policy interventions ● Charging infrastructure ● PV solar power capacity ● Wind energy capacity	● Policy measures ● Neighbourhoods
Indicators for comparison	● Self- consumption ● Peaks in demand and supply ● Battery degradation	● Adoption of EVs and PV solar panels ● PV yield ● Energy demand ● Self-consumption	● Self-sufficiency ● Self-consumption ● Peaks in demand and supply ● Comfort of EV users	● Charging behaviour
Area	● Lombok, Utrecht	● Netherlands	● Fictional (Dutch data sources)	● Netherlands
Theory	-	● Diffusion of innovations	● Environmental self-identity ● Range anxiety	-
Methods	● Simulation of real-time and optimisation algorithms	● Regression analysis ● Bass model of technology diffusion	● Agent-based model	● Regression analysis ● Multi-criteria analysis
Data sources	● LomboXnet ● United States Environmental Protection Agency ● Tesla ● Nissan	● Liander ● Stedin ● Enduris ● Enexis ● Netherlands Vehicle Authority ● Royal Netherlands Meteorological Institute ● Statistics Netherlands ● The Netherlands' Cadastre, Land Registry and Mapping Agency ● Politieke Academie ● GroenLinks	● Liander ● Onderzoek Verplaatsingen in Nederland ● Royal Netherlands Meteorological Institute ● Elia ● United States Department of Energy	● New Motion ● EVBox ● Statistics Netherlands ● The Netherlands' Cadastre, Land Registry and Mapping Agency

Chapter 2

Smart charging and vehicle-to-grid algorithms in a microgrid

Abstract

We present a model developed to study the increase of self-consumption of photovoltaic (PV) power by smart charging of electric vehicles (EVs) and vehicle-to-grid (V2G) technology. Whereas previous studies mostly use large EV fleets in their models, our focus is on a smaller scale. We apply the model to a microgrid in Lombok, a residential neighbourhood in the city of Utrecht, the Netherlands. The microgrid consists of a 31 kWp PV installation, an office, internet servers, three households, and two EVs. Three control algorithms are presented which manage the charging profile of multiple EVs either in real-time or using linear optimisation with predictions for PV power and electricity demand. We perform one-year simulations using data for PV power, EV use, and electricity demand. Simulation results are evaluated on PV self-consumption and peak demand reduction. In addition, we make qualitative statements on battery degradation resulting from the charging strategies based on several indicators. We also simulate changes in microgrid composition, for example by including more EVs. In the simulations, self-consumption increases from 49% to 62–87% and demand peaks decrease by 27–67%. These results clearly demonstrate the benefits of smart charging EVs with PV power. Furthermore, our results give insight into the effect of different charging strategies and microgrid compositions.

2.1 Introduction

The transition to low carbon energy and transport systems requires not only the large-scale adoption of clean technologies and efficiency measures, but also new energy management strategies to efficiently incorporate these innovations in the existing infrastructure. Issues related to the grid integration of clean technologies can occur both at the energy supply side, with technologies such as photovoltaics (PV), and on the demand side, with technologies such as electric vehicles (EV). Sophisticated energy management can help solving these issues and optimise allocation of resources, for instance by charging EVs with PV power instead of electricity from coal or gas-fired power plants.

In the residential sector, there is an imbalance between PV power supply and electricity demand. PV installations produce most electricity during the day (Elsinga & Van Sark, 2014; Reich et al., 2012), while electricity demand of households peaks in the morning and evening. Furthermore, typical EV charging patterns contribute to existing peaks in household electricity demand (E-Laad, 2013). A higher penetration level of PV and EVs will increase power transport over the electricity grid, requiring grid investments to prevent overloads (Castillo-Cagigal et al., 2011b; Eising et al., 2014). Several countries in Europe have started implementing policies to stimulate the self-consumption of locally generated energy (EPIA, 2013). Self-consumption of PV power should increase to ensure grid stability and functioning. In a smart grid the traditional electricity grid or microgrid (i.e. a local, low-voltage distribution system) is combined with information and communication technologies (Verbong et al., 2013). Load shifting is an essential aspect of smart grids and can be used to increase self-consumption of PV power (Matallanas et al., 2012) and off-peak charging of EVs (Foley, Tyther, Calnan, & Ó Gallachóir, 2013). An important advantage of EVs in smart grids is that they can be used both as a flexible demand source and as a storage option, using vehicle-to-grid (V2G) technology (Andersson et al., 2010; Hein, Kleindorfer, & Spinler, 2012; Kempton & Tomić, 2005b; Lund & Kempton, 2008; Sousa, Morais, Soares, & Vale, 2012).

In this chapter, we use a case study to model and simulate the application of smart charging algorithms for EVs. Simulation studies on using EVs for integration of PV in the grid mostly use a high level of aggregation of EVs in their models. For example, two consider the case of using parking lots to integrate EV and PV. Tulpule, Marano, Yurkovich, & Rizzoni (2013) perform a study for a parking lot at a workplace in Columbus, OH, USA and Los Angeles, CA, USA and show the feasibility of such a system as compared to home charging both in terms of costs and CO_2 emissions. Birnie (2009) considers a parking lot in New Jersey, NJ, USA and used a simple approach to determine that most driving needs could be met by solar power in the summer, but not in the winter. Other studies consider EV fleets at a city or region level. For instance, Zhang et al. (2018) show that by using smart charging one million EVs combined with one million heat pumps can reduce excess PV power by 3 TWh for the Kansai Area, Japan. Drude, Pereira Junior, & Rüther (2014) study PV and V2G strategies in urban

regions in Brazil. They conclude the EVs can be used for grid-stabilisation, but that adequate energy policies are needed to avoid destabilisation due to too many cars offering storage for V2G. Tuffner, Chassin, Kintner-Meyer, & Gowri (2012) simulate a distribution system (IEEE 123-node) for Phoenix, AZ, USA weather conditions. They conclude that penetration rates of EV and PV have to be high (>50%) to have a significant impact on the network but that the synergy of these technologies has significant benefits for these high penetration rates.

According to Guille & Gross (2009), EV batteries are too small to make a significant impact on the grid by themselves. However, large-scale deployment of V2G faces many socio-technical barriers (Sovacool & Hirsh, 2009). Our study aims to show the benefits of using EVs and smart grid technology in a microgrid, since such a small-scale project can be realised in the near future. These innovative pilot projects are pivotal in realising the transformation of socio-technical systems such as the energy system as they allow the small-scale experimentation with alternatives to the current system (Kemp, Schot, & Hoogma, 1998; Raven, 2007; Schot & Geels, 2008). Furthermore, studying this project allows us to combine specific real-world empirical data on PV power supply, load demand and EV use. This study thus contributes to the existing literature by exploring alternatives to large-scale deployment of using EVs for integration of PV in the electricity grid.

Our case study is LomboXnet[3], a company providing internet connection to about 2500 people in Lombok, a neighbourhood in Utrecht, the Netherlands. LomboXnet has the ambition to run its activities on locally produced solar power and provides PV power to three houses in the neighbourhood. The company has two battery EVs, which are used for car sharing. Car sharing is becoming increasingly popular worldwide (Shaheen & Cohen, 2013) and also in the Netherlands (Meelen, Frenken, & Hobrink, 2019), and it has a great potential to reduce the environmental impact of personal transportation (Martin & Shaheen, 2011; Mont, Neuvonen, & Lähteenoja, 2014). When used for car sharing, the EVs are regularly stationed at the charge point, making them suitable for grid balancing. This in contrast to other types of EV use such as commuting. The combination of PV, EV, smart grid and car sharing makes LomboXnet an excellent case for studying the integration of clean technologies.

Our research objective is to determine the potential for increasing the self-consumption of PV power with smart charging of EVs for LomboXnet. We simulate three different charging algorithms. The first algorithm uses real-time information, the second uses real-time information and V2G, and the third is an optimisation algorithm using predictions for PV power supply and load demand and V2G.

The remainder of this chapter is organised as follows. In Section 2.2, we introduce our model. Section 2.3 presents our control algorithms and Section 2.4 the indicators used. Section 2.5 contains simulation results. In Section 2.6, we discuss our method and results and in Section 2.7 we draw our final conclusions.

[3] Company website available at http://www.lombox.nl. In Dutch.

2.2 Model description

In this section, we present the structure and components of our model. Figure 2.1 presents an overview of the microgrid of LomboXnet. The five main components of the microgrid are the PV installations, the energy management system, the uncontrollable load, the controllable load, and the connection to the main grid. The uncontrollable load consists of the office building, the internet servers and three households, each with a distinctive type of load curve. The demand from the office building peaks during the day, the internet servers have a constant demand and household demand peaks during the morning and evening. The PV power is used to cover both the uncontrollable and the controllable load. In case of PV power shortage, electricity is drawn from the main grid. In case of excess PV power, electricity is fed back into the main grid.

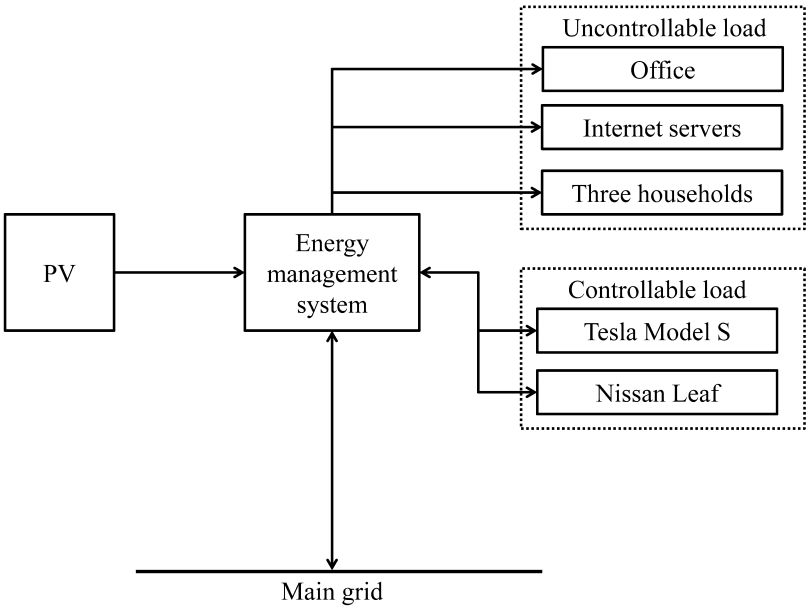


Figure 2.1 Microgrid at LomboXnet, arrows indicate power flows.

2.2.1 PV

The PV installations provide electricity to the microgrid. In total, 31 kWp is installed with a solar energy yield of about 25 MWh per year and a performance ratio (PR) of 74% as measured for the year 2013. The PR is a measure for the overall losses of a PV system and is defined as the ratio of final energy yield of the PV system in kWh/kWp to a reference yield, which takes only solar irradiation into account (Reich et al., 2012). In the Netherlands, the

average PR is 78% (Moraitis & van Sark, 2014). The below average performance of the LomboXnet PV system is explained by the partial shading of several solar panels during the day. The PV power output is directly measured at the solar inverter and available with a resolution of an hour.

2.2.2 Uncontrollable load

The uncontrollable load is the part of the total load that cannot be controlled by the energy management system and must be met at all times. It consists of the electricity demand for the office, the LomboXnet servers and the three connected households. Electricity is provided from the PV installations (first priority), the EV batteries (second priority, when V2G is available) and the main grid.

The load demand of the office and internet servers is measured at LomboXnet with an hourly resolution. The yearly demand in 2012 was 27 MWh. The majority of this demand (19 MWh) is from the internet servers, which constantly use around 2.2 kW. Because there are no measurements available for the households, we use an estimate for the demand. The demand profiles are estimated using a dataset containing 400 unique household profiles as provided by Claessen et al. (2014). The dataset is based on measurements from Liander, the largest utility company in the Netherlands. We select households with a yearly average electricity demand within 30% of 3680 kWh, representative for the houses in the microgrid, resulting in a total of 153 households. This average is higher than the Dutch yearly average of 3480 kWh (Dril, Gerdes, Marbus, & Boelhouwer, 2013). Figure 2.2 presents an Example 24-h load profile. In the figure the peaks at different times caused by the different loads are clearly visible.

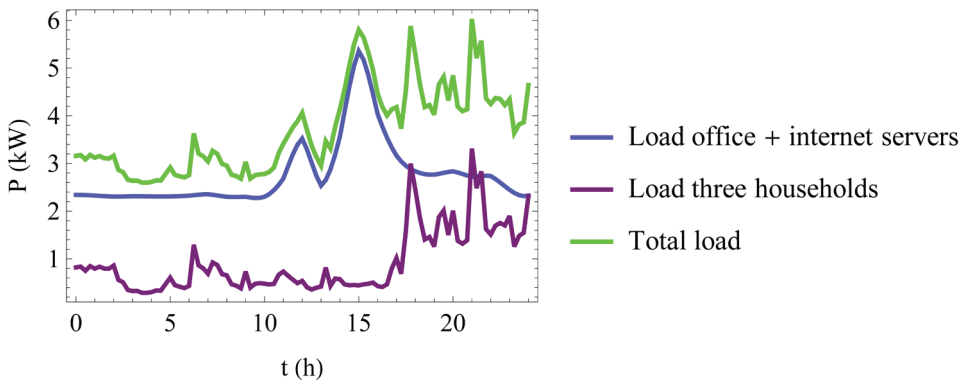


Figure 2.2 Load profile example.

2.2.3 Electric vehicles

Two battery EVs are currently available: a Tesla Model S and a Nissan Leaf. The technical specifications are presented in Table 2.1. Furthermore, a minimum energy level of 20% of the battery capacity is assumed, as well as a power conversion efficiency of 90%.

Table 2.1 Technical specifications of EVs. Data source: U.S. Environmental Protection Agency (2014)

	Tesla Model S	**Nissan Leaf**
Battery capacity (kWh)	85	24
Energy consumption (kWh/km)	0.233	0.211
Range (km)	340	150
Charging power (kW)	22	6.6

The EVs are used for car sharing. Experience at LomboXnet has shown that each car is used for three trips per week on average. These trips have a duration of 3–6 h, a minimum distance of 20 km, and a maximum distance of the full EV range. These numbers are used to simulate driving patterns via a pseudorandom number generator that decides (a) if a trip is made that day, with a 3/7 chance of a trip taking place, (b) trip duration, between the minimum and maximum value, and (c) trip distance, between the minimum and maximum value. For our purposes, a trip means that the EVs are not available at the charge points and that a certain amount of energy is consumed for driving. The electric vehicles need around 10 MWh per year in total to make the trips.

2.2.4 Changes in microgrid composition

LomboXnet considers several extensions of the microgrid, which we also simulate. Possible extensions in the foreseeable future include extra solar panels (3 kWp), two extra households, and three extra EVs. The extra EVs are all Nissan Leafs and include one EV used similar to the other Nissan Leaf and two private EVs, used for commuting. The latter EVs make a trip every workday between 8:00 and 19:00 with a duration of 6–10 h and a distance of 60–90 km. Furthermore, we run simulations for certain changes in microgrid composition. We vary EV model, average electricity demand of the households, and the number of trips the EVs make per week.

2.3 Control algorithms

In this section, we present our three simulated control algorithms. Two are based on real-time (RT), with and without the V2G option, and one is based on linear programming (LP). All algorithms are based on a centralised approach: the energy management system decides the

EV charging patterns, not the individual EVs. We use these three charging schemes to evaluate system performance with RT versus planning strategies and to see the effect of using V2G. The algorithms decide the charging patterns of the EVs, using them as a flexible demand source and in the case of V2G as an electricity storage device. The goal of using such a system for LomboXnet is to increase the consumption of PV power within the microgrid. Our algorithms do not incorporate other factors that might be of interest in addition to PV self-consumption, such as electricity price and power quality. However, the algorithms are easy to program and suitable for our purpose: demonstrating the potential role of EVs in this microgrid.

With our first RT algorithm, RT Control, the EVs only use PV power to charge the batteries, unless there is more demand than PV power to make a trip. In this algorithm V2G is not available. There are technological as well as social barriers to V2G technology (Sovacool & Hirsh, 2009), so it is interesting to explore strategies without V2G. Our second RT algorithm, RT Control + V2G, has the V2G option is available. The EV charges with PV power as much as possible and discharges energy when not enough PV power is available for the uncontrollable load.

While RT Control + V2G is expected to increase the PV self-consumption, it is not necessarily the optimal strategy for EV charging. The algorithm only uses real-time information and is therefore not able to optimise the charging pattern for a longer time period. This is why we also introduce an optimisation algorithm. Constrained optimisation is a technique used often in research on applications of smart grids, examples include Amirioun & Kazemi (2014), González Vayá & Andersson (2012), Guo, Pan, & Fang (2012), and Tanaka et al. (2012). We use linear programming, because increasing PV self-consumption can be formulated as a linear optimisation problem. Furthermore, we have previously shown that LP can reduce peaks significantly more than RT algorithms (Van der Kam & Van Sark, 2014). For LP, PV power supply and load demand must be known in advance, so predictions are necessary. Therefore, we evaluate our algorithm in two ways, with and without taking uncertainties in predictions into account.

2.3.1. No Control (reference charging scheme)

Without a smart grid program, the EVs, if connected, will always charge at maximum capacity until they are full. This reference charging scheme is called No Control and is represented by Equation (2.1).

$$P_i(t) = \begin{cases} P_i^{max} & \textbf{if } E_i(t-1) < C_i \text{ and } t \in t_i^{cp} \\ 0 & \textbf{else} \end{cases} \tag{2.1}$$

With t the time step index, i the EV index, P_i the EV charging power; P_i^{max} the maximum charging power, E_i the energy contained in the battery; C_i the battery capacity, and t_i^{cp} the time steps for which the EV is at the charge point.

In this reference charging scheme, the charging the charging patterns of the EVs cannot be controlled. We model the EV charging patterns as controllable and compare these results to the reference simulations.

2.3.2 Real-time control algorithms

In Figure 2.3, we show the flow of information for the RT algorithms EV charging patterns are decided based on PV power, uncontrollable load, planned EV trips and the state of charge (SOC) of the EV batteries. The SOC is determined based on how much energy the EV charges, discharges, and uses for a trip.

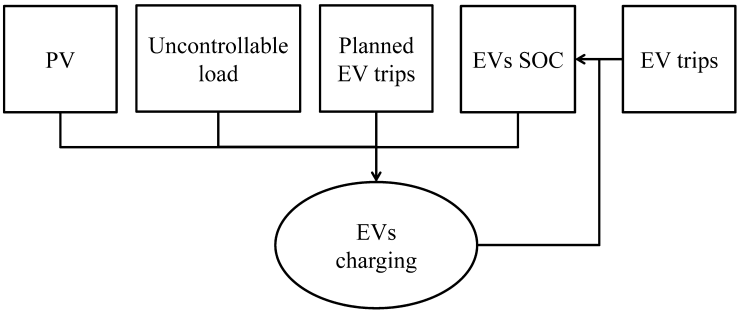


Figure 2.3 Flow of information for RT Control algorithms.

The RT algorithms use the difference between PV power supply and load demand for every time step t. Taking into account the energy content of the EV the charging pattern is then decided. If there is more PV power than electricity demand, the EV starts charging using the excess PV power until the battery is full or until there is no more excess PV power. The EV extracts energy from the grid only when there is a shortage of PV power to make a trip. If there is insufficient PV power to cover load demand, energy can be extracted from the EV. Thus, the algorithms distinguish three power flows as represented in Equation (2.2)

$$P_i(t) = P_i^{PV}(t) + P_i^{grid}(t) - P_i^{out}(t) \tag{2.2}$$

With P_i^{PV} the charging power from PV, P_i^{grid} the power drawn from the grid, P_i^{out} the discharged power. These three components cannot exceed the maximum charging power, see Equation (2.3).

$$|P_i(t)| \leq P_i^{max} \tag{2.3}$$

With P_i^{max} the maximum charging power. Note that it is assumed that the maximum discharging power equals the maximum charging power.

Taking into account the energy needed for trips and maximum charging power, the required amount of energy in an EV for each time step, $E_i^{req}(t)$ is defined in Equation (2.4).

$$E_i^{req}(t) = \begin{cases} E_i^{trip} - P_i^{max} \cdot \left(t_i^{cp} - t\right) + E_i^{min} & \textbf{if } t \in \left(t_i^{cp} - \frac{E_i^{trip}}{P_i^{max}}, t_i^{trip}\right) \\ E_i^{min} & \textbf{else} \end{cases} \tag{2.4}$$

With t_i^{trip} the time of the next trip, E_i^{trip} the energy required for the next trip and E_i^{min} the minimum energy in the battery. The 'if' part of Eq. (2.4) describes that when a trip is planned, the energy level at the start time of the trips must be the energy needed for the trip plus the minimum energy level. The energy level of the time steps before the start time of the trip also have to be at a certain level, taking into account the energy required for the trip, the maximum charging power, and the time left to complete charging. At all other time steps the required energy in the EV is the minimum energy level of the EV, as the described by the 'else' part of Equation (2.4).

When using multiple EVs, a priority function f_i is needed. First, an urgency value U_i is assigned to each vehicle. U_i is based on how much time it takes to charge the vehicle to a sufficient energy level for the next trip and the time left to achieve this, see Equation (2.5). f_i is then calculated as U_i proportional to the sum of U_i for all vehicles, see Equation (2.6).

$$U_i(t) = \left(\frac{t_i^{trip} - t}{t_i^{trip} - t - \left(E_i^{trip} - E_i(t-1)\right)/P_i^{max}}\right)^u \tag{2.5}$$

$$f_i(t) = \frac{U_i(t)}{\sum_i U_i(t)} \tag{2.6}$$

Equation (2.5) contains a power factor u; in the simulations $u = 2$ was used so that the effect is increased for EVs that have a high urgency for charging compared to $u = 1$. However, it was found that the value for u has little effect on the outcome when evaluating system performance for $u = 1, 2$ or 3, so final results should apply for all these values for u.

2.3.2.1 RT Control

With RT Control we model the real-time smart charging of the EVs. The EVs start charging when excess PV power is available, unless there is insufficient PV power to charge enough for a trip. The loading patterns are defined by Equations (2.7) and (2.8).

$$P_i^{PV}(t) = \begin{cases} \eta_i f_i(t)\big(P_{PV}(t) - P_{load}(t)\big) & \textbf{if} \quad P_{load}(t) < P_{PV}(t) \;\; \textbf{and} \;\; E_i(t-1) < C_i \;\; \textbf{and} \;\; t \in t_i^{cp} \\ 0 & \textbf{else} \end{cases} \tag{2.7}$$

$$P_i^{grid}(t) = \begin{cases} E_i^{req}(t) - E_i(t-1) - P_i^{PV}(t) & \textbf{if} \quad E_i(t-1) + P_i^{PV}(t) < E_i^{req} \;\; \textbf{and} \;\; t \in t_i^{cp} \\ 0 & \textbf{else} \end{cases} \tag{2.8}$$

With P_{PV} the PV power, P_{load} load demand and η_i the charging efficiency. If there is more PV power than electricity demand, the EV starts to charge until it is full or until there is no more excess PV power, see Equation (2.7). Equation (2.8) defines that the EV only extracts energy from the grid when there is shortage of PV power to make a trip.

2.3.2.2 RT Control + V2G

With RT Control + V2G energy can be extracted from the EV to cover load demand. Equation (2.9) is added to the equations of RT Control.

$$P_{i>1}^{out}(t) = \begin{cases} \eta_i^{-1} \dfrac{1 - f_i(t)}{N-1}\big(P_{load}(t) - P_{PV}(t)\big) & \textbf{if} \quad P_{load}(t) < P_{PV}(t) \;\; \textbf{and} \;\; E_i(t-1) < C_i \;\; \textbf{and} \;\; t \in t_i^{cp} \\ 0 & \textbf{else} \end{cases} \tag{2.9}$$

With N the number of EVs. Note that in the case of only one EV no priority function is needed and the factor $\frac{1-f_i(t)}{N-1}$ is set to 1.

2.3.3 Linear programming

Increasing self-consumption of PV power by controlling the charging pattern of an EV can be described as a linear optimisation problem and solved by using linear programming. Our objective is to maximise the use of PV, both for charging the EV and using energy from the

EV to cover load demand, and to minimise energy drawn from the grid. This is done under constraints related to factors such as PV power, uncontrollable load and trips to be made. All constraints must be known in advance, therefore we have to use predictions for PV power and the uncontrollable load. We assume the linear program is run at midnight ($t = 0$ is midnight). Fig. 4 presents the information flows for the LP control algorithm. Note that in contrast to the RT algorithms there is no dynamic updating.

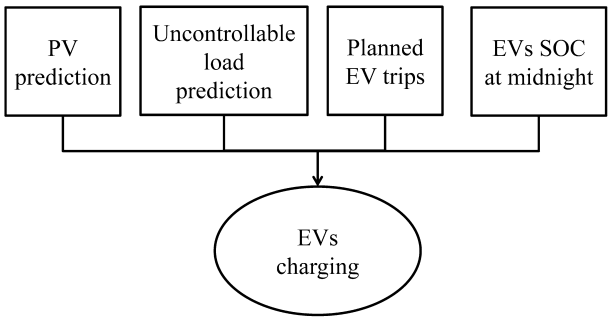


Figure 2.4 Flow of information for LP control algorithm.

For the formulation of the problem, we use P_i^{PV}; P_i^{grid} and P_i^{out} for all time steps t as variables. We formulate our objective function as follows:

$$\sum_i \sum_t k\left(P_i^{PV}(t) + P_i^{out}(t)\right) - P_i^{grid}(t) \tag{2.10}$$

With k a factor to determine the importance of using PV power over drawing energy from the grid. We have based our value of k on trial and error. k must not be too low (~ 1), because then little solar energy is used, and not too high ($\sim 10^3$), because then little energy is extracted from the EV battery. For our simulations, we have set $k = 100$. Our final results are not sensitive to the exact value of k in this order of magnitude. The objective function is maximised, subject to the following constraints:

$$|P_i(t)| \leq P_i^{max}(t) \tag{2.11}$$

$$\sum_{t'=1}^{t} \left(\eta_i \left(P_i^{PV}(t') + P_i^{grid}(t')\right) - \eta_i^{-1} P_i^{out}(t')\right) \leq C_i + E_i^{trip}(t) - E_i(0), \quad \forall t, i \tag{2.12}$$

$$\sum_{t'=1}^{t} \left(\eta_i \left(P_i^{PV}(t') + P_i^{grid}(t')\right) - \eta_i^{-1} P_i^{out}(t')\right) \geq E_i^{trip}(t) - E_i(0), \qquad \forall t, i \tag{2.13}$$

$$\sum_i P_i^{PV}(t) \leq \max[P_{PV}(t) - P_{load}(t)], \qquad \forall t \tag{2.14}$$

$$\sum_i P_i^{out}(t) \leq \max[P_{load}(t) - P_{PV}(t)], \qquad \forall t \tag{2.15}$$

With dummy variable t'. Note that in this case, P_i^{max} is represented as a function of t, contrary to earlier in this chapter. This is done to include that P_i^{max} is in fact zero when an EV is not at the charge point.

Constraint (2.11) ensures that the maximum charging power is not exceeded. Constraints (2.12) and (2.13) ensure that the energy in the EV does not exceed the battery capacity and is sufficient for trips. Constraints (2.14) and (2.15) ensure that not more solar energy is charged than the excess of PV power or discharged than the shortage of PV power. Furthermore, all variables are non-negative.

Executing the linear program requires all variables of the constraints to be known in advance. Therefore, we evaluate the algorithm in two ways: with perfect information, LP – Perfect Information, and with simulated uncertainties in predictions, LP – Uncertainties. Load demand predictions are based on the pattern from the previous day. An exception is made for weekends, since weekend load demand differs significantly from weekdays. However, the data we use includes only a week per household. Because of this limitation predictions for Saturdays will be based on data for Sundays and predictions for Mondays will be based on data for Tuesdays. This results in the following equations:

For Tuesdays, Wednesdays, Thursdays, Fridays and Sundays:

$$P_{load}^{prediction}(t) = P_{load}^{real}(t - 24\text{ h}) \tag{2.16}$$

For Mondays and Saturdays:

$$P_{load}^{prediction}(t) = P_{load}^{real}(t + 24\text{ h}) \tag{2.17}$$

The input for PV is based on PV power predictions. It is assumed that prediction deviates from the real value with standard deviation σ, as follows:

$$P_{PV}^{prediction}(t) = P_{PV}^{real}(t) \pm \sigma \tag{2.18}$$

While it is possible for P_{PV} to be zero, there is a maximum PV yield per time step. To take this into account for each month a profile of maximum PV power P_{PV}^{max} is created. This is done by fitting the function defined in Equation (2.19) to the maximum yield found in the datasets for each month.

$$P_{PV}^{max}(t) = a \cdot \exp(-b^2(t - t_{max})^2) \tag{2.19}$$

After fitting values for a (maximum yield), b (spread) and t_{max} (time step of maximum PV power), P_{PV}^{max} for each month is defined. $P_{PV}^{real}(t)$ can never exceed $P_{PV}^{max}(t)$, no matter how big σ is. In our simulations we assume σ to be 10%. We have tested the results for changes in σ and found that as long as σ is below a threshold value around 20%, changes in σ do not significantly affect results. For LP – Uncertainties the algorithm is executed with the predicted values, while it is evaluated with the real values.

We use linear programming because we want to model an optimisation method for increasing self-consumption. However, some practical issues for our simulations arise by including linear programming. First of all, we do not include the effect that EVs will charge significantly slower when the SOC of a battery approaches SOC = 1. This mechanism cannot be included in the way the linear programming algorithm is defined, because it would alter the constraints for each variation of the variables. For a fair comparison of control algorithms it was therefore chosen not to include this effect in any of the simulations. Furthermore, solving the linear program takes significantly more time than running simulations for the RT algorithms. For this research not enough time or computer power was available to run simulate more than 24 h for linear programming. This is an issue because for every simulation a random value for the SOC at $t = 0$ is set, significantly effecting results as opposed to simulating longer time periods. To provide an estimation of this effect we perform a sensitivity analysis for the value of SOC at $t = 0$.

2.4 Indicators

In this section, we present our indicators. Section 2.4.1 presents our system performance indicators. Furthermore, we use indicators for battery degradation, since the feasibility of a V2G system is dependent on the impact it has on EV battery lifetime. We discuss this in Section 2.4.2.

2.4.1 System performance

We evaluate system performance on self-consumption (SC), energy sent to the grid and relative peak reduction (RPR). Based on the simulations the potential for increasing self-consumption is calculated. Self-consumption is defined as the relative amount of PV power used by the households and the EVs, see Equation (2.20).

$$\mathrm{SC}(T)\frac{\sum_{t=T_0}^{T}\min[P_{PV}(t),P_{load}(t)+\sum_i P_i(t)]}{\sum_{t=T_0}^{T}P_{PV}(t)}\cdot 100\% \tag{2.20}$$

With T the period that is evaluated and T_0 the start time of period T.

As an absolute indicator we give the amount of energy sent to the grid, as defined in Equation (2.21):

$$E_{grid}^{in}(T)=\sum_{t=T_0}^{T}\max\left[P_{PV}(t)-P_{load}(t)-\sum_i P_i(t),0\right] \tag{2.21}$$

Finally, we use relative peak reduction for evaluation. RPR compares the deviation of the average of the load demand for the main grid P_{grid}^{tot}, defined in Equation (2.22), with a control algorithm, $P_{grid,control}^{tot}$, to the No Control reference scenario, $P_{grid,no\ control}^{tot}$, and is defined in Equation (2.23).

$$P_{grid}^{tot}(t)=P_{load}(t)-P_{PV}(t)-\sum_i P_i(t) \tag{2.22}$$

$$\mathrm{RPR}(T)=\left(1-\frac{\sum_{t=T_0}^{T}\left|P_{grid,control}^{tot}-\overline{P_{grid,control}^{tot}}\right|}{\sum_{t=T_0}^{T}\left|P_{grid,no\ control}^{tot}-\overline{P_{grid,no\ control}^{tot}}\right|}\right)\cdot 100\% \tag{2.23}$$

2.4.2 Battery degradation

Factors that impact battery lifetime are: number of cycles, operation temperature, rates of charge and discharge, depth of discharge (DOD), SOC and total energy withdrawn (Bishop et al., 2013). Battery lifetime is often expressed as cycle-lifetime. Manufacturers commonly provide information on cycle-lifetime as a function of DOD for a battery that is discharged from a SOC of 100%. This data is not suitable for our purposes since the charging pattern of the EVs in the simulations consists for a large part of multiple, smaller cycles which do not start at a SOC of 100%. Several models have been proposed to quantify the impact of V2G on battery lifetime (Bishop et al., 2013; Kempton & Tomić, 2005a; Peterson, Apt, & Whitacre, 2010). Furthermore, several EV battery degradation models are available that take smaller battery cycles into account (Hoke, Brissette, Maksimovic, Pratt, & Smith, 2011; Lam, Bauer, & Kelder, 2011; Lunz, Yan, Gerschler, & Sauer, 2012; Marano, Onori, Guezennec, Rizzoni, & Madella, 2009). However, applying these models to our simulations will require making many assumptions regarding factors such as operation temperature and voltage, since the only output of our model is the charging pattern of the EVs. It is outside the scope of this study to present a complete battery model. However, to give an indication of the impact of

the control algorithms on battery lifetime we use three indicators: energy throughput, rate of charge and discharge and SOC. We exclude the battery degradation due to the driving cycles of the EVs, since the output of our simulations only contain information on the charging patterns when the EVs are at the charge point.

We define energy throughput as the total amount of energy charged and discharged in MWh per year. To evaluate the economics of V2G, Kempton & Tomić (2005a) express battery lifetime in energy throughput as a function of cycle lifetime, battery capacity and DOD for which the cycle lifetime was determined. The authors thus assume a linear relation between energy throughput and battery degradation rate at constant DOD. In an experimental study, Peterson et al. (2010) found energy throughput is the strongest indicator for EV battery degradation, regardless of DOD, and found linear relation between energy throughput and battery degradation rate. In a simulation study, Bishop et al. (2013) found EV battery degradation to be most dependent on energy throughput and found a square root relation between energy throughput and battery degradation rate. The latter two studies thus agree that energy throughput is the most important factor in measuring battery degradation, but disagree on the particular relationship.

We present our results for SOC as yearly average. Cycling at high SOC values is found to have a negative effect on EV battery lifetime (Lam et al., 2011; Lunz et al., 2012). However, battery degradation can also result from overdischarge, so too low SOC values must also be avoided. In our simulations we use a minimum SOC of 20% to prevent overdischarge, similar as in Tulpule et al. (2013), though some other studies use a minimum SOC of 30% (Amirioun & Kazemi, 2014; Khayyam, Ranjbarzadeh, & Marano, 2012; Zhang, Tezuka, Ishihara, & Mclellan, 2012).

For rates of charge and discharge we present our results as yearly average and as a frequency distribution. We take the yearly average of the absolute value of the charging rates, assuming charging and discharging have the same effect on battery lifetime. Higher charging rates result in higher battery degradation (Bishop et al., 2013; Hoke et al., 2011; Lam et al., 2011; Peterson et al., 2010).

2.5 Results

This section presents our simulation results. For every case we have run a one-year simulation with 15-min time steps. In Section 2.5.1, we show examples of simulation to illustrate the difference between the algorithms. In Section 2.5.2, we show our main results, Section 2.5.3 presents our results for the battery degradation indicators, and we show our results of changes in microgrid composition in Section 2.5.4.

2.5.1 Example simulations

Figure 2.5 presents examples of 24-h simulations. This figure illustrates the differences in EV charging strategies and how they affect self-consumption. The difference should be minimised between the net load and the PV power. The examples show a day in July, which represents high PV yield and low household load, since the effects of the control systems are more clear here than in a winter situation. In the examples both EVs are away on a trip; in the complete year-long simulations this will occur only 18% of the time. The EV batteries are half full at the start in all examples, except in the case of No Control, for which the batteries have been fully charged the day before.

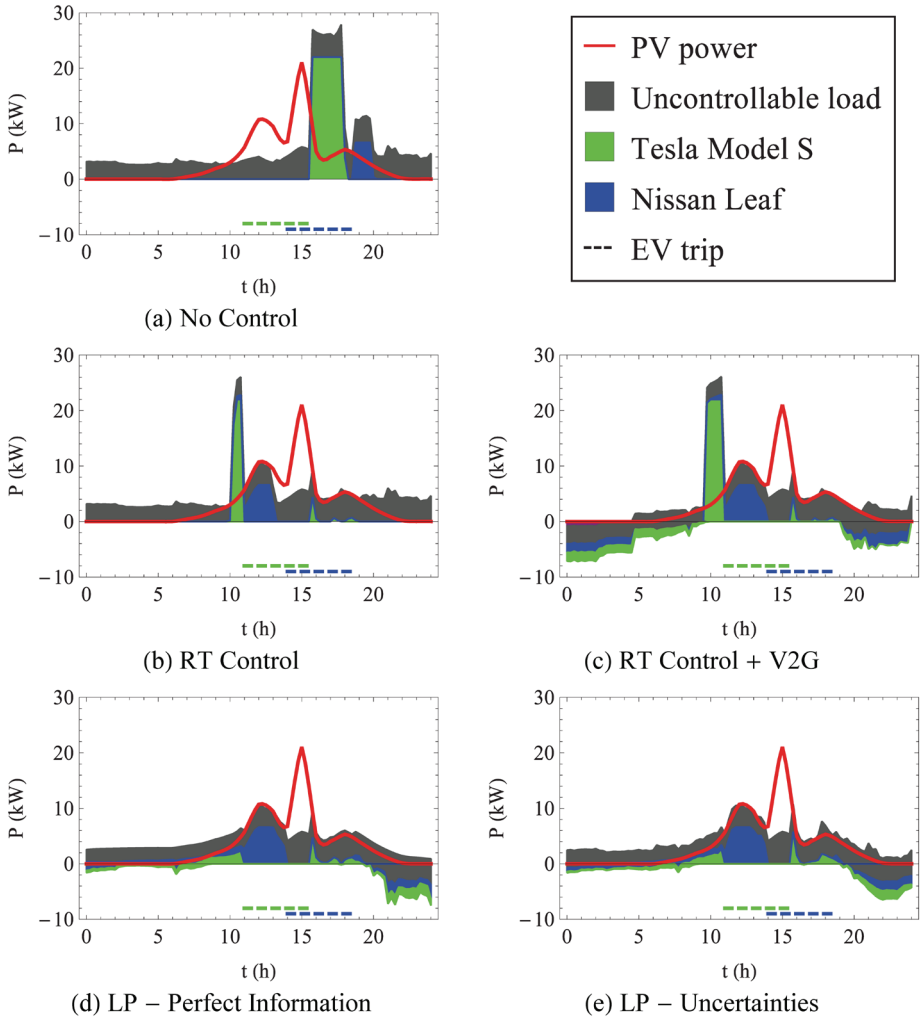


Figure 2.5 24-h simulation runs. The top of the coloured area represents the net load, dashed lines indicate when the EV is away on a trip.

In the case of No Control (Figure 2.5a), the EVs only charge after a trip: in the late afternoon (Tesla Model S) and evening (Nissan Leaf). In the case of RT Control (Figure 2.5b) the Tesla Model S starts charging at 10:00 because it needs the energy for a trip, while the Nissan Leaf starts charging at 11:00 because then there is excess PV. Both EVs also charge when returned from the trip, since there is a small amount of excess PV. In the case of RT Control + V2G (Figure 2.5c), both EVs start discharging in the night, because there is no PV to cover load demand. This results in a large peak in the morning for the Tesla Model S, since it does not have sufficient energy available for the trip during the day. The trip with the Nissan Leaf takes place later in the day, and because energy was discharged in the night more energy can be stored during the afternoon, resulting in a higher self-consumption of PV power than with RT Control. In the evening the energy available in the EVs is discharged to cover load demand. In the case of LP – Perfect Information (Figure 2.5d), both EVs charge much less energy in the morning than in the previous case, because the system takes into account the planned trips. The total amount of discharged power is just enough to have the storage amount available to cover maximum self-consumption in the morning. In the evening the energy available in the EVs is discharged to cover load demand. Note that the LP – Uncertainties (Figure 2.5e) does not deviate much from LP – Perfect Information, although the load curve is somewhat less flat due to deviations from the predictions.

2.5.2 Simulation results

Figure 2.6 presents the load duration curves resulting from the simulations. The load curves clearly illustrate the reduced energy demand, energy sent to the grid and peak demand due to the control algorithms both at the demand and supply side. Peak demand due to charging of EVs for No Control is easily recognizable and indicated in the figure. Linear programming is better at reducing peaks in energy demand than the other charging strategies. Furthermore, the difference between the curve of LP – Perfect Information and LP – Uncertainties is small and visible only at the negative side (excess PV) of the graph.

