Evaluating Electric Vehicle Charging Infrastructure Policies

Wolbertus, R.

Publication date
2020
Document Version
Final published version

Citation for published version (APA):
Wolbertus, R. (2020). *Evaluating Electric Vehicle Charging Infrastructure Policies*. TRAIL.

Evaluating Electric Vehicle Charging Infrastructure Policies

Rick Wolbertus

Delft University of Technology

Cover illustration by Evelien Jagtman

This research has been funded by Nationaal Regieorgaan Praktijkgericht Onderzoek SIA under the grant 2014-01-121 PRO which has been awarded to a consortium led by the Amsterdam University of Applied Sciences

Evaluating Electric Vehicle Charging Infrastructure Policies

Proefschrift

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus Prof.dr.ir. T.H.J.J. van der Hagen,
voorzitter van het College voor Promoties,
in het openbaar te verdedigen op donderdag 27 februari 2020 om 10:00 uur

door

Rick WOLBERTUS
Master of Science in Innovation Sciences
Technische Universiteit Eindhoven, Nederland
geboren te Venlo, Nederland

Dit proefschrift is goedgekeurd door de promotoren:

Samenstelling van de promotiecommissie:

Rector Magnificus	Voorzitter
Prof.dr.ir. C.G. Chorus	Technische Universiteit Delft, promotor
Dr. ir. M. Kroesen	Technische Universiteit Delft, co-promotor
Dr. ir. R. van den Hoed	Hogeschool van Amsterdam, co-promotor

Onafhankelijke leden:

Prof. dr.ir. Z. Lukszo	Technische Universiteit Delft
Prof. dr. G.P. van Wee	Technische Universiteit Delft
Prof. dr.ir. G.P.J. Verbong	Technische Universiteit Eindhoven
Prof. dr. T. Schwanen	Oxford University, Verenigd Koninkrijk

TRAIL Thesis Series no. T2020/4, the Netherlands Research School TRAIL

TRAIL
P.O. Box 5017
2600 GA Delft
The Netherlands
E-mail: info@rsTRAIL.nl

ISBN: 978-90-5584-264-3

Printed in the Netherlands

Voor Anne

Do you understand the things that you've been seeing?
Do you understand the things that you've been dreaming?
Come a little closer, then you'll see

- Cage the Elephant

Preface

The lyrics to the song “Come a little closer” by Cage The Elephant on the previous page put into words the curiousity with which I started this PhD project. The singer of the band described his motivation for writing the lyrics when staring outside his window: “*...I was looking at it, and it looked like an intricate system of boroughs, or an anthill. But then I started thinking that up close inside the houses there were little souls, souls that were walking around and had heartache, and love, and loss and joy.*” Although this thesis is not about heartaches and love, this PhD project has shown me that technology can be accompanied with lots of emotions. New technology brings new behavior; continuously digging deeper and looking closer at what drives this behavior, for me, defines the curiousity you need as a PhD researcher.

Although my curiousity has been the driver throughout this project, I would not have been able to finish without the support of many. First and foremost, I would like to thank my promotors. Caspar, the moment I first walked into your office when I was still looking for a professor to supervise the project, you made me feel welcome and at ease. Throughout the four years you have pushed me to do my best, but most of all to come up with my own ideas and be proud of them. Thank you very much for your valuable comments and insights, they have made me a better researcher. Maarten, thank you a lot for the many of hours of work you have put into looking at my research and reviewing the papers I wrote. This thesis would not have the same quality without your input. Also thank you for the many laughs we had, a day at the office with you was never boring. Robert, thank you for having the confidence to hire me at the start, as I only later understood, was not obvious at all. Your advice has pushed me to keep on looking further and explore new boundaries in research. The compliments and advice has given me the confidence I needed to proceed to develop as a researcher and as a person.

Our project team, with Simone as our project leader. Simone thank you for keeping us to deadlines with as a major accomplished our published book, which nearly seemed impossible. You have kept our bunch of cowboys in line. Jurjen, whose sometimes inimitable brain this project initiated from, thank you such much for your valuable ideas and feedback on my work. Your enthusiasm and creativity is contagious and has helped to form this thesis. A genuine thanks to anyone who has worked on the IDOLaad project throughout the years. Peter, Ilse, Nico, Xiomara, Martijn, Simon, without you this research would not have been possible. A big thank you to all project partners, for providing the data and ideas which were fundamental for this project. Last, thank you to SiA for funding the IDOLaad project.

To all students who have worked on the project, with a special thanks to Bas and Steven who have contributed to two of the chapters. Bas, who would have thought our research would lead to the Dutch 'Word of the year'. Abdullah, Auke, Calvin, Jeroen, Jip, Liam, Lisa, Lotte, Marvin, Nanne, Nigel, Tessa, Raymond, Timothee, Tom, Tugba, Wessel, Xiao Xiao it has been a pleasure working with you.

My fellow PhD students, Sander and Kasper at the Amsterdam University of Applied Sciences. Thank you for letting me complain about Graduate School without any limitations. At Delft University of Technology a special thanks to Baiba and Bing. Baiba thank you a lot for all the advice you have given me, PhD life would not have been so smooth without ýou. Bing thank you a lot for all the memories and laughs. I will not forget our trip to Israel and your cheerfull comments along the way. I am not as skinny as you think. To all my PhD friends from Eindhoven. 'Dr in 't Audt' has been truly helpful in navigating the tricky path of being a PhD student.

Veur mien familie. Mien zussen, Anniek, Lianne en Maryanne, bedank det ge mig migzelf leet zien, vruuger en now. Bedank det ge aaf en toe trots euver mig verteld, zoeals ik trots op ug bun. Veur mien elders, veur ugge steun en det ik mien eigen waeg heb muege vinge. Veur ut zorgen det ik mien niejsjierigheid altied urges in kwiet kos. Pap veur ut doorsteure van elk niejsartikel det ze maar kos vinge euver ut ongerwerp. Mam veur ut altied klaorstaon, auk als ut effe neejt zoe mekkelijk ging.

Als letste hiel vuul dank aan mien lieve Anne. Zonger dig waas dit noeit geluk. Al waare we de aafgelaupe veer jaor soms vaker van elkaar weg den beej elkaar, dien steun waas der altied. Veur dig waare deze jaore auk superzwaor, waordaor ik allein maar mier waardering ken opbringen veurdet ze mig bus blieve supporten. Det we nog lang beej elkaar meuge blieve.

Rick Wolbertus,
Amsterdam, November 2019

Content

1 Introduction

1.1 Background

The emissions of greenhouse gases, such as CO_2, and harmful particles like NO_x , SO_x and PM are rising (Boden, Marland, & R.J., 2015; Hao, Geng, & Sarkis, 2016). These emissions are proven to be linked to global warming and reduced air quality (Davis, Bell, & Fletcher, 2002; IPCC, 2014; Stanek, Sacks, Dutton, & Dubois, 2011). The combustion of fossil fuels in transportation is a major contributor to these emissions; in 2015 transport contributed to 14% of global CO_2 emissions (International Energy Agency, 2016). In Western countries the share of transport in total emissions is even larger; in the USA 27% of CO_2 emissions are attributed to transport of which 83% can be ascribed to road transport (United States Environmental Protection Agency, 2015). In Europe road transport contributes 17.5% to the total CO_2 emissions (European Commission, 2009). While other major industries have shown a downturn in greenhouse gas emissions, transport emissions have continued to rise since 1990. In 2017, transport is the largest greenhouse gas polluting sector in the United States.

Electric vehicles (EVs) show great promise to reduce the emittance of CO_2 (Messagie, Macharis, & Van Mierlo, 2013) and local emissions (Razeghi et al., 2016). Due to better energy efficiency, compared to the internal combustion engine (ICE), and zero tailpipe emissions, EVs can curtail harmful emissions. Currently, a large share of the automobile manufacturers has a Plug-in Hybrid Electric Vehicle (PHEV), Extended Range Electric Vehicle (EREV) or a Full Electric Vehicle (FEV) model for sale or planned. New models gain a lot of media attention and sales of particular models have been considerable (Bowermaster & Alexander, 2017). Current developments show that EVs are likely to gain a significant market share in the years to come (International Energy Agency, 2015).

Despite these developments, the vast majority of new cars sold still makes use of ICE technology. The adoption of EVs is restrained by technological, infrastructural and psychological barriers. The most prominent barriers are high acquisition costs (Egbue & Long, 2015; Hagman, Stier, & Susilo, 2016), range anxiety (Franke & Krems, 2013a, 2013b) and a lack of (public) charging infrastructure (Egbue & Long, 2015; Krupa et al., 2014). With decreasing battery costs (Nykvist & Nilsson, 2015; Nykvist, Sprei, & Nilsson, 2019) and increasing battery capacity in new car models, the first two barriers can likely be overcome in the years ahead. Car makers are building and have announced new models with larger battery capacity at lower prices, in line with developments over the past years. Newly announced models are expected to come to the market at the turn of the decade. Stricter emission regulations in for example the European Union from 2020 onwards require a substantial effort from OEMs to sell zero-emission vehicles. This signals that EVs are becoming available for a wider range of consumers and are becoming a viable alternative for ICE vehicles.

The remaining barrier is a sufficient charging infrastructure for EVs. The development of (public) charging infrastructure is expected to follow the growth of EV sales (International Energy Agency, 2016). However, the deployment of charging infrastructure deals with a chicken-or-egg problem. With a low number of EVs on the road today, the business model of charging infrastructure is not viable (Madina, Barlag, Coppola, Gomez, & Rodriguez, 2015; Schroeder & Traber, 2012) and vice versa with a low amount of charging stations consumers are reluctant to purchase EVs. The development of a public charging infrastructure is however vital for early adaptors. Governments step in to break the chicken-or-egg dilemma and create a public charge network.

1.2 Municipal electric vehicle charging infrastructure policies

Cities play a leading role when it comes to improving air quality by promoting use of EVs. By 2017, nearly 50% of all EVs on the road are to be found in the leading 25 cities across the world (Hall, Cui, & Lutsey, 2018). Cities have a range of policy options to stimulate EVs which amongst others include financial incentives, bans and favours such as free parking and access to toll roads. Many cities choose to facilitate a charging infrastructure to promote EVs. The top 25 cities in terms of EV adoption account for 40% of all charging infrastructure currently in place (Hall et al., 2018). Significant investments have to be in the coming years and policy makers struggle with questions on what effective roll-out strategies are. It is therefore that this thesis focusses on municipal EV charging infrastructure policies.

Box 1. Defining policy maker management

Policy makers can address policy priorities on different levels, from strategic to more tactical and operational. In this thesis the terminology as described below is used to address these options. These descriptions are derived from the work of Loorbach (2010).

Strategic policies	Long term (2-25 years) goal formulations and accompanying set of rules and guidelines
Tactical plans	Medium term (1-3 years) steering activities aimed at a specific (sub-)system
Operational measures	Short term (0-1 years) experiments and actions

The development of a charging infrastructure requires dealing with multiple stakeholders at the tactical level. These are stakeholders in the private and public domain, such as other city departments (such as parking services, energy), grid and charging point operators and non-EV owners (Bakker, Maat, & van Wee, 2014; Wirges, 2016). Plans at the tactical level are made to manage the interests of the relevant stakeholders. Policies makers have two operational measures to reach those tactical plans; these are the roll-out strategy and post roll-out control measures. Policies makers are however unaware in which way these measures facilitate the tactical plans as the effects on the different aspects of the EV charging system are unknown.

To understand the effects of operational measures on tactical goals, it is necessary to comprehend the EV charging system and its interactions. *Figure 1.1* provides a system diagram of the EV charging system from the perspective of municipal policy makers. The EV charging system can be characterised by charging behaviour, which is a result of the interaction between EVs and charging stations. Within the system, EVs are defined by the fleet size and type. The type includes both differences in car type such as the PHEV and FEV (vehicle type) but also user types such as residential users, commuters or taxi drivers. EVs have a charging need that has to be fulfilled by the available charging stations. Charging stations are defined by the number of chargers, the capacity in number of vehicles it can charge and the charging speed.

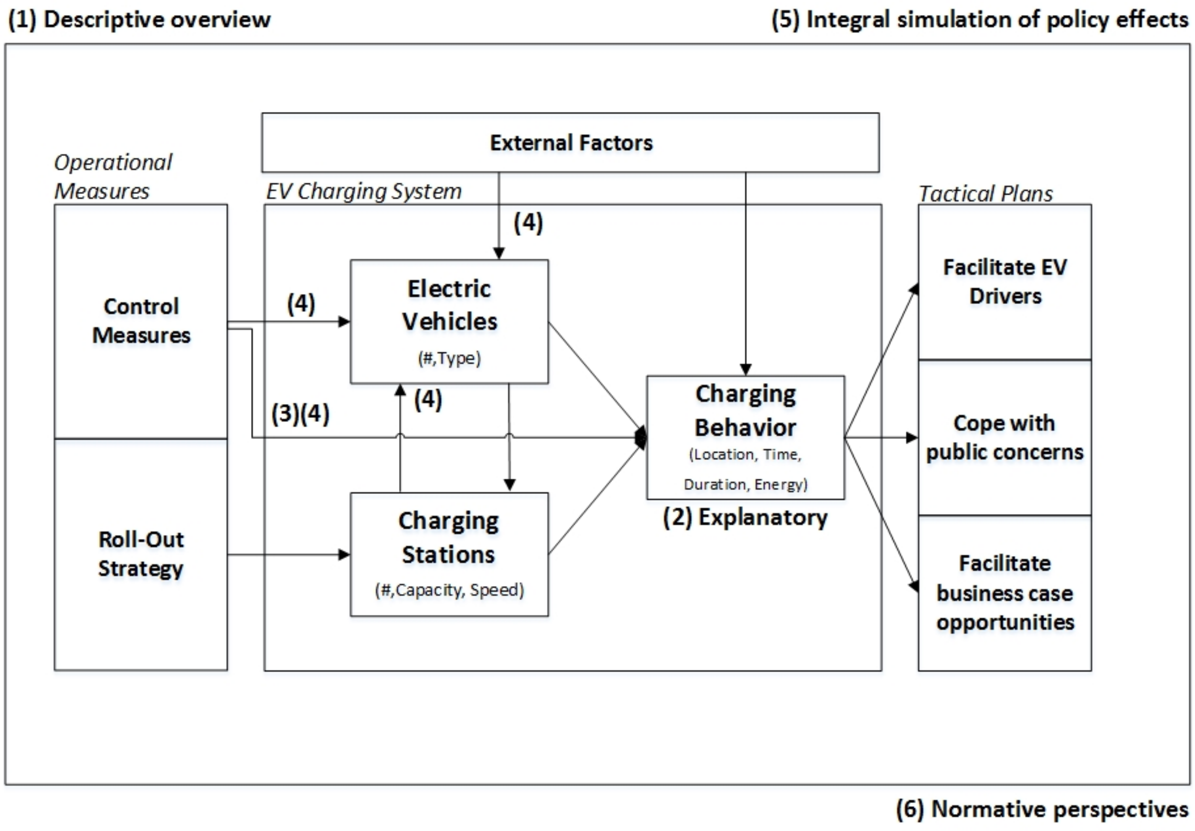


Figure 1.1. System diagram for public charging infrastructure including positioning of studies in this thesis

An important topic in this thesis is how operational measures influence the charging behaviour at a micro level by affecting both the electric vehicles, the charging stations or directly the charging behaviour as such. The interactions in the system are complex and might lead to opposite results for plans at the tactical level. For example, installing a large number of charging stations will facilitate EV drivers the best but does also result to a loss in parking spaces for non-EV drivers. Over-investing leads to a reduced business opportunity but on the other hand it convinces prospective owners to purchase an EV as sufficient charging infrastructure is available to overcome range anxiety issues. Besides the influence of operational policies on the EV charging systems, additional complexity is added due to external factors. These include for example developments of battery costs or charging technologies or policy measures at the (supra-)national level which influence the growth and composition of the stock of EVs (RVO.nl, 2019b).

To aid municipal policy makers in making the right decisions on operational measures it is important to generate knowledge on the EV charging system. This knowledge is descriptive, explanatory, focusses on the direct and indirect of operational measures but also involves an integral simulation to able to investigate the effects on the long term. Additionally, policy makers also deal with the normative perspectives of stakeholders on the EV charging system. The number of stakeholders from the energy, infrastructure and parking domain is growing, making the relations between the stakeholders' interests complicated. Understanding these perspectives is therefore key for successful implementation of policies. Using the system diagram in *Figure 1.1* the relevant knowledge gaps have been identified (indicated with numbers) that correspond to the different studies in this thesis.

Box 2. Research opportunity

This research was facilitated a large data collection effort on public EV charging infrastructure in the four largest Dutch cities (Amsterdam, Rotterdam, The Hague, Utrecht) and The Amsterdam Metropolitan region. Together with companies operating the charging stations, the Amsterdam University of Applied Sciences gathered, structured and cleansed data on charging station utilisation for monitoring and research. This process has resulted in an unique dataset with empirical data on electric vehicle charging behaviour. The dataset is both unique in its size (over 10 million charging sessions as of May 2019) as in the fact that it monitors public charging infrastructure in urban areas.

The collaboration in this research between Delft University of Technology and Amsterdam University of Applied Sciences has resulted in a thesis in which a wide variety of research methods has been used. This mixed method approach provides different perspectives on the EV charging system and therefore allows for new views on the subject.

This research focuses on operational measures policy makers can take to efficiently design a public charging infrastructure and how this design effects the purchase intention for electric vehicles by prospective EV drivers. This leads to the central research question in this thesis:

How and to what extent do operational measures for electric vehicle charging infrastructure influence the goals set in tactical plans and strategic policies for public charging stations in dense urban areas?

To answer the central research question the thesis is organised as follows. The first study describes the context of the Dutch electric vehicle case. This serves as background information on national and local policies which have shaped the system in which the other studies take place. Study two explores and explains the charging behaviour within the public domain to provide a better understanding of the demand and behaviour that policy makers will try to influence. Study three and four focus on operational measures and their effect on charging behaviour and the purchase intention of electric vehicle and the cross-pollination between the two. The fifth study simulates the entire EV charging system in order to explore the impacts of operational policies on tactical plans taking into account the development of external factors. The sixth and final study focuses on the normative perspectives of stakeholders on the EV charging infrastructure system.

1.3 Studies

This thesis uses a mixed method approach to answer the research questions at hand. A wide array of methodologies is used and the best suited method is chosen for each of the sub-questions. The approach and structure used in this thesis is described in more detail in this subsection.

Study 1: Plug-in (hybrid) electric vehicle adoption in the Netherlands: Lessons learned

Understanding the charging behaviour of electric vehicles requires knowledge of the context in which the behaviour is observed. Due to the variety in policies for stimulating adoption of EVs for charging infrastructure, charging behaviour at public charging stations should be analysed with an understanding of the local context. This thesis uses charging infrastructure in the Netherlands as a context. The Netherlands is a frontrunner when it comes to electric mobility. This is expressed in the size and share of the electric fleet (RVO.nl, 2019b) but especially in the number of publicly available charging stations (European Alternative Fuel Observatory, 2018). The first study aims to answer the following research question:

Q1. How has national and local electric vehicle and charging infrastructure policy shaped electric vehicle adoption and charging behaviour in The Netherlands?

Chapter 2 of this thesis gives an in-depth view on the Dutch situation and focuses on the fiscal stimulation of (PH)EVs in the Netherlands and the development of a widespread charging infrastructure. The study relies on data of vehicle types registered and utilisation of charging infrastructure. Descriptive statistics are used to explore relationships between policies and EV adoption and charging behaviour. The study gives the reader the necessary background of the Dutch situation and how this situation is generalizable for other dense urban areas across the world.

Study 2: Fully charged: An empirical study into the factors that influence connection times at EV-charging stations

In order to evaluate the effects of policies on the EV charging system it is first necessary to understand the charging behaviour of EV drivers. Exploring this behaviour already reveals which factors play a major role and how policies can designed accordingly. Charging behaviour in this PhD thesis is defined by four characteristics of a charging session:

- Starting time
- Location
- Duration
- Energy transferred

Research on revealed preferences about the starting time and the location of charging sessions, show that this is mainly at home or at the workplace while being parked at these places (Brady

& O'Mahony, 2016; Idaho National Laboratory, 2015; Khoo, Wang, Paevere, & Higgins, 2014). Yet, for the duration of the charging session, explanatory studies seem to be lacking. Most studies presume that EV charging at public charging stations occurs when the battery level of the car is too low. Charging in public is carried out to create enough range to complete the (next) trip, leading to connection times to charging stations that are equal to charging times (Brady & O'Mahony, 2016; Brooker & Qin, 2015; Dong, Liu, & Lin, 2014). Such assumptions may hold for fast charging stations (Motoaki & Shirk, 2017; Neaimeh et al., 2017; Sun et al., 2016), however, for slower level 2 charging infrastructure (up to 22kW) in the city, charging duration is known to be a complex interplay between parking and refuelling behaviour (Asamer, Reinthaler, Ruthmair, Straub, & Puchinger, 2016; Tu et al., 2015; Zou, Wei, Sun, Hu, & Shiao, 2016). Given this interplay, it is therefore more interesting to study connection times instead of charging times at charging stations to get a better understanding of the factors that play a role in charging behaviour. The following research question is therefore the focus of the second study:

Q2: Which factors and to which extent do these factors influence electric vehicles connection times at charging stations?

To understand the dynamics of connection times a large dataset with charging sessions on public charging infrastructure in the Netherlands is used. Using multinomial logit modelling on this revealed preference data, several types of charging sessions are distinguished in *Chapter 3*. Factors such as the time of day and the built environment are used to further understand the dynamics that take place. This allows for a better understanding of the charging behaviour and why certain operational measures that aim to influence charging behaviour may or may not have the expected effect.

Study 3: Improving electric vehicle charging station efficiency through pricing

The second study reveals that connection times at charging stations can best be explained by parking times. Connections or more related to parking than to the actual charging times. The first study showed that a minority of the time the charging station is actually used for charging. Due to the rival nature of charging stations, unnecessarily long connection times prevent other drivers from access and hamper the business case of charging point operators. The third study therefore focusses on the control measure of time-based fees to reduce connection times and answers the following question:

Q3: How and to what extent can time-based fees help to reduce idle time at electric vehicle charging stations?

To answer this question a stated choice experiment is set-up among EV drivers to estimate the effect of time based fees on the duration of charging sessions. Using a multinomial logit model the effect of such a fee is estimated under circumstances. Latent class choice modelling is used to specify the effect for different user groups.

Study 4: Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments

Due to the relation between parking and charging as demonstrated in Study 2, parking policies (such as free parking) are a popular control measure to both steer charging behaviour as well to promote EV sales (Hackbarth & Madlener, 2013; Hoen & Koetse, 2014). However, policy makers implement these policies often with a single goal in mind (i.e. controlling charging behaviour or promoting EV sales), while cross-pollination between these policies could be expected. To investigate this interrelatedness, Study 4 aims to answer the following research question:

Q4 : How and to what extent do parking policies influence charging behaviour and electric vehicle purchase intention and how are they interrelated?

Using unique natural experimental settings on daytime parking and charging and free parking the effect of these parking policies on both charging behaviour and purchase intention of electric vehicles is estimated. Regression and ordinal regression models are used to estimate the effect size of the policies. For the effect of the same policy a stated choice experiment is conducted among potential EV owners that rely on on-street parking facilities. EV purchase intention is defined as the willingness to buy EVs over vehicles driven by conventional fuels. Purchase behaviour is explained by the vehicles attributes which interact with the charging infrastructure attributes and parking policies which are modelled as a context effect. Mixed logit models are used to model the effect. The results of these separate studies and the relation between purchase policies and control measures for charging infrastructure are the topic of Chapter 5.

Study 5: Large scale introduction of electric vehicle charging infrastructure: An Agent Based model approach

At the city level, policy makers make tactical plans and strategical policies for the (mid-)long term. Charging infrastructure roll-out requires to make plans for the mid-long term but policy makers are reluctant to make decisions as the upfront costs are high and payback periods long. One of the major questions is which 'EV to charging station ratio' is optimal to align with tactical plans. Uncertainty about the right roll-out strategy increases due to technological developments related to the vehicles (i.e. battery sizes) and charging equipment (i.e. higher charging speeds) and the expected but uncertain reciprocal effects between the EV adoption pace and infrastructure roll-out (Sierzchula, Bakker, Maat, & Wee, 2014; Rick Wolbertus, Kroesen, van den Hoed, & Chorus, 2018b). To study these effects and integral perspective of the entire EV charging system at a macro level is needed. Study 5 answers the following research question:

Q5: Which roll-out strategy for charging infrastructure can optimize tactical plans and why?

The effect of operational policies on the tactical goals on the mid-long term an agent based model approach is used. This approach is especially suitable for this research questions as it investigates the interactions between EV drivers, potential EV drivers, charging infrastructure and charging point operators. These interactions take place in a specific geo-spatial context which influences the interactions between the different elements in the system.

In this agent based model, the agents are (1) electric car owners that interact with the available charging infrastructure, (2) other car owners that purchase new cars and (3) charging point operators that place charging stations. In contrast to many other agent based models on EVs, the charging patterns are data-driven and are built using actual charging data. New agents and charging stations are added to the system with policy options to differ in the roll-out strategy such as differentiating in the 'EV to charging station ratio'. Charging behaviour and electric vehicles purchases are a measure of effectiveness of several tactical goals.

Study 6: Stakeholders’ perspectives on future charging infrastructure developments

The tactical goals used in this thesis are a translation of the stakeholders’ goals in the EV charging infrastructure field. The number of stakeholders and their interests is large (Bakker et al., 2014; Helmus & Van den Hoed, 2016; Wirges, 2016) making it complex to satisfy the needs of each and every one of them. Stakeholders have normative perspectives on the entire EV charging system and the operational measures that policy makers want to implement as shown in the system diagram in *Figure 1.1*. Moreover it assumed in these studies that each of the stakeholders only strive to optimize their own goals and these goals are static. Study 6 expands the view on these stakeholders’ perspectives and see how these overlap. It answers the following research question:

Q 6: What perspectives do stakeholders have on future tactical goals for electric vehicle charging infrastructure and how are they (dis-)aligned?

Q-methodology is used to reveal the different perspectives on charging infrastructure. This approach allows to see to which extent these perspectives are related to the different types of stakeholders or whether common ground between the stakeholders can be discovered.

1.4 Relevance

1.4.1 Scientific

The knowledge on electric vehicle charging is developing in line with the growing number of EVs on the road. The number of descriptive studies with real life data from EVs is growing (Hoed et al., 2014; Morrissey, Weldon, & Mahony, 2016; Sadeghianpourhamami, Refa, Strobbe, & Develder, 2018). A number of studies has tried to identify which factors play a role in charging behaviour (Motoaki & Shirk, 2017; Sun, Yamamoto, & Morikawa, 2016; Zoepf, MacKenzie, Keith, & Chernicoff, 2013), yet the number of studies using revealed preference data is limited. So far these studies have mainly been descriptive. Additionally, a fair body of literature on charging infrastructure planning already exists. So far many of the approaches have relied on mathematical optimisations (He, Yin, & Zhou, 2015; Xu, Miao, Zhang, & Shi, 2013) or on the basis of travel patterns (Paffumi, Gennaro, & Martini, 2015; Shahraki, Cai, Turkay, & Xu, 2015). Agent based models have also been developed on the basis of travel patterns and assumptions about charging choices (Gnann, Plötz, & Wietschel, 2018; Torres et al., 2015).

To conclude, so far studies have considered EV charging in a static environment without interaction between different types EV drivers and stakeholders. Studies have mainly been done using a limited amount of revealed data or assumptions have been made on charging behaviour using travel patterns from fossil fuel driven cars. Charging infrastructure optimisations therefore lack a sense of reality in which the dynamics in the EV charging system are mostly disregarded.

The main contribution of this thesis is that it uses a system theory perspective to study how policy makers can most effective intervene to reach tactical goals. Using a mixed method approach to study the system at both the micro and macro level and the interactions between these levels, this thesis provides new insights in the field of electric mobility. It contributes to the knowledge on how policy makers can use operational policies to meet their tactical plans given the rapid external developments. Studies at the micro level, that use a large and unique dataset of revealed charging data, show how charging behaviour can be influenced using operational polices but also allows to investigate the reciprocal effect between EV adoption and charging station placement in the urban environment. The macro level studies show how external developments have shaped and can shape the market while dealing with the stakeholders at hand. The integrated approach at both these levels provides new insights at how micro and macro developments can influence each other.

This thesis focuses at public charging stations in dense urban areas. The dynamics in these areas with a mix of home, workplace and opportunity charging are unique. Additional multiple user groups including taxis and car sharing vehicles make use of the same infrastructure. As the thesis uses a large and unique dataset on public charging stations in the Netherlands, one of the frontrunners in the field of electric mobility, the thesis adds to a better understanding of how EV charging systems will develop.

1.4.2 Societal

This thesis contributes to creating a charging infrastructure for electric vehicles that takes the interests of stakeholders into account. In this way the thesis contributes to the acceleration of electric mobility within urban areas. This should help to reduce air and noise pollution in cities. On a broader scale the uptake of electric vehicles helps to reduce greenhouse gas emissions as means to tackle climate change.

This thesis is part of the SiA Raak funded project IDOLaad. The IDOLaad project has provided the opportunity to carry out (applied) research at the Amsterdam University of Applied Sciences in close cooperation with municipal policy makers from the four largest cities in the Netherlands (Amsterdam, Rotterdam, The Hague and Utrecht) and the Amsterdam Metropolitan area. The project also contains industry partners in the charging infrastructure industry ranging from charging station manufacturers, charging station operators to consultancy agencies. Research questions, methodologies and model assumptions are made in collaboration with these partners in the field. Results of the research are shared with the partners and have led to changes in the policies which has guaranteed societal impact.

At a national level the research contributes to a better understanding of the utilization of public charging infrastructure. Knowledge dissemination through the *National knowledge platform charging infrastructure* helps to get municipalities the necessary information. The research contributes to a better understanding of the necessary charging infrastructure to reach the Dutch goals of 100% electric cars sold in 2030 (RVO.nl, 2011).

In a general sense this research contributes to the efficient roll-out of charging infrastructure in dense urban areas. Urban areas deal with many (potential) EV drivers having to rely on on-street parking and charging. This situation creates a different dynamic and problems (Hookham, 2017) and involves a larger number of stakeholders. The thesis increases understanding of the complexity of the problem at hand and offers insights into which operational policies at a municipal level are effective.

1.5 Author contributions

This thesis builds upon chapters that each are separate papers. The publication status of each of the chapter is shown in *Table 1.1*. The author of this thesis was in the lead in all aspects of the study. Although each of the co-authors have made meaningful contributions to the corresponding papers, as such the author of thesis has been in the lead in all aspects of the studies.

Note: Data collection on charging data that was used in studies one, two, four and five was done by a team at the Amsterdam University of Applied Sciences throughout the duration of the PhD research. They imported, managed and cleansed the data and put the IT infrastructure to be able to use the data for research. The team consists of Simone Maase, Peter Odenhoven, Ilse Vogel, Xiomara Dilrosun, Simon Baars, Martijn Kooij, Thijs Timmermans, Jurjen Helmus and Nico van der Bruggen. Charging data was made available by the charging point operators in the area of the Municipalities of Amsterdam, Rotterdam, Utrecht, The Hague and the metropole region of Amsterdam electric. The companies that provided data are NUON/Vattenfall, Engie, PitPoint Clean Fuels, EVBox, EVNet, Alfen, Ballast Nedam, Greenflux, Allego, Essent, Fastned, Ecotap and LomboXnet. Additionally, the municipality of The Hague provided data on the daytime parking policy which was used in study four. Bas Gerzon, an MSc. student supervised by this thesis author, was also involved in the experimental design and data collection process in study 3. Steven Jansen, an BSc. Student supervised by this thesis author, was involved in the experimental design and evaluation of study 6

Table 1.1 Publication status of each chapter

	Publication status
Chapter 2	Rick Wolbertus & Robert van den Hoed (2019) Plug-in (Hybrid) Electric Vehicle adoption in the Netherlands: Lessons learned. In: Marcello Consistable, Gil Tal, Tom Turrentine (Eds.) Driving Electric Cars – Consumer adoption and use of plug-in electric cars, Springer **Status: Accepted**
Chapter 3	Rick Wolbertus, Maarten Kroesen, Robert van den Hoed, Caspar Chorus (2018) Fully charged: An empirical study into the factors that influence connection times at EV-charging stations, *Energy Policy*, Volume 123, Pages 1-7 https://doi.org/10.1016/j.enpol.2018.08.030 **Status: Published**
Chapter 4	Rick Wolbertus & Bas Gerzon, Improving Electric Vehicle Charging Station Efficiency through Pricing, *Journal of Advanced Transportation*, vol. 2018, Pages 11 https://doi.org/10.1155/2018/4831951 **Status: Published**
Chapter 5	Rick Wolbertus, Maarten Kroesen, Robert van den Hoed, Caspar G. Chorus (2018) Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments, *Transportation Research Part D: Transport and Environment*, Volume 62, Pages 283-297 https://doi.org/10.1016/j.trd.2018.03.012 **Status: Published**

Chapter 6	Rick Wolbertus, Maarten Kroesen, Robert van den Hoed, Caspar Chorus (2019) Large scale introduction of electric vehicle charging infrastructure: An Agent Based model approach **Status: Under review**
Chapter 7	Rick Wolbertus,Steven Jansen, Maarten Kroesen (2019) Stakeholders' perspectives on future electric vehicle charging infrastructure developments, *Futures* **Status: Submitted**

1.6 References

Bakker, S., Maat, K., & van Wee, B. (2014). Stakeholders interests, expectations, and strategies regarding the development and implementation of electric vehicles: The case of the Netherlands. Transportation Research Part A: Policy and Practice, 66(1), 52–64. https://doi.org/10.1016/j.tra.2014.04.018

Boden, T. A., Marland, G., & R.J., A. (2015). Global, Regional, and National Fossil-Fuel CO_2 Emissions. https://doi.org/10.3334

Bowermaster, B. D., & Alexander, M. (2017). The Need for Charging. IEEE Electrification Magazine, 5(March 2017), 59–67. https://doi.org/10.1109/MELE.2016.2644559

Brady, J., & O'Mahony, M. (2016). Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data. Sustainable Cities and Society, 26, 203–216. https://doi.org/10.1016/j.scs.2016.06.014

Davis, D. D., Bell, M. L., & Fletcher, T. (2002). A look back at the London smog of 1952 and the half century since. Environ. Health Perspect, 12(110), A734–A735.

Egbue, O., & Long, S. (2015). Barriers to widespread adoption of electric vehicles : An analysis of consumer attitudes and perceptions. Energy Policy, 48(2012), 717–729. https://doi.org/10.1016/j.enpol.2012.06.009

European Commission. (2009). EU Energy and Transport in Figures. Brussels.

Franke, T., & Krems, J. F. (2013a). Understanding charging behaviour of electric vehicle users. Transportation Research Part F: Traffic Psychology and Behaviour, 21(2013), 75–89. https://doi.org/10.1016/j.trf.2013.09.002

Franke, T., & Krems, J. F. (2013b). What drives range preferences in electric vehicle users ? Transport Policy, 30, 56–62. https://doi.org/10.1016/j.tranpol.2013.07.005

Hackbarth, A., & Madlener, R. (2013). Consumer preferences for alternative fuel vehicles : A discrete choice analysis. Transportation Research Part D: Transport and Environment, 25, 5–17. https://doi.org/10.1016/j.trd.2013.07.002

Hagman, J., Stier, J. J., & Susilo, Y. (2016). Total cost of ownership and its potential implications for battery electric vehicle diffusion. Research in Transportation Business & Management, 18, 11–17. https://doi.org/10.1016/j.rtbm.2016.01.003

Hall, D., Cui, H., & Lutsey, N. (2018). Electric vehicle capitals: Accelerating the global transition to electric drive. Retrieved from https://www.theicct.org/publications/modernizing-regulations-electrification

Hao, H., Geng, Y., & Sarkis, J. (2016). Carbon footprint of global passenger cars : Scenarios through 2050. Energy, 101, 121–131. https://doi.org/10.1016/j.energy.2016.01.089

Helmus, J., & Van den Hoed, R. (2016). Key Performance Indicators of Charging Infrastructure. In Electric Vehicle Symposium 29 (pp. 1–9).

Hoed, R. Van Den, Helmus, J. R., Vries, R. De, & Bardok, D. (2014). Data analysis on the public charge infrastructure in the city of Amsterdam. In EVS27 Symposium, Barcelona, Spain, November 17-20, 2013 (pp. 1–10). https://doi.org/10.1109/EVS.2013.6915009

Hoen, A., & Koetse, M. J. (2014). A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. Transportation Research Part A: Policy and Practice, 61, 199–215. https://doi.org/10.1016/j.tra.2014.01.008

Hookham, M. (2017, July 9). Sparks fly: electric car owners take on charge bay hoggers. The Times. Retrieved from https://www.thetimes.co.uk/article/sparks-fly-electric-car-owners-take-on-charge-bay-hoggers-qp2mnztqw

Idaho National Laboratory. (2015). Plugged In: How Americans Charge Their Electric Vehicles, 1–24. Retrieved from https://avt.inl.gov/sites/default/files/pdf/arra/SummaryReport.pdf

International Energy Agency. (2015). Global EV Outlook 2015.

International Energy Agency. (2016). Global EV Outlook 2016: Beyond one million electric cars.

IPCC. (2014). Climate Change 2014: Mitigation of Climate Chang. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. (O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, K. S. Kadner, Seyboth, … J. C. Minx, Eds.). Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Khoo, Y. B., Wang, C.-H., Paevere, P., & Higgins, A. (2014). Statistical modeling of Electric Vehicle electricity consumption in the Victorian EV Trial, Australia. Transportation Research Part D: Transport and Environment, 32, 263–277. https://doi.org/10.1016/j.trd.2014.08.017

Krupa, J. S., Rizzo, D. M., Eppstein, M. J., Lanute, D. B., Gaalema, D. E., Lakkaraju, K., & Warrender, C. E. (2014). Analysis of a consumer survey on plug-in hybrid electric vehicles. Transportation Research Part A, 64, 14–31. https://doi.org/10.1016/j.tra.2014.02.019

Loorbach, D. (2010). Transition Management for Sustainable Development : A Prescriptive , Complexity-Based Governance Framework. Governance: An International Journal of Policy, Administration, and Institutions, 23(1), 161–183.

Madina, C., Barlag, H., Coppola, G., Gomez, I., & Rodriguez, R. (2015). Economic assessment of strategies to deploy publicly accessible charging infrastructure. EVS28 International Electric Vehicle Symposium and Exhibition, 1–11.

Messagie, M., Macharis, C., & Van Mierlo, J. (2013). Key outcomes from life cycle assessment of vehicles, a state of the art literature review. Electric Vehicle Symposium and Exhibition (EVS27), 2013 World, 1–9. https://doi.org/10.1109/EVS.2013.6915045

Morrissey, P., Weldon, P., & Mahony, M. O. (2016). Future standard and fast charging infrastructure planning : An analysis of electric vehicle charging behaviour. Energy Policy, 89, 257–270. https://doi.org/10.1016/j.enpol.2015.12.001

Motoaki, Y., & Shirk, M. G. (2017). Consumer behavioral adaption in EV fast charging through pricing. Energy Policy, 108(May), 178–183. https://doi.org/10.1016/j.enpol.2017.05.051

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. Nature Climate Change, 5, 329–332.

Nykvist, B., Sprei, F., & Nilsson, M. (2019). Assessing the progress toward lower priced long range battery electric vehicles. Energy Policy, 124(September 2018), 144–155. https://doi.org/10.1016/j.enpol.2018.09.035

Razeghi, G., Carreras-sospedra, M., Brown, T., Brouwer, J., Dabdub, D., & Samuelsen, S. (2016). Episodic air quality impacts of plug-in electric vehicles. Atmospheric Environment, 137, 90–100. https://doi.org/10.1016/j.atmosenv.2016.04.031

RVO.nl. (2011). Plan van Aanpak elektrisch vervoer: 'Elektrisch Rijden in de Versnelling.' The Hague. Retrieved from http://www.rvo.nl/sites/default/files/bijlagen/Plan van aanpak - elektrisch rijden in de versnelling-.pdf

Sadeghianpourhamami, N., Refa, N., Strobbe, M., & Develder, C. (2018). Electrical Power and Energy Systems Quantitive analysis of electric vehicle flexibility : A data-driven approach. International Journal of Electrical Power and Energy Systems, 95, 451–462. https://doi.org/10.1016/j.ijepes.2017.09.007

Schroeder, A., & Traber, T. (2012). The economics of fast charging infrastructure for electric vehicles. Energy Policy, 43, 136–144. https://doi.org/10.1016/j.enpol.2011.12.041

Stanek, L. W., Sacks, J. D., Dutton, S. J., & Dubois, J. J. B. (2011). Attributing health effects to apportioned components and sources of particulate matter: an evaluation of collective results. Atmospheric Environment, 32(45), 5655–5663.

Sun, X. H., Yamamoto, T., & Morikawa, T. (2016). Fast-charging station choice behavior among battery electric vehicle users. Transportation Research Part D: Transport and Environment, 46, 26–39. https://doi.org/10.1016/j.trd.2016.03.008

United States Environmental Protection Agency. (2015). Fast Facts : U.S. Transportation Sector Greenhouse Gas Amissoins 1990-2013. Retrieved from https://www.epa.gov/sites/production/files/2016-02/documents/420f15032.pdf

Wirges, J. (2016). Planning the Charging Infrastructure for Electric Vehicles in Cities and Regions (Doctoral dissertation). Karlsruher Institut für Technologie.

Zoepf, S., MacKenzie, D., Keith, D., & Chernicoff, W. (2013). Charging choices and fuel displacement in a large-scale plug-in hybrid electric vehicle demonstration. Transportation Research Record: Journal of the Transportation Research Board, No. 2385, 1–10.

Razeghi, G., Carreras-sospedra, M., Brown, T., Brouwer, J., Dabdub, D., & Samuelsen, S. (2016). Episodic air quality impacts of plug-in electric vehicles. *Atmospheric Environment*, *137*, 90–100. https://doi.org/10.1016/j.atmosenv.2016.04.031

RVO.nl. (2011). *Plan van Aanpak elektrisch vervoer: 'Elektrisch Rijden in de Versnelling.'* The Hague. Retrieved from http://www.rvo.nl/sites/default/files/bijlagen/Plan van aanpak - elektrisch rijden in de versnelling-.pdf

RVO.nl. (2019a). *Nationale Agenda Laadinfrastructuur*. Utrecht, The Netherlands. Retrieved from https://www.klimaatakkoord.nl/documenten/publicaties/2019/01/08/achtergrondnotitie-mobiliteit-laadinfrastructuur

RVO.nl. (2019b). *Statistics Electric Vehicles in the Netherlands (up to and including March 2019)*. The Hague. Retrieved from https://www.rvo.nl/sites/default/files/2019/04/Statistics Electric Vehicles and Charging in The Netherlands up to and including March 2019.pdf

Sadeghianpourhamami, N., Refa, N., Strobbe, M., & Develder, C. (2018). Electrical Power and Energy Systems Quantitive analysis of electric vehicle flexibility : A data-driven approach. *International Journal of Electrical Power and Energy Systems*, *95*, 451–462. https://doi.org/10.1016/j.ijepes.2017.09.007

Schroeder, A., & Traber, T. (2012). The economics of fast charging infrastructure for electric vehicles. *Energy Policy*, *43*, 136–144. https://doi.org/10.1016/j.enpol.2011.12.041

Stanek, L. W., Sacks, J. D., Dutton, S. J., & Dubois, J. J. B. (2011). Attributing health effects to apportioned components and sources of particulate matter: an evaluation of collective results. *Atmospheric Environment*, *32*(45), 5655–5663.

Sun, X. H., Yamamoto, T., & Morikawa, T. (2016). Fast-charging station choice behavior among battery electric vehicle users. *Transportation Research Part D: Transport and Environment*, *46*, 26–39. https://doi.org/10.1016/j.trd.2016.03.008

United States Environmental Protection Agency. (2015). *Fast Facts : U.S. Transportation Sector Greenhouse Gas Amissoins 1990-2013*. Retrieved from https://www.epa.gov/sites/production/files/2016-02/documents/420f15032.pdf

Wirges, J. (2016). *Planning the Charging Infrastructure for Electric Vehicles in Cities and Regions (Doctoral dissertation)*. Karlsruher Institut für Technologie.

Wolbertus, R. (2016). The jungle of charge tariffs in the Netherlands. Retrieved June 8, 2016, from http://www.idolaad.com/shared-content/blog/rick-wolbertus/2016/charge-tarrifs.html

Wolbertus, R., & van den Hoed, R. (2016). Benchmarking Charging Infrastructure Utilization. In *EVS29 Symposium* (pp. 1–15). Montreal, Quebec, Canada.

Zoepf, S., MacKenzie, D., Keith, D., & Chernicoff, W. (2013). Charging choices and fuel displacement in a large-scale plug-in hybrid electric vehicle demonstration. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2385*, 1–10.

2 Plug-in (hybrid) electric vehicle adoption in the Netherlands: Lessons learned

Wolbertus, R., & van den Hoed, R. (2019). Plug-in (Hybrid) Electric Vehicle adoption in the Netherlands: Lessons learned. In M. Contestabile, G. Tal, & T. Turrentine (Eds.), Driving Electric Cars - Consumer adoption and use of plug-in electric cars. Springer. Manuscript accepted for publication

2.1 Background

The story of electric vehicle (EV) adoption in the Netherlands is known for its high adoption rates of electric vehicles and the relative high share of plug-in hybrid vehicles (PHEVs). In parallel, the development of public charging infrastructure is characteristic resulting in one the highest public charger to vehicle ratio in the world (International Energy Agency, 2017). This chapter focuses on the successful growth of the EV market in the Netherlands and goes deeper in how the fiscal climate has lured consumers into buying a large number of EV and PHEVs in particular. It reflects on the pros and cons of the Dutch policies on stimulating EVs as well as the development of public charging infrastructure development.

In the past ten years the Dutch government has had a set of ambitious goals and subsidy measures to stimulate electric vehicles (EVs) as part of an effort to reduce the emissions from transport. In 2016 ambitions were set to achieve 10% of all new vehicles to have an electric drivetrain (2020), with subsequent increases towards 50% by 2025 (of which 30% full electric) and 100% electric by 2030 (Formula E-Team, 2016). From 2012, generous fiscal incentives were put in place to stimulate EV sales, leading to a spur in sales especially for plug-in hybrid electric vehicles. Up to 2017 the Netherlands is therefore among the countries with the highest adoption rates of EVs in the world.

This chapter studies two defining elements of the Dutch case namely (i) the impact of fiscal incentives on consumer decision (and particularly the high share of PHEVs) and (ii) how the dense public charging network has facilitated EV drivers. Regarding EV penetration, fiscal incentives that have been in place up to 2018 and the resulting EV sales in this period are discussed. Particularly the fiscal measures that stimulated PHEVs in early years and the discontinuation of which lead to a major drop in PHEV sales in later years are reviewed. These serve as an illustration of how substantial shifts lead to major changes adoption decisions. Apart from sheer sales, we will explore actual emission mitigation effects by PHEVs and differences between real life usage of PHEVs and NEDC cycles. Regarding charging infrastructure, the roll-out of public charging stations in the Netherlands is discussed. It sheds light on the problem of on-street parking in urban areas for EVs and provides some possible solutions for public charging based on Dutch practices. In the final part, we reflect on the establishments as well as drawbacks of Dutch policies to stimulate consumers to switch to electric, and provide recommendations for both policy makers as well as for future EV-research to lower barriers for consumers through incentives and provision of charging infrastructure.

The remainder of this chapter is structured as follows: in section 2.2 we describe the context by discussing the fiscal incentives that should affect consumer adoption of EVs and the policies regarding charging infrastructure. In section 2.3 we take a closer look at how effective the policies have been regarding improvements in air quality. The section reviews factors that drive the share of electric kilometres of PHEV drivers. In the fourth section we will have a look at how consumers use the public charging infrastructure and identify three key metrics. The final section concludes this chapter by providing policy recommendations how to further cost-efficiently influence consumer adoption rates and efficient use of charging infrastructure.

2.2 Dutch context on E-mobility

Structured planning on how to stimulate electric mobility in the Netherlands dates back to 2011 when the first plan of action for E-mobility was presented (Netherlands Enterprise Agency, 2011). With ambitions to realize 1 million EVs in 2025, a set of governmental instruments were set in place. Most notably are (i) financial incentives for purchasing and/or leasing EVs, (ii) supporting the rollout of charging infrastructure and (iii) demonstration programs for particular targets groups including commercial and commuter traffic, logistics, taxis and government vehicles. Particularly lease car drivers were supported with tax measures, given their relatively high mileage and kilometres driven in urban areas.

In recent years the ambitions for EV sales have been increased. By 2025 50% of all car sales should be electric; 30% of which should be fully electric, with an intermediate goal of 10% of vehicle sales having a plug by 2020 (Formula E-Team, 2016). Supporting instruments were along similar lines, although financial incentives were significantly altered over the years. Regarding public charging points the supporting role of municipalities has been a major factor. In particular the four main cities Amsterdam, Rotterdam, The Hague and Utrecht as well as the Metropolitan region around Amsterdam (covering 80 municipalities) developed one of the densest charging networks worldwide. The combination of financial incentives and development of charging infrastructure nationwide and in cities provided an environment where the market for electric vehicles surged and made the Netherlands one of the frontrunners of electric mobility worldwide.

2.2.1 Purchase incentive schemes

The Dutch government has come up with a broad incentive scheme to stimulate the sales and lease of electric vehicles. To study the effects of these incentives the four main schemes are discussed, varying from reductions in purchase tax, annual vehicle tax, and two measures aimed at lease business drivers.

1. **Purchase Tax**
   Direct purchase incentives are in place for EVs through a purchase tax that is based on CO_2 emissions. A newly bought vehicle is taxed with a fixed amount based on CO_2 emission bands and an additional amount directly proportional to the CO_2 emitted, determined using NEDC test cycles. Differences in these taxes can be substantial, zero-emission vehicles only pay €365 (2018 levels) while vehicles with more than 162 grams of CO2 emissions pay at least € 12,593 and €458 more for every gram of CO_2 above this threshold.

2. **Annual vehicle tax**
   Zero-emission vehicles are exempt from annual vehicle taxes. Depending on the type of fuel (gasoline or diesel), the weight of the vehicle and the area in which the vehicle is registered, annual taxes are determined. For mid-size passenger cars these taxes are in the range of €800-€1500 per year.

3. **Addition for the private use of a company car tax**
   In the Netherlands nearly 50% of all new sold cars are leased (Vereniging Nederlandse Autoleasemaatschappijen, 2018). Despite being a large portion of new vehicle sales, they constitute less than 10% of the entire vehicle stock. Most (88%) of the leased cars are company leased, which are used for business as well as private use. The Dutch government considers any car that is used privately for more than 500 kilometres on a yearly basis as additional income over which taxes have to be paid. This tax is known as the *addition for the private use of a company car tax,* mostly referred to in Dutch as "*bijtelling"* (addition).