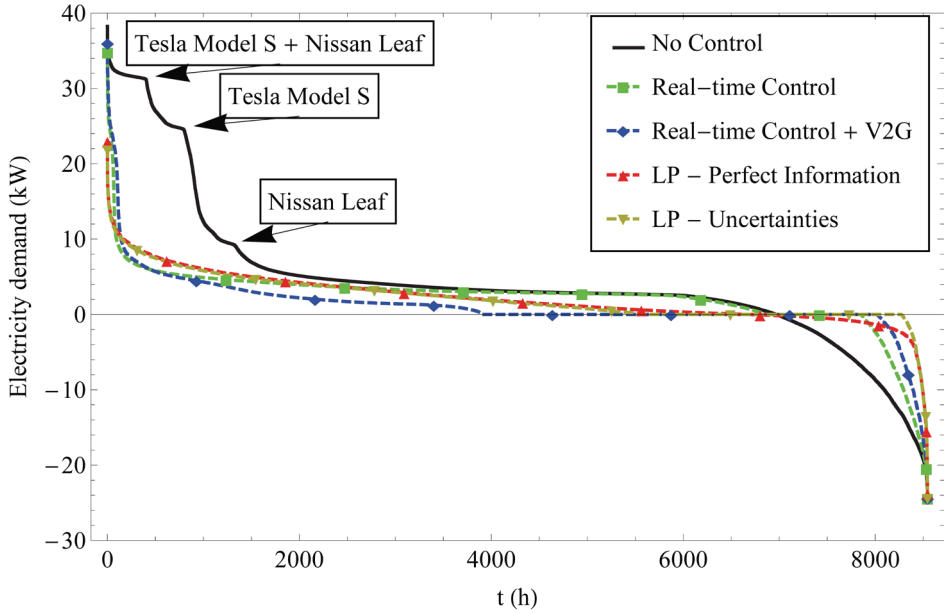


Figure 2.6 Load duration curves resulting from simulations

Table 2.2 presents the indicator scores for each algorithm. Based on our sensitivity analysis on the effect of using 24-h simulations instead of month simulations, we lowered all indicator scores of LP with 7%.

Table 2.2 Simulation results for system performance indicators

Algorithm	SC(%)	Energy to grid (MWh/yr)	RPR (%)
No Control	49	12.4	-
RT Control	62	9.1	27
RT Control + V2G	79	4.8	43
LP – Perfect Information	91	2.0	75
LP – Uncertainties	87	3.4	67

All proposed control systems contribute significantly to increasing self-consumption, reducing the energy sent to the grid and reducing peaks in electricity demand. The linear programming algorithms score highest on all indicators, also when uncertainties are taken into account. The advantage of V2G is also clear from the results, since scores on all indicators are higher for the algorithms that include V2G.

2.5.3 Battery degradation

Table 2.3 and Figure 2.7 show our results for battery degradation indicators. The yearly energy throughput is the same for No Control and RT Control, since in both cases energy is

only discharged during EV trips. For RT Control + V2G the energy throughput for the Tesla Model S is increased by factor 2.3 and for the Nissan Leaf by factor 4.0. Compared to using no V2G, using LP increases energy throughput by factor 3.0 for the Tesla Model S and by factor 4.0 for the Nissan Leaf. The V2G option thus dramatically increases the use of the battery.

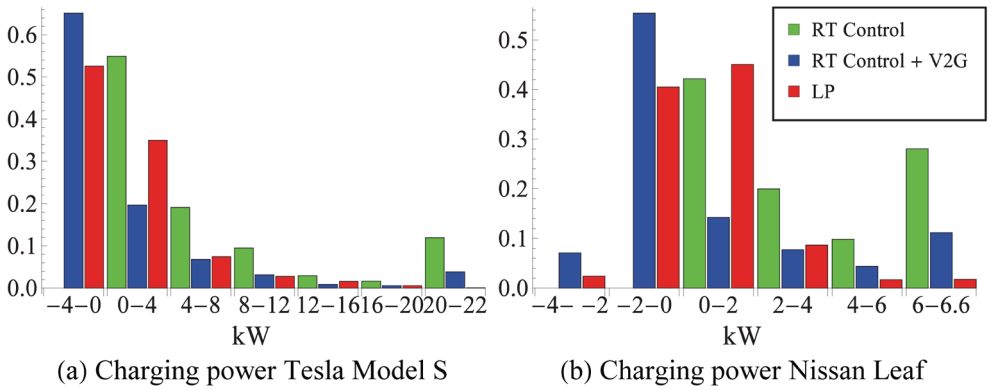
In the case of No Control, the EVs have an SOC below 100% only when charging. Therefore, the average SOC is very high (99%). The average SOC resulting from the control algorithms is much lower, which will have a positive effect on battery lifetime.

In the case of No Control, the EVs always charge at maximum capacity. The average charging power resulting from the control algorithms is considerably lower, which will have a positive effect on battery lifetime. Figure 2.7 shows the frequency distributions of charging power. The results show that discharging occurs only at relatively low charging rates. Furthermore, charging at maximum capacity occurs most often for RT Control, 11% of the total charging time for the Tesla Model S and 28% of the total charging time for the Nissan Leaf, and barely (<2%) for LP.

Summarising, using RT Control will result in minimum battery degradation, since the charging rates and average SOC are much lower than for No Control. V2G will have a significant impact on battery lifetime due to larger energy throughput, which was identified in the literature as the strongest indicator for battery degradation due to V2G. Of the two V2G options, LP is favourable, since it has the lowest charging rates.

Table 2.3 Simulation results for battery degradation indicators.

Algorithm	**Energy throughput (MWh/yr)**		**SOC_{avg} (%)**		**P_{avg} (kW)**	
	Model S	**Leaf**	**Model S**	**Leaf**	**Model S**	**Leaf**
No Control	6.9	2.4	99	99	22	6.6
RT Control	6.9	2.4	65	67	5.7	2.8
RT Control + V2G	16	9.6	50	40	2.6	2.1
LP	21	9.6	51	55	2.3	1.1



(a) Charging power Tesla Model S (b) Charging power Nissan Leaf

Figure 2.7 Frequency distributions for charging power.

2.5.4 Changes in microgrid composition

LomboXnet is considering to expand the microgrid, see Section 2.2.4. We have performed simulations for these expansions; results are presented in Figure 2.8. Our results show that upscaling will lead to lower self-consumption and peak reduction if V2G is used. In the absence of V2G, self-consumption and peak reduction is slightly higher in the upscaled microgrid, although in absolute terms energy sent to the grid increases.

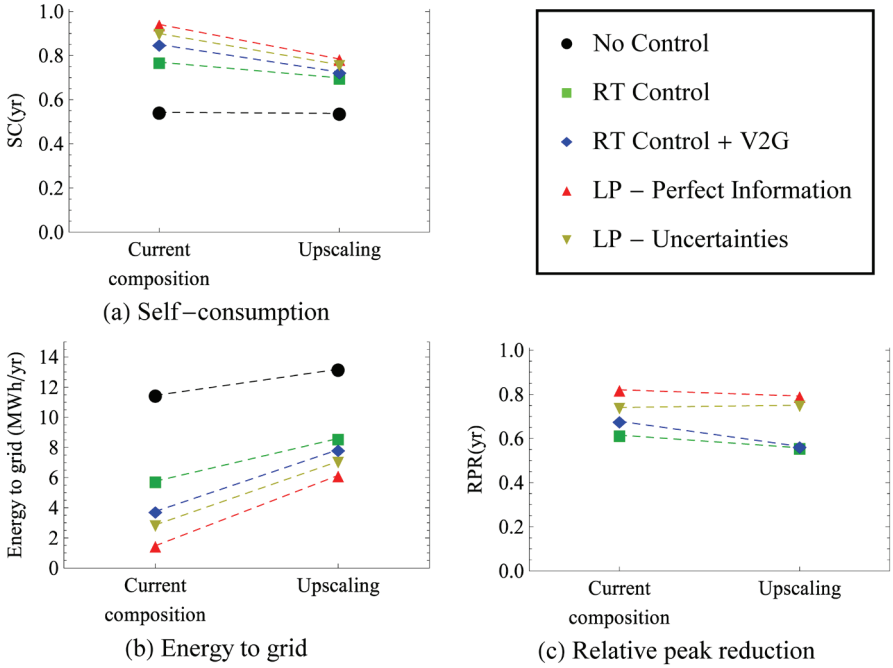


Figure 2.8 Results for upscaling of microgrid.

Figure 2.9 presents our results for variations in trips per week. These results imply that system performance is higher when the EVs make few trips: their function as electricity storage is more important than their function as flexible demand source. Only without a control system making more trips per week increases self-consumption, although only slightly because most of the time the EVs are charged when PV power production is low.

Figure 2.10 presents our results for variation of EV type. The results clearly show that for the microgrid a Tesla Model S, with greater battery capacity and charging power, leads to better system performance than a Nissan Leaf.

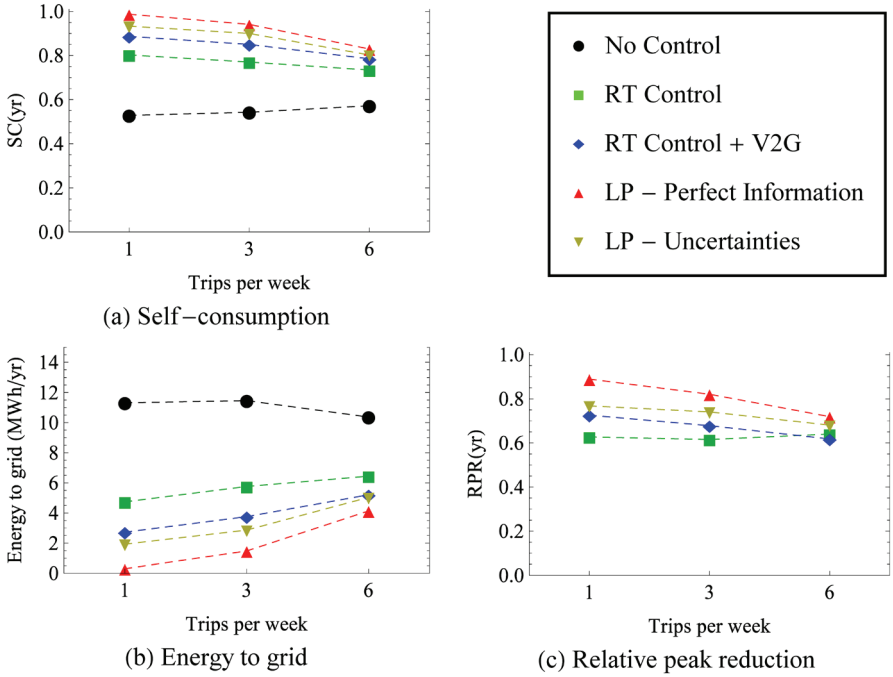


Figure 2.9 Results for variations in EV trips.

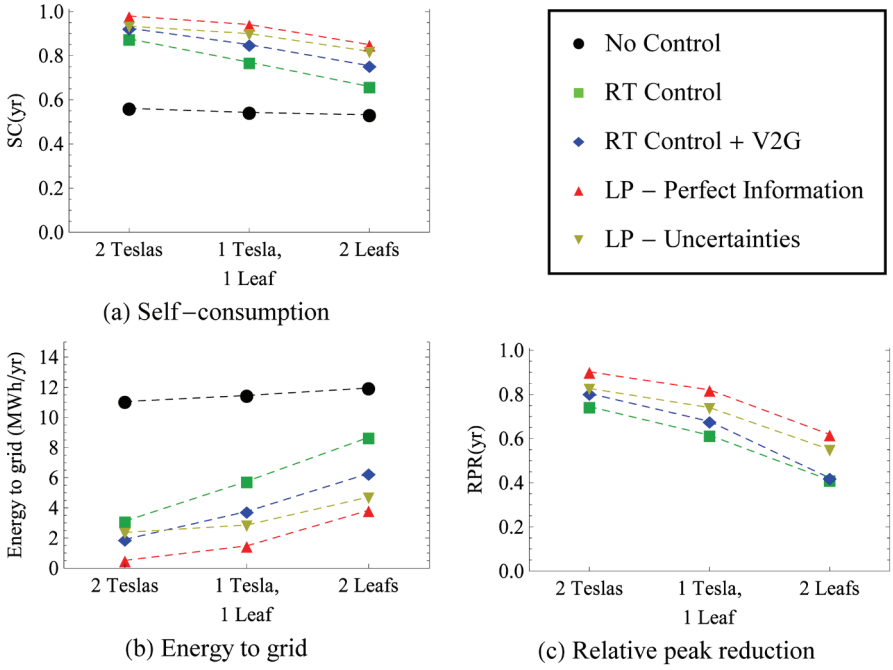


Figure 2.10 Results for variations in EV type.

2.6 Discussion

In this study, we show the increase in self-consumption due to both V2G and optimisation using predictions. Our LP algorithm mainly serves as a way to illustrate the benefits of an optimisation algorithm over the RT algorithms for smart charging. Factors not incorporated in the objective function could be of interest to users of the technology, such as costs or power quality. Furthermore, the algorithm can be improved by enabling dynamic updating, which would allow it to respond to deviations from predictions during the day.

For the LP control algorithm, we have simulated uncertainties in PV power and load demand predictions. However, uncertainties in EV trip times and energy use may arise as well. In our case, these uncertainties will arise for the return time of the EVs, since the EVs will often not have sufficiently charged before the planned starting time of the trip. If the EVs will return earlier than planned, this will have no effect on the charging pattern. If the EVs return later than planned, this will have an effect, because the EV is not available at the charge point. This will not occur often at LomboXnet, since trip times are agreed upon before the cars are rented out. However, to give an indication of how large this effect can be, we have quantified the effect on self-consumption in the extreme case that the EVs are always returned one hour later than planned. We found that self-consumption is decreased with 2%, indicating that uncertainties in trips will have a negligible effect on system performance. However, it should be noted that when such an optimisation algorithm is to be implemented in practice it should incorporate updating every time an EV is returned to be able to deal with these uncertainties.

Based on our indicator set, it is not possible to quantify the impact of the different control algorithms on battery degradation. To use a complete battery model, more information is needed on operating conditions, such as temperature and voltage. Two studies (Bishop et al., 2013; Peterson et al., 2010) that quantified the impact of V2G on battery lifetime stated that energy throughput is the strongest indicator of battery degradation, but have found different relationships of energy throughput and battery degradation. Furthermore, it is not clear how battery degradation due to charging at the charge point compares to battery degradation due to driving and calendric lifetime. However, we can make some qualitative statements on this issue. In a more complete simulation model one of the several available battery models can be used to quantify the impacts on battery lifetime.

In our simulations, we have used a minimum SOC of 20% to prevent over-discharge, similar as in Tulpule et al. (2013). However, several studies use a minimum SOC of 30% (Amirioun & Kazemi, 2014; Khayyam et al., 2012; Zhang et al., 2012). We have performed additional simulations with a minimum SOC of 30%. We found that using this higher minimum SOC has a small but significant impact on self-consumption, which is decreased with 1.5–2.0% for the control algorithms.

Our model contains some weaknesses that affect the quality of our results. Energy loss due to transport through the microgrid was not taken into account in the model. In a similar

research, Claessen et al. (2014) concluded that transport losses in a microgrid are significant. Furthermore, the decrease in maximum charging power of the batteries when nearly full has not been included in the model. The profile for the electricity demand of households is based on a dataset of 400 households from 2007 and 2008. Both measurements were taken at different locations at different times, so it is not known how closely they resemble a typical load demand pattern in Lombok. Moreover, the dataset contains information on aggregated load demand for one week in February; scaling the dataset for a year might not necessarily reflect how electricity demand changes throughout a year. Results can be improved by using a dataset measured in Lombok for a longer time period, preferably for a whole year. Finally, we were limited to using 24-h simulations for LP. If longer simulation times for LP can be used, this will give more accurate results.

2.7 Conclusion

We present a model developed to study the increase in self-consumption of PV power by smart charging EVs using smart grid technology. We apply this model to a case study: the microgrid of LomboXnet. We propose three EV charging control algorithms and have simulated their effect on self-consumption and peak reduction. The simulation results demonstrate that EVs can contribute significantly to well-balanced demand and supply. Self-consumption is increased from 49% to between 62% and 87%, energy sent to the grid reduced from 12.4 MWh (26% of total energy demand) to between 9.1 (19%) and 3.4 (7%) MWh and scores for relative peak reduction range from 0.27 to 0.67. Our LP algorithm not only scores better for self-consumption than RT Control + V2G, but it also halves the largest peak in demand compared to the real-time algorithms, even when taking uncertainties in predictions into account.

The RT control algorithm has the lowest impact on battery lifetime, since not more energy is charged than needed for the EV trips and the charging rate and average SOC is lower than in the reference scenario of No Control. Using V2G dramatically increases battery use which may have a significant impact on battery lifetime. The benefits of V2G will have to be weighed against this issue. Of the two V2G algorithms, LP will have the smallest impact on battery lifetime, since it has the lowest charging rates.

We have shown the effect of changes in microgrid composition. Upscaling the microgrid will lower the scores for our indicators. Furthermore, the results for variations in trips per week show that our smart grid works best for situations where the EVs are regularly situated at the charge point. However, even when EVs make six trips per week, self-consumption will improve when using smart charging and V2G. Finally, our results indicate that using a Tesla Model S (or similar) is preferable to using a Nissan Leaf (or similar), due to the larger battery capacity and charging power of the first.

Despite several model limitations, our results clearly demonstrate the benefits of using smart charging and V2G in a microgrid and show how different sustainable energy and transport technologies can be combined in a manner that will reduce negative impact on the existing energy infrastructure.

Chapter 3

Diffusion of photovoltaic systems and electric vehicles

Abstract

A key issue in smart grid visions is the integration of the energy and mobility systems. Electric vehicles (EVs) can be charged with renewable photovoltaic (PV) solar power, and contribute to the integration of solar power in the electricity network via vehicle-to-grid systems. In such systems the role of consumers becomes crucial as they both generate and store energy. We investigate differences between PV and EV adopter groups and the implications of these differences for the transition to smart energy systems. We study how socio-demographic characteristics of the consumer base influence regional diffusion patterns. In turn, we build scenarios to explore the influence of diffusion patterns on the viability of regional PV-EV integration in terms of energy use and regional self-consumption. The results point out large differences in the spatial diffusion patterns between PV and EV. These differences have implications for the transition to smart sustainable grids; vehicle-to-grid systems may not be viable for certain regions.

3.1 Introduction

Visions of a sustainable future couple the widespread diffusion of electric vehicles to energy supply from renewable sources (Tran, Banister, Bishop, & McCulloch, 2012). In these visions, electric vehicles (EVs) act both as a source of demand (Ipakchi & Albuyeh, 2009) and a storage option for excess renewable energy in vehicle-to-grid (V2G) systems (Kempton & Tomić, 2005b). The adoption and use of renewable energy technologies and electric vehicles by consumers will determine the characteristics of the future electricity grid. Independent micro-grids are a likely outcome when the same consumers adopt both technologies (Palensky & Kupzog, 2013). But if the two technologies appeal to different groups of consumers in different regions, national grids or super-grids may be needed to interconnect local grids (Palensky & Kupzog, 2013; Elliott, 2016).

Understanding these interactions requires a co-adoption perspective (Rai et al., 2016), as well as taking into account consumer heterogeneity and spatial diffusion patterns. We study the early market development of different clean energy technologies to gain insights in which solutions for integrating these technologies in the existing infrastructure are viable and what their potential contribution to a future more sustainable energy and mobility system is.

More specifically, we compare and link the adoption of photovoltaic (PV) solar power and electric vehicles (EVs) by using unique micro-level diffusion data. As a case study we focus on the Netherlands. Our empirical work consists of two parts. First, we analyse the recent diffusion of PV and EV in the Netherlands, and characterize the adopters of these technologies, by linking diffusion data to neighbourhood characteristics via a regression model. This provides insights in the potential for co-adoption and a profile of the early adopters. Using the Bass model of diffusion (Bass, 1969), we estimate future diffusion of PV and EV for different regions of the Netherlands. We use PV self-consumption as a central concept to link these two technologies. PV self-consumption refers to how much electrical energy is consumed by the loads supplied by the local PV solar panels (Castillo-Cagigal et al., 2011a). Higher levels of PV self-consumption will result in decreased stress on the electricity grid and therefore easier integration of PV solar panels in the existing infrastructure. Several countries including China, Japan and Italy have policies in place to increase PV self-consumption of households (Luthander et al., 2015). PV self-consumption can be increased by energy storage and demand side management (DSM) (Luthander et al., 2015). EVs can contribute to load balancing via smart charging and V2G (Van der Kam & Van Sark, 2015). Combining adopter profiles with scenario analysis enables us to investigate the viability of V2G systems and come to policy recommendations.

Our study offers a new approach for taking users into account in energy systems modelling, using a variety of modelling techniques. Hereby, we quantitatively demonstrate the large impact users have on the viability of the EV-PV combination in a future energy system. Our model estimates the viability of V2G systems for different energy scenarios and contributes to the larger effort of integrating insights from social sciences with energy science (Geels et

al., 2016; Kastner & Stern, 2015; Stern et al., 2016). The remainder of the chapter is structured as follows. Section 3.2 discusses the background of our study, Section 3.3 our methodology and Section 3.4 the results. In Section 3.5 we discuss the main contributions, limitations and policy implications of our study and Section 3.6 concludes the chapter.

3.2 Background

The European Union has the ambition to increase adoption levels of both PV solar panels and EVs. Recently, the European Parliament has voted to ensure that by 2030, half of electricity demand should be produced by wind, solar and biomass (Schiermeier, 2018). Furthermore, the European Commission has put forward legislative measures that should support energy consumers to become prosumers with PV solar panels (Hancher & Winters, 2017). EVs are regarded as having the potential benefits of reduced oil consumption and reduced emissions of CO_2 and other pollutants (Bansal, 2005). The European Commission supports a European wide electro-mobility initiative called Green eMotion[4], aiming to facilitate EV market roll-out.

In the Netherlands, PV and EV adoption sharply increased in recent years. In 2016, installed PV capacity rose to 2.1 GWp (IEA-PVPS, 2016). In 2015, the Netherlands ranked 4th in installed PV capacity and 9th in cumulative installed PV capacity for the EU-28 (Eurobserv'ER, 2016). The number of registered battery electric vehicles (BEVs) increased by 40% to 13,105 in 2016, and the number of registered plug-in hybrid EVs (PHEVs) increased by 27% to 9,8903 (RVO, 2017). In 2015, 9.7 % of newly registered cars were EVs, and the Netherlands had the most EV sales within the EU (ACEA, 2018b). Both technologies have large potential for growth, since less than 6% of household rooftops have solar panels, in total providing less than 1% of total annual electricity production, and BEVs and PHEVs combined amount to less than 2% of the total car fleet in the Netherlands. The broadly supported National Action Plan on PV power states a target of 10 GWp in 2023 ("Nationaal Actieplan Zonnestroom," 2016) . The Dutch government has the ambition that by 2030 all new vehicles sold in the Netherlands are zero-emission vehicles (VVD, CDA, D66, & ChristenUnie, 2017).

There is both a daily and seasonal mismatch between household electricity demand and PV production. Most PV power is produced around midday, when demand is low. Demand is high in the winter and low in the summer, as the Netherlands has cool summers and moderate winters. To address the imbalance between PV power supply and household demand several Dutch on-going projects aim at developing smart charging of EVs and V2G.[5] Combined with

[4] See http://www.greenemotion-project.eu/ for program website

[5] For an overview of projects, see https://www.livinglabsmartcharging.nl/en/

being a front-runner in EV deployment, this makes the Netherlands a good case for studying the integration of PV and EV.

The uptake of new technologies usually follows an S-curved pattern where diffusion is initially slow, followed by a take-off phase of fast diffusion before the diffusion levels off and the market is saturated. Rogers (2003) explains this S-curve from social processes where different groups, with different socio-demographic characteristics, decide to adopt the innovation at different points in time, starting with adoption by innovators followed by early adopters, early majority, late majority and laggards. Following Rogers' classification, the diffusion of PV is in the early adoption stage and the diffusion of EV is in the innovator stage in the Netherlands. Insight in the characteristics of innovators and early adopters is pivotal as these are key groups in the diffusion process and shape the early market.

There is a growing body of literature focussing on the drivers and barriers of both PV adoption and EV adoption. In the case of PV adoption, studies have focussed on the role of costs (Balcombe, Rigby, & Azapagic, 2013; Chapman, McLellan, & Tezuka, 2016; Coffman, Wee, Bonham, & Salim, 2016; Qureshi, Ullah, & Arentsen, 2017; Simpson & Clifton, 2017; Vasseur & Kemp, 2015), environmental attitudes (Balcombe et al., 2013), policy incentives (Dong, Sigrin, & Brinkman, 2017; Sarasa-Maestro, Dufo-López, & Bernal-Agustín, 2013), business models (Huijben & Verbong, 2013; Karakaya, Nuur, & Hidalgo, 2016; Rai & Sigrin, 2013), and peer effects (Bollinger & Gillingham, 2012; Graziano & Gillingham, 2015; Palm, 2017; Rai & Robinson, 2013).

Several studies on PV diffusion identify socio-demographic factors drive unique diffusion patterns (Balcombe et al., 2013; Bollinger & Gillingham, 2012; Davidson, Drury, Lopez, Elmore, & Margolis, 2014; Dharshing, 2017; Islam & Meade, 2013; Kwan, 2012; Müller & Rode, 2013; Palmer, Sorda, & Madlener, 2015; Schaffer & Brun, 2015; Sommerfeld, Buys, Mengersen, & Vine, 2017). Factors consistently found to have a positive effect on PV adoption are the proportion of middle-aged residents (Balcombe et al., 2013; Bollinger & Gillingham, 2012; Kwan, 2012) and education level (Bollinger & Gillingham, 2012; Kwan, 2012; Palmer et al., 2015). Interestingly, the effect of income differs among these studies, with some studies finding a positive effect (Dharshing, 2017; Kwan, 2012; Müller & Rode, 2013; Vasseur & Kemp, 2015) and others finding a negative effect (Bollinger & Gillingham, 2012; Islam & Meade, 2013; Schaffer & Brun, 2015; Simpson & Clifton, 2017). Other factors found to have an influence are political preferences (Dharshing, 2017; Kwan, 2012), ethnicity (Kwan, 2012), lifestyle (Palmer et al., 2015), housing density (Graziano & Gillingham, 2015; Kwan, 2012; Müller & Rode, 2013), and house ownership (Balcombe et al., 2013; Davidson et al., 2014).

Research on factors affecting EV adoption has mostly focused on the role of costs, charging infrastructure and individual factors such as range anxiety, emotions, attitude towards the environment and symbolic attributes of EVs (Adnan, Nordin, Rahman, Vasant, & Noor, 2017; Coffman, Bernstein, & Wee, 2017; Rezvani, Jansson, & Bodin, 2015). Furthermore,

several studies stress the influence of socio-demographic factors on EV diffusion (Eising et al., 2014; McCoy & Lyons, 2014; Noori & Tatari, 2016; Saarenpää, Kolehmainen, & Niska, 2013). A notable difference between these studies and studies on PV adoption mentioned earlier, i.e. (Bollinger & Gillingham, 2012; Davidson et al., 2014; Kwan, 2012; Müller & Rode, 2013; Palmer et al., 2015), is that in studies on EV adoption the socio-demographic factors are usually discussed as input for a diffusion model and not the key focus of the research. Factors found to have an effect on EV adoption are income (Eising et al., 2014; McCoy & Lyons, 2014; Saarenpää et al., 2013), size of the local car fleet (Eising et al., 2014), education level (Saarenpää et al., 2013), and family composition (Noori & Tatari, 2016; Saarenpää et al., 2013).

The scientific literature on the influence of socio-demographic factors on PV and EV diffusion patterns allows for indirect comparison of PV and EV adopter groups. In this study we directly compare the socio-demographic characteristics of EV and PV adopters on a neighbourhood level to get insight in the general profiles of both EV and PV adopters.

We complement these profiles with estimations of future diffusion of PV and EV to investigate its impact on the energy system and come to overall conclusions and policy recommendations. Several approaches to diffusion forecast modelling exist, with varying aspects of focus and levels of refinement (Kiesling, Günther, Stummer, & Wakolbinger, 2012; Rao & Kishore, 2010). Models used for forecasting PV diffusion include the Bass model (Dong et al., 2017; Guidolin & Mortarino, 2010; Reeves, Rai, & Margolis, 2017), which has its roots in the diffusion of innovation theory formulated by Rogers (2003) and agent based models (ABMs) (Opiyo, 2015; Palmer et al., 2015; Robinson & Rai, 2015).

ABMs are a popular tool for forecasting EV (Dijk, Kemp, & Valkering, 2013; Eppstein, Grover, Marshall, & Rizzo, 2011; Kangur, Jager, Verbrugge, & Bockarjova, 2017; McCoy & Lyons, 2014; Mueller & de Haan, 2009; Noori & Tatari, 2016; Shafiei et al., 2012; Wolf, Schröder, Neumann, & De Haan, 2015; Zhang, Gensler, & Garcia, 2011). Other studies base their forecasts on methods using s-curves, such as the Fisher-Pry model (Eising et al., 2014), pearl curves (Huth, Kieckhäfer, & Spengler, 2015), and the Bass model (Lee, Park, Kim, & Lee, 2013). In the latter study, the Bass model is combined with discrete choice models and system dynamics. S-curve approaches such as the Bass model offer less flexibility than ABMs, since these are basically an extrapolation of current trends. S-curves are often used as forecasting tools rather than as tools to perform ex-ante policy evaluation. One of the major advantages of ABMs is that such models offer a flexible environment allowing the inclusion of a wide variety of factors such as social networks, subsidy schemes, and information campaigns, while at the same time enabling the use of theoretical models such as the Bass model. A main application of agent-based diffusion models is ex-ante comparison of policies aimed at stimulating diffusion.

We use the Bass model of diffusion to estimate the future diffusion of both technologies. The Bass model of diffusion uses Rogers' classification of adopters; innovators can decide

to adopt an innovation at any point time, while the timing of adoption for all other groups depends on the decisions of other members in the social system. In this epidemic model of diffusion, adoption patterns are ultimately determined by the spread of information amongst consumers. The Bass model is well suited for application on micro-level diffusion data as available in the present study, and has been applied before for both PV diffusion (Dong et al., 2017; Guidolin & Mortarino, 2010; Reeves et al., 2017) and EV diffusion (Lee et al., 2013), as well as for analysing differences in diffusion among regions within a country (Steffens, 1998). We prefer to use the Bass model over other formulations of s-curves since, in contrast to for instance the Fisher-Pry model, its parameters can be directly linked to concepts from innovation diffusion theory, such as the spread of information and heterogeneous consumer groups.

3.3 Methods

This section discusses our data sources and methodology. Our methodology consists of two parts. First, we link PV and EV adoption levels to neighbourhood characteristics via a regression model. This will allow us to contrast and compare the adopter groups for these technologies, using country level data. Second, we investigate the implications of the differences between these adopter groups by estimating future diffusion of PV and EV via the Bass model of diffusion, and link these estimates to the energy systems. Section 3.3.1 presents our data sources, Section 3.3.2 presents our method for the regression analysis and Section 3.3.3 introduces the Bass model of diffusion. Finally, we present our method to link the diffusion of PV and EV to the energy system in Section 3.3.4.

3.3.1 Data

We use a variety of datasets coming from different sources, most of them starting from the year 2005. The data comprise number of PV installations, the number of electric vehicles and public charge points, open data from distribution grid operators, solar irradiation, socio-demographic data, cadastral maps, number of voters of GroenLinks political party (left-wing, green party), number of municipal council members belonging to GroenLinks. Table 3.1 presents specifications of the datasets we have used in our analysis. Most of our data is available at four-digit postal code level (PC4). The Netherlands is divided in 4052 four-digit postal codes with an average of 4160 inhabitants (s.d. = 4134).

Table 3.1 Description of datasets used

Dataset	Source	Description	Spatial resolution	Years
PV installations	Production installation register	PV adoption data including date of placement and nominal power	PC4	1968-2015
Electric vehicles	Netherlands Vehicle Authority	EV adoption data including date of first admission	PC4	1904-2016
Public charge points	Netherlands Vehicle Authority	Public charge points	PC4	2014
Open data distribution grid operators	Liander, Stedin, Enexis, Enduris	Data on energy use of households	PC6	2009-2015
Solar irradiation data	Royal Netherlands Meteorological Institute	Solar irradiation in de Bilt, available per hour for 2014	-	2014
Socio-demographics	Statistics Netherlands	Population and housing characteristics, car fleet	PC4	2009-2014
Cadastral map	The Netherlands' Cadastre, Land Registry and Mapping Agency	Building characteristics	m^2	2015
GroenLinks voters	Stichting Politieke Academie	Number and percentage of GroenLinks voters for the national election 2010 in polling places within neighbourhood	PC4	2010
GroenLinks municipal council members	GroenLinks	Number of municipal council members affiliated with GroenLinks	Municipality	1994-2014

PV installations

In the Netherlands PV installations are registered in the production installation register (PIR), an initiative by the Dutch grid operators. The register contains information on the address of installations, the date of instalment and the nominal power. In the version of the dataset available to us the information on address is aggregated to PC4-level. For installations registered before the 1st of April 2014 we know the date of instalment. For installations registered between the 1st of April 2014 and the third of July 2015 we only have the year of installation. In total 277,373 installations are included in the register.

Electric vehicles and public charge points

In the Netherlands all vehicles are registered by the Netherlands Vehicle Authority (RDW, in Dutch: Rijksdienst voor het Wegverkeer). The register contains information on the vehicle name, type and technical specification, the address of registration and the date of first admission. In the version of the dataset available to us the information on address is aggregated to PC4-level. It contains information on all alternative fuel vehicles, including

passenger cars, business cars, busses, motor bikes and mopeds up to the 12th of May 2016. In total 310,073 alternative fuel vehicles are registered, of which 189,507 passenger cars. 114505 of these are plug-in EVs.

Lease vehicles are often registered at a lease company. A lease vehicle will most often not be located in the same PC-4 area as it is registered. To deal with this issue we exclude PC-4 areas with major lease companies from our analysis, since the total number of EVs registered in that area will highly overestimate the total number of EVs actually located in that same area. Based on a web search, we have identified 39 PC4 areas with large lease companies (see Table A.1 in Appendix A) with a total number of 42619 EVs registered (37% of the total EV fleet).

Also registered by the RDW are the public charge points. The dataset includes information on the location, owner and technical specifications on all public and semi-public charge points in the Netherlands. In the version of the dataset made available to us the information on the location is aggregated to PC4-level and contains charge points registered before the 1st of January 2015, 7589 in total.

Open data distribution grid operators

The four major grid operators of the Netherlands publish data on the energy use of households (Enduris, 2016; Enexis, 2016; Liander, 2016; Stedin, 2016). In this study we make use of the data on yearly electricity use of households, aggregated to PC4-level, and the profile of the yearly electricity use of an average household. Data on the latter one is published by Liander and available for a whole year with a one-hour resolution. The four major grid operators cover 92% of all postal codes of the Netherlands.

Solar irradiation

For our model of PV production, we use solar irradiation data as measured in 2014 in the Bilt, the Netherlands (latitude: 52.11°, longitude: 5.18°) by the Royal Netherlands Meteorological Institute (KNMI, 2018). The interval of the measurement for radiation data was 10 minutes and for the temperature and pressure values one hour.

Socio-demographic data

Most of the socio-demographic data we use in our analysis comes from the Statistics Netherlands (CBS, in Dutch: Centraal Bureau voor de Statistiek). The CBS collects, edits and publishes national statistics related to societal needs (CBS, 2018). Methods include collecting data from other registers, surveys and interviews. The variables we use in our analysis are from the years 2009 to 2014 and are aggregated to PC4-level.

Cadastral map

The Netherlands' Cadastre, Land Registry and Mapping Agency (in Dutch: Kadaster) publishes the cadastral map of the Netherlands. Municipalities are responsible for recording

data on all buildings in the Netherlands, and the data is made available for the whole of the Netherlands. The map includes information on the location of addresses, the building footprint and the function of the buildings. We use the register to calculate the amount of rooftops and the building footprint of buildings with a residential function for every four-digit postal code of the Netherlands.

GroenLinks voters

The organisation Politieke Academie offers data-analyses of voters in the Netherlands. We use their data for the absolute number and percentage of GroenLinks voters for the national elections of 2010. GroenLinks got 624732 votes, 6.6% of total votes. In this election every voter was permitted to vote anywhere in the municipality of residence. At request it was also possible to vote in other municipalities. One should thus be careful with interpreting what the percentage of voters in a PC4-area says about the inhabitants of the area.

GroenLinks municipal council members

We acquired a dataset from the political party GroenLinks which contains the number of municipal council members affiliated with GroenLinks. Since 1994, GroenLinks has had 309 council members, serving 481 terms in 161 different municipalities.

3.2 Characterization of PV and EV adopters

To characterize PV and EV adopters we performed two ordinary least squares (OLS) regressions, one with the number of PV installations per person and one with the number of EVs per person as the dependent variable. The level of our regression analysis is four-digit postal codes (PC4). The Netherlands is divided in 4052 four-digit postal codes with an average of 4173 inhabitants (with standard deviation of 4130). We log-transformed the dependent variables to produce normally distributed model residuals. Furthermore, before log-transforming we add the number 1 to the dependent variable, to deal with zeros in the dataset. This results in the following model:

$$\log(Y_i + 1) = \alpha + \beta\, X_i + \epsilon \tag{3.1}$$

Where Y_i is the dependent variable for PC4 code i, X_i the vector of explanatory variables for postal code i, α the intercept, β the vector of coefficients for the explanatory variables and ϵ the random error coefficient. This analysis assumes spatially independent errors.

Our model enables us to characterize PV and EV adopters by yielding the best predictors for historical adoption at the neighbourhood level. We cannot be sure whether an explanatory variable drives the adoption process or rather serves as a proxy for an adoption driver. It is therefore important to interpret model results as predictors and not as drivers of adoption.

Based on the current EV and PV literature, various potentially related independent variables are included, presented in Table 3.2. To address the spatial structure of the neighbourhood, we include the address density. From what has been established in previous analyses, PV adoption tends to be lower in high density environments (Graziano & Gillingham, 2015; Kwan, 2012; Müller & Rode, 2013) whereas EV adoption has found to correlate positively with urbanity (Eising et al., 2014). Also the classical adoption factors age, education are income are included (Rogers, 2003).

Some studies on PV adoption have identified lower adoption rates among younger adults (Balcombe et al., 2013; Kwan, 2012). For EV no strong indications could be found in previous research. To clarify age effects, in this study we include the proportions of younger (25-45) and older (45-65) middle age groups.

Level of education is found as a factor predicting PV and, generally, EV adoption (Bollinger & Gillingham, 2012; Coffman et al., 2017; Davidson et al., 2014; Islam & Meade, 2013; Kwan, 2012; Saarenpää et al., 2013; Vasseur & Kemp, 2015). We include the percentage of lower educated in a neighbourhood, and consequently expect a negative effect of this factor on adoption.

Interestingly, the effect of income differs among PV studies, with some studies finding a positive effect (Dharshing, 2017; Kwan, 2012; Müller & Rode, 2013; Vasseur & Kemp, 2015) and others that see higher adoption among lower income groups (Bollinger & Gillingham, 2012; Islam & Meade, 2013; Schaffer & Brun, 2015; Simpson & Clifton, 2017). Uncertainty about the income effect is also present in the EV literature (Coffman et al., 2017), though several studies do find a positive effect of income on EV adoption (Coffman et al., 2017; Eising et al., 2014; McCoy & Lyons, 2014; Saarenpää et al., 2013).

We have additionally included a variable for household size, following indications in both the EV and PV literature that family households are more likely to adopt (Saarenpää et al., 2013; Sommerfeld, Buys, Mengersen, et al., 2017).

Studies on both PV and EV adoption are cautious about the influence of environmental awareness (Adnan et al., 2017; Balcombe et al., 2013; Coffman et al., 2017; Dharshing, 2017; Rezvani et al., 2015; Saarenpää et al., 2013; Schaffer & Brun, 2015; Sommerfeld, Buys, & Vine, 2017). To investigate the role of environmental awareness in PV and EV adoption, we included the percentage of voters for GroenLinks, the Dutch green party.

To capture municipal policy favouring EV and PV, we have included a dummy variable indicating the presence of the GroenLinks in the municipal council. This party favours both technologies heavily, as part of a broader sustainability agenda.[6]

[6] See https://groenlinks.nl/standpunten for the political stance of GroenLinks (in Dutch)

Table 3.2 Description of independent variables used in regression models. The variables are explained and it is specified in which model they are used. Finally, we include the expected the effect of the variables will be on adoption levels, based on earlier literature. + indicates that positive effects have been found, - indicates that negative effects have been found, and +/- indicates that both positive and negative effects have been found. Empty cells indicate that, to our knowledge, earlier literature has not studied the effect of these variables on PV adoption or EV adoption

Variable name	Variable description	Data source	Used in model for:	Expected effects on PV adoption	Expected effects on EV adoption
Address density (per km^2)	Number of addresses per km2	Kadaster	PV and EV	-	+
Age 25-45 (%)	Percentage of population between age 25 and 45	CBS	PV and EV	-	
Age 45-65 (%)	Percentage of population between age 45 and 65	CBS	PV and EV	+	
Household income (Euro)	Average income of households	CBS	PV and EV	+/-	+/-
Household size (persons)	Average number of persons per household	CBS	PV and EV	+	+
Lowly educated (%)	Percentage of population with education level not higher than primary school or vmbo (lower vocational education)	CBS	PV and EV	-	-
GroenLinks municipal council members since 2006 (Y/N)	Whether or not GroenLinks had alderman in 2006-2014	GroenLinks	PV and EV		
GroenLinks voters 2010 (%)	Percentage of GroenLinks voters for the national elections of 2010	Politieke Academie	PV and EV		
Household rooftops (pp)	Number of household rooftops per person	Kadaster	PV		
Total building footprint (m^2 pp)	Total building footprint of households in m^2	Kadaster	PV		
Passenger vehicles (pp)	Number of passenger vehicles per capita[7]	CBS	EV		+
Public charge points (pp)	Number of public charge points per person	RDW	EV		

[7] The variable passenger vehicles (pp) contains some outliers, due to vehicles registered at company addresses. The Dutch statistics agency has also published a cleaned dataset with solely private cars on the "neighbourhood" (N=3096) level (CBS, 2016b). This is an aggregation level comparable to the (N=4048) postcode areas of this study. In this dataset no neighbourhoods have > 1 car per inhabitant. Based on this dataset, we have decided to remove all neighbourhoods with more than 1 car per capita from our analysis

We have additionally included variables exclusively for PV: the number of rooftops per person, as control for total market size, and the total building footprint of households per person in the area, as an approximation for the size of rooftops. Finally, we have included two dependent variables exclusively for EV: the number of passenger vehicles per person, as control for total market size and expected to have a positive effect (Eising et al., 2014), and publicly available charge points per capita, as indicator for municipal policy (local government's play a large role in the build-up public charging structure in the Netherlands).

3.3.3 Estimating future diffusion of PV and EV

To estimate future diffusion of PV and EV, we use the Bass model of diffusion. The model describes the typical S-curve of innovation adoption and assumes that purchase decisions are influenced by external sources and internal sources, which creates two distinct groups of adopters: the innovators and the imitators. The mathematical formulation of the model is:

$$\frac{f(t)}{1-F(t)} = p + qF(t) \tag{3.2}$$

Where $f(t)$ is the change of the installed base fraction, $F(t)$ is the installed base fraction, p is the coefficient of innovators and q is the coefficient of imitators.

The cumulative number of adopters can be described by:

$$A(t) = m\frac{1-e^{-(p+q)(t-t_0)}}{1+\frac{q}{p}e^{-(p+q)(t-t_0)}} \tag{3.3}$$

Where $A(t)$ is the cumulative number of adopters, m is the total market size and t_0 is the time at which diffusion starts. We then predict the amount of PV adopters and EV adopters by fitting Equation (3) to the available data, using a non-linear least squares method based on the numerical global optimisation algorithm *NMinimize* in Wolfram Mathematica 11.1.

We made an estimate of the total market size (parameter m). For PV, we assume the market size to be equal to the number of rooftops in an area, while for EV we assume the market size to be equal to the number of vehicles in an area. We consider both estimates to be optimistic, since not every rooftop is suitable for PV and not every vehicle could be replaced by EV. The results from our study can therefore be considered optimistic; both on how much PV can contribute to electricity production and on how much EVs can contribute to load balancing. We have performed a sensitivity analysis on total PV and EV market size to investigate the effect of our estimates on the final results.

The Bass model describes aggregated diffusion patterns, and is not bound to a specific spatial scale. The model could hold for cities, countries, continents or the world, dependent on the

specific patterns of the technology diffusion. However, the model is not useful for small scales, for our case the neighbourhood level, since there is not enough aggregation of adopters.

In our study, we modelled the diffusion of so-called NUTS-3-regions in the Netherlands (Eurostat, 2018). The Netherlands is divided into 40 NUTS-3-regions, which are used for analytical purposes and are constructed based on a nodal classification principle (CBS, 2016a). The uptake of EV and PV in these areas shows the typical pattern of aggregated innovation diffusion. One of the major advantages of using the NUTS-3-level is that a large share of commuting takes place within these regions, so that it is reasonable to assume that EVs stay within the same area during the day.

3.3.4 Consequences for the transition to sustainable energy

We use the results from the Bass model of diffusion to investigate the impact of PV and EV diffusion and the energy system. In order to do so, we link several datasets and run simulations on the potential contribution of V2G systems to increasing the PV self-consumption of NUTS-3-regions in the Netherlands. Figure 3.1 presents an overview of our method, while the rest of this section details the data sources and calculation methods for the different model elements.

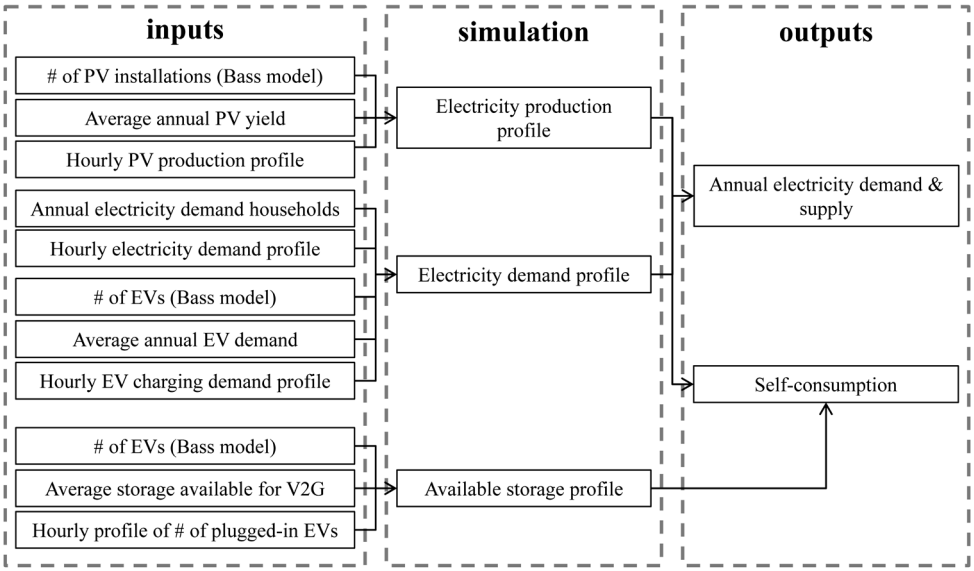


Figure 3.1 Overview of our method to calculate the impact of PV and EV diffusion on the energy system for each NUTS-3 region in the Netherlands. We use the number of PV installations and EVs as predicted by the Bass model and combine this with data and estimates of average PV yield, household electricity demand, EV charging demand, available storage for V2G and hourly profiles to construct hourly profiles for electricity production, demand and available storage. The first two of these are used to calculate the annual electricity demand and supply, while all three profiles are used to calculate the self-consumption of a region.

3.3.4.1 PV-power production

We compare the estimated annual energy yield of PV installations to total annual electricity demand for each NUTS-3 area. We estimate the annual energy yield by multiplying the amount of PV systems, following from the Bass model, with the average nominal power of the PV systems and the specific PV yield.

We use the following assumptions. First, we assume that the average nominal power of PV systems is constant over time. Since 2011 the average nominal power of new PV systems has remained roughly constant, varying between 3.8 and 4.2 kWp. The current average nominal power of PV systems does vary between different NUTS 3-areas, from 2.4 to 5.5 kWp. However, it is not clear what this current variation will mean for future PV-installations. Therefore, for the sake of simplicity, we choose a constant average nominal power across the NUTS-3-areas. Secondly, we assume the specific annual PV yield to be 875 kWh/kWp, which is the current adopted average PV yield for the Netherlands (Van Sark et al., 2014). As the efficiency of PV systems is expected to increase due to technological developments, this yield can be expected to increase as well. However, PV systems will increasingly be installed in residential areas where some rooftops are better suitable for PV than others, for instance due to orientation and shading, decreasing the average PV yield. To investigate this effect, we perform a sensitivity analysis with varying PV yields and PV orientations.

We ran additional simulations to explore how a possible transition towards a system in which PV solar panels produce enough energy to cover all demand for residential electricity and EV charging, We calculated the average nominal power needed for this scenario to be 12.9 kWp, more than three times the current average of 4 kWp. Though the efficiency of PV solar panels still increases, it seems unlikely that increases in efficiency will be enough to reach this average nominal power of rooftop PV systems. However, factors other than increased efficiency could also contribute to an increased PV yield per household. Current experiments with local energy cooperatives (Kalkbrenner & Roosen, 2016; Van der Schoor & Scholtens, 2015) or crowdfunding (Candelise, 2016) show promising signs of allowing consumers to invest in PV systems not placed on their own rooftop. As a transition to a system based on 100% PV seems unlikely, we include these results from our simulations in as an ‘extreme’ benchmark scenario, and relate the results to the discussion of off-grid PV solar based systems.

We model hourly PV yield with the open source package PVLIB (Andrews, Stein, Hansen, & Riley, 2014), based on KNMI solar irradiation data. Specifications of the Sanyo HIP-225HDE1 module and the Enphase Energy M250 inverter were used as input for the model. The modelled PV modules have an azimuth of 180 degrees and a tilt of 37 degrees, which are the optimal conditions for PV production in the Netherlands (Litjens, Van Sark, & Worrell, 2017). Figure 3.2 presents the resulting PV-power production. As the diffusion of PV solar panels progresses more panels will be installed on rooftops with sub-optimal orientation. This will alter the shape of the hourly PV yield profile. Solar panels directed to

the east will produce more energy in the morning as compared to solar panels directed to the south, and solar panels directed to the west will produce more energy in the evening compared to other directions. To investigate the effect of PV panel orientation we include different PV orientations in our sensitivity analysis.

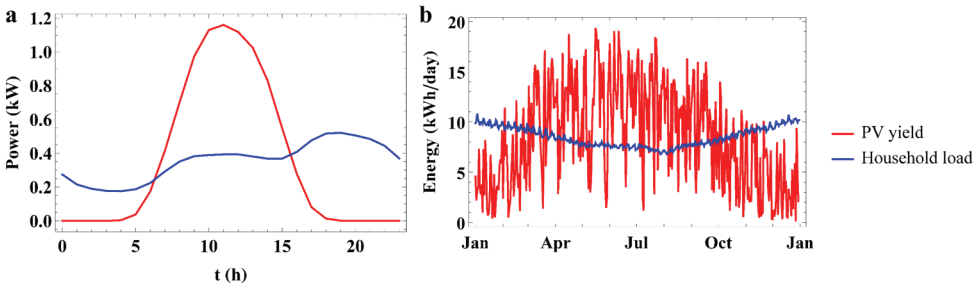


Figure 3.2 PV yield and household load profiles, a) hourly PV yield (3.5 kWp system size) and household load, both averaged over a whole year; b**)** daily PV yield (3.5 kWp, 2014) and household load. The total annual PV yield covers total annual household electricity demand. PV yield is modelled with PV LIB (Andrews et al., 2014) using data provided by KNMI (2018), household load is based on data provided by grid-operator Liander (2016)

3.3.4.2 Electricity demand households

We calculate the annual electricity demand from aggregating the data on total household electricity demand of 2015 as provided by the four major Dutch DSOs to the NUTS-3 level (Enduris, 2016; Enexis, 2016; Liander, 2016; Stedin, 2016). Finally, we assume that the total household electricity demand stays constant over time. The growth in household electricity demand in the EU-15 has been very limited, only 1%/yr in the period 2000-2010 and household electricity demand is projected to decline with 0.6%/yr in the period 2010-2020 and 0.3%/yr in the period 2020-2030 (European Commission, 2008). Given these small effects we deem our assumption to be reasonable. The hourly profile of household demand is based on data published by Liander (2016) and presented in Figure 3.2.

3.3.4.3 Electricity demand EVs

To calculate the annual electricity demand of EVs, we assume that EVs drive on average the same distance as passenger vehicles do now, around 13,000 km per year for the Netherlands (CBS, 2018). Assuming an average driving efficiency of 0.2 kWh/km and an average battery conversion efficiency of 90%, the annual electricity demand of an EV is ~2900 kWh. We then construct an hourly demand profile for EVs based on data from June and December 2012 published by the foundation E-Laad (E-Laad, 2013). We thus assume that the charging patterns of EVs stay the same over the years. It is uncertain how realistic this assumption is,

because of the developments in the field of smart charging. Smart charging (i.e. shifting in time of EV charging patterns) could, in addition to vehicle-to-grid, further increase self-consumption of PV-power, but is outside of the scope of this study.

3.3.4.4 Self-consumption

We define self-consumption as the percentage of locally produced (within the region) PV power used within an area, either by the households or EVs connected to charge points. Note that we use the concept of self-consumption on a regional scale, and not on the household level for which it is typically used. A high level of self-consumption is beneficial for the integration of distributed energy sources in the electricity grid, since power transport over the grid decreases when the energy produced is consumed locally. PV self-consumption can be increased by storing energy in batteries or shifting demand to times of energy production (DSM) (Luthander et al., 2015). For the present study we only look at the potential contribution of EVs to increase self-consumption, because it is currently not attractive for Dutch consumers to invest in PV storage systems, as the national net-metering policy and the adoption level of PV storage systems is negligible. The Dutch government has announced to change the net-metering policy (VVD et al., 2017), which will most likely result in a more positive business case for PV storage in the future.

In order to calculate the total self-consumption for the NUTS-3 areas, we use the hourly profiles for PV yield, household demand and EV demand. By comparing the PV yield with the electricity demand, we can determine the surplus or shortage of PV power to cover demand for each hour of the year. We then assume that all the EVs in a NUTS-3 area can be used for storage when stationary. Using a simplified storage model, we calculate the annual self-consumption for each region. The model allows for the EVs as mobile storage units to be charged during times of surplus PV power, and discharged during times of shortage of PV power, to cover household electricity demand. In case not enough storage capacity is available to deal with the surplus of PV power, the produced electricity is fed back to the grid. To determine what percentage of the EV fleet is stationary, we use data based on a 2005 Swiss mobility survey (González Vayá & Andersson, 2012). We run this model for a whole year, starting at January 1st to December 31st, with a time resolution of one hour.

Next, we need to use the following assumptions. Both the charging and discharging efficiency of the EVs is 90% (Van der Kam & Van Sark, 2015). We assume that EVs remain within the same NUTS 3-area. The NUTS 3-area are defined so that a large share of commuting takes place within the NUTS 3-region (CBS, 2016a). In the results presented in this chapter we assume the average battery capacity available for V2G services to be 5 kWh. This is one third of the average battery capacity of 15 kWh in the current EV-fleet.[8] There is

[8] Based on the 28 most popular EV models in the Netherlands, which cover 93% of the total EV fleet

of yet no clear idea on how much battery capacity of EVs could be used for V2G services. Given this uncertainty, we chose to perform a sensitivity analysis for available battery capacity.

A factor that can affect the potential contribution of V2G to increasing PV self-consumption is the maximum charging rate of individual EVs. The maximum charging rate sets a cap to how much energy can be stored in EVs for each time-step. In our model, we aggregate all EVs in a region to determine the self-consumption. The data on EV charging and the percentage of car fleets that are stationary as a function of time of day is on an aggregate level. One advantage of this aggregation is that it takes less computational time to run our model, but a disadvantage is that we cannot keep track of the individual charging rates and SOC levels of the EVs. To determine the charging rate needed to increase PV self-consumption, we calculate the average charging rate per EV in a region for each time-step. In doing so we can determine whether the needed charging rate per EV is feasible.

The charging rate of an EV is affected by its SOC level. When the SOC level approaches 100% the charging rate will decrease significantly. This effect is not included in our model, we present a sensitivity analysis for available battery capacity instead.

3.4 Results

This section presents and discusses our results. Section 3.4.2 presents the results of our regression analysis, Section 3.4.3 presents our estimations for the future diffusion of PV and EV, and Section 3.4.4 links our future diffusion estimates to the energy system. Finally, Section 3.4.5 presents our sensitivity analysis.

3.4.1 EV and PV diffusion

The current distribution of EV and PV in the Netherlands in the 40 NUTS-3 regions (Figures 3.3a and 3.3b) shows that the two technologies have different spatial adoption patterns. Figures 3.3c and 3.3d show the density of our measures of market size, household rooftops and passenger vehicles. The density for both market sizes is highest in the urbanized areas of the Netherlands, and lower in the rural areas. The density of passenger vehicles is particularly high (1144 vehicles per square kilometre) in the NUTS-3 region agglomeration The Hague, the region with the highest population density.

PV is relatively popular in rural areas, especially in the North-eastern part of the Netherlands, while EV is popular in urbanized areas, especially in the Western part of the Netherlands where the major cities are located. The percentage of household rooftops with PV installations varies between regions from 2.5% to 15%, which means that the diffusion of PV has reached the stage of early adopters, according to Rogers' classification. The

percentage of EVs in the total vehicle fleet varies between regions from 0.29% to 1.7%, which means that the diffusion of EV is still in the innovator phase.

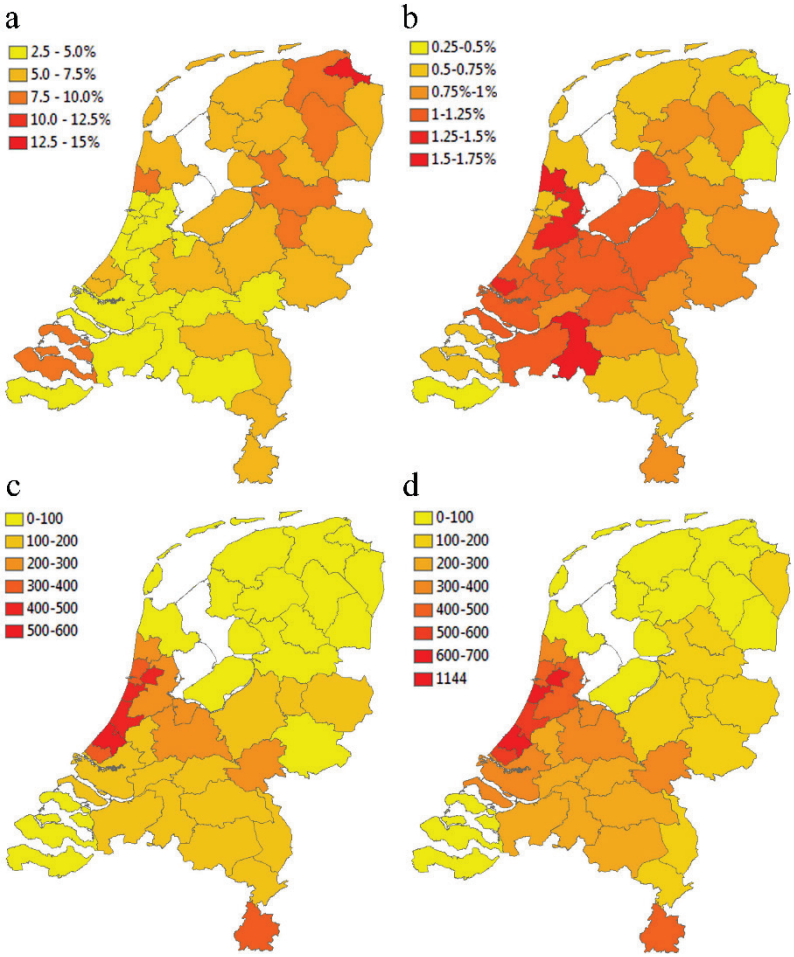


Figure 3.3 Current market share and market size of PV and EV per NUTS-3 area, a) percentage of household rooftops with PV-installations, b) percentage of EVs in total vehicle fleet, c) number of household rooftops per square kilometre, d) number of passenger vehicles per square kilometre. For the whole of the Netherlands, 5.5% of household rooftops have PV solar panels. In total EVs cover 1.5% of the car fleet. We exclude EVs registered in a postal code containing a large lease company in our analysis. The number of EVs not registered in such a postal code cover 0.95% of the total car fleet.

3.4.2 Characterization of PV and EV adopters

This section presents the results from our regression analyses. Table 3.3 presents the coefficient estimates and the diagnostics of our analyses for total PV adoption and total EV adoption in the Netherlands. Based on these results we can establish a general profile of PV

adopters and EV adopters, and in turn compare these characteristics. The explanatory variables used in the models are described in Section 3.3.2. Appendix A contains Tables A.2, A.3, and A.4, which present the summary statistics. We have checked the models with the variance inflation factor, and found that there is no issue with multicollinearity in our models.

Table 3.3 General profile of PV adopters and EV adopters. The table presents the coefficient estimates for the log transform of the total number of PV installations per person and the log transform of the total number of EVs per persons (PC4 areas) for the Netherlands. Standard errors in parentheses, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The results allow the comparison of the characteristics of the PV and EV adopter groups. The data sources of the variables are described in Section 3.3.1, the variables are described in Section 3.3.2.

Variable	**Estimates of coefficients for the log transform of PV installations (pp)**	**Estimates of coefficients for the log transform of EVs (pp)**
(Intercept)	-0.0131 *** (0.0039)	0.00472 (0.00390)
Address density (1000 * km^{-2})	-0.00106 *** (0.00016)	0.00000114 (0.000149)
Age 25-45 (%)	-0.0000699 (0.0000570)	-0.0000168 (0.0000544)
Age 45-65 (%)	0.000231 *** (0.000062)	-0.000180 ** (0.000061)
GroenLinks city council members since 2006 (Y/N)	0.000231 *** (0.000062)	0.00106 ** (0.00039)
GroenLinks voters 2010 (%)	0.000801 *** (0.000094)	-0.000144 (0.000093)
Household income (k Euro)	-0.000514 *** (0.000047)	0.000116 ** (0.000045)
Household rooftops (pp)	-0.00165 (0.00351)	-
Household size (persons)	0.0165 *** (0.0010)	-0.000816 (0.000945)
Lowly educated (%)	-0.000298 *** (0.0000036)	-0.00000259 (0.0000339)
Passenger vehicles (pp)	-	0.0212 *** (0.0036)
Public charge points (pp)	-	1.75 *** (0.24)
Total building footprint (m^2 pp)	0.000503 *** (0.000026)	-
Diagnostics		
Observations	3020	2986
R^2	0.453	0.057
Adjusted R^2	0.450	0.053
F Statistic	248.7 (p-value: 0.000)	17.83 (p-value: 0.000)

PV adopters generally live in areas with low address density, large houses and a middle-aged population with a lower than average income and an overrepresentation of GroenLinks voters. Additionally, a larger household size has a positive effect on PV adoption, whereas a larger share of people with low education levels has a negative effect. The adjusted R-squared is 0.437, comparable to R-squared values found in similar PV diffusion studies (Bollinger & Gillingham, 2012; Graziano & Gillingham, 2015). This profile of PV adopters stands in contrast to EV adopters, who generally live in areas with a large vehicle fleet, a higher than average income, and lower levels of middle-aged residents. Municipal policy plays a part in EV diffusion, as indicated by the positive effects on EV adoption of the build-up of public

charge points and GroenLinks party council members. The adjusted R-squared for this model is lower than for PV (adj. R-squared=0.053). This indicates that EV adopters are a more diverse group than PV adopters, with a higher variation in socio-demographic characteristics.[9]

3.4.3 Estimating future diffusion of PV and EV

Figures 3.4a and 3.4b give the estimated Bass model diffusion curves for EV and PV for each region. The model results indicate that, based on current diffusion, total market saturation (all household rooftops) of PV could already be reached by 2035, while for EV total market saturation (all passenger vehicles) is not reached until 2045. Furthermore, the figures illustrate the large differences in adoption speed for the different regions.

In Figure 3.4a, one line stands out: the orange line with the fastest diffusion rate. This line corresponds to the region of North-eastern Groningen. A possible explanation for the high market share is a specific subsidy scheme for this region. A large gas field is located in North-eastern Groningen, and the region has suffered from earthquakes due to gas drilling. To compensate its inhabitants for damages due to earthquakes, several subsidy schemes are available, including subsidies to have solar panels installed.[10]

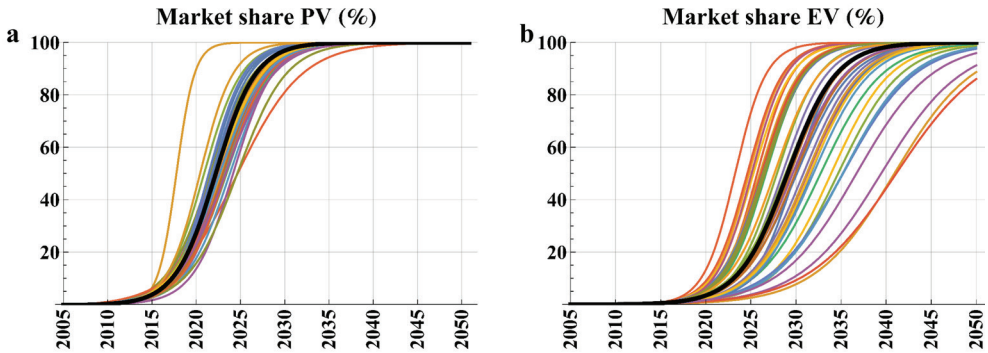


Figure 3.4 Results from the Bass model, a) projections of PV diffusion, and b) projections of EV diffusion. The thick black line gives the diffusion curve for the whole of the Netherlands, while the other lines represent the different NUTS 3-areas. The colour coding is consistent across both figures.

[9] In our robustness analysis, we found one outlier to have an influence on the results for EVs. When taking out this outlier, the significant variables as presented remain significant with the same sign, but low education becomes a positive predictor and household size become a negative predictor. Furthermore, the adjusted r-squared value becomes 0.185, indicating a better fit with the data. Our results for PV are not sensitive to outliers, indicating that as adoption levels increase outliers will have a lesser impact on results.

[10] See https://www.snn.nl/alle-subsidie (in Dutch)

3.4.4 Consequences for the transition to sustainable energy

For each region we modelled and calculated the potential to move to an integrated energy and mobility system where consumers consume locally produced renewable energy. We compare the annual amount of locally produced PV-power to the annual electricity demand of households.

Figures 3.5a and 3.5b provide model results assuming an average nominal power of PV systems of 4 kWp, which is equal to the current average in the Netherlands. Figure 3.5a shows that, when PV market saturation is reached, annual PV power production is 31% of electricity demand of households and EVs. Figure 3.5b indicates that storage in EVs to match supply and demand is pivotal to reach 100% self-consumption. Furthermore, the figures show large differences between regions, especially in the period 2020-2030, since PV adoption speed is then on the steep part of the S-curve. When total market saturation is reached, large differences remain in the potential to meet electricity demand with PV power, due to the number of household rooftops available to install PV solar panels.

Figures 3.5c and 3.5d present the results from the simulations with an average nominal power of PV systems of 12.9 kWp. In this scenario, the annual PV yield is equal to the annual energy demand. The patterns are similar to the patterns shown in figures 3.5a and 3.5b, and clearly demonstrate the potential of V2G technology to increase self-consumption levels.

Figure 3.5e shows the total electricity demand for EV charging as percentage of the total electricity demand. These results hold for both PV diffusion scenarios. The results illustrate the potentially large impact of EV diffusion on electricity demand. When EV diffusion reaches market saturation, EV charging demand could make up almost 40% of total electricity demand nationally, varying between 30% and 53% for the different NUTS-3 regions.

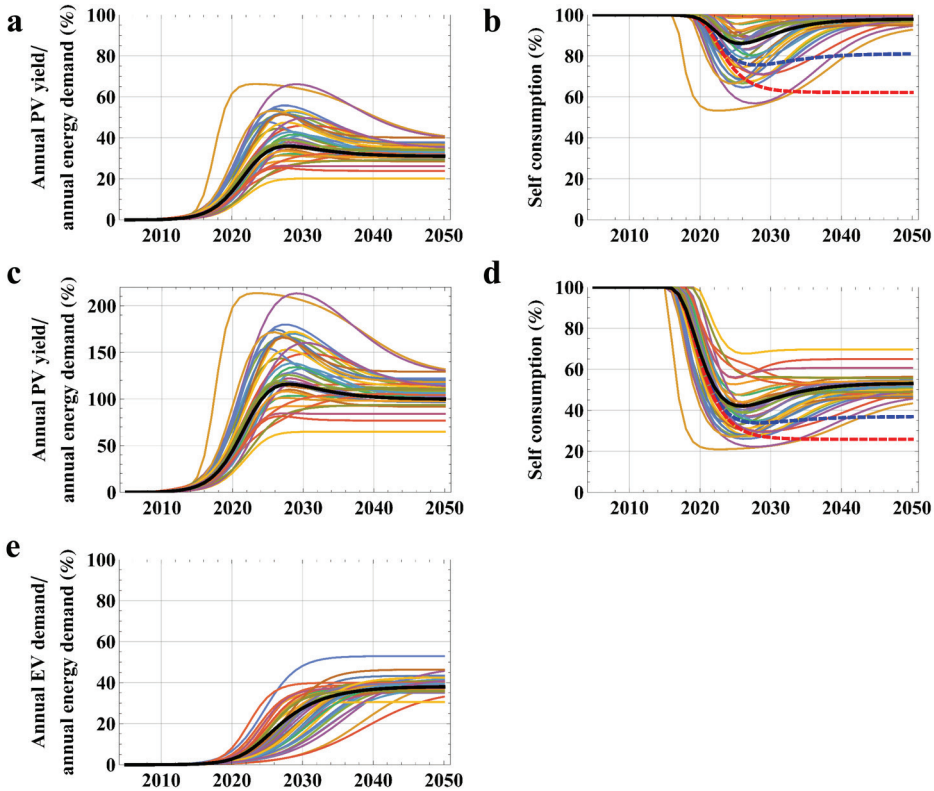


Figure 3.5 Model results for development in PV-power production and development in self-consumption, a) projections of PV-power production/electricity demand with average nominal power of 4 kWp, b) projections of self-consumption with average nominal power of 4 kWp and on average 5 kWh per EV available for V2G services, c) projections of PV-power production/electricity demand with average nominal power of 12.9 kWp, d) projections of self-consumption with average nominal power of 12.9 kWp and on average 5 kWh per EV available for V2G services, e) projections of EV charging demand/electricity demand. The thick black line gives the average for the whole of the Netherlands, while the other lines represent the different NUTS 3-areas. The colour coding is consistent across all figures. In the graphs for self-consumption, the red dashed line represents the level of self-consumption of the Netherlands without EV charging and the blue dashed line represents the level of self-consumption of the Netherlands when no V2G is used.

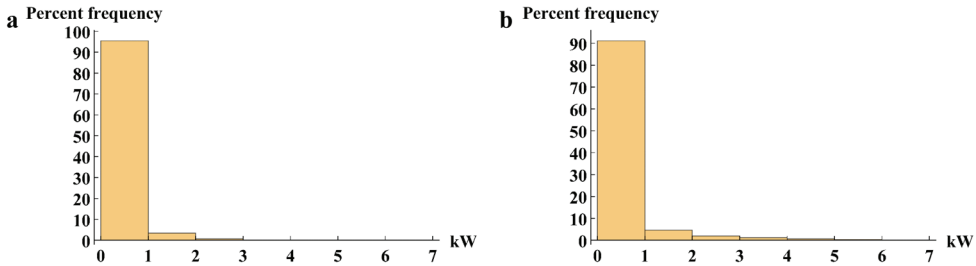


Figure 3.6 Model results for the frequency distribution of average charging power of the EV over the period 2005-2050. For this time period we calculated for each hour the charging power needed for the EVs and for V2G services and divided this by the number of EVs available at a charge point. a) Results for the scenario with average nominal power of 4 kWp and on average 5 kWh per EV available for V2G services, b) Results for the scenario with average nominal power of 12.9 kWp and on average 5 kWh per EV available for V2G services

Figures 3.6a and 3.6b show frequency distributions of the average charging power per EV for each time-step of our simulations. For most charging sessions, which include the charging power needed for load balancing via V2G technology, charging power is below 1 kW. The average charging power never exceeds 7 kW. The charging power available in current EV charge points often exceeds 3 kW indicating that the charging power needed for the EVs in our scenarios should be feasible in practice.

In Figure 3.7, we map our model results on the map of the Netherlands, using the average nominal power of 4 kWp. In some rural regions PV-power production is high, covering up to 70% of household and EV electricity demand. In urban areas in the western part of the Netherlands PV power production remains limited, especially in the area of Greater Amsterdam, where production levels exceed 30% of demand only after 2025. Because PV-power production is relatively low, the demand for load balancing is low, and small EV-fleets can suffice to reach high amounts of regional self-consumption. However, in regions in the where EV-fleets, such as North-East and the South, are small self-consumption levels are low.

In Figure 3.8, we map our model results, using the average nominal power of 12.9 kWp. The issue arising from PV and EV diffusion is clear from these maps. In the Western and Eastern regions PV and EV diffusion is such that high self-consumption can be achieved. However, even with an average nominal power of 12.9 kWp the total PV-power in these regions is too low to cover household and EV demand. In contrast, in the South and North there is excess PV-power. Combined with a lack of EVs for load balancing, self-consumption is low in these regions. Furthermore, the lag of EV diffusion compared to PV diffusion is clear in the maps; regional self-consumption is lowest in 2025, while in 2050 it is higher again.

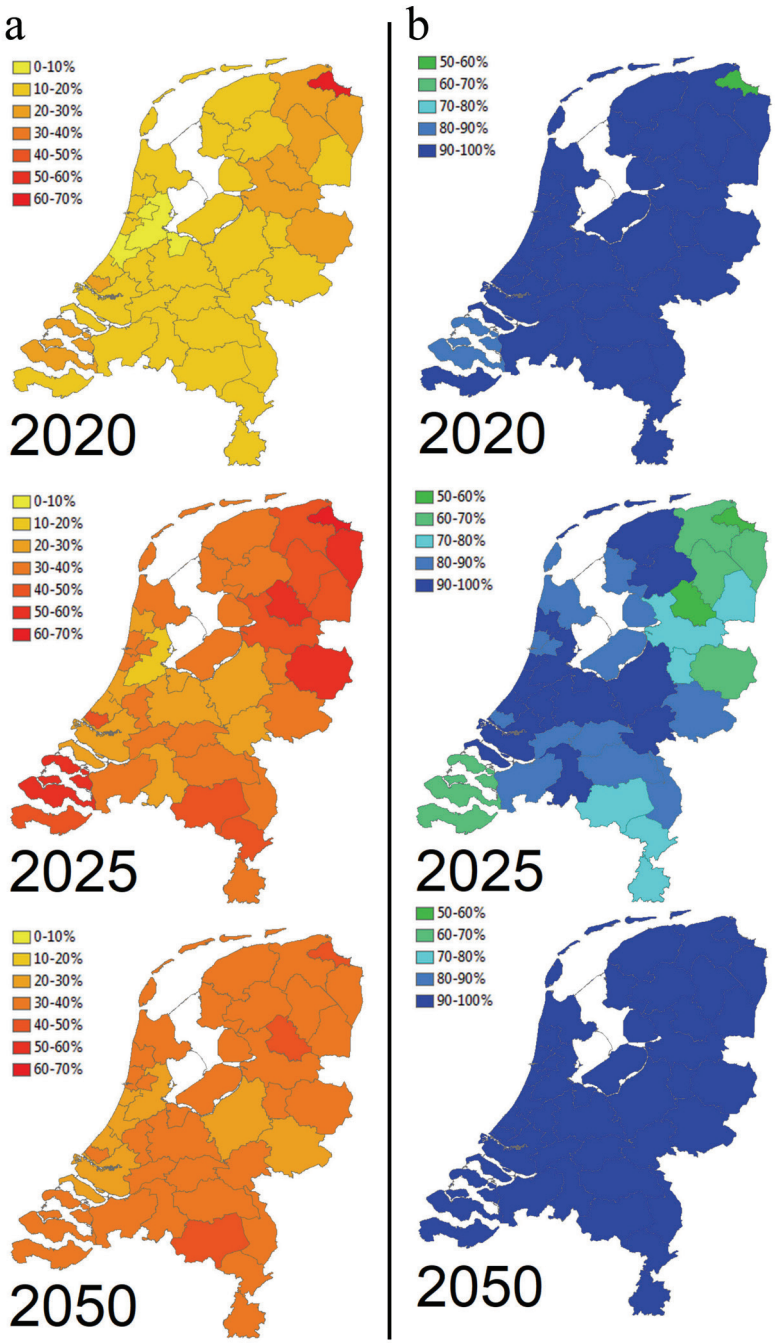


Figure 3.7 Map of model results for 2020, 2025 and 2050, a) PV-power production / household electricity demand, b) self-consumption of households. We assume an average nominal power of PV systems of 4 kWp and an average battery capacity of 5 kWh per EV available for V2G

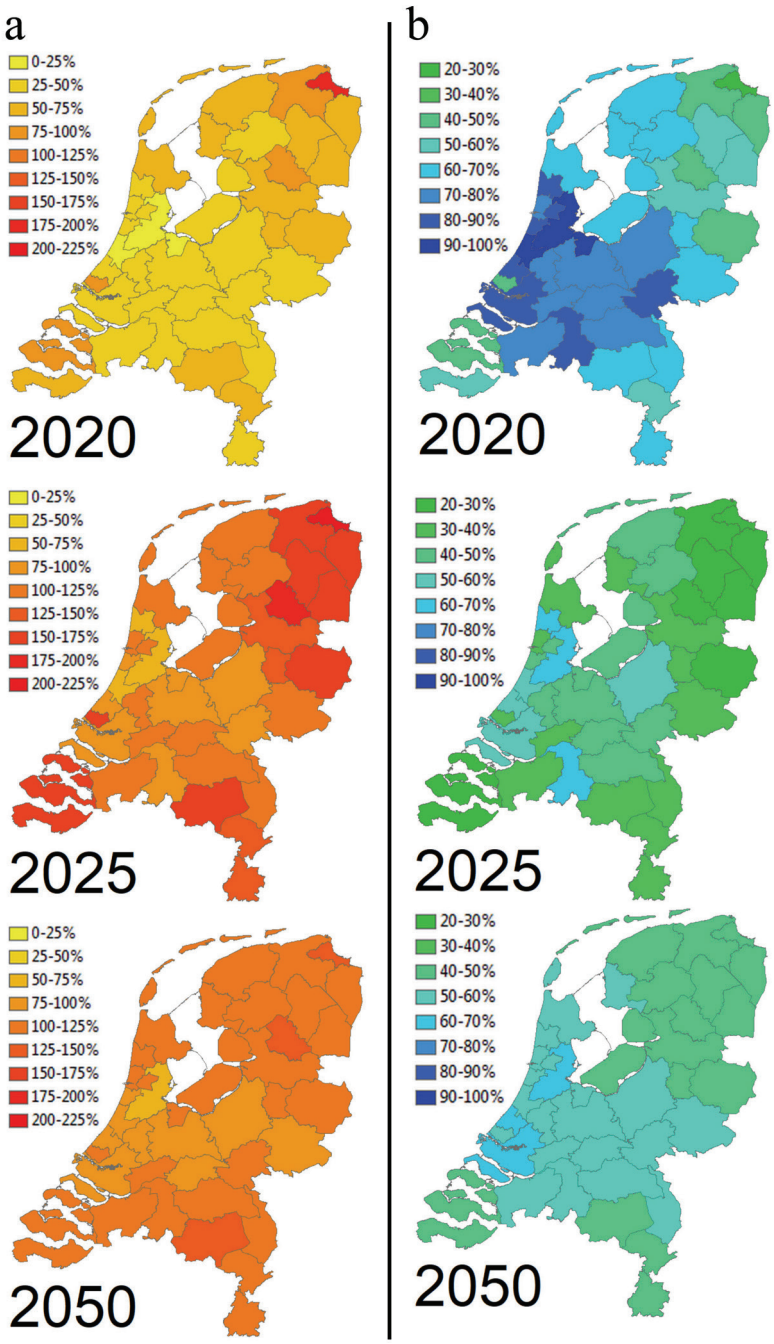


Figure 3.8 Map of model results for 2020, 2025 and 2050, a) PV-power production / household electricity demand, b) self-consumption of households. We assume an average nominal power of PV systems of 12.9 kWp and an average battery capacity of 5 kWh per EV available for V2G

3.4.5 Sensitivity analysis

This section presents a sensitivity analysis for the national average PV self-consumption, our main indicator. The relation of variables such as market size, average nominal PV power and EV storage size with annual PV yield and EV charging demand is linear. However, in the calculation for PV self-consumption all these factors interact non-linearly.