   The addition to the income level, over which income taxes need to be paid, is calculated on the basis of the catalogue price of a new car. Depending on the CO_2 emissions of the vehicle, 0% to 25% of the new car value is added to the yearly income. The addition tax has been used by policymakers in recent years to steer CO_2 emissions of newly-purchased vehicles. An overview of the changes in this tax since 2012 is shown in *Table 2.1*. The percentage of addition tax is set for 5 years on the moment the car is registered[1]. Notable changes can be seen in 2013 where both Battery Electric Vehicles (BEVs) and PHEVs were strongly favoured through 0% addition tax, and increases in addition tax in subsequent years particularly for the 0-50 gram category, making PHEVs increasingly less favourable.

---

[1] For vehicles with more 50 grams of CO_2 emissions the addition tax varied between 14% and 22% depending on fuel type and CO_2 emissions. This was simplified to 22% in 2018 for all vehicles. In the text we have limited ourselves by focussing on EVs. A complete overview, going back to 2011 can be found on the website of the Dutch tax authority: https://www.belastingdienst.nl/bibliotheek/handboeken/html/boeken/HL/thema_s-vervoer_en_reiskosten.html#HL-21.3.4

Table 2.1 Addition tax for leased vehicles per CO_2 emission category from 2013 to 2019

Year	0 grams CO_2 emission (only BEV)	0-50 grams CO_2 emission (PHEVs)	>50 grams CO_2 emission (non EVs)
Pre-2012	0%	14%	14-25%
2012	0%	0%	14-25%
2013	0%	0%	14-25%
2014	4%	7%	14-25%
2015	4%	7%	14-25%
2016	4%	15%	14-25%
2017	4%	22%	22%
2018	4%	22%	22%
2019	4% < €50,000 22%>€50,000	22%	22%

4. **Environmental Investment Deduction (EID)**

Beside a reduction in addition tax the Dutch government has also provided businesses with the opportunity to get a tax reduction on the yearly depreciation costs. EVs have been placed on the Environmental Investment Deduction (MIA) list which allows a certain percentage of the investment to be deducted from the company profit tax (25%). This reduction is 36% from the depreciation costs, which are maximised at €50,000. The MIA largely favours entrepreneurs and freelancers with own businesses, given their opportunity to deduce company car investments as environmental investment.

2.2.2 Impacts of different incentives

The above incentives target different vehicle owners and powertrain types in different ways. The first two incentives (purchase tax and annual vehicle tax) mainly benefit private car owners. However although the *vehicle purchase tax* could build up to a significant amount, it only compensates for a part of the higher EV prices generally observed in the market. The *annual vehicle tax* only provides a relatively small additional incentive.

The *addition measure* is directly aimed at the company car lease market and provides a much more powerful incentive for lease drivers than purchase taxes for private users. Over the lifetime of the lease contract the addition tax would largely compensate the price premium for EVs, thereby enabling to drive electric at similar costs as gasoline cars. Given that in early years (2013) the addition for PHEVs was at the same level as BEV (0%), PHEVs were largely favoured thanks to the absence of range limitations together with the relatively low price premium compared to BEVs.

All in all, the set of incentives put in place provide a scheme that particularly favours company cars and small business owners. This market was deliberately targeted in the plans of action (RVO, 2011) but partly lead to unforeseen consequences, particularly the surge of PHEVs, making the Netherlands the country with the highest market share of PHEVs. The private car market enjoyed far fewer incentives. This approach was taken amongst others because the Dutch tax system does not allow for a further deduction in price for private EV buyers besides the purchase tax. A direct incentive for private buyers turned out to be complicated. Given the characteristics of the Dutch vehicle market the focus on company cars was quite rational: close to 50% of all new vehicles sold are company lease cars, while the average purchase price for company cars is much higher than for the private market. Especially when the tax benefits were introduced in early 2013, the EV market mainly had models available in the higher price segment. Targeting this segment was therefore most effective and opportune.

2.2.3 Electric vehicle sales

How did these financial instruments play out on the sales of EVs? An overview of the EV sales from 2012 to 2018 is given in *Figure 2.1*. EV sales took off in 2012 and first spiked at the end of 2013 when the addition tax for PHEVs was raised from 0% to 7%. In the last month of 2013 many drivers ordered a PHEV to profit from the lower tax for another 5 years. Additionally there was a small bump in BEV sales as the addition tax was raised from 0 to 4%. Altogether, EVs had a market share over 15% of newly sold vehicles in December of 2013. Even higher market shares followed in the December months of 2015 and 2016. This was also facilitated by the rising amount of available EV models on the market, particularly PHEVs such as the Mitsubishi Outlander, which sold nearly 10,000 vehicles in those two years. By the end of 2016, just before taxes for PHEVs were to be raised to 15%, more than 20% of all new vehicles sales were PHEVs and BEVs. A last spike in PHEV sales occurred in late 2016 when taxes were raised to a level that was equal to gasoline and diesel cars. PHEV sales have since fallen flat and the number of vehicles on the road has slightly decreased due to exports.

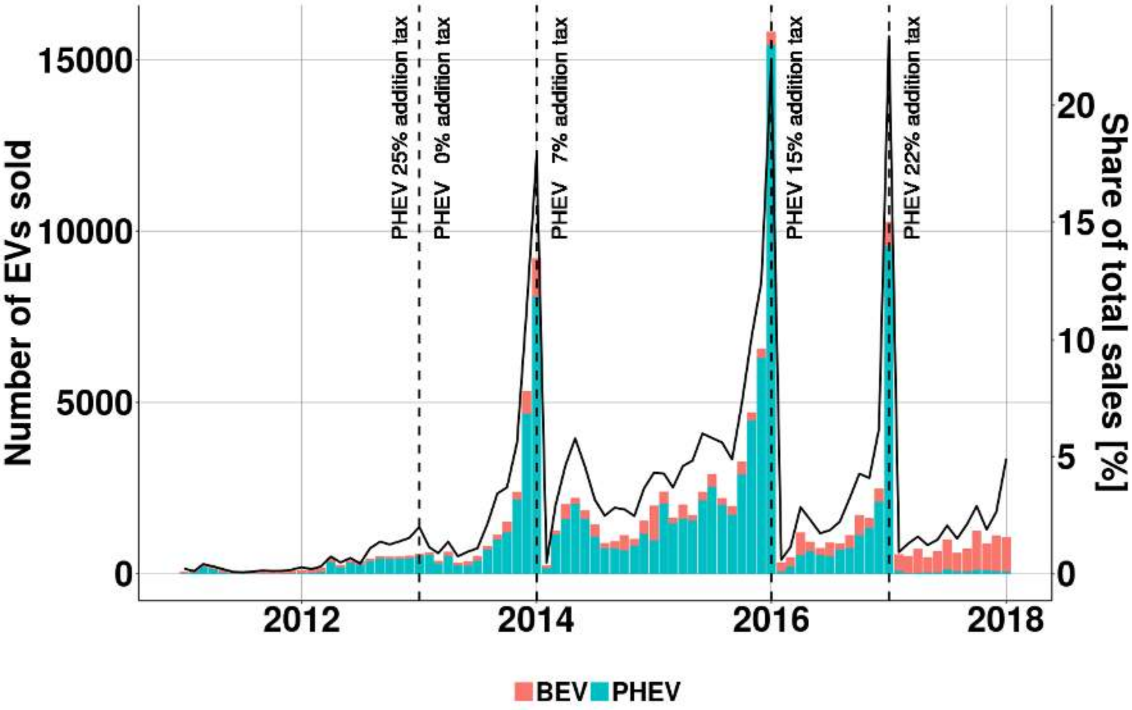


Figure 2.1 EV Sales in the Netherlands since 2012, separated in BEV and PHEV (coloured bars). Share of total vehicle sales per month (black line), based on car registration data of the Dutch road authority (RDW, 2018).

BEV sales, although enjoying much of the same or better benefits as PHEVs, remained at a slow but steady pace until late 2016. After the subsidies for PHEVs were cut at the end of 2016 lease drivers turned to BEVs. BEV sales have been on a steady rise since early 2017, accounting for 3-4% of all sales in the first months of 2018.

The fiscal incentives have played a very powerful role in the sales of EVs in the Netherlands. The sheer size of the incentive has made PHEVs and to a lesser extent BEVs an economic alternative to regular fossil fuel powered vehicles. The end-of-year spikes as well as the drop in PHEV sales from 2017 onwards illustrate just how influential these incentives have been. Beside the fiscal measures, it is worthwhile mentioning other supporting drivers for EV sales in the Netherlands. Particularly in inner cities where parking pressures are high, having an EV provides preferential access to parking spots equipped with chargers, especially as in the Netherlands there is no fine for long connections to charging stations. Combined with the economics of leasing EVs, this has provided an additional motivation for EV purchases. Similarly a range of companies (e.g. banks, consultancies) with strong corporate social responsibility policies have provided restrictions to leasing polluting cars and have encouraged their employees to lease EVs. Several cities in the Netherlands have provided a positive climate for purchasing EVs by supporting measures such as free parking, free charging and facilitating placement of charging infrastructure close to candidate EV drivers' homes. Nevertheless, the fiscal incentives to make these vehicles come in the same price range have been instrumental in its success. A last important enabling factor has been the development of public charging infrastructure, which we will discuss below.

2.2.4 Roll-out of charging infrastructure

An important part of the Dutch policy in stimulating EVs has been the development of charging infrastructure for public usage. Given that charging and related range anxiety is generally seen as one of the main barriers for electric mobility, and that in the Netherlands an estimated 65% of households do not have a dedicated parking space with charging facilities, enabling public charging infrastructure has been one of the priorities in Dutch EV policy.

At national level, financial support was given to a program set up in 2009 by joint grid operators (ELaadNL) to develop a public charging network of 10,000 charging points nationwide. This was complemented by municipal initiatives to develop public chargers through public tenders in the 4 major cities in the Netherlands. By May 2018 the Netherlands has one of the most dense public charging infrastructures worldwide with almost 17,500 public chargers installed (Netherlands Enterprise Agency, 2018), which corresponds to nearly one public charger every 7 electric vehicles. The dense charging infrastructure is generally seen as one of the success factors in overcoming the first hurdles for purchasing electric vehicles (Sierzchula, Bakker, Maat, & Wee, 2014).

In the early stages of the roll-out of charging infrastructure, the main focus was on placing charging stations on more strategic locations such as city centres. However as EV adoption started to take off also among those that relied on on-street parking facilities, the focus shifted to a more demand driven roll-out (J. R. Helmus, Spoelstra, Refa, Lees, & Van den Hoed, 2018). EV drivers could request a charging station to be placed near their home while these charging stations remained publicly accessible. When few electric vehicles were on the road this also meant that those drivers also created a private parking spot in their street as the accompanied parking area was exclusively accessible by electric vehicles. In areas with high parking pressure this served as an additional incentive for potential buyers.

Due to the demand-driven roll-out strategy the ratio between the number of electric vehicles and public chargers has remained relatively stable and one of the lowest of the world (European Alternative Fuel Observatory, 2018). *Figure 2.2* shows an overview of the number of public chargers in the 4 major municipalities and the ratio to the number of EV drivers using this public charging infrastructure. The number of EV drivers is defined as the number of exclusive charging cards that have accessed a particular charging station. Private charging infrastructure and fast chargers are not included in these graphs. Apart from the steady growth in the number of charging stations, the figure shows how higher EV sales at the end of years 2015 and 2016 lead to peaks in the EV to charger ratio in the same months. It is only near the end of 2016, when the highest number of EVs was sold, that the ratio of EVs to charging stations increased from around 5.5 to 7. The ratio provides a metric for the level of public charging infrastructure required to support EV adoption, also in consideration of the fact that a great deal of EVs are known to only make use of the public chargers few times over the years, and otherwise rely on private charging infrastructure.

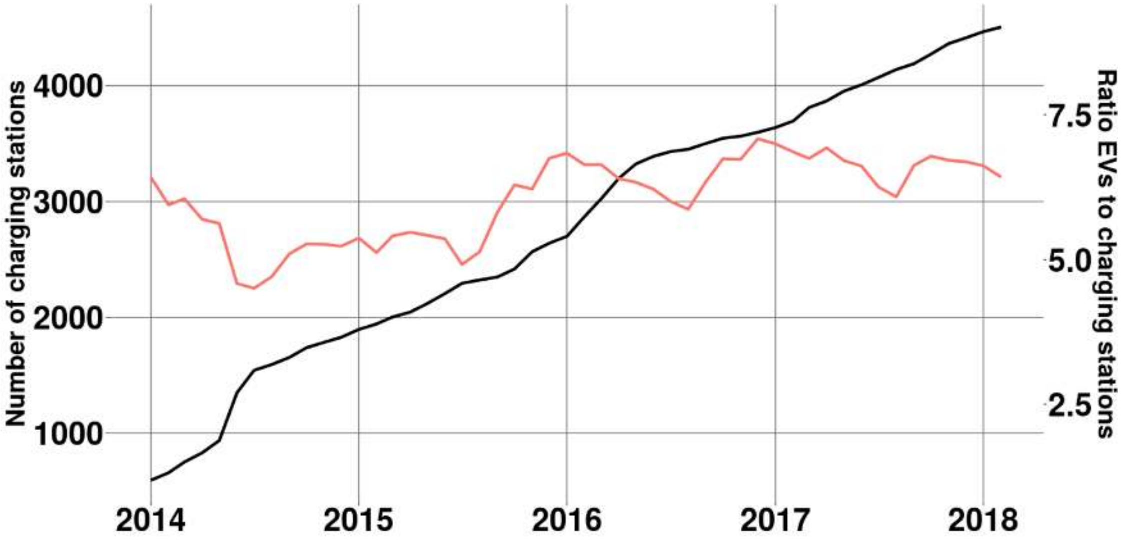


Figure 2.2 Number of public charging stations (black) and the ratio "number of unique users" to "public charging stations" (red) in the four major cities and the metropolitan region Amsterdam in the Netherlands (CHIEF, 2018)

The Dutch government has also been pushing to provide interoperable standards that allow everyone to get access to public charging stations with a single charging card. The so-called Open Charge Point Protocol (OCPP) provided access for all EV drivers across all charging stations lowering the barrier for charging station usage. In several countries competing MSPs and limited interoperability hamper widespread access to charging stations leading to lower utilization.

2.3 Effectivenes of EV adoption support policies

With relatively high EV sales, the Netherlands became known as one of the countries that most supported EV adoption, particularly PHEVs. The question is to what extent the policies have been effective in mitigating vehicle tailpipe emissions. In the Netherlands, the debate mainly focused on the extent to which PHEV drivers actually charge and drive on electricity. Attention was also devoted to the effectiveness of the public charging infrastructure provided and its actual utilisation. This section presents findings of early studies on charging behaviour on PHEVs in the Netherlands and explores insights into the utilization of public charging stations and related concerns for policymakers.

2.3.1 Plug-in hybirid vehicles utilisation

Comparison with drive cycle assessments

The real use of PHEVs in the Netherlands and share of electric kilometres driven has been point of national debate. Expectations of emission reductions brought by PHEVs were largely based on the results of NEDC cycle tests. However, the NEDC cycle is not representative of real world driving. Moreover, PHEV users may fail to drive on electricity due to a number of reasons, ranging from limitations in available charging facilities to resistance to charging the vehicle on a regular basis. The question around real use of PHEVs is important for policymakers seeking to establish effective incentive schemes that realize air quality improvements and CO_2 emission reductions.

A first study looking into this topic comes from Ligterink, Smokers & Bokers (2013). They found that PHEV users in the Netherlands more often used gasoline than assumed in the NEDC test cycle. Their findings resulted in a more structural monitoring of PHEV usage in the Netherlands, research that was continued until 2016 (Ligterink & Smokers, 2016). Monitoring of fuel usage and charging habits was based on fuel card data, that registered both the use of charging stations (public and private) as well as that of regular gasoline pumps. The study includes 4 years of charging and refuelling data (2013-2016).The study compared for different vehicle models on the Dutch market the average percentage of electric kilometres as expected from NEDC cycles with actual percentage of kilometres on electricity for the whole group (average). The results published in 2016 (see *Table 2.2*) show that on average the number of kilometres driven on electricity for PHEVs is far below the test cycle results. Particularly PHEVs with relatively small battery sizes tend to drive significantly fewer electric kilometres than assumed in NEDC cycles, in most cases less than half of that. Only the BMW i3 has comparable electric mileage to the NEDC cycles, which is likely due to the large battery pack in these vehicles. Striking is that the share of electric kilometres is stable across the different years, indicating that drivers have a stable charging routine where one might have hypothesized shifting norms over time.

Ligterink & Smokers continued their efforts to monitor the PHEV usage on a yearly basis and included more vehicle models once data became available. It was not until 2016 that their results caused a public debate about major subsidy amounts being spent on stimulating sales of PHEVs while only limitedly contributing to reduced emissions. As a result the addition tax came increasingly under scrutiny. Eventually the advantage for PHEVs was abolished. Sales of PHEVs collapsed accordingly, after spiking one last time at the end of 2016.

These results were rather remarkable as studies in other countries found that the percentage of electric kilometres driven by PHEVs was rather high (Ge, Mackenzie, & Keith, 2017; Idaho National Laboratory, 2015; Zoepf, MacKenzie, Keith, & Chernicoff, 2013). Studies in the US indicate that Chevrolet Volt drivers averaged 75% of all miles driven electric and those with workplace charging even 83%. In the Netherlands the Chevrolet Volt and Opel Ampera drivers only averaged 49%.

Table 2.2 Share of electric driven kilometres per vehicle type. From Ligterink & Smokers (2016)

		Share of electric driven kilometres (yearly average)			
Vehicle	**NEDC cycle % electric**	**2013**	**2014**	**2015**	**Q1 2016**
Opel Ampera	77%	48%	49%	46%	46%
Chevrolet Volt	77%	47%	48%	46%	48%
Toyta Prius-Plug-in Hybrid	50%	17%	18%	17%	18%
Volvo V60 PHEV	67%	26%	25%	24%	27%
Mitshubitishi Outlander PHEV	68%	29%	34%	31%	33%
Audi e-tron	67%			31%	31%
VW Golf GTE	66%			28%	30%
Ford C-Max plug-in hybrid	64%			34%	28%
Mercedes- Benz c350e	55%			23%	25%
VW Passat GTE	67%			29%	30%
BMW i3 range extended	86%		89%	87%	85%
Average	NEDC cycle	68%	67%	67%	66%
	Practice	35%	33%	30%	31%

The main reason that may explain the differences between the Dutch and US studies is that the Dutch PHEVs were leased, where in the US the PHEVs were purchased by private owners. Ligterink & Smokers (2016) used fuel card data provided by lease companies to calculate PHEV utilization, thereby limiting the study to lease fleets (note that this is a significant portion of the PHEV market; given that around 90% of all EVs are leased in the Netherlands (RVO.nl, 2016)). There may be differences in motivation between private users and company car users in purchasing PHEVs. Given the high cost premium for private users, this group may have been more motivated to realize fuel cost savings. In a lease construction, many drivers are free to use their fuel card, leading to limited or no incentive to reduce on fuel costs. The drivers personally do not have an incentive to save on fuel costs and therefore are less motivated to recharge their car. The additional possible inconvenience, i.e. seeking for an available charging point is not offset by possible cost savings. Hence business drivers in the Netherlands could profit from lower addition tax but did not have to care about fuel savings.

Charging Behaviour of PHEVs

PHEVs in the Netherlands tend to drive less electric kilometres than assumed in the NEDC cycle, but charging data in four major Dutch cities shows how PHEVs are responsible for a significant portion of total EV charging sessions and in absolute terms do contribute to emission reductions. A study by Van den Hoed et al. (2016) sought to quantify the contribution of PHEVs to total EV charging sessions and kilowatt-hours charged relative to BEVs in a urban context. Data from charging sessions on public infrastructure were gathered and analysed, where sessions were attributed to BEVs, PHEVs and an unknown category in all those cases where the charging data did not provide sufficient information to determine whether a PHEV or BEV had been charging.

We have analysed the utilization of the charging infrastructure based on a set of more than 5 million charging transactions involving more than 4000 charging points until early year 2018. The same dataset as in Wolbertus & Van den Hoed (2016) has been used but data gathering has continued until March 2018. Data on the charging sessions in the cities of Amsterdam, Rotterdam, The Hague, Utrecht and 80 municipalities part of the so-called Metropolitan Region Amsterdam has been gathered. For each of the charging sessions data as shown in *Table 2.3* has been collected. The database is referred to as the Charging Infrastructure Efficiency Forecast (CHIEF) database.

Table 2.3 Data variables, examples and descriptions

Variable	**Example**	**Description**
RFID	60DF4D78	RFID Code of charging card
Charging point operator	Essent	Owner of the charging point
Location_skey	456	Unique location key per charging station
City	Amsterdam	City in which charging point is placed
Address	Prinsengracht 767	Address charging point is placed
Start Connection Date Time	24-04-2015 13:56:00	Start date and time of charging session
End Connection Date Time	24-04-2015 17:14:00	End date and time of charging session
Charging Time	1:45:00	Time the car is charging
Volume	6.73	Amount charged [kWh]

The analysis showed that PHEVs used public charging station only slightly less than would be expected by the number of vehicles on the road. Between 2014 and 2017 on average 85% of all EVs on Dutch roads were PHEVs. *Figure 2.3* shows that in the same period on average a share of 75% of all charging sessions on public infrastructure networks in the four major cities were performed by PHEVs. Only in 2018 the share of transactions by PHEVs has reduced to 55-60% mainly due to the shifts in the EV fleet composition towards BEV. This suggests that the share of PHEV drivers that never charge may be limited and at least is not the norm. A significant share of PHEV drivers charge frequently, although some may skip a charging session if a convenient charging location is not accessible. This idea was re-enforced by additional analysis of Ligterink & Smokers (2016), showing that a small portion of users hardly ever charged but that the majority of PHEV drivers charged regularly. Nearly 25% of all PHEV drivers charged more than once a day.

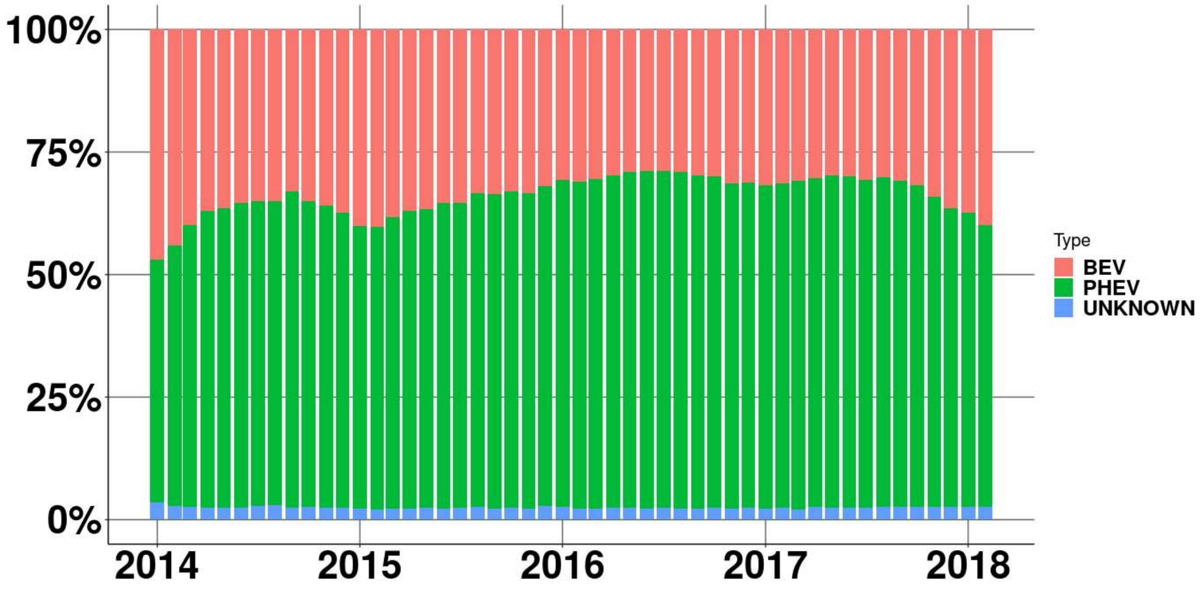


Figure 2.3 Share of charging sessions by type of electric vehicle on public charging stations in the four major cities and the metropole region Amsterdam in the Netherlands (CHIEF, 2018)

Not surprisingly in terms of average kilowatt hours charged per session PHEVs lag behind BEVs, given the larger size of batteries of the latter. *Figure 2.4* shows the contribution of electricity charged by PHEV and BEVs. Until early 2018 PHEVs have been responsible for more than half of the total electricity charged by EVs in the four major cities, and as such have made a considerable contribution to emission reductions. PHEVs may in practice drive less electric than expected based on the NEDC drive cycle, but the sheer size of the PHEV fleet in the Netherlands has in fact contributed to a significant share in electric kilometres driven in urban environments. A further step would be to compare the actual emission reductions with invested subsidies between BEVs and PHEVs.

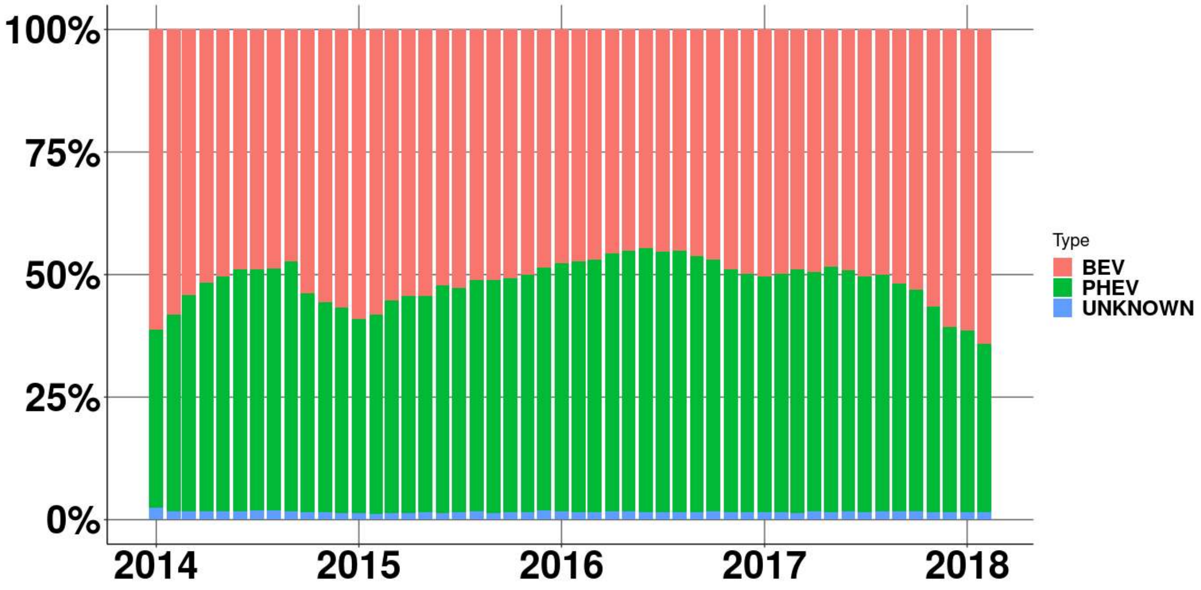


Figure 2.4 Number of kWh charged by type of electric vehicle in the four major cities and metropole region Amsterdam in the Netherlands (CHIEF, 2018)

2.3.2 Secondary effects

Apart from the direct contribution of PHEVs to electric kilometres driven, possible secondary effects of PHEV sales in the Netherlands can be reflected upon. For one, PHEVs have contributed to EVs (vehicles with a plug) becoming a legitimate alternative to gasoline vehicles for a fairly large public. The accumulated fleet of 120,000 EVs still only reflects 1.5% of the total Dutch vehicle market but is beyond a small niche market and not limited to an elite group but in relatively mainstream lease markets. Yet, EV drivers are still a predominantly middle aged male group with above average education and income levels. BEV drivers are however slightly more technology and environmentally orientated while PHEV drivers often indicated that financial reasons were the main driver behind their purchase (Hoekstra & Refa, 2017).

A large group of drivers have experienced driving electric, have developed charging routines and are likely to be able to make more informed decisions on pros and cons of EVs. Similarly the sales of PHEVs stimulated the development of public charging infrastructure to a point that it is one of the densest charging networks worldwide and has in a way helped to overcome the first chicken-egg problem for EVs. It would be worthwhile to further study these more qualitative effects of PHEVs to make a nuanced evaluation of the effectiveness of the PHEV favouring subsidy schemes in the Netherlands. In the coming years it would also be very useful to monitor the choices of current PHEV drivers in their next vehicle choice. Many of the lease contracts have a lifespan of 4 to 5 years which faces these drivers with the decision to go full electric or not.

2.4 Charging infrastructure utilisation

Beside large investments in the number of vehicles on the road through government tax breaks, there has also been a significant investment in public charging infrastructure in the Netherlands. The extent to which the charging infrastructure provided is actually used is important, because not only do policymakers need to legitimise the investments made but also the additional pressure on public space and parking opportunities that developing the charging infrastructure has caused. Moreover, understanding utilisation of public charging infrastructure provides insights into the business opportunities for companies seeking to build and operate public charging points. The question is how much is the charging infrastructure used, and to what extent can public investment in charging infrastructure be justified.

We have particularly focused on: (i) utilization rate, (ii) charge/connection ratio, and (iii) connection times. These are discussed in turn in the following sections. Where possible a comparison is made with relevant other cities and/or countries.

2.4.1 Utilisation rate

Utilization rate is defined as the amount of time charging points are connected with EVs divided by the total available time. 100% indicates that all charging points are fully occupied; 0% indicates that all charging points are always accessible. For most municipalities in the Netherlands charging infrastructure has been built aiming to strike a difficult balance between providing sufficient accessibility to charging points and not having over-capacity of charging infrastructure in order not to give up parking spots for under-utilized charging spots in neighborhoods with high parking pressure.

Figure 2.5 shows the development of utilization rates in the four major cities and metropolitan region. The figure shows that the extent to which the charging infrastructure is occupied varies from around 20-30% in the Hague, Rotterdam and MRA, to 35-40% in Amsterdam and Utrecht). It also shows seasonal effects, with lower utilization rates in summer vacation periods. In all regions the utilization rates show an upward trend; indicating that the utilization of charging infrastructure is steadily increasing by several percentage points per year.

Figure 2.5 Historic development of average utilization rate across several cities (January 2014 - March 2018)

Occupancy of 30-40% may seem low. However policymakers do not strive for 100% as this would limit accessibility for new EV drivers. In fact as a rule of thumb policymakers in Dutch cities generally regard a utilization rate of 50% as high and a legitimate percentage at which to consider adding charging points in that neighborhood. Charging station occupancy is relatively high compared to other countries as many of the charging stations were installed for so-called primary use. This means that the charger mainly functions as a home or office charger for those that have to park their car in public. In the Netherlands the majority of home owners (estimates are in the range of 60-80%) rely on on-street parking facilities. A smaller amount of charging stations were installed for so-called secondary use. These charging stations are meant to facilitate visitors in the area. However as both types of chargers are public, they can be used interchangeably for both purposes.

The importance of providing primary chargers is supported by a stated choice experiment involving 149 respondents who relied on on-street parking, that indicated that lack of accessible charging opportunities near home is one of the biggest barriers to EV adoption (Wolbertus, Kroesen, van den Hoed, & Chorus, 2018). The willingness-to-pay to have a ‘private’ charging station in public is with €2248–€2557 in the range of the cost of installing a charging station at home. It is considered very important for prospective EV owners that rely on on-street parking to be able to charge their car near their home. High utilization rates may thus not only frustrate current EV drivers in being able to charge, but also demotivate candidate EV drivers to purchase an EV.

These averages give a good overview of how much charging infrastructure is used in Dutch cities as a whole. However, they do not account for differences across locations within the cities. *Figure 2.6* shows the distribution of charging station occupation within the cities over the course of a month (March 2018). While the median occupancy rate is somewhere between 15-30% across the cities, some charging stations are nearly always occupied while some remain empty. Local authorities track the occupancy of single charging stations and those in their surroundings and if these are too high in a certain area this can be a reason to place additional stations nearby.

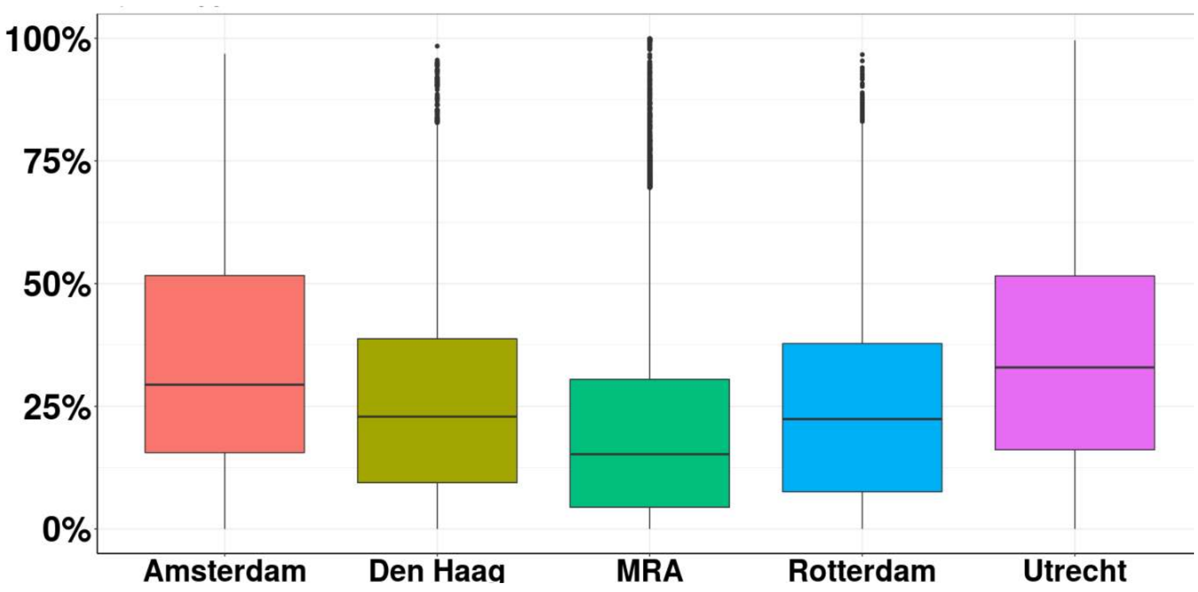


Figure 2.6 Boxplot of utilization rates across charging stations in The Netherlands in March 2018 (CHIEF, 2018)

Apart from locational differences, utilization is also influenced considerably by time of day. *Figure 2.7* provides an overview of utilization rates of two exemplary charging stations over 24hours, averaging out all days in March 2018. This includes both weekdays as weekends. The figure illustrates how charging stations may differ in daily charging profiles. While both charging stations have an average utilization rate of about 50% their usage profile is completely different. As a result utilization rates vary geographically depending on different urban environments and shares of residential versus office buildings.

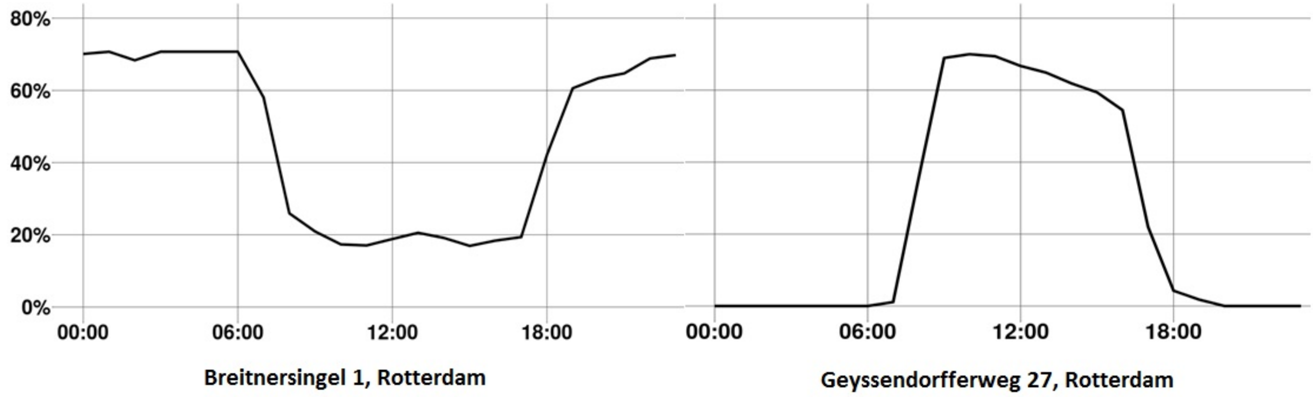


Figure 2.7 utilization rates over the course of a day (average over March 2018, Rotterdam) (CHIEF, 2018)

Utilization rates may thus differ from station to station, as well as from hour to hour. As a result there may be charging stations that are relatively under-utilized, with a negative impact on the business case and possible scrutiny from local inhabitants that valuable parking space is lost on charging stations that are seldom used. On the other hand, there are charging stations that tend to be over-utilized, with a positive effect for the business case but possible frustrating effects for EV drivers that are dependent on charging facilities but find all charging stations in use.

Reducing both over- as well as under-utilization are major concerns for policymakers. Measures that policymakers can take to avoid or reduce *under-utilization* include applying window times at charging stations, i.e.: making charging spots available to non-EVs after a certain time, e.g. 10 pm (Wolbertus & van den Hoed, 2017b). Another option is to attract additional user groups with complementary charging profiles to the same charging infrastructure. An example is that of attract electric car sharing schemes and electric taxis to charging places otherwise only used by residential building EV owners (J. Helmus & van den Hoed, 2015).

Common measures to reduce *over-utilization* of charging points in Dutch cities include placing new charging points or charging hubs extending the number of charging points at one location when certain thresholds in utilization are reached. Particularly the strategy to place them on-demand means that the charging station will be used by at least the EV driver who requested it. A new public charging station is only built if the EV user requesting it does not have access to off-street home or workplace charging . This means that usage on a near daily basis per charging station is almost guaranteed. Helmus et al. (2018) have demonstrated that on-demand charging stations lead to more transactions with higher kWh charged than ‘strategically’ placed secondary charging points that should provide opportunity charging, albeit with a smaller number of unique users. The latter may be explained by the logic that “strategic” poles are placed at points of interest such as shopping malls and are used by those who visit them. The demand-driven strategy is a typical element of the Dutch rollout strategy.

The roll-out of infrastructure has created charging stations that are used for home and office charging but are also available to visitors at times when they are not occupied by their primary users. At more than 800 vehicles, the city of Amsterdam has one of the largest electric taxi fleets in Europe which relies on the dense charging infrastructure. Free floating electric car sharing schemes, such as Car2Go and Hyundai Car sharing, have flourished in the city, while in other EV friendly cities such San Francisco and San Diego comparable schemes had to be shut down due to lack of charging infrastructure. In other cities such as Madrid the shared electric vehicles rely on centralized charging hubs, while in Amsterdam the EVs can be parked and charged across the city.

2.4.2 Connection times

A second topic that has been subject of debate in the Netherlands is the connection times of EVs at public charging points. Given that there is no penalty for leaving a car at a charging station once fully charged, EV drivers are likely to leave their car connected much longer than strictly needed. *Figure 2.8* provides an overview of connection times of all transaction over 2017 in the four cities and MRA. Slightly over 25% of all charging sessions are shorter than 4 hours, probably in the majority of cases related to secondary charging use. Striking is that more than 40% of the sessions are between 8 and 16 hours, which most likely relates to overnight parking/charging of inhabitants owning an EV. Close to 5% of all sessions are longer than 24 hours and less than 1% are longer than 72 hours. The latter is important to note as the issue of ‘long-parking’ became a point of debate in the national media and there was widespread perception that this was the norm. However evidence shows that long sessions are an exception.

Nevertheless, long sessions are a burden on the availability of charging infrastructure (Wolbertus & van den Hoed, 2017a). Whereas only 5% of all sessions are over 24hours, they are responsible for more than 25% of the total occupancy of the infrastructure. Providing incentives to disconnect charged EVs and making them available to other EV drivers is important for improving both accessibility and the business case of charging points.

Something to consider here is that a great deal of EVs start charging in the evening, so disconnecting EVs from the chargers as soon as the battery is fully charged means doing this at nighttime. Not only is this inconvenient for EV drivers but it would also result in limited increase of utilization of the charging point. As can be seen from start-connection times in the database (CHIEF, 2018), demand for charging reduces sharply after 10pm. Hence stimulating EV drivers to disconnect their cars when charging overnight does not make much sense. Instead such measures should target charging sessions with connection times longer than 16 hours. Options available for incentivizing drivers to disconnect their EV from the charger once the session is complete include providing time incentives (Wolbertus & Gerzon, 2018) and the use of apps that allow nudging fellow EV drivers to disconnect their car. This system is currently in use in the Netherlands and works on a voluntary basis for EV users, possibly complemented by an incentive program.

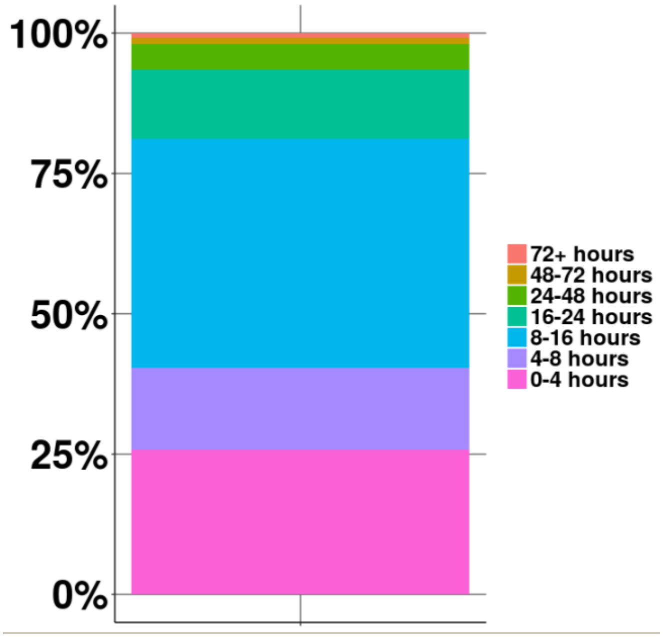


Figure 2.8 Distribution of connection times in different time bins (based on 2017 data in G4/MRA)(CHIEF, 2017)

2.4.3 Charge Time Ratio

In the previous section we showed how connection times at Dutch charging points are relatively high. In this section we show how actual charging only lasts a small share of the time the EV is connected to the charger. *Figure 2.9* shows the charge time ratio, defined as charging time divided by connection time, for the G4/MRA. Where average connection times are 9-10 hours, actual charging times are close to 2-3 hours. On average the charge time ratio is between 0.15-0.22, indicating that more than 75-85% of the time EVs are connected they are not charging. As such they are not using the charging infrastructure, which theoretically would have been available to other EV users.

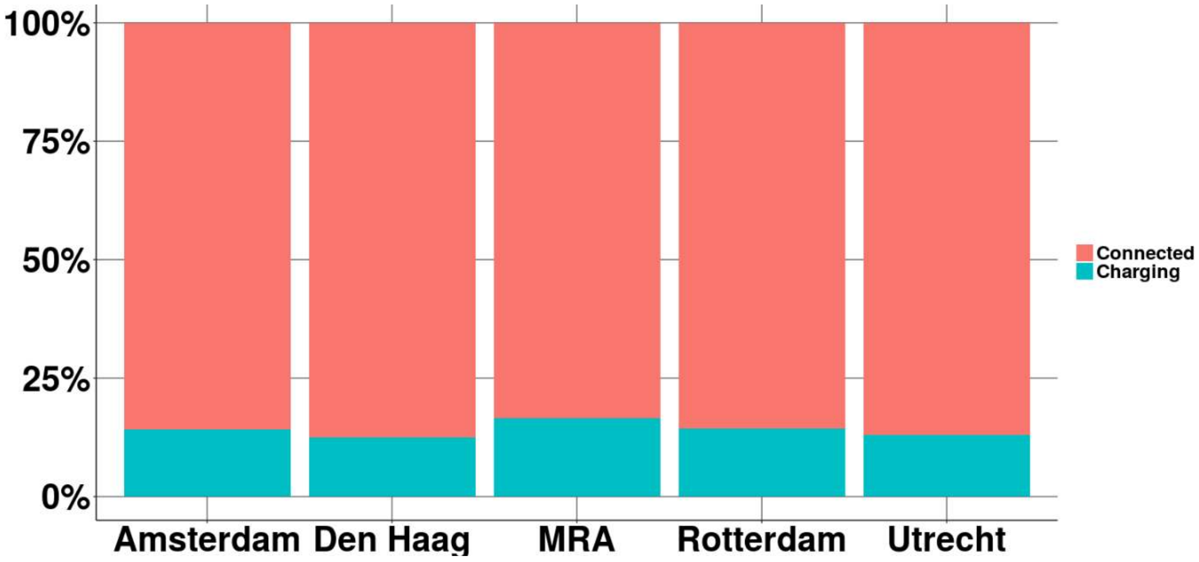


Figure 2.9 Charge time ratio for G4/MRA (CHIEF, 2018)

Low charge time ratios can largely be explained by the fact that charging infrastructure in residential areas is mainly used overnight, when re-parking a car is not an option. However destination charging also shows a relatively lower charge time ratio that one would have expected. Most problematic are longer sessions (24+ hours) which are likely to have charge time ratios of less than 10%.

Combining this analysis with utilization rates leads to the following picture. Utilization rates indicate that on average 30-40% of the time charging points are occupied. Charge time ratios indicate that 15-25% of this connection times are used for charging. Combined this implies that on average only 5-10% of the total time actual charging takes place on current infrastructure, thereby raising questions regarding inefficiency of capacity utilization and low business case opportunities for public chargers. One might argue that incentives should be used to convince EV drivers to repark their car once fully charged (excluding night times), thereby enabling higher utilization. Alternatively one might argue that this lower utilization may just be the price for facilitating EV adoption in city centers. Given that there are no alternatives for most EV drivers without an own parking facility in city centers at this point, the lower utilization may be justifiable for policy makers in order to facilitate clean mobility in their cities. In the midlong term rapid chargers may become a serious alternative. In the meantime, it is recommendable that policy makers put in place incentives to reduce ‘long sessions’ (e.g. longer than 24hours).

A charging mode where connection times and charging times are much closer is fast charging. But the model of fast charging is quite different. Public chargers are relatively slow chargers and do not allow EV drivers to wait and disconnect their car once fully charged. At fast chargers half an hour is usually sufficient, much similar to gas stations with ICE vehicles. In the current situation where EVs do not have sufficient range, combined with the need for public, on-street charging facilities in urban areas leads to a suboptimal overall capacity utilization of on street chargers.

Improving charge time ratios and utilization rates is a major theme for policymakers in the Netherlands. Research by Wolbertus & Gerzon (2018) shows that in general tariff structures are supported by most EV drivers, as long as they do not interfere with their primary charging needs. As such incentives can play a role to improve utilization rates and are likely to improve the business case and lessen the need for additional rollout of charging infrastructure. However, it will come at costs for EV drivers, either financially (e.g. through tariff structures), in terms of more limited accessibility (due to higher utilization rates) or in terms of inconvenience to disconnect their cars.

2.5 Conclusion and recommendations

The electric mobility history in the Netherlands provides interesting material to reflect on the interplay between regulation, uptake of EVs by consumers and the utilization of infrastructure by EV drivers. This has allowed us to study how consumers react on policy measures and how they use public charging infrastructure. Particular in the Dutch case is the significant incentive schemes for stimulating EV sales in combination with the strong development of public charging infrastructure. These factors have played an important role in the breakthrough of EVs, but also lead to questions concerning selective stimulation of particular technologies (PHEVs) and target groups (business lease) as well as discussions on the investments in a public charging network.

It can be concluded that the regulatory context and financial incentives have played a determining role in the Dutch uptake of EVs in general and PHEVs in particular. Where in early years there was little to no differentiation in the level of financial incentives between PHEVs and BEVs, PHEVs were largely favored by consumers due to lack of range anxiety and generally lower purchase prices compared to BEVs. The shift in available subsidies for PHEVs between 2013 and 2018 and subsequent dramatic reductions in PHEV sales illustrate the determining role the subsidy schemes played in driving adoption. The shifting support to PHEVs can hardly be characterized as a stable, long term regulatory context and have been scrutinized for both over- (2013-2015) as well as under-subsidizing (2017-2018) PHEVs. The need for a more balanced subsidy scheme, factoring in different price premiums of PHEVs versus BEVs as well as taking into account actual driving and charging behavior is one of the lessons learnt from the Dutch case.

The policy choice to focus on business lease drivers has had both up- and downsides. This target group had been chosen due to their high mileage, relative low age of lease vehicles and relative high average price of lease vehicles. Financial incentives have been very effective to stimulate this group to move towards electric.

PHEVs have been the preferred choice for many lease drivers in the Netherlands. Data from charging and fueling cards have shown that PHEVs tend to drive much less electric kilometers than the NEDC cycle would predict. Apart from limited incentives for PHEV drivers to charge, it shows how particularly PHEVs with small batteries fall short of NEDC expectations. Despite these limitations, charging data also showed how PHEVs were responsible for more than half of all kWhs charged on the public charging infrastructure and have played a substantial role in reducing emissions of air pollutants from vehicles in urban areas. A more balanced approach in stimulating PHEVs should be considered, in which the size of the battery is considered, together with measures for stimulating actual charging by PHEVs such as providing the users with free charging credits. Lastly, where company cars have been a successful policy focus, it has proven to be much harder to make the desired shift to stimulate private users to purchase EVs. Chapter 7 on Norway (note: not in this thesis) has provided evidence on the level and type of incentives that may be required in order to turn a large part of the latter group of car users into EV adopters. However given the substantial differences between the two countries, also in terms of vehicle and fuel taxation, adopting a similar approach in the Netherlands appears problematic .

A second theme of this chapter concerns the public charging infrastructure in the Netherlands. Most prominent concerns for policy makers include (i) under-utilization (limited use, low business case, scrutiny of local community), (ii) over-utilization (access limitations for EV drivers, failed charging sessions), and (iii) low charge time ratios (long connections with short charging times). Municipalities in the Netherlands seek to strike a difficult balance between providing sufficient accessibility to charging points without providing over-capacity, because the latter implies ineffective rollout of expensive charging stations while giving up scarce parking spots.

Data shows that charging infrastructure utilization depends on location and time characteristics. Neighborhoods with high income tend to attract more EV users, leading to high charging demand. Furthermore residential areas tend to lead to charging profiles with demand peaks at night versus office neighborhoods with peaks during the day. The demand-driven strategy applied in many Dutch cities to select which locations require new charging stations has proved to be effective in increasing utilization rates in the early phases of rollout. Also attracting different target groups (e.g. electric car sharing scheme, electric taxis) has increased utilization rates and complementary charging profiles. This target group approach provides policymakers with options for improving the utilization of charging infrastructure. Taxis and sharing systems have shown to have distinctly different charging profiles than regular residents and can thereby fill in the gaps in available chargers.

Given the concerns about effective use of public charging infrastructure, policymakers have to balance over- and under-utilization of charging infrastructure, while devising ways to increase charge time ratios. Further investigating measures such as window times, attract new target groups (e.g. taxis, sharing concepts), set up tariff structures as economic incentives and stimulate more social incentives (such as the social charging app) should be carried out to come to a structured instrumentation for optimized use of charging infrastructure.