Figure 3.9 presents our results for variation of PV market size and EV market size for both our scenarios. Figure 3.10 shows our results for variation of the average nominal power of PV systems and available EV battery capacity for V2G services assuming 100% market share. The key message arising from these results is that with current average nominal power of PV systems, issues with regional PV self-consumption arise with high market penetration, while low market penetration of EVs is sufficient to solve these issues. However, with high nominal power of PV systems PV self-consumption might become a problem early in the diffusion process, and large EV fleets can be key to address this issue.

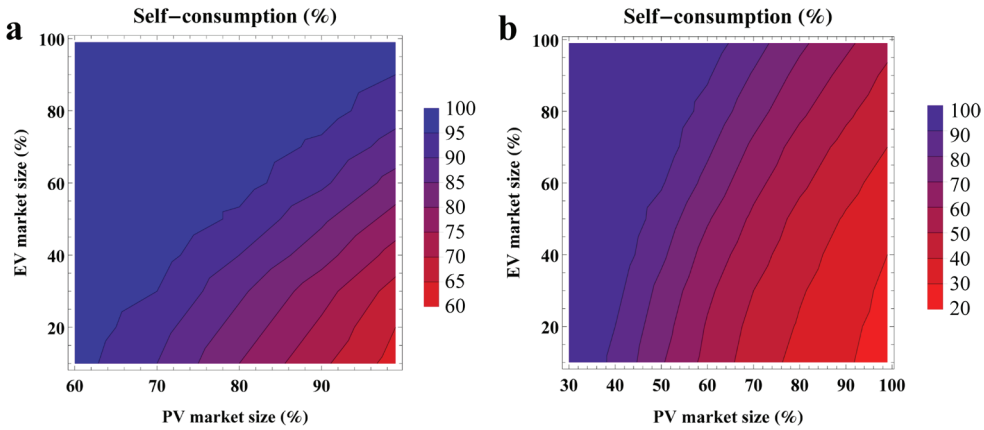


Figure 3.9 Contour plots of the results from the sensitivity analysis on the effect of PV market size and EV market size on self-consumption. PV market size is measured as percentage of total household rooftops, and EV market size is measured as percentage of total passenger vehicles. a) Results for the scenario with average nominal power of 4 kWp and on average 5 kWh per EV available for V2G services, b) Results for the scenario with average nominal power of 12.9 kWp and on average 5 kWh per EV available for V2G services

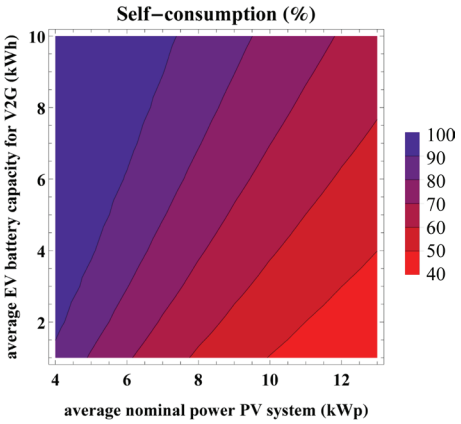


Figure 3.10 Contour plot of the results from the sensitivity analysis on the effect of average nominal power of PV systems market size and average EV battery capacity available for V2G services. For this analysis we assume that 100% of household rooftops have PV installed and 100% of passenger vehicles are EVs

Finally, Tables 3.4 and 3.5 show our results for varying PV orientation. We ran simulations with all PV panels directed south, east and west. Additionally, we ran one "mixed" scenario with one third of the PV panels directed south, one third directed east and one third directed west.

In our scenario with average nominal PV power of 4 kWp, the levels of self-consumption do not differ much amongst these scenarios. However, the PV yield does, and varies between 80-87% of the optimal scenario of all panels directed south. In this case, having all panels directed south is the most attractive scenario. However, when average nominal power increases, a trade-off of annual PV yield and PV self-consumption will arise, as shown by the results in Table 3.5. The hourly PV production profile of panels directed east or west is better aligned with household demand and EV charging and availability profiles than the hourly PV production profiles of PV panels directed south. In these scenarios, annual self-consumed PV power is higher than the scenario with all panels directed south. These results indicate that as average nominal power of PV panels increases, having PV panels of mixed orientation can have large benefits for a grid manager.

Table 3.4 Results from the sensitivity analysis on the effect of PV orientation on national PV self-consumption and annual PV yield, and the product of these factors the annual self-consumed PV yield. In the mixed orientation one third of the PV panels is directed south, one third is directed east and one third is directed west. We assume an average nominal power of 4 kWp and on average 5 kWh per EV available for V2G services. Furthermore, we assume that 100% of household rooftops have PV installed and 100% of passenger vehicles are EVs.

Orientation	Self-consumption (%)	Annual PV yield (TWh)	Annual self-consumed PV yield (TWh)
South	98.1	17.6	17.2
East	99.6	14.1	14.1
West	99.8	14.3	14.3
Mixed	99.7	15.3	15.3

Table 3.5 Results from the sensitivity analysis on the effect of PV orientation on national PV self-consumption and annual PV yield, and the product of these factors the annual self-consumed PV yield. In the mixed orientation one third of the PV panels is directed south, one third is directed east and one third is directed west. We assume an average nominal power of 12.9 kWp and on average 5 kWh per EV available for V2G services. Furthermore, we assume that 100% of household rooftops have PV installed and 100% of passenger vehicles are EVs.

Orientation	Self-consumption (%)	Annual PV yield (TWh)	Annual self-consumed PV yield (TWh)
South	52.9	56.7	30.0
East	75.7	45.5	34.4
West	76.6	46.2	35.3
Mixed	70.6	49.5	34.9

3.5 Discussion

We have analysed the diffusion of PV and EV in The Netherlands. Stark differences are observed between the spatial patterns of EV and PV diffusion. The main contribution of this study is the establishment of the geographical misfit between EV and PV diffusion and the implications this has for the transition to smart energy systems. We provide further evidence for the claim that space matters in energy transitions (Hansen & Coenen, 2015) and investigate the viability of V2G systems for different regions in the Netherlands.

Differences in diffusion patterns can be partially explained by differences in socio-demographic characteristics of the adopter groups. Several of the key predictor variables for PV adoption, such as household size, education level, age and address density have been identified before as important predictors (Davidson et al., 2014; Dharshing, 2017; Graziano & Gillingham, 2015; Kwan, 2012). We found the average income in a neighbourhood to be a negative predictor of PV adoption levels, which is consistent with some studies (Bollinger & Gillingham, 2012; Islam & Meade, 2013; Schaffer & Brun, 2015; Simpson & Clifton, 2017), but opposite to others (Dharshing, 2017; Kwan, 2012; Müller & Rode, 2013; Vasseur & Kemp, 2015). Furthermore, we found that neighbourhoods with a high amount of GroenLinks voters to have high PV adoption levels, further indicating that environmental awareness plays a role in PV adoption (Balcombe et al., 2013; Dharshing, 2017; Schaffer & Brun, 2015; Sommerfeld, Buys, & Vine, 2017).

We have identified the passenger vehicles per person, municipal policy, household income, and age as significant predictors for EV adoption. Passenger vehicles is a positive predictor, which could be due to EVs being popular or more acceptable as second car, as found in previous studies (Haugneland & Kvisle, 2015; Ramjerdi & Rand, 1999; Skippon & Garwood, 2011; Van Haaren, 2012).

There are also some notable differences with earlier literature. Age has not been identified before as a strong predictor, while our model did not show significant results for address density, household size and education level, which were found to be important in earlier studies (Coffman et al., 2017; Eising et al., 2014; Saarenpää et al., 2013). Furthermore, our

model explains less of the variation in EV adoption levels than in PV adoption levels, indicating that EV adopters are a more diverse group than PV adopters. These results stand in contrast with the results of Rai et al. (2016), who found PV adopters to be likely to consider purchasing a plug-in vehicle. Though there is some consistency among the literature on socio-demographic variables predicting PV and EV adoption, the discrepancies between studies seem to suggest differences among countries, indicating the importance of local circumstances in adoption of clean energy technologies.

We show to what extent users may contribute to a transition towards a smart grid based on de-centralized renewables by extrapolating initial diffusion data via the Bass model of diffusion. A main issue we have identified is the large variation of PV diffusion for different regions of the Netherlands. The regional variation not only lies in the rate of diffusion but also in potential for the households to install PV-systems on their rooftops. EVs have a large potential to increase regional self-consumption of PV power via V2G technology. However, the number of EVs might not be sufficient to achieve high levels of self-consumption, especially for some regions with both high PV adoption and low EV adoption. Furthermore, EV diffusion clearly lags behind PV diffusion. Our scenarios demonstrate that, while V2G systems have clear benefits, PV and EV are not "in sync". Not only do the supply and demand patterns differ, also different regional diffusion pattern affect the viability of such systems. Our results indicate that different grid architectures are suitable for different types of regions: while in urban regions micro-grids may be efficient, it might be necessary to strengthen grid connections between rural areas to areas where electricity demand is high. Therefore, it is pivotal to take regional adoption into account when constructing energy scenarios.

We have run scenarios with the current average nominal power of PV systems and with the average nominal power needed to cover 100% of electricity demand on an annual basis. For both scenarios it seems likely that non-distributed generation facilities will continue to play a role in the energy production. In the first scenario, annual PV yield only covers around 30% of total electricity demand. In our second scenario, PV self-consumption levels become so low that it seems unlikely to be easily solved, either by V2G services or other types of solutions.

We use several simplifying assumptions to calculate coverage of electricity demand by PV yield and self-consumption, e.g. household energy demand stays constant, the nominal power of PV-systems remains the same, and EVs have 5 kWh of storage available. These parameters can easily be adapted when more data becomes available. We have performed a sensitivity analysis for several of the most uncertain factors in our model. The results from this analysis showed that with current average nominal power of PV systems PV-self consumption will become an issue only with high PV adoption levels, and could potentially be solved easily with relatively small EV-fleets. However, when PV yield per PV installation increases issues with PV self-consumption will arise much earlier in the diffusion process, and large EV-fleets will be needed for load balancing. Such issues could be partially solved by having PV

solar panels with more eastward or more westward orientations, since the hourly production profile of panels with such orientations is better aligned with hourly residential demand, EV charging, and EV availability profiles.

Our work explores the dynamics of the energy transition in the Netherlands, but we do not claim to make accurate predictions of the diffusion processes. The assumptions we base our model on, such as total market sizes for PV and EV and availability of EVs for V2G-services, are optimistic with respect to the potential of PV power production and self-consumption. Our scenarios should therefore be interpreted as optimistic as well. Since the diffusion of both PV and EV is still in an early phase, we claim that our model results are rather useful explorations of future diffusion, but are unsuitable for accurate market size prediction, since energy technologies may have different lengths of take-off phases (Bento & Wilson, 2016). Furthermore, we do not take into account possible issues that may arise like grid access costs, uncertainty about battery durability and high amounts of waste or second-life batteries. Our study assumes that households can only use PV technology for energy production and only do load balancing with V2G technology. We thus ignore competition with other technologies in electricity or mobility, which may hinder PV and EV diffusion.

The Bass model as employed in this study has been criticised for not taking into account the systemic nature of the diffusion of clean energy technologies (Dijk et al., 2013; Kiesling et al., 2012). These authors argue to use more complex diffusion models such as agent-based models for scenario building. Though we recognize these criticisms, we chose to use the Bass model, because a) its validity is widely tested, and the diffusion theory it rests on has also proven useful for clean energy technology diffusion (Geels & Johnson, 2018; Guidolin & Mortarino, 2010; Hansen, Narbel, & Aksnes, 2017; Lund, 2006), and b) we focus on adoption and scenarios on a regional level for an entire country. The Bass model is suitable for application on micro-level diffusion data of all PV and EV in the entire country. Micro-level data on parameters included in more complex models, such as attitudes towards a technology, would entail a different survey-based research design. Gathering such data for all regions of a country would require a very large survey, making such models difficult to apply to an entire country. For future research on sub-country level, it would be worthwhile to explore the application of complex diffusion models, when more data becomes available.

A second limitation of our approach of taking into account all PV and EV adoption in a whole country is that we use data from neighbourhoods for identifying adopter characteristics. This means that we should carefully interpret the results because of the "ecological fallacy" (Robinson, 1950): relationships found on the group level not necessarily transfer to the level of individuals in these groups. Indeed, a recent paper uses data with a lower level of aggregation to clarify the negative correlation between income and PV adoption as found in this chapter as well as in other studies (Tidemann, Engerer, Markham, Doran, & Pezzey, 2019). The authors use socioeconomic data from Australia of mesh

blocks[11] with a mean population of 57, much lower than the mean population of 4160 of PC4-areas in the Netherlands, to link PV adoption a broad socioeconomic index that includes variables such as employment, mortgage payments, number of bedrooms number of occupants, and motor vehicle ownership. The results show that the correlation of socioeconomic status and PV adoption is negative at postal code level, but positive mesh block level. While we do not know whether these results will translate to the Dutch case, they underline the importance of interpreting the results of our regression at the neighbourhood level, and not the individual level.

Based on our findings we can articulate some policy recommendations. Grid operators could prepare for these regional differences by exploring solutions other than V2G for grid balancing. To stimulate PV and EV diffusion in regions where diffusion has been slow, policies could be aimed at consumer groups currently underrepresented in one of the adopter groups, to ensure that the diffusion does continue beyond innovators and early adopters. Results from our regression analysis show that EV adoption is positively correlated with our proxies for progressive EV policies implemented a municipal level. While this does not prove that municipal policy drives EV diffusion, it does mean that that could be the case. Municipalities that want to stimulate EV adoption can take advantage of this insight by implementing policies aiming to stimulate further diffusion, of which the results should in turn be evaluated to further clarify the link between local policy and adoption. Such policies could for instance be targeted at middle-aged people, who are underrepresented in the group of EV-adopters.

When diffusion increases and more adoption data becomes available, the accuracy of our model results will increase. The model can be applied to other regions and other distributed generation or storage technologies as long as sufficient data is available. An interesting future technology to include could be PV system batteries, since these could further increase PV self-consumption in areas or time-frames in which V2G systems are insufficient to achieve high levels of PV self-consumption.

3.6 Conclusion

We have performed a study in which we focus on how consumer adoption of PV solar panels and electric vehicles (EV) may influence the transition towards smart sustainable grids. Based on historical diffusion data of PV and EV in the Netherlands, we have characterized the adopter groups of these technologies and build scenarios for future diffusion. Furthermore, we investigate how the joint deployment of these technologies may impact the

[11] Mesh block is a geographical unit used in the Australia and New Zealand censuses

local energy system and assess the viability of the integration of PV and EV in vehicle-to-grid systems. We find large differences in the spatial diffusion patterns of PV and EV using 40 regions in the Netherlands, which will have impact on the viability of vehicle-to-grid systems. Despite limitations inevitable in scenario studies, we demonstrate that taking spatial diffusion patterns into account is important in energy planning and give an example of how integrating socio-economic models and diffusion data contribute to energy systems modelling.

Chapter 4

An agent-based model of sustainable charging

Abstract

The combination of electric vehicles (EVs) and intermittent renewable energy sources has received increasing attention over the last few years. Not only does charging electric vehicles with renewable energy realize their true potential as a clean mode of transport, charging electric vehicles at times of peaks in renewable energy production can help large scale integration of renewable energy in the existing energy infrastructure. We present an agent-based model that investigates the potential contribution of this combination. More specifically, we investigate the potential effects of different kinds of policy interventions on aggregate EV charging patterns. The policy interventions include financial incentives, automated smart charging, information campaigns and social charging. We investigate how well the resulting charging patterns are aligned with renewable energy production and how much they affect user satisfaction of EV drivers. Where possible, we integrate empirical data in our model, to ensure realistic scenarios. We use recent theory from environmental psychology to determine agent behaviour, contrary to earlier simulation models, which have focused only on technical and financial considerations. Based on our simulation results, we articulate some policy recommendations. Furthermore, we point to future research directions for environmental psychology scholars and modellers who want to use theory to inform simulation models of energy systems.

4.1 Introduction

The recent rise in electric vehicle (EV) adoption is generally seen as positive, as EVs potentially provide a cleaner alternative to traditional vehicles. Yet for EVs to realize this potential, individual consumers do not only need to adopt EVs, they also need to use the technologies and infrastructure in a sustainable way (Steg, 2016). EVs are a clean mode of transport when charged with energy from renewable sources, such as wind energy and photovoltaic (PV) solar energy. Furthermore, EVs could contribute to the integration of intermittent renewable energy sources into the grid; as a source of flexible demand or as storage in vehicle-to-grid (V2G) systems (Van der Kam, Meelen, Van Sark, & Alkemade, 2018). However, charging large EV-fleets poses challenges to the electricity grid, since both total and instantaneous peak demand might increase significantly, possibly leading to severe local congestion at transformer stations (Eising et al., 2014) and higher electricity market prices (Ensslen et al., 2018b). Currently, EVs are typically charged in the early evening, when electricity demand of households is high and renewable energy production is low (E-Laad, 2013). EV users should thus be encouraged to act in a more sustainable way, by actively or passively shifting charging demand or to take part in smart charging or vehicle-to-grid schemes operated by parties such as aggregators.

There are several types of interventions to encourage people to act in a more sustainable way (Steg, 2016) (e.g. charging their EV's at times of surplus of sustainable energy) including different policy instruments, for instance regulations, financial incentives or information campaigns. Other factors influencing sustainable EV charging include the driving needs of EV drivers, the available charging infrastructure, renewable energy capacity, and other sources of energy demand, such as households. In the present study, we capture the influence of different policy instruments on sustainable EV charging with an agent-based model (ABM). Such models are useful tools for investigating strategies stimulating behavioural change, as they allow systematic explorations of changes in social systems over long time periods, which would be costly and impractical to test in real life. Furthermore, the flexible architecture of ABMs allows the incorporation of empirical data, where available, leading to more realistic scenarios.

Given the complexity of many energy systems, it is not surprising that ABMs are an increasingly popular tool among energy scholars. Typical topics of ABMs are energy transitions (Holtz et al., 2015; Köhler et al., 2018; F. G. N. Li, Trutnevyte, & Strachan, 2015), energy demand (Gotts & Polhill, 2017; Jensen, Holtz, & Chappin, 2015), and diffusion of innovations, e.g. of electric vehicles (Dijk et al., 2013; Eppstein et al., 2011; Kangur et al., 2017; McCoy & Lyons, 2014; Mueller & de Haan, 2009; Noori & Tatari, 2016; Shafiei et al., 2012; Zhang et al., 2011), PV solar panels (Opiyo, 2015; Palmer et al., 2015; Robinson & Rai, 2015), green electricity contracts (Krebs, 2017), and smart meters (Zhang, Siebers, & Aickelin, 2016). Most ABMs in the field of energy are focused on *ex ante* policy evaluation (Rai & Henry, 2016). Recognizing the many uncertainties of future energy systems,

exploring scenarios through ABMs can provide insight in the potential effect of policies, thereby supporting the identification of robust policies for the energy transition (Holtz et al., 2015).

Several ABMs have been proposed to study the future of electric vehicle charging. Mallig, Heilig, Weiss, Chlond, & Vortisch (2016) model EV ownership and electricity demand in the Greater Stuttgart area, for three scenarios with different market penetration and charging opportunities. Agents are household members, and only the agents with travel ranges suitable for EVs, own an EV. All agents charge at home or, when possible, at the workplace or shopping area, and are not subject to a specific charging strategy. Study results indicate that EV charging peaks occur in the evening, at times when no surplus of renewable energy can be expected. This indicates a need for intelligent charging strategies, which shift the charging of EVs to times when a surplus of renewable energy is available. Olivella-rosell et al. (2015) propose a probabilistic agent-based model of electric vehicle charging demand to analyse the impact on distribution networks in Barcelona. Agents can charge at trip destinations and base their charging behaviour on range anxiety and energy price. The electricity market and aggregator are also represented as an agent. It is concluded that direct or indirect control of EV charging can reduce the negative impact of EVs on the grid. Waraich et al. (2013) use an agent-based traffic demand model to model electricity demand of EVs. They build on the existing model MATSim (MATSIM-T, 2008), which is a large scale agent-based traffic model, with four hubs, and includes roads and traffic jams. Several charging schemes are simulated; *dumb charging*, *dual tariff charging* and *smart charging*. In the dual tariff charging scheme, agents determine their charging behaviour based on the electricity price. In the smart charging scheme, a central utility controls the charging behaviour. The model determines whether EV charging and other loads violate physical network conditions. They conclude that smart charging schemes including communication between EVs and the grid can overcome grid issues that arise from dual tariff charging schemes.

The discussed simulation models let user behaviour be determined by driving needs and costs. Although financial (e.g. costs and benefits) or hedonic (e.g. pleasure and comfort) considerations affect the likelihood to engage in pro-environmental behaviour, normative considerations (e.g. the right thing to do) also are an important factor promoting pro-environmental behaviour. More specifically, a growing body of research shows that individuals are not rational decision makers who carefully balance costs and benefits to maximise the utility of their behaviour, and that normative considerations are important predictors for pro-environmental behaviour in general (Lindenberg & Steg, 2007; Steg, 2016; Steg, Bolderdijk, Keizer, & Perlaviciute, 2014; Steg et al., 2015). Research suggests that normative considerations may in some cases even be a more important predictor of pro-environmental behaviour than financial incentives (Kobus, Mugge, & Schoormans, 2013; Schmalfuß et al., 2015). Moreover, the effect of financial incentives may decrease when the incentive is no longer in place (Bolderdijk, Knockaert, Steg, & Verhoef, 2011). Hence,

simulation models of EV charging rely too much on cost and benefit assumptions, ignoring important psychological drivers of behaviour (Sovacool et al., 2015).

We incorporate recent theory from environmental psychology on the concept of environmental self-identity in the modelling of EV charging to address these normative considerations. Environmental self-identity is the extent to which one sees oneself as an environmentally friendly person, and has been found to promote different pro-environmental behaviours (Van der Werff, Steg, & Keizer 2013a, 2014a, 2014b), including sustainable charging (Peters et al., 2018). Furthermore, we incorporate range anxiety, that is the anxiety about the loss of flexibility in individual mobility, as research has shown that this is an important factor influencing the acceptance of sustainable charging behaviour (Franke & Krems, 2013b; Will & Schuller, 2016). Especially the more unexperienced EV-drivers do not estimate their range needs accurately, resulting in range anxiety (Franke & Krems, 2013b). Note that range anxiety is not a normative consideration, but a hedonic one.

Our ABM consists of EV drivers, charge points, renewable energy supply, and the built environment. EV drivers decide where and when to charge their vehicle, depending on driving needs, agent characteristics and policy interventions. We mainly use data sources from the Netherlands, a front-runner country in EV deployment. The Netherlands had the third most EV sales within the EU in 2018, after Germany and France (ACEA, 2018b), and the Dutch government has the ambition that by 2030 all new vehicles sold in the Netherlands are zero-emission vehicles (VVD et al., 2017). Furthermore, several on-going projects experimenting with and develop smart charging of EVs and V2G.[12] This makes the Netherlands an excellent case for studying the transition towards the integration of clean transport and renewable energy.

The purpose of this chapter is to present a proof-of-principle ABM, demonstrating the viability of our approach in modelling EV charging demand. In particular, our aim is to demonstrate how ABMs can be used for a systematic comparison of potential policy interventions that target sustainable charging of consumers. Contrary to earlier ABMs focussing exclusively on financial incentives, we include a model incorporating important psychological drivers of behaviour, such as environmental self-identity and range anxiety. In order to ensure realistic scenarios, our model is based on empirical data as much as possible. However, some psychological variables in our model are difficult to parameterize. We explore the importance of these uncertainties with model exploration techniques (Kwakkel & Pruyt, 2013). We evaluate agent behaviour on the system level by using energy demand and supply, and user satisfaction as indicators.

This chapter is further organised as follows: we first describe the model used in more detail, then present several simulation runs and end with a discussion of our model and simulation results.

[12] For an overview of projects, see https://www.livinglabsmartcharging.nl/en/

4.2 Model description

This section describes our model. We first present an overview and then discuss the separate elements in depth. The model is implemented in NetLogo (Wilensky, 1999), and the code is available online (Van der Kam, Peters, Van Sark, & Alkemade, 2019b). The online version of our model contains a model description following the ODD (Overview, Design, Details) protocol (Grimm et al., 2010).

4.2.1 Model overview

Figure 4.1 presents an overview of our model. Agents represent EV drivers that either move, charge, or do nothing. The agents move towards and over grid cells, which have a function (residential, commercial, office or none). At some grid cells agents can charge their EV. Included in their environment are local sources of energy demand and energy supply, and policy interventions targeting charging behaviour. These factors influence how the agents charge. We measure model output using the indicators (1) self-sufficiency, (2) self-consumption, (3) peak net demand, (4) peak oversupply, and (5) kms – electric. The first four are related to the balance of energy demand (of the buildings and EVs) and supply (of local intermittent energy sources). The last indicator is related to whether the EVs are charged sufficiently to meet driving demands and thus to user satisfaction.

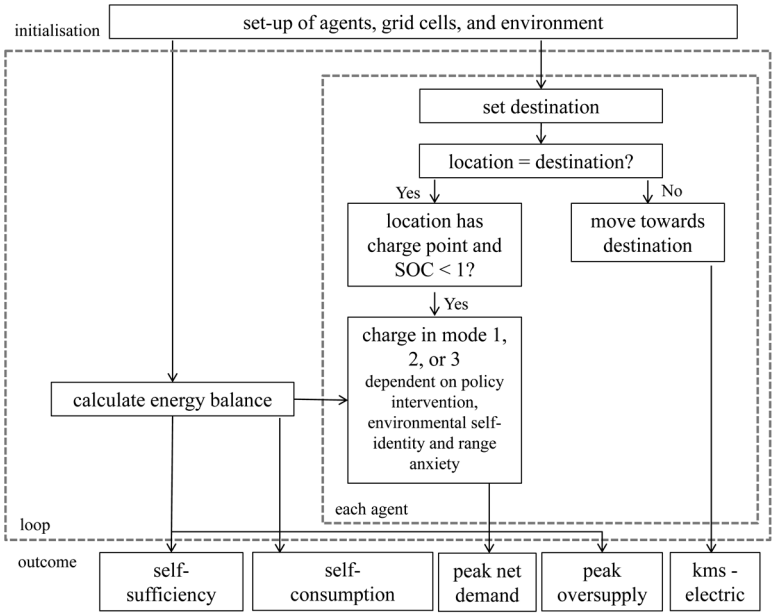


Figure 4.1 Overview of the model

Sources of electricity demand in the model are the households of the agents and the service sector (offices, shops, hospitals, schools, etc.) scaled to the number of agents using Dutch statistics. Sources of electricity supply are PV solar energy and wind energy. At each time-step, the energy balance between the total electricity demand of the residential and service sector and the total electricity supply from renewable energy sources is calculated. The agents either drive towards a destination or stay at their location. If the agents are not moving, they can charge their EV if a charge point is available. The agents can charge their vehicle in three different modes. We distinguish these modes by how much renewable energy is used to charge the EVs. The three modes are:

- **Mode 1:** the EV always charges at maximum capacity (until the battery is full)
- **Mode 2:** the EV always charges at maximum capacity until the battery level is at a specific minimum level chosen by the agent, and only charges additionally in times of renewable energy surplus
- **Mode 3:** the EV only charges at times of renewable energy surplus.

Mode 1 is considered the least sustainable charging mode, and mode 3 the most sustainable charging mode. The modes available to agents depends on the policy in place. Table 4.1 shows which modes are available for the different policy interventions. In what follows, we discuss each policy intervention and how this is operationalized in our ABM.

Table 4.1 Charging modes available for different policy interventions

Policy intervention	Possible charging modes
No intervention	Mode 1
Dual tariff scheme	Mode 2
Automated smart charging	Mode 3
Information and feedback	Mode 1, 2, or 3 (depending on environmental self-identity and range anxiety)

Under the policy intervention *information and feedback*, the mode that the agent chooses to charge in is dependent on the numerical difference between its environmental self-identity and its range anxiety. A high value for environmental self-identity leads to an agent charging more sustainable, while a high value for range anxiety leads the agent to charge less sustainable.

In our implementation of the model, we use discrete time-steps, with one time-step representing five minutes. Each grid cell represents 2 km x 2 km and the model landscape comprised 66 km x 66 km, i.e. 4356 square km^2.

Tables 4.2-4.4 present the state variables for the agents, grid cells and environment respectively.

Table 4.2 State variables of agents

Name	Description	Domain	Static?
Location	Location of agent	Coordinates	N
Vehicle model	Specific EV model, this determines battery size	EV models in NL	Y
Home	Grid cell where the agents' home is located	Coordinates	Y
Home-charge?	Whether an agent can charge at home	{true, false}	Y
Destination	Destination of trip (can also be current location of agent)	Coordinates	N
Next-trip	Time when agent will start its next trip (and change destination)	minutes	N
SOC	State-of-charge of the battery in the EV	[0;1]	N
Charging?	Whether the agent is charging	{true, false}	N
Environmental self-identity	Score for environmental self-identity	[-1;1]	N
ω_{ESI}	Weighing factor for environmental self-identity	[0;1]	N
Inc_{ESI}	Increment in environmental self-identity	[0;1]	N
Dec_{ESI}	Decrement in environmental self-identity	[0;1]	N
Range anxiety	Score for range anxiety	[0;1]	N
ω_{RA}	Weighing factor for range anxiety	[0;1]	N
Inc_{RA}	Increment in range anxiety	[0;1]	N
Dec_{RA}	Decrement in decreasing range anxiety	[0;1]	N

Table 4.3 State variables of grid cells

Name	Description	Domain	Static?
Location	Location of the grid cell	Coordinates	Y
Function	The function of the grid cell	{residential, commercial, office, none}	Y
Charging-point?	Whether an EV can be charged at this cell	{true, false}	Y
Charging-power	Maximum charging power of charge point at this point	kW	N
Available?	Whether a charging-point is available (not occupied or reserved by an agent)	{true, false}	N

Table 4.4 State variables of the environment

Name	Description	Domain	Static?
Time	Time of the year	minutes	N
PV capacity	Total installed PV capacity in the model	MWp	Y
PV production	Real-time power supply from PV	kW	N
Wind capacity	Total installed wind energy capacity	MW	Y
Wind production	Real-time power supply from wind turbines	kW	N
Energy demand residential	Real-time power demand of residential buildings	kW	N
Energy demand service sector	Real-time power demand of service sector	kW	N
Policy intervention	Which policy intervention, aimed at increasing use of renewable energy for EV charging, is implemented	{No intervention, dual tariff scheme, automated smart charging, information and feedback}	Y
Unlimited-charging?	Whether every destination has an available charge point	{true, false}	Y
Social-charging?	Whether agents move their EV away from a public or semi-public charge point if battery is full	{true, false}	Y
Central control?	Whether there is a central control system (relevant for the policy intervention *automated smart charging*)	{true, false}	Y

4.2.2 EV fleet

The EV fleets in the model are based on the current EV fleet in the Netherlands, using data from the Netherlands Vehicle Authority (RDW, in Dutch: Rijksdienst voor het Wegverkeer). Agents are randomly assigned an EV from this dataset. We chose to only use FEVs in our model, and not plug-in hybrid electric vehicles (PHEVs). We think modelling FEVs is more interesting than PHEVs because they have a larger battery capacity than PHEVs and can therefore have a larger impact on the grid. Furthermore, FEVs are dependent on charging infrastructure, unlike PHEVs, and its drivers will therefore more likely experience range anxiety than PHEV drivers. The relevant characteristic is the battery capacity of the EV. As an alternative, the model allows for a manual input of battery size, which is then the same for all agents. The number of EVs is a variable in our model. In the simulations, the total EV fleet consists of 500 vehicles. As long as the vehicle fleet is not very small (e.g. <50 vehicles), our final results are not sensitive for the number of EVs, since in our model energy demand and charging infrastructure scale with the number of EVs.

To determine the speed of the EVs we use data from a large, annually recurring study into Dutch mobility, "Onderzoek Verplaatsingen in Nederland (OViN) 2016". The average speed found in the OViN database is 19 km per hour, so at each time-step an EV can move 0.8 patch.

4.2.3 Layout of area

In our model, the world consists of a residential area, an office area and a commercial area. Figure 4.2 shows a screenshot of the area as implemented in NetLogo (Wilensky, 1999). The layout of the area is based on design by the modellers. The residential area, commercial area and office area are fixed for each simulation. However, the exact location of both houses and charge points is determined randomly, and varies for each simulation. In order to determine the distance between patches, we compared the average annual distance driven by agents in the model to the average annual distance driven by passenger vehicles in the Netherlands in 2016 (CBS, 2018), which is 11800 km. By doing so, we have set the distance represented by patches to 2 km per patch.

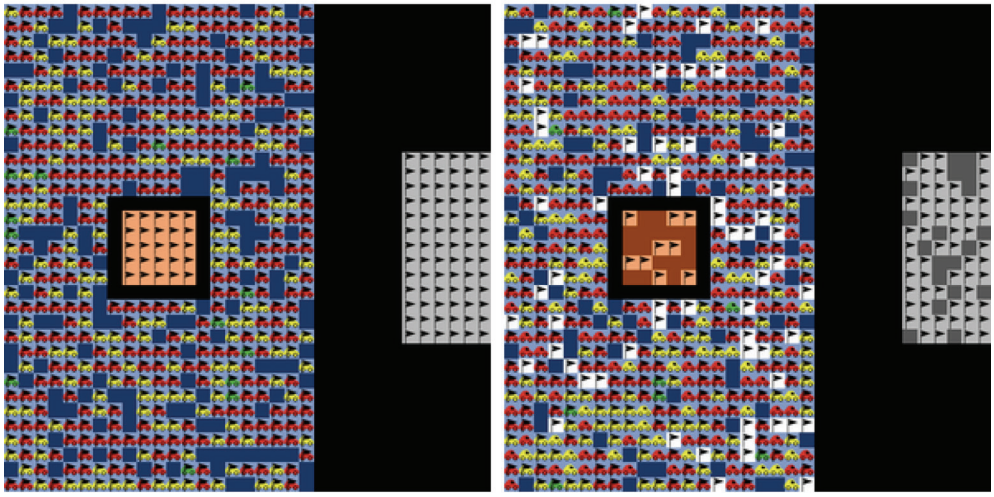


Figure 4.2 Screenshots of model implemented in NetLogo with unlimited charge points (left) and limited charge points (right). The agents are represented as vehicles, the colour represents charge mode (red = charge mode 1, yellow = charge mode 2, green = charge mode 3). The blue area is a residential area, with light blue indicating households, the grey area is an office area, and the orange area is a commercial area. Flags indicate charge points. Charge points can be private (light blue), public (white) or semi-public (light grey in the office area and light orange in the commercial area). Houses and public charge points are randomly distributed over the residential area.

4.2.4 Charge points

Agents can charge a depleted battery at private charge points (at their house), semi-public charge points (at an office or at a shop) and public charge points (in the residential area). One parameter in our model is the availability of charge points. This parameter can be changed between unlimited availability, in which case every house has a charge point and offices and shops have enough charge points available for each agent, and limited availability, in which case we base the number of private, public, semi-public and fast charge points in our model on the Dutch situation per July 31 2017 (RVO, 2017), see Table 4.5.

Table 4.5 Number of charge points per 500 EVs in the Netherlands on 31-7-2017. Data source: (RVO, 2017)

Type of charge point	# of charge points per 500 passenger EVs
Private	324
Public	62
Semi-public	67
Fast charging	3

Many agents have a private charge point at their house. This means that only that agent can access this charge point. In our model, private charge points have a maximum power capacity of 6 kW.

Public charge points are accessible by all agents. In our model, public charge points are randomly distributed over the residential area. Only agents that do not have a private charge point use the public charge points. When these agents go home, they select a public charge point that is not occupied and as close to their home as possible. When all public charge points are occupied they go to their house, and are thus not able to charge their vehicle. The model has the option that, when an EV is fully charged, the agent will drive the vehicle home, and thus frees the charge point. When this option is not selected, the EV will occupy the charge point until the agent needs the EV for a trip to the office area or the shops. The public charge points have a maximum power capacity of 6 kW.

Semi-public charge points are private charge points made accessible to others by their owners. Such charge points are common in for instance shopping malls, office buildings and parking garages (RVO, 2017). In our model, semi-public charge points can be found in the office area and the commercial area. In order to determine how the total number of semi-public charge points is divided between these two areas, we have investigated the charging demand of the agents in both areas. Through running simulations, we found that charging demand in the office area is 6.7 times greater than the charging demand in the commercial area, and we have divided the semi-public charge points accordingly. To our knowledge, there is no data available to check whether this division is accurate for the Netherlands. When all charge points are occupied, the agents have to wait to charge their vehicle. The model has the option that, when an EV is fully charged, the agent will free the charge point. When this option is not selected, the EV will occupy the charge point until the agent needs the EV for a

trip to house or the shops. The public charge points have a maximum power capacity of 6 kW.

Fast charge points are public or semi-public charge points with a maximum power capacity of 46 kW (AC) or 50 kW (DC). For the sake of simplicity, we have not integrated fast charge points in the present model. When we would implement fast charge points, agents would have to weigh fast charging their EV at a location far from their destination against slow charging their EV at a location close to their destination. We think that adding this consideration would make our model more complicated, while it does not contribute to the research objective.

4.2.5 Calculating the energy balance

As the model runs, the energy balance influences the charging process. The energy demand comes from the households and the service sector. The household demand profiles are estimated using a dataset containing 400 unique household profiles with a time resolution of 15 minutes as provided by Claessen et al. (2014). The dataset is based on measurements from distribution system operator Liander. The demand profiles of the service sector are based on an American dataset (Deru et al., 2011), adapted to Dutch conditions by Voulis, Warnier, & Brazier (2017). The dataset includes demand profiles with a time resolution of 1 hour for hospitals, hotels, offices, schools, shops, and restaurants, which in our model are scaled to the number of households (agents) as in Table 1 in (Voulis et al., 2017). The demand profiles for households and the service sector are interpolated to 5 minutes time resolution.

Renewable energy supply can be from either PV or wind. We model PV yield with a time resolution of 5 minutes with the open source package PVLIB (Andrews et al., 2014), based on Royal Netherlands Meteorological Institute (KNMI) solar irradiation data (KNMI, 2018). Specifications of the Sanyo HIP-225HDE1 module and the Enphase Energy M250 inverter were used as input for the model. The modelled PV modules have an azimuth of 180 degrees (directed South) and a tilt of 37 degrees, which are the optimal conditions for PV energy generation in the Netherlands (Litjens et al., 2017). We assume the specific annual PV yield to be 875 kWh/kWp, which is the average PV yield for the Netherlands (Van Sark et al., 2014). There is no data on wind energy generation with a fine time resolution available for the Netherlands. Therefore we use aggregate 15 minute data from Belgian onshore wind farms (Elia, 2018), as it can be expected that Belgian results can be used for the Dutch case given that they are relatively small, neighbouring countries, both with a coast at the North Sea. According to this data 1 MW installed wind capacity produces 1.8 GWh per year, i.e. a capacity factor of 20.5%. We have interpolated the data to a 5 minutes time resolution.

The total energy demand depends on the number of agents in the model. The energy demand of the households and the service sector is scaled to the number of agents. The energy

supply depends on the installed capacity for PV and wind. Equations (4.1)-(4.3) describe the calculation:

$$\text{total energy demand} = N_{agents}\left(E_{household} + E_{service,profile}\right) \tag{4.1}$$

$$\text{energy supply} = C_{PV}E_{PV,profile} + C_{wind}E_{wind,profile} \tag{4.2}$$

$$\text{energy balance} = \text{energy supply} - \text{total energy demand} \tag{4.3}$$

With N_{agents} the number of agents in the simulation, $E_{household}$ the energy demand for 1 household, $E_{service,profile}$ the profile for energy demand of the service sector per household, C_{PV} the installed PV capacity, $E_{PV,profile}$ the profile for PV energy supply, C_{wind} the installed wind energy capacity, and $E_{wnd,profile}$ the profile for wind energy supply.

4.2.6 Driving behaviour of agents

In order to simulate realistic driving behaviour, we use the OViN 2016 dataset (CBS, 2016c). This dataset contains one-day transport diaries of a randomly chosen set of correspondents in the Netherlands. From this dataset we have extracted all one-day diaries of vehicle owners. Then, we selected all one-day diaries in which the vehicle owner travels between home and work or a shop. From this subset of the data, we extract the start times of the trips and the destination. At the start of each day in the simulation, an agent randomly chooses a one-day diary from a corresponding day of the week (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday). At the corresponding time, the agent will then drive the vehicle to home, the office or a shop. Based on the OViN dataset, we have calculated the number of vehicle-owners that do not make daily use of their vehicle. Agents have a corresponding chance to select an empty diary and stay at home during the day. The vehicle battery is depleted dependent on the distance driven and estimated energy use per km driven (0.2 kWh/km). The underlying assumption of using this data is that EVs will be used in the same manner as vehicles are used now.