2.6 References

European Alternative Fuel Observatory. (2018). Electric vehicle charging infrastructure: Total number of PEV charging positions. Retrieved July 1, 2018, from http://www.eafo.eu/electric-vehicle-charging-infrastructure

Formula E-Team. (2016). *Electric Transport Green Deal 2016-2020*. The Hague. Retrieved from https://www.greendeals.nl/wp-content/uploads/2016/04/Green-Deal-Electric-Transport-2016-2020.pdf

Ge, Y., Mackenzie, D., & Keith, D. R. (2017). Gas anxiety and the charging choices of plug-in hybrid electric vehicle drivers. *Transportation Research Part D*. http://doi.org/10.1016/j.trd.2017.08.021

Helmus, J. R., Spoelstra, J. C., Refa, N., Lees, M., & Van den Hoed, R. (2018). Assessment of public charging infrastructure push and pull rollout strategies: the case of the Netherlands. *Energy Policy*, *121*, 35–47. http://doi.org/https://doi.org/10.1016/j.enpol.2018.06.011

Helmus, J., & van den Hoed, R. (2015). Unraveling User Type Characteristics : Towards a Taxonomy for Charging Infrastructure. *EVS28 International Electric Vehicle Symposium and Exhibition*, 1–16.

Hoekstra, A., & Refa, N. (2017). Characteristics of Dutch EV drivers. In *Electric Vehicle Symposium 30* (pp. 1–13). Stuttgart.

Idaho National Laboratory. (2015). Plugged In: How Americans Charge Their Electric Vehicles, 1–24. Retrieved from https://avt.inl.gov/sites/default/files/pdf/arra/SummaryReport.pdf

International Energy Agency. (2017). *Global EV Outlook 2017: Two million and counting. IEA Publications*.

Ligterink, N. E., & Smokers, R. T. M. (2016). *Monitoring van plug-in hybride voertuigen (PHEVs) april 2012 t/m maart 2016*. Delft.

Ligterink, N. E., Smokers, R. T. M., & Bolech, M. (2013). Fuel-electricity mix and efficiency in Dutch plug-in and range-extender vehicles on the road, 1–4. http://doi.org/10.1109/EVS.2013.6914979

Netherlands Enterprise Agency. (2011). *Electric Mobility gets up to speed: 2011-2015 Action Plan*. The Hague.

Netherlands Enterprise Agency. (2018). *Statistics Electric Vehicles in the Netherlands*. Retrieved from https://www.rvo.nl/sites/default/files/2017/10/Elektric vehicles-Special-Analysis over 2016 ENG.pdf

RVO.nl. (2016). *Special: Analyse over 2015*. The Hague. Retrieved from http://www.rvo.nl/sites/default/files/2016/01/Special Analyse over 2015.pdf

Sierzchula, W., Bakker, S., Maat, K., & Wee, B. Van. (2014). The in fluence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194. http://doi.org/10.1016/j.enpol.2014.01.043

Van den Hoed, R., Helmus, J., & Kooij, M. (2016). *Laadgedrag van PlugIn Hybride Elektrische Voertuigen op publieke laadpunten*. Amsterdam. Retrieved from http://www.idolaad.nl/gedeelde-content/publicaties/publicaties-algemeen/laadgedrag-van-plugin-hybride-ev.html

Vereniging Nederlandse Autoleasemaatschappijen. (2018). *Autoleasemarkt in cijfers 2017*. Retrieved from https://www.vna-lease.nl/website/iedereen/feiten-cijfers/infographics-2017

Wolbertus, R., & Gerzon, B. (2018). Improving electric vehicle charging station efficiency through pricing. *Journal of Advanced Transportation*, *2018*, 1–11. http://doi.org/doi.org/10.1155/2018/4831951

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. G. (2018). Policy effects on charging behaviour of Electric Vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. *Transportation Research Part D: Transport and Environment*, *62*, 283–297. http://doi.org/https://doi.org/10.1016/j.trd.2018.03.012

Wolbertus, R., & van den Hoed, R. (2016). Benchmarking Charging Infrastructure Utilization. In *EVS29 Symposium* (pp. 1–15). Montreal, Quebec, Canada.

Wolbertus, R., & van den Hoed, R. (2017a). Charging station hogging : A data-driven analysis. In *Electric Vehicle Symposium 30* (pp. 1–14). Stuttgart.

Wolbertus, R., & van den Hoed, R. (2017b). Managing parking pressure concerns related to charging stations for electric vehicles : Data analysis on the case of daytime charging in The Hague. In *European Battery, Hybrid & Fuel Cell Electric Vehicle Congress* (pp. 1–8). Geneva, Switzerland.

Zoepf, S., MacKenzie, D., Keith, D., & Chernicoff, W. (2013). Charging choices and fuel displacement in a large-scale plug-in hybrid electric vehicle demonstration. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2385*, 1–10

3 Fully charged: An empirical study into the factors that influence connection times at EV-charging stations

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. (2018). Fully charged: An empirical study into the factors that influence connection times at EV-charging stations. Energy Policy, 123(August), 1–7. https://doi.org/10.1016/j.enpol.2018.08.030

Abstract
This study is the first to systematically and quantitatively explore the factors that determine the length of charging sessions at public charging stations for electric vehicles in urban areas, with particular emphasis placed on the combined parking- and charging-related determinants of connection times. We use a unique and large data set – containing information concerning 2.6 million charging sessions of 64,000 (i.e., 60% of) Dutch EV-users – in which both private users and taxi and car sharing vehicles are included; thus representing a large variation in charging duration behaviour. Using multinomial logistic regression techniques, we identify key factors explaining heterogeneity in charging duration behaviour across charging stations. We show how these explanatory variables can be used to predict EV-charging behaviour in urban areas and we derive preliminary implications for policy-makers and planners who aim to optimize types and size of charging infrastructure.

3.1 Introduction

Electric Vehicles (EVs) show great promise to reduce locally harmful emissions such as NO_x SO_x and PM (Razeghi et al., 2016) and greenhouse gasses such as CO_2 (Rangaraju, De Vroey, Messagie, Mertens, & Van Mierlo, 2015), triggering widespread positive attention among policy makers and researchers alike. However, three important barriers currently hamper widespread adoption, being high upfront purchase costs, limited driving range and a lack of public charging infrastructure (Coffman, Bernstein, & Wee, 2016; Egbue & Long, 2015; Liao, Molin, & Wee, 2017; Rezvani, Jansson, & Bodin, 2015). Falling battery prices (Nykvist & Nilsson, 2015) and plans for new, more affordable long range EV models suggest that the barriers of price and range can be overcome.

However, private sector investments in the roll-out of a charging infrastructure have been lagging behind these vehicle developments due to the well-known chicken-and-egg problem (e.g. Struben & Sterman, 2008). To stimulate the adoption of EVs and overcome the chicken-and-egg problem, governments at various levels are keen to help with funding charging infrastructure. Yet, in developing such charging infrastructure, policy makers face the challenge of efficiently using tax payers' money. this challenge is exacerbated by rapid technological developments such as fast charging stations (up to 350 kW) and (static and dynamic) wireless charging which further complicate decision-making. This is because such developments increase the risk of investments into potentially soon-to-be-obsolete technology rendering them worthless. In addition, new behavioural patterns, such as changing charging frequencies depending on battery size, that differ from current refuelling behaviour are not yet well understood, making it difficult to predict demand (and to optimize charging infrastructure). In the end, however, postponing the decision on how and when to roll-out which charging opportunities could increase the barrier for candidate EV drivers and thereby hamper the transition to a more sustainable transport system.

As alluded to above, efficient planning of charging infrastructure for electric vehicles (EVs) involves accurate modelling of charging demand. In predicting EV charging demand, understanding variations in the starting time and location of charging sessions is recognized to be of key importance; as such it comes as no surprise that several recent studies have been devoted to modelling demand variations (across space and time) in EV charging. While earlier work was based on the tradition of optimal planning (He, Yin, & Zhou, 2015; Nie & Ghamami, 2013), more recent studies have moved towards a more behaviourally oriented perspective (Morrissey, Weldon, & Mahony, 2016; Neaimeh et al., 2017; Sun, Yamamoto, & Morikawa, 2016).

An important aspect of demand for charging stations is missing in these studies. By nature, electric vehicle charging stations are not accessible to other users when used. When planning to meet demand it is therefore necessary to know for how long the charging station will be occupied by a given user at a given time. Yet variations in the duration of charging sessions in the public domain are not well understood. What makes predicting the duration of these sessions particularly difficult, is that it results from an interplay between refueling and parking behaviour; also when fully charged, vehicle owners may wish to occupy the charging station for parking reasons (Faria, Baptista, & Farias, 2014; Gerzon, 2016; Wolbertus & van den Hoed, 2017), and this effect may be exacerbated by local policies which provide EV-owners with parking/charging locations for free (Wolbertus, Kroesen, van den Hoed, & Chorus, 2018). New refueling behaviours also comes with establishing new social norms, which can vary in different circumstances (Caperello, Kurani, & TyreeHageman, 2013). Understanding the factors that drive these behaviours is important for efficient charging infrastructure planning as it allows policy makers to optimize planning itself or to create policy measures such as pricing strategies to steer behaviour into the desired direction.

This study is the first to systematically and empirically explore the factors that determine the length of charging sessions at public charging stations for EVs in urban areas. We use an unique and large data set – containing relevant information concerning 2.6 million charging sessions of 84,000 (i.e., 70% of) Dutch EV-users – in which both private users, taxi and car sharing vehicles are included; thus representing a large variation in charging duration behaviour. By estimating a statistical model, we identify key factors that explain heterogeneity in charging duration behaviour. We show how these explanatory variables can be used to predict EV-charging behaviour in urban areas and we derive preliminary planning and policy implications regarding the optimal design of charging infrastructure (-related policies).

3.2 Literature review

Most currently available charging infrastructure planning studies work under the assumption that EV charging at public charging station occurs when the battery level of the car can no longer meet the travel needs of the driver and that the charging there is only done to create enough range to complete the (next) trip, leading to connection times to charging stations that are equal to charging times (Brady & O'Mahony, 2016; Brooker & Qin, 2015; Dong, Liu, & Lin, 2014). Such assumptions may hold for fast charging stations (Motoaki & Shirk, 2017; Neaimeh et al., 2017; Sun et al., 2016), however, for slower level 2 charging infrastructure in the city, charging duration is known to be a complex interplay between parking and refueling behaviour by a variety of drivers, such as taxis (Asamer, Reinthaler, Ruthmair, Straub, & Puchinger, 2016; Tu et al., 2015; Zou, Wei, Sun, Hu, & Shiao, 2016) and car sharing vehicles (Van der Poel, Tensen, Van Goeverden, & van den Hoed, 2017), each with different recharging demands. As different types of drivers make use of the same infrastructure, understanding the interplay between these factors is of key importance.

Some studies do recognize that EV drivers can recharge during longer dwelling times. These studies then tend to assume that vehicles will recharge each time they are parked for a longer time or they ignore the fact that charging stations are rival goods (Paffumi, Gennaro, & Martini, 2015; Shahraki, Cai, Turkay, & Xu, 2015). In addition, these studies do not account for other intentions to charge (e.g. using a charging station mainly for the ease of parking), the effect of local parking policies such as free parking for EVs (Wolbertus et al., 2018) and particular pricing structures.

It has been recently recognized that pricing strategies form a possible solution to influence connection times. The effects of such strategies have been studied by Gerzon (2016) using a stated choice survey. He found that pricing by the hour caused a significant reduction in connection times. Motoaki & Shirk (2017) find that a fixed fee at fast charging stations increases the time connected to a charging station compared to the free charging situation, as users tend to want to get their money's worth. These results suggest that pricing strategies could possibly serve as a policy tool to influence charging behaviour.

Studies that make use of real life data from EVs or charging stations do mention variations in charging and connection times. These studies mainly point at the start of the sessions as the most important factor that determines the length of the charging session

(Sadeghianpourhamami, Refa, Strobbe, & Develder, 2018). Morissey et al. (2016) consider charging session length; they compare fast and slow public chargers and find that, not surprisingly, charging times are shorter at fast charging stations. Robinson, Blythe, Bell, Hübner, & Hill (2013) took a closer look by identifying different types of charging behaviour based on activity type. They however only considered charging times –which barely differed across activities in their data– and not connection times. Kim, Yang, Rasouli, & Timmermans (2017) focused on factors that influence inter-charging event times; they identified two different user type groups, regular and random, and found significant differences between these groups.

In sum: while providing very valuable insights into charging behaviours, the current literature studies connection times to charging stations in a manner that does not reflect the full complexity and subtlety of real charging behaviour in a city context. The wide variety in charging durations is currently only acknowledged in descriptive studies but a systematic and quantitative analysis of the factors that drive the variation in durations is missing. This research contributes to the understanding of charging infrastructure planning by modelling (variation in) the time connected to charging stations based on a large dataset of charging sessions using public charging infrastructure. This dataset provides an unique insight into charging behaviours not only because of its sheer size but also because it encompasses the entire public charging infrastructure within four cities, allowing for an analysis of different (local) policies and EV-owner types which use and compete for the same charging stations.

3.3 Methodology

Data were collected from public charging stations in the four major Dutch cities (Amsterdam, Rotterdam, The Hague and Utrecht) between 2014 and 2016. The data were provided by the charging point operators in these areas. Note that charging stations in these areas were accessed by swiping a RFID-card and then connecting a charging cord to the vehicle. Data were collected concerning the starting point (clock time) of the charging session, its duration, the amount of kWh charged, and the location; a unique anonymous RFID code related all relevant sessions to the RFID-card. In total 2,692,446 Sessions were recorded in this period. Sessions with a length shorter than 5 minutes and longer than 300 hours were excluded from the dataset. Additionally, sessions without any charge were not taken into account during the analysis as such data seemed unreliable. Many of these short sessions without any or little charge were considered to be most likely due to an error while connecting the car to the charging station, requiring the user to swipe the card multiple times. Also sessions with a charging speed over 50 kW were removed, as the charging stations in the dataset were not capable of offering these speeds. After this filtering process 2,531,841 (i.e., 94% of the original data points) sessions were left for the analysis.

Timing data were transformed to separate time-of-day and day-of-the-week variables. Information about charging station and user type was made available by the charging station operators. Charging station type categories were as follows: regular (2 outlets, 11kW), charging hub (at least 4 outlets clustered together) or fast charging station (50kW). A price variable was added to the model. Prices at all charging stations were at a kWh basis and fixed at a city level due to tendering processes in which the cities set fixed prices for a time period. The only exception being charging point provider “EVNet”, which, at an earlier time, placed charging stations at more strategic locations in the cities. To prevent the price variables to represent the differences between cities, we also included a dummy variable for each of the cities. Here, the city of Utrecht served as the reference category. User type categories were as follows: regular, car sharing vehicle or taxi. For regular users two different sub-categories were extracted, being frequent and non-frequent, on the basis of the number of observed charging sessions (20 charging sessions turned out to provide a useful cut-off point). Data on the time of day were transformed as follows: from 5 AM to 9 AM was considered morning, from 10 AM until 3 PM afternoon, from 3 PM until 10 PM evening and from 10 PM until 5 AM night. This particular transformation was chosen based on the distribution of connection times as shown in *Figure 3.2*.

Information about the area in which the charging station was located was retrieved from The Netherlands Statistics (CBS Statline, 2016). Data about the built environment was gathered at the sub-sub-district level, which contains several buildings. In addition, information about the number of residential homes, public and social housing, and offices were gathered. We used the number of vehicles per squared kilometer as a proxy for parking pressure. Information on paid parking areas was retrieved from the four municipalities. GPS locations of the charging stations were matched with paid parking areas using the sp package in R (Bivand, Pebesma, & Gomez-Rubio, 2013; Pebesma & Bivand, 2005).

An obvious candidate to model the type of dependent variable in our data (note that connection times were measured at a so-called ratio-level) is linear regression. However, the distribution of connection times was found to be highly non-normal (see *Figure 3.1*; Kolmogorov-Smirnov test: D(2,531,841)=0.217, p <0.001), making linear regression unsuitable as an analysis technique and implying the need for a transformation of the connection time variable. Straightforward transformations such as log or square root transformations could not be applied due to the multiple peaks in the distribution. The peaks in the distribution suggest that heterogeneity in connection times results from qualitatively different types of charging behaviour occurring within the dataset. To explore categories of qualitatively different charging sessions, a binning technique was used with several cut-off points. The following bins were identified: 0-1.5 hours, 1.5-7 hours, 7-11 hours, 11 to 24 hours and longer than 24 hours. The selection of the bin sizes is elaborated in the next section (3.4.1). Here, it is important to note that, since the bins reflect qualitatively different types of charging behaviour, we decided to apply a multinomial logistic regression (rather than an ordered logistic regression), to model and explore the effects of different factors on this outcome. Data were analyzed using the Latent Gold software (Vermunt & Magidson, 2006). An indicator for the ID of the user was added to the model as primary sampling unit to take into account repeated observations.

3.4 Results

3.4.1 Descriptive results – identification and interpretation of bins

The distribution of connection times at charging stations binned per half hour is shown in *Figure 3.1*. The data is maximized at 72 hours as the distribution has a very long tail with a maximum of 298 hours. Close inspection of the figure shows that there are several segments to be recognized, including short sessions (up until 1.5 hours) which account for 15% of all sessions, representing EV-drivers that are only stopping to refill their car to be able to continue their trip; note that this segment seems to be represented in the modeling efforts described in (Brady & O'Mahony, 2016; Brooker & Qin, 2015; Dong et al., 2014). The next segment (between 1.5 and 7 hours) can mainly be attributed to visitors on the network, which park their car for a longer time at a charging station during a visit. The distribution spikes between 7 and 11 hours duration; most sessions in this segment start during the night or in the morning. A fourth segment with duration between 11 and 24 hours contains mostly overnight sessions starting at the end of the afternoon or during the evening. The tail of the distribution starts at a duration of 24 hours; we call this segment long charge. Although sessions in this segment only account for 6% of all sessions they do keep charging stations occupied for 27% of the total observed time, making them policy-relevant.

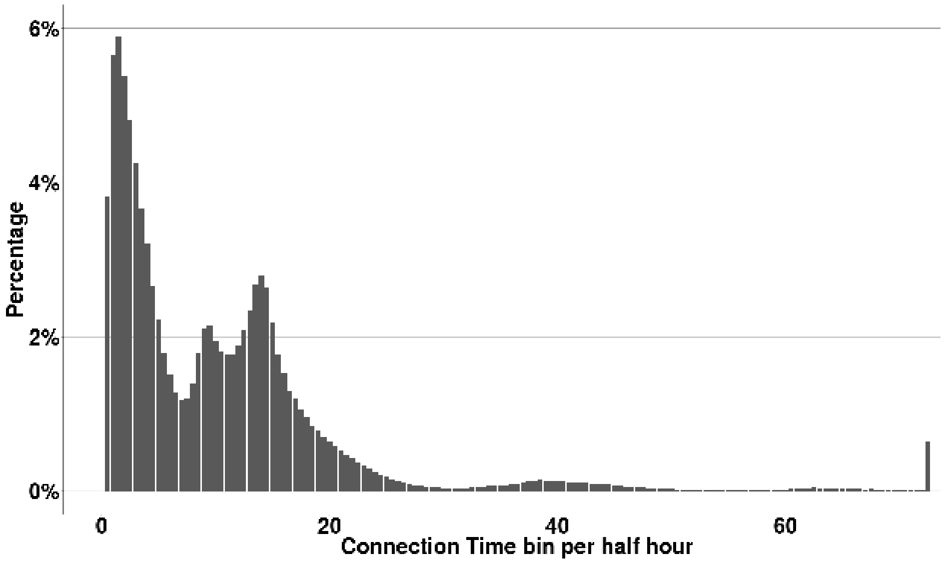


Figure 3.1 Distribution of connection times binned per half hour

A charging session's starting time has significant influence on the duration of the session. *Figure 3.2* shows the distribution of connection durations over the week for different times of day. The figure shows a clear repeating pattern for working days and a slightly shifted pattern during weekends. Short sessions up to 1.5 hours occur mainly in the afternoon (due to visitors) but the distribution also features a peak in the morning. This peak in the morning disappears in the weekends, which suggests that it is likely related to workplace charging. Nearly half of the charging sessions starting in the afternoon has a length of in between 1.5 and 7 hours. Sessions with a 7-11 hour duration mostly occur during the morning, but a significant portion also occurs late in the evening or during the night. This bin seems not only to represent workplace charging but also late overnight charging in the vicinity of one's residence. Sessions with longer durations, between 11 and 24 hours, peak in the late afternoon and early evening when drivers arrive home from work. Sessions longer than 24 hours only take a small portion of the total amount of sessions during working days but they peak significantly at Friday and Saturday night, suggesting a typical over-the-weekend parking habit.

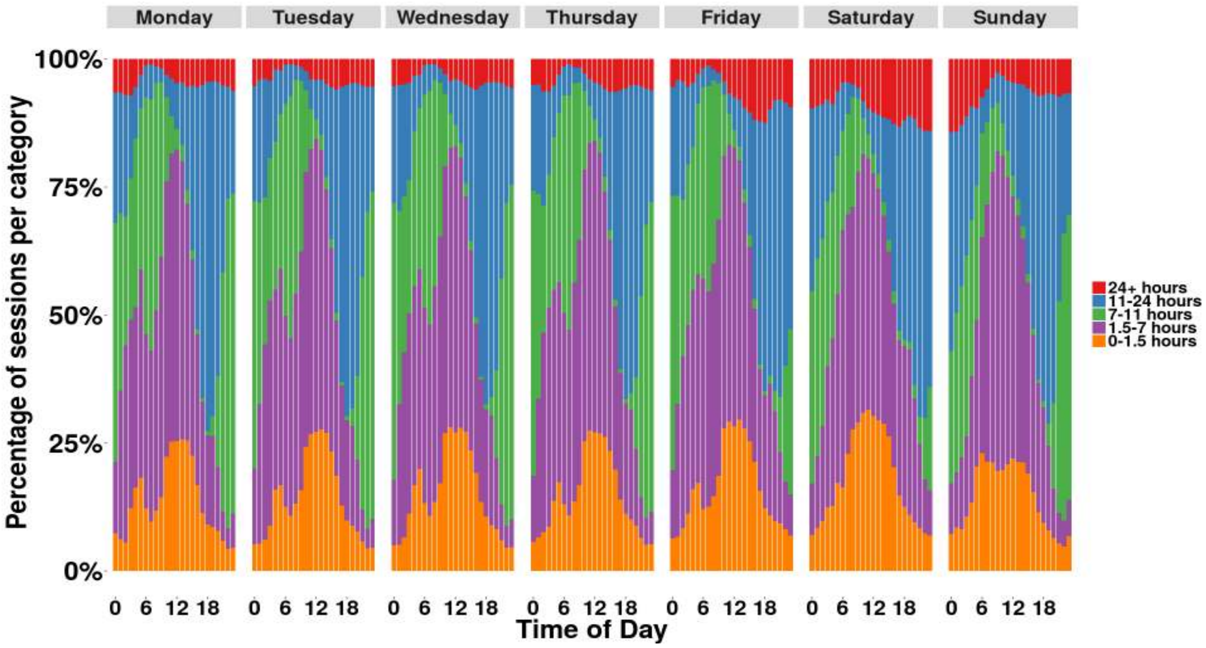


Figure 3.2 Distribution of connection times over the week

Based on the distributions of the durations of sessions, and their (i.e., the duration) occurrence at particular times of day, the different bins can be classified as follows: 0-1.5 hour sessions represent stop & charge behaviour, mainly used for actual refueling of the vehicle and occurring mostly during the afternoon. Park & charge is the name of the bin for sessions with 1.5 to 7 hours of connection. This bin represents, although not exclusively, visitors that park their car for a longer time while leaving it to recharge. Work & charge behaviour is attributed to 7 to 11 hour sessions which mainly occur in the morning, coinciding with morning traffic peak due to commuters; yet this bin also captures late night chargers of which sessions finish the next morning. Drivers recharging their EV in the late afternoon or early evening more often have a 11 to 24 hour connection time, representing typical overnight or home & charge sessions. The last category is the long sessions which have a higher occurrence at Friday and Saturday night, representing typical weekend parking sessions. Although the bins have been named to the behaviour they most likely represent in the eyes of the authors and based on descriptive statistics, we emphasize that these names do not exclusively represent the types of behaviour. These names have been used for readability reasons. The results of a more systematic and quantitative approach to evaluate the nature of connection durations at charging stations is presented in the next paragraph.

3.4.2 Descriptive statistics

Table 3.1 shows the descriptive statistics for the main variables that are included in the model. The number of individuals (charging stations or users) are given when possible. Both the number of charging sessions and the total number of hours connected to the charging station per variable is presented. For the duration bins it is good to note that there are relatively a large number of sessions below 7 hours (47%) but they only account for 12% of the connection hours. The sessions above 24 hours have a high mean connection time (47 hours) indicating that there is a long tail in the distribution of connection times.

Table 3.1 Descriptive statistics

Variable	Number of individuals	Number of charging sessions	Hours connected to charging station	Mean connection time
Duration bin				
0-1.5 hours		400,558 (15.8%)	323,422 (1.2%)	0.8 hours
1.5-7 hours		804,458 (31.8%)	2,812,083 (10.8%)	3.5 hours
7-11 hours		355,768 (14.1%)	3,243,855 (12.6%)	9.1 hours
11-24 hours		819,704 (32.4%)	12,537,271 (47.7%)	15.3 hours
24+ hours		151,353 (6.0%)	7,209,409 (27.6%)	47.6 hours
Day of the week				
Monday		369,922 (14.6%)	3,666,802 (14.1%)	9.9 hours
Tuesday		389,372 (15.4%)	3,756,545 (14.4%)	9.6 hours
Wednesday		392,170 (15.5%)	3,757,452 (14.4%)	9.6 hours
Thursday		391,348 (15.5%)	3,876,661 (14.9%)	9.9 hours
Friday		375,404 (14.8%)	4,251,672 (16.3%)	11.3 hours
Saturday		315,168 (12.4%)	3,546,883 (13.5%)	11.2 hours
Sunday		298,457 (11.8%)	3,270,022 (12.6%)	10.9 hours
Time of Day				
Morning		370,358 (14.6%)	2,356,822 (9.3%)	6.4 hours
Afternoon		752,799 (29.7%)	5,898752 (22.6%)	7.8 hours
Evening		1,156,553 (45.7%)	14,765,927 (56.2%)	12.8 hours
Night		252,131 (10.0%)	3,104,539 (11.8%)	12.3 hours
Type of charger				
Level 2	3,490 (98.6%)	2,467,878 (97.4%)	25,812,611 (98.8%)	10.4 hours
Charge Hub	29 (0.8%)	39,346 (1.6%)	296,995 (1.1%)	7.5 hours
Fast charger (50 kW DC)	20 (0.6%)	24,617 (1.0%)	16,436 (0.1%)	0.7 hours
User Type				
Taxi	336 (1.3%)	46,034 (1.8%)	339,766 (1.3%)	7.4 hours
Frequent	17,166 (26.4%)	2,092,221 (82.6%)	23,467,036 (89.9%)	11.2 hours
Visitors	46,643 (71.8%)	205,629 (8.1%)	943,137 (3.6%)	4.6 hours
Car sharing	818 (0.5%)	187,957 (7.4%)	1,376,101 (5.1%)	7.3 hours

The majority of charging sessions starts at working days, and these sessions are about 1.5 hours shorter than during the weekend. *Figure 3.2* already showed that is mainly caused by more sessions that last longer than 24 hours. As explained earlier evening sessions are the majority of the charging sessions due to the demand driven roll-out system and they are by far the longest charging sessions as most of them last until the next morning. The majority of charging stations within the dataset are of level 2 type, with only 20 fast charging stations in the dataset. The model results are therefore discussed with a focus on the implications for level 2 charging stations. Fast charging sessions are, as expected, much shorter than sessions at charging hubs or level 2 chargers.

For the different users we see that the majority of unique users are actually visitors (72%). Despite this larger number of unique users they only account for 8% of the total amount of sessions and only 3% of the total occupation measured in hours. For frequent visitors and car sharing vehicles the opposite applies, their share in charging sessions is greater than their share in unique users.

3.4.3 Model results

In *Table 3.2* results for model estimation are presented; note that long charge sessions (24+ hours) were used as a reference category, and that the explanatory categorical variables, time of day, day of the week and type of charger were dummy coded. Interactions between variables have been tested but did not provide a significant improvement in the model fit nor in a better interpretability of the model results. Most variables are significant and of the expected sign (see below), but note that the effects of many variables are relatively small compared to the constants. In general, the model provides a significant improvement (LL_β= -3052058) compared to the null model (LL_0=-4120764) despite that –as could be expected– a significant amount of unexplained variation in connection duration remains.

Timing

Time-of-day was dummy coded using the morning as a reference. Wednesday, a regular working day, served as reference for the day-of-the-week variable. The model results show that the timing (i.e., the starting point) of the charging sessions has the greatest impact on how long the session will last. Short sessions (stop & charge or park & charge) are more likely to occur in the morning and afternoon than during the evening or night, as suggested by parameters for the evening and night dummy variables which are significant and negative. These short sessions are equally likely to happen across working days. Significant negative parameters are obtained for weekend days, with the exception of Saturday. This result is intuitive, since during Fridays and Sundays less kilometers are driven (due to less work related traffic) whereas Saturdays generate shopping related traffic which is likely to correspond to charging behaviour of the stop & charge and park & charge types. The timing parameters for work & charge are negative for the afternoon and evening dummies, showing that charging behaviour associated with the work & charge bin (see previous section for elaboration) is most likely to occur in the morning or night. A negative parameter was also obtained for the Friday dummy. This effect for Fridays can mainly be explained by the lack of sessions which start very late in the evening but do not end during the next morning (and in that sense contrasts with a normal working day). For sessions with a duration between 11 to 24 hours (home & charge) we find a positive dummy for the evening, signaling that these sessions mainly start after working hours; also this result is intuitive. A negative parameter is found for the Friday dummy, indicating that this behaviour is replaced by long sessions during the Friday night, as this variable is also negative for all other options. Most likely these are sessions that last throughout the entire weekend. These results show that knowing the timing of demand for charging provides important information concerning the duration of the corresponding charging sessions. The fact that the relative importance of the time-of-day factors is high, suggests that charging behaviour is to a considerable extent habitual.

Table 3.2 Model estimation results

	Stop & charge *0-1.5 hours*	**Park & charge** *1.5-7 hours*	**Work & charge** *7-11 hours*	**Home & charge** *11-24 hours*	**Long charge** *24+ hours*
Intercept	3.2182**	4.7381**	4.4408**	2.4339**	
Time of Day					
Morning (ref.)					
Afternoon	-0.6058**	-1.0402**	-3.0575**	0.2186**	
Evening	-1.6433**	-2.0761**	-3.1030**	1.2998**	
Night	-2.5737**	-2.8124**	-0.9075**	0.7410**	
Day of the week					
Monday	-0.1266**	-0.062**	0.0256	0.0719**	
Tuesday	-0.0558**	-0.0253	0.0128	0.0087	
Wednesday (ref.)					
Thursday	-0.1255**	-0.1033**	-0.1644**	-0.1517**	
Friday	-0.5997**	-0.6596**	-1.2141**	-0.7651**	
Saturday	-0.7900**	-0.9211**	-1.9219**	-1.0579**	
Sunday	-0.5996**	-0.4251**	-0.6546**	-0.1923**	
User Type					
Taxi (ref.)					
Frequent	-0.9925**	-0.6437**	-0.4010**	-0.5945**	
Visitors	1.3998**	1.6110**	0.6851**	-0.3917*	
Car sharing	0.5508**	0.7232**	-0.0409	-0.6511**	
City Characteristics					
% Dwellings living	-0.6595**	-0.9009**	-0.7196**	-0.1775*	
% Dwellings business	-0.7239**	0.1646	0.1832	-0.5771**	
% Dwellings public	0.7855	0.0595	0.2978	0.1735	
% Dwellings Social	-0.4425	-0.3400	-1.0163*	-0.2499	
Charging station density (charging stations/km2)	0.0473**	-0.0715**	-0.0117**	0.0015**	
Paid parking	-0.3132**	-0.4445**	-0.4600**	-0.4222**	
Parking pressure	-0.0023**	0.0004	-0.0001*	0.0002	
City Dummy					
Amsterdam	-0.1558*	-0.3324**	-0.4216**	-0.2404**	
The Hague	0.2350**	0.2247**	0.2117**	0.1428**	
Rotterdam	0.0975	0.0632	0.0275	0.1463**	
Utrecht (ref.)					
Price	1.8766**	0.1779	0.6019	-0.955	
Type of charger					
Level 2 charger (ref.)					
Fast Charger	6.4502**	2.3835**	0.8644	0.2001	
Charge Hub	0.6339**	0.8224**	0.5703**	0.0351	
Number of observations	2531841				
Nul-Loglikelihood	-4120764				
Final loglikelihood	-3048663				
ρ^2	0.2601				

*significant at 0.05 level

**significant at 0.01 level

User types

User types were also dummy coded in which the taxi category served as reference category. Estimation results show that frequent users have tendencies for longer charging sessions, which is intuitive in light of the fact that these users are more likely to live in the area and therefore charge overnight and during the weekend. Signs of parameters for the visitor user type suggest that visitors are more likely to show park & charge behaviour and also very short sessions up to 1.5 hours, which is in line with expectations as these represent typical visiting parking behaviours. Taxis were expected to have a large number of short sessions to refill their car in between picking up customers. Results, however, show that they are actually more likely to exhibit home charging behaviour in contrast to other user types, indicating that many EV-taxi drivers live in the city were they charge overnight. Only charging overnight is sufficient for an entire day of driving. Car sharing vehicles, as expected, have a positive and significant parameter for stop & charge and park & charge sessions. These vehicles are used more intensively and are not parked for a long amount of time as they are then picked up by another user. These results show that different user types have different distributions of connection times at charging stations.

City characteristics

Parameters associated with city characteristics show that the type of built environment is correlated with charging behaviour. The betas for residential areas show that these areas are more prone to exhibit home & charge behaviour and very long sessions, most likely referring to residents leaving their car connected over the weekend. The same holds for business areas in which the parameters suggest more park or work & charge behaviour, most likely by employees or visiting costumers. The estimates for the public buildings variable show that public buildings have a stronger tendency to attract work & charge behaviour. These could refer to visitors to e.g. the city hall who leave their car connected while there. Very long charging sessions are less likely to happen in these areas. The parameter estimates for social buildings were not significant.

Charging station density has a relatively big (but still small) positive effect on 7-11 hour charging sessions and a small negative effect on 24+ hour charging sessions. A possible explanation for this result is that because areas with a high density are also more likely to have a high demand, the throughput will be higher, resulting in shorter charging sessions. Paid parking has a positive effect on very long sessions and also on stop & charge behaviour. Such very short sessions are intuitive in light of the fact that drivers have to pay a parking fee in line with parking literature (e.g. Shoup, 2005). Very long sessions could be explained by EV owners that have a parking permit, making them more likely to leave their car parked and connected over the weekend. Parking pressure seems to have little effect on the duration of the connection to charging stations. The city dummies included in the model are significant but their effects are small. Hence, to some extent they account for differences between the cities (e.g. in infrastructure).

Charging station characteristics

The price variable reveals a positive significant effect for smaller sessions. This is in line with expectations as fast charging stations and strategically placed charging stations by “EVNet” had slightly higher prices compared to others. The results indicate that EV drivers used charging stations with higher prices more often for short charging sessions. As expected, charging at fast charge stations results in much shorter connection times than level 2 charging (which served as the reference category); users specifically choose this type of charging station if they are in needed of refueling their vehicle. Also note that these fast charging stations are (often) paid for by the minute, making longer connection times than necessary unnecessarily costly. Charging hubs, which are combinations of several level 2 chargers at one place, are more likely to serve park & charge behaviour, although parameter-sizes do not indicate a large effect. The model suggests that these hubs are often used by visitors and car sharing users and serve as a recognizable point where the user is more certain to find an available charging station than at single stations. They are less likely to be used for home and long charging.

3.5 Conclusion and policy implications

This paper is the first to systematically and empirically study the factors that influence connection times of Electric Vehicles (EVs) at charging stations. Our overview of the literature shows that many studies that try to optimize charging infrastructure roll-out strategies, treat EV charging demand as a spatial-temporal issue (i.e. they focus on the location and starting time of charging sessions). However, we argue that, due to the rival nature of charging stations, predicting the charging sessions *duration* is crucial; also in determining the right number of charging stations, such duration information is of great importance. What makes analysis of charging duration particularly difficult in an urban context, is the fact that charging stations are not solely used for refueling but for a combination of parking and refueling. An additional complication factor is that different types of users such as inhabitants, commuters, visitors, taxis and new modes such as shared electric free floating cars are all competing for the same charging stations. So far, the combined nature of parking and charging behaviours, and competing demands by different user types, have not been empirically investigated in an integral fashion. This research has filled this gap using a uniquely large dataset containing several millions of charging sessions, over a timespan of three years, at public electric charging stations in the highly urbanized Western part of The Netherlands, being one of the front-runners on electric mobility.

Estimation results show that time-of-day-related variables and the type of charging station have the most substantial effect on the duration of the connection to the charging station. More specifically, results show that –especially for level 2 charging stations (up to 11 kW)– connection duration is very much aligned with parking behaviour and preferences: due to the lower charging speed at these stations, EV drivers tend to leave their vehicle parked at a charging station for a longer time while they are (for example) at work or sleeping. Results even show that a significant proportion of the charging sessions last longer than one day, keeping charging stations occupied for almost 30% of the time in total. Especially, for those drivers that do not have a private parking spot and depend on curbside parking, level 2 charging stations are vital to serve daily recharging (and parking) needs. Fast charging stations tend to serve a different purpose as behaviour at such stations is more like regular refueling behaviour, with short connection times aimed at the ability to complete the intended trip. Technology advancements allowing higher charging speeds are therefore also more likely to result in shorter connection times at these types of stations compared to level 2 stations, where behaviour coincides with parking. From an investor perspective it makes sense to focus more on shorter sessions if investment costs get higher. Policy makers can use this research combined with cost figures (e.g. (Madina, Zamora, & Zabala, 2016)) to see which type of charging infrastructure provides the most benefit for EV drivers from a cost perspective.

Our results also suggest that policy makers should be aware that simply providing areal coverage with charging stations will not necessarily meet charging demand in every area. That is because the type of dwelling also determines the connection duration and also the timing of the charging session. Areas with mostly one type of dwelling are expected to experience peak demand, while mixed neighborhoods could well serve different users with less charging stations due to variation in demand over time. Results also suggest that further investigation is needed into how different type of users such as car sharing vehicles, taxis and visitors can make use of charging stations by home owners. These different user types have different connection times at charging stations, implying that installing curb sides chargers could serve multiple types of users at the same time with limited interference.

Our results may assist policy makers and planners in their attempts to predict demand for charging stations and to adjust accordingly the number and type of chargers in certain neighbourhoods, or implement policies to increase efficiency at charging stations such as time-based fees. Other options include stimulating charger sharing by establishing social norms or allowing EV drivers to connect through applications on their mobile phone. At closed locations, such as parking garages, charger sharing could be reached by a 'valet' type of service. Implementing these measures however should be done with great care and taking into account the local parking situation. For example time-based fees might not be the best solution for overnight on-street parking but could do well in high parking pressure areas that have a lot of daytime parking. Furthermore, our research shows that future research looking into combining insights from the scholarly literature into parking with insights into connection times at level 2 charging stations has the potential to offer better insights in the quite particular kinds of new parking and EV-charging behaviours at these stations. Combining the right parking policies with EV charging could prove to be difficult. Especially with the growing battery sizes of vehicles, cars may possibly not fully refill if parking times are limited. On the other hand our analyses show that a significant amount of sessions last longer than 24 hours, keeping valuable charging sports unnecessarily occupied. To design the right policies to tackle this problem, policy makers also need to combine insights from both the charging and parking literatures. In contrast, we show that fast charging stations serve a different type of demand. A promising line of research would be to explore whether technological advances would allow shorter recharging times, if fewer of these stations could serve the needs of those that depend on curbside parking, resulting in a smaller loss of public space.

3.6 References

Asamer, J., Reinthaler, M., Ruthmair, M., Straub, M., & Puchinger, J. (2016). Optimizing charging station locations for urban taxi providers. *Transportation Research Part A: Policy and Practice*, *85*, 233–246. http://doi.org/10.1016/j.tra.2016.01.014

Bivand, R. S., Pebesma, E. J., & Gomez-Rubio, V. (2013). *Applied spatial data analysis with R* (Second). New York, NY: Springer.

Brady, J., & O'Mahony, M. (2016). Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data. *Sustainable Cities and Society*, *26*, 203–216. http://doi.org/10.1016/j.scs.2016.06.014

Brooker, R. P., & Qin, N. (2015). Identification of potential locations of electric vehicle supply equipment. *Journal of Power Sources*, *299*, 76–84. http://doi.org/10.1016/j.jpowsour.2015.08.097

Caperello, N., Kurani, K. S., & TyreeHageman, J. (2013). Do You Mind if I Plug-in My Car? How etiquette shapes PEV drivers' vehicle charging behaviour. *Transportation Research Part A: Policy and Practice*, *54*, 155–163. http://doi.org/10.1016/j.tra.2013.07.016

CBS Statline. (2016). Kerncijfers wijken en buurten 2016. Retrieved April 18, 2016, from https://www.cbs.nl/nl-nl/maatwerk/2016/30/kerncijfers-wijken-en-buurten-2016

Coffman, M., Bernstein, P., & Wee, S. (2016). Electric vehicles revisited : a review of factors that affect adoption. *Transport Reviews*, 1–15. http://doi.org/10.1080/01441647.2016.1217282

Dong, J., Liu, C., & Lin, Z. (2014). Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. *Transportation Research Part C: Emerging Technologies*, *38*, 44–55. http://doi.org/10.1016/j.trc.2013.11.001

Egbue, O., & Long, S. (2015). Barriers to widespread adoption of electric vehicles : An analysis of consumer attitudes and perceptions. *Energy Policy*, *48*(2012), 717–729. http://doi.org/10.1016/j.enpol.2012.06.009

Faria, M. V., Baptista, P. C., & Farias, T. L. (2014). Electric vehicle parking in European and American context: Economic, energy and environmental analysis. *Transportation Research Part A: Policy and Practice*, *64*, 110–121. http://doi.org/10.1016/j.tra.2014.03.011

Gerzon, B. (2016). *Understanding the effects of price incentives on charging behaviour*. Master thesis, Delft University of Technology, Delft, The Netherlands.

He, F., Yin, Y., & Zhou, J. (2015). Deploying public charging stations for electric vehicles on urban road networks. *Transportation Research Part C: Emerging Technologies*, *60*, 227–240. http://doi.org/10.1016/j.trc.2015.08.018

Kim, S., Yang, D., Rasouli, S., & Timmermans, H. (2017). Heterogeneous hazard model of PEV users charging intervals : Analysis of four year charging transactions data. *Transportation Research Part C*, *82*, 248–260. http://doi.org/10.1016/j.trc.2017.06.022

Liao, F., Molin, E., & Wee, B. Van. (2017). Consumer Preferences for Electric Vehicles : a Literature Review. *Transport Reviews*, 1–24.

Madina, C., Zamora, I., & Zabala, E. (2016). Methodology for assessing electric vehicle charging infrastructure business models. *Energy Policy*, *89*, 284–293. http://doi.org/10.1016/j.enpol.2015.12.007

Morrissey, P., Weldon, P., & Mahony, M. O. (2016). Future standard and fast charging infrastructure planning : An analysis of electric vehicle charging behaviour. *Energy Policy*, *89*, 257–270. http://doi.org/10.1016/j.enpol.2015.12.001

Motoaki, Y., & Shirk, M. G. (2017). Consumer behavioural adaption in EV fast charging through pricing. *Energy Policy*, *108*(May), 178–183. http://doi.org/10.1016/j.enpol.2017.05.051

Neaimeh, M., Salisbury, S. D., Hill, G. A., Blythe, P. T., Sco, D. R., & Francfort, J. E. (2017). Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles, *108*(June), 474–486. http://doi.org/10.1016/j.enpol.2017.06.033

Nie, Y. (Marco), & Ghamami, M. (2013). A corridor-centric approach to planning electric vehicle charging infrastructure. *Transportation Research Part B: Methodological*, *57*, 172–190. http://doi.org/10.1016/j.trb.2013.08.010

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, *5*, 329–332.

Paffumi, E., Gennaro, M. De, & Martini, G. (2015). Transportmetrica A : Transport Science Assessment of the potential of electric vehicles and charging strategies to meet urban mobility requirements. *Transportmetrica A: Transport Science*, *11:1*(January 2015), 22–60. http://doi.org/10.1080/23249935.2014.913732

Pebesma, E. J., & Bivand, R. S. (2005). Classes and methods for spatial data in R. *R News*, *5*(2)

Rangaraju, S., De Vroey, L., Messagie, M., Mertens, J., & Van Mierlo, J. (2015). Impacts of electricity mix, charging profile, and driving behaviour on the emissions performance of battery electric vehicles: A Belgian case study. *Applied Energy*, *148*(X), 496–505. http://doi.org/10.1016/j.apenergy.2015.01.121

Razeghi, G., Carreras-sospedra, M., Brown, T., Brouwer, J., Dabdub, D., & Samuelsen, S. (2016). Episodic air quality impacts of plug-in electric vehicles. *Atmospheric Environment*, *137*, 90–100. http://doi.org/10.1016/j.atmosenv.2016.04.031

Rezvani, Z., Jansson, J., & Bodin, J. (2015). Advances in consumer electric vehicle adoption research : A review and research agenda. *Transportation Research Part D*, *34*, 122–136. http://doi.org/10.1016/j.trd.2014.10.010

Robinson, a. P., Blythe, P. T., Bell, M. C., Hübner, Y., & Hill, G. a. (2013). Analysis of electric vehicle driver recharging demand profiles and subsequent impacts on the carbon content of electric vehicle trips. *Energy Policy*, *61*, 337–348. http://doi.org/10.1016/j.enpol.2013.05.074

Sadeghianpourhamami, N., Refa, N., Strobbe, M., & Develder, C. (2018). Electrical Power and Energy Systems Quantitive analysis of electric vehicle flexibility : A data-driven approach. *International Journal of Electrical Power and Energy Systems*, *95*, 451–462. http://doi.org/10.1016/j.ijepes.2017.09.007

Shahraki, N., Cai, H., Turkay, M., & Xu, M. (2015). Optimal locations of electric public charging stations using real world vehicle travel patterns. *Transportation Research Part D: Transport and Environment*, *41*, 165–176. http://doi.org/10.1016/j.trd.2015.09.011

Shoup, D. (2005). *The high cost of free parking*. American Planning Association.

Sun, X. H., Yamamoto, T., & Morikawa, T. (2016). Fast-charging station choice behaviour among battery electric vehicle users. *Transportation Research Part D: Transport and Environment*, *46*, 26–39. http://doi.org/10.1016/j.trd.2016.03.008

Tu, W., Li, Q., Fang, Z., Shaw, S., Zhou, B., & Chang, X. (2015). Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach. *Transportation Research Part C: Emerging Technologies*, (3688). http://doi.org/10.1016/j.trc.2015.10.004

Van der Poel, G., Tensen, T., Van Goeverden, T., & van den Hoed, R. (2017). Charging free floating shared cars in metropolitan areas. In *Electric Vehicle Symposium and Exhibition 30* (pp. 1–11). Stuttgart.

Vermunt, J. K., & Magidson, J. (2006). *LATENT GOLD ® 4 . 0 USER ' S GUIDE*. Belmont, MA: Statistical Innovations Inc.

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. G. (2018). Policy effects on charging behaviour of Electric Vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. *Transportation Research Part D: Transport and Environment*, *62*, 283–297. http://doi.org/https://doi.org/10.1016/j.trd.2018.03.012

Wolbertus, R., & van den Hoed, R. (2017). Charging station hogging : A data-driven analysis. In *Electric Vehicle Symposium 30* (pp. 1–14). Stuttgart.

Zou, Y., Wei, S., Sun, F., Hu, X., & Shiao, Y. (2016). Large-scale deployment of electric taxis in Beijing : A real-world analysis. *Energy*, *100*, 25–39. http://doi.org/10.1016/j.energy.2016.01.06

4 Improving electric vehicle charging station efficiency through pricing

Wolbertus, Rick, & Gerzon, B. (2018). Improving electric vehicle charging station efficiency through pricing. Journal of Advanced Transportation, 2018, 1–11. https://doi.org/doi.org/10.1155/2018/4831951

Abstract

Recent studies show that charging stations are operated in an inefficient way. Due to the fact that electric vehicle (EV) drivers charge while they park, they tend to keep the charging station occupied while not charging. This prevents others from having access. This study is the first to investigate the effect of a pricing strategy to increase the efficient use of electric vehicle charging stations. We used a stated-preference survey among EV drivers to investigate the effect of a time based fee to reduce idle time at a charging station. We tested the effect of such a fee under different scenarios and we modelled the heterogeneity among respondents using a latent class discrete choice model. We find that a fee can be very effective in increasing the efficiency at a charging station but the response to the fee varies among EV drivers depending on their current behaviour and the level of parking pressure they experience near their home. From these findings we draw implications for policy makers and charging point operators who aim to optimize the use of electric vehicle charging stations.

4.1 Introduction

The transport sector in Europe, which accounts for a quarter of greenhouse gas emissions, is the only main sector that has not been able to reduce emissions over the past 25 years (European Environment Agency, 2017). Electric vehicles (EVs) show great promise to meet CO_2 reduction targets in the transport domain and to reduce local air pollution (Razeghi et al., 2016). Adoption of these vehicles is starting to take off (International Energy Agency, 2016) as the main barriers, being the purchase price and the limited range due to high battery costs (Nykvist & Nilsson, 2015), are overcome by the introduction of more affordable, long range EVs into the market. One of the opportunities EVs offer in comparison to other Alternative Fuel Vehicles (AFVs) (Flynn, 2002) is the possibility to charge the car while being parked. This reduces the need for fast refuelling stations. Cars are parked 90-95% of the time (Paffumi, Gennaro, & Martini, 2015), which provides the opportunity to overcome problems of limited range and long recharging times even with currently available short range vehicles. This requires instalment of (public) charging infrastructure at places where users park their cars such as at home, at work or at public facilities such as shopping centres (Morrissey, Weldon, & Mahony, 2016).

Investments in the necessary charging infrastructure have been trailing due to chicken-and-egg related problems. In order to solve this, governments stepped in to facilitate basic public charging infrastructure. Efficient use of the limited available charging stations is important in early adoption phases to ensure a positive experience for early adopters and to reduce resistance among non-adopters (Bakker, Maat, & van Wee, 2014). Effective usage triggers high throughput which in turn creates a positive business case for charging point operators (Madina, Zamora, & Zabala, 2016). Descriptive statistics in the scientific literature (Desai, Chen, & Armington, 2018; Wolbertus & van den Hoed, 2016) and experiences in the field (Morris, 2016), however, show that efficiency at both slow- and fast charging stations is not optimal. At slow (level 2) public charging stations (up to 11 kW) only 20 to 40% of the time connected to the charging station is actually used for charging. At fast charging stations these rates are better, but idle times are more costly because charging speeds are higher.

Currently, many charging point operators use a business model that is based upon the sales of the energy transferred, not providing an incentive for the driver to move the vehicle once fully charged. Charging point operators are seeking ways to improve the efficiency of their operations without interfering with the user experience. Learning from parking studies (e.g Shoup, 2005; Pierce & Shoup, 2013), the introduction of time-based fees could help to increase the efficiency of charging station capacities. Although it is known that fees influence the decision to charge (Wen, Mackenzie, & Keith, 2016), there is little knowledge about how fees influence the decision to move the vehicle once fully charged. Straightforward implementation of a time-based fee could prove not to be the optimal solution, because it could interfere with a ‘parking is charging’ regime; the advantage EVs have over other AFVs. Moreover there are large differences in the way EV drivers use public charging infrastructure. This depends amongst others on the location (e.g home or work) and the time of day (Helmus & van den Hoed, 2015). Besides such circumstantial differences, there is a diversity among drivers in their parking and charging patterns (Franke & Krems, 2013). Such differences could also influence the way time-based fees are influencing the behaviour of EV drivers. For a successful implementation of a time-based pricing structure, heterogeneity among EV drivers in their parking- and charging behaviour is important to understand and take into account.

This paper aims to add to the understanding of the effect of time-based fee structures on charging behaviour and the underlying factors that drive heterogeneity of EV drivers’ responses to a new pricing scheme. The effect of a time-based fee during different situations is estimated using a stated choice survey in which respondents are asked whether or not they would move their EV once fully charged. Heterogeneity is addressed using socio-demographic characteristics of respondents. In addition, since all respondents were actual EV-drivers, their regular charging behaviour and vehicle characteristics were also used as underlying explanatory variables. By using a latent class discrete choice model, different user types are identified across which the effect of a time-based fee differs.

In section 4.2 a literature overview is presented, which is followed by an outline of the structure of this paper. In section 4.3 the methodology of the stated preference choice experiment is further explained, followed by the data collection process in section 4.4. Results of the model estimations are shown in section 4.5, followed by an interpretation of the results and their meaning in the policy context in section 4.6.

4.2 Literature

This literature review addresses two topics, first the heterogeneity in charging behaviour and the factors that drive the decisions to charge and second literature on the influence of pricing on charging behaviour. The relevant knowledge gaps are identified and the last paragraph describes how these gaps are filled with this contribution.

4.2.1 Heterogeneity in charging behaviour

The field of charging behaviour has been found to be under increasing interest of scholars. The number of studies that model charging behaviour based upon assumptions or criteria (e.g. Frade, Ribeiro, Gonçalves, & Antunes, 2011; Guo & Zhao, 2015; He, Wu, Yin, & Guan, 2013) or driving data from conventional cars (e.g. Brooker & Qin, 2015; Shahraki, Cai, Turkay, & Xu, 2015; Zhang, Shaffer, Brown, & Samuelsen, 2015) for infrastructure planning is increasing. More recently, attention has shifted towards analysing differences in charging patterns from actual EV drivers. Studies that discuss heterogeneity in charging behaviour fall into two categories, those that discuss heterogeneity in charging patterns (e.g. home, workplace and public charging) and those that study heterogeneity in the factors that drive charging decisions (e.g. pricing and routine behaviour).

The number of studies that investigate heterogeneity in charging patterns using actual driving- or charging data from EVs is small due to the limited number of vehicles on the road. However, with the growing number of EVs on the road, it can be observed that the number of such studies also begins to increase. A number of studies such as by Azadfar, Sreeram, & Harries (2015), Robinson, Blythe, Bell, Hübner, & Hill (2013) and Morrissey et al. (2016) describe charging behaviour and try to derive general conclusions from this. They identify patterns often corresponding to home and workplace charging, the two most dominant modes currently used. Heterogeneity among charging profiles was more systematically addressed by several studies such as Robinson et al. (2013) and Desai et al. (2018) which both used cluster analysis to identify several charging profiles. Van den Hoed & Helmus (2015) identified 6 different user types based on charging data in the city of Amsterdam. Franke & Krems (2013) identified two different user battery interaction styles among EV drivers in a trail in Germany, some users preferred to interact with the battery level of the vehicle, while others displayed more opportunity driven recharge styles. Sadeghianpourhamami, Refa, Strobbe, & Develder (2018) make use of charging data to determine different user types to assess their flexibility in charging behaviour and therefore their suitability for load shifting purposes. They identify three different user groups using k-means clustering: home, workplace and park-to-charge charging. The results are largely in line with Robinson et al. (2013).

In studies that investigate the factors that drive charging decisions, heterogeneity among EV drivers is often modelled by using random parameter logit models (Hou, Ouyang, Wang, & Xu, 2013; Jabeen, Olaru, Smith, Braunl, & Speidel, 2013; Xu, Meng, Liu, & Yamamoto, 2017; Yu & Mackenzie, 2016; Zoepf, MacKenzie, Keith, & Chernicoff, 2013). These studies find differences in how EV drivers interpret e.g. distances to charging stations and different charging speeds. Latent class analysis is used to investigate heterogeneity among the determining factors of charging decisions is by Wen, Mackenzie, & Keith (2016). Although they identified three different user groups, these were not linked to actual recharge patterns found in studies based on actual charging behaviour such as in Robinson et al. (2013), Van den Hoed & Helmus (2015) and Sadeghianpourhamami et al. (2018) but on socio-demographic and vehicle characteristics. The only study that does make such a link is by Kim, Yang, Rasouli, & Timmermans (2017) who used a latent class hazard duration model to identify differences in user groups in inter-charging session duration. The predefined two groups were based upon charging (ir)regularity. Latent class analysis showed that charging behaviour and vehicle characteristics can predict whether users are (ir)regular chargers.

The overview shows that random parameter models are mostly used to capture heterogeneity in decision rules in charging decisions. Descriptive studies however more focus on clustering users based on their behaviour. Linkage between these methodologies is mostly missing with the exception of Kim et al. (2017).

4.2.2 Price incentives for charging behaviour

The effect of pricing strategies to steer charging behaviour has mainly been studied in the context of so-called smart charging (Galus, Vaya, Krause, & Andersson, 2012). Smart charging is the concept in which pricing is used to prevent peaks in grid loads, to let charging coincide with renewable energy production or to feed back into the grid during high energy demand. An overview of the various modes of smart charging is given by García-villalobos et al. (2014) and Tamis, van den Hoed, & Thorsdottir (2017). Price setting usually happens in a centralised manner by so-called aggregators as individual users do not have enough volume to trade on energy markets. Setting the price is done dynamically based on current energy prices or using more static time-of-use prices in which differences are made between e.g. day and night (Galus et al., 2012). Generally in studies based on stated choice experiments, a significant positive effect of price on the decision to post-pone or to leave control to an aggregator is found (Daina, Sivakumar, & Polak, 2017). There are, however, studies indicating that too complex pricing strategies have a negative effect on reaching set goals (Layer, Feurer, & Jochem, 2017).

Besides the influence of price incentives for ‘smart charging’ a few studies have looked into the influence of pricing on more general charging behaviour. Latinopoulos, Sivakumar, & Polak (2016) looked into price setting in relation to charging decisions combined with parking reservations. They find that EV drivers are willing to pay more to ensure charging station availability. Wen, MacKenzie & Keith (2016) model the choice to start charging with mixed- and latent class models, in which they include the price of the charging session based upon a stated preference survey among EV drivers. In the latent classes they do find differences on price sensitivity between respondents.

In studies that make use of charging data Sun, Yamamoto, & Morikawa (2016) find that EV drivers in Japan are willing to make longer detours for free charging stations from their route than for paid chargers. Motoaki & Shirk (2017) find that installing a flat fee at fast charging stations resulted in longer charging sessions and less energy transfer per minute connected. Users wanted to get the most out of the money they paid. Consequently, users also fill their car beyond 80% after which charging becomes less efficient. Such inefficient use of the time connected to a charging station with flat fees or other non-time based fees was found to be even worse at slower (level 2) charging stations in the Netherlands. Wolbertus & van den Hoed (2016) found that only 20% of the time connected to a charging station was actually used for charging. Charging behaviour at ‘lower’ power outlets is more related to parking behaviour in which vehicles stay in the same place for much longer times than is needed to recharge the car. Also on level 2 charging stations in the United States, Francfort (2015) found that installing time-based fees reduced charging times. The report however does not quantify the precise reduction the fee caused after charging was first free.

To summarize, there are various indications that pricing strategies can have an influence on charging behaviour. The studies indicate the location, timing, duration and the willingness to give up control over the charging process can be influenced. The charging station choice could also be influenced if prices vary enough. However, a quantification of the effect of pricing strategies is missing, especially for time-based strategies.

4.2.3 Knowledge gaps and contributions

In sum, this overview has shown that a growing body of literature is investigating charging behaviour of EV drivers using revealed preference data. Descriptive studies and random parameter models show that heterogeneity is present in charging patterns and in the determining factors which drive the decisions regarding where, how long and how much to charge. Understanding this heterogeneity is crucial to correctly predict charging demand. Links between descriptive studies which often show clear habitual patterns and studies that model heterogeneity in charging decision rules are sparse. Furthermore, the literature on determining factors focusses on the decision to charge (or not) and not on the duration of the charging session.

The effect of price on the charging sessions is mainly studied in the context of ‘smart charging’ in which the user is asked to hand over a certain amount of control over the charging process for a lower price. Information about price sensitivity mostly comes from stated preference studies or studies that investigate the difference between paid- and free chargers. These studies often find significant effects of such price changes. Literature from other domains, such as parking (Pierce & Shoup, 2014; Pu, Li, Ash, Zhu, & Wang, 2017), suggests that behaviour could be well steered by setting the price level and pricing mechanism.

This study contributes by shedding more light on the effect of pricing mechanisms on charging behaviour while taking the heterogeneity of EV drivers in their charging behaviour into account. It does so by looking more at current charging patterns described in the literature. Using a stated preference study on the decision to end a charging session once completely charged, given a certain price per hour, it is investigated how such a pricing strategy can lead to more efficient charging station use. Actual charging patterns are used to simulate scenarios about the timing, location and parking pressure of charging sessions under which the effect of a time based fee is tested. Moreover, the participants, all EV owners, are asked about their recharging patterns.

This information is used in a discrete choice latent class model to determine if these charging patterns lead to a different evaluation of the proposed pricing mechanism.

4.3 Methodology

A stated choice study was performed among EV drivers, in which they were asked to imagine that they were charging their electric vehicle at a level 2 public charging station. They were presented with the scenario in which the EV was fully charged two hours after having started the charging session. The two hours is the average time needed to recharge (Wolbertus & van den Hoed, 2016). The driver is asked to make the choice to move his vehicle away from the charging station within the next hour. If the driver does not comply, he will be faced with an additional time-based fee. Such a fee was not applicable between 23:00 and 8:00 hours as this would hamper overnight charging sessions and would only create empty charging spots due to the fact that during these hours demand for charging is generally very low.

Different charging scenarios were constructed including the most important factors. These factors were determined by a literature review and interviews with policy makers and EV drivers. Three factors were identified as most relevant in the decision to move the vehicle once the charging session was finished. First, the timing of the charging session in the day, which often coincides with location due to habitual patterns of drivers such as charging at home or work. Second, the time until the next drive was relevant; drivers indicated that they would not likely move their car if the parking period after a finished charging session was very short. Last, drivers also indicated that parking pressure, or the ability to park somewhere close without too much hassle was relevant. An overview of the variables and their levels is shown in *Table 4.1*.

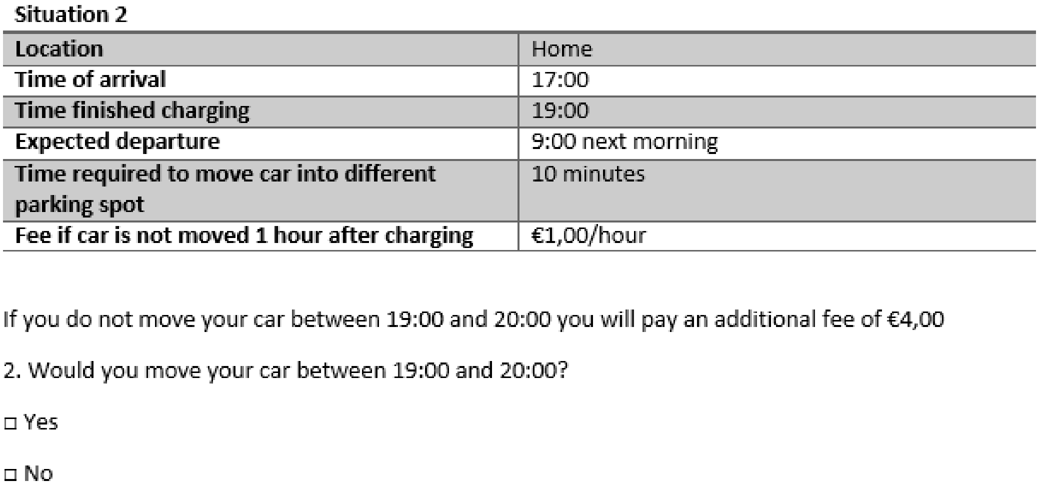
Table 4.1 Overview of variables used in stated choice experiment

Variable	Levels
Fee (€)	€0.25/hour €1/hour €1.75/hour
Time to move car	5min 10min 15min
Time until next drive	2 hours 5 hours 8 hours
Time of day and location	9:00 at work 14:00 at home 17:00 at home

As input to establish the right levels to represent the timing of the charging session, evidence from charging patterns in literature was taken. Jabeen et al. (2013) and Hoed, Helmus, Vries, & Bardok (2014) showed that significant differences exist between home and workplace charging, the two most dominant modes of charging. These are represented in the survey as 9:00 at work and 17:00 at home. During weekends different patterns arise, in which charging peaks are observed during the afternoon, represented by the 14:00 at home level in the experiment.

The time until the next drive variable levels are based upon typical charging patterns observed in the Netherlands (Wolbertus & van den Hoed, 2017). Three levels are chosen based upon a review of the data: removal of the vehicle within 2 hours, 5 hours and 8 hours after a finished charging session. The two hour level resembles short sessions mainly observed during the morning and afternoon, the five hour level resembles morning sessions ending in the afternoon and the 8 hour level represents sessions of more than 10 hours, often overnight.

During interviews with policy makers and EV drivers about a potential fee, an often mentioned comment was that EV drivers were willing to move the vehicle once fully charged, but they did not have the opportunity to park elsewhere without cruising for a parking spot for a considerable amount of time. Parking pressure in the surroundings of the charging station is resembled by the *time to move the car* variable. The variable represents the time cruising for a parking spot and the additional walking time to reach the destination. The variable is set with a 5 minute interval with a maximum of 15 minutes as it was expected that drivers would not remove their car if cruising time would be longer. Finally we resemble an hourly fee for using the charging station without actually charging with a variable that was set on three levels from *low* (€0.25/hour), to *medium* (€1.00/hour; similar as the regular charging costs) and *high* (€1.75/hour). Levels are still below average parking costs. Total fee costs, based upon the fee level multiplied with the remaining number of hours of parking and with exceptions between 23:00 and 8:00, are pre-calculated. An exemplary choice set (translated from Dutch) is showed in *Figure 4.1*.



Situation 2

Location	Home
Time of arrival	17:00
Time finished charging	19:00
Expected departure	9:00 next morning
Time required to move car into different parking spot	10 minutes
Fee if car is not moved 1 hour after charging	€1,00/hour

If you do not move your car between 19:00 and 20:00 you will pay an additional fee of €4,00

2. Would you move your car between 19:00 and 20:00?

☐ Yes

☐ No

Figure 4.1 Exemplary choice set

The experimental design was based upon Taguchi's (1987) orthogonal arrays. The design uses 3^4 dimensions, resulting into nine different choice sets. Each respondent was faced with each of these nine choices. In the second part of the survey respondents were asked about their social demographic characteristics. Additional information about their electric vehicle (type), reason of purchase and their recharging behaviour on public charging stations was asked at the end of the survey.

To analyse the data both a binary logit and a latent class discrete choice model were estimated. The time & location, time until next drive and the time to move the car variables were effect coded. For each of the categorical variables the first value was chosen as a reference point. This reference level is indicated in the results. In effect coding the sum of all the coefficients equals zero. This implies that the coefficient for the reference category can be calculated as the negative sum of the coefficients (Bech & Gyrd-Hansen, 2005). Z-values and p-values are not derived for these reference levels. The continuous fee variable was calculated with the shown fee multiplied with the time until the next drive variable in order to capture the total cost of not moving the car. Non-linear versions of the fee variable were tested but did not provide a better model fit. The logit model was estimated using BIOGEME (Bierlaire, 2003).

To capture the heterogeneity among the EV drivers a latent class discrete choice model was estimated. Latent class choice models are particularly useful in this case, since they divide behaviour into groups of different EV drivers. As seen in the analyses by Jabeen et al. (2013) and Helmus & Van den Hoed (2015) based upon real charging data, defining different user types is very well possible. Other models, such as mixed logit models, assume a continuous distribution of the taste parameters, making it impossible to link the heterogeneity to the discretely defined user groups. Latent class models are therefore the most suited in this case and can provide the most insight for policy makers as such a discrete distribution into classes provides a richer, and often more understandable interpretation of the heterogeneity among EV drivers. For the latent class model, predictor variables for class membership were entered as co-variates in the model. The model is estimated using Latent GOLD 4.0 (Vermunt & Magidson, 2006). The number of classes was determined using ρ^2 and Bayesian Information Criterion (BIC) values.

4.4 Data collection

Respondents were recruited via email using the database from the Dutch association for electric drivers (Vereniging Elektrische Rijders). In total 559 people were contacted of whom 128 (23%) responded. Additional EV drivers were recruited via an online EV driver platform and through a message by Dutch charging station organisation ‘ELaadNL’ on social medium platform Twitter. In total 168 respondents completed the online survey. After filtering out incomplete surveys and unrealistic responses, 119 responses were useful. Each respondent was asked to fill in 9 different choice sets, resulting in 1058 choices in total which were used for the model estimation.

The respondents were mainly male (92%) and the income level was distributed upwards in comparison the Dutch average (CBS, 2015). This profile is consistent with the average Dutch EV owner (Hoekstra & Refa, 2017). *Table 4.2* presents the sample distributions of socio-demographic and background characteristics. In contrast to the average Dutch EV owner, the respondents mostly consisted of Full Electric Vehicle (FEV) owners (RVO.nl, 2016). Nearly 90% of Dutch EV owners has a Plug-in Hybrid Electric Vehicle (PHEV), while in the sample this is only 32.2%. Moreover they were more likely to own the car instead of leasing it, which is also inconsistent with the current population of EV owners. The majority of the respondents indicated to have a private charging point at home instead of relying on on-street parking and public charging overnight.

Table 4.2 Socio-demographic figures of respondents to the survey

Gender	
Male	92.2%
Female	7.8%
Age	
0-30	2.1%
30-60	79.2%
60+	16.6%
Unknown	2.1%
Annual income	
<€50,000	18.7%
€50,000 - €75,000	23.3%
€75,000 - €100.000	14.5%
€100,000 - €125,000	24.9%
>€125,000	18.5%
Type of EV	
FEV	67.8%
PHEV	32.2%
Car ownership	
Privately owned	67.3%
(Company) Leased	32.7%
Private charging point	
Private at home	77.2%
Public at home	22.8%

4.5 Results

4.5.1 The logit model

First, a standard logit model is estimated to assess the overall effects of the attributes on the choice to move the EV from the charging station to another parking spot (once fully charged). *Table 4.7* shows the results of this analysis and the estimated coefficients for the standard model.

The results show that, as expected, a fee increases respondents' utility and thus increases the probability to move the car. For the *time of day* variable we find that users are more willing to move their vehicle during the evening hours than at the middle of the day. An explanation might be that drivers are not going elsewhere after 19:00 hours and are willing to move their car for neighbours. The interpretation of the *time to move* variable is not straightforward as only the '10 minutes' value has a positive and significant effect. It is unclear why the '15 minute' value is not significantly different from zero. A similar effect can be seen in the time until the next drive variable, where a longer parking time gives a higher utility for the '5 hour' value, but no significant effect is found for the '8 hour' value. A possible explanation is that the fee is relatively high when there are 8 hours until the next drive regardless of the hourly based fee. The effect of the 8 hour variable would then be partially captured by the fee variable.

Table 4.3 Results of binary logit model estimation

Attribute	**Coefficient**	**z-value**
Constant	-0.413**	-3.172
Fee	0.297**	8.521
Time to move car 5 min (ref. cat.) 10 min 15 min	-0.208 0.299** -0.090	2.266 -0.868
Time until next drive 2 hours (ref. cat.) 5 hours 8 hours	-0.521 0.500** 0.021	3.950 0.135
Time of day and location 9:00 at work (ref. cat.) 14:00 at home 17:00 at home	0.080 -0.479** 0.399**	-3.900 3.054
Model fit		
Nul loglikelihood	- 699.033	
Final Log Likelihood	- 547.409	
ρ2	0.217	

** Significant at the 0.05 level
*Significant at the 0.10 level

In general, the model yields plausible results, but non-linear effects in the time to move the car and time until next drive variables are hard to interpret. The effect of implementing a fee is significant and has the highest relative contribution of the variables in the model. The model provides a reasonable fit to the data; the ρ^2 value of 0.217 indicates a substantial reduction of the Final LL compared to the Null LL.

4.5.2 The latent class discrete choice model

To assess heterogeneity in the responses of respondents to the pricing scheme, a latent class choice model was estimated. In this model it is assumed that there exist latent (unobserved) segments in the population, which have different sets of parameters along which the asses the choice attributes. For example, there may be a group which is very price-sensitive (high parameter value for the ‘fee’ variable), while another group is very sensitive to parking pressure (high parameter value for the ‘time to move’ variable). The latent classes are inferred from the distributions of the choice parameters emerging from the observed choices using the maximum likelihood principle.

A benefit of using a latent class choice model to reveal heterogeneity in the parameters, is that additional explanatory variables can be included in the model to explain latent class membership. For example, it may be plausible to assume that a lease driver who does not have to pay the price of charging (or staying connected) himself, is less likely to belong to a 'price-sensitive' class/segment. A systematic overview of the model is shown in *Figure 4.2*.

In the present application, the following four variables are entered into the model as predictors of class membership: having a full electric- (FEV) or plug-in hybrid electric vehicle (PHEV), whether the car was owned or leased, if the participant already moved their car away from the charging station once fully charged and if the participant experienced high parking pressure in the neighbourhood near their home. Socio-demographic variables were also included as predictors of class membership, but these turned out to be insignificant. In line with Kim et al. (2017) we therefore focused on the vehicle- and charging characteristics. Overall, predictors were found to vary across the different classes in a meaningful way.

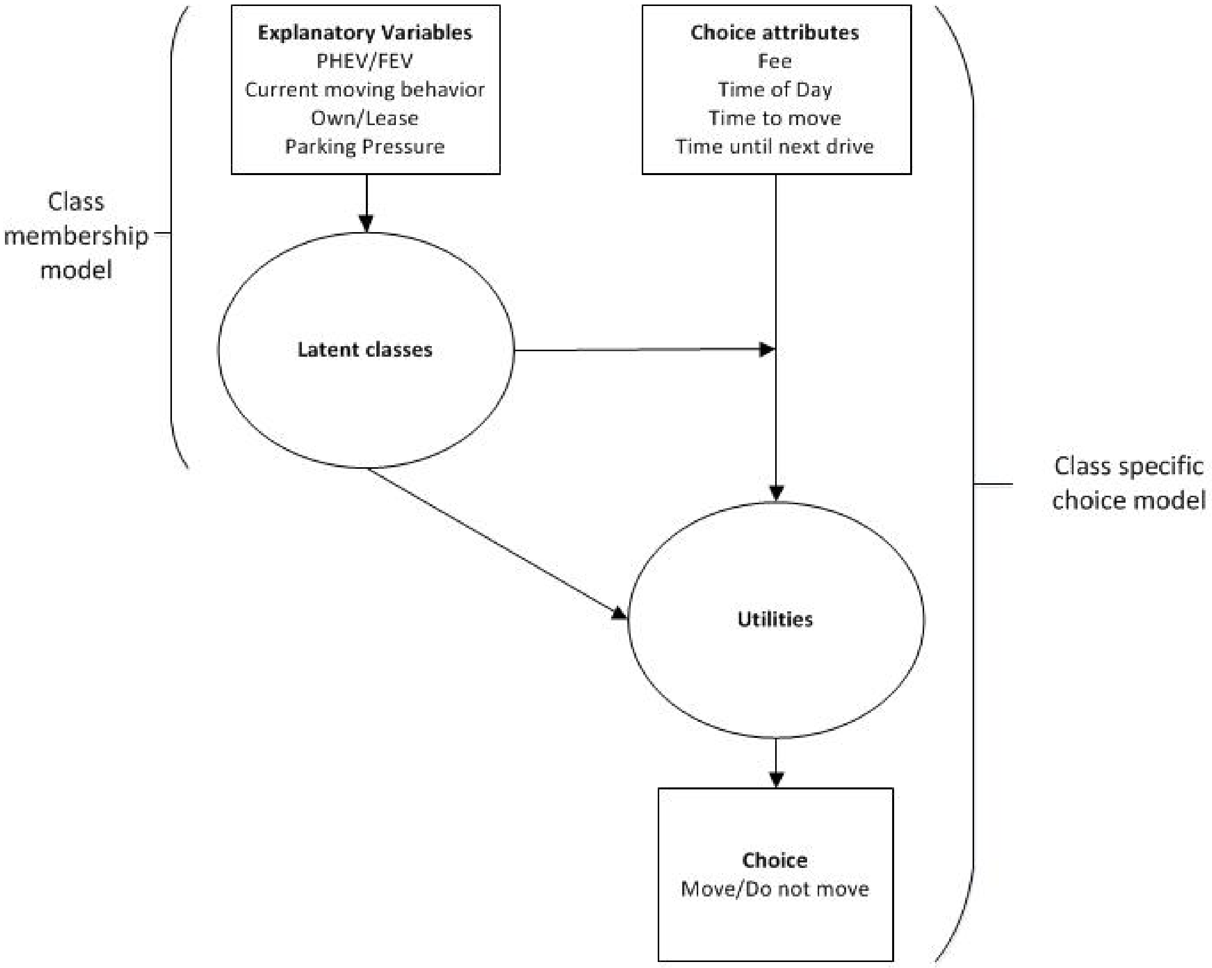


Figure 4.2 Visual representation of the latent class choice model, reproduced from (Walker & Li, 2006)

To estimate the optimal number of classes, consecutive Latent class models (LCMs) were estimated with the number of classes ranging from 1 to 5. *Table 4.4* shows the various model fit indicators for each of the estimated models. The Bayesian Information Criterion (BIC) indicator points to a 3 or 4 class model. To determine the optimal number of classes the predictors in the 3 and 4 class models were assessed. The parameter estimates in the 4 class model could not be meaningfully interpreted, especially as the class sizes became too small. Therefore the 3 class model was chosen as the best fit.

Table 4.4 Model fit estimators for different number of latent classes

Number of classes	Number of parameters	Log Likelihood	BIC (LL)	ρ2
1	11	-547.409	1133.051	0.2169
2	30	-429.102	958.565	0.3861
3	45	-361.750	885.912	0.4825
4	60	-330.085	884.789	0.5277
5	75	-310.849	908.446	0.5553

The results of the latent class model estimation are shown in *Table 4.5*. In general the LCM provides a substantial improvement in model fit ($\rho^2 = 0.483$ vs. 0.217). The classes have clear different meanings when we look at how they interpret the coefficients.

Table 4.5 Results of latent class model estimation

	Class1		**Class2**		**Class3**	
	Coefficient	**z-value**	**Coefficient**	**z-value**	**Coefficient**	**z-value**
Intercept	-2.333**	-5.836	1.503	1.683	-2.998	-1.294
Predictors						
Fee (€)	0.813**	5.268	0.854	1.128	0.003	0.006
Time to move car						
5min (ref. cat.)	1.175		1.774		1.223	
10min	0.215	0.796	-0.598	-0.460	0.182	0.161
15min	-1.390*	-1.947	-1.177	-0.152	-1.406	-0.931
Time until next drive						
2 hours (ref. cat.)	-1.244		0.590		1.767	
5 hours	1.860**	3.280	0.383	0.050	-1.704	-0.880
8 hours	-0.617	-0.898	-0.973	-0.124	-0.063	-0.110
Time of day and location						
9:00 at work (ref. cat.)	0.456		-1.688		-0.398	
14:00 at home	-1.779**	-3.400	0.756	0.098	-1.320	-0.947
17:00 at home	1.323**	1.989	0.932	0.120	1.718	1.261
Model fit						
Log Likelihood	-361.751					
ρ2	0.483					

*Significant at the 0.10 level

** Significant at the 0.05 level

Class 1: Members of class 1 do seem sensitive to all four variables. A time-based fee increases the chance of moving the car for respondents in the first class. For the members of the first class the *time to move the car* variable only has a significant negative parameter for the 15 minute level. This shows that severe parking pressure can be of influence on the decision to move the car. This effect was already captured in the membership model for class 3. The *time until the next drive* variable has an expected effect for the 2 and 5 hour levels but surprisingly has no significant effect for the 8 hour level in class 1. As predicted, the longer the duration of the remaining parking time, the more likely drivers are willing to move their car. The insignificance of the 8 hour parameter could be explained by the effect of the duration and could be partly captured by the fee. The *time of day* and *location* variables are in line with the binary logit model, in which we see that drivers are more likely to move their car in the evening at home than during the afternoon.

Class 2 and 3: Are relatively insensitive to most of the variables as we see that none of the variables is significant. This is especially relevant for the time-based fee and can be explained by the fact they either nearly always move (class 2) or nearly always stay (class 3). The intercepts (although not significant for class 2 and 3) play a dominant role in the observed probabilities for members in these two latter classes. Implementing a time-based fee for the latter groups would thus not be as effective. The latter can be related back to the membership model where the same respondents stated that they experienced high parking pressure near their homes and therefore might not see opportunities to park their car elsewhere once fully charged.

The class membership model is displayed in *Table 4.6*. For the predictors of class membership the *Currently moving* and *Parking pressure at home* variables were found to have a significant effect on class membership.

- **Class 1:** Members did not have a specific profile according to the covariates in the model. Class 1 represents the largest group of respondents (60%) and they are the most responsive to the hourly fee.
- **Class 2:** Members nearly always indicated to remove the car from the charging station during the experiment also indicated that this was their current behaviour. They also did not perceive parking pressure at home in comparison to members of the other classes.
- **Class 3:** Members experience more parking pressure near their homes. This could be one of the main drivers why they almost never choose to move the EV from the charging point.

Table 4.6 Class membership model for 3-class model

Class membership model	**Class 1**		**Class 2**		**Class 3**	
Class size	60.0%		30.9%		9.1%	
% Choice to move (observed)	53.8%		93.6%		13.2%	
	Coefficient	**z-value**	**Coefficient**	**z-value**	**Coefficient**	**z-value**
Intercept	0.981	2.430	0.303	0.683	-1.284	-2.066
Attributes						
Full Electric	0.165	0.437	-0.186	-0.431	0.021	0.038
Lease	0.395	0.950	-0.425	-0.886	0.031	0.050
Currently moving	-0.397	-1.041	1.232**	2.937	-0.835	-1.391
Parking pressure at home	-0.690	-1.544	-0.978*	-1.777	1.668**	2.728

** Significant at the 0.05 level
*Significant at the 0.10 level

4.6 Conclusion

This paper has examined the influence of a time-based fee on the decision to remove an EV from a charging station once fully charged. Results from a stated choice survey that have been analysed in a binary logit model show that such a fee can be effective and can result in more efficient use of charging stations. Other factors influencing the choice, such as parking pressure, time until next drive and the time of day were also found to be relevant, although straightforward interpretation was not always possible.

To assess the heterogeneity among EV drivers regarding the time-based fee, a discrete choice latent class model was estimated. Additional variables about the type of EV and charging behaviour of the respondents were added to the model as predictor of class membership. Results show that three types of users could be distinguished; those that responded to the fee, users that always moved their car once fully charged and those that refused to move, regardless of the set fee level. Membership variables showed that members of the second class indicated that indeed this behaviour belonged to their normal charging behaviour. Members of the third class were more likely to experience parking pressure when parking at home. Users in the third class might not see the opportunity to park their car elsewhere once fully charged. Such distinctions are important for policy makers because those that experience parking pressure are mostly drivers who rely on curb side charging and parking because they make use of public charging infrastructure on a daily basis. Although in some countries the majority of EV drivers have charging facilities at home; the needs of future drivers, which might be more dependent on on-street parking and charging facilities, have to be taken into account by policy makers. This is especially relevant in more dense urban areas. Municipal policy makers can make distinctions between inhabitants and visitors, possibly relieving the impact of a time-based fee for those that experience parking pressure in the city they live in.

The results show that taking into account the heterogeneity among respondents can be very relevant. Using a discrete choice latent class approach has the benefit that results are easier to interpret for policy makers, as users are divided into clear groups. This allows for assessing biases among respondents groups. In this case early adopters can display distinct different charging behaviour regarding on- and off-street charging at home, which resulted in a different acceptance of the proposed pricing scheme.

4.7 Discussion

This research is limited by the fact that the respondents are not completely representative for the population of Dutch EV drivers. The research was aimed solely at EV drivers as it was believed that non-EV drivers did not have the experience to correctly predict what their response would be to the scenarios in the choice experiment. This limited our search to members of the Dutch association for EV drivers. The respondents drove more full- instead of plug-in hybrid electric vehicles and were less likely to be company lease drivers compared to the population of Dutch EV drivers. From practical experience it is known that company lease drivers very often do not have to pay for charging costs themselves. They are therefore less aware of the costs and they could therefore be more reluctant moving the vehicle once fully charged even when presented with a time-based fee. Although no effect was found for having company lease car in the latent class membership model, future research could look more into differences between private owners and company lease drivers.

For charging point operators the results of this study show that implementing a time-based fee could result in a higher efficiency in charging station usage. The results show that even with a modest fee, to not frustrate EV drivers, a substantial improvement could be reached. In the final design of the fee, the charging point operators would have to take into account the segment of drivers that experience severe parking pressure and are therefore not willing or able to move their vehicle away from the charging station once fully charged. The design of the fee could focus on only preventing very long charging sessions (e.g. >24 hours) as suggested by Wolbertus & Van den Hoed (2017). This would also prevent misuse by EV drivers would could set the charging speed at a very low rate to prevent them from completing the charging session. Another important factor that has to be taken into account when considering an implementation of a time based fee is the precondition that the policy is only effective when the fee is communicated clearly. This requires all costs related to the time-based fee to be at least specified in the transaction data and the bill and preferably beforehand at the charging location.

This study builds on various studies that investigate the effects of pricing strategies to influence charging behaviour. The results are in line with previous studies (Latinopoulos et al., 2016; Motoaki & Shirk, 2017; Sun et al., 2016) which also find that pricing strategy can be an effective strategy to steer charging behaviour. This study has been the first to quantify this effect for a time based fee. Moreover, in addition to previous studies, this study added the influence of charging behaviour (as a variable in the model). Finally, it has provided a segmentation of EV drivers using characteristics of their car, their current behaviour and the effect of parking pressure. This segmentation has proved to be useful, as the time based fee was assessed differently by the three different segments found in this study. Doing so this paper has given additional insight into the motivations of charging behaviour in an urban context.

As the literature review showed, many applications can benefit from dynamic price signals in the context of smart charging, charging station efficiency or station reservation. Such price signals make sense from the perspective of the problem owner, the grid operator, the charging point operator or the parking manager respectively. However as electric vehicle charging is a combination of these different areas, it is evident that implementation of each of these pricing strategies is not in the interest of the EV driver. Dynamic price setting should be considered carefully for each application separately.

Future research could also look at heterogeneity among more charging decisions such as charging station choice. Understanding differences in user groups can be important for policy makers for the spatial planning of a charging infrastructure. Further understanding of pricing effects can also be important in being able to steer charging behaviour to goals of stakeholders. This research and others have shown that clustering users based upon their charging behaviour and vehicle characteristics is useful to capture heterogeneity in charging decision rules.

4.8 References

Azadfar, E., Sreeram, V., & Harries, D. (2015). The investigation of the major factors influencing plug-in electric vehicle driving patterns and charging behaviour. *Renewable and Sustainable Energy Reviews*, *42*, 1065–1076. http://doi.org/10.1016/j.rser.2014.10.058

Bakker, S., Maat, K., & van Wee, B. (2014). Stakeholders interests, expectations, and strategies regarding the development and implementation of electric vehicles: The case of the Netherlands. *Transportation Research Part A: Policy and Practice*, *66*(1), 52–64. http://doi.org/10.1016/j.tra.2014.04.018

Bech, M., & Gyrd-Hansen, D. (2005). Effects coding in discrete choice experiments. *Health Economics*, *14*(10), 1079–1083. http://doi.org/10.1002/hec.984

Bierlaire, M. (2003). BIOGEME: A free package for the estimation of discrete choice models. In *Proceedings of the 3rd Swiss Transportation Research Conference*. Ascona, Switzerland.

Brooker, R. P., & Qin, N. (2015). Identification of potential locations of electric vehicle supply equipment. *Journal of Power Sources*, *299*, 76–84. http://doi.org/10.1016/j.jpowsour.2015.08.097

Daina, N., Sivakumar, A., & Polak, J. W. (2017). Electric vehicle charging choices: Modelling and implications for smart charging services. *Transportation Research Part C: Emerging Technologies*, *81*, 36–56. http://doi.org/10.1016/j.trc.2017.05.006

Desai, R. R., Chen, R. B., & Armington, W. (2018). A Pattern Analysis of Daily Electric Vehicle Charging Profiles : Operational Efficiency and Environmental Impacts. *Journal of Advanced Transportation*, *2018*(January), 1–15.

European Environment Agency. (2017). *Annual European Union greenhouse gas inventory 1990–2015 and inventory report*. Copenhagen.

Flynn, P. C. (2002). Commercializing an alternate vehicle fuel : lessons learned from natural gas for vehicles, *30*, 613–619.

Frade, I., Ribeiro, A., Gonçalves, G., & Antunes, A. (2011). Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal. *Transportation Research Record: Journal of the Transportation Research Board*, *2252*, 91–98. http://doi.org/10.3141/2252-12

Francfort, J. E. (2015). *The EV Project Price / Fee Models for Publicly Accessible Charging*. Idaho Falls, Idaho.

Franke, T., & Krems, J. F. (2013a). Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour*, *21*(2013), 75–89. http://doi.org/10.1016/j.trf.2013.09.002

Franke, T., & Krems, J. F. (2013b). Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Psychology and Behaviour*, *21*, 75–89. http://doi.org/10.1016/j.trf.2013.09.002

Galus, M. D., Vaya, M. G., Krause, T., & Andersson, G. (2012). The role of electric vehicles in smart grids. *Wiley Interdisciplinary Reviews: Energy and Environment*, (July). http://doi.org/10.1002/wene.56

García-villalobos, J., Zamora, I., Martín, J. I. S., Asensio, F. J., & Aperribay, V. (2014). Plug-in electric vehicles in electric distribution networks : A review of smart charging approaches. *Renewable and Sustainable Energy Reviews*, *38*, 717–731. http://doi.org/10.1016/j.rser.2014.07.040

Guo, S., & Zhao, H. (2015). Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective. *Applied Energy*, *158*, 390–402. http://doi.org/10.1016/j.apenergy.2015.08.082

He, F., Wu, D., Yin, Y., & Guan, Y. (2013). Optimal deployment of public charging stations for plug-in hybrid electric vehicles. *Transportation Research Part B: Methodological*, *47*(2013), 87–101. http://doi.org/10.1016/j.trb.2012.09.007

Helmus, J., & van den Hoed, R. (2015). Unraveling User Type Characteristics : Towards a Taxonomy for Charging Infrastructure. *EVS28 International Electric Vehicle Symposium and Exhibition*, 1–16.

Hoed, R. Van Den, Helmus, J. R., Vries, R. De, & Bardok, D. (2014). Data analysis on the public charge infrastructure in the city of Amsterdam. In *EVS27 Symposium, Barcelona, Spain, November 17-20, 2013* (pp. 1–10). http://doi.org/10.1109/EVS.2013.6915009

Hoekstra, A., & Refa, N. (2017). Characteristics of Dutch EV drivers. In *Electric Vehicle Symposium 30* (pp. 1–13). Stuttgart.

Hou, C., Ouyang, M., Wang, H., & Xu, L. (2013). An assessment of PHEV energy management strategies using driving range data collected in Beijing. *2013 World Electric Vehicle Symposium and Exhibition (EVS27)*, 1–10. http://doi.org/10.1109/EVS.2013.6914772

International Energy Agency. (2016). *Global EV Outlook 2016: Beyond one million electric cars*.

Jabeen, F., Olaru, D., Smith, B., Braunl, T., & Speidel, S. (2013). Electric vehicle battery charging behaviour: Findings from a driver survey. *36th Australasian Transport Research Forum (ATRF), Brisbane, Queensland, Australia*.

Kim, S., Yang, D., Rasouli, S., & Timmermans, H. (2017). Heterogeneous hazard model of PEV users charging intervals : Analysis of four year charging transactions data. *Transportation Research Part C*, *82*, 248–260. http://doi.org/10.1016/j.trc.2017.06.022

Latinopoulos, C., Sivakumar, A., & Polak, J. W. (2017). Response of electric vehicle drivers to dynamic pricing of parking and charging services : risky choice in early reservations. *Transportation Research Part C*, *80*, 1–34. http://doi.org/10.1016/j.trc.2017.04.008

Layer, P., Feurer, S., & Jochem, P. (2017). Perceived price complexity of dynamic energy tariffs : An investigation of antecedents and consequences. *Energy Policy*, *106*(July 2016), 244–254. http://doi.org/10.1016/j.enpol.2017.02.051

Madina, C., Zamora, I., & Zabala, E. (2016). Methodology for assessing electric vehicle charging infrastructure business models. *Energy Policy*, *89*, 284–293. http://doi.org/10.1016/j.enpol.2015.12.007

Morris, D. Z. (2016). Tesla Will Charge Users for Hogging the Supercharger. Retrieved January 19, 2017, from http://fortune.com/2016/12/17/tesla-supercharger-fees/

Morrissey, P., Weldon, P., & Mahony, M. O. (2016). Future standard and fast charging infrastructure planning : An analysis of electric vehicle charging behaviour. *Energy Policy*, *89*, 257–270. http://doi.org/10.1016/j.enpol.2015.12.001

Motoaki, Y., & Shirk, M. G. (2017). Consumer behavioral adaption in EV fast charging through pricing. *Energy Policy*, *108*(May), 178–183. http://doi.org/10.1016/j.enpol.2017.05.051

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, *5*, 329–332.

Paffumi, E., Gennaro, M. De, & Martini, G. (2015). Transportmetrica A : Transport Science Assessment of the potential of electric vehicles and charging strategies to meet urban mobility requirements. *Transportmetrica A: Transport Science*, *11:1*(January 2015), 22–60. http://doi.org/10.1080/23249935.2014.913732

Pierce, G., & Shoup, D. (2013). Getting the Prices Right. *Journal of the American Planning Association*, *79*(1), 67–81. http://doi.org/10.1080/01944363.2013.787307

Pierce, G., & Shoup, D. (2014). Response to Millard-Ball et al.: Parking Prices and Parking Occupancy in San Francisco. *Journal of the American Planning Association*, *79*(4), 336–339. http://doi.org/10.1080/01944363.2014.918480

Pu, Z., Li, Z., Ash, J., Zhu, W., & Wang, Y. (2017). Evaluation of spatial heterogeneity in the sensitivity of on-street parking occupancy to price change. *Transportation Research Part C: Emerging Technologies*, *77*, 67–79. http://doi.org/10.1016/j.trc.2017.01.008

Razeghi, G., Carreras-sospedra, M., Brown, T., Brouwer, J., Dabdub, D., & Samuelsen, S. (2016). Episodic air quality impacts of plug-in electric vehicles. *Atmospheric Environment*, *137*, 90–100. http://doi.org/10.1016/j.atmosenv.2016.04.031

Robinson, a. P., Blythe, P. T., Bell, M. C., Hübner, Y., & Hill, G. a. (2013). Analysis of electric vehicle driver recharging demand profiles and subsequent impacts on the carbon content of electric vehicle trips. *Energy Policy*, *61*, 337–348. http://doi.org/10.1016/j.enpol.2013.05.074

RVO.nl. (2016). *Special: Analyse over 2015*. The Hague. Retrieved from http://www.rvo.nl/sites/default/files/2016/01/Special Analyse over 2015.pdf

Sadeghianpourhamami, N., Refa, N., Strobbe, M., & Develder, C. (2018). Electrical Power and Energy Systems Quantitive analysis of electric vehicle flexibility : A data-driven approach. *International Journal of Electrical Power and Energy Systems*, *95*, 451–462. http://doi.org/10.1016/j.ijepes.2017.09.007

Shahraki, N., Cai, H., Turkay, M., & Xu, M. (2015). Optimal locations of electric public charging stations using real world vehicle travel patterns. *Transportation Research Part D: Transport and Environment*, *41*, 165–176. http://doi.org/10.1016/j.trd.2015.09.011

Shoup, D. (2005). *The high cost of free parking*. American Planning Association.

Sun, X. H., Yamamoto, T., & Morikawa, T. (2016). Fast-charging station choice behavior among battery electric vehicle users. *Transportation Research Part D: Transport and Environment*, *46*, 26–39. http://doi.org/10.1016/j.trd.2016.03.008

Taguchi, G. (1987). *System of experimental design: engineering methods to optimize quality and minimize costs*. Unipub/Kraus International Publications.

Tamis, M., van den Hoed, R., & Thorsdottir, H. (2017). Smart Charging in the Netherlands. In *European Battery , Hybrid & Electric Fuel Cell Electric Vehicle Congress* (pp. 1–10).

Vermunt, J. K., & Magidson, J. (2006). *LATENT GOLD ® 4 . 0 USER ' S GUIDE*. Belmont, MA: Statistical Innovations Inc.

Walker, J. L., & Li, J. (2006). Latent lifestyle preferences and household location decisions. *Journal of Geographical Systems*, *9*(1), 77–101. http://doi.org/10.1007/s10109-006-0030-0

Wen, Y., Mackenzie, D., & Keith, D. R. (2016). Modeling the Charging Choices of Battery Electric Vehicle Drivers by Using Stated Preference Data. *Transportation Research Record: Journal of the Transportation Research Board*, *2572*, 47–55. http://doi.org/10.3141/2572-06

Wolbertus, R., & van den Hoed, R. (2016). Benchmarking Charging Infrastructure Utilization. In *EVS29 Symposium* (pp. 1–15). Montreal, Quebec, Canada.

Wolbertus, R., & van den Hoed, R. (2017). Charging station hogging : A data-driven analysis. In *Electric Vehicle Symposium 30* (pp. 1–14). Stuttgart.

Xu, M., Meng, Q., Liu, K., & Yamamoto, T. (2017). Joint charging mode and location choice model for battery electric vehicle users. *Transportation Research Part B*, *103*, 68–86. http://doi.org/10.1016/j.trb.2017.03.004

Yu, H., & Mackenzie, D. (2016). Modeling Charging Choices of Small-Battery Plug-In Hybrid Electric Vehicle Drivers by Using Instrumented Vehicle Data. *Transportation Research Record: Journal of the Transportation Research Board*, *2572*, 56–65. http://doi.org/10.3141/2572-07

Zhang, L., Shaffer, B., Brown, T., & Samuelsen, G. S. (2015). The optimization of DC fast charging deployment in California. *Applied Energy Journal*, *157*, 111–122. http://doi.org/10.1016/j.apenergy.2015.07.057

Zoepf, S., MacKenzie, D., Keith, D., & Chernicoff, W. (2013). Charging choices and fuel displacement in a large-scale plug-in hybrid electric vehicle demonstration. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2385*, 1–10.

5 Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. G. (2018). Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. Transportation Research Part D: Transport and Environment, 62. https://doi.org/10.1016/j.trd.2018.03.012

Abstract

Policy makers are looking for effective ways to promote the adoption of electric vehicles (EVs). Among the options is the roll-out and management of charging infrastructure to meet the EV drivers' refuelling needs. However, policies in this area do not only have a long-term effect on the adoption of EVs among prospective owners, they also have short-term impacts on the usage of public charging infrastructure among current EV owners and vice-versa. Presently, studies focusing on both effects simultaneously are lacking, missing out on possible cross-pollination between these areas. This study uniquely combines stated and revealed preference data to estimate the effect of particular policy measures aimed at EV adoption, on the one hand, and charging behaviour, on the other. Using a large dataset (1.7 million charging sessions) related to charging behaviour using public charging infrastructure in the Netherlands we quantify the effects of (i) daytime-parking (to manage parking pressure) and (ii) free parking (to promote purchase of EVs) policies on charging behaviour. To estimate the effects of these particular policies on EV purchase intentions, a stated choice experiment was conducted among potential EV-buyers. Results show that cross-pollinations between EV charging and adaptation policies exist and should be taken into account when designing policies for EV adoption.

5.1 Introduction

Electric vehicles (EVs) show great promise to help reduce emissions of greenhouse gases (Rangaraju, De Vroey, Messagie, Mertens, & Van Mierlo, 2015) and local pollutants such as NO_x, SO_x and PM (Razeghi et al., 2016). Despite these potential environmental benefits, the market share of electric vehicle is still relatively small although it should be noted that sales are rapidly growing (International Energy Agency, 2016). Three major barriers have been identified that prevent large scale adoption of EVs: Range anxiety (Carley, Krause, Lane, & Graham, 2013; Franke & Krems, 2013b), high acquisition costs (Egbue & Long, 2015; Hagman, Stier, & Susilo, 2016) and a lack of (public) charging infrastructure (Egbue & Long, 2015; Krupa et al., 2014). The first two barriers can be overcome by technological developments of batteries that drive down costs. In the last years the price per kWh storage has fallen rapidly (Nykvist & Nilsson, 2015) and automakers are announcing affordable long range cars (200+ miles) for the period 2018-2022, signalling that EVs are becoming available for a wider range of consumers.

As EVs rely on a new refuelling network, the development of (public) charging infrastructure, or Electric Vehicle Supply Equipment (EVSE) infrastructure, is expected to follow the growth of EV sales. However, the deployment of public charging infrastructure faces a chicken-or-egg dilemma. With a low number of EVs on the market today, the business model of charging infrastructure is not viable (Madina, Zamora, & Zabala, 2016; Schroeder & Traber, 2012) and investments in this kind of charging infrastructure is trailing. The development of a public charging infrastructure is however vital for early adopters of EVs especially for those that rely on on-street parking. This problem is particulary prevalent for those that live in multi-unit dwellings or in dense urban areas. Axsen & Kurani (2012) estimate that in the United States only 50% of new vehicle buyers have direct access to minimal level 1 charging, although this varies from region to region. As home charging accounts for approximately 80% of all charging sessions (Idaho National Laboratory, 2015a), facilitating a public charging infrastructure in these areas should be a focus point in accelerating the EV adoption process (Hardman, Tal, et al., 2017).