Figure 4.3 presents an overview of how agents move and decide to charge. The agent reads in the diary the time it starts its next trip and what the destination of that trip is (home, office, or commercial area, see Figure 4.1 for the lay-out of the area). If the agent is not at its destination it will move in a straight line towards it with a speed of 0.8 patch per time-step. Our model does not consider roads. If the agent is at its destination and the battery is not completely full (SOC < 1) the agent can charge its vehicle (the charging process is described in the next section).

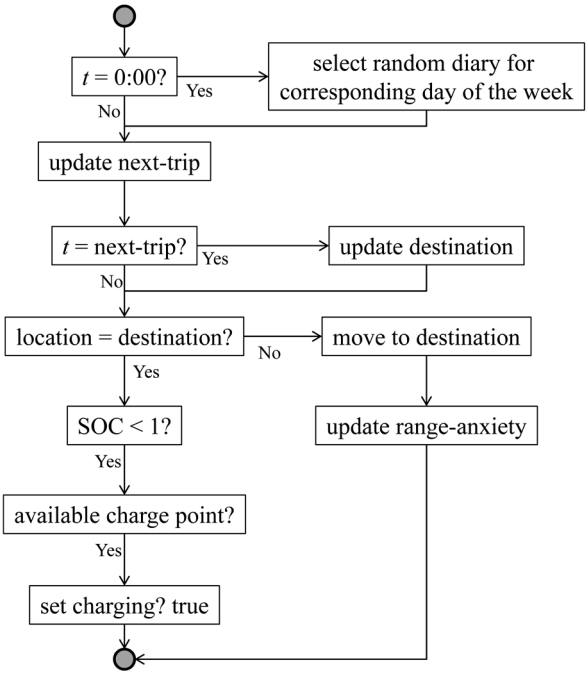


Figure 4.3 Overview of moving of agents and deciding to charge

Not all agents can charge at their home. These agents thus have to charge at public or semi-public charge points. The agents can charge at the semi-public charge points when they visit the office or commercial area, otherwise they have to use public charge points. In our model, the agents have to make a reservation for a charge point (e.g. via an app), see Figure 4.4. Note that if a simulation is run with unlimited charging agents can charge at each location and reserving is not necessary.

When running simulation with "social charging", agents will receive a message when they are at a public or semi-public charge point and their battery is full.[13] The agent will then move its EV to the closest patch with no charge point. Note that if a simulation is run with unlimited charging agents can charge at each location and social charging is not necessary.

[13] For an example of social charging in practice see: https://www.social-charging.com

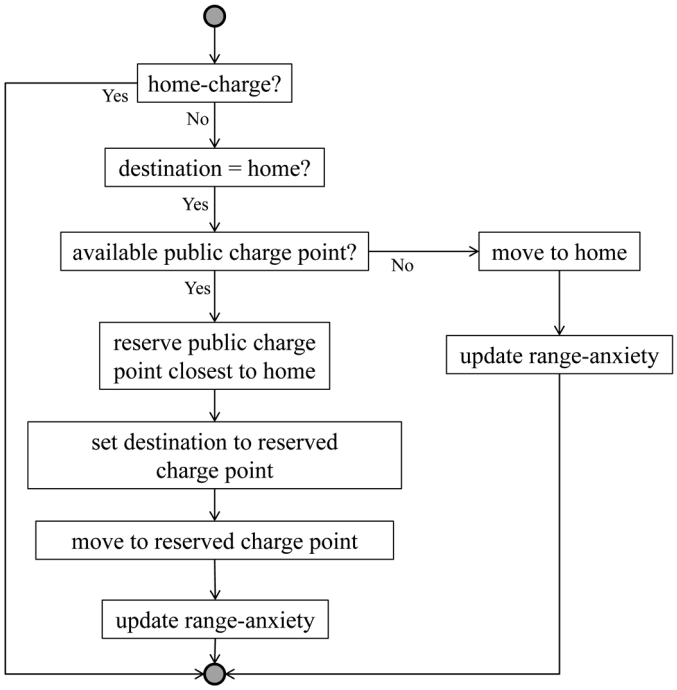


Figure 4.4 Overview of reserving a charge point

4.2.7 Charging behaviour of agents

As discussed in the model overview, agents can charge their vehicle in three different modes, which are distinguished by how much renewable energy is used to charge the EVs. The option available to agents depends on the policy intervention in place. We base our policy interventions on the strategies to encourage pro-environmental behaviour as classified by Steg (2016). In the model, we implement three policy interventions aimed at encouraging agents to charge their EVs in a sustainable way. These are (1) *dual tariff scheme*, (2) *automated smart charging*, and (3) *information and feedback*. The results of our ABM will show whether and how different interventions will lead to different outcomes, EV charging demand and user satisfaction at the system level, i.e. self-sufficiency, self-consumption and user satisfaction. Table 4.1 shows which modes are available for the different policy interventions. In what follows, we discuss each policy intervention and how this is operationalized in our ABM.

In the absence of a specific intervention, agents charge in mode 1, in which the agents always charge at maximum capacity, see Figure 4.5. This serves as a baseline scenario.

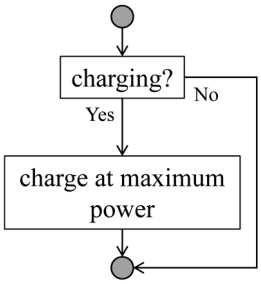


Figure 4.5 Overview of charge mode 1

The intervention *dual tariff scheme* is based on the strategy *changing costs and benefits of behaviour* (Steg, 2016). This intervention is similar to previous simulation studies cited in the literature review, in which the agent is assumed to be a rational actor optimizing costs and benefits. In order to stimulate sustainable charging, policies can be implemented that change the costs and benefits of charging at specific times. In our model, we implement a dual tariff charging scheme; the price of charging is high when there is a shortage of renewable energy to cover the electricity demand of the buildings, while it is low when there is a surplus of renewable energy. With this policy in place, we assume that agents will always charge their EV to a minimum level (mode 2). However, the agents will only charge their EV beyond this minimum when the price is low. EVs set this minimum level to the energy they need to drive from their home to the patch with a commercial or office function that is furthest away from their home, so that they can always make a trip. Even when people charge until their battery is full, this charging session will not strengthen environmental self-identity, as people will ascribe their charging decision to the fluctuating price rather than to themselves. Hence, subsequent sustainable charging will not be promoted. Therefore, agents always charge in mode 2, unless a different policy intervention will be adopted, see Figure 4.6.

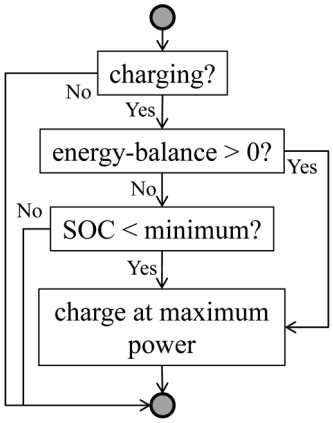


Figure 4.6 Overview of charge mode 2

The intervention *automated smart charging* is based on the strategy *reducing cognitive effort* (Steg, 2016). Pro-environmental behaviours are often considered to be costly in terms of effort (Steg et al., 2014). Strategies to encourage sustainable charging can reduce the cognitive effort required for sustainable charging. In automated smart charging systems, EV drivers do not actively monitor sustainable energy production and decide when to charge their EV. EVs will automatically charge at times of renewable energy abundance, and not charge when there is no renewable energy available. In our model, we assume that all EV drivers will take part in an automated smart charging system. Our model simulates two variations of this system, one in which there is central control over the charge points and one in which there is no central control. When there is a central control system, the system can monitor exactly how much renewable energy is available, and let the EVs charge with limited power so that the total charging power used for the EVs does not exceed the amount of excess renewable energy. If there is no central control, the agents charge at maximum power when there is excess renewable energy, since they are not aware of how many other agents want to charge at that time step, and therefore cannot calculate the limit to prevent using more energy than the excess renewable energy. Again, both variations of the system are not likely to strengthen environmental self-identity, as people's EVs will be charged automatically. Hence, agents will not ascribe this sustainable charging behaviour to themselves and subsequent sustainable charging will not be promoted. As long as this intervention is in place, the agents will charge in mode 3, see Figure 4.7.

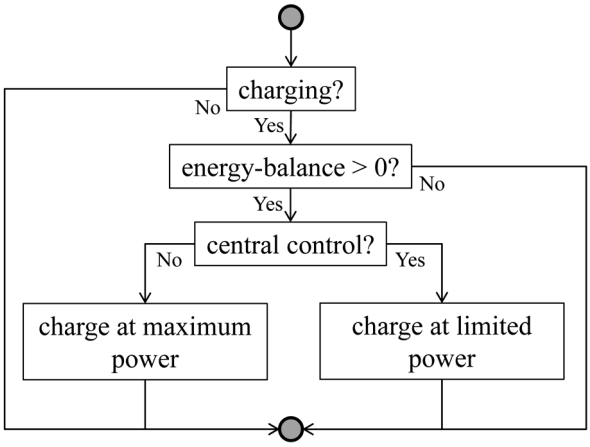


Figure 4.7 Overview of charge mode 3

The intervention *information and feedback* is based on a combination of the strategies information and feedback on costs and benefits and taking advantage of people's desire to be consistent (Steg, 2016). The charging option agents choose is dependent on their

environmental self-identity and range anxiety, see Figure 4.8.[14] We assume that people with a stronger environmental self-identity are more willing to shift their charging behaviour than people with a weaker environmental self-identity. We assume that people with stronger range anxiety are less willing to shift their charging behaviour than people with weaker range anxiety.

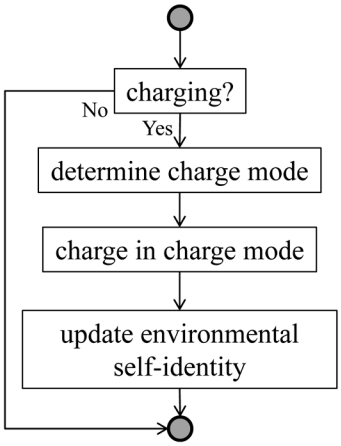


Figure 4.8 Overview of EV charging under the information and feedback intervention

Equations (4.4) and (4.5) show how agents choose a charge mode:

$$\text{charging mode} = \begin{cases} \text{mode 1} & \textbf{if} \quad \omega_{\text{ESI}}\text{ESI} - \omega_{\text{RA}}\text{RA} \leq -\frac{1}{6} \\ \text{mode 2} & \textbf{if} \quad -\frac{1}{6} < \omega_{\text{ESI}}\text{ESI} - \omega_{\text{RA}}\text{RA} \leq \frac{1}{6} \\ \text{mode 3} & \textbf{if} \quad \omega_{\text{ESI}}\text{ESI} - \omega_{\text{RA}}\text{RA} > \frac{1}{6} \end{cases} \tag{4.4}$$

$$\omega_{\text{ESI}} + \omega_{\text{RA}} = 1 \tag{4.5}$$

With ESI the score for environmental self-identity, RA the score for range-anxiety, ω_{ESI} the weighing factor for environmental self-identity and ω_{RA} the weighing factor for range anxiety, which together should add to 1. We want to set up the boundary values in such a way that agents that do not experience range anxiety but also do not act sustainably charge in mode 1, while agents with a high environmental self-identity charge in mode 3. To

[14] Agents only update their environmental self-identity when they ascribe their sustainable charging session to themselves (intrinsically motivated charging), and not to the policy in place (extrinsically motivated charging). In the absence of a policy intervention, agents are not aware on whether they charged sustainably. With the interventions *dual tariff scheme* and *automated smart charging* agents are extrinsically motivated to charge sustainably. Hence, environmental self-identity is only relevant for the intervention *information and feedback*.

determine the boundary value between the charging mode we choose as a reference case $\omega_{\mathrm{ESI}} = \omega_{\mathrm{RA}} = 1/2$. ESI varies between -1 and 1. We chose -1/6 and 1/6 as boundary values, because it divides the domain -1/2 to 1/2 in three equal parts.

Environmental self-identity can be strengthened by making agents aware of their past pro-environmental behaviour (Van der Werff, Steg, & Keizer 2014a, 2014b). More specifically, research has shown that individuals who became aware that they engaged in pro-environmental behaviour scored higher on environmental self-identity than agents who became aware that they often refrained from engaging in pro-environmental behaviour (Van der Werff, Steg, & Keizer 2014b). Therefore, the agents receive individual feedback during their charging sessions. The feedback displays the amount of sustainably produced energy used for charging the EV battery compared to the total amount of energy used for the charging session. This proportion indicates the extent to which agents acted sustainably. The larger amount of the energy used for charging is sustainably produced, the more agents become aware that they acted sustainably and the more environmental self-identity will be strengthened. When only a small amount of the energy used for charging is sustainably produced, agents will become aware that they did not act sustainably and environmental self-identity will be weakened.

4.2.8 Updating environmental self-identity and range anxiety

In the beginning of the simulation, the agents are assigned a random value from a uniform distribution for both environmental self-identity and range anxiety.[15] Environmental self-identity is updated during charging (with policy intervention *information and feedback*) and range anxiety gets updated during moving. Equations (4.6) and (4.7) present the calculations:

$$\mathrm{ESI}(t) = \begin{cases} \mathrm{ESI}(t-1) + \mathrm{Inc}_{\mathrm{ESI}} & \textbf{if} \quad \text{charging? } \textbf{and} \text{ energy-balance} > 0 \\ \mathrm{ESI}(t-1) - \mathrm{Dec}_{\mathrm{ESI}} & \textbf{if} \quad \text{charging? } \textbf{and} \text{ energy-balance} < 0 \\ \mathrm{ESI}(t-1) & \textbf{else} \end{cases} \tag{4.6}$$

With $\mathrm{Inc}_{\mathrm{ESI}}$ the increment by which environmental self-identity can get increased, $\mathrm{Dec}_{\mathrm{ESI}}$ the decrement by which environmental self-identity can get decreased, and P_{charge} the power used for charging. The minimum value of ESI is -1 and the maximum value is +1. Studies on environmental self-identity have typically focussed on strengthening environmental self-identity, and not on weakening. We can therefore not estimate the values of $\mathrm{Inc}_{\mathrm{ESI}}$ and $\mathrm{Dec}_{\mathrm{ESI}}$ based on empirical data. Based on findings by Van der Werff, Steg, & Keizer (2014b), we

[15] We choose a uniform distribution for the sake of simplicity, to the best of our knowledge there is no data on the distribution, mean, and standard deviation of environmental self-identity and range anxiety and how these factors relate to sustainable charging among the general population or EV drivers. We did check whether our results are sensitive to the distribution used in the initialisation and found no significant impact.

suspect that it is easier for environmental self-identity to strengthen than it is to weaken, which is reflected in our parameter estimation by setting the value of $\mathrm{Inc}_{\mathrm{ESI}}$ higher than the value of $\mathrm{Dec}_{\mathrm{ESI}}$.

$$\mathrm{RA}(t) = \begin{cases} \mathrm{RA}(t-1) + \mathrm{Inc}_{\mathrm{RA}} & \textbf{if} \quad \text{moving?}\ \textbf{and}\ \mathrm{SOC} = 0 \\ \mathrm{RA}(t-1) - \mathrm{Dec}_{\mathrm{RA}} & \textbf{if} \quad \text{moving?}\ \textbf{and}\ \mathrm{SOC} > 0 \\ \mathrm{RA}(t-1) & \textbf{else} \end{cases} \tag{4.7}$$

With $\mathrm{Inc}_{\mathrm{RA}}$ the factor with which range anxiety can get increased, $\mathrm{Dec}_{\mathrm{RA}}$ the factor with which range anxiety can get decreased. The minimum value of RA is 0 and the maximum value is +1. Again, we cannot estimate the values of $\mathrm{Inc}_{\mathrm{RA}}$ and $\mathrm{Dec}_{\mathrm{RA}}$ based on empirical data. We expect not being able to drive has a large impact on range anxiety, and hence give $\mathrm{Inc}_{\mathrm{RA}}$ a higher value than $\mathrm{Dec}_{\mathrm{RA}}$ in our simulations. EVs can continue to drive if the battery is empty in our simulations, which is not possible in reality for FEVs. FEVs would not be able to drive with an empty battery and another solution fsor transportation would have to be found. We leave this out of our model, since incorporating this would add more complexity, while it does not serve our research objective, which is related to charging behaviour.

4.2.8 Indicators

We use five indicators to evaluate the simulation results: (1) self-sufficiency, (2) self-consumption, (3) peaks in net energy demand, (4) peaks in energy oversupply, and (5) kms driven using the battery as energy source. The first four indicators are related to the balance between demand and supply, while the fifth indicator is related to user satisfaction.

Self-sufficiency is the percentage of energy demand that can be met by locally produced renewable energy, while self-consumption is the percentage of locally produced renewable energy that is used within the area (Litjens et al., 2017). Sources of demand are the households, the service sector and the EVs. At times when production of renewable energy exceeds demand, the energy is sent elsewhere, since there is no storage or curtailment in our model. We implicitly assume that our model area has a grid connection to the surrounding world. Furthermore, we present the highest peaks of both demand exceeding supply (peak net demand) and supply exceeding demand (peak oversupply). From the perspective of an electricity grid manager, high levels of self-sufficiency and self-consumption and low peaks are beneficial, since it reduces the grid capacity is needed to manage energy flows.

To indicate user satisfaction, we calculate the percentage of kms driven using the battery as energy source (in our model agents still drive when their battery is empty). In reality, FEVs would not have been able to drive these kms. The reason that EVs are not charged sufficiently can be either because there was not enough renewable energy to charge the EV (when agents

charge in mode 3), or an insufficient number of charge points to cover all needed charging sessions.

4.3 Selected simulation experiments

In this chapter, we focus on the effects of the different policy interventions on the balance of energy demand and supply and user satisfaction. First, we define two "main" scenarios; one in which 50% of energy demand can be met with renewable energy and one in which 100% of energy demand can be met with renewable energy. These results give insight on the impact of the type of policy intervention on our indicators. When available we used empirical data to ensure realistic outcomes of the simulation experiments. This was not possible for the parameters related to environmental self-identity and range anxiety. To address lack of empirical input, we both present time series, illustrating how ESI and RA impact charging behaviour, and a sensitivity analysis, showing the effect of the uncertainty in these parameters.

We ran several series of simulations to compare the effect of different policy interventions under different scenarios. Table 4.6 presents the settings for input parameters we have used. We have used different PV and wind capacities, based on a calculation of the energy demand from the households, service sector and electric vehicles. We determined the load of the EVs by running simulations with no policy intervention. In our first scenario, the total renewable energy production should cover about 50% of total energy demand, while in our second scenario this is about 100% (we use the term 'about' because the energy demand of EVs is not exactly the same in all simulations, due to variations in trips and availability of charging infrastructure across different simulations, see Figure 4.9). In these scenarios PV and wind account for 50% of annual renewable energy production each. Finally, we have varied the charging infrastructure. We have run simulations with unlimited and limited charge points, and have varied the availability of social charging (only relevant with a limited number of charge points), and central control (only relevant for automated smart charging).

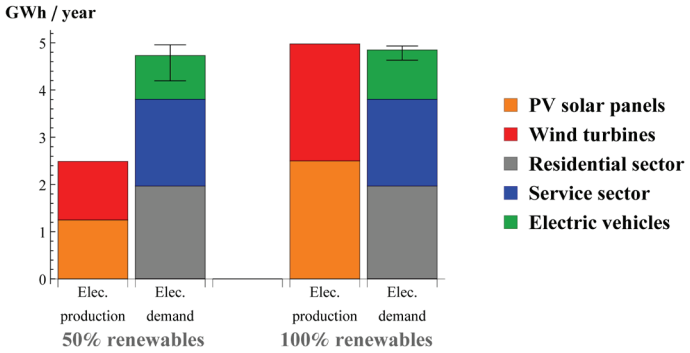


Figure 4.9 Electricity production in demand for the scenarios with 50% renewables and 100% renewables. The error bar indicates the total variation in electricity demand of the electric vehicles

Table 4.6 The number of simulations and the values and bounds for input parameters for the simulation experiments

Simulation experiment	Main	Solar versus wind	Sensitivity analysis
# of simulations	150	330	7200
Vehicle fleet	500 FEVs	500 FEVs	500 FEVs
PV capacity (MWp)	{1.4, 2.9}	[0, 2.9]	{1.4, 2.9}
Wind capacity (MW)	{0.7, 1.4}	[0, 1.4]	{0.7, 1.4}
Policy intervention	{No intervention, dual tariff scheme, automated smart charging, information and feedback}	{No intervention, dual tariff scheme, automated smart charging, information and feedback}	Information and feedback
Unlimited-charging?	{True, False}	{True, False}	{True, False}
Social-charging?	{False, True}	{False, True}	{False, True}
Central control?	{False, True}	{False, True}	False
ω_{ESI}	0.5	0.5	[0, 1]
Inc_{ESI}	0.02	0.02	[0, 0.05]
Dec_{ESI}	0.01	0.01	[0, 0.05]
Inc_{RA}	0.1	0.1	[0, 0.5]
Dec_{RA}	0.0001	0.0001	[0, 0.0005]

EV fleet composition, driving needs, available charging infrastructure, and the profiles for energy demand and renewable energy production are all based on real-life datasets. In absence of studies comparing the strength of the effects of environmental self-identity and range anxiety on charging behaviour, we have used the value 0.5 for ω_{ESI}, meaning that environmental self-identity and range anxiety have an equally important influence on which charging modes the agents choose, as (Eq. 4.7). In order to estimate Inc_{ESI}, Dec_{ESI}, Inc_{RA}, $Dec_{RA,}$ we have experimented extensively with the model, since it is not possible to derive estimations from empirical evidence. We tried to set these values in such a way that (a) average ESI has a tendency to increase in scenarios with high renewable energy supply, (b) the time-scale average ESI changes noticeably is neither too short (e.g. hours) or too long (e.g. months), (c) RA increases strongly when an agent has an empty battery as compared to the decrease when an agent can make the desired trip, and (d) the time-scale average RA changes noticeably is neither too short (e.g. hours) or too long (e.g. months). Even though this may be not be a strong method of parameterisation, the results can still give us valuable insights in what we *could* expect from such a policy intervention. To indicate how important these uncertainties are, we have varied these parameters in a sensitivity analysis with a wide uncertainty band, see Table 4.3.

For each of the possible settings in our two main scenarios, we have run 5 simulations covering one year of time in the model. The number of settings for each simulated scenario is 4 [policy interventions] * 2 [types of charging infrastructure] * 2 [social charging or not] * 2 [central control or not] = 32. However, social charging is only possible if charging infrastructure is limited, and central control is only possible when the policy automated smart

charging is implemented. Our total number of simulations is thus 2 [scenarios] * 15 [settings] * 5 [simulations per setting] = 150 simulations. In order to determine the variation of the results of these 5 simulations for the same set of parameters, we have calculated the ratio of the standard deviation and the average for each set of simulations. For the indicators self-sufficiency, self-consumption, and user satisfaction this ratio is in the order of magnitude of $\sim 10^{-4}$, indicating very little variation. The variation is higher for the peaks in net energy the variation in some cases, with the ratio of the standard deviation and average varying between 0 and 0.07. This is still not a very large variation, indicating that 5 is a sufficient number of simulations; more simulations will not lead to significantly different results.

The sensitivity analysis covers the highly uncertain parameters related to environmental self-identity and range anxiety with 7200 additional simulations (1200 runs per setting of renewable energy capacity, charging infrastructure and social charging with wide uncertainty bounds, see Table 4.6). We used the Saltelli sampling technique (Saltelli, 2002) in the SALib.analyze[16] package for Python. Additionally, we wanted to get insight in the effect of having either more PV solar energy or more wind energy in the energy mix. We performed additional simulation experiments varying the ratio of PV solar energy to wind energy from 0 to 1 with steps of 0.1 while keeping the total production of renewable energy constant, resulting in 2 [scenarios] * 15 [settings] * 11 [simulations varying the ratio of PV solar energy to wind energy] = 330 simulations.

4.3.1 Main results and solar versus wind

This section presents the results of our main scenarios and the solar-vs-wind simulations. In order to see which variables have the highest impact on the results we did an Analysis of Variance (ANOVA) test on the simulation outcomes. Figure 4.10 presents the *p*-values resulting from the ANOVA test. The results show that the renewable energy capacity and policy have the highest impact, while the ratio of PV solar capacity to wind capacity does not have a significant impact on the results. Hence, we exclude the ratio of PV solar capacity to wind capacity from our analysis in the remainder of this chapter.

[16] https://salib.readthedocs.io/en/latest/api/SALib.analyze.html

Figure 4.10 Heat map of the p-values of the ANOVA test on the main simulation results and the solar-vs-wind simulation results

4.3.1.1 Scenario with 50% renewables

Figure 4.11 presents the results for our scenario with 50% renewables. The results of the simulations with unlimited charging show that all policy interventions increase the levels of self-sufficiency and self-consumption as compared to *no intervention.* The level of increase is similar for the interventions, except under the policy intervention *automated smart charging* with central control, which shows a significantly larger increase. Self-sufficiency is even higher than 50%, which is possible because of the lower demand for EV charging due to constraints in times where it is allowed to charge. This lower demand can be seen in the score for kms – electric, which is significantly lower than the kms driven in the other policy interventions. This makes implementing this policy intervention unpractical, because there is not enough renewable energy production to let the agents drive only on renewable energy. Even without a central control system a significant amount of kms could not have been driven using the battery. Hence, *automated smart charging*, regardless the level of control, is not the preferred policy in scenarios with 50% renewables.

Another noteworthy result in this 50% renewables scenario is the large increase in peak net demand. The increase is so large because all agents with SOC < 100% at charge points will start charging when the energy balance is positive. Furthermore, the peak in overproduction is not lowered under the policy interventions, except for *automated smart charging* with central control.

We have run simulations with limited charging capacity both with and without social charging. In general, the effects of the different policy interventions are similar as with simulation series 1. An extra variable to pay attention to is the difference between having social charging or not. While for most indicators having social charging or not has a very

limited effect on our indicators, the scores for self-consumption and kms – electric are in general significantly higher when social charging is implemented, illustrating the potential benefits of such a system. The only real negative impact of social charging is found in the peak in net energy demand for the policy intervention *information and feedback*, which is 65% higher with social charging. With social charging the charging infrastructure is used more efficiently, so more agents will charge at times of renewable surplus, resulting in the higher peak in net energy demand.

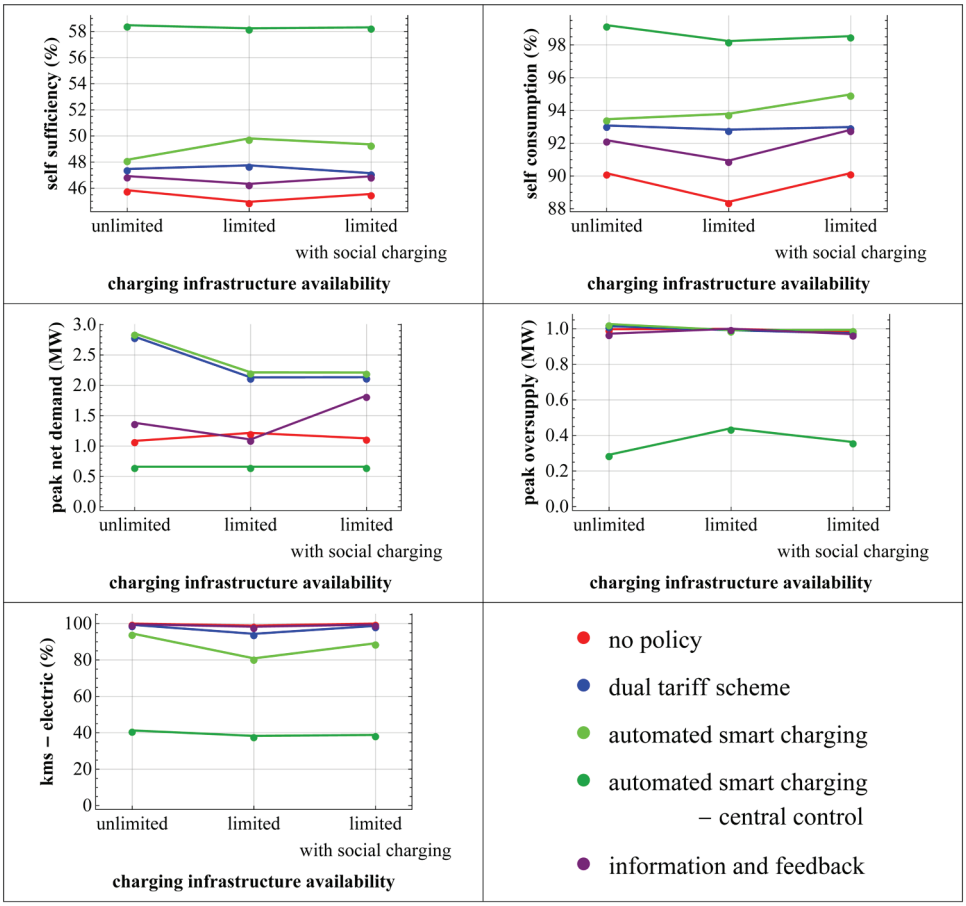


Figure 4.11 Results for the scenario 50% renewables

4.3.1.2 Scenario with 100% renewables

Figure 4.12 presents the results for our scenario with 100% renewables. In general, in the scenario with unlimited charging the effects of the different policy interventions are similar to effects observed in the scenario with 50% renewables. One difference we would like to discuss here is for *automated smart charging* with central control. While this policy

intervention still has the lowest score by far for kms – electric, the score is much higher than in the scenario with 50% renewables. With so much renewables such a system might be acceptable for users if solutions are found for the remaining kms. However, the peak in supply is reduced only to a limited extent, indicating that peaks in renewable energy production are too high to be reduced using smart charging. This is also reflected in the scores for self-sufficiency and self-consumption. While all policy interventions increase these scores, self-sufficiency and self-consumption do not exceed 79% and 76% respectively.

We have run simulations with limited charging capacity both with and without social charging. In general, the effect of the different policy interventions are what one would expect given the results presented earlier, and the additional results found for the effects of limited charge points, social charging, and high renewable capacity as discussed for the scenario with 50% renewables.

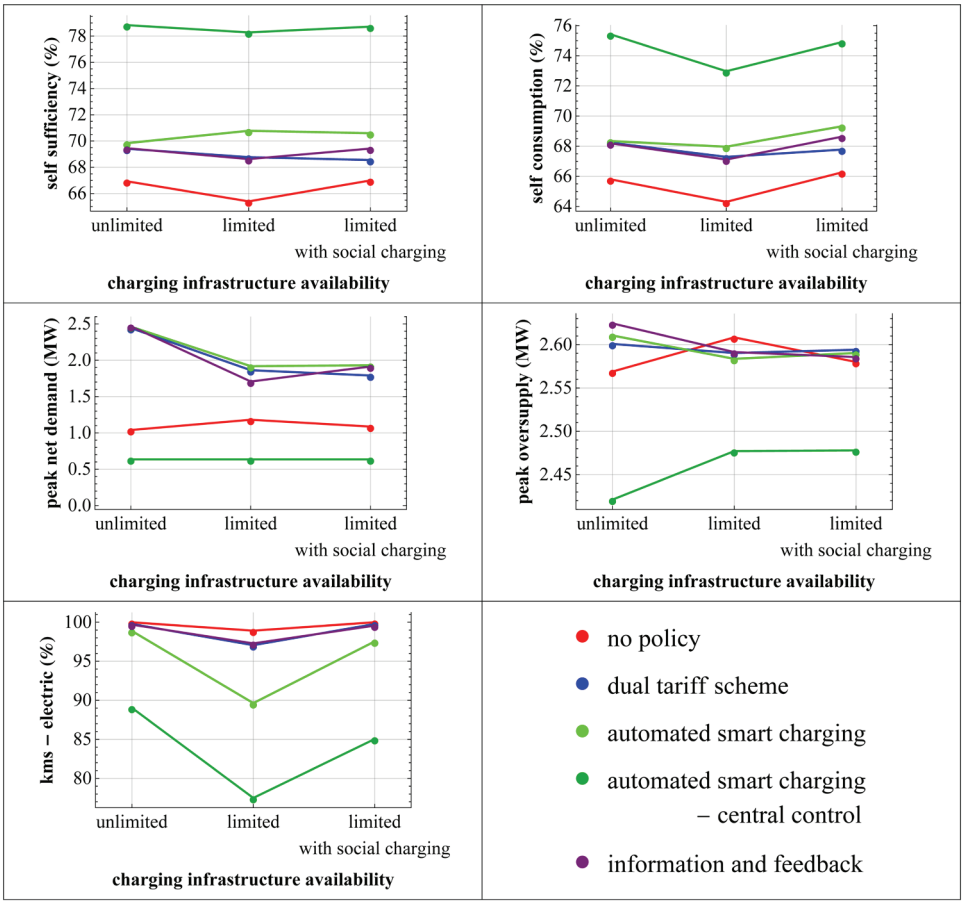


Figure 4.12 Results for the scenario 100% renewables

4.3.2 Environmental self-identity and range anxiety

Figure 4.13 presents the development of the number of agents in different charging modes for simulations with the policy intervention *information and feedback* and Figure 4.14 shows the individual and mean scores for environmental self-identity and range anxiety for the 1st of April for example simulations.[17] Given the difficulty with the parameterization of the variables related to environmental self-identity and range anxiety, the value of these results is in comparing the different simulations to each other, instead of focusing on one example.

These figures illustrate the mechanisms underlying the results presented in Figures 4.11 and 4.12. Figure 4.13 shows that the seasonal variation is an important driver in changes in charging modes. A limited charging infrastructure will limit the number of agents charging sustainably. Implementing social charging allows more agents to charge sustainably because of a more efficient use of the limited infrastructure. In the simulations with limited charging infrastructure, the number of agents in charge mode 3 is more stable than the number of charge modes 1 and 2, indicating that in these cases many agents have scores for ESI and RA close to the boundary between these charge modes. Figure 4.14 shows that there is indeed a cluster of agents in charge mode 3 in all simulation settings. The size of the cluster does depend on the simulation settings. In our 100% renewables scenario with unlimited charging infrastructure the agents all have very high scores for ESI, because most charging sessions will have a high percentage of renewable energy input. With high scores for ESI for all agents, RA is the factor that explains variation in charging behaviour.

[17] The online article version of this chapter also contains an animation of how environmental self-identity and range anxiety vary throughout a simulated year (Van der Kam, Peters, Van Sark, & Alkemade, 2019a)

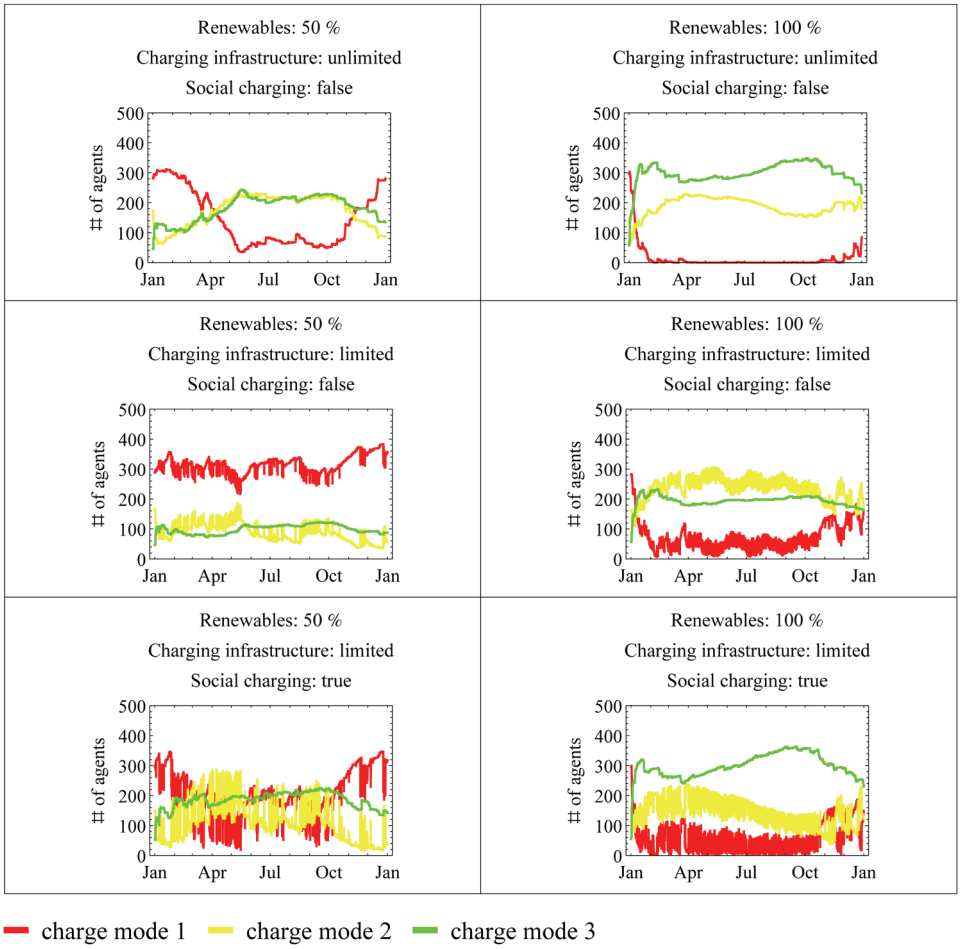


Figure 4.13 Example simulations of the number of agents for each different charging mode for the scenarios 50% renewables and 100% renewables under the policy intervention information and feedback

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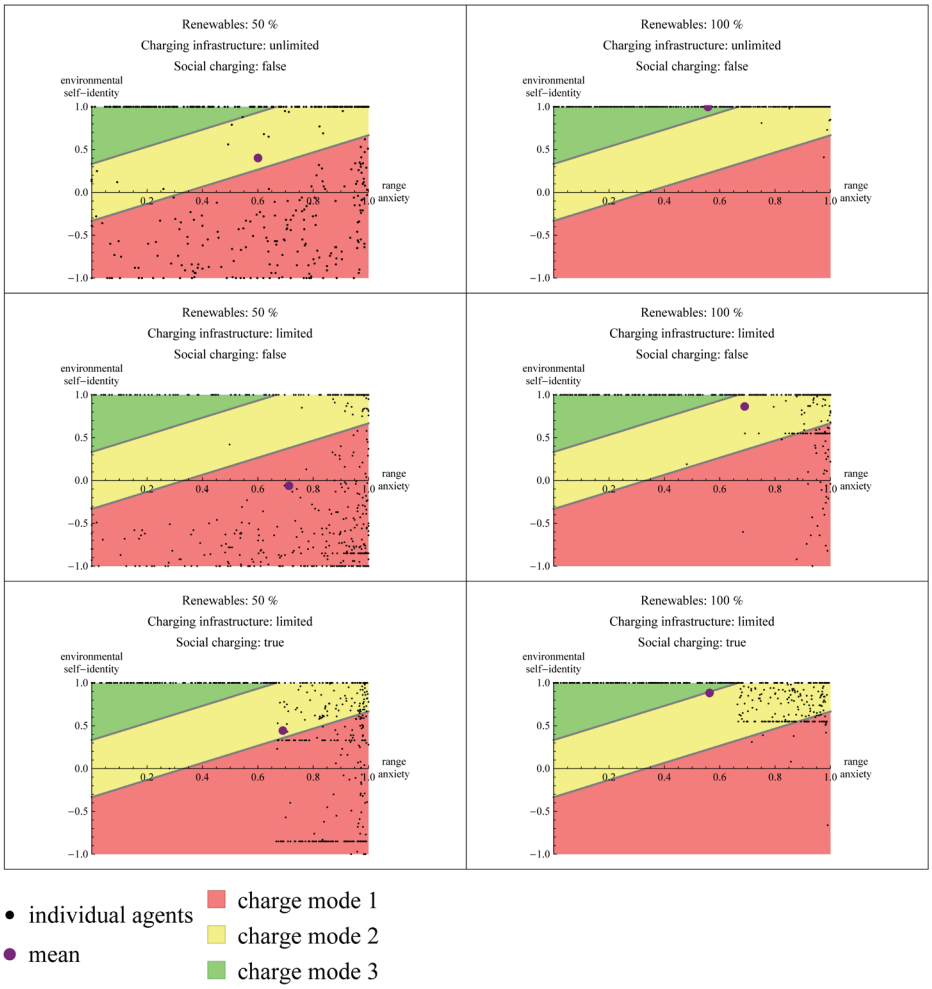


Figure 4.14 Example simulations of the scores for environmental self-identity and range anxiety for each agent, the mean of these scores, and the charge mode they correspond to for the scenarios 50% renewables and 100% renewables under the policy intervention information and feedback

4.3.3 Sensitivity analysis for the policy intervention information and feedback

Here, we present the results of our sensitivity analysis. In order to see which variables have the highest impact on the results we did an ANOVA test on the simulation outcomes. Figure 4.15 presents the *p*-values resulting from the ANOVA test. The results show that for the parameters specific to the policy intervention *information and feedback* variation in the weighing factor has the biggest impact on the results. This is not surprising, given that the impacts of increases and decreases in environmental self-identity and range anxiety vary with the weighing factor.