As the market seems to fail, (local) governments step in to facilitate a public charge network; charging infrastructure development has been at the centre of attention for municipal policy makers to promote the adoption of EVs. They consider efficient planning of charging infrastructure to be important to meet drivers' refuelling needs (Frade, Ribeiro, Gonçalves, & Antunes, 2011), and to satisfy interests of other stakeholders involved (Wirges, 2016). An increase in parking pressure, a problematic business case and potential grid overload are among the conflicts among stakeholders policy makers encounter when considering EVSE-policies (Bakker, Maat, & van Wee, 2014). On the other hand, municipalities are considering other ways to promote EVs including measures such as free parking, access to HOV/Bus lanes and monetary incentives (Bjerkan, Nørbech, & Nordtømme, 2016).

With an expanding market for EVs and EVSEs, interest in studies that measure the effectiveness of policies for EV adoption and of the deployment and management of charging infrastructure is growing (see next section for a review of this literature). However, available studies focus *either* on the (strategic level, long term) policy effects on EV adoption rates *or* on (tactical, short term) policy effects on current EV-owners' usage of public charging infrastructure, missing out on possible cross-pollination between these polices. For example, implementation of highly restrictive policies regarding charging infrastructure may well have a (negative) impact on both charging behaviour of current EV-owners and EV-purchase intentions of current

ICE-owners. Understanding these combined short and long run implications of charging infrastructure demand management is crucial for policy makers who want to avoid triggering unintended policy-effects, and more generally, design optimal policies.

This study fills this crucial knowledge gap by uniquely combining natural experiments and stated choice experiments to estimate the effects of charging policies on both charging behaviour of EV-owners and EV adoption intentions of non-owners. More specifically, based on a large dataset on charging behaviour using public charging infrastructure in the Netherlands the effects of daytime-parking (to manage parking pressure) and free parking (to promote EVs) policies on charging behaviour are analysed. To estimate the effects of these policies on EV purchase intentions a stated choice experiment is conducted among car owners that rely on public infrastructure for charging their EVs. Section 5.2 presents a literature review and identifies the knowledge gaps to be filled with the research in this paper. In section 5.3, the methodology of three experiments to investigate the effect of the two policies is outlined. This section includes a detailed description of the policies and how the experiments were set up and data were gathered. The results of these three experiments are presented and discussed in section 5.4. The last section provides a conclusion and discusses the policy implication of the results.

5.2 Literature review

5.2.1 Charging behaviour

Research on charging behaviour has started with using travel patterns from ICE vehicles and tried to infer charging decisions from these patterns (Liu, 2012; Sathaye & Kelley, 2013). Moving beyond this, exploratory work was done which tried to model the decision to start charging. Franke & Krems (2013a) developed a model in which they incorporated the EV's range, range appraisal by users and specific mobility needs. Franke & Krems (2013a) assumed that if the remaining range dropped below a certain comfortable level and the mobility needs could not be met, the driver would want to charge his car. However, during the evaluation of a trial, they observed high levels of habitual charging behaviour, which seemed to be more opportunity driven in ways comparable to mobile phone battery recharging (Franke & Krems, 2013b). These findings have since then been confirmed in a growing body of literature around the world. Descriptive studies in The United states (Idaho National Laboratory, 2015b), Australia (Jabeen, Olaru, Smith, Braunl, & Speidel, 2013; Speidel, Jabeen, Olaru, & Harries, 2012), England (Robinson, Blythe, Bell, Hübner, & Hill, 2013; Wardle, 2015), Canada (Toronto Atmospheric Fund, 2015), Ireland (Morrissey, Weldon, & Mahony, 2016) and the Netherlands (Hoed, Helmus, Vries, & Bardok, 2014; Spoelstra & Helmus, 2015) confirm such behavioural patterns. In particular, these studies generally indicate two peaks in starts of charging sessions, one in the morning, reflecting "business charging", and one in the late afternoon, reflecting "home charging". These studies identified differences in charging behaviour by type of users (Helmus & van den Hoed, 2015) and described the influence of free charging and other price sensitivities (Idaho National Laboratory, 2015b; Wardle, 2015).

More recently, a body of work has focussed on assessing the determining factors that influence the decision to charge. Using stated preference techniques Wen, McKenzie & Keith (2015) asked drivers about mid-trip charging and found that the State-of-Charge (SoC), dwell time and price are important factors that influence this decision. Jabeen et al. (2013) asked drivers to their most and least favourite option when presented with options for home, workplace and public charging. Time of day, time charging and price were varied across the categories. A strong preference was observed for home charging especially among solar panel owners. Latinopoulos, Sivakumar & Polak (2017) provided additional insight to charging behaviour, by modelling in and out-of-home-charging. They show that out-home-charging is more common for those that have the opportunity to charge at work or when it is offered for free. Daina (2014) has looked at several factors that could influence the decision to delay charging allowing 'smart charging' technologies that could reduce the impact of EVs on the grid. Daina (2014) showed that EV users are willing to allow flexibility as long as this does not influence the range needed for the next trip.

Using revealed preference data Zoepf et al. (2013) looked at charging choices by PHEV drivers with a small battery pack. They found that the number of miles driven on electricity greatly increases if the PHEV is charged every time a car stops for more than 3 hours, an indication that the 'parking is charging' regime is an efficient mode. Using the same dataset as Zoepf et al. (2013) and a matching dataset with electric vehicle charging stations Yu & MacKenzie (2016) examined charging location choices in more detail. Their results showed a better model fit, but similar conclusions were drawn from the data. Using data from full electric vehicles, Sun, Yamamoto, & Morikawa (2016) studied fast charging choices in Japan. They found that users are willing to detour up to 1.75 km on working days and 750 meters on non-working days. A remarkable finding is that even at fast charging stations the SoC at which drivers initiate their charging sessions is on average over 50%, this in contrast with the assumptions in many planning studies that fast charging is mainly done with low SoC (Shahraki, Cai, Turkay, & Xu, 2015; Zhang, Shaffer, Brown, & Samuelsen, 2015). More recently Xu et al. (2017) have looked at linkages between charging station location, timing and mode of charging. They estimated a joint charging mode and location model on actual charging sessions showing that the time has a strong correlation with mode and location and that a dense and free public charging infrastructure results in an increasing number of public charging sessions.

In sum, the charging behaviour literature has over time developed from modelling exercises, including those based upon ICE travel patterns, into more descriptive and explanatory empirical work, as real world charging data are becoming more and more available. Whereas earlier work was mostly focused on assessing the factors determining the decision to start charging, more recent (modelling) work has focussed on capturing heterogeneity across EV drivers using more sophisticated discrete choice models. The number of factors and model structures that have been considered is growing but still limited, and many factors that play a role on other than the starting-dimension of the charging behaviour (e.g. location, duration) have not yet been explored empirically. Finally, the effects of policies that were designed to influence charging behaviour have only been investigated in stated preference studies.

5.2.2 EV purchase intentions and charging infrastructure

A large and growing body of literature has investigated the factors that play a role in the EV purchase intention. Three recent literature reviews (Coffman, Bernstein, & Wee, 2016; Liao, Molin, & Wee, 2017; Rezvani, Jansson, & Bodin, 2015) have analysed the findings from over 50 different studies. They find evidence that internal factors, the EV properties, especially range and price have a large effect on purchase intention. The evidence for external factors such as fuel prices and consumer characteristics is mixed. Especially in studies with revealed preference data these effects are found to be insignificant. Significant effects are found for financial policy measures (Hardman, Chandan, et al., 2017) which directly influence the internal factors of the car. Policy measures such as free parking (Cherchi, 2017; Fearnley, Pfaffenbichler, Figenbaum,

& Jellinek, 2015; Hoen & Koetse, 2014) and access to HOV/Bus lines (Bjerkan et al., 2016; Chorus, Koetse, & Hoen, 2013) have provided mixed evidence in support of a positive effect on EV purchase intention.

Although the need for public recharging is generally low, especially in multi-car households, if home charging is available (Jakobsson, Gnann, Plötz, Sprei, & Karlsson, 2016), a lack of it would hamper market adoption. The number of studies that have taken into account the effect of charging structure on EV-purchase intentions is limited. The effects of (perceived) EVSE availability on stated purchase intentions have been assessed by studies of Carley et al. (2013) and Bailey, Miele & Axsen (2015). Both studies show weak or no significant correlations between recalling public EVSEs and the willingness to buy an EV. More important was the possibility of installing charging equipment at home. These studies also showed that awareness of EVSEs is low at the time the surveys were taken, which was 2011 and 2013 respectively. In the first study only 12% or respondents recalled having seen a public charger and in the second study only 18%. More recently, Cherchi (2017) has taken into account charging infrastructure availability and other parking policies and found that availability did have a positive effect on purchase intention; this study however focussed on availability of charging infrastructure away from home. Ensslem, Jochem, Schäuble, & Babrowski (2013) also find that interoperability across charging station and borders, especially in border regions, is mentioned as an important factor driving purchase decisions.

Gnann & Plötz (2015) reviewed several studies that looked at the interaction with infrastructure and EV adoption. They compare various studies which also looked at other AFVs such as natural gas and hydrogen and discussed the peculiarities of electric vehicles. They find that for a successful introduction infrastructure should be directly available, the business case for infrastructure has to viable on short or medium long term and fuel prices have to be below ICE alternatives. For the EV market they find that infrastructure should be more widespread because of longer refuelling times but that a large part of this could be dealt with due to the possibility to recharge at home.

A more top-down approach is adopted by a number of studies that use sales figures to assess the impact of charging infrastructure on the adoption of EVs. Comparing the adoption rates and their policy incentives across different countries, Sierzchula et al. (2014) found that charging station investments were twice as effective as tax benefits in promoting the sales of electric vehicles. Mersky, Sprei, Samaras & Qian (2016) have looked at municipal and regional adoption rates in Norway and also found that charging infrastructure presence had a significant positive effect on the number of EV purchases. They do note that the direction of this correlation is difficult to determine as charging stations are also build in response to local EV demand. Li et al. (2017) try to address this problem by modelling network effects in the sales of EVs in 353 metropolitan areas in the United States. Taking these effects into account they still find that investing in charging infrastructure is twice as effective as direct financial incentives. These results are thus well in line with the findings of Sierzchula et al. (2014).

5.2.3 Knowledge gaps and contributions

In sum, a large number of studies have focussed on the factors, including policy interventions, that determine EV-purchase intentions, showing that the properties of EVs themselves play a dominant role. The role of charging infrastructure policies is still under debate, as stated preference studies find only small effects of actual availability of public infrastructure even though absence of a home charging opportunity is seen as a crucial obstacle. Revealed preference studies find positive effects but have difficulty determining the direction of causality when assessing the impact of public charging infrastructure on EV sales. However, the number of studies is growing, including comparisons with other AFVs; results presented in these studies provide preliminary evidence for a positive effect of charging infrastructure availability on EV sales. No specific studies were found that took into account the design of policies for optimizing the utilization of public charging infrastructure and their effects on EV-purchase intentions. The latter is vital especially for those prospective EV-owners who live in urban environments without private parking facilities, as for them, charging at home in public is likely to be the dominant mode of charging.

This research contributes in three different ways to the current understanding of charging behaviour and EV purchase intention. The first contribution is to assess the effectiveness of certain policies that try to control charging behaviour; to this aim, we use a large dataset of actual charging sessions of public charging infrastructure, under different policy contexts. Secondly, using a stated preference experiment, evidence is provided for the importance of charging infrastructure availability on the purchase intention of EVs. The experiment focuses explicitly on those prospective owners who do not have private parking facilities (as is the case in many highly urbanized areas throughout the world), and therefore rely on on-street parking facilities and public charging infrastructure. This group has so far been ignored in the literature. The last and main contribution of this study lies in combining and cross-linking charging behaviour control policies with purchase intention and EV purchase policies with charging behaviour. Connections between these policy- and behavioural dimensions have so far not been made. A visual representation of the concept that is studied in this research is given in *Figure 5.1*, where dotted lines indicate the new area of research and solid lines the current state of the art.

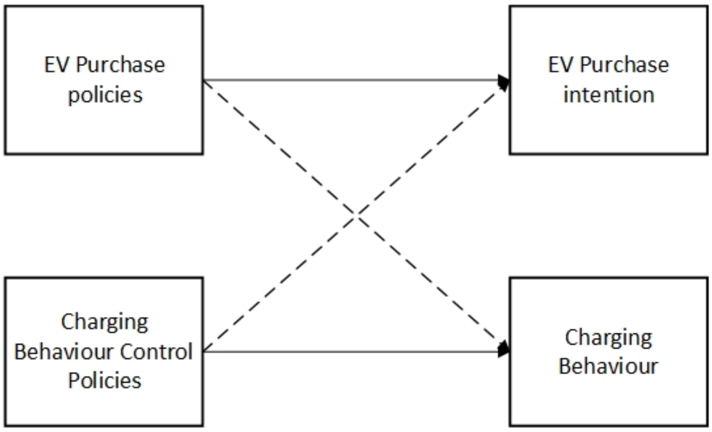


Figure 5.1 Model of policies influencing EV purchase intention and Charging Behaviour

To investigate these relationships, case studies of such policies are investigated in this paper. More specifically, we study a unique combination of three different experiments in which two policies are considered. These two particular policies are selected because they illustrate how policy makers at the local level are trying to deal with different interests of stakeholders. More specifically, following the framework developed in *Figure 5.1*, our case studies are interesting to consider because they concern policies that can simultaneously have desirable and unwanted side effects on EV purchase intentions and charging behaviour. Furthermore, the fact that these policies have already been implemented in the Netherlands at a relatively large scale provides the opportunity to systematically analyse these effects. Additionally, the chosen case studies are selected for providing us with very advantageous ‘natural experiment’ conditions for *daytime charging* – as well as with comparable conditions across four cities which allows us to control for many spatial-temporal effects for *free parking*. This combination of factors makes the two selected case studies ideal for investigating the impacts of local EV- and charging-related policies.

First, as a charging behaviour control policy, a *daytime charging* policy is investigated. This policy aims to reduce the impact of charging stations on parking pressure. This case study provides a good example of policies that are relevant in dense urban areas with a lot of on-street parking facilities. Moreover, it is a typical transition policy in which municipalities try to cope with interests of different actors, in this case the EV and non-EV driver. Literature in the EV adoption domain also suggests that perceived barriers in refuelling behaviour can be an obstacle in purchasing an EV (Egbue & Long, 2015) making it possible to investigate the conceptualised cross-link. The second case study concerns a *free parking* policy. *Free parking* is often mentioned and studied as an EV purchase policy for which the evidence is a mixed bag, this paper provides additional insight in the effect of this policy for prospective owners with private parking facility. The cross-link between EV purchase policies in charging behaviour is also relevant as evidence from the parking literature (Shoup, 2005) suggests that this policy can have an effect on the parking and charging behaviour of EV-owners.

5.3 Methodology

This paper estimates the effects of two local policies on charging behaviour and purchase intention: (1) daytime charging to alleviate parking pressure due to unoccupied parking spots at charging stations and (2) free parking for electric vehicles (while these are connected to the charging station) to promote the sales of electric vehicles. In the following, we will elaborate on these specific policies.

5.3.1 Experiments

5.3.1.1 Daytime charging

Municipalities are advised to exclusively reserve parking spots next to public charging stations to ensure availability for electric drivers. When charging stations are underutilised compared to average parking occupancy this can lead to increased parking pressure in neighbourhoods with relatively abundant charging infrastructure. To deal with this problem, municipalities can implement a daytime charging policy. Daytime charging implies that the parking spot next to a charging station is exclusively reserved for electric vehicles for the indicated part of the day. A street sign (see *Figure 5.2*) is put up to indicate the designated times. Beyond these hours both electric and gasoline driven cars are allowed to use the parking spot, in order to relieve parking pressure at the most strenuous times.

Figure 5.2 Street sign to indicate that parking spot is exclusively reserved for charging vehicles between 10:00 and 19:00

With regard to the effects on charging behaviour, it is expected that this policy will increase the difficulty of EV drivers to access charging stations after 19:00 as non-EV users can also park at these spots making. Occupation of the charging station is therefore expected to be lower in the hours beyond 19:00 at charging stations with the daytime charging policy implemented. Should this be the case, the policy has the intended effect of relieving parking pressure in the area surrounding the charging station. As a second-order effect on purchase intentions, it is assumed that the daytime restriction will reduce the purchase intention for EVs, since home charging availability is an important factor in EV adoption (Carley et al., 2013). Hence, if uncertainty arises about availability because of the daytime charging policy, this could reduce EV purchase intention.

The municipality of The Hague (The Netherlands) implemented daytime charging starting in January 2013 at charging stations in areas in which parking spot occupancy was over 90%. In total, 79 charging stations were selected, but due to an unknown error at the municipal services, 20 charging stations did not receive a daytime charging sign; the resulting random assignment of policy-measures created the ideal conditions for a natural experiment. This is important, as it rules out potential endogeneity effects (e.g. policies being implemented in response to observed behaviour such as in this case, high on street parking rates); this allows for a clear identification of causality when studying policy effects on behaviour. Daytime charging was set between the periods 10:00 and 19:00. Charging stations in areas with parking pressure below 90% remained exclusively available for EVs. By September 2015 the municipality corrected the error and also put up the road signs at the 20 charging stations that first did not have this sign installed.

The occupancy of the charging stations during and beyond the daytime charging times is compared, to estimate if the policy has an effect on charging station occupancy. Our analysis focuses on the increase in charging station occupancy after 19:00 as this is line with the policy. The increase between 19:00 and 0:00 is chosen as measurement value as profiles show that, on average, after 0:00 the increase in occupation is minimal. Using linear regression models the effect of the daytime charging policy is statistically evaluated while controlling for three factors: Spatial characteristics of the surroundings, if the charging station is in a paid parking area and the number of parking spots reserved alongside the station (1 or 2).

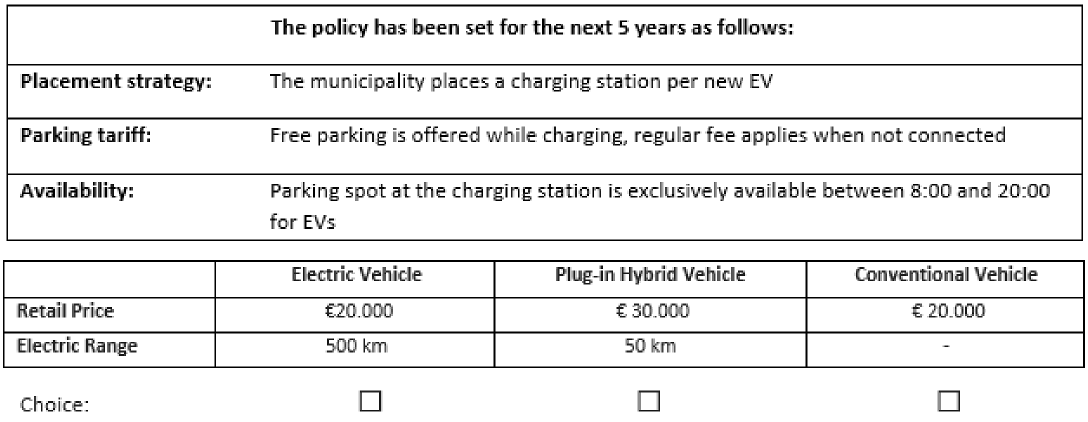
5.3.1.2 Free Parking

An often mentioned policy to increase EV sales is free parking for electric vehicles (Bjerkan et al., 2016; Sierzchula et al., 2014). Based on a literature overview, Liao et al. (2017) find, however, that the evidence for a positive effect of this policy is mixed. Despite the inconclusiveness of the currently available research it remains a popular incentive for municipalities to implement this policy, as it provides a direct and visible incentive for potential buyers. Parking literature suggests that a side effect of this policy could be that parking duration increases (Shoup, 2005). An increase in parking duration could lead to inefficient use of charging resources as longer connection times do not necessarily impose more charging. In turn high occupancy may increase difficulty of EV drivers to find a charging spot and may drive down business case due to lower daily usage.

Free parking policies can be executed in two different ways. First, free parking can be offered everywhere in a city for electric vehicle even when it is not charging. Second, free parking can be offered only when the EV is connected to a charging station. The second version is considered in the experiment that is evaluated, with the constraint that the policy only holds for on-street parking spots and not for parking garages. Note that the considered policy holds both for inhabitants and visitors. The expectations are that this policy results in an increase in the time that the EVs are connected to the charging station in line with current insights from ‘regular’ parking. This aspect will also hold for inhabitants as they do not have an incentive to move their car once it is fully charged as they have to move their car into a paid parking spot. The city of Utrecht has implemented a free parking policy for EVs, which will be continued until at least the end of 2017. Free parking is only offered when the EV is actually connected to the charging station. Parking at regular parking spots requires paying a parking fee or having a parking permit. To assess if EV-connection duration is actually longer in paid parking areas were EVs are allowed to park for free we estimate an ordinal logistic regression model of (EV-) parking/connection duration. In this model we predict an (ordinalised) measure for parking duration in Utrecht as well as several other municipalities, while controlling for time and space differences for each charging session.

5.3.1.3 Purchase intention

To estimate the impact of abovementioned policies on the purchase intention a stated choice survey was conducted. In this survey respondents were asked to make a choice among three types of vehicles (EV, PHEV and Conventional) each with a certain price and range. Each choice was made under a different policy setting. The policy setting included variations of the daytime charging and free parking policy and additionally included the placement strategy of the municipality. *Figure 5.3* gives an example of the choice task that respondents faced.



	The policy has been set for the next 5 years as follows:
Placement strategy:	The municipality places a charging station per new EV
Parking tariff:	Free parking is offered while charging, regular fee applies when not connected
Availability:	Parking spot at the charging station is exclusively available between 8:00 and 20:00 for EVs

	Electric Vehicle	**Plug-in Hybrid Vehicle**	**Conventional Vehicle**
Retail Price	€20.000	€ 30.000	€ 20.000
Electric Range	500 km	50 km	-
Choice:	☐	☐	☐

Figure 5.3 Example of a choice task

Policies were represented as context variables which were told to be valid for the 5 years to come and which were varied across choice sets (Molin & Timmermans, 2010). Placement strategy was varied in which municipalities placed a charging station per every 1, 2 or 4 new EVs. Parking fee policy was noted as either being free, free while charging or with a regular tariff applied. The availability of the parking spot was noted as either exclusively available for EVs, or as daytime charging between 8:00 and 22:00, or as being always available for all type of vehicles. Retail prices for EVs and PHEVs were varied (€20k, €25k and €30k); for the conventional vehicle these were held constant at €20k. Electric range for the EV (200km, 350km, 500km) and the PHEV (25km, 50km, 75km) were also varied across alternatives. The experiment had a 3^3 dimension for the policy context and 3^4 dimension for the vehicle characteristics. Taguchi (1987) orthogonal arrays were used to develop the choice sets. The total of 81 choice sets were blocked by 3 policy designs to reduce the choice load for respondents. Each respondent was faced with 9 choice sets and thus 3 different policy scenarios. Respondents were also informed about other characteristics of the vehicles such as the gasoline range, fuel price per km, road taxes and charging speed. A detailed list can be found in *Appendix 5.A*. Information was kept constant among the choice sets and represented at each choice.

To account for heterogeneity in preferences the data are analysed using mixed logit models (Train, 2009). The Bison Biogeme software package is used to this end (Bierlaire, 2003). Constants are estimated for the electric and conventional vehicle; the utility function of the plug-in hybrid vehicle includes both these constants. Policy variables are only included for the EV and PHEV utility functions as they do not apply to the conventional vehicle. Models were tested with 125 to 1000 Halton draws; estimates remained constant if the numbers of draws were increased.

5.3.2 Data Collection

5.3.2.1 Daytime charging

The effects on charging and parking behaviour of the daytime charging policy experiments are evaluated using data on charging sessions from public charging stations in The Hague, the Netherlands. Charging stations can be used by swiping a RFID card, identifying the user. Data is stored for each charging session and provided by several charging point operators to a central database. The data contains relevant information about the location and timing of the charging session and provides an anonymous code to identify the user.

The entire database contains 146,977 charging sessions in the city of The Hague during the period of January 2014 to September 2015. Additional information about which charging stations had daytime charging implemented at which time was provided by the municipality of The Hague. Selecting only charging stations that were eligible for the daytime charging policy (79 out of 392 in total) left 21,023 charging sessions. After filtering out sessions above 100 kWh (as no cars have battery packs above 100 kWh) and sessions shorter than 1 minute, which both are considered as erroneous, 20,856 charging sessions remained for our empirical analyses. The data were then aggregated per charging station and hourly level for each weekday, to calculate the average occupancy rate of each charging station and the relative number of charging sessions per hour. Each charging station has two sockets, which implies that when only one of the sockets is used the occupancy ratio is 50%. Average occupancy rate per hour is calculated from the date the charging station is first used until the set end-date of the dataset, 23:59 August 31st 2015. For the average occupation ratio only the weekdays are taken into account, as weekend charging can show very different behaviour and parking related problems are usually very different as well. *Table 5.1* shows the descriptive statistics of the data presented for each of the groups.

Table 5.1 Descriptive statistics of charging stations

	No. of charging stations	
Total	**79**	
Policy		
Daytime parking	59	
No daytime parking	20	
Dedicated parking spots		
1	26	
2	53	
Paid parking		
Paid	43	
Free	36	
	Mean	**SD**
Area Living (% total buildings in the sub-district)	48.58%	23.00%
Area Business (% total buildings in the sub-district)	6.72%	10.79%
Area Public (% total buildings in the sub-district)	1.23%	3.24%

To control for spatial differences in both the analyses, data on the percentage of buildings used for housing, business, social and public are retrieved from the Dutch Central Bureau of Statistics (CBS Statline, 2016) and are matched to a charging station at the sub-district level. Information about the number of reserved parking spots and paid parking areas was provided by the municipality of The Hague. Variables that served as a proxy for charging station density were tried but were found to be insignificant.

5.3.2.2 Free Parking

To examine the effect of free parking (for EVs) on EV-charging behaviour we analyse charging data of the four major cities in the Netherlands (Amsterdam, Rotterdam, The Hague, Utrecht) in 2015 and 2016. Of these four cities, only the city of Utrecht has implemented a policy that allows free parking for EVs while they are charging. For this analysis, the same source is used as in the case of daytime charging in The Hague (see previous section). In this case, over 1.7 million charging sessions are selected. The charging session data were enriched with data on paid parking areas of all cities, which were matched to the GPS locations of the charging stations using the *sp* package in R Studio (Bivand, Pebesma, & Gomez-Rubio, 2013; Pebesma & Bivand, 2005).

Table 5.2 shows the descriptive statistics of the selected charging sessions and the mean connection times for the various categories. The connection time of charging sessions was not normally distributed, but showed two peaks (of 0-4 hours and 8-16 hours connection time or duration). As this would violate the assumptions of linear regression, the decision was made to recode the connection time (our dependent variable) into an ordinal variable and perform an ordinal regression analysis. To this end, the following categories were used: 1: 0-6 hours; 2: 6-16 hours; 3: 16-24 hours; 24+ hours.

Table 5.2 Descriptive statistics for analysis data free parking policy

Variable	% Of charge data	Mean Connection time	SD Connection time
Cities			
Utrecht	13%	10.59	11.79
Amsterdam	47%	10.83	19.83
Rotterdam	22%	10.29	27.39
The Hague	17%	10.38	18.43
Total sessions	2,124,960		
Total	100%	10.60	20.76
Paid	*66%*	*10.81*	*22.78*
Free	*34%*	*10.18*	*15.93*
Utrecht	13%	10.59	11.79
Paid	*48%*	*11.41*	*13.09*
Free	*52%*	*9.83*	*10.41*
Amsterdam	47%	10.83	19.83
Paid	*85%*	*10.89*	*20.72*
Free	*15%*	*10.51*	*13.55*
Rotterdam	22%	10.29	27.39
Paid	*48%*	*10.39*	*36.93*
Free	*52%*	*10.19*	*12.92*
The Hague	17%	10.38	18.43
Paid	*54%*	*10.54*	*12.22*
Free	*46%*	*10.18*	*23.77*
Time of Day			
Morning (5:00-10:00)	15%	6.54	13.83
Afternoon (10:00-16:00)	30%	8.17	23.64
Evening (16:00-22:00)	46%	13.02	18.57
Night (22:00 – 05:00)	10%	12.67	27.08
Part of the week			
Week	61%	10.02	20.65
Weekend	39%	11.51	20.89
Year			
2015	38%	10.64	23.65
2016	62%	10.57	18.75
	Mean	**SD**	
Area Living (% total buildings in the sub-district)	48.58%	23.00%	
Area Business (% total buildings in the sub-district)	6.72%	10.79%	
Area Public (% total buildings in the sub-district)	1.23%	3.24%	

In the analysis the results are controlled for spatial-temporal differences as is common in parking literature (Kelly & Clinch, 2009; Pu, Li, Ash, Zhu, & Wang, 2017). The same spatial variables are used as in the daytime charging study; we expanded this set with dummy variables identifying each of the cities. The city of Amsterdam is used as reference level for these city level factors. In terms of temporal differences, the starting time of the charging session is used to derive the time of day and the day of the week in which the charging session takes place. The day of the week is dummy coded for week versus weekend days (Friday, Saturday, Sunday) in which weekdays are the reference level. For time of day, the evening serves as a reference. Additionally, the year was included as a control variable (with 2015 serving as the reference level).

5.3.2.3 Purchase intention

It was hypothesized that public charging station policy of a city was mostly relevant for those that make most use of it. Those that have the possibility to install their own charging station at home are very unlikely to make use of the public infrastructure within the same city. Respondents for the stated preference study were therefore recruited among citizens that did not have their own parking facility and therefore required on-street parking. Respondents were recruited by distributing letters in the cities with an active charging infrastructure policy (Rotterdam, The Hague) and without such a policy (Leiden, Delft) with a request to participate in an online survey. Additionally, to prevent a positive EV bias (Smith, Olaru, Jabeen, & Greaves, 2017), people were recruited face to face with a similar paper version of the stated preference study. The survey started with a question on whether or not the respondent had a drivers' license, a negative answer resulted in exclusion from the experiment.

Respondents were asked to perform 9 choice tasks in which they were asked to choose which car they would purchase. Data was collected using an online (112 respondents) and paper-and-pencil (37 respondents) totalling 149 useful responses and 1327 choice observations. *Table 5.3* displays the demographics of the respondents.

Table 5.3 Demographic distribution of respondents

Age	<35 years	23%
	35-65 years	57%
	>65 years	20%
Income	<€25,000	13%
	€25,000 -€45,000	17%
	>€45,000	51%
	Unknown	19%
Gender	Male	70%
	Female	30%
Education level	Higher education	70%
	College	24%
	High School	6%
Full Employment	Yes	62%
	No	38%
No. of cars	0	11%
	1	64%
	2	19%
	2+	6%

The demographics show that males, higher educated and high income respondents are over represented in comparison to the general population (CBS, 2016). Employment rate of the respondents is relatively low but can be explained by a significant number of elderly (>65 years) that participated in the experiment. 11% of respondents answered that they did not own a car, but these respondents did indicate that they considered buying a car in the next 3 years. These numbers suggest that sufficient heterogeneity exists to identify possible socio-demographic interactions. Deviations from socio-demographic distributions in the population at large imply that estimation results should not be translated directly into population wide estimates of policy effects. Since the aim of this study was to identify the existence and size of policy effects, rather than attempting to predict market shares for EVs in the population, we consider our data to be sufficient.

5.4 Results

5.4.1 Daytime charging policy: Effect on charging behaviour

Figure 5.4 shows the average occupancy ratio over the day during the period January 2014 – August 2015 for the two categories of charging stations. It can be seen that the average occupancy (by EVs) is relatively low, i.e., 15% during the daytime and 25% during the night time. It can also be observed that charging stations with daytime charging policies have nearly the same occupation throughout the day and higher occupancy during evening and night times. For charging stations without daytime charging policies a more distinct profile is visible with higher occupancy in the night and a lower occupancy during day time. This clearly suggests that the implemented policy is effective in reducing usage of charging stations as mere (free) parking spots by EV-owners, especially during the evening and night time.

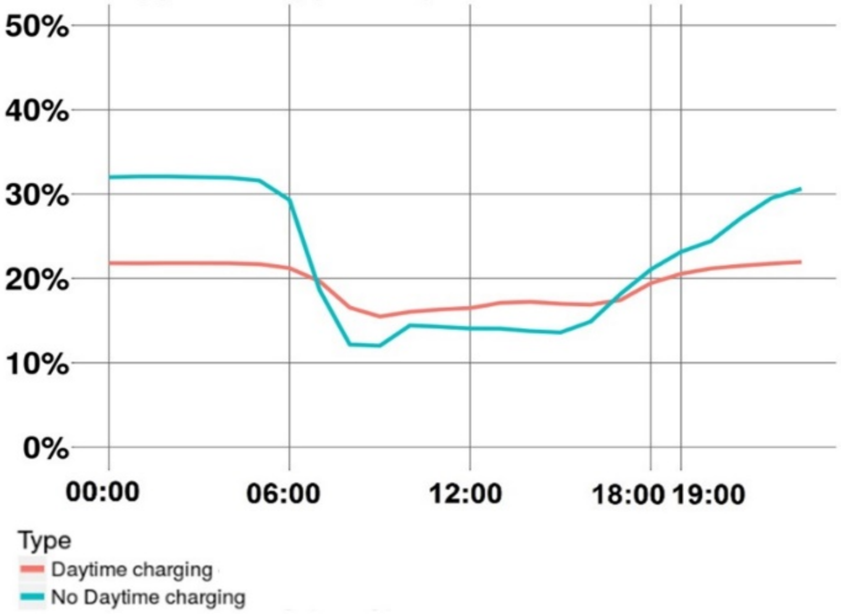


Figure 5.4 Charging station occupancy throughout the day for daytime and no daytime charging for 2014- August 2015

To assess whether the day-time charging policy has a statistically significant effect on the (average) occupancy ratio, while controlling for possible confounding factors, a linear regression is performed using the change in occupancy rate between 7 PM and midnight as the dependent variable. A positive (negative) sign for an estimated parameter implies that an increase in the associated variable leads to an increase (decrease) in the increase in occupancy rate. Expectations – based on intuition and inspection of *Figure 5.4* – are that there will be a negative effect associated with the Daytime charging policy. The results of the linear regression (*Table 5.4*) show that charging stations which have the daytime charging policy implemented have, as expected, less increase in occupancy rates between 19:00 and 0:00, compared to those stations without this policy. The model shows that implementation of the daytime charging policy leads to 3.6 percentage points less increase in occupancy, when controlling for other factors; a modest but significant effect. This result implies that the policy reaches the intended effect which is making room for non-EV drivers looking for a parking spot. Although parking sessions of these vehicles are measured indirectly the results clearly suggest that these parking spots have become inaccessible for EV drivers because they are occupied by non-EVs.

Table 5.4 Results of linear regression on charging station occupancy increase between 19:00 and 0:00 before September 2015

	Estimate	**Std. Error**	**t value**
Intercept	0.008	0.014	0.62
Daytime charging	-0.036*	0.006	-5.79
Area living	0.039*	0.019	2.01
Area business	-0.051	0.037	-1.38
Area public	-0.191*	0.086	-2.21
2 Dedicated parking spots	0.029*	0.006	4.79
Free parking	0.006	0.006	1.06
R2	0.189		

*significant at the p<0.05 level

While not of direct interest in the present study, the effects of the control variables are plausible. For example, in areas with more buildings dedicated to housing the occupancy increase between 19:00 and 0:00 is larger. This can be explained by the fact that EV drivers arrive at home after work in these hours. Areas with more buildings dedicated to businesses have no significant effect on occupancy increase and areas with a more public function show a negative impact on occupancy increase in the evening. This effect is plausible as such building often have opening hours during the day. If the charging station has two dedicated parking spots for electric vehicles this positively influences the increase in occupancy rate. This is also a logical effect, as availability could be limited by ICE vehicles parked next to the charging station. No significant effect was found for free parking, which is also plausible as most users between 19:00 and 0:00 are residents with a parking permit, cancelling out the effect of parking prices.

5.4.2 Free parking policy: effect on charging behaviour

The results of the ordinal regression are shown in *Table 5.5*. A positive (negative) parameter suggests that an increase in the associated variable leads to an increase (decrease) in connection duration. Focussing on the free parking policy, the attention should go to the interaction between the 'city of Utrecht'-dummy coefficient and the paid parking-coefficient. Within this particular paid parking area, free parking for EVs is offered. The fact that the interaction is positive and significant indicates that connection times in this area are longer, compared to paid parking areas in other cities. In other words: offering free parking for EVs in a zone which requires paid parking for conventional cars results in longer EV-connection times; this is in line with expectations. The results also show that the effect of paid parking Utrecht is larger than the paid parking parameter, showing that connection duration of sessions in Utrecht is actually longer inside paid parking areas than outside. An explanation for this finding is that, although free parking for EVs applies in both areas, EVs are more restricted to the spot at the charging station because paid parking applies at parking spots next to the charging stations. Therefore, users are de-incentivised to move their car once it is fully charged because they have to pay a parking fee if they move their car.

Table 5.5 Results of Ordinal regression on connection duration

	Estimates	**Std. err.**	**t-value**
Paid Parking	-0.136 *	0.005	-24.89
Cities			
Den Haag	-0.116 *	0.007	-16.84
Rotterdam	0.026 *	0.006	4.14
Utrecht	-0.129 *	0.007	-18.10
Time			
Afternoon	-1.790 *	0.004	-468.83
Night	0.216 *	0.004	57.35
Morning	-1.219 *	0.004	-312.50
Weekend	-0.017 *	0.003	-6.19
Year 2016	-0.009 *	0.003	-3.39
Spatial characteristics			
Area living	0.730*	0.007	98.23
Area business	0.019	0.015	1.33
Area public	0.340*	0.047	7.28
Interactions			
Paid Parking * The Hague	0.191*	0.009	22.43
Paid Parking * Rotterdam	0.045*	0.008	5.75
Paid Parking * Utrecht	0.298*	0.009	32.573
Intercepts			
0-6 -> 6-16 hours	-0.566 *	0.007	-83.82
6-16-hours -> 16-24hours	0.063*	0.007	9.349
16-24 -> 24+ hours	2.711*	0.007	377.29

*Significant at the $p < 0.05$ level

The controlling factors show that in general parking in paid parking areas is shorter than in non-paid parking areas, which is in line with general parking theory although the effect is much smaller than expected, most likely because a large number of regular users (which have parking permits) make use of the charging infrastructure. Small differences exists between the cities, for which several reasons can exist, e.g. charging infrastructure roll-out intensity and city lay-out. Time factors play an important role in determining the length of the charging session. Charging sessions starting in the evening and night last much longer because these cars stay connected overnight. In the afternoon a lot of short sessions take place, while in the morning such sessions are combined with ‘workplace’ charging resulting in slightly longer sessions than in the afternoon. Differences between week and weekend session and in 2015 and 2016 are minimal. Areas with a focus on housing have longer sessions, most likely because users also stay here overnight. Buildings dedicated to business have no significant effect on charging times while built environment with a public function leads surprisingly to longer charging times.

5.4.3 Purchase intention

In *Table 5.6* the results of the mixed logit model are presented. All variables are modelled as continuous variables as this specification provided the best model fit (adjusted for parsimony). Interactions with several socio-demographic variables have been tested but since these did not provide significant results they are left out of the final model (note that this too, suggests that the fact that our respondents are not fully representative of the population in terms of socio-demographic dimensions, is inconsequential). A multinomial model has been tested as well (Final LL = -1389.428) but the mixed logit model provided the best fit, suggesting that there were high levels of heterogeneity in unobserved utility.

Placement strategy of charging stations is the policy with the largest effect on FEV and PHEV purchase intention in the model estimation. It is effect is nearly twice as big as the parking fee policy and almost three times larger than the effect of availability policies. The parameters show that having to share the public charging station with more owners has a negative impact on FEV and PHEV purchase intention. The effect was found to be more than twice as big for FEV as for PHEV. This makes sense as certainty about the availability of a charging station at home is less important for PHEVs as they have a gasoline back-up. The parameter for the parking fee policy on FEV is significant and negative, showing that offering cost reductions in parking fees is a positive influence on FEV purchase intention. Such an effect was, however, not found for the PHEV which is in contrast with our expectations; it was expected that PHEV drivers would be relatively sensitive to financial policies. The results give an indication that offering free parking could be more effective to enhance sales of FEVs compared to sales of PHEVs. The availability policy, which included the daytime policy has a significant and positive sign for the FEV but is not significant for the PHEV. This indicates that making parking spots next to charging stations exclusively available for EVs could enhance EV sales. The model shows that restricting this exclusivity, by implementing daytime charging or allowing ICE vehicles to park next to charging stations, reduces the purchase intention for FEVs. Such an effect is not found for PHEVs which could be explained by the same reasons as in the placement policy; PHEVs have a back-up option if the charging station is not available.

Constants for the EV are large, mainly because price is not included in the utility function for the gasoline car (as it did not vary across gasoline car alternatives). The sigmas for both EV and conventional are large compared to the constants indicating that base preferences for either electric or gasoline driven cars vary across respondents significantly. Separate beta’s were estimated for the price for FEV and PHEV (-0.224 and -0.209 respectively) but this gave a reduction in model fit (Final LL = -863.268). As the beta’s did not differ a lot a single price parameter was estimated. The results show that price plays an important factor in the purchase decision as was hypothesized. Separate betas for the range were estimated as different effects were expected. The results show that range for FEV is significant and positive, implying that purchase intention increases with range. The range parameter for PHEVs is however not significant. This was expected as we hypothesized that PHEV users mainly use their car for short (e.g. home-work) distances and range therefore would not be important.

Table 5.6 Results of Mixed Logit Model

Estimates	**Value**	**Rob. Std.**	**90% confidence interval**		**Rob. t-value**	**p-value**
			Low	*High*		
Constant EV	6.410	1.000	-1.392	1.250	6.39	0.00
Constant Conventional	-0.071	0.800	4.765	8.055	-0.09	0.93
Price	-0.217	0.026	-0.260	-0.174	-8.34	0.00
Range EV	0.005	0.001	0.003	0.007	4.42	0.00
Range PHEV	0.000	0.004	-0.006	0.007	0.08	0.94
Placement EV	-1.110	0.203	-1.444	-0.776	-5.44	0.00
Placement PHEV	-0.485	0.181	-0.783	-0.187	-2.68	0.01
Parking Fee EV	-0.617	0.185	-0.921	-0.313	-3.34	0.00
Parking Fee PHEV	-0.089	0.158	-0.350	0.170	-0.57	0.57
Availability EV	0.448	0.188	0.139	0.757	2.39	0.02
Availability PHEV	0.055	0.167	-0.219	0.330	0.33	0.74
Sigma EV	3.940	0.606	2.943	4.937	6.51	0.00
Sigma Conventional	3.900	0.428	3.196	4.604	9.10	0.00
Number of observations	1327					
Number of individuals:	149					
Null log likelihood	-					
Final log likelihood	-860.243					
_P_2	0.408					

The estimate for the Willingness-To-Pay (WTP) for range (€22.40/km) is at the low end of the spectrum observed in the meta-study performed by Dimitropoulos, Rietveld, & Ommeren (2013). Dimitropoulos, Rietveld, & Ommeren however also included different type of alternative fuel vehicles and includes studies that date back to the 1970s. Due to advances in battery prices and more EVs on the road with greater range making range could have become a less valuable attribute of the electric car. Our results are in line with more recent findings in Germany (Hackbarth & Madlener, 2013) which have found a WTP of €16-€33 per km of electric range. WTP for sharing a charging station with one EV less is €2248-€2557 which is somewhat above the price of installing a private charging station of +/- €1500 (Madina et al., 2016). The willingness to pay for free parking (€1421) far exceeds the costs of a parking permit in the study areas (+/- €150 annually) (Municipality of Leiden, 2017). Respondents could have taken into account that they do not have to pay for this permit for several years and that free parking could be applicable in other cities as well.

5.5 Conclusion and policy implications

This paper has investigated the research gap consisting of the cross-links between the effects of EV purchase and charging policies. Our literature review shows that a growing body of research has shed light on the factors determining the purchase (intention) of prospective owners for EVs and that more real world information is becoming available on how the charging of EVs can be controlled by charging behaviour management schemes. Research on the cross-links between these policy-effects has however been missing so far. This paper has filled this gap by analysing the effects of two case studies, concerning daytime charging and free parking, on both charging behaviour of EV-owners and on purchase intentions of non-owners, through an unique combination of natural and stated choice studies. We have focused on the context of public charging stations in dense urban areas.

Regarding daytime charging policies, our findings indicate that this policy is indeed effective in decreasing parking pressure due to underutilised EV-charging stations. Occupation of charging points in the evening appears to be lower where daytime charging policies are implemented. The results of our choice experiment however shows that creating uncertainty about the availability of charging stations near home, through e.g. daytime charging, reduces the purchase intention for full EVs.

Concerning free parking policies (for EVs), our results show that offering free parking has a positive effect on the purchase intention of full EVs. However, our analysis of this policy as implemented in the city of Utrecht and its effect on the connection duration of charging sessions shows a possible negative side-effect of this policy. Compared to other cities and even in free parking areas, we find that charging sessions in Utrecht were considerably longer than elsewhere, also when controlling for a variety spatial-temporal characteristics.

The results of our case studies show that investigating these cross-links between EV purchase policies, EV charging policies and there intended effects is a relevant subject of study, as these cross-effects may be non-trivial. The case study concerning free parking policy shows that, on the one hand, the policy could have a positive effect on purchase intention, while, on the other hand, it also influences the connection duration of charging sessions, which could lead to inefficient use of charging stations. Vice versa, this paper shows through a case study of daytime charging that controlling charging behaviour (through charging demand management measures) can be effective but that such a restrictive policy negatively influences EV-purchase intentions. Although the cross-effects of such policies do not appear to be dominant in either determining charging behaviour or purchase intention, they are too important to ignore by policy makers who aim to design policies that are effective at one level (e.g. stimulating EV-ownership) without having negative side effect at another level (e.g. parking pressure). Indeed, policy makers in cities throughout the world are seeking for effective ways to promote EVs and at the same time manage EV charging infrastructure. This research shows that policy makers should not only focus on the direct effects on the intended policy but also take into account possible (negative) side effects. The presented case studies, each evaluated with an unique database on charging behaviour, show that these side effects do exist and therefore should be taken into account when evaluating the effect of proposed or implemented policies.

Cross-links between policies are of course not limited to charging behaviour control and purchase policies. As an example such policies may also interfere with grid management, which could become a major issue in the context of a large scale introduction of EVs. For example, daytime charging policies could encourage EV drivers to start their charging session earlier to ensure they have a charging station available; and charging sessions that otherwise would have started later in the evening could align with a peak in electricity demand in the late afternoon and early morning. Although we encourage further research where interests of several stakeholders such as the mobility and energy sector have to be aligned, we consider such wider implications and cross-links outside of the scope of this paper.

This paper has also contributed into insights in EV charging behaviour and purchase in dense urban areas where (prospective) owners depend on public charging infrastructure. Current literature indicates that home and workplace charging are the dominant modes. Much focus is however on the planning of (fast) charging for longer trips, home and workplace charging for those that rely on public charging remains an underexposed field of study. This focus can be explained as currently the majority of EV owners belongs to a high income group which often has private charging infrastructure. If EVs however reach the masses, those that depend on on-street parking should be taken into account when planning for the charging infrastructure. Especially policy makers in cities, where on-street parking is more common, shall face the dilemma of how to organise this charging infrastructure efficiently. The results presented in this paper not only indicate the effect of the tested policies but also give an indication of how these charging stations are used in general.

Potential pitfalls in our analyses that could be improved in future work lie in determining the effect of policy measures on the purchase intention. Note that given the set-up of the experiment, which only considers parking policies and a limited amount of vehicle characteristics, we cannot rule out that the salience of such policies may have been overemphasized in the eyes of participants. A two-step approach in which respondents would first (i.e. in stage one) are asked to evaluate the choice alternatives without the policy context, could help in reducing any possible bias in future work. Furthermore, inclusion of more variables, and more variation in vehicle-characteristics which in our study were being held constant, could provide a further means to eliminate hypothetical bias. The aim of this paper was to indicate that such policies do have a substantial effect on purchase intention and further research, both with stated and revealed preferences, could further reveal the importance of these policies compared to other factors. The stated preference study was aimed at those respondents that rely on on-street charging facilities; this focus was motivated by pointing out that such a group is currently underrepresented in studies. Note also that the case study policies we consider would have most effect on this subset of the population. Further research could look into effects of policies for those EV-users that do have home-charging possibilities and potentially set up a comparison between these groups in terms of their response to charging policies. The natural experiments benefited from situations which allowed comparisons of several policies measures on aspects of charging behaviour. However, also these case studies were not without limitations. The daytime charging experiment lacked data from actual gasoline cars parking in the freely available spots because of the policy. The parking behaviour of these vehicles had to be derived from the absence of EVs in this spot. Despite these limitations we believe that this paper has provided compelling evidence that the cross-links between the effects of EV-charging policies are a relevant topic of study and should be the subject of more future research.

5.6 References

Axsen, J., & Kurani, K. S. (2012). Who can recharge a plug-in electric vehicle at home? *Transportation Research Part D: Transport and Environment*, *17*(5), 349–353. http://doi.org/10.1016/j.trd.2012.03.001

Bailey, J., Miele, A., & Axsen, J. (2015). Is awareness of public charging associated with consumer interest in plug-in electric vehicles ? *Transportation Research Part D: Transport and Environment*, *36*, 1–9. http://doi.org/10.1016/j.trd.2015.02.001

Bakker, S., Maat, K., & van Wee, B. (2014). Stakeholders interests, expectations, and strategies regarding the development and implementation of electric vehicles: The case of the Netherlands. *Transportation Research Part A: Policy and Practice*, *66*(1), 52–64. http://doi.org/10.1016/j.tra.2014.04.018

Bierlaire, M. (2003). BIOGEME: A free package for the estimation of discrete choice models. In *Proceedings of the 3rd Swiss Transportation Research Conference*. Ascona, Switzerland.

Bivand, R. S., Pebesma, E. J., & Gomez-Rubio, V. (2013). *Applied spatial data analysis with R* (Second). New York, NY: Springer.

Bjerkan, K. Y., Nørbech, T. E., & Nordtømme, M. E. (2016). Incentives for promoting Battery Electric Vehicle (BEV) adoption in Norway. *Transportation Research Part D: Transport and Environment*, *43*, 169–180. http://doi.org/10.1016/j.trd.2015.12.002

Carley, S., Krause, R. M., Lane, B. W., & Graham, J. D. (2013). Intent to purchase a plug-in electric vehicle : A survey of early impressions in large US cites. *Transportation Research Part D: Transport and Environment*, *18*(18), 39–45. http://doi.org/10.1016/j.trd.2012.09.007

CBS Statline. (2016). Kerncijfers wijken en buurten 2016. Retrieved April 18, 2016, from https://www.cbs.nl/nl-nl/maatwerk/2016/30/kerncijfers-wijken-en-buurten-2016

Cherchi, E. (2017). A stated choice experiment to measure the effect of informational and normative conformity in the preference for electric vehicles. *Transportation Research Part A: Policy and Practice*, *100*, 88–104. http://doi.org/10.1016/j.tra.2017.04.009

Chorus, C. G., Koetse, M. J., & Hoen, A. (2013). Consumer preferences for alternative fuel vehicles: Comparing a utility maximization and a regret minimization model. *Energy Policy*, *61*, 901–908. http://doi.org/10.1016/j.enpol.2013.06.064

Coffman, M., Bernstein, P., & Wee, S. (2016). Electric vehicles revisited : a review of factors that affect adoption. *Transport Reviews*, 1–15. http://doi.org/10.1080/01441647.2016.1217282

Daina, N. (2014). Modelling Electric vehicle use and charging behaviour. *PhD Thesis at Imperial College London*.

Egbue, O., & Long, S. (2015). Barriers to widespread adoption of electric vehicles : An analysis of consumer attitudes and perceptions. *Energy Policy*, *48*(2012), 717–729. http://doi.org/10.1016/j.enpol.2012.06.009

Ensslem, A., Jochem, P., Schäuble, J., & Babrowski, S. (2013). User Acceptance of Electric Vehicles in the French-German Transnational Context. In *13th WCTR, July 15-18, 2013–Rio de Janeiro, Brazil* (pp. 1–23). Retrieved from http://www.wctrs-society.com/wp/wp-content/uploads/abstracts/rio/selected/1183.pdf

Fearnley, N., Pfaffenbichler, P., Figenbaum, E., & Jellinek, R. (2015). *E-vehicle policies and incentives - assessment and recommendations* (TØI report). Retrieved from https://www.toi.no/getfile.php?mmfileid=41187

Frade, I., Ribeiro, A., Gonçalves, G., & Antunes, A. (2011). Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal. *Transportation Research Record: Journal of the Transportation Research Board*, *2252*, 91–98. http://doi.org/10.3141/2252-12

Franke, T., & Krems, J. F. (2013a). Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour*, *21*(2013), 75–89. http://doi.org/10.1016/j.trf.2013.09.002

Franke, T., & Krems, J. F. (2013b). What drives range preferences in electric vehicle users ? *Transport Policy*, *30*, 56–62. http://doi.org/10.1016/j.tranpol.2013.07.005

Gnann, T., & Plötz, P. (2015). A review of combined models for market diffusion of alternative fuel vehicles and their refueling infrastructure. *Renewable and Sustainable Energy Reviews*, *47*, 783–793. http://doi.org/10.1016/j.rser.2015.03.022

Hackbarth, A., & Madlener, R. (2013). Consumer preferences for alternative fuel vehicles : A discrete choice analysis. *Transportation Research Part D: Transport and Environment*, *25*, 5–17. http://doi.org/10.1016/j.trd.2013.07.002

Hagman, J., Stier, J. J., & Susilo, Y. (2016). Total cost of ownership and its potential implications for battery electric vehicle diffusion. *Research in Transportation Business & Management*, *18*, 11–17. http://doi.org/10.1016/j.rtbm.2016.01.003

Hardman, S., Chandan, A., Tal, G., & Turrentine, T. (2017). The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. *Renewable and Sustainable Energy Reviews*, *80*(March), 1100–1111. http://doi.org/10.1016/j.rser.2017.05.255

Hardman, S., Tal, G., Turrentine, T., Axsen, J., Beard, G., Daina, N., … Pontes, J. (2017). Driving the Market for Plug-in Vehicles - Developing PEV Charging Infrastructure for Consumers Lessons from Academic Research & Empirical Data, (October).

Helmus, J., & van den Hoed, R. (2015). Unraveling User Type Characteristics : Towards a Taxonomy for Charging Infrastructure. *EVS28 International Electric Vehicle Symposium and Exhibition*, 1–16.

Hoed, R. Van Den, Helmus, J. R., Vries, R. De, & Bardok, D. (2014). Data analysis on the public charge infrastructure in the city of Amsterdam. In *EVS27 Symposium, Barcelona, Spain, November 17-20, 2013* (pp. 1–10). http://doi.org/10.1109/EVS.2013.6915009

Hoen, A., & Koetse, M. J. (2014). A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. *Transportation Research Part A: Policy and Practice*, *61*, 199–215. http://doi.org/10.1016/j.tra.2014.01.008

Idaho National Laboratory. (2015a). Plugged In: How Americans Charge Their Electric Vehicles, 1–24. Retrieved from https://avt.inl.gov/sites/default/files/pdf/arra/SummaryReport.pdf

Idaho National Laboratory. (2015b). What Use Patterns Were Observed for Plug-In Electric Vehicle Drivers at Publicly Accessible Alternating Current Level 2 Electric Vehicle Supply Equipment Sites ?, 1–4.

International Energy Agency. (2016). *Global EV Outlook 2016: Beyond one million electric cars*.

Jabeen, F., Olaru, D., Smith, B., Braunl, T., & Speidel, S. (2013). Electric vehicle battery charging behaviour: Findings from a driver survey. *36th Australasian Transport Research Forum (ATRF), Brisbane, Queensland, Australia*.

Jakobsson, N., Gnann, T., Plötz, P., Sprei, F., & Karlsson, S. (2016). Are multi-car households better suited for battery electric vehicles? - Driving patterns and economics in Sweden and Germany. *Transportation Research Part C: Emerging Technologies*, *65*, 1–15. http://doi.org/10.1016/j.trc.2016.01.018

Krupa, J. S., Rizzo, D. M., Eppstein, M. J., Lanute, D. B., Gaalema, D. E., Lakkaraju, K., & Warrender, C. E. (2014). Analysis of a consumer survey on plug-in hybrid electric vehicles. *Transportation Research Part A*, *64*, 14–31. http://doi.org/10.1016/j.tra.2014.02.019

Latinopoulos, C., Sivakumar, A., & Polak, J. (2017). Modeling Electric Vehicle Charging Behavior: What Is the Relationship Between Charging Location, Driving Distance, and Range Anxiety? *Transportation Research Board, 96th Annual Meeting*.

Li, S., Tong, L., Xing, J., & Zhou, Y. (2017). The Market for Electric Vehicles : Indirect Network Effects and Policy Design. *Journal of the Association of Environmental and Resource Economists*, *4*(1), 89–133.

Liao, F., Molin, E., & Wee, B. Van. (2017). Consumer Preferences for Electric Vehicles : a Literature Review. *Transport Reviews*, 1–24.

Liu, J. (2012). Electric vehicle charging infrastructure assignment and power grid impacts assessment in Beijing. *Energy Policy*, *51*, 544–557. http://doi.org/10.1016/j.enpol.2012.08.074

Madina, C., Zamora, I., & Zabala, E. (2016). Methodology for assessing electric vehicle charging infrastructure business models. *Energy Policy*, *89*, 284–293. http://doi.org/10.1016/j.enpol.2015.12.007

Mersky, A. C., Sprei, F., Samaras, C., & Qian, Z. (Sean). (2016). Effectiveness of incentives on electric vehicle adoption in Norway. *Transportation Research Part D*, *46*, 56–68. http://doi.org/10.1016/j.trd.2016.03.011

Molin, E. J. E., & Timmermans, H. J. P. (2010). Context dependent stated choice experiments: The case of train egress mode choice. *Journal of Choice Modelling*, *3*(3), 39–56. http://doi.org/10.1016/S1755-5345(13)70013-7

Morrissey, P., Weldon, P., & Mahony, M. O. (2016). Future standard and fast charging infrastructure planning : An analysis of electric vehicle charging behaviour. *Energy Policy*, *89*, 257–270. http://doi.org/10.1016/j.enpol.2015.12.001

Municipality of Leiden. (2017). Parkeertarieven voor bewoners. Retrieved June 8, 2017, from https://gemeente.leiden.nl/themas/zones-tarieven/parkeertarieven/bewoners/

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, *5*, 329–332.

Pebesma, E. J., & Bivand, R. S. (2005). Classes and methods for spatial data in R. *R News*, *5*(2).

Rangaraju, S., De Vroey, L., Messagie, M., Mertens, J., & Van Mierlo, J. (2015). Impacts of electricity mix, charging profile, and driving behavior on the emissions performance of battery electric vehicles: A Belgian case study. *Applied Energy*, *148*(X), 496–505. http://doi.org/10.1016/j.apenergy.2015.01.121

Razeghi, G., Carreras-sospedra, M., Brown, T., Brouwer, J., Dabdub, D., & Samuelsen, S. (2016). Episodic air quality impacts of plug-in electric vehicles. *Atmospheric Environment*, *137*, 90–100. http://doi.org/10.1016/j.atmosenv.2016.04.031

Rezvani, Z., Jansson, J., & Bodin, J. (2015). Advances in consumer electric vehicle adoption research : A review and research agenda. *Transportation Research Part D*, *34*, 122–136. http://doi.org/10.1016/j.trd.2014.10.010

Robinson, a. P., Blythe, P. T., Bell, M. C., Hübner, Y., & Hill, G. a. (2013). Analysis of electric vehicle driver recharging demand profiles and subsequent impacts on the carbon content of electric vehicle trips. *Energy Policy*, *61*, 337–348. http://doi.org/10.1016/j.enpol.2013.05.074

Sathaye, N., & Kelley, S. (2013). An approach for the optimal planning of electric vehicle infrastructure for highway corridors. *Transportation Research Part E: Logistics and Transportation Review*, *59*, 15–33. http://doi.org/10.1016/j.tre.2013.08.003

Schroeder, A., & Traber, T. (2012). The economics of fast charging infrastructure for electric vehicles. *Energy Policy*, *43*, 136–144. http://doi.org/10.1016/j.enpol.2011.12.041

Shahraki, N., Cai, H., Turkay, M., & Xu, M. (2015). Optimal locations of electric public charging stations using real world vehicle travel patterns. *Transportation Research Part D: Transport and Environment*, *41*, 165–176. http://doi.org/10.1016/j.trd.2015.09.011

Shoup, D. (2005). *The high cost of free parking*. American Planning Association.

Sierzchula, W., Bakker, S., Maat, K., & Wee, B. Van. (2014). The in fluence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194. http://doi.org/10.1016/j.enpol.2014.01.043

Smith, B., Olaru, D., Jabeen, F., & Greaves, S. (2017). Electric vehicles adoption: Environmental enthusiast bias in discrete choice models. *Transportation Research Part D: Transport and Environment*, *51*, 290–303. http://doi.org/10.1016/j.trd.2017.01.008

Speidel, S., Jabeen, F., Olaru, D., & Harries, D. (2012). Analysis of Western Australian Electric Vehicle and Charging Station Trials, (Iea 2011).

Spoelstra, J. C., & Helmus, I. J. (2015). Public charging infrastructure use in the Netherlands : A rollout - strategy assessment. *European Battery, Hybrid and Fuel Cell Electric Vehicle Congress*, 1–10.

Sun, X. H., Yamamoto, T., & Morikawa, T. (2016). Fast-charging station choice behavior among battery electric vehicle users. *Transportation Research Part D: Transport and Environment*, *46*, 26–39. http://doi.org/10.1016/j.trd.2016.03.008

Toronto Atmospheric Fund. (2015). *Fleetwise ev300*. Retrieved from http://taf.ca/wp-content/uploads/2014/09/FleetWise-EV300-Findings-Report-16-June-2015.pdf

Train, K. (2009). *Discrete Choice Methods with Simulation* (2nd ed.). New York, NY: Cambridge University Press.

Wardle, J. (2015). The rapid charge network. In *European Battery, Hybrid and Fuel Cell Electric Vehicle Congress*. Brussels.

Wen, Y., Mackenzie, D., & Keith, D. (2015). Modeling charging choices of BEV owners using stated preference data. *EVS 28, KINTEX, Korea*.

Wirges, J. (2016). *Planning the Charging Infrastructure for Electric Vehicles in Cities and Regions (Doctoral dissertation)*. Karlsruher Institut für Technologie.

Xu, M., Meng, Q., Liu, K., & Yamamoto, T. (2017). Joint charging mode and location choice model for battery electric vehicle users. *Transportation Research Part B*, *103*, 68–86. http://doi.org/10.1016/j.trb.2017.03.004

Yu, H., & Mackenzie, D. (2016). Modeling Charging Choices of Small-Battery Plug-In Hybrid Electric Vehicle Drivers by Using Instrumented Vehicle Data. *Transportation Research Record: Journal of the Transportation Research Board*, *2572*, 56–65. http://doi.org/10.3141/2572-07

Zhang, L., Shaffer, B., Brown, T., & Samuelsen, G. S. (2015). The optimization of DC fast charging deployment in California. *Applied Energy Journal*, *157*, 111–122. http://doi.org/10.1016/j.apenergy.2015.07.057

Zoepf, S., MacKenzie, D., Keith, D., & Chernicoff, W. (2013). Charging choices and fuel displacement in a large-scale plug-in hybrid electric vehicle demonstration. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2385*, 1–10.

Appendix 5.A: List of additional information provided in choice tasks

	Electric Vehicle	**Plug-in Hybrid Vehicle**	**Conventional Vehicle**
Range Gasoline	-	600 km	750 km
Fuel price per km	€0.04/km	€0.07/km	€0.10/km
Road tax	€0/year	€450/year	€450/year
Charging speed home/work	25 km range/hour	25 km range/hour	-
Charging speed fast charging	300 km range/hour	-	-

6 Charging infrastructure roll-out strategies for large scale introduction of electric vehicles in urban areas: A simulation study

Wolbertus, R., van den Hoed, R., Kroesen, M. & Chorus, C.G. (2019). Charging infrastructure roll-out strategies for large scale introduction of electric vehicles in urban areas: A simulation study. Transportation research Part A: Policy and Practice. Manuscript under review

Abstract

On the eve of the large scale introduction of electric vehicles, policy makers have to decide on how to organise a significant growth in charging infrastructure to meet demand. There is uncertainty about which charging deployment tactic to follow. The main issue is how many of charging stations, of which type, should be installed and where. Early roll-out has been successful in many places, but knowledge on how to plan a large scale charging network in urban areas is missing. Little is known about return to scale effects, reciprocal effects of charger availability on sales, and the impact of fast charging or more clustered charging hubs on charging preferences of EV owners. This paper explores the effects of various roll-out strategies for charging infrastructure that facilitate the large scale introduction of EVs, using agent based simulation. In contrast to previously proposed models, our model is rooted in empirically observed charging patterns from EVs instead of travel patterns of fossil fuelled cars. In addition, the simulation incorporates different user types (inhabitants, visitors, taxis and shared vehicles) to model the diversity of charging behaviours in an urban environment. Different scenarios are explored along the lines of the type of charging infrastructure (level 2, clustered level 2, fast charging) and the intensity of rollout (EV to charging point ratio). The simulation predicts both the success rate of charging attempts and the additional discomfort when searching for a charging station. Results suggest that return to scale and reciprocal effects in charging infrastructure are considerable, resulting in a lower EV to charging station ratio on the longer term.

6.1 Introduction

In most countries electric vehicles (EVs) constitute less than a 1% of all vehicles on the road (International Energy Agency, 2018). Rapid growth in the number of vehicles is expected in the next years due to a decrease in battery costs and increase in driving ranges (Nykvist, Sprei, & Nilsson, 2019). At the eve of the large scale introduction of EVs, policy makers are looking for the optimal approach to scale up charging infrastructure to facilitate increased charging demand. The chicken-or-egg dilemma related to charging infrastructure could prove to be the largest bottleneck to facilitate a rapid transition to electric mobility.

Policy makers face difficult decisions about the right approach to deploy charging infrastructure. The main question(s) they face is how many and which type of charging stations should be installed where. These are long-term tactical decisions, as infrastructure investment costs are high and payback periods long. Insight into the effect of different roll-out strategies is therefore considered crucial. The main questions come down to operational decisions for policy makers such as: how many charging stations should be installed relative to the number of EVs on the road? Which EV to charging station ratio is optimal to service EV drivers and provides business opportunities for charging point operators (CPOs)? What is the trade-off in service to EV drivers between accessibility (ability to charge) and convenience (e.g. proximity and charging time)? Are charging stations best clustered in centralised hubs or should they be spread throughout a city to provide maximum geographical coverage? Can return to scale effects be expected? Can new fast charging technologies with increased charging speeds (from 50kW up to 350kW) provide an alternative centralised solution in urban environments? Policy makers urgently need insights into which reciprocal effects between investments in charging infrastructure and EV adoption exist, to be able to capitalize on them in their decision making. To address these policy questions, charging infrastructure can best be seen as a complex system (J R Helmus, Hoed, & Lees, 2019) in which EV drivers compete and interact with each other for available charging stations. Charging stations are a rival good, in the sense that charging at a particular station prevents other EV drivers from access to that location. Competition takes place within geo-spatial boundaries and between different types of users such as residents, taxi drivers or shared EVs (J. Helmus & van den Hoed, 2015). EV drivers not only interact with each other but also with the CPO as this stakeholder monitors the utilisation of current stations to adjust the supply of new charging stations. Potential new EV drivers take into account charging convenience when they decide which cars to purchase. Therefore reciprocal effect between the EV adoption pace and infrastructure roll-out is expected (Sierzchula, Bakker, Maat, & Wee, 2014; Wolbertus, Kroesen, van den Hoed, & Chorus, 2018) but the extent to which this plays out is uncertain. Additionally, when charging infrastructure is expanded, return to scale effects might exist. Yet, due to the rival nature of the charging stations it is uncertain if and to which extent a larger charging network is used more efficiently. It is necessary to address these complexities in research on charging infrastructure, to able to provide accurate and meaningful impact assessments of different roll-out strategies.

To study the effect of charging station roll-out strategies on the EV charging system, an agent based model (ABM) is built and employed. The ABM presented in this paper addresses three related processes; (i) the charging choice, (ii) the charging station deployment and (iii) the vehicle purchase process. The agent based approach is ideally suited to investigate the EV charging system, since it is able to handle two important features, namely, it allows simulation of interactions between agents (between EV agents, CPO agents and non-EV car owners) and it acknowledges the fact that the geo-spatial context is highly relevant. Due to these specificities, various researchers have already used ABMs to model the uptake of EVs (Krupa et al., 2014; Noori & Tatari, 2016; Silvia & Krause, 2016), the charging behaviour of EVs (Olivella-rosell, Villafafila-robles, & Sumper, 2014; Sweda & Klabjan, 2015; Torres et al., 2015) and more recently the relation between charging infrastructure and EV uptake (Gnann, Plötz, & Wietschel, 2018). In contrast to this previous work, this study uses a data-driven approach to operationalise the ABM. In particular the charging behaviour is derived from an empirical dataset which contains approximately 2 million actual charging sessions. It focusses on the urban area in which competition between different user groups for public charging infrastructure is intense since many users rely on on-street charging infrastructure for their daily charging needs. Furthermore it uses established research to address the relationship between EV adoption and charging infrastructure. This gives new and empirically rooted insights for policy makers in their roll-out strategy decisions.

In the remainder of this paper, first previous work carried out on EV adoption and charging in relation to charging infrastructure deployment is reviewed after which the research gap is identified (section 6.2). In section 6.3 we present the method and the data to support the choices in the design of the ABM. Section 6.4 discusses the results of the simulations and the conclusions are presented in section 6.5.

6.2 Previous work

Research interest in EVs and charging infrastructure has grown extensively over the past years in line with the rise in numbers on the road. In this section an overview is given of the work done on (i) EV adoption and its relationship to charging infrastructure and (ii) on roll-out strategies for charging infrastructure. As both fields are researched intensively, the overview focuses (albeit not exclusively) on ABM approaches on these two topics.

6.2.1 EV adoption and charging infrastructure

Literature overviews on EV adoption studies (Coffman, Bernstein, & Wee, 2016; Liao, Molin, & Wee, 2017; Rezvani, Jansson, & Bodin, 2015) show that a lack of charging infrastructure is one of the main barriers for consumers to purchase an EV. Hardman et al. (2017) and Gnann & Plötz (2015) review papers with an explicit focus on the relationship between EV adoption and charging infrastructure and found that availability of home charging is the most important factor in the decision to adopt electric vehicles. Studies in this area mostly rely on data from surveys or stated choice experiments, while the use of revealed preference data is scarce (Hardman et al., 2017). A notable exception in this regard is the research by Sierzchula et al. (2014) which analyses data on EV adoption in 30 countries and found charging infrastructure to be the main predictor of adoption rates (although causality may operate in both directions).

Besides stated and revealed preferences techniques, EV adoption is also studied with ABMs. Typically, the main reason to use an ABM is to model the interactions with other agents. This allows for studies on social relations such as the neighbour effect (Axsen, Mountain, & Jaccard, 2009). Most models use an “if-then” decision rule for the agents’ purchase decisions (Eppstein, Grover, Marshall, & Rizzo, 2011; Gnann, Plötz, Kühn, & Wietschel, 2015; Kangur, Jager, Verbrugge, & Bockarjova, 2017; Silvia & Krause, 2016). In these models the observed parameter (e.g. utility or cost) is compared to other available options and the most favourable option is chosen. Other studies (Kieckhäfer, Wachter, & Spengler, 2017; Shafiei et al., 2012) use more advanced multinomial logit models for the EV adoption choice. The input parameters result in a choice probability for each agent after which a random wheel procedure is applied.

These models are more in line with the latest choice models and allow for more validation of the decisions on which variables to include (Araghi, Bollinger, & Lee, 2014; Holm, Lemm, Thees, & Hilty, 2016; Le Pira et al., 2017).

Although ABM studies consider the relation with other EV agents, relatively few models take available charging infrastructure into account (Kangur et al., 2017; Kieckhäfer et al., 2017; Shafiei et al., 2012; Silvia & Krause, 2016). If included, the relation is modelled in a static sense, in which charging infrastructure is a given and no interaction between the purchase decision and infrastructure development is allowed for. An exception is the work by Gnann, Plötz and Wietschel (2018) which models the CPO as an agent which decided on charging. The stock of charging stations also influences the assessment of potential EV buyer agents of their ability to fulfil their travel needs. This work however assumed that all agents had home charging availability without competition from other agents. This makes the analysis less suitable for urban environments in which a large share of inhabitants relies on public on-street parking and charging.

To conclude, research on EV adoption has identified charging infrastructure availability as one of the main barriers to a large scale introduction of EVs. However, in ABM studies of EV adoption charging infrastructure has hardly been considered or only in a static sense. The reciprocal relationship between EV adoption and charging infrastructure development has received very little attention in ABMs, despite other research pointing out that charging infrastructure is a key barrier in uptake of EVs.

6.2.2 Charging infrastructure utilisation

In line with the number of papers on EV adoption, the number of studies on charging infrastructure utilisation and charging behaviour increases. Research has progressed from stated choice studies (Jabeen, Olaru, Smith, Braunl, & Speidel, 2013; Latinopoulos, Sivakumar, & Polak, 2017) and estimations with travel data (Brooker & Qin, 2015; Shahraki, Cai, Turkay, & Xu, 2015; Xi, Sioshansi, & Marano, 2013), to revealed charging data for descriptive (Morrissey, Weldon, & Mahony, 2016; Sun, Yamamoto, & Morikawa, 2016; Wolbertus, Kroesen, van den Hoed, & Chorus, 2018a) and explanatory research (Sun et al., 2016; Wolbertus, Kroesen, van den Hoed, & Chorus, 2018a; Zoepf, MacKenzie, Keith, & Chernicoff, 2013). In general, the research confirms the need for home, workplace and opportunity driven charging stations and fast charging along corridors.

These studies focus on past usage of charging infrastructure. Studies that try to optimise charging infrastructure roll-out often make use of travel patterns from gasoline driven vehicles. For EV fast charging, Motoaki (2019) observes two approaches in the literature to do so: a node-serving and a flow-capturing approach. He concludes that the flow capturing works best to predict inter-city charging demand but that in practice local motivations play a much larger role in actual deployment strategies. For slower level 2 (up to 22kW) charging infrastructure researchers make use of dwell time as a proxy for charging demand (Paffumi, Gennaro, & Martini, 2015; Shahraki et al., 2015).

The number of studies that use ABMs for both charging infrastructure roll-out and utilisation is limited. The available models use travel behaviour to estimate charging demand. The models assume that the driver charges at the end of a trip (under certain conditions) when a charging station is available (Torres et al., 2015; Vijayashankar, 2017). Additionally, the CPO is modelled in the decision to place a charging station (Gnann et al., 2018; Pan, Zhao, Yu, &

Zhang, 2019). The decision to place a charging station is based on the potential business case. Results from Gnann et al. (2018) show that level 2 charging stations for opportunity charging hardly ever become profitable and requires subsidies for the foreseeable future. These studies assume that vehicles have private charging facilities for overnight charging. The only exception to our knowledge is a model developed and applied by Helmus et al. (2019) and Vermeulen et al. (2018). This model uses charging patterns from actual charging events instead of travel information as input and only assumes public charging infrastructure for home charging. These papers however only model a static environment and do not consider growth scenarios with a CPO agent.

6.2.3 Contributions

This study contributes to previous studies on the following aspects. First, a large dataset on actual charging patterns is used to model the charging behaviour of agents. Previous models have mainly relied on travel patterns from gasoline vehicles and have made assumptions about charging choices. The approach used here, more closely resembles the new behavioural patterns EV drivers have, which is an interplay between parking and refuelling (Wolbertus et al., 2018a). Secondly, an urban area is modelled in which most of the home and workplace charging is done on public charging stations. Previous models assume home and workplace charging at private charging stations. These are always available and used without any interaction with other EV drivers. The proposed model includes considerable more interaction between EV drivers compared to previous models, to more accurately represent the complex system of on-street EV charging in an urban context. Moreover, this model includes traffic from visitors and charging demand from other modalities such as shared vehicles and a taxi fleet which allows a more realistic simulation of the the urban environment. Thirdly, this research models the relationship between the charging infrastructure and EV adoption based upon a choice experiment, while previous models use assumptions about this relationship.

The developed ABM is used to evaluate three case studies in the city of Amsterdam which address prominent questions by policy makers. These questions evolve around the three main aspects of charging infrastructure deployment which are how many and which type of charging stations should be placed where. The first study addresses the ratio between EVs and charging stations. The studies vary the threshold for the number of new EV drivers to place a new charging station. The second study compares a clustered approach in which charging hubs are created to an approach in which single charging stations are placed across the city. The last study compares fast charging stations to level 2 charging stations, to see if high powered charging stations can be a substitute for lowered stations. The city of Amsterdam is used as a case study as it is a city that already has a substantial number of charging stations in place and expects considerable growth due to the city plans to ban all non-electric vehicles by 2030 (City of Amsterdam, 2019). All simulations run up to 2025, a period in which substantial growth infrastructure has to be made.

All three studies aim at investigating patterns due to changes in technology that current models could not yet foresee. The results allow policy makers to make well informed decisions on the charging infrastructure roll-out tactics with clearly defined performance indicators in mind. These performance indicators include amongst other things the service level in terms of successful charging sessions but also the convenience in terms of additional miles travelled to find an available charging station. In addition to performance indicators for the charging infrastructure, the research provides insights in the reciprocal effect between charging infrastructure and EV adoption. Together with information on the return to scale effects in charging infrastructure deployment it gives policy makers more insight in how their tactics contribute to policies at the strategic level.

6.3 Methodology

6.3.1 Conceptualization

6.3.1.1 Overview

The model contains three types of agents that operate in the environment of the city of Amsterdam in which charging stations are situated. The agents are EV drivers, non-EV car owners and the CPO. The interaction between these agents in simulated in three processes. These are (1) the charging process in which the EV driver interacts with available charging stations and other EV drivers, (2) the process of purchasing a vehicle of non-EV car owners in which they take current charging infrastructure utilization into account and (3) the instalment process of new charging stations by the CPO as part of the placement tactic, which depends on the charging station utilization. An overview of the elements and their interactions in the model is given in *Figure 6.1*. The concepts behind these processes are discussed below.

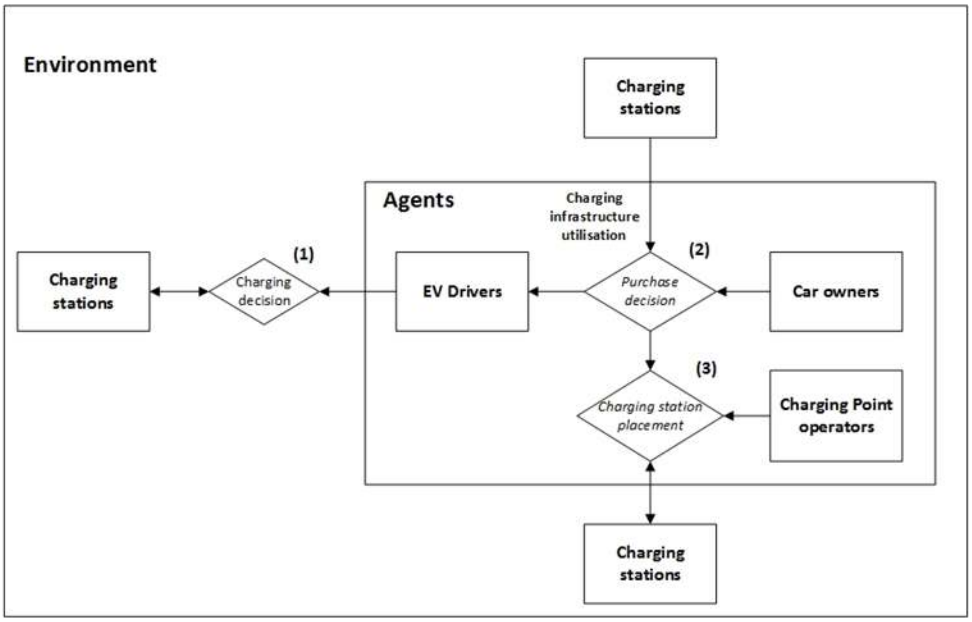


Figure 6.1 Conceptualisation of model

6.3.1.2 Electric Vehicle Drivers

Charging behaviour is the result of the choice of an individual EV driver to charge its car. Charging behaviour is here defined by its location, the time connected to the charging station, the energy transferred and the time until the next charging session. Analysis of charging patterns reveals heterogeneity in charging behaviour across users and different user types (Helmus & Van den Hoed, 2015). Each EV driver has its own distinct charging patterns. The behaviour at the individual level is habitual, e.g. EV drivers charge at a limited amount of locations (Wolbertus & Van Den Hoed, 2017) and often around the same time. It is therefore assumed that EV drivers attempt to charge at their favourite charging location, closest to their destination. If the favourite location is not available, the driver searches for an available charging station in its proximity. It is assumed that distance is an important factor in location choice (Axhausen; & Polak, 1991) and that drivers have a maximum willingness to walk (Waerden, Timmermans, & De Bruin-Verhoeven, 2017), which varies across drivers. Charging station locations are assumed to be known to the driver, but current occupancy is unknown.

Once the EV driver has chosen a charging station, it determines how long and how much it wants to charge. Previous research (Wolbertus et al., 2018a) has shown that the charging process conceptualised as ‘charge when empty’, is an insufficient explanation for observed charging patterns. Charging an EV is an interaction between refuelling and parking behaviour. Connection time and energy transferred are therefore correlated to the starting time of the charging session. The best proxy to simulate charging behaviour is to observe charging patterns across time from current EV drivers.

In the urban environment not only habitual users such as residents and commuters make use of charging infrastructure. Visitors, taxi drivers and electric car sharing services are important users of the systems. It is of interest how these different user types interact with each other and how a single infrastructure can serve the demand from different user types. The behaviour of these other user types is not habitual but does have distinct patterns (Van der Poel, Tensen, Van Goeverden, & van den Hoed, 2017). The charging sessions of these types of users are therefore conceptualised as a homogeneous groups of one time visitors to the charging infrastructure in the city.

6.3.1.3 Car owners

Car owner agents that consider purchasing a vehicle are conceptualised to make a choice between a gasoline driven, a plug-in hybrid (PHEV) or a full electric vehicle (FEV), all with similar performances. For the latter two, it has been found that purchases have been restricted by three main barriers: price, driving range and available charging infrastructure (Coffman et al., 2016; Liao et al., 2017). The price and range of the vehicle are connected to developments of battery technology (Nykvist et al., 2019). These developments are considered a given and thus exogenous. To overcome the charging infrastructure barrier, home charging availability is considered the most important. Home charging in urban environments is often done at the kerbside located charging infrastructure. As awareness of public charging positively correlates with the willingness to purchase an EV (Bailey, Miele, & Axsen, 2015) the car owner considers charging availability near home during the purchase decision.

Charging availability differs between neighbourhoods, but is not enough to explain different adoption rates across these areas. Purchase decisions are found to be heterogeneous across different user groups (Bjerkan, Nørbech, & Nordtømme, 2016; Gnann et al., 2015). Differences between these users groups are attributed to factors such as income (Montfort, Visser, & Poel, 2016) and environmental awareness (Kangur et al., 2017). This paper conceptualises these factors in a single preference for an electric or gasoline driven vehicle. The factors and thus preferences are often concentrated at the neighbourhood level (Kangur et al., 2017; Rodrigues, Bolognesi, Melo, Heymann, & Soares, 2019). The preference for EVs is therefore assumed heterogeneous across but homogeneous within neighbourhoods. To best asses the preferences, past adoption rates per neighbourhood are used as a proxy.

6.3.1.4 Charging Point Operator

In the charging station placement process three important factors play a role. Namely where, how many of which type of charging stations should be placed (Motoaki, 2019). The decision to place a charging station is made by the CPO. The CPO optimises its business case and accordingly only places a new charging station if there is sufficient demand. In the urban area demand is best expected where home charging is needed, i.e. where the (prospective) EV owner lives. This is a so-called demand driven roll-out strategy (Helmus et al., 2018). The CPO adds a charging station in case a new EV is bought and insufficient charging infrastructure in the neighbourhood is available. The CPO decides on the number and type of charging stations to be placed.

6.3.2 Operationalization

To operationalise the model both a description of the agents and their relevant parameters and the processes of each of the agents is given. *Table 6.1* provides the operationalization of the elements in the system and their characteristics, which is discussed in more detail in the following paragraphs.

Table 6.1 Overview of elements in ABM and their parameters

Agent	Parameters
EV Drivers habitual	- Charging profile o Favourite charging location o Connection duration o Interval between charging sessions o kWh - Battery size - Maximum walking distance - State (Connected or disconnected)
EV Drivers non-habitual	- Charging profile o Number of sessions o Distribution of locations o Connection duration o kWh - Maximum walking distance
Car owners	- Purchase decision moment - Attitude towards EV - Home Location - Maximum walking distance
Charging Point Operator	- Number of charging stations to be added - Type of charging station to be added
Environment	
Charging stations	- Location - Capacity (No. of EVs) - Charging speed (Regular/Fast 50-350kW)

6.3.2.1 EV drivers

6.3.2.1.1 Charging profiles habitual

The charging profile is defined by (i) a favourite charging location, (ii) the connection duration, (iii) number of kWhs to be charged and (iv) an interval until the next charging session. These profiles are determined on the basis of charging data from the city of Amsterdam (see section 6.3.3) in which an anonymous RFID-tag (from now onward "agent") is used to determine which charging sessions are performed by the same user. A favourite charging location per agent is selected, based upon the most used charging station. The charging pattern in terms of connection duration and interval between sessions is determined for each time of day (per half hour) and day of the week. The probability of a specific connection duration or interval is based upon the relative number of times the duration/interval has been observed at a particular time of day and day of the week. The number of kWhs to be charged is determined by the same approach, with the difference that there is no relationship with the day of the week. Each agent tracks its own state, be it connected or disconnected. If disconnected, an agent has a time at when it next wants to charge, the so called Next Connection time. If connected, the agent's status is updated and the time it disconnects is determined based upon the selected connection duration.

The model allows EV agents to use different charging stations if the favourite charging station is occupied by other agents. It is assumed that an agent only uses charging stations within a certain perimeter of the favourite charging station. *Figure 6.2* gives an illustration of charging points within given walking distances of a charging station in the Amsterdam South area. Note that the figure displays distances as the crow flies for illustrative purposes albeit the model calculates actual walking distances through the OSRM package in R (Luxen & Vetter, 2011).

Figure 6.2 Charging stations within different ranges of walking distance in the Amsterdam-South area

Analysis of the maximum walking distance based on observed charging events away from the favourite charging station, reveals that this distribution is nearly uniform (see Appendix 6.C). The agent in the model is randomly assigned a maximum walking distance between 200 and 600 meters rounded to 50 meters. Agents can travel up to 1500 meters to a fast charging station despite their maximum walking distance. Agents are assumed to travel to a fast charging station by car back and forth without walking.

6.3.2.1.2 Non-habitual charging

To account for the charging sessions of EVs that are not explicitly modelled as agents, a probabilistic approach is used. These charging sessions are modelled as the result of behaviour of temporary agents whose charging behaviour is sampled from a single distribution. The number of sessions is determined from past observations of the number of non-habitual charging events. Given the time of day and day of the week in the model, a number of temporary agents attempt to charge. The location the temporary agents want to charge is sampled from the distribution across the charging stations. The connection process is similar to the agents. The maximum walking distance for temporary agents is fixed at 450 meters. The agent's identifier is set to "Non-habitual" when data on the charging sessions is gathered. When the non-habitual charging session ends, no new time is set for a next charging session.

6.3.2.1.3 Charging process

The charging process is modelled as displayed in *Figure 6.3*. At each time stamp the model controls which agents and how many non-habitual agents want to charge. The agent checks the availability of their favourite (or assigned in case of non-habitual agents) charging station. If the charging station is not available, it considers the charging stations within the maximum walking distance of that agent. From these stations, the next station to connect to is sampled with choice probabilities that are calculated using a multinomial logit model. This model is estimated with a combination of 2017 revealed charging data and a stated choice experiment described in Wolbertus & Van den Hoed (2019). This model includes walking distance and an identifier for charging hubs or fast charging stations as variables. The agent checks the availability of the chosen station and continues this process until no more options are available. If no options are available, the session is considered as failed. The model tracks the distance between the charging stations travelled.

If a charging station is available, the agent connects and the number of cars connected to the charging station is updated. When connected, the agent samples a connection duration (depending upon the time of day and day of the week) and the number of kWh to be charged. When the agent has no data in its charging profile for the given day of the week, only the time of day is considered. Based upon the connection duration, the time to disconnect is determined. If the charging session is noted as failed, the agent still determines its connection time as if the session has succeeded. This is done to be able to set the time it next connects. Data about the connection duration, kWhs charged, location, and distance travelled and the success of the charging session are stored in a charging session database. When an agent disconnects, the time between charging sessions is sampled depending on the time of day and day of the week. The charging process in case of fast charging is similar, but connection duration are determined differently; the connection time is the amount of kWh to be charged divided by the charging speed. Only FEV vehicles (battery size > 24kWh) have the ability to fast charge.

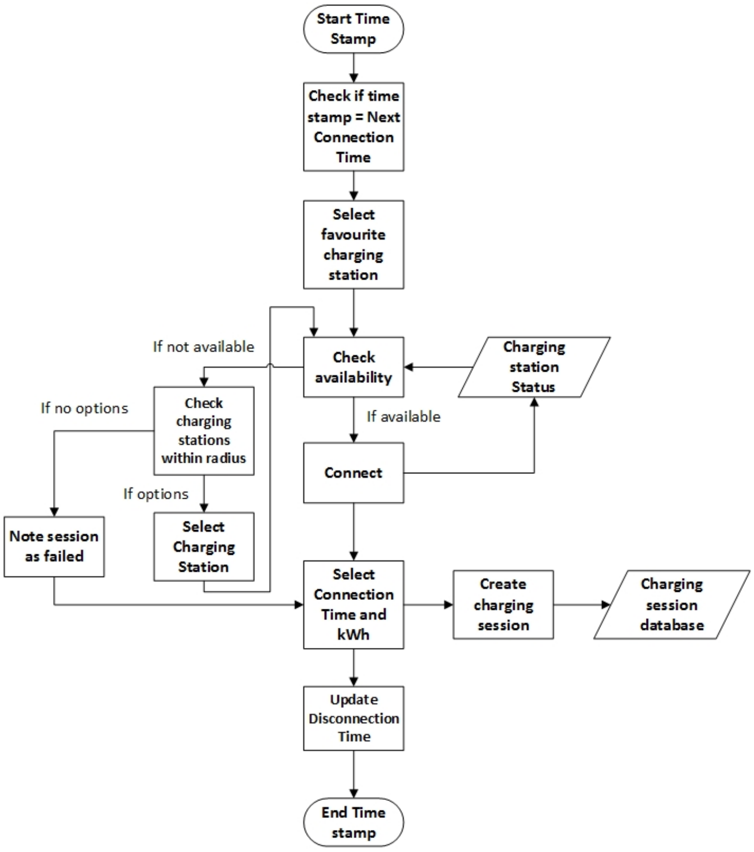


Figure 6.3 Overview of the charging process

6.3.2.2 Car Owners

The purchase process of a new vehicle for car owner agents is modelled as shown in *Figure 6.4*. Each car owner has a specific purchase date, which is randomly attributed to the agents. Dates across 15 years were used, approximately the ratio between new cars sold and the stock of cars in the Netherlands. If the date in the model is equal to the purchase date, the purchase process is initiated. To this end the discrete choice model on purchase decisions in Wolbertus, Kroesen, van den Hoed, & Chorus (2018b) is used. This model estimates the choice probabilities of full electric, plug-in hybrid electric and gasoline driven cars. Factors that are taken into account are a general tendency towards EVs (EV constant), the price and the ratio between the number of EVs and charging stations. Other factors used in the model by Wolbertus et al. (2018b) are kept constant. Car owner agents observe the ratio of number of frequent users and charging stations within the maximum walking distance of their home location. This ratio is obtained from the previous month of the simulation. The price of the cars is related to the exogenous developments of battery technology. The car owners are separated into different neighbourhoods. For each of these neighbourhoods the general attitude towards electric vehicles is determined, based upon the share of EVs (agents) from the total number of cars in the neighbourhood. Each of the car owners has a home location linked to a parking spot in the neighbourhood. The maximum walking distance of each car owner varies randomly between 200 and 600 meters. Once all information is obtained, the agent calculates the different utilities for each option and the corresponding choice probabilities, consequently the car choice is sampled.

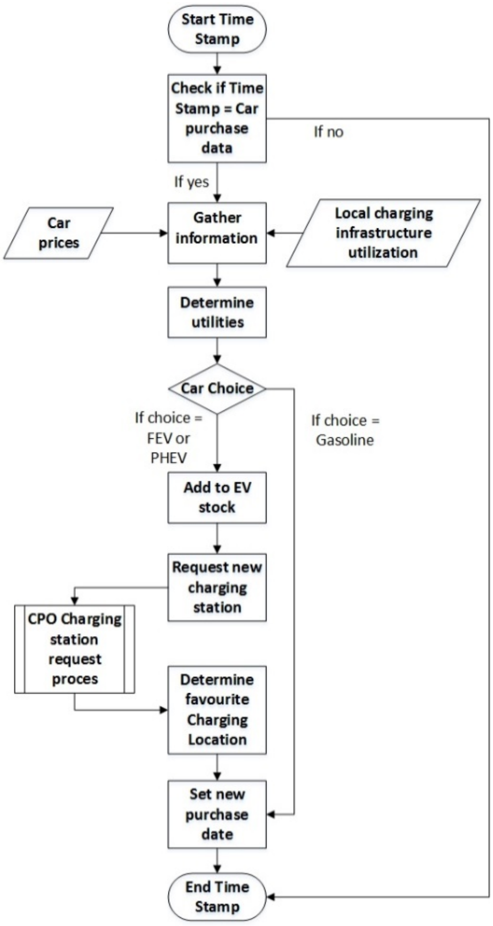


Figure 6.4 Overview of Car purchase process

When a PHEV or a FEV is purchased, the new EV agent is assigned a charging pattern of an existing EV agent. Depending on the choice of a FEV or a PHEV, the pattern of agent with more or less than 24 kWh is copied, respectively. The new EV agent is added to the stock of agents. The first connection date is sampled from connection dates of EV agents which are beyond the current time in the model. The favourite charging station is chosen on the basis of proximity to the home location. If the CPO (see 3.2.3) adds a new charging station at the home location, this station is chosen. It is assumed that the number of so-called non-habitual EV charging sessions grows at a similar pace as the number of agents in the model. At each month the number of non-habitual charging sessions to be created at each time of day is updated on the basis of the number of agents.

6.3.2.3 Charging point operator

The charging station placement process is initiated after the purchase process. The CPO measures the ratio between users and charging stations within the walking distance of the particular agent that requests a new charging station. If the ratio exceeds a threshold (which is varied in the simulation), the CPO decides to place an additional charging station. The CPO has three options which is to (1) add a regular charging station (at the home location of the new EV owners, capacity two agents), (2) to increase the capacity (with two agents) of the closest existing station or (3) to add a fast charging station. Fast charging stations are placed on locations of existing gas stations.

6.3.2.4 Charging Stations

Charging stations are objects modelled within a geo-spatial environment. They have a fixed location, a capacity for the number of EVs that can be charged simultaneously and a charging speed. The location is indicated with GPS coordinates and the walking distance between the charging stations is calculated with the Open Source Routing Machine (Luxen & Vetter, 2011). Standard capacity for a charger is two agents, which can be expanded. Fast charging stations have a larger charging speed (which can be varied between 50-350 kW).

6.3.3 Data

The charging profile per agent is created from data of the public charging infrastructure in Amsterdam (Wolbertus et al., 2018a, 2018b). Data from 2017 (682,709 charging sessions) are used to create the charging profiles and the data from 2018 (1,080,925 charging sessions) are used for verification. Data on the time of day, energy transferred (kWh), connection time and location of the charging session are stored per unique EV driver that is identified by a RFID-tag which is used to activate the charging station. Only RFID tags that are found to charge more than 30 times at a same location are used to create a charging profile. In addition, the data are filtered to exclude agents that are taxi drivers and shared car schemes as they are found to display non-habitual behaviour. Data on the start and end times of charging sessions are rounded to the nearest half hour. For each RFID a probability distribution per half hour and day of the week is created for the connection duration and the time between the charging sessions. An overview of the distributions across all agents is given in Appendix A. In total 3941 unique charging profiles are extracted from the data. These represent 10% of all users in the system but these users account for 58% of all charging sessions.

For those charging sessions that are not performed by RFID tags with more than 30 sessions, data were merged into a single distribution. The distribution of connection durations is made per half hour of the day, per day of the week. The kWh distribution is per half hour of the day. Additionally, two other distributions are made. First, a distribution of the average number of sessions per half hour, which serves as a proxy for the number of charging sessions that should be started on that timestamp. Second, as the created temporary agents do not have a favourite location, a probability distribution of the locations was made. In case a new charging station is added, it is given the mean probability. The distribution of charging behaviour for non-agent charging sessions is shown in Appendix 6.B.

In total 201,l339 car owners are modelled in Amsterdam. The home location is determined by the GPS locations of publicly available parking spots in Amsterdam (Municipality of Amsterdam, 2019). Each car owner agent has a specific attitude towards EVs related to the share of EV in its neighbourhood. This share is based on the ratio of agents to the total number cars per neighbourhood (CBS Statline, 2016). To determine the EV specific attitude per neighbourhood the share of EVs is compared to the national average in the Netherlands in 2017 (RVO.nl, 2019). The initial price of the car is determined with the choice model from Wolbertus et al. (2018) and the share of EVs sold in 2017 as input. The price of the car is split into a fixed price for the car without battery and a battery price. The price of the battery is discounted with 18% each year, the average drop in battery price over the last years (Nykvist et al., 2019). The battery is estimated to be 47% of the total car costs for a full electric vehicle and 10% for a plug-in hybrid electric vehicle when initialised.

6.3.4 Simulation process

The simulation period starts on the 1st of January 2018. The connection status or first time to connect for an agent is retrieved from the verification data. The simulated environment is the city of Amsterdam which contains 1148 charging locations at the start of the simulation. Standard fast charging speed is set at 50kW. Each model runs four times, mean results are displayed. The simulation period runs from 1st of January 2018 until the 31st of December 2024. The time interval in the simulation is set to 30 minutes. Simulation takes places in RStudio (RStudio Team, 2015). An overview of the simulation steps is shown in *Figure 6.5*. The order of simulation is as follows. At each timestamp agents first disconnect from the charging station. After the disconnection process, the simulation connects agents whose next connection time is equal to the time stamp in the model. After the agents have connected, the temporary non-habitual agents connect. If the time stamp is equal to the first day of the month the car purchase and charging station placement process is initialised. As a result, the stock of EVs and the charging stations are updated.

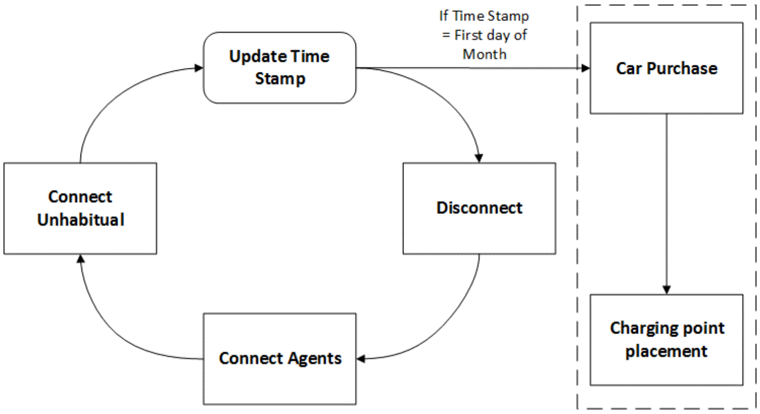


Figure 6.5 Simulation iteration process

At the end of each time stamp data are gathered about the charging sessions. For each agent and non-habitual charging session data are gathered on the location, time of day, session length and number of kWh charged. Additionally the system checks at each time stamp how many EV agents and charging stations are active within the system. Analysis of the data occurs at a weekly basis as this provides a consistent time frame across which the system can be evaluated. The simulation is verified with 2018 charging data from the same dataset as described in section 3.2.1.1. Verification is done over the period of a year to compare if charging patterns match those that were observed in real life. Wilcox tests are used to compare distributions of charging behaviour. Generally the model validates well on all charging parameters. For example, Wilcox test (p=0.82) verifies that the model validates well on the connection duration of agents. Additionally, we compared the number of charging sessions over the period of 2018 as shown in *Figure 6.6*. The simulation validates the general upward trend in the number of sessions well. The simulation however misses the seasonal variation with a lower number of sessions during summer and somewhat higher demand in winter. With regard to the aim of the simulation, comparing different roll-out strategies, the validation is considered sufficient as it estimates within a reasonable range.