Figure 4.15 Heat map of the p-values of the ANOVA test on the sensitivity analysis results for the policy intervention information and feedback

The results of our sensitivity analysis show that the uncertainty in the parameters related to ESI and RA are important for our results. Basically, they determine how much the agents move towards the extreme of always charging in charge mode 1 or always charging in charge mode 3. The success of an information and feedback campaign thus relies to a large extent on how important these factors are in real-life for charging behaviour.[18]

4.4 Discussion and conclusion

We have presented an ABM aiming to explore the consequences different policies might have on people's EV charging behaviour. More specifically, we have focussed on the integration of clean energy and transport via so-called *smart charging*. Our model expands previous models of EV charging by incorporating recent insights from environmental psychology on important psychological drivers of pro-environmental behaviour. This way, our models do not solely focus on driving needs and costs, but also incorporate normative considerations. Furthermore, we have compared the effect of policy interventions targeting either external or internal motivations of EV drives. In our models, we have used empirical datasets as much as possible to construct realistic scenarios.

The results show that the amount of renewables and policy interventions have the largest impact on our indicators (self-sufficiency, self-consumption, peaks in net demand and oversupply, and the number of kms driven using the battery as energy source), while the ratio of PV solar capacity to wind capacity does not have a significant impact. Hence, we ignored the ratio of PV solar capacity to wind capacity in our further analyses. While all forms of

[18] For the interested reader we have included all our simulation results in the supplementary material of the online article version of this chapter (Van der Kam et al., 2019a)

sustainable charging do increase the values of self-sufficiency and self-consumption, they do so only moderately. Higher scores for these indicators are associated with less kms being driven using the battery as energy source, which would lead to low satisfaction of EV drivers. Under all other policy interventions without central control, the peak in net energy demand will increase significantly, while the peak in overproduction is similar to the situation without intervention. While *automated smart charging* with central control requires lower grid capacity compared the other interventions, as is reflected in the low peaks in net demand and oversupply, the available energy for EV charging is currently too limited for such a system to work in practice. Hence, these results indicate the limited potential for sustainable charging to contribute to integrating intermittent renewables in the electricity grid. This is partly solved when the capacity of renewables is higher (as can been seen in our 100% renewable scenario), This is in line with other research showing that the vast majority of people allows automated smart charging to some extent, especially when a minimum charge or range is guaranteed (Bailey & Axsen, 2015; Bauman et al., 2016; Ensslen et al., 2018a; Will & Schuller, 2016). Yet, peaks in oversupply will become higher as well, denoting the necessity of additional (stationary) storage for load balancing.

In scenarios with limited charging infrastructure, the issue of empty batteries is significantly reduced when social charging is implemented, illustrating the potential benefits of such a system. The only real negative impact of social charging is found in the peak in net energy demand for the policy intervention *information and feedback* in the scenario with renewables covering 50% of total electricity demand, which is 65% higher with social charging. Hence, policy makers could promote the use of social charging via apps especially in areas in which the grid is able to deal with additional peak demand without having an increase in local congestion at transformer stations.

We summarize these points in Table 4.7. The table indicates the effects of the different policies on the energy system and user satisfaction and can help identify robust policies for smart charging. One evident conclusion is that while *automated smart charging* can have great benefits, the disadvantages are also very large. Both *dual tariff scheme* and *information and feedback* have more moderate positive and negative effects.

Table 4.7 Indication of whether a policy intervention has a positive (+), very positive (++), extremely positive (+++), negative (-), very negative (--), extremely negative (---) or no effect (+/-) compared to having no intervention. We consider positive to be high scores for self-sufficiency, self-consumption, and kms - electric, and low scores for peaks in net demand and oversupply, and vice versa. We have based these indications on the simulation results

Policy intervention	**No inter-vention**	**Dual tariff scheme**		**Automated smart charging**				**Information and feedback**	
Social charging?	**True**	**False**	**True**	**False**	**True**	**False**	**True**	**False**	**True**
Central control?	n.a.	n.a.	n.a.	**False**	**False**	**True**	**True**	n.a.	n.a.
Self-sufficiency (%)	+/-	+	+	++	++	+++	+++	+	+
Self-consumption (%)	+/-	+	+	++	++	+++	+++	+	+
Peak net demand (MW)	+	--	--	--	--	+++	+++	++	+
Peak oversupply (MW)	+/-	+/-	+/-	+/-	+/-	+++	+++	+/-	+/-
kms - electric (%)	+	-	+/-	--	--	---	---	+/-	-

The difference in effects of the policy interventions with no central control is small, especially in the scenarios with 50% renewables. Our results thus indicate that an information and feedback campaign targeting EV drivers' environmental self-identity can have similar positive effects as interventions using either variable pricing or automated smart charging. Introducing variable pricing in practice could have significant drawbacks. Firstly, such a system would require new regulations on energy pricing. Furthermore, stimulating load shifting behaviour with price incentives is generally difficult: often the financial benefits do not compensate the effort and inconvenience of changing behaviour (Dogan, Bolderdijk, & Steg, 2014; Kobus et al., 2013). The implementation of automated smart charging requires large changes in both technology and regulation. Furthermore, automated smart charging would take away control of users. Consumers are often reluctant to engage in such programs due to privacy and autonomy concerns (Sintov & Schultz, 2015). Moreover, both policies do not target EV drivers' intrinsic motivation, making long-term behavioural change not more likely (Bolderdijk et al., 2011). An information and feedback campaign targeting environmental self-identity does not face these drawbacks, as users are more likely to ascribe their sustainable charging session to themselves (intrinsically motivated charging). Given the similar outcomes on a system level, this policy intervention has preference over the others. Future research could study different types of feedback to strengthen environmental self-identity.

The time series we presented for the simulations of the policy intervention *information and feedback* indicate that the renewable energy capacity and the variation of renewable energy production are main drivers of how many agents charge sustainably. Furthermore, the results show that agents do not perform homogeneous charging behaviour because the scores for environmental self-identity and range anxiety vary across their domain for most of our scenarios, except for our 100% renewables scenario with unlimited charging infrastructure, in which the agents have very high scores for environmental self-identity but vary in their scores for range anxiety. This illustrates that such a policy, which relies on voluntary participation in sustainable charging, can create a heterogeneous group of EV drivers, which

has implications for policies aiming to increase sustainable charging. Policy makers could focus on increasing environmental self-identity and/or decreasing range anxiety, and might have to use different incentives for different groups of EV drivers.

Although our model enriches the literature on simulations of EV charging by incorporating environmental psychology, it also has some drawbacks. One gap is that the research on environmental self-identity typically studies how environmental self-identity can be strengthened rather than weakened. From a practical perspective it is clear why research has solely focused on the strengthening of environmental self-identity. From a modeller's perspective however, studying how environmental self-identity could be weakened would add valuable information to construct the dynamics of the important drivers of agent behaviour. Furthermore, we are not able to parameterize or estimate the variables related to range anxiety and environmental self-identity. We have added a section showing the development of these variables in our simulations and a sensitivity analysis to provide some insight as to how different scores on these variables affect the results. To solve parameterization issues, future research could conduct Discrete Choice Experiments (Bailey & Axsen, 2015) or Conjoint Analyses (Leijten et al., 2014) that determine the relative importance of these constructs for sustainable charging.

In this chapter, we have presented a limited number of simulations. We have focussed on renewable energy capacity, different policy interventions, limited versus unlimited charging capacity, social charging, and central control. The simulation model could be applied to many more cases; interesting directions could be variations in charging infrastructure, energy demand, battery size and depletion of the batteries, including stationary storage, and including PHEVs in the EV fleet. Furthermore, the model can be used for simulations of other cities, regions or countries, as long as sufficient data is available.

To summarize, we have demonstrated ABMs to be a suitable tool for exploring the future of EV charging, and make a first step towards more realistic scenarios going beyond purely technical and financial considerations. The model allows to highlight the different concerns in moving towards a renewable energy and transport system, and is able to provide an estimate of what factors are most important and which issues can arise. Where we could not follow such empirical rigor we performed a sensitivity analysis to indicate the importance of uncertainty in these areas. Based on our results, we have articulated several policy recommendations. Furthermore, our research points to certain gaps in environmental psychology literature, and indicates directions worthwhile to pursue for environmental psychology scholars who want to use theory to inform future policy making using simulation modelling. In doing so, environmental psychology could play a more prominent role in modelling of energy systems, leading to richer simulation models and theories and thereby supporting the identification of robust policies to promote the transition to a new energy system.

Chapter 5

Charging behaviour and charging infrastructure roll-out

Abstract

Electric vehicles (EVs) are a key technology in sustainable transportation *and* energy systems. EVs have the potential to perform important functions as a clean mode of personal transportation as well as a source of flexible demand and/or storage for intermittent renewable energy sources. While this potential is widely recognized by scholars and policy makers, using EVs for grid services can decrease their availability for transportation, possibly making EVs less attractive for consumers. While EVs hold the promise of being a key technology in integrated sustainable energy and transport systems on the long term, the trade-offs between the different functions of EVs are currently not explicitly addressed in policies for charging infrastructure roll-out. This chapter argues that local conditions should be considered by policy makers when making these trade-offs. The built environment and electricity grid are important examples, but also charging behaviour. In this study, we analyse charging behaviour and link it to five policy measures related to charge point placement, cost-effectiveness of charging infrastructure, and integration in a sustainable electricity grid: (1) *increase the number of charge points*, (2) *reduce hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging*. We develop a framework in which we identify indicators to determine how charging behaviour can inform which (if any) of these measures to pursue. Following this, we compare charging behaviour in neighbourhoods, based on a large dataset containing one million charging sessions in the Netherlands. Furthermore, we relate charging behaviour to the policy targets via a multi-criteria analysis. Our analysis shows that there is large variation in charging behaviour, and allows us to evaluate the coherency of different policy mixes.

5.1 Introduction

Electric vehicles (EVs) are envisioned to play an important role in both future sustainable transport and energy systems. EVs contribute to reducing greenhouse gas and local pollutant emissions in the transport sector (Malmgren, 2016; Nikitas, Kougias, Alyavina, & Njoya Tchouamou, 2017). In the energy sector, EVs can contribute to load balancing with technologies such as smart charging and vehicle-to-grid (V2G) (Mwasilu, Justo, Kim, Do, & Jung, 2014). These technologies can also facilitate the integration of intermittent renewable energy sources in the electricity grid, for instance by shifting charging demand to times of high photovoltaic (PV) solar power. Recognizing these benefits, governments throughout Europe are stimulating the transition to e-mobility, as one of the options to reach European climate targets as set by the Paris agreement (European Commission, 2015).

While the good news thus is that EVs can be a very useful technology in the transition to sustainability of multiple sectors, this also brings challenges in developing coherent policy mixes for stimulating and supporting increased EV adoption. The development of coherent policy mixes is receiving increasing attention by scholars and policy makers, as this is an important factor for accelerating the broad transition towards sustainability (Kern, Rogge, & Howlett, 2019). Developing coherent policy mixes gets increasingly complex when multiple sectors are involved (Rogge & Reichardt, 2016), as is the case for e-mobility.

There are tensions between the functions of EVs as a mode of transportation and as part of a sustainable energy system. Specifically, how EV are best charged is not the same for each of these functions. To illustrate this point, we can think about the duration of charging sessions. In order to ensure high availability of EVs for transportation, the time needed to charge to a sufficient state-of-charge (SOC) of EV batteries is preferably short. Shorter durations of charging sessions also enable more efficient use of a charge point, as it is available more often. On the other hand, cost-effective integration of charging infrastructure in the existing electricity grid requires longer durations of charging sessions, as the longer the EV battery is available for grid balancing the better. The pressure on the electricity grid caused by large scale adoption of EVs can be alleviated by spreading out charging demand via smart charging. This will lead to longer charging times. Grid pressure alleviation also is realized by shifting demand to times of high renewable energy production and discharging of EVs in V2G systems.

These trade-offs have to be addressed by policy makers concerned with public charging infrastructure roll-out. While private charge points can fulfil the needs of many EV drivers, public charging infrastructure will most likely continue to play an important role in enabling the transition to e-mobility (Hardman et al., 2018). In Europe, various governmental levels are stimulating the build-up of public charging infrastructure. At EU level, the European Parliament and Council have committed member states to build sufficient public charging infrastructure to support their national EV fleet (European Parliament and The Council of the European Union, 2014). National governments have implemented a variety of policy

measures, which include setting of national targets, subsidizing public charging stations, and information campaigns (Cansino, Sánchez-Braza, & Sanz-Díaz, 2018). Furthermore, member states decide whether and how to implement dynamic energy tariffs (Greening, 2010), which could be used to stimulate shifting of EV charging demand. Municipalities also play an important role, as this is typically the level at which charge point placement is decided (Egnér & Trosvik, 2018; Heidrich et al., 2017; Helmus, Spoelstra, Refa, Lees, & Van den Hoed, 2018).

An example of a country that has been very active in building public charging infrastructure is the Netherlands. The Netherlands is one of the front-runner countries in e-mobility, with the highest market share of EVs within the EU-28 in 2018 (ACEA, 2019), and the Dutch government has expressed the ambition that by 2030 all new vehicles sold in the Netherlands are zero-emission vehicles (Rijksoverheid, 2019b). The number of EVs registered in the Netherlands is 18% of the total EVs registered within the EU-28 countries (EEA, 2018), but the country contains 28% of all public charge points (ACEA, 2018a). A recent publication of the Dutch Ministry of Economic Affairs presents the vision that charging infrastructure should optimally accommodate smart electric transport in the Netherlands, meaning that the charging infrastructure should be sufficient to avoid hindering EV adoption, but also cost-effective as part of a future smart energy system, which will increasingly be based on sustainable energy (Ministry of Economic affairs, 2017). Furthermore, the Dutch government has recently announced to invest 5 million Euro in bidirectional charging stations, which should support the integration of intermittent renewable sources via V2G technology (Rijksoverheid, 2019a). Dutch municipalities, the government layer responsible for charging infrastructure, are thus tasked with developing charging infrastructure that supports high EV adoption, doing so cost-effectively, and integrating the charging infrastructure in a smart and sustainable energy system.

To determine how local charging infrastructure should be further implemented, municipalities should take charging behaviour into account. For example, in a neighbourhood where the charge points are often occupied, a municipality might want to expand the charging infrastructure to accommodate the expected growth in EV adoption. However, if many of these EVs only charge for a short time but continue to be connected to the charge point, so-called "charge point hogging" (Wolbertus & Van den Hoed, 2017), it might be better to incentivize EV users to remove their EV after having charged, in order to make more efficient use of existing charging infrastructure. Another example is that charging with solar energy is most interesting for EVs connected to a charge point for a long time during the day while not charging, and can thus offer the flexibility needed to shift its charging demand to times of high solar power production.

In this chapter, we link charging behaviour to several policy measures commonly found in the literature for further charging infrastructure roll-out, which are designed to increase the availability, cost-effectiveness, and integration with intermittent renewable energy sources of charging infrastructure. The policy measures are: (1) *increase the number of charge points*,

(2) *reduce hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging*. We base our analysis on a large dataset of charging sessions of around one million charging sessions at public charge points in the Netherlands by card holders of NewMotion, a large e-mobility service provider (EMSP) in the Netherlands. To the best of our knowledge, this is the first study to use a large dataset of charging behaviour to evaluate different policies measures for public charging infrastructure roll-out that explicitly address the different roles EVs can play in future sustainable energy and transport systems.

Our analysis consists of three steps. First, we identify several indicators that characterize the charging behaviour relevant for evaluating which policy measure would fit best for a certain area. Second, we link these indicators to neighbourhood data on charging infrastructure and EV users. Third, we link aggregate charging behaviour at neighbourhood level to the policy options in a multi-criteria analysis, and compare the results of the multi-criteria analyses of between the neighbourhoods to. Together, these steps provide (1) a method to link charging behaviour to charging infrastructure related policy, and (2) identification of potentially coherent policy mixes, and (3) further insight in charging behaviour.

The rest of this chapter is organized as follows: Section 5.2 presents a concise review of the literature on charging infrastructure roll-out. Section 5.3 presents our framework, containing the policy targets we investigate and which charging behaviour indicators are relevant to assess the suitability of pursuing these targets. Section 5.4 presents our data, how we calculate the indicators from our data, and the method we use in our multi-criteria analysis. Section 5.5 presents our results. Section 5.6 discusses the contributions and limitations of our research, and Section 5.7 concludes the chapter.

5.2 Background

In an effort to address challenges for charging infrastructure roll-out, a growing body of research on public EV charging infrastructure has emerged. Several relevant environmental, economic and societal factors for charge point placement have been identified (Guo & Zhao, 2015), of which demand for charging is one of the most important (Chakraborty, Bunch, Lee, & Tal, 2019). Challenges for public charging infrastructure in roll-out are that there is a search for viable business models (Madina, Zamora, & Zabala, 2016; Zhang et al., 2018), pressure on the electricity grid is increased by EV charging (Eising et al., 2014), and public charge points take up a significant portion of public space, which is especially relevant when parking spots with charge points are reserved for EVs (Steinhilber, Wells, & Thankappan, 2013).

Studies focused on predicting the demand for charging consider both the location of the demand and the variation of the demand over time. The developed planning tools use data input such as mobility research data (Andrenacci, Ragona, & Valenti, 2016; De Gennaro,

Paffumi, Scholz, & Martini, 2014; Jiang, Jing, Cui, Ji, & Wu, 2018; Olivella-rosell et al., 2015; Smith, Shahidinejad, Blair, & Bibeau, 2011; Wang, Zhang, & Ouyang, 2015), EV pilot projects (Azadfar, Sreeram, & Harries, 2015; Khoo, Wang, Paevere, & Higgins, 2014; Speidel & Bräunl, 2014; Sun, Yamamoto, & Morikawa, 2016), surveys (Kristoffersen, Capion, & Meibom, 2011), or a combination of several of these inputs (Mallig et al., 2016; Xu, Çolak, Kara, Moura, & González, 2018). Many studies take the perspective of electricity grid managers and investigate the potential impact of EV charging on the electricity grid, and how this pressure can be reduced through smart charging and/or V2G (Azadfar et al., 2015; Hu, Morais, Sousa, & Lind, 2016). These studies focus on the variation of demand through time rather than location (Bauman et al., 2016; Blasius & Wang, 2018; Daina, Sivakumar, & Polak, 2017; Van der Kam & Van Sark, 2015; Weis, Jaramillo, & Michalek, 2014; Wolinetz, Axsen, Peters, & Crawford, 2018), or use a coarse spatial resolution (Ensslen et al., 2018b; Van der Kam et al., 2018; Waraich et al., 2013). As EV adoption increases, large datasets on public charging sessions become available as a data source. Such datasets have been used for descriptive studies (Morrissey, Weldon, & O'Mahony, 2016; Neaimeh et al., 2017; Van den Hoed, Helmus, De Vries, & Bardok, 2013), distinguishing types of EV users (Helmus & Van den Hoed, 2015), and evaluating public charging infrastructure roll-out strategies (Helmus et al., 2018).

While the aforementioned studies mostly describe or simulate charging behaviour, other studies have focussed on explaining charging behaviour. Charging tariffs play an important role in deciding where to charge (Chakraborty et al., 2019), but there is often also a strong habitual component (Zhang et al., 2018), influence of social norms (Caperello, Kurani, & TyreeHageman, 2013), and influence of range anxiety (Franke & Krems, 2013a, 2013b; Franke, Neumann, Bühler, Cocron, & Krems, 2012; Geske & Schumann, 2018). Several studies have investigated how to influence charging behaviour, in particular shifting demand to off-peak times to avoid grid congestion. Demand shifting can be stimulated by financial incentives (Chakraborty et al., 2019; Ensslen et al., 2018b; Nicolson, Huebner, & Shipworth, 2017), and by giving EV users feedback on how shifting their demand helps with load balancing and reducing CO_2 emissions (Bailey & Axsen, 2015; Will & Schuller, 2016). Furthermore, range anxiety and preferences for a minimum range should be taken into account for users to accept smart charging and V2G (Geske & Schumann, 2018; Will & Schuller, 2016). The early stages of EVs deployment are a good opportunity to influence charging behaviour as new social norms are still forming, especially for people who recently purchased an EV (Roy, 2017).

Other studies have focused on the connection time of EVs (Khoo et al., 2014; Morrissey et al., 2016; Wolbertus, Kroesen, Van den Hoed, & Chorus, 2018) and charge point hogging (Speidel & Bräunl, 2014; Wolbertus & Van den Hoed, 2017). Since charge points are used not solely for the purpose of recharging but also as a parking spot (Faria, Baptista, & Farias, 2014), it is often attractive for EV users to leave their EV plugged until they make their next trip, especially in cities where parking pressure is high. Wolbertus & Van den Hoed (2017)

show that this behaviour is indeed very common for public charge points with up to 11 kW maximum power output in the four major Dutch cities. For fast chargers, often placed along the highway, connection times are much shorter and charge point hogging is not as common (Morrissey et al., 2016; Wolbertus et al., 2018). With low levels of EV adoption and a sufficient charging infrastructure charge point hogging is not a major issue, but this will change as EVs become more mainstream. Inefficient use of public charge points will lead to a high number of charge points needed to meet charging demand. This results in increased costs for charge point instalment and operation, use of public space, and pressure on the grid, as many EVs charging at the same time can cause high peaks of electricity demand. Measures to reduce idle plug-in time include fees, rewards, connecting EV users via an app denoted as "social charging", valet charging, and unplugging (Wolbertus & Van den Hoed, 2017).

Summarizing, the spatial and temporal aspects of charging demand, efficient use of charging infrastructure, and integration of charging infrastructure in smart grids are all important topics in the scientific literature on charging infrastructure roll-out. Where earlier studies had to rely on EV pilot projects, surveys, or general mobility data, large datasets of charging sessions increasingly form the empirical basis of studies of charging behaviour. Such studies have been used to inform or evaluate charge point placement, and incentives for behavioural change, e.g., regarding smart charging and charge point hogging. However, a holistic approach to policies for charging infrastructure roll-out is missing. Our contribution lies in developing a framework that links charging behaviour to a set of policy measures that explicitly address the different functions of EVs in sustainable transport and energy, and applying this framework to a large dataset of charging sessions. In doing so, we clarify the trade-offs for policy makers who have to weigh the availability, efficiency, and sustainability of building up public charging infrastructure.

5.3 Framework

Based on our literature review, we identified five policy measures that contribute to one or more high level policy goals, i.e., to support large EV fleets, the cost-effectiveness of charge point roll-out, and charging with sustainable energy. These are: (1) *increase the number of charge points*, (2) *reduce hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging*. Each measure has its advantages and disadvantages, and can solve different kind of issues. The availability of charging infrastructure is increased by measures 1 and 2, the cost-effectiveness is increased by measures 2, 3 and 4, and the integration of renewables with EV charging is increased by measures 3 and 5. The measures are not mutually exclusive, but reducing charge point hogging (measure 2) will limit the flexibility needed for shifting EV charging demand (measures 3-5). In this section, we shortly discuss each measure. Following this, we present a decision tree that links charging behaviour to these policy measures. Policy

makers can use this decision tree to identify which policy measure is most suited for further developing charging infrastructure in a particular area.

5.3.1 Increase the number of charge points

Building more charge points increases the availability of charging infrastructure, and thereby increases the comfort of EV users and reduces range anxiety of EV users (Dong, Liu, & Lin, 2014; Neubauer & Wood, 2014). Disadvantages are that increasing the number of charge points leads to higher total cost for installation, maintenance and operation, and the local electricity grid may have to be strengthened in order to supply enough electricity for EV charging. Moreover, building a high number of charge points can be a problem in cities that have limited public (parking) space available.

5.3.2 Reduce hogging

Reducing charge point hogging increases the availability of existing infrastructure, resulting in a more cost-effective charging infrastructure. A disadvantage is that to reach this policy target EV users would have to be incentivized to move their EV (Wolbertus & Gerzon, 2018), which is especially problematic in areas with high parking pressure.

5.4.3 Vehicle-to-grid

EVs can be used for grid management, such as ancillary services and storage for renewable energy. These kind of services are enabled with V2G technology (Kempton & Tomić, 2005b). There are several disadvantages of V2G for EV users. Implementing V2G systems requires flexibility of EV users (Gerritsma, Alskaif, Fidder, & Sark, 2019), as it will lead to longer charging times. Furthermore, EV users will have to give control of the charging process to an algorithm, grid manager or aggregator, since using EVs for grid management will require real-time information grid conditions. Also, participating in V2G schemes may increase degradation of EV batteries (Wang, Coignard, Zeng, Zhang, & Saxena, 2016). Given these disadvantages for EV users, they will have to be incentivized to participate in such a system.

5.4.4 Overnight charging

One peak in EV charging demand typically occurs in the evening, when EV users return home, coinciding with peaks in household electricity demand (E-Laad, 2013). Encouraging EV users to shift their charging demand to the night is beneficial for grid management, since large peaks in electricity demand can be avoided. However, EV users have to be incentivized to shift their demand, or a system which does this automatically has to be implemented. Furthermore, charging EVs at lower power than the maximum power capacity will lead to longer charging times.

5.4.5 Solar charging

EVs are an especially clean mode of transportation when charged with PV solar power and can contribute to integration of PV solar power when EV charging is aligned with times of high PV solar power production. Next to the evening peak, EV charging demand peaks in the morning (E-Laad, 2013), which is typically linked to commuters arriving at their location of work. This peak can be shifted to better align with generation of PV solar power, which is highest in the late morning and early afternoon. For automatic shifting of charging demand, a form of automated smart charging based on algorithms would have to be implemented. *Solar charging* is interesting for EV users wanting to reduce their carbon footprint, but EV users could also be incentivized with lower charging fees for *solar charging*.

5.4.6 Decision tree

Table 5.1 present a summary of the policy measures, and Figure 5.1 presents a decision tree, which shows how charging behaviour can inform policy design. The logic underlying the decision tree is as follows: by looking at the idle connection time, i.e. time connected to a charge point but not charging, one can identify whether there is flexibility in EV charging. If the idle connection time is low, and the total connection time is high, the number of charge points should be increased in that area to prepare for higher EV adoption rate (left hand branch of tree). If the idle connection time is high, there is opportunity to increase the cost-effectiveness of charging infrastructure. The cost-effectiveness can be increased either through better integration with the grid and potentially renewable energy sources (*vehicle-to-grid*, middle branch) or by increasing the availability of charge points (*reduce hogging,* right hand branch), the latter of which is relevant only when the total connection time is high and the charge points are thus often occupied. Policy makers have to decide which of these goals is more relevant for that particular area. Of course, policy makers can also decide not to use the flexibility of idle connection time and build more charge points to increase the

comfort of EV drivers, but for this analysis we assume that policy makers want to make efficient use of existing infrastructures.

The policy measures *overnight charging* and *solar charging* are compatible with *more charging points*, *vehicle-to-grid* and each other, and depend on charging behaviour on specific times of the day. If many EVs are charging in the evening and still connected to charge points in the night, the evening peak can be reduced by charging the EVs overnight, thereby reducing the impact of EV charging on the electricity grid. If many EVs are charging in the morning and still connected to charge points when solar energy production is high, the demand can be shifted to charge EVs with solar energy, thereby decreasing the impact of EV charging on the grid and increasing the integration with renewable energy. *Reduce hogging* could in principle be compatible with *overnight charging* and *solar charging* by encouraging EV users to remove their EV when fully charged, but in such a system it would have second priority after the demand has been shifted, which is why we have not included it in our scheme.

Table 5.1 Advantages, disadvantages, and optimal conditions for different policy targets to further develop public charging infrastructure

Policy measure	Contributes to high-level policy goal	Advantages	Disadvantages	Effective measure in neighbourhoods with
Increase the number of charge points	● Availability	● Comfort of EV drivers ● Reduces range anxiety	● High costs ● Increased pressure on grid ● Increased use of public space	● Low idle connection time ● High total connection time
Reduce hogging	● Availability ● Cost-effectiveness	● Less charge points needed to support EV fleet	● EV users have to move EV when charged sufficiently	● High idle connection time ● High total connection time
Vehicle-to-grid	● Cost-effectiveness ● Sustainability	● Decreased pressure on grid ● EVs as storage for renewables	● Incentives and automation system needed ● Long charging times ● Potentially decreased battery life	● High idle connection time
Overnight charging	● Cost-effectiveness	● Decreased pressure on grid	● Incentives and automation system needed ● Long charging times	● High charging time during evening peak ● High idle connection time during night
Solar charging	● Sustainability	● Integration with renewables ● Decreased pressure on grid	● Incentives and automation system needed ● Long charging times	● High charging time during morning ● High idle connection time during solar hours

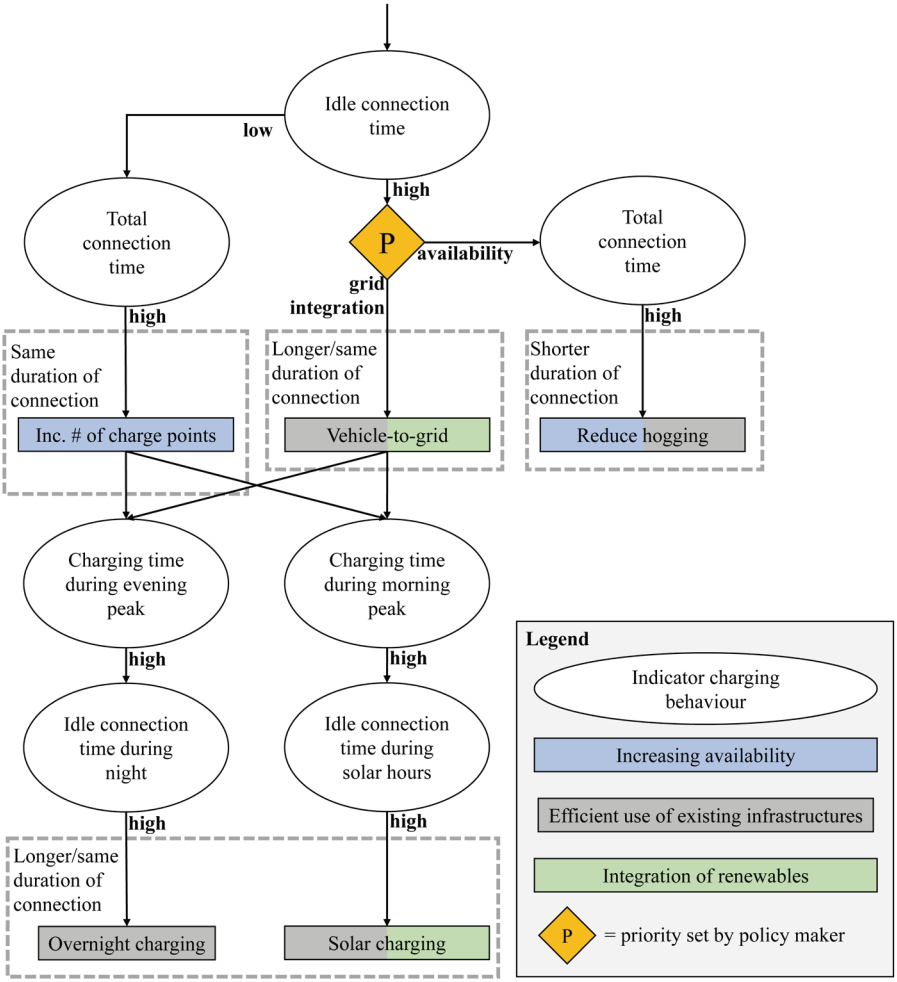


Figure 5.1 Decision tree for implementation of policy measures for public charging infrastructure roll-out

5.4 Data and Methods

This section presents our data sources and methodology. We apply our framework to our dataset of charging sessions, which is described in Section 5.4.1. First, we calculate the indicators as presented in Figure 5.1 and Table 5.1 for charging behaviour aggregated to four-digit postal code (PC4) level, see Section 5.4.2. By linking these indicators to data on the population and local (use of) charging infrastructure, we can characterize what sort of neighbourhoods a certain behaviour takes place in, see Section 5.4.3. We do so via negative binomial regression analyses, see Section 5.4.4, Next to the regression analyses, we link the

indicators to the five policy measures via a multi-criteria analysis (MCA), see Section 5.4.5. We use these results to compare optimal policy measures amongst neighbourhoods, which can in turn be used to identify coherent policy mixes.

5.4.1 Data

5.4.1.1 Charging sessions

Our dataset contains 1048575 charging sessions that took place in in the period 27 December 2016 to 2 September 2018 by card holders of NewMotion. In total, the dataset contains 6895 unique EV users and 24955 unique charge points. Table 5.2 presents the variables in the dataset after cleaning of the dataset as described later in this section. It describes the variable names and in what unit it is expressed. There are 818634 lines of data that is complete, which is 78% of the total dataset. We have added two variables to the dataset by looking up the technical specification of the EV models in the database of the e-mobility company EV-Box (EVBox, 2019). The variables we added are: (1) the type of vehicle (full electric vehicle (FEV), plug-in hybrid electric vehicle (PHEV), or e-motorcycle), and (2) the maximum charging rate of the EV. Table B.1 in Appendix B presents summary statistics.

Table 5.2 Description of dataset of charging sessions after data cleaning process

Variable Name	Description	Unit
user_postal_code	Postal code of EV user residence	PC6
start_datetime_local	Start time charging session	Date (minutes)
end_datetime_local	End time charging session	Data (minutes)
duration	Duration of charging session	Seconds
volume	Energy charged	kWh
charge_point_postal_code	Postal code of charge point	PC6
charge_point_country	Country of charge point	Netherlands
make	EV producer	1 of 27 companies
model	EV model	1 of 78 models
batterycapacity	Battery capacity	kWh
user_id_cat	ID of EV user	1 of 5337 unique IDs
charge_point_serial_cat	ID of charge point	1 of 15348 unique IDs
max_power	Maximum power output of charge point	W

In our analysis, we have only used data on charging sessions of which (1) the data is complete, (2) the charge point is located in the Netherlands, (3) the charged volume does not exceed the battery capacity of the EV, and (4) the charged volume divided by the duration of the charging session does not exceed the maximum power output of the charge point. These data cleaning steps have resulted in 847433 usable charging sessions (81% of the total dataset). With steps 3 and 4 of the data cleaning process, we removed data which is technologically impossible, but we expect that some errors remain due to errors in measurement or registration.

We use data from 2017 and 2018 in our analysis, which are the complete years in the dataset. We do so to prevent monthly changes in charging patterns to have an influence on the profile (some months would have more data points than others). We include charging sessions starting in 2016 and ending in 2017 and charging session starting in 2018 and ending in 2019. After selecting for this time period, we are left with 744400 charging sessions for our analysis (71% of the total dataset and 91% of the complete lines of data).

5.4.1.2 Population and area data

To calculate charge point density, we use data on the number of inhabitants and the area size per four-digit postal code (PC4). For the number of inhabitants per postal code, we use the 2018 data from Statistics Netherlands (CBS) of the Netherlands (CBS, 2018). For the area size we use data from the 2018 cadastral map as published by The Netherlands' Cadastre, Land Registry and Mapping Agency.

5.4.2 Calculation of indicators

Figure 5.1 and Table 5.1 present the indicators (total connection time, idle connection time, and charging time) we use to link charging behaviour to policy design. In this section, we describe how we calculate these from our data. We aggregate the time-steps to 15 minutes and calculate the indicators on PC4 level. The Netherlands is divided in 4052 four-digit postal codes with an average of 4173 inhabitants (with standard deviation 4130). In our analysis, we only take into account PC4 areas with at least one charging session by a card holder of NewMotion. These are 2511 postal codes in total with an average of 6233 inhabitants (with standard deviation 4348).

5.4.2.1 Total connection time

In our dataset both the start and end times of charging sessions are given. We define the total connection time as the total time that EVs are connected to charge points. For each PC4 area we take the average connection time per charge point.

5.4.2.2 Idle connection time and charging time

To calculate the charging time and idle connection time we need to determine the charging profile for each charging session. Our dataset does not contain information on the power output over time or when an EV stops charging (but is still connected to the charge point). This means that we have to make some significant simplifications to calculate charging profiles. The relevant variables in the data for this analysis are the volume that was charged, the maximum power output of the charge point, and the maximum charge rate of the EV. An EV often charges at a lower rate than the maximum power (Gerritsma et al., 2019); the charging profile depends on factors such as power losses, the EV type, the state of charge (SOC) of the battery, the outside temperature, the grid conditions, the car battery management system, etc. Given that we do not have that information, the power output over time is calculated by assuming the EV charges at either the maximum power of the charge point or the maximum charge rate of the EV at 100% efficiency (the lowest value of the two, see Figure 5.2 for an illustration). This means that we overestimate the actual power output over time and the time the EV needed to be charged. It is therefore important to interpret the results regarding charging time and idle connection time as an indicator suitable for comparing neighbourhoods and users, but not as an absolute measure.

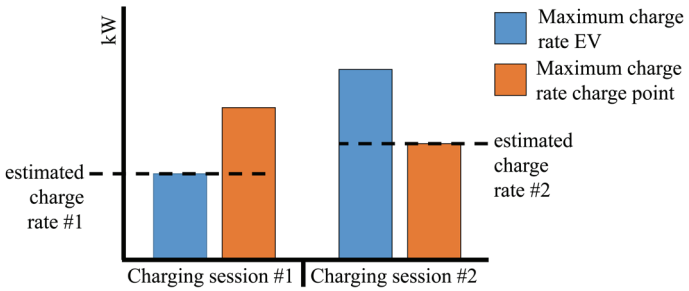


Figure 5.2 Estimation of charge rate in a charging session

With our estimated charging profile we calculate the charging time as the time the EV was connected to a charge point and charging. The idle connection time, then, is the time the EV was connected to the charge point and *not* charging.

For the policy measure *overnight charging*, we need to define the time of the evening peak and night-time. Looking at the resulting charging profile of weekdays in our data (see Figure 5.3), the evening peak starts around 17:00 and ends around 22:00. Charging demand is lowest overnight, and starts increasing from around 6:00. Therefore, we set the time of the evening peak from 17:00-22:00 and define night-time as 22:00-6:00. Furthermore, we calculate the idle connection time in the night of EV users that have charged during preceding the evening peak, because this reflects the charging demand that can actually be shifted.

Under the policy measure *solar charging*, EVs postpone their charging needs in the morning to times of high PV solar power production. Based on the charging profile (see Figure 5.3), we define morning charging to be between 6:00, when charging demand starts rising after the night, and 12.00, when the morning peak in charging is over. The cut-off points for when PV solar power production is high will always be somewhat arbitrary, as in practice it is dependent on weather conditions, such as cloudiness and temperature, which vary throughout a day as well as a year (seasonal changes). On average, PV solar production in the Netherlands is high in mid-to-late morning and early afternoon.[19] We choose to define high PV from 9:00 to 15:00. As with *overnight charging*, we calculate the idle connection time during solar hours of EV drivers that also charge during the morning on the same day in order to measure charging demand that can be shifted.

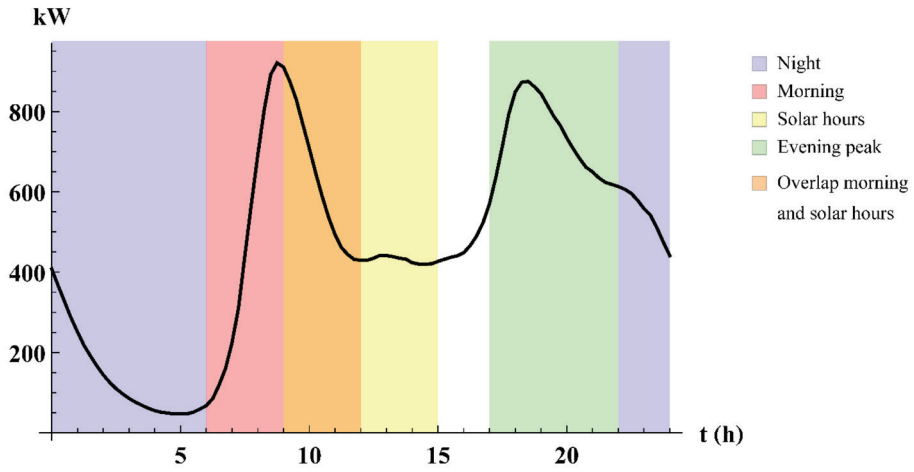


Figure 5.3 Resulting week profile of average charging power charging power of charging sessions by NewMotion card holders for weekdays including defined cut-off times

[19] Based on 2014 solar irradiation data and southward facing PV solar panels, see Figure 3.2

5.4.3 Additional statistics

To characterize the neighbourhoods in which a specific charging behaviour takes place often, we link the indicators to several variables of charging infrastructure and EV users.

5.4.3.1 Charging infrastructure

The data contains unique IDs and locations of the charge points. We calculate charge point density in two ways: by dividing the total number of charge points within each PC4 area by the total population, and by dividing it by the area size. The data also contains information on the maximum charge rates of the charge points. We take the average maximum charge rate of the charge points within a PC4 area. Our data contains the postal codes of charge points and unique user IDs for each charging session.

5.4.3.2 EV users

Our data contains unique user IDs for each charging session. For each PC4 area, we determine the ratio of EV users who have charged there more than once to the total number of EV users. We also determine whether an EV user is charging near home, we compare the five-digit postal code (PC5) of the EV user with the PC5 of the charge point. If these are the same, we consider the EV user to charge near home. Dutch PC5 areas have a median area of 0.15 km^2, which we consider reasonably close to home, compared to PC6 areas that have a median area of 0.005 km^2 and PC4 areas that have a median area of 5.5 km^2. This is not a perfect measure. Firstly, there is substantial variation in the size of PC5 areas (mean = 0.88 km^2 and standard deviation = 4.3 km^2 in the areas we consider in our analysis). Furthermore, the EV user might live close to an adjacent PC5 area where the EV is charged. Finally, what constitutes a reasonable distance from home differs between people. It is therefore important to consider this indicator as indicative for the percentage of EV users charging near home, rather than a precise measurement.

5.4.4 Regression model

We link the indicators to neighbourhood characteristics relating to charging infrastructure and EV users via a negative binomial regression model. We choose this type of model because the distributions of the dependent variables are highly skewed, even after log transforming, and the variance is much greater than the mean. A negative binomial regression model requires count data. All our dependent variables measure time, so as input for the model we use the time-steps in which that specific behaviour takes place for each

neighbourhood, at a resolution of 15 min. The neighbourhood characteristics we look at are charge point density (per inhabitant and per km^2), the average maximum charge rates of charge points, recurring EV users, and EV users charging in the same PC5 area as where they live (home users). As a control variable, we also include the number of charge points in our regression model. We base our selection on (1) the data available to us, and (2) whether we expect a correlation or think a correlation could provide interesting information for policy makers.

We include charge point density as a key indicator for the characteristics of charging infrastructure in a neighbourhood. We do not have any prior expectation on how it links with charging behaviour. A low charge point density could lead EV drivers to move their EV to another parking spot when having charged sufficiently, but they would have to be aware of this low density and be concerned about other EV drivers wanting to charge. We expect the average maximum charge rate of charge points to have a negative correlation with the connection time and charging time, because a higher charge rate will lead to the EVs being charged sufficiently in a shorter time. This could also lead to longer idle connection times, but it could also be the case that the maximum charge rate has a negative effect on idle connection time, as hogging behaviour has been found to be less common at fast chargers (Morrissey et al., 2016; Wolbertus et al., 2018).

We include two variables on the EV users that visit the charge points, EV users that visit a neighbourhood more than once (recurring users), and the EV users that charge near their home (home users). Charging behaviour has a strong habitual component (Zhang et al., 2018) and is influenced by social norms (Caperello et al., 2013). We expect that a high percentage of recurring EV users and home users will make it easier for new charging norms to form in that particular area, and therefore we think it is interesting to include this variable in our analysis. We have no a priori expectation on how the percentage of recurring users influence charging behaviour, but we do have expectations on the link between charging behaviour and the percentage of home users. We expect home users to have longer connection and idle connection times, because they will have their EV parked often overnight and throughout the weekends. Furthermore, we expect the evening peak to be higher, because this peak results mostly from EV users coming home after work. During the day however, we expect many EV users do not charge near home, but near their work, which is why we expect a negative effect on charging time during the morning and idle connection time during solar hours.

5.4.5 Multi-criteria analysis

To compare the fit of neighbourhoods for implementing a specific policy measure between each other, we perform a MCA. A MCA allows to incorporate multiple criteria which measure different qualities in a decision process. There are many methods to perform a MCA, ranging from weighted sum or product to hierarchical models. In our analysis, the criteria are

all numeric variables that measure time, so we opt to take a simple MCA approach, namely the weighted product method. We take the product instead of the sum, because for our case the fit of a policy measure depends on *all* formulated criteria being a good fit, e.g. if many EVs charge during the evening peak, but none of them stay connected after having charged during the night, the demand cannot be shifted to night-time. Furthermore, we divide the criteria by the maximum value for that criterion, so that the scales are comparable. This results in the following calculation:

$$s_i = \prod_n w_n \frac{x_{i,n}}{\max(x_n)} \tag{5.1}$$

Where i is the index for PC4 areas, s_i is the MCA score for PC4 area i, w_n is the weighing factor for criteria n, $x_{i,n}$ the value of criterion n for PC4 area i, and $\max(x_n)$ the maximum value of criterion n, and σ_x the standard deviation of criteria x. The preferred values for w_n might differ for different policy makers depending on their priority and other factors such as grid capacity. For the sake of simplicity, we set $w_n = 1$ for each criterion n.

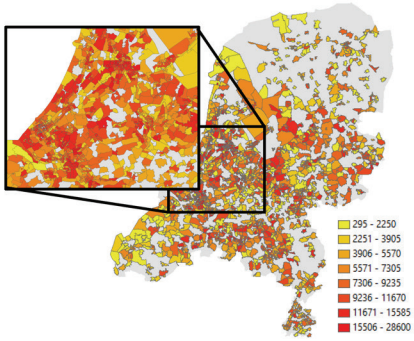
We correlate and plot the results of the MCA for neighbourhoods. This way, we can look for patterns in the results, and can see whether we can identify coherent policy mixes for specific neighbourhoods.

5.5 Results

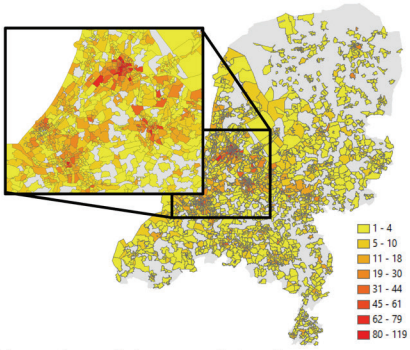
This section presents our results. Section 5.5.1 present the indicators we calculated from our data, and includes several maps and aggregated charging profiles. Section 5.5.2 presents the results from our regression analyses, and Section 5.5.3 presents the results from the MCA.

5.5.1 Charging infrastructure and charging behaviour

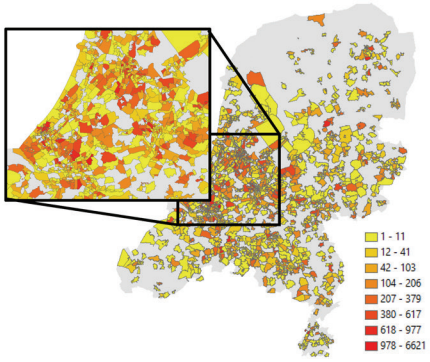
Figure 5.4 shows maps for the number of inhabitants, where NewMotion card holders have charged, and charging sessions in the time period considered in our analysis (for reference, we have included a map of the Netherlands, see Figure 5.4d). The maps show that these factors are distributed differently throughout the Netherlands. Compared to the number of inhabitants, the number of charge points where NewMotion card holders have charged are concentrated in Amsterdam, Utrecht, and Rotterdam. However, most charging sessions take place outside of the major city centres in suburban areas.



a) number of inhabitants in areas where NewMotion card holders have charged



b) number of charge points where NewMotion card holders have charged



c) number of charging sessions by NewMotion card holders in 2017 and 2018

d) reference map of the Netherlands

Figure 5.4. Inhabitants in areas with at least one charging session by NewMotion card holders, number of charge points where NewMotion card holders have charged, and charging sessions by NewMotion card holders in 2017-2018 in PC4 areas located. The densely populated Randstad area is enlarged. The figure also includes a map of the Netherlands for reference (d). Grey areas do not have a data point

Figure 5.5 shows the resulting weekly charging profile for all NewMotion card holders averaged over 2017 and 2018. The figure shows clear morning and evening peaks for weekdays, while in the weekend the peak is in the late afternoon. The patterns for PHEVs and FEVs are very similar. One difference is that the evening peak lasts longer for FEVs, due to larger battery size and thus longer charging of FEVs. For the morning peak this is not the case. This could indicate that FEV drivers do not charge their EV in the morning as often as PHEV drivers, but instead have enough range to only charge when they have arrived home in the evening. Another thing to note is that the charging demand for both types is roughly the same. FEVs only make up roughly 42% of the EV users in this analysis. It is not surprising that PHEVs charge less than FEVs given that PHEVs can also use the internal combustion engine. Assuming other factors, such as efficiency and driving patterns, are equal between

the two EV types, it seems that PHEV users, at least the ones in this dataset, use the battery for a majority of their distance driven.

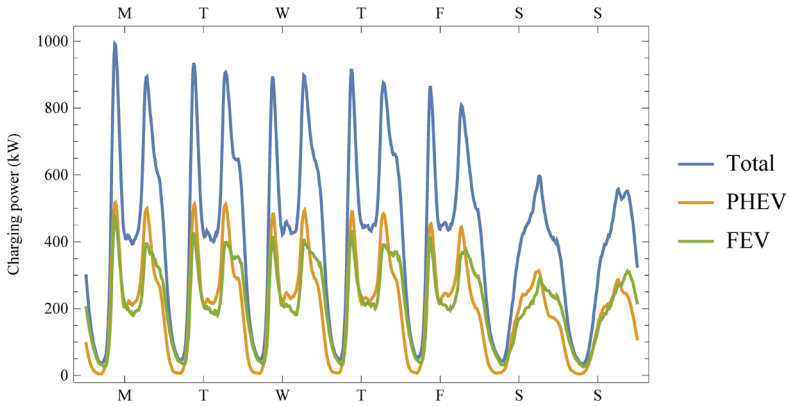


Figure 5.5 Resulting week profile of average charging power of NewMotion card holders. Ticks on the horizontal axes indicate 12.00

Figure 5.6 and Table 5.3 show the variation of the indicators per PC4 area. All distributions follow a power law, which is why the x-axes and y-axes of the histograms have a logarithmic scale (we added 1 before log transforming to include zeroes). We can also see that there is a large variation in connection time, the idle connection time, and the idle connection time in the night and during solar hours, varying from 0% to around 90%. The charging time in the evening varies from 0% to 28%, and the charging time in the morning varies from 0% to 17%. This indicates that connection, idle connection, and charging is highly concentrated in a small portion of the total neighbourhoods.

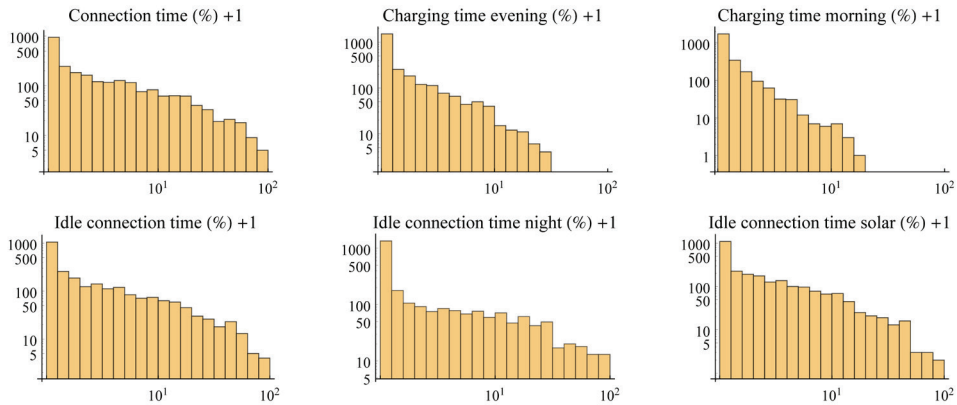


Figure 5.6 Histograms of charging behaviour indicators at PC4 level (log-log scale, the unit is connection time divided by the total time considered in this analysis, which is 2 years for the connection and idle connection time, 5 hours / 24 hours * 2 years for the charging time evening, 8 hours / 24 hours * 2 years for idle connection time night, and 6 hours / 24 hours * 2 years for charging time morning and idle connection time solar)

Table 5.3 Summary statistics of charging behaviour indicators at PC4 level (the unit is connection time divided by the total time considered in this analysis, which is 2 years for the connection and idle connection time, 5 hours / 24 hours * 2 years for the charging time evening, 8 hours / 24 hours * 2 years for idle connection time night, and 6 hours / 24 hours * 2 years for charging time morning and idle connection time solar)

Variable	N	Mean	St. Dev.	Min	Q1	Median	Q3	Max
Connection time (%)	2511	4.375	9.843	0.003	0.090	0.694	3.845	95.033
Idle connection time (%)	2511	3.714	8.815	0	0.047	0.483	3.051	90.595
Charging time during evening peak (%)	2511	1.053	2.570	0	0.007	0.121	0.805	28.027
Idle connection time during night (%)	2511	4.494	11.445	0	0	0.160	3.027	93.086
Charging time during morning (%)	2511	0.426	1.112	0	0.011	0.094	0.367	17.477
Idle connection time during solar hours (%)	2511	2.884	6.964	0	0.032	0.462	2.469	89.806

Figure 5.7 shows the relation between these indicators via pairwise plot, correlations, and analysis of variance (ANOVA) tests. First of all, we can see that the connection time and idle connection time are extremely strongly correlated. This indicates that in areas where the availability of charging infrastructure is relatively low, there is a lot of flexibility to either reduce hogging or implement V2G. Furthermore, the charging time in the evening and idle connection time in the night have a strong correlation, indicating that in neighbourhoods with a large evening peak in charging demand there is often the potential to postpone charging. Finally, the charging time in the morning and idle connection time during solar hours have the weakest correlation out of these examples, and we can see that there are many neighbourhoods that have either a lot of EV charging and the morning or a lot of EVs hogging in the afternoon, and not both as would be ideal for solar charging.

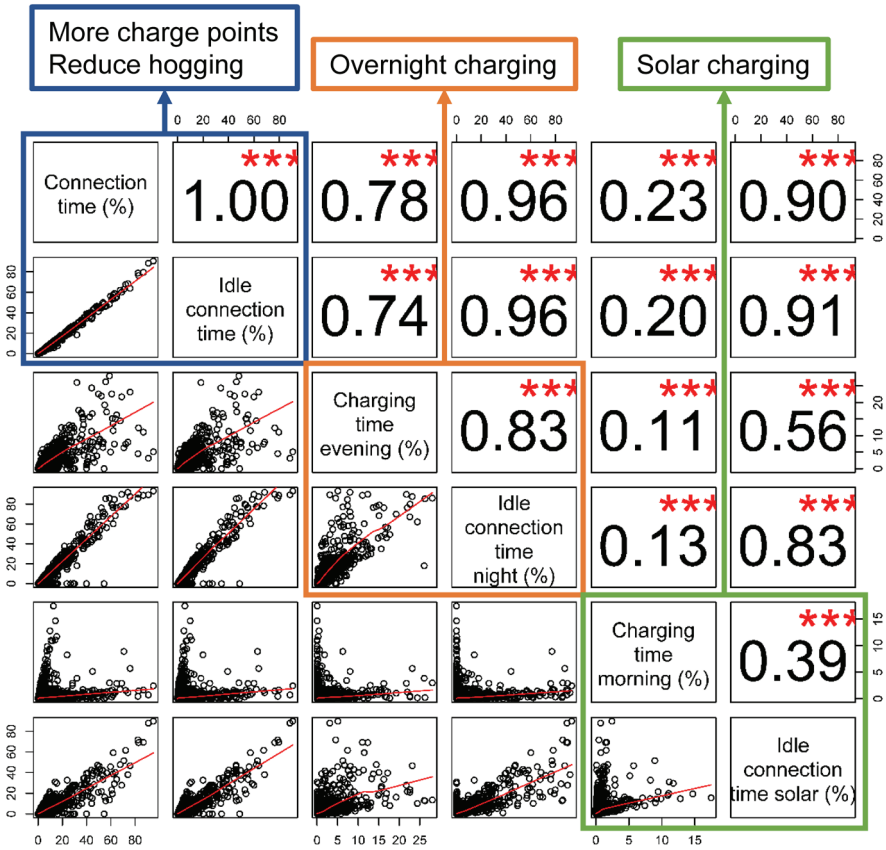


Figure 5.7 Comparison of charging behaviour indicators at PC4 level: pairwise plots, correlations, and indications of p-values resulting from an ANOVA analysis, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The red trend line is drawn using the LOWESS smoother function (Cleveland, 1981). The figure highlights pairs of indicators relevant for a specific policy measure

Figure 5.8 shows the distribution of our additional statistics (Figure B.1 in Appendix B presents correlations and pairwise plots). The distributions of the charge points per km^2, charge points per inhabitant, charging sessions, charge points per session, and home users are highly skewed and presented with a logarithmic scale on the x-axis. Furthermore, there is large variation in all these variables, indicating that charging infrastructure and the EV users that charge differs to a great extent among neighbourhoods. Another noteworthy result is that most neighbourhoods have charge points with an average maximum charge rate of 11 kW. Looking at the EV users, we can see that the percentage of users that return to the same charge point has two peaks on the extreme (no user returns for another charging session, or every EV user charges at least twice in that area), and resembles a normal distribution in between the extremes. Also, the results show that the number of EV users that live in the same areas where they charge is generally low, and in a lot of neighbourhoods only visiting EV users were charging.

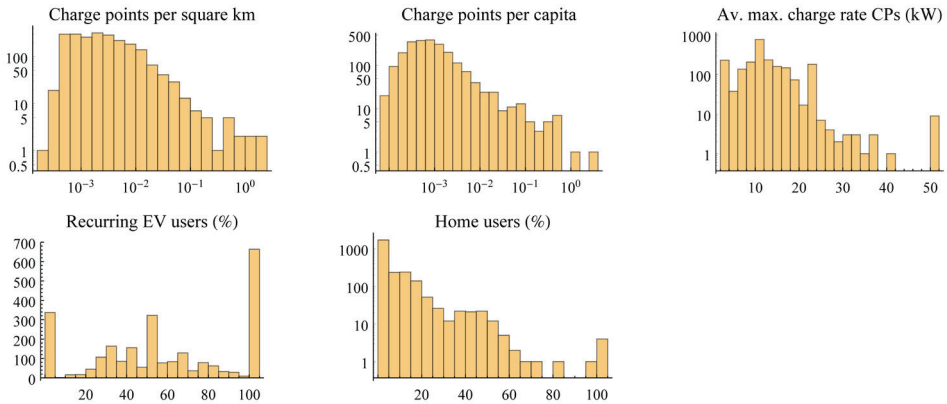


Figure 5.8 Histograms of additional statistics on charging infrastructure and EV users at PC4 level. Note that the histograms of charge points per square km and charge point per capita are presented on log-log scale, and the y-axis are log scaled for the histograms of the average maximum charge rates of charge points and home users

5.5.2 Regression analysis

Table 5.4 presents the results of our regression model, see Table B.2 in Appendix B for summary statistics. The results show that charge point density as measured by area size is negatively correlated with all charging behaviour indicators. This indicates that in areas where charge points are rarer, they are used more often. The results of charge point density measured by population size are somewhat different. We find no significant correlation with connection time and idle connection time during solar hours, and a positive correlation with charging time during the morning. The latter effect might be due that charging in the morning often takes place at the location of work, at which municipalities and/or companies have invested in public charging infrastructure.

As expected, we find the maximum charge rate to have a negative correlation with the connection time and charging time during the evening. Furthermore, we find a negative correlation with idle connection time. Surprisingly, we do not find a significant negative correlation with the charging time during the morning. It turns out that EV drivers prefer charge points with high charge rates more in the morning than at other times of the day, which explains this finding (the charging goes faster, but there is more of it).

Finally, we find positive correlations between recurring users and home users with all charging behaviour indicators. The positive correlations of home users and the charging behaviour indicators is in line with our expectations, except for charging time in the morning and idle connection time during solar hours, for which we expected a negative correlation. This indicates that also in residential neighbourhoods *solar charging* can have high potential.

Table 5.4 Results of the negative binomial regression model. The table presents the coefficients for the charging behaviour indicators and model diagnostics. Standard errors in parentheses, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The values for theta are significant, which indicates that using a negative binomial regression model is preferred to a Poisson regression model for this data. We have included the log-likelihood for the fitted model and the null model, and McFadden's pseudo-R^2 as an indicator for goodness-of-fit; these indicate that the goodness-of-fit is low for these models

Variable	Connect-ion time (15 min)	Idle connect-ion time (15 min)	Charging time during evening peak (15 min)	Idle connect-ion time during night (15 min)	Charging time during morning (15 min)	Idle connection time during solar hours (15 min)
Charging infra-structure						
CPs p km2	-0.025 ***	-0.0251 ***	-0.0162 *	-0.0244 **	-0.0332 ***	-0.0280 ***
	(0.006)	(0.0064)	(0.0072)	(0.0088)	(0.0068)	(0.0067)
CPs per inhabitant	-0.729 (0.378)	-0.842 *	-1.17 *	-2.89 ***	3.19 ***	0.073 (0.424)
		(0.402)	(0.45)	(0.61)	(0.43)	
Av. Max. Charge Rate (kW)	-0.0325 ***	-0.0359 ***	-0.0328 ***	-0.0435 ***	0.0092 (0.0068)	-0.0210 **
	(0.0059)	(0.0063)	(0.0071)	(0.0088)		(0.0067)
EV users						
Recurring EV users (%)	0.0188 ***	0.0193 ***	0.0181 ***	0.0211 ***	0.0154 ***	0.0180 ***
	(0.0010)	(0.0011)	(0.0012)	(0.0015)	(0.0012)	(0.0012)
Home users (%)	0.0601 ***	0.0648 ***	0.0469 ***	0.0722 ***	0.0132 ***	0.0526 ***
	(0.0030)	(0.0032)	(0.0036)	(0.0044)	(0.0034)	(0.0034)
Control variables						
CPs	0.109 ***	0.109 ***	0.0969 ***	0.105 ***	0.140 ***	0.119 ***
	(0.005)	(0.005)	(0.0057)	(0.007)	(0.005)	(0.005)
Constant	7.31 ***	7.08 ***	4.63 ***	6.11 ***	3.82 ***	5.49 ***
	(0.11)	(0.12)	(0.13)	(0.16)	(0.13)	(0.12)
Diagnostics						
N	2203	2203	2203	2203	2203	2203
Theta	0.458	0.406	0.318	0.211	0.354	0.365
	(0.011)	(0.010)	(0.008)	(0.006)	(0.009)	(0.009)
Log-likelihood (fitted model)	-21564.0	-20847.9	-14590.5	-16907.0	-13922.2	-17380.6
Log-likelihood (null model)	-22350.7	-21539.0	-14963.7	-17299.6	-14369.8	-17878.1
McFadden's pseudo-R^2	0.0352	0.0321	0.0249	0.0227	0.0311	0.0278

5.5.3 Multi-criteria analysis

This section presents the results from the MCA. Our MCA does not allow to make absolute decisions on which policy target to pursue, but does allow for comparison between neighbourhoods. Therefore, we use the results from this analysis to compare neighbourhoods amongst each other, and identify potentially coherent policy mixes.

Figure 5.9 presents the results of the MCA for neighbourhoods, using pairwise plots, correlations and p-values from ANOVA tests. Strong correlation of MCA scores for different policies indicate that these policy mixes together can form a coherent policy mix in certain neighbourhoods. A correlation cannot provide a complete picture though, so it is also important to look at the pairwise plots. Neighbourhoods with a good fit for both policy measures are located the upper right side of the graphs. The results indicate *increase the number of charge points*, *vehicle-to-grid*, and *overnight charging* will very often all have a good fit with the same neighbourhoods, and thus could make sense to combine in a policy mix. The correlation between *reduce hogging* and *vehicle-to-grid* is also very strong, but the policy measure *reduce hogging* aims to reduce connection time, meaning there will be less flexibility for using the EV for ancillary services or as storage for renewable energy. Therefore, these two policy measures will not make for a coherent policy mix. Neighbourhoods with high MCA scores for *solar charging* often have low MCA scores for the other neighbourhoods, meaning that it will often make sense to only implement this policy measure, and not as part of a policy mix.

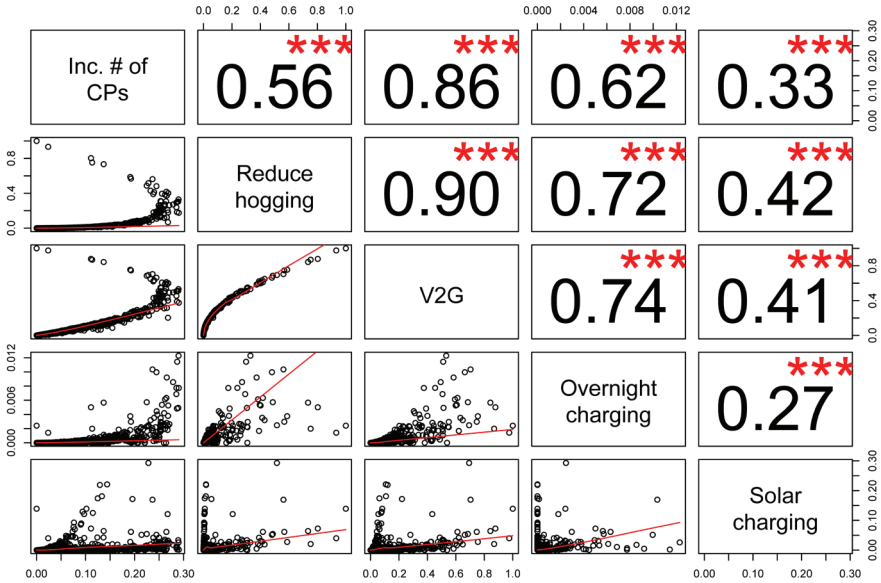


Figure 5.9. Results of the MCA for PC4 areas: pairwise plots, correlations, and indications of p-values resulting from the ANOVA analysis, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The red trend line is drawn using the LOWESS smoother function (Cleveland, 1981)

5.6 Discussion

5.6.1 Contributions

We distinguish three main contributions of this chapter to e-mobility research. First, we highlight incoherence in long-term visions of e-mobility that include EVs as a clean mode of transport and as a stabilizing mechanism in sustainable electricity grid, specifically for how charging infrastructure is developed. Second, we develop a framework that links charging behaviour to a set of policies that explicitly support different high-level policy goals. Third, we add to the increasing number of studies that provide empirical evidence of actual EV charging behaviour.

Our framework relates charging behaviour to five policy measures for public charging infrastructure: (1) *increase the number of charge points*, (2) *reduce hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging*. These measures contribute to high level goals for e-mobility, either by supporting large scale adoption of EVs by increasing availability of charging infrastructure (*increase the number of charge points*, *reduce hogging*), increasing cost-effective use of existing charging infrastructure (*reduce hogging*) or electricity infrastructure (*vehicle-to-grid*, *overnight charging*, *solar charging*), or integration with renewable energy (*vehicle-to-grid*, *solar charging*). Crucially, these policy measures cannot all be combined in a single, coherent policy package. Policy measure 2 aims to reduce the time EVs are connected to a charge point, while long connection times are necessary for optimal functioning of policy measures 3-5. Furthermore, the optimal charging behaviour for implementing these policy measures differs. Therefore, policy makers responsible for public charging infrastructure should take charging behaviour into account in policy design.

By applying our framework to a large dataset of charging sessions, we highlight several aspects of charging behaviour relevant for policy design. A key finding is that the distributions of connection time, idle connection time, and charging time follow a power law, and there is large variation in these behaviours amongst neighbourhoods. These results indicate that EV charging is highly concentrated in relatively a small number of areas of the Netherlands. Also, we find a very strong correlation with connection time and idle connection time, indicating that there is a lot of potential to use the existing charging infrastructure more efficiently, or to make us of the flexibility offered by EVs for grid services and aligning charging demand with renewable energy production.

We use a negative binomial regression to link our main indicators to neighbourhood characteristics on charging infrastructure and EV users. These results show that the use of charging infrastructure is higher when charge point density is lower, indicating that the charge points are unequally spread as compared to charging demand. The only exception is the correlation between charge point density and charging time in the morning, possibly because many EV drivers charge near their work, where municipalities and companies might

have invested in public charging infrastructure more as compared to residential areas. Furthermore, we found that the connection time, idle connection time, and charging time in the evening is lower in areas with a higher maximum charging capacity, in line with Morrissey et al. (2016) and Wolbertus et al. (2018).

We find that the percentages of recurring EV users and EV users charging near their home (home users) are positively correlated with connection time, idle connection time, and charging time. High values for these indicators have a good fit with the policy measures that require behavioural change (2-5). Hence, this finding has interesting implications for policy makers, as it might be easier for new charging behaviour norms to form in these areas. Contrary to our expectations, we find the percentage of home users to be positively correlated with charging time in the morning and idle connection time during solar hours. *Solar charging* could thus also be an interesting policy measure in residential areas.

We use a MCA to link charging behaviour to the policy measures, and use the results to compare the fit for the policy measures between neighbourhoods. The results show that neighbourhoods that have a good fit with the policy measures *increase the number of charge points* often also have a good fit with *vehicle-to-grid* and *overnight charging*. These three policy measures are not mutually exclusive, so this could be a coherent policy mix for these areas, at least from the perspective of what policies fit with charging behaviour. Furthermore, we found a very strong correlation between the fit of neighbourhoods to implement *reduce hogging* and to implement *vehicle-to-grid*. In neighbourhoods that have a good fit with both policy measures, the best choice of policy depends on factors such as parking pressure, grid conditions, and priority of policy makers. Finally, we found that neighbourhoods with a good fit for *solar charging* often do not have a good fit with other policy measures. This implies that policy makers wanting to increase the integration of EVs with PV solar power could target very specific neighbourhoods to implement systems or incentives to match EV charging demand with PV solar power supply.

5.6.2 Limitations

Our data contained some limitations that could impact our results. There could be a selection bias in our population, since we only had data on NewMotion card holders. We do not know whether this user group behaves differently than other EV users. Given that our estimated charging pattern followed the commonly found pattern of peaking both in the morning and the evening, see for example (Helmus et al., 2018; Khoo et al., 2014; Smith et al., 2011; Xu et al., 2018), we suspect that there is not a major difference between NewMotion customers and other EV users. NewMotion card holds could also have a membership at other EMSPs, but we suspect this to be limited, given that since 2011 the e-mobility sector in the Netherlands has allowed for members of EMSPs to charge at charge points operated by a party with whom they do not have a (direct) contract, also known as EV-roaming (Ferwerda,

Bayings, Van der Kam, & Bekkers, 2018). More important could be that the EV users do not only use public charge points, but also charge privately. Our results thus reflect only charging behaviour at public charge points, rather than all charging behaviour. Furthermore, the Netherlands has a very high number of public charge points per EV as compared to other countries, which could mean that these results do not translate well to other countries.

Another limitation is that our data does not contain the power output over time or the time when the EV was fully charged. Therefore, we had to estimate the charging rate of the EV. To do so we set the charging rate at either the maximum charging rate of the EV or the charge point, depending on which is lower. The charging rate of an EV depends on both internal factors, such as the SOC and the battery management system, and external factors, such as temperature and grid conditions. Typically, an EV charges at a lower rate than its maximum, it is thus likely that we overestimate the charging rate in our analysis. Other research found the charge rate of FEVs and PHEVs to be 23% lower and 14 % lower than their maximum charge rate respectively (Gerritsma et al., 2019). To give some indication of how much we overestimate idle connection time, we can compare our results with Helmus et al. (2018) and Wolbertus & Van den Hoed (2017). Both studies analysed hogging behaviour in the Netherlands based on two different datasets (both of more than one million charging sessions) which both included how long the EV was charging. Helmus et al. (2018) found average idle connection times to be between 40-75% of the total connection time, and Wolbertus & Van den Hoed (2017) found it to be 75-85%. Based on our method, we find idle connection time to be on average 73% of the total connection duration. Hence, it is likely that we provide a reasonable estimate of idle connection times, though it certainly is possible that we overestimate it. Since we focus on the *difference* between idle connection rates across neighbourhoods rather than the absolute value, we do not think our analysis is substantially affected by this potential overestimation.

Our analysis does not allow to decide which and how many different policies to implement. We compare the indicators relative to each other, and our method does not allow to determine in absolute terms which policy is the best. While for charge point operators, city planners and grid operators it might be attractive to implement different policies and incentives throughout the Netherlands to locally optimize EV charging from their perspectives, too many variation in policies within a small region could make public charging unclear to EV users. Additional research is needed to determine to how to balance localized optimization of charging infrastructure with ease-of-use.

5.7 Conclusion

Summarizing, the present chapter contributes to a better understanding of EV charging behaviour and how it relates to the visions for the future role of EVs. A particular challenge for designing policy for public charging infrastructure roll-out is that e-mobility is envisioned

to function both as a clean mode of transportation and as part of a sustainable electricity system, preferably at minimal costs. Translating these high-level policy goals to local policies is not trivial, as the implementations are different. Analyzing local charging behaviour can provide some much-needed guidance for policy design, and we provide a framework to link charging behaviour to specific policy measures. By applying this framework to a large dataset of charging sessions, we show that there is great variation in local charging behaviour which has implications for what constitutes optimal policy mixes. While our analysis has been able to identify potentially coherent policy mixes by looking at charging behaviour, we stress that policy makers need more than just behaviour to inform policy design; other factors such as local grid conditions and parking pressure are also important. Ultimately, our take-home message is that policy makers should always look at local conditions for determining the best way forward for public charging infrastructure roll-out.

We end with an outlook by discussing several trends that may significantly change EV charging behaviour in the future, which will have implications for the fit of neighbourhoods with our discussed policy measures.

Firstly, there is an ongoing discussion amongst policy makers and firms working in the EV charging field on whether future charging infrastructure should be mostly DC fast chargers or normal AC chargers. If the future charging infrastructure will be mostly based on normal AC chargers, then charging behaviour will probably not change much. However, we can expect changes in behaviour if DC fast chargers become dominant. Instead of charging at home, at work, or on the street, EV users could make quick stops at DC fast chargers along the highway or at specific charge point hubs in the city. This will result in low charge point hogging behaviour, and high localized peaks in demand, with little flexibility to shift demand. While fast chargers might make e-mobility more attractive to certain consumers, it is thus likely to reduce the potential for EVs to be a stabilizing mechanism in electricity grids.

Secondly, an increase in EV battery capacity will lead to EV users not having to charge as often, because they can drive larger distances after a single charging session. If they indeed charge less often, there will be less flexibility in charging sessions to shift demand, because the ratio of charging time to connection time will increase (if connection times stay similar and charged volume increases). However, if the number of charging sessions does not decrease with larger EV batteries, there could be more flexibility in EV charging (if connections times stay similar and average driving distances do not increase substantially) do not increase substantially.

Finally, mobility use may change considerably; examples are that car sharing may become more popular or autonomously driving vehicles may breakthrough. For car sharing, it is yet too difficult to tell how charging behaviour will change, as it depends on the driving behaviour of car sharers and the logistics of car sharing companies. Autonomously driving cars could offer the benefit of automatically disconnecting from a charge point when charged sufficiently, and moving to charge points at locations that can make the most use of additional flexibility in the grid.

Chapter 6

Conclusion

This thesis explores the benefits and limits of using EVs as a source of flexible demand and/or storage in smart energy systems (SES) by studying SES as socio-technical systems. More specifically, I investigate the potential contribution of EVs to the integration of intermittent renewable energy sources in the electricity grid, and how this contribution is influenced and constrained by technology and consumer behaviour. To realize SES, I argue, not only total smart energy technology (SET) adoption is important, but also differences between spatial and temporal patterns of diffusion of SETs and use of SETs. There are many studies available on the adoption of single SETs, see e.g. Karakaya & Sriwannawit (2015), Nolan & O'Malley (2015), and Rezvani et al. (2015), but we do not know much about how the diffusion of these technologies compare and how they will be used in SES. By using simulation models to directly link SES functioning to consumer behaviour and analysing large micro-level datasets on actual diffusion and charging behaviour, I provide insight into: (1) what constitutes optimal consumer behaviour in SES, (2) how consumers actually behave, (3) how current patterns in behaviour could impact the development and functioning of SES, (4) how consumer behaviour can change, and (5) which technical and behavioural factors have the largest impact on SES functioning.

The simulation models incorporate technical and social aspects of SES. Simulation models of energy systems are a valuable tool for energy policy design, as these can be used for virtual experimentation with future energy systems and how policies could impact these. Furthermore, simulation models allow for formalization and integration of knowledge from different fields, thereby making it possible to study the impact of several factors simultaneously. Indeed, a rich literature has emerged presenting simulation models of SES (Kikuchi, 2017; Ringler, Keles, & Fichtner, 2016). However, in many models of energy system the role of consumer behaviour is under-addressed. I see two main reasons for this. Firstly, models of traditional hierarchical energy systems did not have a need for detailed sub-models of consumer behaviour, but could instead rely on aggregated data of consumer energy demand. Secondly, technological and economic aspects are easier to quantify than psychological, sociological, and ethical aspects, and therefore easier to incorporate in simulation models. However, these latter factors are also important drivers of consumer energy behaviour (Peters et al., 2018; Sovacool et al., 2015; Verkade & Höffken, 2017). Models on flexible energy demand exclude main drivers of demand shifting by focussing solely on technical and economic aspects (Pfenninger et al., 2014). In order to include a more realistic view of consumers, I incorporate theories and concepts from innovation studies and environmental psychology in simulation models of SES.

Integrating the technical and the social in a single model also brings challenges. In particular, an important challenge for a modeller of socio-technical systems is to deal with the different kinds of uncertainties and simplifications of the technical and social system components, which impact the predictive power of models. Where technological performance is often predictable to a high degree, or at least with a well-defined uncertainty margin, behaviour of social groups shows nonlinear interactions between individuals

themselves and their environment. While the simulation models in this thesis made some simplifications for the technologies, the submodels of technical components can be considered predictive to a high degree. The submodels of social components should rather be regarded as explorative. Where possible, I have integrated real-world data in order to ensure that these explorations are done within realistic boundaries.

Taken together, the results lead to two main conclusions. Firstly, the results show that there can be great benefits for grid management in combining intermittent renewable energy sources with EVs via smart and/or vehicle-to-grid, but that it can only be a partial solution for load balancing in scenarios with high renewable energy uptake. Secondly, consumer adoption and charging behaviour varies greatly, which influences the extent to which these benefits can be realized in certain regions and neighbourhoods.

The rest of this section is organized as follows. Section 6.1 explains the main conclusions and how these are supported by the results from this thesis. Section 6.2 translates the findings to policy recommendations. Finally, Section 6.3 provides directions for further research.

6.1 Main findings

The first main conclusion is that EVs have significant but limited potential to contribute to load balancing in energy systems with high renewable energy uptake. This conclusion is supported by the simulation model results for the indicators self-consumption and peak reduction. Self-consumption measures the relative amount of locally produced energy used by local loads, and is used as an indicator in chapters 2-4. Increasing self-consumption reduces power flows over local grids. A second factor relevant for load balancing is the reduction of peaks in electricity demand and supply, which is used as an indicator in chapters 2 and 4. Reducing peaks decreases the required capacity of local grids.

Self-consumption depends on many aspects, such as renewable energy and storage capacities, supply and demand profiles, and EV charging strategy. Chapter 2 studies different charging strategies for the case study of LomboXnet. This chapter presents three different charging algorithms aiming to increase the use of locally produced PV solar energy for EV charging as compared to uncontrolled EV charging, each with an increased level of technological complexity. The first algorithm uses real-time information on grid conditions and driving needs to determine the charging process, the second algorithm is similar to the first but includes the option to discharge (V2G), and the third algorithm takes V2G one step further with optimizing charging demand based on predictions of electricity demand and production. Each higher level of technological complexity adds a roughly equal number of percentage points to the PV self-consumption ratio. Chapter 3 investigates the impact of adoption levels of PV solar panels and EVs on PV self-consumption. The results show that using V2G technology leads to large increases in self-consumption as compared to uncontrolled EV charging for projected adoption levels in the Netherlands. Chapter 4

focusses on renewable energy capacity, charging infrastructure size and charging strategy. In this chapter, EV drivers decide which charging strategy to follow based on external factors (policy interventions) and internal factors (environmental self-identity and range anxiety). Again, the different charging strategies lead to considerable increases in self-consumption as compared to uncontrolled charging. Still, all chapters show that smart charging and V2G are not sufficient to reach 100% self-consumption in scenarios with high capacity of variable energy sources.