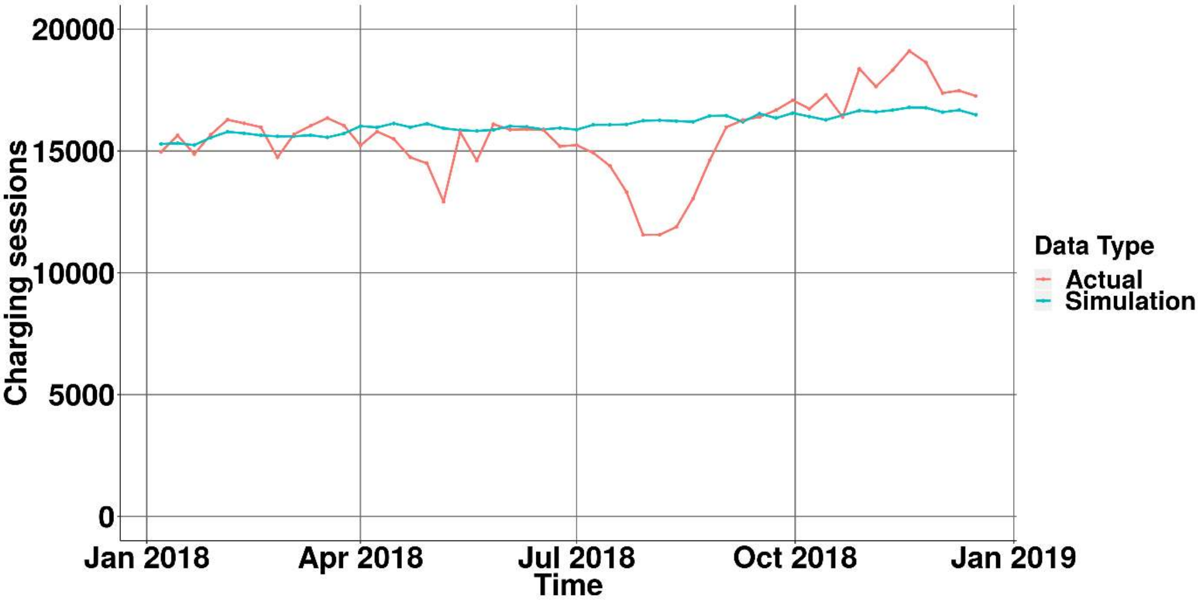


Figure 6.6 Comparing validation set and simulation in terms of number of charging sessions

6.3.5 Experiments

The model is used to test three types of hypothetical roll-out strategies which are being considered by policy makers. These roll-out strategies are single level 2 stations, clustered level 2 stations and fast charging stations.

Study 1: Charging station placement threshold variation
This study uses a roll-out strategy in which the CPO places a new level 2 charging station at the home location of a new EV owner. This is done if the ratio of agents to charging stations within the walking distance of an EV driver exceeds a threshold. This threshold is varied in the first study between 2 to 7 with a step of 1. At the start of the simulation, the ratio between agents and charging stations is 3.4, the current ratio. With a low ratio of e.g 2, a higher number of charging stations shall be placed as this threshold more easily exceeded. Higher thresholds lead to a lower number of stations relative to the number of EVs. Results are evaluated in terms of number of charging stations, reciprocal effect on EV sales, charging point utilisation (number of sessions and kWhs) and the share of failed sessions.

Study 2: Comparison of a charging hub to single charging station tactic
The single charging station strategy of study 1 is compared to a charging hub roll-out strategy. In the charging hub tactic, level 2 charging stations are added to the closest existing location, expanding the capacity at that location. If no locations are available within the given range, an additional charging station is added. The threshold for adding a charging station is fixed at three (which is the integer closest to the current ratio). Evaluation takes place in terms of the total number of locations and stations, the share of failed sessions, the share of sessions at favourite location and the number of kilometres of cruising for charging stations. The results of the charging hubs station tactic are compared to a single charging station roll-out.

Study 3: Fast charging station roll-out at different charging speeds
This study adds fast charging stations instead of level 2 charging stations. In this scenario, fast charging stations are not placed at the home location but at locations of gas stations in the city.

In this scenario the fast charging speed is varied for the charging stations placed. These charging speeds are 50kW, 175kW and 350kW along the common standards for fast charging in the market. Iteration time of the model is set to 30, 15 or 5 minutes accordingly, to be able to fully simulate the effect of faster charging speeds. No restriction is assumed on the charging speed by the vehicle, except that PHEVs cannot fast charge. Agents can travel up to 1500 meters to a fast charging station despite their maximum walking distance. During the purchase and charging station placement process the capacity for a fast charging station (50kW) is assumed to be 10 times as big as regular charging station, which corresponds to the ratio of connection times between regular and fast charging speeds. This capacity is adjusted according to the speeds (50-175-350kw) of the added fast charging stations. Threshold is again set at 3 EVs per charging station. Results are evaluated in terms of number of stations, failed sessions and additional kilometres travelled.

6.4 Results

6.4.1 Study 1: Charging station placement threshold variation

Figure 6.7 and *Figure 6.8* show the model results in terms of number of charging stations and EVs respectively. For the lower thresholds (2 and 3) the number of EV agents and charging stations grow at an exponential rate. Due to the low threshold for the CPO, the number of charging stations grows fast, as for every second EV agent added a charging station is placed. In the long run this results in a higher number of new EV agents; prospective owners are more inclined to buy an EV because of the low ratio between EVs and charging stations and the resulting high availability of charging nearby. The results illustrate the reciprocal effect between EVs and available charging stations. A higher number of EV agents then also results in more charging sessions. For the higher thresholds the growth in EV agents remains approximately linear in the short run. The number of charging stations barely grows as the threshold to place a new charging station is almost never reached. Despite this, still a number of car owners decide to purchase an electric vehicle, on the basis of decreased purchase prices. Deploying the right EV:Charging station ratio can result in the acceleration of EV sales.

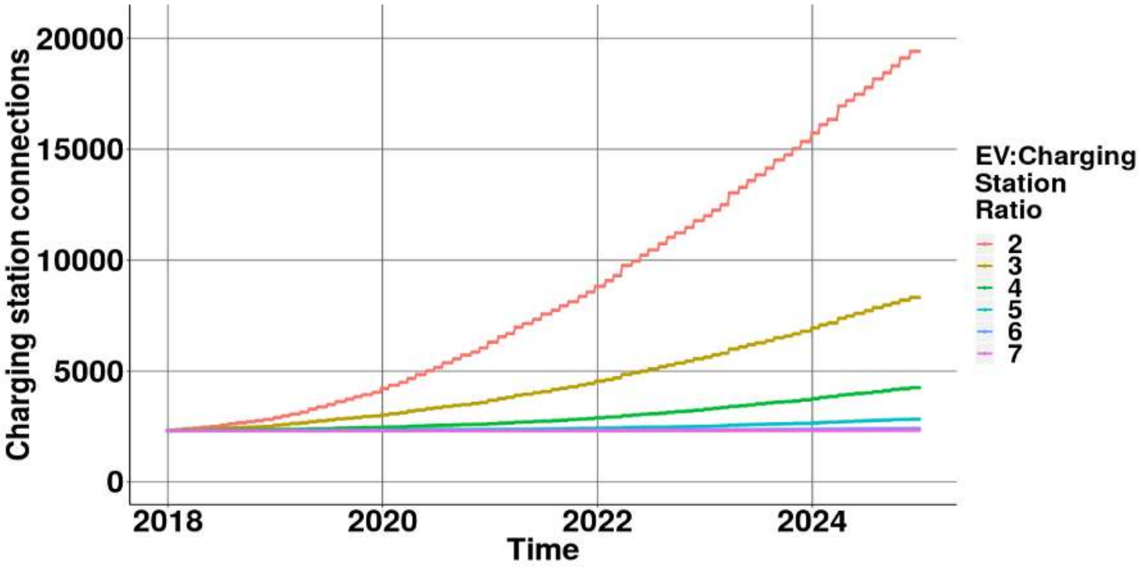


Figure 6.7 Charging station connections for each EV:Charging station ratio simulated over time

Figure 6.7 shows that the number of charging stations to be added for the lower threshold is significant. If a threshold of 2 is maintained this means a near tenfold increase in 7 years' time. If a similar ratio as in the current system is maintained (~3) the number of stations should grow by a factor of 4. The big difference in size can be attributed to the lower number of expected EV drivers (*Figure 6.8*). For the higher thresholds, limited growth is expected as the number of electric vehicles remains small.

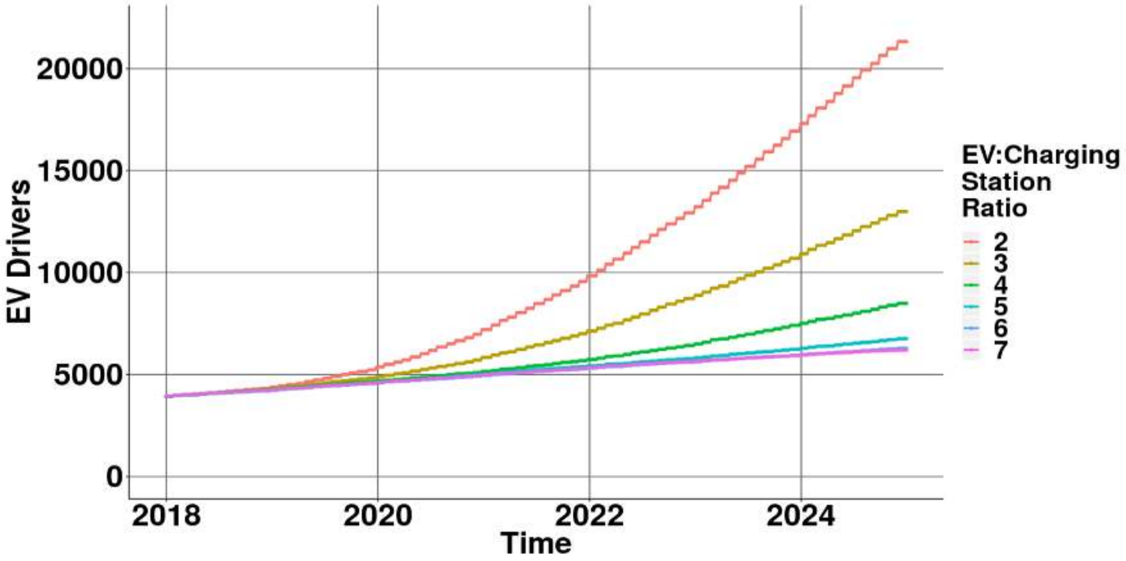


Figure 6.8 Number of EV Driver for each EV:Charging station ratio simulated over time

For each of the thresholds the share of failed sessions of the total per week is shown in *Figure 6.9*. On average the results show that approximately 2.2% of sessions fail due to a lack of available charging stations at the start of the simulation. It is not possible to empirically validate this number (failed sessions are not registered) but in general the actual number of failed sessions is thought of as being rather low in Amsterdam, due to the extensive charging infrastructure.

The results show that there are increasing 'returns on investment' in charging infrastructure. If a similar EV:Charging station ratio is deployed as in the current situation (~3), the number of failed sessions decreases with nearly 75% over the period of seven years. This decrease can be attributed to network formation of charging infrastructure. With an increasing charging network size, each agent gets multiple options to charge within their acceptable walking distance. Such return to scale effects are absent for the higher thresholds, because these networks have not yet reached the critical density for such effects to exist. This suggests that in time, policy makers and charging point operator can maintain higher EV:Charging station ratios without reducing the chance for EV drivers in finding an available charging station.

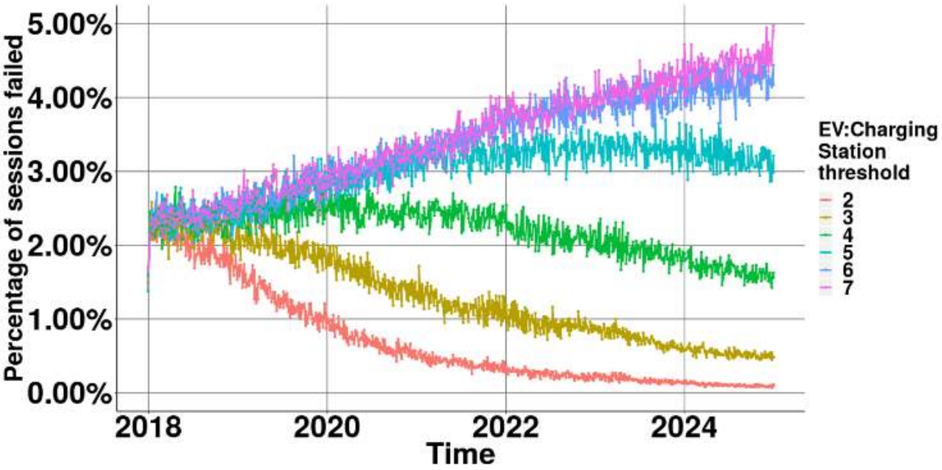


Figure 6.9 Share of failed sessions per threshold over time

Results show that CPOs can expect increasing 'returns on investment' in time for any EV:charging station threshold. Despite that the number of sessions per charging station decreases for the lower thresholds (*Figure 6.10 Left*), the number of kWh sold increases over time (*Figure 6.10 Right*). This is mainly due to the higher number of FEVs. The largest share of newly added agents (99%) drives an FEV. FEVs charge more kWh per session. At a ratio in which the number of failed sessions stays approximately equal, the turnover in terms of number of kWh roughly doubles in 7 years' time. This results in a substantially better business case for CPOs. For higher EV:Charging station ratios the business case can be nearly twice as good for the lower thresholds as idle times are reduced. For policy makers this implies reduced investments of public funding to facilitate the charging infrastructure for EVs.

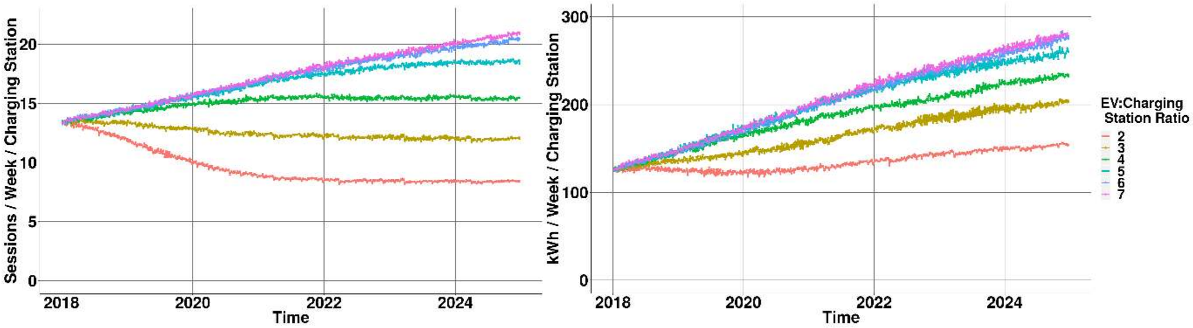


Figure 6.10 Frequency of use in number of sessions per charging station (Left) and kWh per charging station (right) per week

6.4.2 Study 2: Comparison of a charging hub to single charging station tactic

In the second study a roll-out tactic with single charging stations or charging hubs is compared at the equal threshold level of 3. For the charging hub tactic, charging stations were added to existing locations (blue). The total number of charging connections (*Figure 6.11)* however is only slightly less than in a tactic in which single charging stations were placed at new locations (red). In the longer term charging hubs can facilitate the same EV:Charging station threshold with fewer charging connections, although the difference is minimal. The centralisation incentivizes agents mainly use a single location. Therefore agents are not counted as frequent users across multiple locations, leading to slightly lower EV:Charging station ratios.

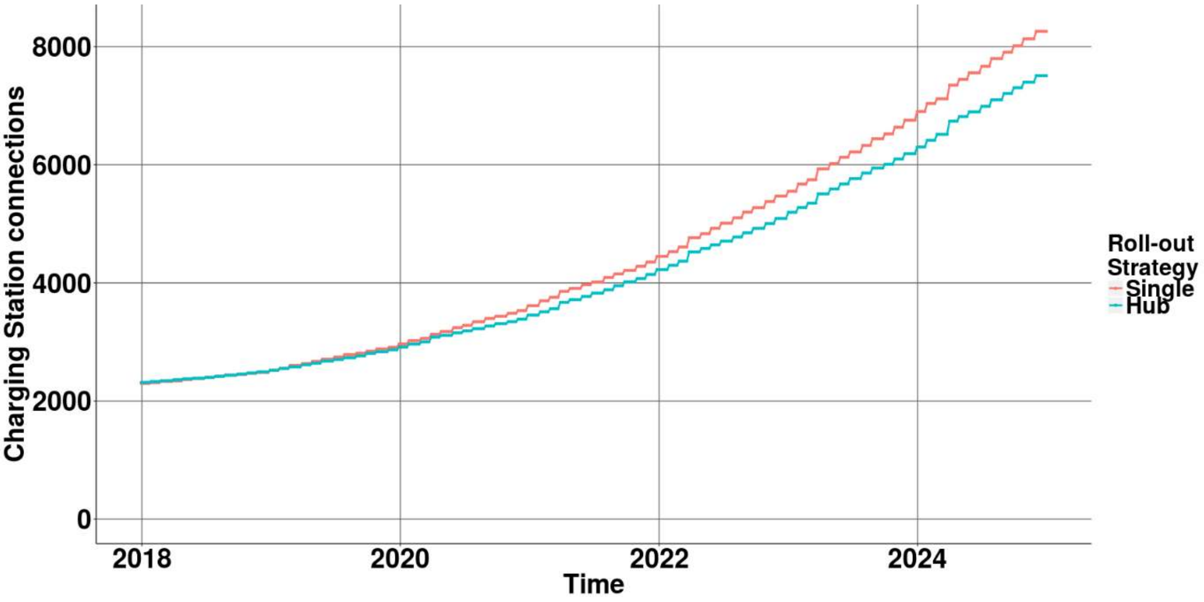


Figure 6.11 Charging connections for single (red) and hub (blue) roll-out tactic

Despite having to install slightly less charging stations, the hub roll-out tactic performs significantly worse (*Figure 6.12*) in terms of providing available charging stations for EV drivers. The share of failed sessions is up to four times as large in 2024 compared to the single roll-out tactic. This is due to the fact that there are hardly any increasing returns of scale for the hub tactic. The number of alternatives at different locations does not increase for EV drivers and networks effects stay similar to the start of the simulation. Especially charging stations that are placed in locations without alternatives within given walking distances perform significantly worse (share of sessions that fail are up to 20%).

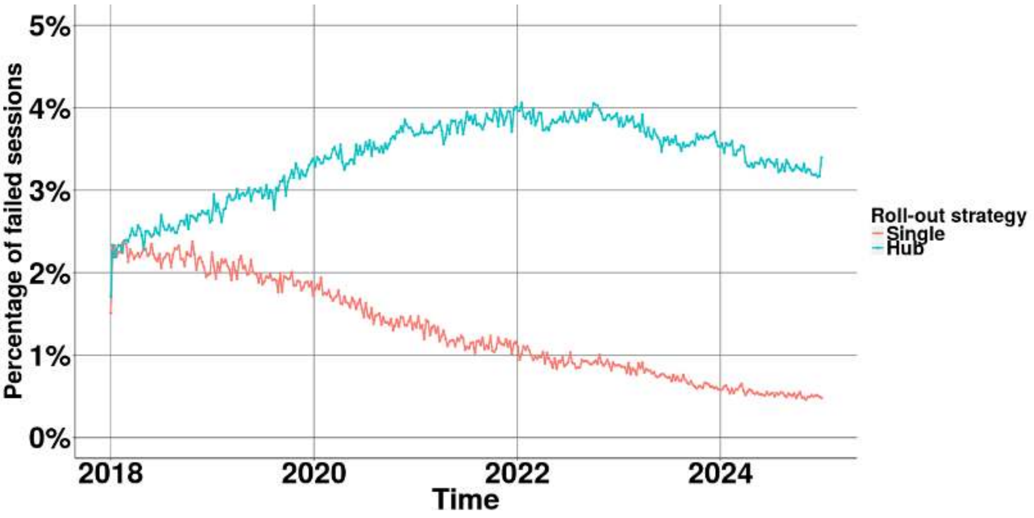


Figure 6.12 Share of failed sessions for single and hub roll-out tactic

The charging hub roll-out tactic performs less in terms of failed sessions but better in terms of a reduced number of kilometres vehicles are cruising to find a charging station (*Figure 16.3*). The number of charging attempts that succeed at the first try is significantly higher for the hub (95% at the end of simulation) than for the single station tactic (80%). This culminates in a significantly smaller distance that agents are driving to find an available charging station. Results show a higher convenience level for the EV driver, which has more certainty that charging stations closest to her or his preferred destination are available, despite the fact that there is a lower probability of having the possibility to actually charge. This result suggests that policy makers face trade-offs between providing charging accessibility on the one hand and convenience on the other, and could consider a hybrid roll-out tactic to optimise both factors.

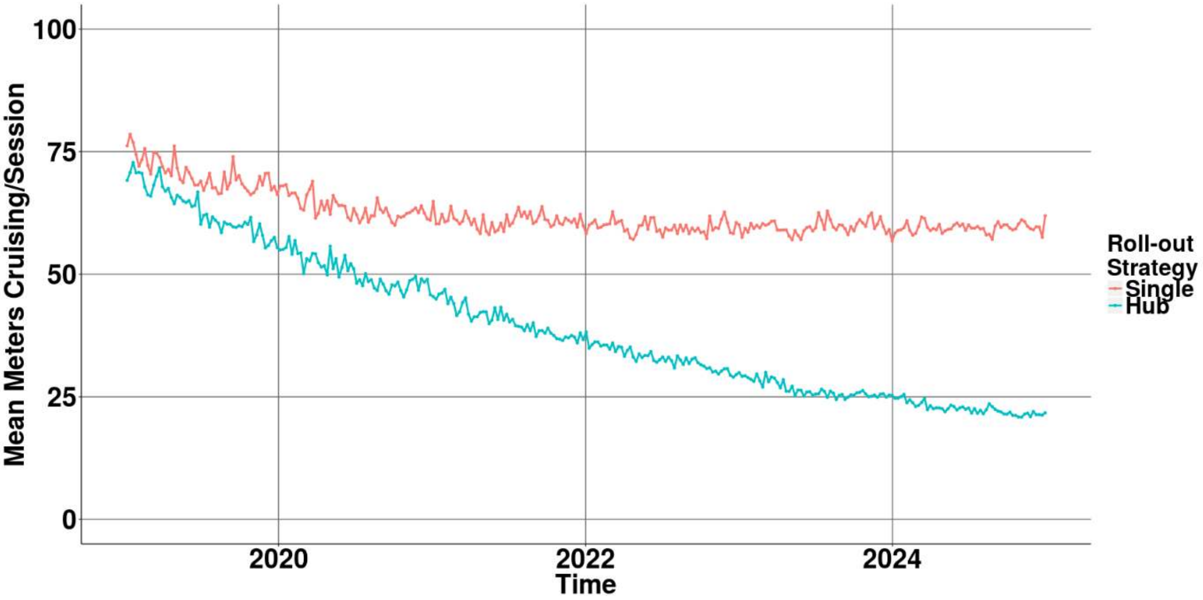


Figure 6.13 Cruising for charging stations per roll-out tactic in mean meters travelled

6.4.3 Study 3: Fast charging station roll-out at different charging speeds

The third study compares the single and hub tactic with three different roll-out strategies in which fast charging stations are placed at current locations of gas stations. Simulation shows that up to a factor 4-5 less fast charging stations (in absolute terms) are needed compared to regular chargers, as is to be expected (1000-2000 fast chargers in 2025 versus 7000-8000 stations for hubs/regular chargers – see *Figure 6.14*). When accounted for the model assumption that fast charging stations are considered having the capacity of 10 regular chargers (for 50kW), then number of stations grows more substantially in the fast charging station scenario in relative terms. This is due to the fact that charging demand becomes more centralised. Centralisation results in a higher number of unique users per station. Therefore the CPO will add new charging stations more frequently than in the single station strategy. When evaluated in terms of costs (Schroeder & Traber, 2012), the results suggests that in total costs the fast charging option is more economical than the single charging station model. This would however require a substantial number of chargers at a single site sharing the same grid connection (Nicholas & Hall, 2018).

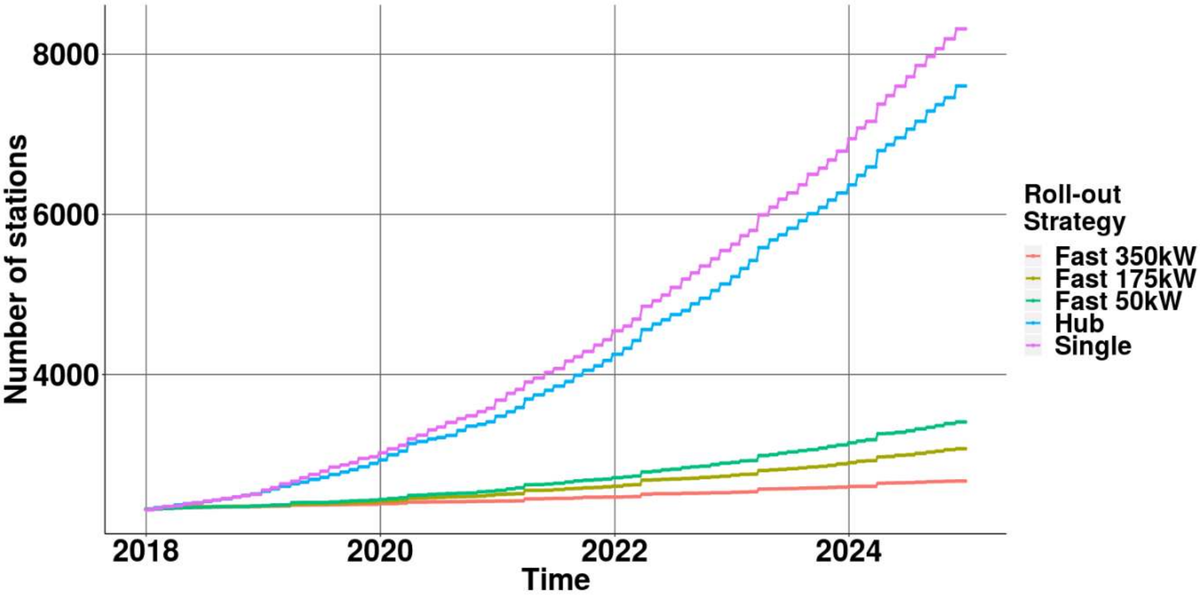


Figure 6.14 Number of installed charging stations per simulated roll-out strategy over time

The service level in terms of number of failed sessions at fast charging stations is lower than the charging hub strategy but significantly higher (up to 3-4x times) than the single charging station model (*Figure 6.15*). Differences between the different charging speeds are minimal. Increased charging speeds do not lead to a lower share of failed sessions as the number of charging stations is lower. The number of failed sessions at the fast charging stations themselves is very low (~0.1%). Some level 2 charging station have a very high share of failed sessions (20-30%), which indicates that some areas are underserved by the locations of fast charging stations as agents have a limited driving distance. New sites for fast charging stations or adding more regular chargers in the vicinity of those locations that are underserved may solve these issues.

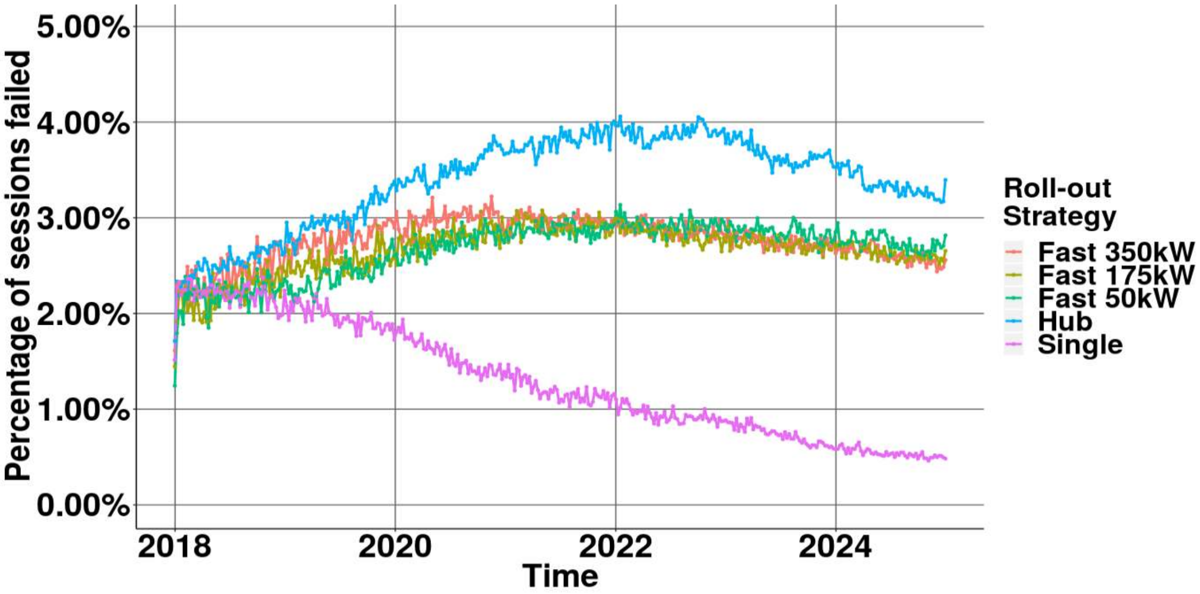


Figure 6.15 Percentage of sessions failed per roll-out strategy over time

In terms of discomfort for drivers, the additional number of kilometres travelled is higher in case of fast charging stations. This finding can be supported by several intuitive reasons. First, the additional distance that agents are willing to travel is larger than with level 2 chargers. Secondly, agents prefer to first charge at a level 2 station rather than at a fast charging station. With a growing number of agents and thus higher occupancy of level 2 stations, more agents are diverted to fast charging stations, resulting in additional cruising traffic. Travelling to and from the fast charging stations occurs by car, while travelling from an alternative level 2 stations is by foot. Comparing the additional inconvenience for the EV drivers therefore should be calculated in time (not in kilometres), which should include the time spent at the fast charging station. *Figure 6.16* compares the additional time per session spent for the different roll-out strategies. It is assumed that travel speed by car is 22km/hour (CROW, 2015), travelling by foot is 5km/hour. Travel times to fast charging stations are calculated as twice the one-day distance by car. The time charging at fast charging stations is added to the travel time. For level 2 charging stations, the travel time is regarded as covering the distance once by car and two times by foot.

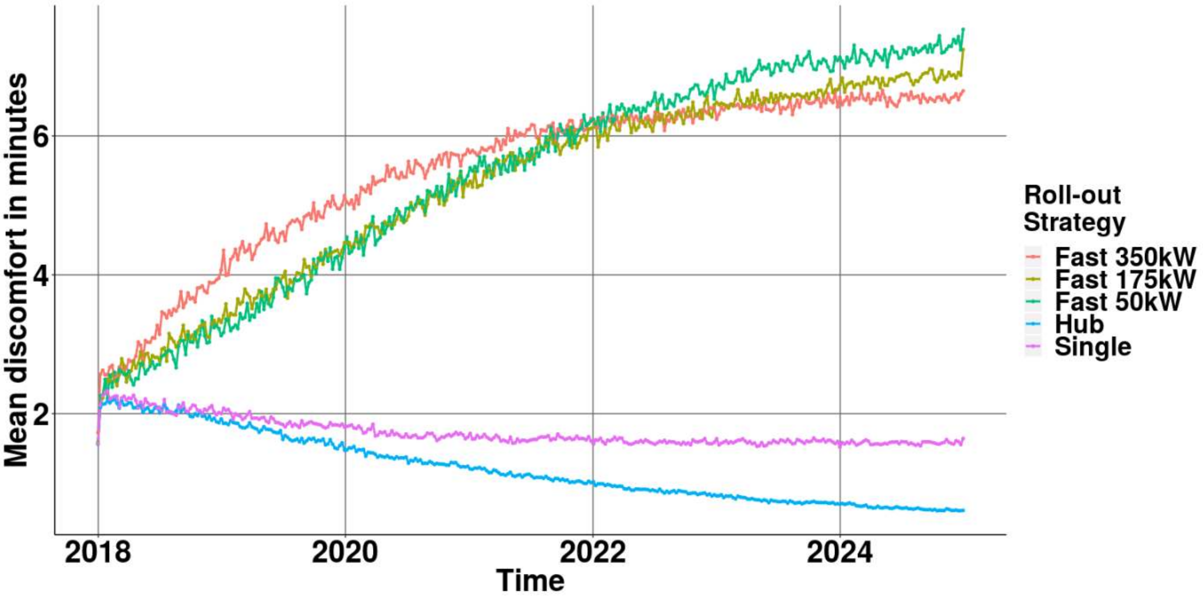


Figure 6.16 Mean discomfort per charging session in time per roll-out strategy over time

Figure 6.16 shows that roll-out strategies with fast charging stations result in more discomfort (in terms of time) for the EV driver. Remarkably, despite shorter charging times, the 350kW charging stations lead to more discomfort during the first years of the simulation. This is because agents are more likely to detour to these stations because the higher charging speed makes them more preferable as an alternative and thus the first alternative. On the short run, the additional travel time to the charging station plays a bigger role, but on the longer run it is the charging time which is dominant. In the model EV drivers are assumed to first try to connect at the level 2 station closest to their home. If agents learn that a fast charging station along their route to home is always available, it could lead to a significant reduction in discomfort time. In that case discomfort for drivers in a 350kW fast charge strategy is comparable to level 2 roll-out strategies with an EV:Charging station ratio of four to five.

6.5 Conclusion

6.5.1 Results, their interpretation and implications for policy

This paper has built and applied an ABM to assess roll-out strategies for EV charging stations in the urban environment. The model aids policy makers in making long-term decisions on how many of which type of charging stations should be placed where. Previous models have mainly been built on assumptions about charging behaviour with the use of travel patterns, while this model uses a large dataset of actual charging behaviour to distil charging patterns. This has resulted in a more realistic simulation of the charging behaviour and the effect on charging infrastructure roll-out. This paper has further specified a CPO agent which decides on when to place a new charging station. This agent does so on the basis on the ratio between EV drivers and charging stations available in an area. Potential EV drivers also take this ratio into account when evaluating the decision to purchase a new vehicle. In this way it has been possible to model the reciprocal effect between EV purchases and the charging station availability.

The results of the first study, in which new single charging stations were placed, show that the reciprocal effect can be substantial. A two-fold increase in the number of charging stations could lead to more than a doubling in the number of EV drivers. A higher threshold for placing new stations (resulting in less stations relative to new EVs), resulted in (approximately) linear growth in the short term. This shows that sufficient charging infrastructure can be a powerful catalyst in driving EV adoption. This effect is especially present if the ratio between EVs and charging stations is very low. Investing in sufficient charging stations for those that rely on on-street charging facilities results in an increased adoption pace. If the threshold is kept at similar levels as the current system's ratio between EVs and charging stations (3.4), the systems' performance in terms of successful sessions will increase. This result is due to return to scale effects, in which growth in network provides more alternatives to EV users. This suggests that policy makers and CPOs may in time increase the ratio between EVs and charging stations without affecting service levels. This increases efficiency with lower impacts on the grid and public space and would have a positive impact on the business case of public chargers due a higher number of sessions per charging station.

Comparison of the charging hub and single charging stations roll-out strategy (study 2) reveals that policy makers deal with trade-offs in charging accessibility (always able to charge) and convenience (measured in additional cruising distance and time). Charging hubs provide less, up to a factor 3, accessibility due to reduced network effects and return to scale, but provide more convenience (reducing average cruising distance by up to ~70%). This higher convenience results from the idea that EV drivers have their favourite charging location available more often and have to cruise less to find an available spot. The charging hub tactic has less negative impact on public space and grid integration but a there is a trade-off with charging accessibility. A possible solution lies in the use of a hybrid roll-out strategy in which empty spots are filled to create networks with critical densities and central locations are expanded.

Results of the fast charging station deployment study (study 3) suggest that fast charging stations can be a replacement for level 2 stations, especially if charging speeds are high (175-350kW). Location choice for fast charging stations is important as underserved areas can be a potential bottleneck. Level 2 charging stations without a fast charging station near, are often occupied. Fast charging requires the EV driver to detour additionally, but learning behaviour by drivers could minimize the detour. Additional discomfort comes from charging times, but as charging speeds increase and battery packs of EVs increase, this could result in comparable levels of discomfort to gasoline cars or roll-out strategies with a limited number of level 2 charging stations. Charging times however remain the largest barrier for fast charging stations to become the preferred charging option in urban areas. Due to technological constraints it can still take multiple years before the majority of EVs can reach higher charging speeds. Policy makers should therefore monitor developments in charging speed both the charging as the vehicle side and adjust their policies to these developments.

All three studies revealed that policy makers face a trade-off in their roll-out strategies between providing sufficient charging accessibility (able to charge) and charging convenience (charging with minimal time loss) from the EV driver perspective. Mixed roll-out strategies, in which sufficient charging stations create network formation, and thus return to scale benefits, and charging hubs and possible back-ups of fast charging stations provide possible solutions in which the policy maker can best satisfy the EV driver demand both in terms of accessibility and convenience. Note that such solutions are often very location specific, as the results of the fast charging simulations show, and thus optimal solutions may vary from city to city. The general idea however of creating network with hubs as often available places serves EV drivers the best. The results also showed that with increasing network size the business case for charging point operators improves. Together with increasing battery packs this provides good opportunities for a viable business case for CPOs in the near future. This also allows policy makers to better handle the interest of other stakeholders such as grid operators, which for example can allocate places in the grid where higher demand from fast charging stations or hubs is possible.

6.5.2 Limitations and future work

The ABM in this paper presented a new approach to simulate the charging behaviour and demand of EVs. The model assumed that charging demand is directly correlated with travel patterns but rather is the result of an interplay between parking and charging needs. With the use of a large dataset of revealed charging patterns the large scale introduction of EVs in the urban area is simulated. The charging patterns of future agents are copied from existing agents. This approach has limited flexibility in terms of representing learning behaviour of EV drivers. Most prominently this is observed in the fast charging scenarios in which the EV drivers are assumed to drive to their favourite level 2 charging location before considering a fast charging station. If the agent could learn from previous attempts in which they find level 2 stations mostly occupied and fast charging stations available and choose to first attempt fast charging, this could result in less cruising traffic. Future work should implement learning algorithms for agents as this in time could lead to new patterns.

The model has focussed on the urban environment as this environment has a unique public charging demand which so far has been lacking in other research. The combination of on-street overnight and office charging combined with different electric modes creates a different dynamic. The focus and use of data only in this urban environment however provides a limited view on the total charging demand of EV drivers. For example, EV drivers that charge overnight in the city can also have access to workplace charging elsewhere. A reduced availability of public charging in the city could result in a shift in their charging behaviour in place and time to the workplace. Such a scenario becomes more likely as battery capacity of EVs grows and the need to recharge daily decreases. EV drivers have to option to choose which charging mode they prefer instead of simply choosing the available charging station. Other factors such as price and parking preference could become more dominant in charging choices.

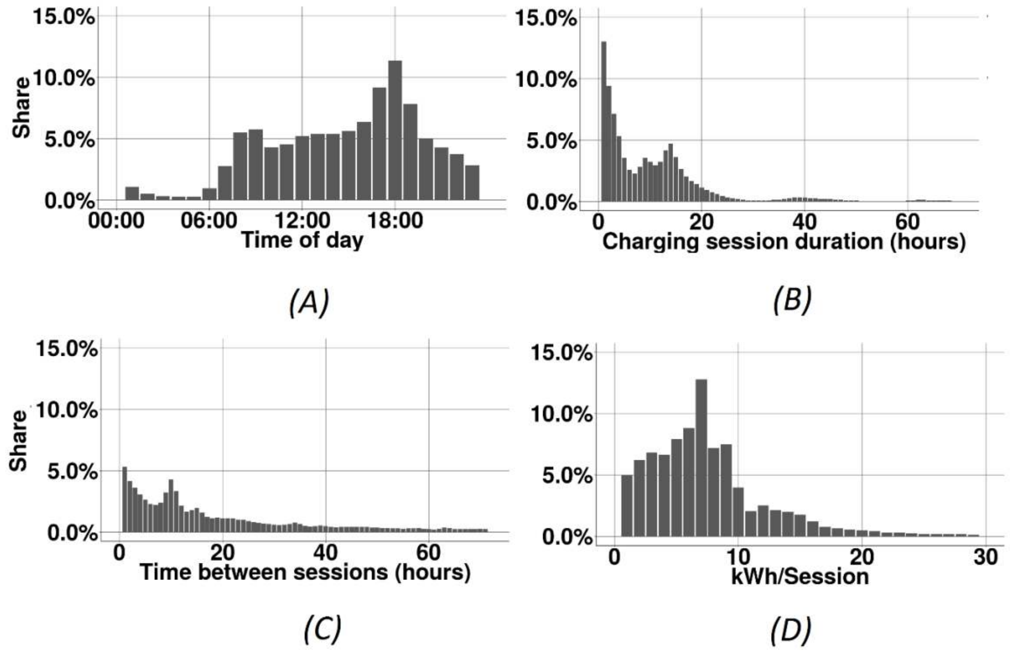
Our results suggest that charging behaviour is a result of a combination of travel and parking behaviour and the interaction of the EV driver with various technological constraints. The technical properties in this research have only been addressed by distinguishing between PHEVs and FEVs. Yet, battery and charging capacity also can play a dominant role in charging choices. The model for example relies on previous charging patterns of FEVs in which short (up to 40kWh) and long-ranged (>70kWh) are most prevalent as these vehicles were available during the initialisation period. Yet, mid-ranged FEVs can get a substantial share in the years to come. As these cars are not yet on the market, it is difficult to estimate what their charging behaviour will look like. Further research in how technological features of the car, such as battery capacity, level 2 and fast charging capabilities are needed to enrich ABMs. This would allow for even more realistic simulation of the EV charging system.

In general the model has proved to be able to calculate a large range of different roll-out scenarios and assess these on multiple aspects. This helps policy makers to make decisions on the long term about these strategies and adjust them when necessary. Such flexibility is crucial for policy makers and industry partners to provide sufficient charging infrastructure in the future with an exponential growth in EVs on the road.

Acknowledgments

We are grateful for the funding provided by SIA in the RAAK-PRO for the IDOLaad project of which this research is part of. We are also grateful for the cooperation of the participating municipalities and companies in the project for providing the relevant data.

Appendix 6.A: Charging Patterns of Agents

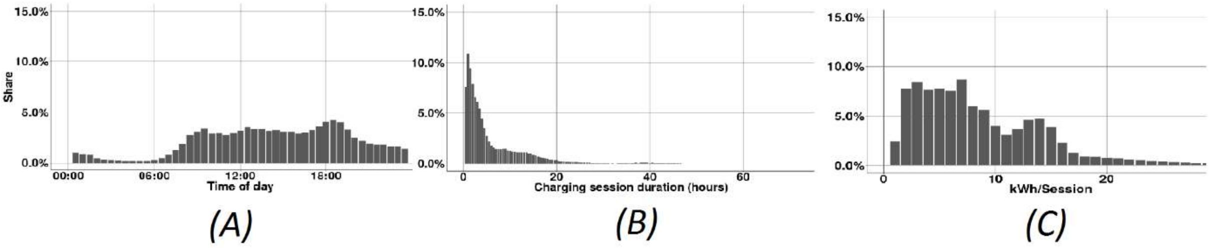


(A) (B)

(C) (D)

Figure 6.17 Charging patterns of agents, with (A) distribution of start times, (B) Connection duration and (C) Time between sessions and (D) kWh distribution

Appendix 6.B: Charging patterns of non-habitual users



(A) (B) (C)

Figure 6.18 Charging patterns of non-habitual users, with (A) distribution of start times, (B) Connection duration and (C) kWh distribution

Appendix 6.C: Distribution of observed maximum walking distances

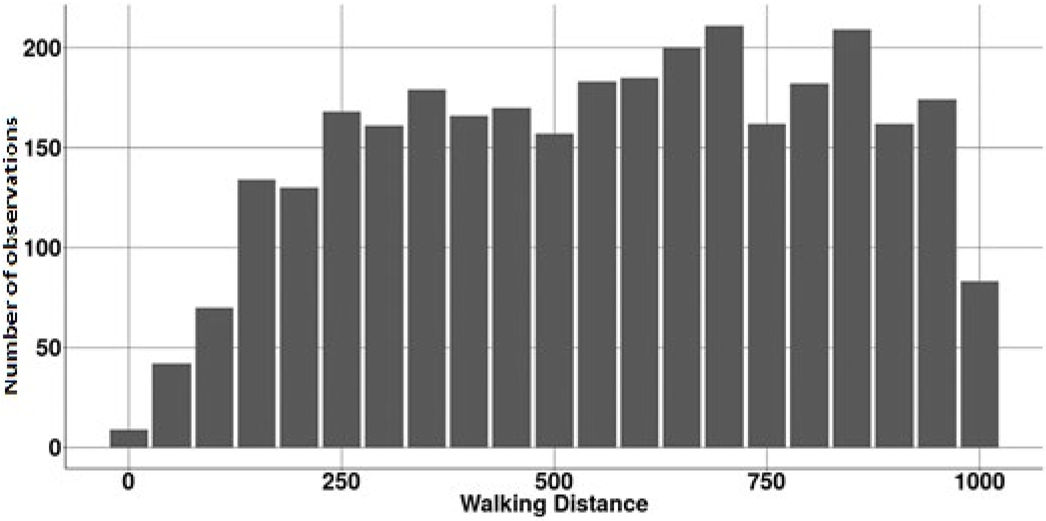


Figure 6.19 Distribution of maximum walking distance per agent

6.9 References

Araghi, Y., Bollinger, L., & Lee, E. P. (2014). Informing agent based models with discrete choice analysis. *Social Simulation Conference*. Retrieved from http://ddd.uab.cat/pub/poncom/2014/128005/ssc14_a2014a30iENG.pdf

Axhausen;, K. W., & Polak, J. W. (1991). Choice of parking : Stated preference approach. *Transportation*, *18*(1), 59–81.

Axsen, J., Mountain, D. C., & Jaccard, M. (2009). Combining stated and revealed choice research to simulate the neighbor effect : The case of hybrid-electric vehicles. *Resource and Energy Economics*, *31*, 221–238. https://doi.org/10.1016/j.reseneeco.2009.02.001

Bailey, J., Miele, A., & Axsen, J. (2015). Is awareness of public charging associated with consumer interest in plug-in electric vehicles ? *Transportation Research Part D: Transport and Environment*, *36*, 1–9. https://doi.org/10.1016/j.trd.2015.02.001

Bjerkan, K. Y., Nørbech, T. E., & Nordtømme, M. E. (2016). Incentives for promoting Battery Electric Vehicle (BEV) adoption in Norway. *Transportation Research Part D: Transport and Environment*, *43*, 169–180. https://doi.org/10.1016/j.trd.2015.12.002

Brooker, R. P., & Qin, N. (2015). Identification of potential locations of electric vehicle supply equipment. *Journal of Power Sources*, *299*, 76–84. https://doi.org/10.1016/j.jpowsour.2015.08.097

CBS Statline. (2016). Kerncijfers wijken en buurten 2016. Retrieved April 18, 2016, from https://www.cbs.nl/nl-nl/maatwerk/2016/30/kerncijfers-wijken-en-buurten-2016

City of Amsterdam. (2019). *Clean Air Action Plan*. Amsterdam. Retrieved from https://www.amsterdam.nl/en/policy/sustainability/clean-air/

Coffman, M., Bernstein, P., & Wee, S. (2016). Electric vehicles revisited : a review of factors that affect adoption. *Transport Reviews*, 1–15. https://doi.org/10.1080/01441647.2016.1217282

CROW. (2015). De Wadden snelste per auto, Culemborg per ov. Retrieved June 27, 2019, from https://kpvvdashboard-16.blogspot.com/

Eppstein, M. J., Grover, D. K., Marshall, J. S., & Rizzo, D. M. (2011). An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy Policy*, *39*(6), 3789–3802. https://doi.org/10.1016/j.enpol.2011.04.007

Gnann, T., & Plötz, P. (2015). A review of combined models for market diffusion of alternative fuel vehicles and their refueling infrastructure. *Renewable and Sustainable Energy Reviews*, *47*, 783–793. https://doi.org/10.1016/j.rser.2015.03.022

Gnann, T., Plötz, P., Kühn, A., & Wietschel, M. (2015). Modelling market diffusion of electric vehicles with real world driving data – German market and policy options. *Transportation Research Part A*, *77*, 95–112. https://doi.org/10.1016/j.tra.2015.04.001

Gnann, T., Plötz, P., & Wietschel, M. (2018). Can public slow charging accelerate plug-in electric vehicle sales? A simulation of charging infrastructure usage and its impact on plug-in electric vehicle sales for Germany. *International Journal of Sustainable Transportation*, *0*(0), 1–15. https://doi.org/10.1080/15568318.2018.1489016

Hardman, S., Tal, G., Turrentine, T., Axsen, J., Beard, G., Daina, N., … Pontes, J. (2017). Driving the Market for Plug-in Vehicles - Developing PEV Charging Infrastructure for Consumers Lessons from Academic Research & Empirical Data, (October).

Helmus, J., & van den Hoed, R. (2015). Unraveling User Type Characteristics : Towards a Taxonomy for Charging Infrastructure. *EVS28 International Electric Vehicle Symposium and Exhibition*, 1–16.

Helmus, J R, Hoed, R. Van Den, & Lees, M. H. (2019). Exploring a Complex Systems Approach to Charging Infrastructure : implications for researchers and policy makers. In *Electric Vehicle Symposium 32* (pp. 1–17). Lyon, France.

Helmus, J R, Spoelstra, J. C., Refa, N., Lees, M., & Van den Hoed, R. (2018). Assessment of public charging infrastructure push and pull rollout strategies: the case of the Netherlands. *Energy Policy*, *121*, 35–47. https://doi.org/https://doi.org/10.1016/j.enpol.2018.06.011

Helmus, Jurjen R., Wachlin, S., Vermeulen, I., & Lees, M. H. (2019). *SEVA: A Data driven model of Electric Vehicle Charging Behavior*. Retrieved from http://arxiv.org/abs/1904.08748

Holm, S., Lemm, R., Thees, O., & Hilty, L. M. (2016). Enhancing Agent-Based Models with Discrete Choice Experiments. *Journal of Artificial Societies and Social Simulation*, *19*(3). https://doi.org/10.18564/jasss.3121

International Energy Agency. (2018). *Global EV Outlook 2018*. Retrieved from http://centrodeinnovacion.uc.cl/assets/uploads/2018/12/global_ev_outlook_2018.pdf

Jabeen, F., Olaru, D., Smith, B., Braunl, T., & Speidel, S. (2013). Electric vehicle battery charging behaviour: Findings from a driver survey. *36th Australasian Transport Research Forum (ATRF), Brisbane, Queensland, Australia*.

Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology*, *52*, 166–182. https://doi.org/10.1016/j.jenvp.2017.01.002

Kieckhäfer, K., Wachter, K., & Spengler, T. S. (2017). Analyzing manufacturers ' impact on green products ' market diffusion e the case of electric vehicles. *Journal of Cleaner Production*, *162*, 11–25. https://doi.org/10.1016/j.jclepro.2016.05.021

Krupa, J. S., Rizzo, D. M., Eppstein, M. J., Lanute, D. B., Gaalema, D. E., Lakkaraju, K., & Warrender, C. E. (2014). Analysis of a consumer survey on plug-in hybrid electric vehicles. *Transportation Research Part A*, *64*, 14–31. https://doi.org/10.1016/j.tra.2014.02.019

Latinopoulos, C., Sivakumar, A., & Polak, J. (2017). Modeling Electric Vehicle Charging Behavior: What Is the Relationship Between Charging Location, Driving Distance, and Range Anxiety? *Transportation Research Board, 96th Annual Meeting*.

Le Pira, M., Marcucci, E., Gatta, V., Inturri, G., Ignaccolo, M., & Pluchino, A. (2017). Integrating discrete choice models and agent-based models for ex-ante evaluation of stakeholder policy acceptability in urban freight transport. *Research in Transportation Economics*, *64*, 13–25. https://doi.org/10.1016/j.retrec.2017.08.002

Liao, F., Molin, E., & Wee, B. Van. (2017). Consumer Preferences for Electric Vehicles : a Literature Review. *Transport Reviews*, 1–24.