Smart charging and V2G do not necessarily reduce peaks; it depends on the extent to which EV charging is centrally coordinated. In Chapter 2, the charging strategies that are based on real-time information input result in high peaks in demand when EVs need to charge at maximum rate in order to have sufficient energy to make the next trip. The charging strategy based on optimisation and prediction does reduce the highest peak in demand by roughly 40%. The results of Chapter 4 show that, unless there is central coordination of EV charging, high peaks in EV charging demand can occur when many EV drivers start charging simultaneously during times of high renewable energy production. Both chapters show that the peaks in oversupply of renewable energy cannot be reduced by EVs, as there is too little capacity to use all the excess renewable energy for EV charging.

The results thus confirm other findings on the benefits of smart charging, V2G, and load shifting in general (Hossain et al., 2016; Mwasilu et al., 2014; Sovacool, Axsen, & Kempton, 2017). The limits that are identified for increasing self-consumption and reducing peaks in demand and supply indicate that we need more than just EVs to develop a stable clean electricity system; other solutions for load balancing will have an important role to play in the energy transition. Hereby I provide further evidence for the claim that the future smart grid will probably consist of a diverse mix of balancing options (Elliott, 2016). These options can either be implemented locally, such as stationary storage, or at a larger geographical scale, such as connecting different regions via super-grids.

The second main conclusion is that there is great heterogeneity in consumer behaviour, which influences the viability of smart charging and vehicle-to-grid for different regions and neighbourhoods. A well-established fact from innovation studies is that technology diffusion is a social process in which some consumers have a higher degree of innovativeness than others, who decide whether to adopt an innovation based on whether their peers have done. Also, we know that adopter groups for different technologies do not necessarily have the same characteristics. Environmental psychology tells us that people have different attitudes towards the environment and different pro-environmental behaviours which can change over time. Consequently, the models presented in this thesis show a greater heterogeneity in consumer behaviour as compared to similar models based on static utility functions to inform behaviour. Additionally, the analyses of large data-sets show great differences in consumer adoption as well as behaviour. The different approaches used in this thesis allow to highlight

the relation between consumers and the energy system. In particular, the results point to the importance of diffusion processes, EV use, and charging behaviour.

The *diffusion* of PV solar panels and EVs in the Netherlands is the focus of Chapter 3. These diffusion processes are not aligned, both in time and through space. Furthermore, the adopter groups of these technologies have very different characteristics. The type of grid problems and available solutions for load balancing emerging from the energy transition can thus vary widely between regions. Furthermore, the chapter finds that there are discrepancies between studies that identify socio-demographic variables predicting PV solar panels and EV adoption, which suggests differences in adoption patterns between countries. These results underline the importance of local circumstances in energy transitions on local, regional, and national scales, in line with Hansen & Coenen (2015).

The effect of *EV use* on PV self-consumption is investigated in Chapter 2. Here, the number of trips EVs take per week is varied to see how that impacts PV self-consumption. This impact is not obvious, as a higher charging demand allows for more opportunity to charge during PV power production, but the EV has to be stationary at the charge point at those times as well. The results from this chapter show that, when smart charging algorithms are used, more EV trips will lead to lower levels of PV self-consumption. This indicates that, from the perspective of integration renewables in the energy system, it is better if EVs are not used often.

Charging behaviour of an EV fleet is modelled in Chapter 4 as an outcome that depends on external factors, such as renewable energy capacity, availability of charging infrastructure, and policy interventions. Depending on the policy intervention, EV drivers charge at any time or shift (a part) of their charging demand to times of high local renewable energy production. The results highlight the trade-off of using EVs as a comfortable mode of transport and as a means for grid management. One of the modelled policy interventions stimulates EV drivers to shift their demand by providing information and feedback on their past charging behaviour. Under this policy intervention EV charging behaviour not only depends on external factors but also on internal factors (range anxiety and environmental self-identity), leading to heterogeneous charging behaviour. The results show that an advantage of heterogeneous charging behaviour is that peaks in charging demand are lower than when agents perform homogenous charging behaviour.

This thesis does not only investigate how policy interventions influence charging behaviour, but also how charging behaviour can influence policy design, in Chapter 5. Policy makers have formulated multiple goals for charging infrastructure roll-out. These include building sufficient charging infrastructure to support high EV uptake, efficient use of public space, efficient use of existing electricity and charging infrastructures, and supporting the integration of renewable energy. These goals are not always aligned, e.g. smart charging leads to longer durations of charging sessions, and therefore less efficient use of charge points. Studying current charging behaviour can inform policy makers on how to make these trade-offs by identifying distinct problems and opportunities for developing charging

infrastructure in specific neighbourhoods. Based on a large data-set of charging sessions, this chapter shows that charging behaviour differs greatly between neighbourhoods and EV users. Aligning EV charging demand with local electricity production might thus not be the focus for every neighbourhood, as the charging behaviour in some neighbourhoods does not have a good fit with for solar charging as compared to other options for charging infrastructure roll-out.

6.2 Policy recommendations

This thesis illustrates that robust policies for the energy transition need to be based on a holistic systems perspective. While many clean energy technologies are available, simply stimulating their adoption with tax benefits and subsidies is not enough, as current patterns in adoption and use of these technologies are not aligned with efficient integration in existing infrastructures. Without changes in these patterns, continued growth of these technologies will lead to problems in grid management, which in turn hinders further adoption.

Another challenge for governing the energy transition is that achieving this transition requires changes in and integration of multiple sectors, for which different departments of government have the end-responsibility. The interests of these different sectors with respect to sustainability are not always the same. E-mobility is a good example of this: using EVs as a stabilizing mechanism in smart grids reduces their availability as a clean mode of transportation.

Not only are different departments of government involved with the energy transition, but also different levels. Where some policy measures are handled at the national level (e.g. subsidies, tax benefits, dynamic electricity tariffs), other measures are best designed locally (e.g. stimulating adoption in specific neighbourhoods, charging infrastructure roll-out). Governing energy transitions thus requires coordination between different departments, and between local, regional, and national governments.

This section provides some guidance for handling these challenges by translating the results of this thesis into several policy recommendations. I discuss several examples of policy measures related to increasing adoption and to stimulating behavioural change. Furthermore, I discuss how progress in the energy transition for these aspects could be measured, which could in turn facilitate coordination between different governmental bodies.

The first recommendation is that adoption of PV systems, EVs, smart charging, and V2G should be stimulated in general, but with more attention to the spread of adoption and how adoption affects the electricity grid. The high growth rates of PV systems and EVs are cause for (some) optimism for combating climate change, but the market penetration levels are still low for both technologies. In order to reduce CO_2 emissions, adoption should continue to be stimulated, through national measures such as subsidies, tax benefits and requirements for

new buildings related to energy efficiency and instalment of charge points. Subsidies could also stimulate the development of a smart charging infrastructure to support the high PV and EV uptake. The recently announced national subsidy for the instalment of 427 smart charging stations in the Netherlands is a good start. Municipalities can also play a role here, by requiring the support of smart charging and V2G in tenders for new public charge points.

Next to measures stimulating adoption in general, policy makers should implement measures to stimulate PV solar panels and EV adoption in areas where diffusion has been slow. Examples are to make it easier for flat-dwellers to put solar panels on the rooftop of their flat, which is a matter of national taxation and building regulations, and to develop public charging infrastructure in areas where there is less opportunity to install home chargers, which is a matter for municipalities.

The second recommendation is that changes in use of clean energy technologies should be stimulated. Policy measures aiming to change behaviour are typically more controversial than stimulating adoption, but governments can at least play an enabling role, for instance by allowing for dynamic electricity tariffs (national level) and requiring public charging infrastructure to support smart charging and V2G (municipalities and regional governments). This thesis describes three policy options available to stimulate behavioural change and their main advantages and disadvantages. The results do not provide an answer to which is preferred, but rather highlight the trade-offs between these, which must be taken into account in policy design.

Firstly, centrally controlled automation of EV charging can achieve large benefits for grid operators, but may significantly reduce comfort for EV drivers, because the EV may not always be charged sufficiently for spontaneous trips. EV drivers might also be reluctant to participate in such programs due to concerns for privacy and autonomy.

Secondly, financial incentives can encourage demand shifting and discourage charge point hogging, but it is uncertain whether the financial benefits are enough to compensate for loss of comfort. Furthermore, not everybody might have the ability to react to these price incentives, because they are dependent on high availability of personal transportation or park their EV in an area with high parking pressure.

Thirdly, information campaigns and feedback mechanisms can increase charging with renewable energy, through providing information on how much renewable energy was used in a charging session, and decrease charge point hogging, through messaging services for EV drivers such as social charging apps. Information campaigns and feedback mechanisms will not lead to behavioural change for every EV driver, but the group that does may significantly support grid integration. On a general level, information campaigns could emphasize that load balancing of local grids is a sustainability issue, and adopting PV solar panels or EVs comes with certain responsibilities for grid management for households. An advantage of the issue of local grid management is that it makes sustainable energy very tangible for local

communities, which could make awareness campaigns very effective. Websites and apps could be developed by grid operators to inform households when to charge their EV.

To facilitate coordination between different governmental bodies, new indicators should be developed to report on the progress in the energy transition. Indicators for adoption and use of smart energy technologies should be reported not just at national level, but also at local and regional. Furthermore, adoption indicators should take into account the interrelatedness of diffusion of multiple technologies in specific areas by reporting on: (1) adoption of energy producing technologies, (2) adoption of energy consuming technologies, (3) adoption of technologies for load balancing (e.g. demand shifting, storage), and (4) relate these to local grid capacity. Indicators for the use of smart energy technologies in specific areas should include: (1) self-sufficiency, (2) self-consumption, and (3) CO_2-free kilometres driven.

6.3 Directions for further research

This section provides several directions for further research. Specific suggestions for data collection and model improvements are made in the discussion sections of the research chapters. Here, I discuss broader avenues for further research. In particular, I highlight co-adoption of SETs as an important determinant for SES functioning and in need of further research, and incentives to stimulate load balancing that target EV user groups other than individual consumers. The section ends with a discussion on directions for modelling socio-technical systems.

One interesting direction for further research could be to further investigate co-adoption of SETs. We have seen that there are major differences between the diffusion of PV systems and EVs, and that this disparity has major implications for the energy transition. To the best of my knowledge, only one other study exists that compares PV and EV adoption (for northern California), and this study did find PV adoption to be linked to EV adoption (Rai et al., 2016). However, this finding was based on PV adopters reporting to consider buying an EV, not actually having bought one. A cross-country comparison based on actual diffusion data could further clarify the role of co-adoption of these technologies in SES development.

Other technologies could also be included in studies on co-adoption, such as home storage and hydrogen vehicles. It seems likely that adoption of home storage technology is strongly correlated with PV adoption, especially in countries with a stable electricity grid where there is little need for back-up power for households. Home storage is interesting for grid management because it could be a load balancing solution in areas with few EVs, and be complimentary to V2G during times when there is little flexibility in EV charging. EV batteries could have a second life as stationary home storage (Heymans, Walker, Young, & Fowler, 2014), which would be an additional benefit of having large EV fleets. While it

currently seems that EVs will be the dominant form of clean personal transportation, a breakthrough of hydrogen vehicles will change the role mobility can play in load balancing. Hydrogen production through electrolysis can also contribute to load balancing, and is not dependent on the vehicle being connected to a charge point as with EVs. Given that current adoption levels of hydrogen vehicles are very low, diffusion models of hydrogen vehicles cannot rely on large diffusion datasets, which makes the Bass model of diffusion as applied in Chapter 3 not a proper method for modelling diffusion. Instead, agent-based models based on survey data amongst early adopters of hydrogen vehicles and EVs would be a more suitable approach.

This thesis focusses on the behaviour of individual consumers and how this behaviour can change. Organizations such as governments and commercial firms can also adopt EVs for the vehicle fleet. EVs can be very interesting for fleet managers because they have high mileage and purchase rates, and fleet managers have indeed been a large group amongst early adopters of EV (Sierzchula, 2014). It could thus be interesting for policy makers to develop interventions aimed at stimulating fleet managers to contribute to load balancing. Further research could identify viable business models for stimulating load balancing for commercial fleet managers. I hypothesize that financial incentives will have a greater effect on commercial fleet managers than on individual consumers, as fleet managers have a stronger profit-incentive. Furthermore, fleet managers often already base their business on sophisticated logistics software which could relatively easily incorporate dynamic charging tariffs. If trends in mobility such as car sharing and autonomous driving continue, individual car ownership might decrease significantly, and identification of effective load balancing incentives for fleet managers will only become more relevant.

A fruitful direction for modelling socio-technical systems would be to design modular simulation models, with the modules being a set of coherent theories and assumptions. The point would not be to integrate multiple, possibly incoherent, theories in one simulation, but rather to run several simulations to assess how different theories or interpretation of theories affect the model dynamics and outcomes. As we have seen, a modeller of socio-technical systems encounters different kinds of uncertainties, which are not all quantifiable. Sometimes, implementation of theory in a formal model is rather ambiguous. Furthermore, different theories will highlight other elements of a system, and it is not always clear which theory is most appropriate for a specific model, especially when validation against empirical data is not possible. However, it would be ill-advised to just ignore factors that are not easy to quantify, because essential drivers of the modelled system could be left out (Pfenninger et al., 2014).

The high flexibility of ABMs allows for incorporation of many different types of theories and conceptual models, including equation-based models (Hoekstra et al., 2017). Hence, they could provide a test-bed for applying multiple theories or theory interpretations to the same

case. Nice examples are given by Robinson & Rai (2015), who implement various PV adoption models, Muelder & Filatova (2018), who test various implementations of the Theory of Planned Behaviour (Ajzen, 1991) in a model of PV adoption, and Polhill & Gotts (2017), who compare several implementations of Goal Framing Theory (Lindenberg & Steg, 2007) in an energy demand model. This modelling strategy is analogous to the modular approach proposed by Geels & Johnson (2018) for studying diffusion of socio-technical systems. In such an approach, different conceptual models highlight specific elements that together lead to a broad understanding of the object of study. Such a broader understanding is highly relevant for a topic as complex as the energy transition. Following the advice of Stirling (2010), such modular models, when documented transparently and accessibly, could clearly demonstrate how specific assumptions and uncertainties lead to different evaluations of technologies and policies, and provide a very strong basis for robust policy design for accelerating the energy transition.

Appendix A: Supporting information for Chapter 3

This appendix contains supporting information for Chapter 3. Additional supplementary material can be found in the online article version of this chapter (Van der Kam et al., 2018).

Table A.1 Identified major lease companies with corresponding 4-digit postal code, based on an extensive web search. We exclude these postal codes from our analysis.

Lease company	Postcode-4
Mistergreen Electric Lease B.V.	1011
RCI Financial Services	1119
BEMA Finance	1175
Koops Furness Lease	1311
Leaseplan	1314
Autoplanning Algemene Lease Maatschappij BV	1322
Stern Lease B.V.	1446
Europcar/Multirent/National Car Rental Haarlem	2031
Schiphol/ALD Automotive	2132
BMW Nederland B.V./BMW Group Financial Services	2289
Kamsteeg Auto Lease	2321
Achilles Autolease	2516
Stichting Nederlandse Mobiliteit 2.0/PSA Finance Nederland	3011
AA Lease B.V./Sixt/ Ames Autolease	3316
Business Lease Nederland B.V.	3439
Europcar/NS/Greenwheels	3521
Santander Lease/Justlease/Sternrent/Terberg Leasing	3526
car2go/Mercedes-Benz Financial Services Nederland	3528
MultiLease B.V/ Go Lease B.V.	3543
Business Lease Nederland B.V.	3708
MKB Lease B.V.	3812
Volkswagen Leasing B.V./DutchLease Nederland	3824
Broekhuis Lease	3845
Arval Lease	3991
Alcredis Finance/A.R.M. Autoleasing	4131
Kyoto Lease	4451
ING Car Lease/ Alphabet Lease/GE Capita	4817
Opel Nederland	4822
Autopon Lease	5232
Athlon Car Lease B.V.	5611
Tesla Motors/ Driessen AutoLease B.V.	5628
J&T AutoLease	5688
H4 Car Lease B.V.	7418
Lease Unlimited	7421
Total Car Lease	7468
Huiskes-Kokkeler Autolease	7554
Friesland Lease B.V.	9201
Century Auto Lease	9480
Noordlease B.V./AutoLease Groningen	9723

Table A.2 Summary statistics of variables used in regression models

Statistic	N	Mean	St. Dev.	Min	Q1	Median	Q3	Max
Inhabitants	4,020	4,173.34	4,134.44	0	685	2,675	6,826	28,600
PV systems	4,025	68.57	68.57	0	16	43	97	1,359
EVs	4,025	28.02	204.22	0	2	8	22	7464
Address density (per km^2)	4,025	923.21	1,704.87	0	46.1	159.5	1036	15670
Age 25-45 (%)	3,994	23.74	6.59	1.56	20.21	22.81	25.91	100
Age 45-65 (%)	4,006	30.43	6.35	3.33	27.13	30.39	33.33	100
GroenLinks voters (2010) (%)	3,321	6.11	3.16	0.20	4.12	5.49	7.22	25.91
GroenLinks city council members since 2006 (Y/N)	4,025	0.373	0.484	0	0	0	1	1
Household income (Euros)	3,575	35,899.2	6,661.87	11,800	31,700	35,600	39,350	106,800
Household rooftops	4,025	1,249.70	1,216.22	1	234	843	1,980	7,804
Household size (persons)	4,020	2.348	0.342	1.13	2.17	2.37	2.55	5
Lowly educated (%)	3,215	47.49	8.17	10	43	48	52	75
Passenger vehicles	4,021	1,879.70	1,791.45	6	399	1,322	2,970	22,549
Public charge points	4,025	1.86	3.62	0	0	1	2	43
Total building footprint (m^2)	4,025	116,578	104,015	2.12	295.8	871.81	1,803.34	5,654.4

Table A.3 Summary statistics of variables as used in the regression model for PV adopters. The *N* for these variables is lower than in the original datasets, because we have removed rows with incomplete data

Statistic	N	Mean	St. Dev.	Min	Q1	Median	Q3	Max
Log (PV systems (pp) + 1)	3,020	0.022	0.13	0	0.011	0.018	0.026	0.097
Address density (per km^2)	3,020	1178.77	1882.07	0.03	83.36	317.34	1573.9	15667.0
Age 25-45 (%)	3,020	24.31	5.44	8.99	20.95	23.23	26.32	52.46
Age 45-65 (%)	3,020	29.40	4.57	9.78	26.64	29.24	32.26	48.55
GroenLinks voters (2010) (%)	3,020	6.07	4.86	0.2	4.10	5.49	7.20	25.91
GroenLinks city council members since 2006 (Y/N)	3,020	0.383	0.49	0	0	0	1	1
Household income (Euros)	3,020	35441.5	6222.89	19,000	31,400	35,300	38,800	106,800
Household rooftops (pp)	3,020	0.32	0.07	0.01	0.30	0.34	0.37	0.66
Household size (persons)	3,020	2.31	0.31	1.23	2.14	2.34	2.50	3.57
Lowly educated (%)	3,020	47.56	8.13	10	43	48	52	75
Total building footprint (m^2 pp)	3,020	32.63	10.97	6.13	24.65	32.16	39.97	87.40

Table A.4 Summary statistics of variables as used in the regression model for EV adopters. The *N* for these variables is lower than in the original datasets, because we have removed rows with incomplete data, removed postal codes with a lease company located in it, and have removed postal codes with a value of passenger vehicles per person higher than 1.

Statistic	**N**	**Mean**	**St. Dev.**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Log (EVs (pp) + 1)	2,986	0.004	0.009	0	0.002	0.003	0.004	0.421
Address density (per km^2)	2,986	1170.84	1877.29	3.22	82.60	313.82	1563.28	15666.97
Age 25-45 (%)	2,986	24.25	5.38	8.50	20.93	23.21	26.24	52.46
Age 45-65 (%)	2,986	29.27	4.48	9.78	26.68	29.66	32.26	48.55
GroenLinks voters (2010) (%)	2,986	6.06	3.12	0.2	4.08	5.47	7.18	25.91
GroenLinks city council members since 2006 (Y/N)	2,986	0.382	0.49	0	0	0	1	1
Household income (Euro)	2,986	35436.70	6218.07	19,000	31,400	35,300	38,800	106,800
Household size (persons)	2,986	2.31	0.31	1.23	2.14	2.34	2.51	3.57
Lowly educated (%)	2,986	47.60	8.10	10	43	48	52	75
Passenger vehicles (pp)	2,986	0.475	0.086	0.181	0.429	0.487	0.533	1
Public charge points (pp)	2,986	0.0004	0.0008	0	0	0.0002	0.0005	0.011

Appendix B: Supporting information for Chapter 5

Table B.1 Summary statistics of variables in the NewMotion dataset linked to the maximum charge rate of EVs based on EV-Box data (EVBox, 2019). For several variables the summary of the counts are presented

Variable	N	Mean	St. Dev.	Min	Q1	Median	Q3	Max
user_postal_code (count)	1003730	163.1	292.2	1	8	44	193	8394
duration (s)	1048575	36274.8	46972.2	2	8653	26366	47678	604765
volume (kWh)	1048575	9.5	11.9	0.001	2.93	6.63	9.38	248.801
charge_point_postal_code (count)	951014	71.4	179.0	1	3	11	53	8394
charge_point_country (count)	1048575	74898.2	278140.0	3	12	115	509	1041260
make (count)	952607	32848.5	49829.4	1	544	5772	36514	188558
model (count)	952607	11760.6	28420.0	1	178	1643	9036	186487
batterycapacity (kWh)	952607	24.6	26.9	4	9	12	24	100
user_id_cat (count)	1048575	42.0	123.3	1	2	6	22	3478
charge_point_serial_cat (count)	1048575	42.0	123.3	1	2	6	22	3478
max_power (kW)	954838	10.9	8.3	0	3.7	11	11.04	450
Maximum charge rate EV (kW)	952607	20.3	38.8	2	3.7	3.7	7.4	120

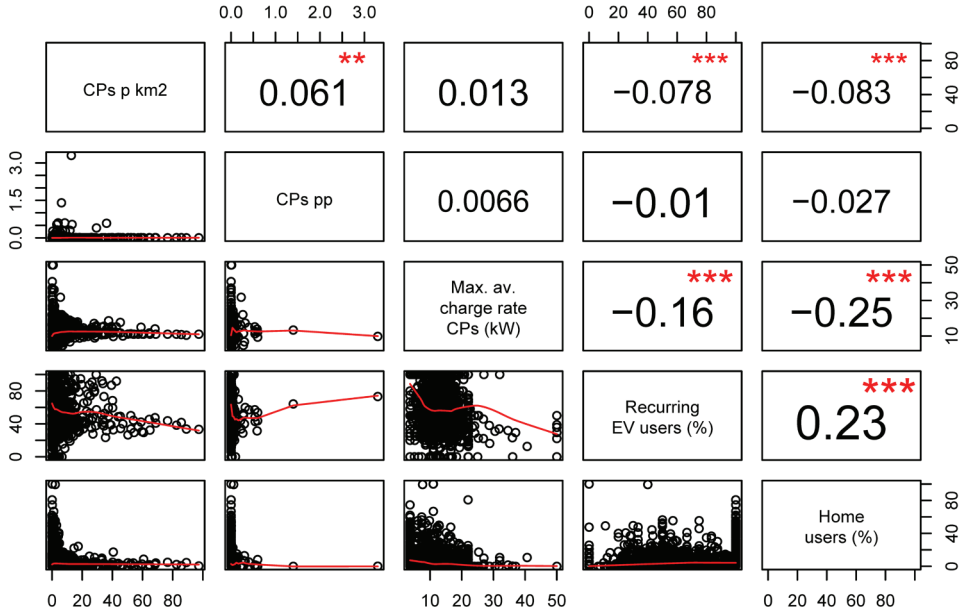


Figure B.1 Relation between indicators for PC4 areas: pairwise plots, correlations, and indications of p-values resulting from the ANOVA analysis, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The red trend line is drawn using the LOWESS smoother function (Cleveland, 1981)

Table B.2 Summary statistics of variables as used in regression models. We selected charging sessions that take place in 2017 and 2018, and removed data with missing values, technologically impossible values, invalid values, and areas with zero inhabitants

Variable	N	Mean	St. Dev.	Min	Q1	Median	Q3	Max
Connection time (15 min)	2203	13733.72	21221.97	2	302	3938	18379	173285
Idle connection time (15 min)	2203	11402.16	18264.62	0	182	2875	14764	150274
Charging time during evening peak (15 min)	2203	711.84	1254.29	0	13	134	856	10456
Idle connection time during night (15 min)	2203	4365.84	7603.16	0	5	347	5592	60737
Charging time during morning (15 min)	2203	509.50	1120.04	0	12	93	410	13333
Idle connection time during solar hours (15 min)	2203	2469.31	4033.21	0	40	613	3164	37755
CPs	2203	6.67	10.21	1	1	3	8	119
CPs p km^2	2203	3.17	8.00	0	0.20	0.76	2.66	97.27
CPs pp	2203	3.17	8.00	0	0.20	0.76	2.66	97.27
Average maximum charge rate CPs (kW)	2203	12.11	5.51	3.68	9.56	11.04	14.68	50
Recurring EV users (%)	2203	59.47	31.66	0	37.5	55	100	100
Home users (%)	2203	6.55	11.07	0	0	1.23	10.07	100

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Summary

Energy and transport are two major contributors to global greenhouse gas emissions. Ensuring a sustainable future on planet Earth requires both sectors to rapidly and radically reduce their reliance on fossil fuels. This can be achieved by large-scale adoption of clean energy technologies, such as photovoltaic (PV) solar panels and electric vehicles (EVs). Clean energy technologies such as photovoltaic (PV) solar panels can produce electricity without emitting CO_2, which in turn can be used to charge electric vehicles (EVs). However, integrating these technologies in the existing electricity grid is challenging, due to the variable electricity production of PV solar panels and high peaks in demand for EV charging. Smart charging of EVs can be one way to reduce the negative impact of both technologies on the electricity grid, by aligning EV charging demand with renewable energy production. EV batteries can also be used as storage for renewable energy in vehicle-to-grid (V2G) systems. However, realizing the potential of smart charging and V2G requires consumers to adopt these technologies, shift EV charging demand, and allow for discharging of EVs. This would be a drastic change from the current situation, where consumers typically perform passive roles in the electricity system, and are used to high availability of electricity and personal transportation. The extent to which consumers will change their behaviour is a major source of uncertainty in assessing the future of smart charging and V2G.

This thesis analyses and qualifies this uncertainty by developing various simulation models that incorporate technical as well as social aspects of smart charging and V2G. More specifically, I investigate the potential contribution of EVs to the integration of intermittent renewable energy sources in the electricity grid, taking into account constraints posed by the relevant technologies as well as consumer behaviour. The simulation models incorporate theories and concepts from energy science, innovation science, and environmental psychology. This multi-disciplinary approach allows to directly relate consumer behaviour to the functioning of system performance indicators, such as self-consumption (local consumption of locally produced energy), reduction of peaks in electricity demand and supply, and comfort of EV drivers. I incorporate empirical data to ensure realistic model outcomes, and explore system boundaries through sensitivity analyses when such data is lacking. Furthermore, I analyse large datasets on the diffusion of PV solar panels and EVs as well as on EV charging behaviour to investigate how actual consumer adoption and behaviour varies throughout the Netherlands.

Chapter 2 investigates how algorithms for smart charging and V2G influence the extent to which EVs can contribute to load balancing. I explore this in a simulation model of a micro-grid in the area of Lombok, in Utrecht, the Netherlands. The algorithms align EV charging demand with PV solar power production in order to increase local self-consumption of PV power. I develop three algorithms, which use either real-time grid information or optimise charging demand based on predictions of local electricity demand and supply. The model shows that these charging algorithms can significantly increase PV self-consumption, thereby reducing the negative impact of PV solar panels and EVs on the local electricity grid.

Chapter 3 compares the spatial and temporal diffusion patterns of PV solar panels and EVs in the Netherlands. This is important, because EVs can only contribute to local load balancing of PV power if these technologies are located in the same area. I investigate whether this these technologies are adopted by the same consumers by linking diffusion data to neighbourhood characteristics, and by extrapolating this data using the Bass model of diffusion. The results show that the adoption of PV systems, the adoption of EVs, and the expected growth of these technologies are not evenly distributed across the regions of the Netherlands. The disparity between PV and EV adoption indicates that smart charging and V2G may not be viable for every region.

Chapter 4 explores the effects of several policy interventions that stimulate aligning EV charging demand with renewable energy production. Given that smart charging and V2G do not have direct benefits for consumers, it is likely that policy interventions are needed to incentivize participation in such schemes. I present an agent-based model that explores the advantages and disadvantages of several policy interventions: (1) *dual tariff scheme*, (2) *information and feedback*, and (3) *automated smart charging*. In particular, I highlight *information and feedback* as an interesting policy intervention. The model results indicate that this policy intervention can increase charging with renewable energy by targeting the intrinsic motivation of EV drivers. Targeting intrinsic motivation seems to more likely lead to long-term behavioural change than financial incentives and automation.

Chapter 5 develops a framework for how local charging behaviour can inform policy design for public charging infrastructure roll-out, and applies this to investigate differences in charging behaviour. Policy makers concerned with public charging infrastructure roll-out are tasked with balancing multiple policy goals, such as support of large EV fleets, cost-effectiveness, and sustainability, which requires different implementations of charging infrastructure. For instance, efficient use of charge points requires charging sessions to be short, but using EVs for load balancing requires charging sessions to be long. Assessing charging behaviour can guide policy makers in determining the best route for charging infrastructure development. To provide insight in how charging behaviour can inform policy, I present a framework that relates several indicators of charging behaviour to five policy measures linked to different high-level policy goals: (1) *increase the number of charge points*, (2) *reduce hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging*. I apply the framework to a large dataset of charging sessions in the Netherlands. The results show that charging behaviour varies greatly between neighbourhoods, which implies that policy for charging infrastructure roll-out is best designed locally.

All in all, my results lead to two main conclusions. Firstly, there can be great benefits for grid management in combining intermittent renewable energy sources with EVs via smart and/or V2G. However, this can only be a partial solution for load balancing in scenarios with high renewable energy uptake. Secondly, consumer adoption and charging behaviour varies greatly, which influences the extent to which the envisioned benefits of smart charging and V2G can be realized in certain regions and neighbourhoods.

Samenvatting

Zowel de energiesector als de transportsector stoten veel broeikasgassen uit. Een duurzame toekomst vereist dat beide sectoren snel en radicaal overschakelen van fossiele brandstof naar schone energiebronnen, zoals zon- en windenergie. Fotovoltaïsche (PV) zonnepanelen produceren elektriciteit zonder hierbij CO_2 uit te stoten, wat vervolgens gebruikt kan worden om elektrische auto's op te laden. Het integreren van deze technologieën in het bestaande elektriciteitsnetwerk brengt wel grote uitdagingen met zich mee. Het elektriciteitsnetwerk is namelijk niet berekend op de variabele energieproductie van zonnepanelen en de hoge pieken in elektriciteitsvraag voor het laden van elektrische auto's. Slim laden kan hier een oplossing bieden, door de laadsnelheid af te stellen op de productie van duurzame energie. De accu's van de auto kunnen ook gebruikt worden als opslag voor duurzame energie, om later energie terug te leveren aan het net. Dit wordt ook wel *vehicle-to-grid* (V2G) genoemd. Om het potentieel van deze systemen te realiseren, is het belangrijk dat consumenten deze technologieën adopteren maar ook hun laadgedrag afstellen op duurzame energieproductie. Dit is een radicale verandering ten opzicht van het huidige energiesysteem, waarin consumenten passieve gebruikers, en gewend aan een hoge beschikbaarheid van elektriciteit. Er is veel onzekerheid omtrent de mate waarin consumenten hun gedrag zullen veranderen, wat het lastig maakt om in te schatten hoeveel slim laden en V2G kunnen bijdragen aan toekomstig netbeheer.

Deze thesis analyseert en kwalificeert deze onzekerheid met het ontwikkelen van verschillende simulatiemodellen die technische én sociale aspecten van slim laden en V2G integreren. Met deze modellen onderzoek ik het potentieel van elektrische auto's om bij te dragen aan de integratie van variabele duurzame energiebronnen in het elektriciteitsnet. Ik maak een inschatting van het technisch potentieel van slim laden en V2G, maar ook hoe consumentengedrag dit potentieel beïnvloedt. De simulatiemodellen zijn gebaseerd op theorieën en concepten uit de energie-wetenschappen, innovatiewetenschappen, en milieu-psychologie. Met deze multidisciplinaire aanpak kan ik consumentengedrag direct linken aan indicatoren op systeemniveau, zoals eigenverbruik (van lokale energiebronnen), het verminderen van pieken in elektriciteitsvraag en -aanbod, en het comfort van elektrische autobezitters. Ik baseer de modellen zoveel mogelijk op empirische data om ervoor te zorgen dat de modeluitkomsten realistisch zijn. Waar dit niet mogelijk is gebruik ik gevoeligheids-analyses om de grenzen van het gemodelleerde systeem te verkennen. Ook analyseer ik grote datasets over de diffusie van PV systemen, de diffusie elektrische auto's, en laadgedrag om verschillen in consumentengedrag in Nederland in kaart te brengen.

Hoofdstuk 2 onderzoekt hoe algoritmen voor slim laden en V2G de mate waarin elektrische auto's kunnen bijdragen aan het balanceren van het net beïnvloeden. Ik doe dit d.m.v. een simulatiemodel van een lokaal net in de buurt Lombok in Utrecht, Nederland. De algoritmen passen de laadsnelheid van de elektrische auto's aan naarmate de zonnepanelen meer of minder energie produceren, om het eigenverbruik van lokaal geproduceerd zonne-

energie te verhogen. Ik ontwikkel drie algoritmen, die ofwel gebaseerd zijn op real-time informatie, ofwel op voorspellingen van vraag en productie. Het model laat zien dat deze algoritmen het eigenverbruik significant kunnen verhogen, en daarmee de impact van zowel zonnepanelen als elektrische auto's op het lokale net verminderen.

Hoofdstuk 3 vergelijkt de ruimtelijke en temporele dimensies van de diffusie van PV zonnepanelen en elektrische auto's in Nederland. Dit is relevant, omdat de elektrische auto's alleen het eigenverbruik van lokale zonne-energie kunnen verhogen als deze in dezelfde buurt staan als de zonnepanelen. Ik onderzoek of PV zonnepanelen en EV door dezelfde consumenten worden geadopteerd door diffusie-data te linken aan buurt-karakteristieken en de diffusiedata te extrapoleren op basis van het diffusie model van Bass. De resultaten laten zien dat de adoptie van zonnepanelen, de adoptie van elektrische auto's, en de verwachte groei hiervan ongelijk verdeeld zijn over Nederlandse regio's. Deze ongelijke verdeling betekent dat slim laden en V2G niet in elke regio een goede oplossing kunnen zijn.

Hoofdstuk 4 verkent de effecten van een aantal beleidsinterventies die het afstellen van de elektriciteitsvraag voor het laden van elektrische auto's op de productie van duurzame energie stimuleren. Slim laden en V2G hebben geen directe voordelen voor consumenten, er zijn dus stimuleringsmaatregelen nodig om de participatie in deze laadstrategieën te vergroten. Ik presenteer een *agent-based model* dat de voor- en nadelen van een aantal beleidsinterventies verkent: (1) *variabele tarieven*, (2) *informatie en feedback* en (3) *geautomatiseerd slim laden*. Ik beargumenteer dat *informatie en feedback* een interessante beleidsinterventie is. Het model laat namelijk zien dat deze beleidsinterventie duurzaam laden kan stimuleren door zich op de intrinsieke motivatie van elektrische autobezitters te richten. Dit type maatregelen die hebben een grotere kans om te leiden tot gedragsverandering op de lange termijn dan maatregelen zoals financiële prikkels of automatisering.

Hoofdstuk 5 ontwikkelt een methode om lokaal laadgedrag mee te nemen in beleidsontwikkeling voor publieke laadinfrastructuur, en gebruik deze methode om verschillen in laadgedrag te onderzoeken. Beleidsmakers die verantwoordelijk zijn voor de uitrol van publieke laadinfrastructuur moeten meerdere beleidsdoelen balanceren zoals het ondersteunen van grote aantallen elektrische auto's, de effectieve inzet van financiële middelen en publieke ruimte, en duurzaamheid. Deze doelen hebben verschillende implicaties voor de uitrol van laadinfrastructuur, die niet altijd goed samengaan. Zo is het bijvoorbeeld voor efficiënt gebruik van laadinfrastructuur belangrijk dat laadsessies zo kort mogelijk zijn, terwijl voor duurzaam laden van elektrische auto's vaak langere laadsessies nodig zijn. Het analyseren van laadgedrag via de in dit hoofdstuk ontwikkelde methode kan beleidsmakers helpen in het maken van dit soort afwegingen. Deze methode relateert een aantal indicatoren voor laadgedrag aan vijf beleidsmaatregelen die bijdragen aan verschillende van de genoemde beleidsdoelen: (1) *verhoog het aantal laadpunten*, (2) *ontmoedig laadpaalkleven*, (3) *vehicle-to-grid*, (4) *'s nachts laden*, en (5) *laden met zonne-energie*. Ik pas de methode toe op een grote dataset van laadsessies in Nederland. De

resultaten laten zien dat laadgedrag sterk varieert tussen verschillende buurten. Dit impliceert dat beleid voor de uitrol van laadinfrastructuur het best lokaal kan worden ontwikkeld.

Ik vat mijn resultaten samen in twee hoofdconclusies. Ten eerste, elektrische auto's kunnen een grote bijdrage leveren aan het efficiënt integreren van variabele duurzame energiebronnen door slim te laden en V2G in te zetten. Deze bijdrage is uiteindelijk wel beperkt, er zullen dus ook andere technologieën en maatregelen nodig zijn voor het stabiliseren van energiesystemen met veel zonne- en windenergie. Ten tweede, er zijn grote verschillen in adoptie en laadgedrag, en dit beïnvloed de mate waarin elektrische auto's kunnen bijdragen aan het balanceren van het net in sommige regio's en buurten.

List of abbreviations

ABM	Agent-based model
AC	Alternating current
ANOVA	Analysis of variance
BEV	Battery electric vehicle
CBS	Centraal Bureau voor de Statistiek
CO_2	Carbon-dioxide
CP	Charge point
DC	Direct current
DOD	Depth of discharge
DSM	Demand side management
DSO	Distribution system operator
EV	Electric vehicle
EU	European Union
FEV	Full electric vehicle
GWh	Giga Watt hour
GWp	Giga Watt peak
h	Hour
ICE	Internal combustion engine
km	Kilometre
km^2	Kilometre squared
KNMI	Koninklijk Nederlands Meteorologisch Instituut
kW	Kilo Watt
kWh	Kilo Watt hour
kWp	Kilo Watt peak
LP	Linear programming
m^2	Meter squared
MCA	Multi-criteria analysis
MW	Mega Watt
MWh	Mega Watt hour
NL	Netherlands
NUTS-3	Nomenclature des unités territoriales statistiques-3
OLS	Ordinary least squares
OViN	Onderzoek verplaatsingen in Nederland
PC4	Four-digit postal code
PC5	Five-digit postal code
PC6	Six-digit postal code
PHEV	Plug-in hybrid electric vehicle
PIR	Production installation register

pp	Per person
PR	Performance ratio
PV	Photovoltaic
RDW	Rijksdienst voor het Wegverkeer
RPR	Relative peak reduction
RT	Real-time
SC	Self-consumption
SES	Smart energy system
SET	Smart energy technology
SOC	State of charge
TSO	Transmission system operator
TWh	Tera Watt hour
USA	United States of America
V2G	Vehicle-to-grid
W	Watt
yr	year

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Curriculum Vitae

Mart van der Kam (Amsterdam, 1989) obtained his BSc in Physics & Astronomy from Utrecht University in 2011, and his MSc in Sustainable Development from the same university in 2014. His MSc thesis investigated the combination of PV solar energy and electric vehicles. Having gotten enthusiastic about doing research on this topic, Mart started his PhD in Innovation Studies at the Copernicus Institute of Sustainable Development of Utrecht University. During his PhD, Mart developed simulation models on how the impact of PV solar panels and electric vehicles on the electricity grid can be reduced through smart charging and vehicle-to-grid. In particular, he focused on integrating insights from engineering with theory from the social sciences in these models. He published his work in various scientific journals and presented at several national and international conferences, including two in Barcelona.

After his time at Utrecht University came to an end, Mart was employed at Eindhoven University Technology as a researcher on the harmonization of communication protocols for electric vehicle charging. In March 2020, Mart will continue his academic career as a postdoc at the University of Geneva, further pursuing his interest in combining engineering and social science in simulation models of sustainable energy systems.

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