Luxen, D., & Vetter, C. (2011). Real-time routing with OpenStreetMap data. In *19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* (pp. 513–516). New York: Association for Computing Machinery.

Montfort, K. Van, Visser, J., & Poel, G. Van Der. (2016). Voorspellen van benodigde infrastructuur van publieke laadpalen voor elektrische auto's. *Tijdschrift Vervoerswetenschap*, *52*(2), 2–13.

Morrissey, P., Weldon, P., & Mahony, M. O. (2016). Future standard and fast charging infrastructure planning : An analysis of electric vehicle charging behaviour. *Energy Policy*, *89*, 257–270. https://doi.org/10.1016/j.enpol.2015.12.001

Motoaki, Y. (2019). Location-Allocation of Electric Vehicle Fast Chargers — Research and Practice †. *World Electric Vehicle Journal*, *10*(1), 10–16. https://doi.org/10.3390/wevj10010012

Municipality of Amsterdam. (2019). City Data. Retrieved August 5, 2018, from https://data.amsterdam.nl/

Nicholas, M., & Hall, D. (2018). *Lessons learned on early electric fast-charging deployments*. Washington DC, United States.

Noori, M., & Tatari, O. (2016). Development of an agent-based model for regional market penetration projections of electric vehicles in the United States. *Energy*, *96*, 215–230. https://doi.org/10.1016/j.energy.2015.12.018

Nykvist, B., Sprei, F., & Nilsson, M. (2019). Assessing the progress toward lower priced long range battery electric vehicles. *Energy Policy*, *124*(September 2018), 144–155. https://doi.org/10.1016/j.enpol.2018.09.035

Olivella-rosell, P., Villafafila-robles, R., & Sumper, A. (2014). Probabilistic Agent-Based Model of Electric Vehicle Charging Demand to Analyse the Impact on Distribution Networks, 1–26. https://doi.org/10.3390/en8054160

Paffumi, E., Gennaro, M. De, & Martini, G. (2015). Transportmetrica A : Transport Science Assessment of the potential of electric vehicles and charging strategies to meet urban mobility requirements. *Transportmetrica A: Transport Science*, *11:1*(January 2015), 22–60. https://doi.org/10.1080/23249935.2014.913732

Pan, A., Zhao, T., Yu, H., & Zhang, Y. (2019). Deploying Public Charging Stations for Electric Taxis : A Charging Demand Simulation. *IEEE Access*, *PP*(c), 1. https://doi.org/10.1109/ACCESS.2019.2894780

Rezvani, Z., Jansson, J., & Bodin, J. (2015). Advances in consumer electric vehicle adoption research : A review and research agenda. *Transportation Research Part D*, *34*, 122–136. https://doi.org/10.1016/j.trd.2014.10.010

Rodrigues, L., Bolognesi, H. M., Melo, J. D., Heymann, F., & Soares, F. J. (2019). Spatiotemporal model for estimating electric vehicles adopters, *183*. https://doi.org/10.1016/j.energy.2019.06.117

RStudio Team. (2015). RStudio: Integrated Development for R. Boston, MA: RStudio, Inc. Retrieved from http://www.rstudio.com/

RVO.nl. (2019). *Statistics Electric Vehicles in the Netherlands (up to and including March 2019)*. The Hague. Retrieved from https://www.rvo.nl/sites/default/files/2019/04/Statistics Electric Vehicles and Charging in The Netherlands up to and including March 2019.pdf

Schroeder, A., & Traber, T. (2012). The economics of fast charging infrastructure for electric vehicles. *Energy Policy*, *43*, 136–144. https://doi.org/10.1016/j.enpol.2011.12.041

Shafiei, E., Thorkelsson, H., Asgeirsson, E. I., Davidsdottir, B., Raberto, M., & Stefansson, H. (2012). An agent-based modeling approach to predict the evolution of market share of electric vehicles : A case study from Iceland. *Technological Forecasting & Social Change*, *79*, 1638–1653. https://doi.org/10.1016/j.techfore.2012.05.011

Shahraki, N., Cai, H., Turkay, M., & Xu, M. (2015). Optimal locations of electric public charging stations using real world vehicle travel patterns. *Transportation Research Part D: Transport and Environment*, *41*, 165–176. https://doi.org/10.1016/j.trd.2015.09.011

Sierzchula, W., Bakker, S., Maat, K., & Wee, B. Van. (2014). The in fluence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043

Silvia, C., & Krause, R. M. (2016). Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. *Energy Policy*, *96*, 105–118. https://doi.org/10.1016/j.enpol.2016.05.039

Sun, X. H., Yamamoto, T., & Morikawa, T. (2016). Fast-charging station choice behavior among battery electric vehicle users. *Transportation Research Part D: Transport and Environment*, *46*, 26–39. https://doi.org/10.1016/j.trd.2016.03.008

Sweda, T. M., & Klabjan, D. (2015). Agent-Based Information System for Electric Vehicle Charging Infrastructure Deployment. *Journal of Infrastructure Systems*, *21*(2), 04014043. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000231

Torres, S., Barambones, O., De Durana, J. M. G., Marzabal, F., Kremers, E., & Wirges, J. (2015). Agent-based modelling of electric vehicle driving and charging behavior. In *2015 23rd Mediterranean Conference on Control and Automation, MED 2015 - Conference Proceedings* (pp. 459–464). https://doi.org/10.1109/MED.2015.7158791

Van der Poel, G., Tensen, T., Van Goeverden, T., & van den Hoed, R. (2017). Charging free floating shared cars in metropolitan areas. In *Electric Vehicle Symposium and Exhibition 30* (pp. 1–11). Stuttgart.

Vermeulen, I., Helmus, J. R., van den Hoed, R., & Lees, M. (2018). Simulation of Future Electric Vehicle Charging behaviour - Effects of transition from PHEV to FEV -. In *Electric Vehicle Symposium 31* (pp. 1–5). Kobe, Japan.

Vijayashankar, A. (2017). Modeling electric vehicle charging infrastructure deployment and usage with an agent-based approach. *Master Graduation Paper*. Retrieved from http://sparkcity.org/sparkcity-symposium-charging-behavior-by-anand-vijayashankar/#more-2035

Waerden, P. Van Der, Timmermans, H., & De Bruin-Verhoeven, M. (2017). Car drivers ' characteristics and the maximum walking distance between parking facility and final destination. *The Journal of Transport and Land Use*, *10*(1), 1–11. https://doi.org/http://dx.doi.org/10.5198/jtlu.2017.568

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. (2018a). Fully charged: An empirical study into the factors that influence connection times at EV-charging stations. *Energy Policy*, *123*. https://doi.org/10.1016/j.enpol.2018.08.030

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. G. (2018b). Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. *Transportation Research Part D: Transport and Environment*, *62*. https://doi.org/10.1016/j.trd.2018.03.012

Wolbertus, R., & Van Den Hoed, R. (2017). Charging station hogging: A data-driven analysis. In *EVS 2017 - 30th International Electric Vehicle Symposium and Exhibition*.

Wolbertus, Rick, Kroesen, M., van den Hoed, R., & Chorus, C. (2018). Fully charged: An empirical study into the factors that influence connection times at EV-charging stations. *Energy Policy*, *123*(August), 1–7. https://doi.org/10.1016/j.enpol.2018.08.030

Wolbertus, Rick, & Van den Hoed, R. (2019). Electric Vehicle Fast Charging Needs in Cities and along Corridors. *World Electric Vehicle Journal*, *10*(2), 45. https://doi.org/10.3390/wevj10020045

Xi, X., Sioshansi, R., & Marano, V. (2013). Simulation–optimization model for location of a public electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment*, *22*, 60–69. https://doi.org/10.1016/j.trd.2013.02.014

Zoepf, S., MacKenzie, D., Keith, D., & Chernicoff, W. (2013). Charging choices and fuel displacement in a large-scale plug-in hybrid electric vehicle demonstration. *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2385*, 1–10.

7 Stakeholders’ perspectives on future electric vehicle charging infrastructure developments

An adapted version of this chapter has been submitted as:
Wolbertus, R., Jansen, S., & Kroesen, M. (2019). Stakeholders’ perspectives on future electric vehicle charging infrastructure developments. Futures (Submitted).

Abstract

Charging infrastructure development is vital for the adoption of electric vehicles (EVs). Yet, on the surface, there seems to be significant disagreement about when, how and which kind of charging infrastructure should be developed and most importantly, for what reasons. Differences in stakeholders’ perspectives regarding the roll-out of EV charging infrastructure may be expected, but should they prove irreconcilable they may stall the roll-out. However, to date, it remains unknown what these stakeholders’ perspectives are, how they are aligned across stakeholders, which topics are heavily debated and which are agreed upon. This study uses Q-methodology to identify different perspectives on the roll-out of EV charging infrastructure. The analysis shows that stakeholders mainly differ in the extent fast charging should play an important role, the degree smart charging should be the standard in charging and how much government should intervene with infrastructure roll-out. There is a consensus on the importance of interoperability of charging stations. The four different perspectives were supported across different stakeholders, which supports the idea that perspectives are not strongly linked to the stakeholders’ interests.

7.1 Introduction

With an increase in the number of electric vehicles (EVs) (International Energy Agency, 2017), charging infrastructure to facilitate these vehicles is becoming critical. The number of charging stations trails compared to the number of vehicles. Exponential growth of the number of EVs is predicted if battery prices continue to fall as in recent years (Nykvist & Nilsson, 2015; Nykvist, Sprei, & Nilsson, 2019; Shafiei et al., 2012). A slower roll-out of charging infrastructure compared to the uptake of EVs is becoming the major bottleneck in EV adoption (Maia, Teicher, & Meyboom, 2015; R. Wolbertus, Kroesen, van den Hoed, & Chorus, 2018). Scholars point to the chicken-and-egg dilemma that stems from the problematic business case for public electric vehicle chargers (Madina, Zamora, & Zabala, 2016; Schroeder & Traber, 2012) as the main cause for the low number of public chargers. Other causes receive less attention in the debate. It has been suggested that different perspectives from a large range of stakeholders on the roll-out strategy of charging infrastructure may lead to a slow adoption pace (Bakker, Maat, & van Wee, 2014). Yet, this topic has remained unexplored from an empirical perspective.

Policy makers have to make mid- and long-term strategic decisions about roll-out strategies for charging infrastructure. Payback periods for infrastructure investments for emerging technologies are relatively long (Burnham et al., 2017). Different charging technologies, old ones and new alike, are competing for the policy makers’ interest. These include destination charging, (ultra-)fast charging, static and dynamic wireless charging and the re-emerging of battery swapping as an option to replace charging. The large number of, and variety in stakeholders that want to have a stake, complicates the issue. Utilities, grid operators, automakers, new entrants, governments and oil companies all invest into charging infrastructure (Wirges, 2016). These stakeholders have different ideas about how the market should look like and how it should (or should not) be regulated. Policy makers are looking to see which topics should be addressed most urgently according to the stakeholders in the field. Although the interests of the stakeholders in the charging infrastructure industry have been described before (Bakker et al., 2014; Wirges, 2016), a systematic overview of how these interests translate into perspectives on electric vehicle infrastructure development is missing. Moreover these studies do not stipulate how these interests are aligned or are in disagreement.

To reveal the shared perspectives on the future of EV charging across the stakeholders we use Q-methodology, a method which is particularly suitable to reveal subjective viewpoints on a topic (Brown, 1980). In this paper, we argue that Q-methodology is useful and adds to current stakeholder analysis especially in the field of future studies. In contrast to stakeholder analysis, Q-methodology proceeds from the idea that perspectives are shared across stakeholders. In our case this allows us to gain an understanding of the long-term perspectives regarding the future of charging and identify the largest areas of dispute that need policy makers’ attention. From the Q-experiment with 39 stakeholders from 9 different industries the results show that there are four different perspectives on charging infrastructure developments. The four different perspectives are further analysed to see which issues are the most prominent and how the stakeholders from different industries are divided across these perspectives. The results show that new areas which have previously had not been found in other stakeholder analyses are seen as most important.

As such, the paper has two contributions, namely a methodological one (showing how Q-methodology may be employed to reveal future perspectives among stakeholders) and a substantive one (showing which particular points of consensus and dissensus exist among stakeholders regarding the future of electric charging). While the second contribution may seem specific to the Netherlands, it should be noted that Dutch situation resembles one of the front-runners on public charging infrastructure. As such, it is likely that the substantive topics of conflict identified in this study (regarding the role of smart charging, fast charging and the level of government intervention) also arise in many other countries across Europe and outside. Indeed, the Dutch situation can be regarded as an exemplary case for the conflicts that will likely arise in dense urban areas that exist across the world.

The remainder of this paper is organised as follows. Section 7.2 is literature review on stakeholder analysis in charging infrastructure and addresses the Q-methodology approach. Section 7.3 provides an introduction to the charging infrastructure market and topics at hand. Section 7.4 of this paper presents the methodology used. In section 7.5 we present the results, which include the different perspectives and how they are distributed across the stakeholders. The section also highlights the main areas of consensus and conflict. In the final section we provide conclusions and policy implications.

7.2 Literature review and approach

EVs and the development of charging infrastructure are much discussed topics in the scientific literature. Regarding charging infrastructure most papers have focussed on optimal roll-out strategies given certain demand and supply. Many modelling techniques take a multi-actor approach to optimise supply of charging infrastructure (Collantes, 2007; Gnann, Plötz, Kühn, & Wietschel, 2015; Harrison & Thiel, 2017). Interests of stakeholders are captured in formulas in which they will try to optimise their own utility (Hajer, 2006; Sweda & Klabjan, 2015; Torres, Bader, Romeral, Lux, & Ortega, 2013). Yet, such models offer a simplified version of reality in which stakeholder interests are much more complex and multi-dimensional. Stakeholder analysis techniques offer the opportunity to better understand the decision making process in certain contexts (Brugha & Varvasovszky, 2000).

Only a limited number of studies have focussed on stakeholder interest in the electric vehicles business and charging infrastructure in particular. Bakker et al. (2014) and Wirges (2016) described the interests of the main stakeholders in the field and tried to identify the major hurdles to overcome. They find that developing a charging infrastructure that suits all stakeholders interests is hard due to issues on grid integration of (fast) chargers and the allocation of charging stations within parking regimes. Steinhilber, Wells, & Thankappan (2013) found similar issues as the previous studies but also took a broader perspective on the market looking at R&D subsidies and technological developments. They find that the fast technological developments are not yet heading in one single clear direction.

Besides using (semi-)structured interviews as a way to unveil the stakeholders' interests a few studies use different techniques. Warth, Gracht, & Darkow (2013) used a delphi approach to identify the most likely scenario for the future. Furthermore, using latent class analysis they found three clusters of stakeholders that have similar perspective on the future. These clusters mainly differed on the significance they see for the car industry in general and less specific for EVs. Although identifying different clusters, they did not show how the different stakholders were distributed along these perspectives. Zimmermann, Darkow, & Gracht (2012) integrated delphi with participatory backcasting methodology to investigate the electric mobility market in Germany. Their analysis focussed on the factors that are relevant in developping a preferred future for electric mobility. Three main issues that were found were the consumer preferences, market structure and government intervention. These issues were used to create possible futures after which delphi method was applied to reach a favourable future for all stakeholders.

Q-Methodology
These previous studies on electric vehicle stakeholder perspectives (Bakker et al., 2014; Steinhilber et al., 2013; Warth et al., 2013; Wirges, 2016; Zimmermann et al., 2012) made use of different types of stakeholder analysis. Stakeholder analysis is a method used to gain a better understanding of "*- and possibly identify opportunities for influencing- how decisions are made in a particular context*" (Brugha & Varvasovszky, 2000, p239). The idea behind stakeholder analysis is that each stakeholder pursues his own interests and develops an accompanying discourse. Discourse is defined as "*an ensemble of ideas, concepts, and categories through which meaning is given to social and physical phenomena, and which is produced and reproduced through an identifiable set of practices*" (Hajer, 2006, p67). A technology discourse is therefore how stakeholders think and talk about a specific technology at hand. Stakeholder analysis, especially in the case of new technologies, draws on the idea that "*organizations seek to develop discourses that suit their particular interests and advance their preferred technologies*" (Munir & Phillips, 2005, p1667).

Policy makers should look towards the issues in which the largest conflict arises and in which the largest diversity of opinions exist. This can be best be done through the process of *constructive conflict* (Cuppen, 2012). Q-methodology is especially suited to stimulate this conflict as it forces respondents to choose to prioritize between the opinions they (dis-)agree the most (see section 7.4.2 on how). In contrast to traditional stakeholders analysis, in Q-methodology it is argued that these discourses or perspectives can be shared across different stakeholders and are not necessarily directly in line with their interests (Cuppen, 2012). Q-methodology does not aim to represent the different stakeholders, but rather be representative of the different perspectives (Risdon, Eccleston, Crombez, & Mccracken, 2003). There is a large diversity in opinions across and within stakeholders as they learn from each other through interactions. Other methods assume that stakeholders have their opinions and only later engage with one other to reach a consensus, Q-methodology assumes that such practices already take place and therefore ideas spread. Therefore it could be that stakeholders already reach consensus on certain parts.

This paper proceeds from the idea that despite the different interests of the stakeholders, this does not lead to an equal number of different perspectives on how charging infrastructure should be developed. The expectation is that there a few major topics that stakeholders debate about and there is consensus on various topics. Revealing these points of disagreement and agreement is crucial for the effective roll-out of future charging infrastructure as it allows policy makers to more specifically address the topics of debate instead of trying to meet all interests of stakeholders.

To this end the discourses on charging infrastructure development in the Netherlands are characterized. The Netherlands is chosen as a case study because it is a frontrunner in public charging station deployment with over 36.000 public charging stations available by the end of 2018, as such having one of the highest density of publicly available charging infrastructure in the world (European Alternative Fuel Observatory, 2018). So we expect that points of disagreement and agreement have crystallised to a greater extent than in other countries. The Dutch case is specific, however, in the sense that it is characterised by a high number of level 2 charging stations on the street, which are mainly used for home charging (70% of the Dutch rely on on-street parking).

7.3 Charging infrastructure discourse

The charging infrastructure discourse is described in this section and is divided into five main topics. These five topics were derived from analysing sources such as policy documents and white papers on the matter. The topics and the corresponding discourse is described. A glossary of charging infrastructure terms can be found in *Appendix 7.A*.

7.3.1 Charging technologies

The charging of an EV can be done in various ways. Most commonly the car is parked and connected through a cable to a charging station which can supply various types of power. Usually, in the public domain, this is either level 2 or fast charging. The car can also be charged while driving (so-called dynamic charging), for example, through overhead lines providing the charging power. Both the static and dynamic power can also be supplied wirelessly through a magnetic field that transfers the power to the vehicle. The other option is to completely switch the battery for a full one at a special designed station. The battery can then be charged at another time.

Due to the roll-out strategies of local and national governments, the focus for many policy makers has been on level 2 charging technologies at places were cars park with a back-up of fast charging alongside highways. These charging technologies are the mature technologies that are readily available. Level 2 wireless charging is still in an experimental phase. Dynamic (wireless) charging is hardly considered in the Netherlands and certainly not to the extent as in Sweden or Japan (Connolly, 2017). In earlier years battery swapping was considered as interesting but after the demise of the technology in the early 2010’s (Noel & Sovacool, 2016) it has not been considered. Recent re-emergence of the technology is China (Xu, Yao, & Zeng, 2015) has sparked interest but has not resulted in specific plans elsewhere. There have been only a few hydrogen electric cars on the road (Netherlands Enterprise Agency, 2018) mainly due to the lack of models on the market but also due to the low number of refuelling stations. The technology which showed great promise in the early 2000’s never took off. Interest however remains, especially among current producers of hydrogen. The debate in the Netherlands has mainly revolved around the question on whether to go on with a high number of level 2 chargers or a lower number of fast chargers.

7.3.2 Local and national policy

Local and national government in the Netherlands have been pro-active in facilitating the roll-out of charging infrastructure. After an initial roll-out by joined distribution system operators (Elaad) which started in 2009, larger municipalities and regions continued a demand-driven roll-out. This roll-out strategy implies that charging infrastructure was mainly placed to facilitate those drivers that rely on on-street parking and charging (Helmus, Spoelstra, Refa, Lees, & Van den Hoed, 2018). These on-street level 2 charging stations were co-funded by national and local governments through so-called Greendeals (Formula E-Team, 2016). Local governments have invested in charging infrastructure in the past years mainly by tendering the deployment of charging infrastructure providing a concession for a single party to exploit the charging stations. Some municipalities however opted for an open market model in which several charging point operators are allowed to compete on placing charging stations. The exploitation of fast charging stations alongside the highways was not subsidized and taken on by several market players. The different policy approaches to the market have sparked debate on to which extent local and national policy makers should intervene and subsidize this market.

7.3.3 Integration with energy systems

As EVs draw a lot of power from the electricity grid, questions have arisen about the robustness of the electricity grid. As the adoption of EVs is likely to coincide with more renewable and intermittent energy, attempts are made to match supply and demand of electricity. The integration of electric vehicles in the grid has received a lot attention in the Netherlands. Early roll-out of charging stations was therefore facilitated by the foundation ELaad, formed by the Dutch grid operators. This allows them to monitor and experiment with concepts such as smart charging (García-villalobos, Zamora, Martín, Asensio, & Aperribay, 2014; Tamis, van den Hoed, & Thorsdottir, 2017) and vehicle-2-grid (Kempton, Perez, & Petit, 2014). These technologies could reduce peak load on the electricity grid. The pro-active role of ELaad has resulted in strong discourse that emphazises smart charging technologies as a potential way to reduce grid investments and to use renewable energy more efficiently. However, not all actors agree with the pro-active role of grid operators in facilitating charging infrastructure. They would like to see a less prominent role for grid operators resulting in a (legally bound) strict division of the utilities and grid operators. Furthermore the debate concentrates on to which extent smart charging should be implemented and how users should be involved. Should the user be allowed to override a lower charging power when necessary or should the user have to agree to lower the power beforehand? Meanwhile, other technologies such as centralised storage are also competing to solve the same issue of intermittency. Yet, there is no consensus on how such technologies should be designed. Stakeholders in these industries find that charging infrastructure for electric vehicles should fit within the transition to sustainable energy.

7.3.4 Market formations

The market for EV charging is still developing and as such standards for the charging plug and payment have not crystallised. As the potential market is very large, many technologies are still competing to become dominant in the market. There are therefore many ideas around of how the market should be organised and which parties should play which role. The access to public charging station and the fast charging cable standard are the two most prominent examples.

Access to charging stations in the Netherlands has from the early start been regulated by mobility service providers. They grant the driver access to the charging station with an RFID-tag or card. The Netherlands has always been keen on the fact that charging stations can be accessed with any RFID-tag. Through the development of the Open Charge Point Interface Protocol (OCPI), the Netherlands has been trying to promote this throughout Europe. Service providers however, at the moment do not provide ad-hoc access to charging stations, something prescribed by the European commission (European Commission, 2013). Other network operators are therefore developing a more expensive credit and debit card access.

Another issue with interoperability among charging stations has been through fast-charging cable standards. Four major charging standards have been developed with the European dominated Combined Charging standard (CCS), the Japanese ChaDeMo standard, the Chinese GB-T standard and a separate standard for Tesla. Many of the fast charging stations provide all the major standards for cars that are on the market. However some automakers push for separate charging networks such as the Tesla supercharger network, the European IONITY network which only provides CCS and recent announcements by for example Jaguar to provide a dedicated network for their cars (Hawkins, 2018).

7.3.5 Integration of charging stations in public space and parking

The final important issue discussed is the integration of charging stations in public space and parking policies. On-street charging also requires the reservation of parking spots alongside charging stations. The reservation of a parking spot can be a sensitive issue in the early phase of adoption especially when parking pressure in an area is high. The idea of a private parking spot for the EV driver can cause serious complaints and lawsuits by non-EV drivers (Wolbertus & van den Hoed, 2017). Meanwhile, cities try to reduce the number of parking spots on street or move them underground. Current roll-out practices are very often not aligned with these parking policies. Public space planners also fear a growing number of charging stations in the street reducing the accessibility of sidewalks. These discussions are often linked the choice of charging technology. Wireless charging reduces the need of additional street furniture. Others propose more fast charging stations in the city which can handle more vehicles per charging station, especially if charging speeds increase.

7.4 Methodology

To reveal stakeholders' perspective on the future of EV charing in the Netherlands, this paper makes use of the Q-methodology (Brown, 1980; Stephenson, 1935). Q-methodology is small-sample method which is quantitative in nature (i.e. based on factor analysis), but, at the same time, based on qualitative research principles, most notably, the principle of contextuality (Brown, 1980). As mentioned above, it is ideally suited to reveal shared viewpoints on a particular subject. To elicit these viewpoints respondents are asked to rank-order a set of statements of opinion regarding the subject under investigation. By rank-ordering (in Q-method parlance: Q-sorting) these statements, as opposed to rating them individually as is done in a typical survey, subjects are required to evaluate each statement vis-à-vis the others. Hence, respondents do not only need to consider whether they agree or disagree with a particular statement, but also the extent to which the statement is actually important to their way of thinking. In this process, a person's holistic viewpoint on the subject matter is revealed. By subjecting the resulting Q-sorts (viewpoints) to a (by-person) factor analysis clusters of similar Q-sort may be identified, which then reflect *shared* viewpoints on the subject matter.

Q-methodology proceeds in five steps (Brown, 1980; Exel & Graaf, 2005). The first step is to determine the concourse, which can be thought of as all statements of opinion regarding a particular subject (Brown; 1980). Hence, it reflects all the ideas, arguments, beliefs, etc. that are communicated (in text or verbally) about a particular subject. Since the concourse often contains too many statements to handle in the Q-sorting task, the next step is to make a representative selection, called the Q-sample. Then, participants are selected for the Q-sorting task, the so-called P-sample. This selection is not random (as in a typical survey) but strategic, ideally the P-sample (as a whole) should represent all existing perspectives in the field. In the fourth step the Q-sample is included in a rank-ordering task, which is administrated to the set of strategically selected participants. The statements do not have to be completely ordered, but a partial ordering, using a forced distribution (e.g. ranging from -5 to +5), suffices (Brown, 1980). With respect to the condition of instruction, participants are usually asked to indicate their level of (dis)agreement with each statement. The resulting rank-orderings are referred to as Q-sorts and reflect the various viewpoints regarding the subject under study. In the fifth step, common perspectives are revealed by subjecting the Q-sorts to a (by-person) factor analysis (Brown, 1980). By applying the factor analysis participants with similar Q-sorts (perspectives) are clustered together (i.e. they will load on the same factor). Next, a rotation method can be applied to achieve simple structure. Based on the resulting factor loading matrix, common viewpoints can be revealed by computing the (standardized) factor scores, which can then be translated to the original forced distribution that was used in the Q-sorting task.

7.4.1 Defining the concourse and Q-sample (Step 1 and 2)

To determine the concourse relevant statements are sampled from different sources to capture all relevant ideas, arguments and beliefs regarding (the future of) electric vehicle charging in the Netherlands. These sources include scientific papers, policy documents, white papers, reports and magazines on charging infrastructure. The list used for this research can be found in *Appendix 7.B*. A longlist of over 200 statements was gathered from these sources. From this longlist a subset of 44 statements is selected which is representative of the entire concourse to be used in the Q-sorting task (the Q-sample). This is line with the common size of such a set between 40 to 50 statements (Exel & Graaf, 2005). To select a representative Q-sample from the concourse we use a structure to sort the statements. The statements are first inductively categorized the concourse into five themes, namely (1) Local and national policy, (2) Charging technologies, (3) Integration with energy systems, (4) Market formations and (5) Integration of charging stations in public space and parking. Next, within each theme statements were selected that adequately captured the variety of opinions present within that particular theme. In line with common practice in Q-methodology, the selection of statements is not driven by the number of times certain statements are voiced but is focused on ensuring that the variety of statements in the Q-sample is representative of the entire concourse. The statements should as much differ from one another as possible(Brown, 1980).

7.4.2 Respondents and data gathering (Step 3 & 4)

The aim of this study is to identify different perspectives across the stakeholders in the field (Risdon et al., 2003). Therefore a large number of different stakeholders as identified by Bakker, Maat & Van Wee (2014) and Wirges (2017) are approached. On top of that, several scholars and consultancy firms are contacted. In practice they often inform and advice policy makers on policies making their opinions relevant in the debate, despite having no specific stake in the direction taken. Consumers are represented by special consumer interest groups in the field of (electric) mobility. In total 108 different stakeholders across 9 different industries are asked to participate in the Q-sorting task. The contacted participants were not randomly selected but were known to the researchers to have varying opinions on charging infrastructure developments. This variety was known due to previous voiced opinions in the studied sources or through personal contacts. This is important in Q-methodology as it is important to have a "*balanced inclusion of the variety of perspectives that exists within the stakeholder population*" (Cuppen, 2012).

Participants contact details were acquired through the personal contacts of the authors of this paper and approached via email with a request to fill out an online version of the Q-sorting task using the FlashQ software (Hackert & Braehler, 2007). Participants were first asked in June 2018 with a one-time reminder two weeks after the initial contact. In total 39 respondents completed the questionnaire. *Table 7.1* presents an overview of the number of stakeholders that replied per stakeholder category.

Table 7.1 Response rate per industry category

Industry	Stakeholders contacted	Participants	Response rate
Government (National)	5	2	40%
Government (Local/regional)	18	7	39%
Service Provider	12	3	25%
Grid operator	9	6	67%
Charging point operator	16	5	31%
Car manufacturer	7	2	29%
Research/Education	10	5	50%
Consultancy	12	7	58%
Charging point manufacturer	5	1	20%
Other	13	1	8%
Total	**108**	**39**	**36%**

In the survey participants were first asked to sort the statements into three categories, namely agree, neutral or disagree. After this initial task the respondents had to place the same statements in a forced distribution (see *Figure 7.1*). The strength of using Q-methodology is that this makes the respondents evaluate the statements in relation to each other. In this way respondents are making, at least implicitly, (½ * 44 * (44-1) 946 judgements (in the case of 44 statements as in this study), instead of making 44 single judgements as in a standard questionnaire.

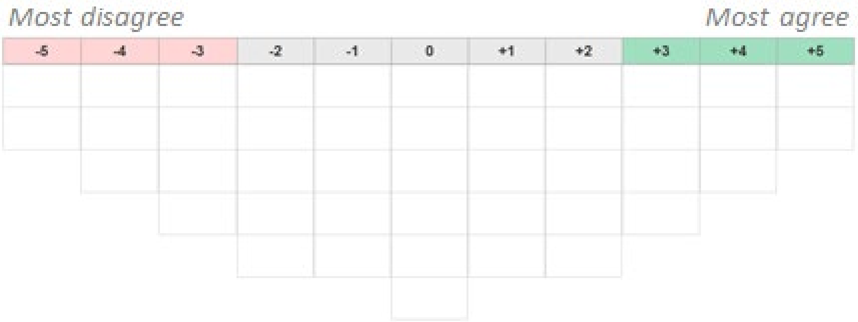


Figure 7.1 Distribution along which Q-statements have to be sorted

After the sorting task participants had the opportunity to comment on their highest and lowest scoring ranked statements to provide further explanation. Responses were treated anonymously but respondents did have the opportunity to declare their field of work. Only one person did not declare their field of work.

7.4.3 Analysis (Step 5)

To reveal shared perspectives among the experts, we use a principal component analysis (PCA) on the transposed data matrix. This means that respondents' Q-sorts are treated as 'variables' and the 44 statements as 'cases'. Hence, applied in this fashion, the PCA reveals clusters of similarly ordered Q-sorts, which reflect the *shared* viewpoints on the topic. Solutions with different numbers of factors extracted (1-7) were tested. The different solutions (see *Table 7.2*) were compared on three criteria, namely the variance explained, the Eigenvalue and the number of factors that did not reach the minimum number of 3 respondents loading on it, a criterion identified by Brown (1980). The 4 and 5-factor solution were identified as candidates as they explained the most variance while still having 3 respondents loading on each factor. The 4-factor solution was considered optimal for two reasons. Firstly, after the 4-factor solution, the decrease in Eigenvalue (and increase in variance explained) was relatively small, indicating that the 4-factor solution was able to parsimoniously capture most of the shared variance. And secondly, adding a fifth factor provided little new information as in this solution the first and fourth factor had a high correlation between the factor scores (r= 0.69). In the 4-factor solution all correlations between factor scores were below 0.5.

Table 7.2 Characteristics of results of VARIMAX rotation

Number of factors	**Variance explained**	**Eigenvalue**	**Number of factors without minimum of 3 respondents**
1	36%	14.15	0
2	45%	3.55	0
3	52%	2.72	0
4	58%	2.08	0
5	62%	1.80	0
6	66%	1.59	1
7	70%	1.41	3

To identify factor exemplars (i.e. respondents loading only on a single factor) the rotated factor matrix was further examined (varimax rotation was used to this end). Only respondents that loaded on a single factor were identified as factor exemplars. Using a significance level of 1% level the threshold for a significant factor loading is 0.37 ($2.48*1/\sqrt{N} = 0.37$, with N=44). With this threshold 16 respondents loaded on two factors. Using Watts & Stenners' (2005) approach, this threshold was raised to have a minimum number of respondents loading either on none or two or more factors. Using 0.45 as a cut-off point provides a minimum of two respondents loading on two factors and four respondents on zero factors. An overview of the different cut-off points and the number of respondents loading on none or two factors is given in *Appendix 7.C*. Using only the Q-sorts of the factor exemplars, an idealized factor array is produced (for each factor) which is shown in *Table 7.3*.

Table 7.3 Statements and factor array for each perspective

No.	**Statement**	**A**	**B**	**C**	**D**
	Local and national Policy				
1	The Netherlands is a worldwide leader in charging infrastructure due to the policy of the department of economic affairs	0	-1	-2	0
2	The government should only play a role in setting a framework for public charging infrastructure	-2	0	-2	-1
3	The government should keep supporting public charging infrastructure financially	-1	-4	2	1
4	Municipalities should implement a pro-active instead of reactive policy to cope with the growth of public charging infrastructure	5	1	-1	4
5	Local government should play a role in charging infrastructure rollout, because (public space) issues are mainly local	3	1	-1	4
6	Politicians should promote electric mobility because Dutch industry can profit from this	1	-1	0	1
7	Politicians should promote electric mobility to achieve sustainability goals	3	2	0	3
8	The current government is doing too little to realise enough charging stations by 2030	-1	-3	2	1

9	Subsidizing public charging stations disrupts the market	-2	-2	-3	-2
10	The difference in available charging infrastructure between rural and urban areas is too big. Investments in rural areas are needed.	1	-2	2	0
11	The zero-regret policy of the department of economic affairs, which keeps all options regarding charging technologies, has proven to be effective.	0	-2	0	-1
	Charging Technologies				
12	Public fast charging stations are crucial to promote the sales of electric vehicles	3	-3	1	2
13	The combination of a base network of charging stations at destinations (home/work) and a base network of fast charging stations is crucial	5	3	0	5
14	Fast charging will be become similar to refuelling	0	2	-3	-2
15	The demand for charging stations at semi-public and business parking locations shall increase faster than the demand for public charging stations	0	-3	3	2
16	In 2030 a part of the fleet will be electric, but other (clean) technologies shall also play a role	1	1	1	-3
17	Charging electric cars with a plug is an intermediate step to wireless charging	-2	-1	1	-3
18	It is desirable that we only use fast charging stations in 10 years' time	-5	0	-3	-4
19	Battery swapping is good alternative for fast charging	-4	1	1	-4
	Integration with Energy systems				
20	Smart charging shall become an essential factor in a stable electricity grid	2	5	5	5
21	The electricity grid is not capable of handling the current increase of charging stations	1	4	3	0
22	With a growing number of EVs, investments in grid reinforcements can be prevented by using EV batteries for energy storage	0	3	4	3
23	The primary goal of a charging network should be to accommodate the EV driver. Integration into the grid is subordinate	4	-5	-2	-4
24	Dynamic pricing should be allowed to incentivize users to charge at more – for the electricity grid- favourable times	2	0	1	3
25	Smart charging won't work as users find it too much of a hassle	-3	-4	-4	-5
26	Vehicle-2-grid is increasingly important for balancing the grid given the increase in renewable energy	-2	2	4	-2
27	Using only fast charging, we are not able to optimally make use of renewable energy	2	-2	5	1
28	Smart charging is only relevant within the context of capacity management of a grid connection for a single location	-2	-2	-5	-5
	Market formations				
29	It is essential that interoperability of charging cards is guaranteed at European level	4	5	4	4
30	It is up to the market to create an appropriate mix (private, semi-public, public and fast) of charging opportunities	-1	0	-2	2
31	Grid operators should focus on their primary task and should be not be actively involved in the rollout of charging infrastructure	0	-1	-4	-2
32	At all times It should be clear what the EV driver is paying for the electricity charged	4	3	-1	3
33	Charging stations shall be soon profitable	1	2	2	1
34	Charging infrastructure for smaller municipalities should be tendered at a regional level, as economies of scale will result in a positive business case	2	-1	3	0
35	Government should ensure that all charging stations are accessible independent of type of car or brand	2	4	3	-3
36	For a successful transition to electric mobility it is necessary that car manufacturers are actively involved with deploying charging infrastructure	-3	-5	-1	1
37	The deployment of a dedicated charging infrastructure for only one brand delays the adoption of electric vehicles	-1	3	0	-1
38	Municipalities should not give long term concessions for charging stations on the street but leave it to the market	-4	0	-3	2
39	Fast charging stations should be provided a level playing field with gasoline stations along the highway	3	1	-2	2
	Integration in public space and parking				
40	If you can charge your car within 15 minutes, it is not necessary to furnish entire inner cities and residential areas with charging stations	-4	4	-5	0
41	Instead of spreading individual charging stations across a neighbourhood, charging stations should be clustered at special parking areas	-3	-4	2	0
42	Public charging stations should be integrated in current street furniture such as lamp posts or the side walk	-1	0	0	-1
43	Charging stations are obstructive objects in the public space	-3	2	-4	-3
44	Charging stations are impossible to integrate into current parking policies	-5	-3	-1	-2

7.5 Results

The factor analysis reveals four different perspectives. These are labelled as (A) EV Drivers first by policy, (B) an open, smart and fast charging network , (C) smart charging priority and (D) wired electric only and open markets. Below, the four perspectives are interpreted in detail. The distinguishing statements (those with statistically significant different factor loadings compared to other factor) per perspective are used to this end. After the perspectives are examined, the statements on which there is a consensus are discussed. Finally it is explored how the perspectives can be related to the different fields of industry. Statements are referred to by their number and the score in the given in the specific viewpoint (e.g. statement 24: score 4 is shown as 24:4). Statements in green are the most in agreement with and red in disagreement.

7.5.1 Perspectives

Perspective A: EV drivers first by policy
This perspective is shared by 15 respondents and explains 23% of the variance. This perspective puts the EV driver at the centre point of development of charging infrastructure. Integration of charging points into the electricity network should be sub-ordinate to this goal (23:4). Moreover in this perspective it is considered important that EV drivers should be well aware of what they are paying for charging (32:4). This perspective sees a mix of private, semi-public and public charging points as the way forward (13:5). Fast charging is important to tackle range anxiety (12:3) but is not expected to become the dominant charging mode (18:-5 & 40:-4).

Respondents sharing this perspective see a significant role for (local) policy makers in designing the charging infrastructure for the future. The respondents believe local policy makers should have a pro-active role in the roll-out of charging infrastructure (4:5 & 5:3). Local policy measures such as integration in the parking policy are not considered an issue (44: -5). Moreover respondents feel that municipalities should keep in control by regulating the market with long term concessions (38:-4). It is therefore no surprise that the majority of local policy makers were found to load on this factor. This is discussed in further detail below.

This perspective resembles current practices especially among the larger municipalities in the Netherlands. Local governments are in control and try to balance the interests of different partners involved. However their main focus is on facilitating the EV driver. A larger number of electric vehicles on the road will improve air quality within the cities.

Perspective B: An open, smart and fast charging network
Perspective B is shared by 6 respondents and explains 13% of the variance. This perspective differs from the other perspectives by a positive attitude towards fast charging. It sees a fast charging network within the city as a replacement for a large number of level 2 charging stations (40:4 & 14:2). In contrast to possibility of fast charging as a replacement for level 2, respondents belief that fast charging stations are not crucial to the uptake of EVs (12:-3). It is possible that respondents see a large number of workplace charging stations (13:3) and electric vehicles with a larger range as the main solution. Respondents in this perspective do not pose that fast charging cannot be smart charging. For them integration with the electricity network is most vital (23:-5, 25:-4 & 20:5). A possible solution is to include battery storage alongside fast charging stations (22:3).

The respondents are also very keen on an open charging infrastructure network. They do not like the idea of automakers investing in their own dedicated networks (36:-5) as they think this will hamper the transition to electric mobility (37:3). They see a role for the government to make sure that all vehicles can charge at each of the charging stations (35:4). However, this is as far as government should go. Further financial investment should not be necessary (3:-4). This perspective draws support in various fields (local government, service providers and grid operators) but is mainly supported by consultants. The idea behind this perspective mainly draws on more future technologies such as ultra-fast charging and foresees a more mature charging infrastructure market.

Perspective C: Smart charging priority

This perspective is shared by 5 respondents and explains 12% of the total variance. Respondents that share this perspective consider smart charging as an essential part of the EV charging system (20:5). Respondents feel that smart charging is a concept that can be applied in a broader sense and can not only be applied to capacity management at a certain location (28: -5). Respondents do not believe that the EV drivers will experience smart charging as a hassle (25:-4). Similar technologies such as Vehicle-2-grid (26:4) and battery storage (22:4) are seen as solutions to make optimal use of renewable energy whilst charging.

In contrast to perspective B, respondents in perspective C do not see fast charging as a solution for the future. Respondents do not believe that fast charging is a substitute for overnight charging (40: -5), which can also be attributed to the idea that they do not consider charging stations as obstacles in the public space (43: -4). One of the objections to fast charging is that it cannot optimally make use of renewable energy (27:5).

This perspective is mainly supported by charging point operators. None of the grid operators loaded on this factor. This may be explained by the observation that respondents with this perspective object to the idea that grid operators should have a passive role in creating a future charging infrastructure (31: -4).

Perspective D: Wired electric only and open markets

This perspective is shared by 7 respondents and explains 9% of the variance. This perspective emphasises that the current wired charging technology will remain dominant and contain a mix of home, destination and fast charging (13:5). Respondents dislike the idea of wireless charging (16: -3) or battery swapping (19: -4). They also do not consider the idea of other alternative fuels in the mix in the future (17: -3). This focus on battery electric cars with wired charging is in line with their idea about the importance of smart charging (20:5, 25: -5, 28: -5) which is more suitable for a wired charging solution.

Respondents in this perspective have a very specific view of the role of government. They expect a pro-active role (4:4) of local governments (5:4). However they do not want governments to take full control. It should be up to the market to provide the necessary mix of charging infrastructure (30:2). This open market idea is also supported by the fact that they are the only group of respondents that does not see a role for the government in ensuring a single charging standard (35:-3).

The perspective is supported by a large variety of stakeholders. The perspective is specific as it is the only one that has a strong opinion about the technological developments, other perspectives did not consider these as the most important points. The role of government is the market is also very specific. It should be pro-active but not intervene with the ideas of market parties.

7.5.2 Consensus

The idea all perspectives highly agreed upon was that charging stations across Europe should be accessible with all charging cards (statement 29). This is not strange as many stakeholders in the Netherlands have been active with promoting this idea. Also in practice this has already been implemented. The perspectives are in agreement that they are neutral about the success of the charging infrastructure market in the Netherlands as a result of national government policy (statement 1). They are also all slightly optimistic about the business case of public charging stations (statement 33). The early incentives to make this business case possible also did not create imbalances in the market. Such interventions were thus allowed (statement 9). In general most of the topics the respondents agreed upon were did not have a high score (with the exception of statement 1).

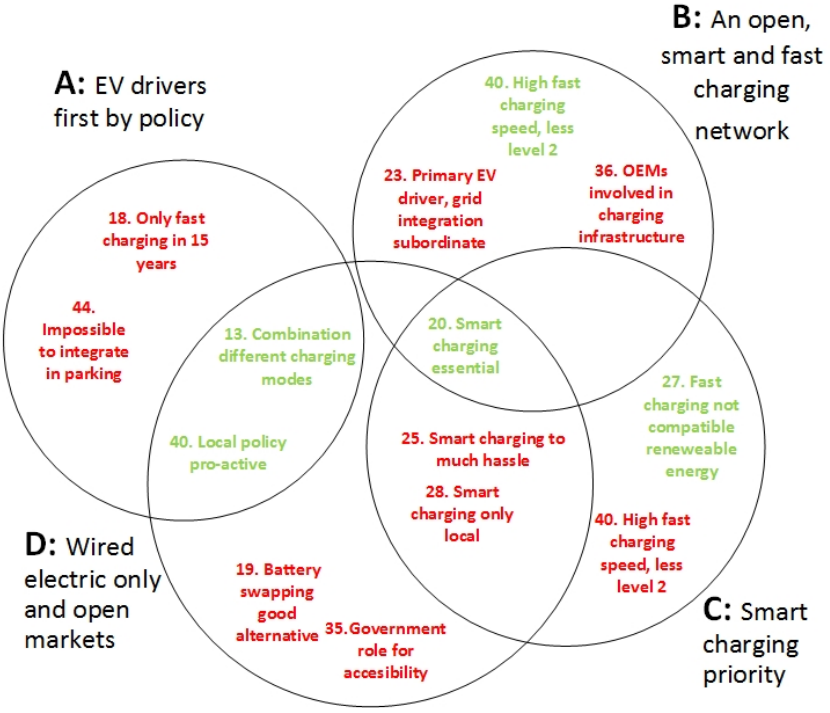


Figure 7.2 Visual overview of alignment of perspectives. Green represents statements in agreement with, red in disagreement

Also across several, but not all perspectives, there is consensus on distinct topics. A visual overview of how the different perspectives and their most relevant (rephrased) statements are aligned is shown in *Figure 7.2*. Most perspectives are aligned in that smart charging is essential for a stable electricity grid (statement 20). As well, respondents that share perspectives A and D agree that a combination of different charging modes (statement 13) is the way forward and this roll-out should be developed with pro-active local policy (statement 40). Although participants that share perspective B see on a dominant role for fast charging they agree with participants in perspective C that fast charging is not so much compatible with renewable energy.

7.5.3 Conflict

The factor analysis also revealed which statements and topics caused the most conflict among the four different perspectives. Three major topics showed the largest disagreement among the respondents which are the role of fast charging in the future infrastructure, the extent in which smart charging is a priority and how active governments should intervene in rolling out charging infrastructure. An overview of how the different visions see these topics is given in *Table 7.4* in which '+' indicates agreement, '-' disagreement and '0' a neutral standpoint.

Table 7.4 Overview of points of conflict

Issue	**A: EV drivers first by policy**	**B: An open, smart and fast charging network**	**C: Smart charging priority**	**D: Wired electric only and open markets**
Large role for fast charging	0	+	-	0
Smart charging as priority	0	+	+	+
Active role for governments	+	-	0	0

The first main conflict is between those that see a major role for fast charging and those that do not. There are many different perspectives on the role of fast charging in the future infrastructure. While respondents in perspective B see a major role for fast charging, respondents in perspective C rather have as little as fast charging as possible. As respondent 31 (CPO-statement 18) puts it: "*The fast charging network is necessary for the transition to electric mobility, but it should be abolished on the long term.* " Those that disagree mention consumer comfort and grid integration as major hurdles in switching to fast charging as dominant charging mode. Those in favour mainly mention the business case and public space issues as motivation to switch to fast charging. "*The costs per kWh (for AC charging) are too high. Faster charging = cheaper charging*" (11-CPO-Statement 33). The statements provide evidence that those in favour and those not, argue about different aspects of the technology. Respondents in perspective A and D see the importance of fast charging but see it as a part of an integral network of charging infrastructure which also includes home and destination charging. Respondent 37 (Grid operator – Statement 13) states: "*As EV-driver you need both: Cheap home or workplace charging and premium ultra-fast charging along the way for long drives*".

The second main area of conflict is the priority that should be given to smart charging when rolling-out charging infrastructure. All the four perspectives agree that smart charging technology is essential for managing future grid overloads due to increased electricity demand by EVs (statement 20). Also all the perspectives agree that smart charging should not create too much hassle for the EV driver (statement 25). Yet there is significant disagreement regarding the extent smart charging should be prominent in the roll-out of charging infrastructure. Respondents in perspective A agree that the EV driver should be put first, especially during the early phase of EV adoption. Respondent 13 (Local government- statement 23) states: *"It depends to a great extent on the phase of the roll-out, but the EV-driver should always be put first. Right now, everyone should be able to rely 100% on the charging station it uses. This is of the utmost importance, all other things are subordinate. Even in the future, the wishes of the EV driver are more important than the wishes of the grid operator."* The debate specifies on the idea that charging stations should be limited in their charging speed (during specific times) or that the EV-driver should always be allowed to charge at maximum speed to facilitate an optimal experience. The underlying generic choice is between a system with smart charging by design or a user-controlled version.

The last area that came out as a prevalent issue of dispute is the role of governments in facilitating charging infrastructure. Especially those in perspective A and B are in in disagreement. Respondents in perspective A see a large role for local government. They do not see that the market can solve the social issues at hand. " *(...) The market aims for the largest profit on the short term. (....) We should steer towards the bigger picture – market parties cannot do so, the government will have to.* (Respondent 35 – unknown – statement 30). Respondents in other perspectives are more careful about government intervention. Especially at the national level and for fast charging stations they do not see the value of government intervention other than in standard setting. Respondent 1 (unknown) comments on statement 30: "*The market is mature enough. There is no need for government involvement other than rule setting and public space planning.*" There is serious disagreement between the perspectives on how active governments should be in facilitating or operating charging infrastructure. Perspective A (active involvement) and perspective B (only standard setting) provide the complete opposites, while perspectives C and D see a more active role in a transition period. According to respondents in these perspectives the role of the government should slowly be phased out. In general, local governments are considered needed for the considerable future in pro-active planning of spatial and parking issues regarding charging infrastructure.

7.5.4 Industry roles

Stakeholder analysis would link the conflicts that have risen to the interests of the respondents' industry a person is affiliated to. To analyse how these perspectives and the conflicts are linked to the various industry roles, the number of respondents per industry that loaded on each factor are compared. *Table 7.5* shows the number of respondents that loaded each of the perspectives. Those in the 'none' column loaded either on none (below the 0.45 threshold) of the perspectives or on multiple perspectives.

Table 7.5 Number of respondents per industry that loaded on a perspective

	Perspective				
Industry	**A**	**B**	**C**	**D**	**None**
Government (National)	1			1	
Government (Local/regional)	4	1		2	
Service Provider		1	1		1
Grid operator	2	1		1	2
Charging point operator	2		3		
Car manufacturer	2				
Research/Education	2			1	2
Consultancy	2	3	1		1
Charging point manufacturer				1	
Not specified/Other				1	

The results show that most perspectives receive support from a large variety in stakeholder. In general there is no clear relationship between the industry the respondents worked in and on which perspective they loaded. Only the relatively high number of local government employees loading on perspective A is an exception to this. The relationship between perspective A and local governments can be explained by the large role of local governments are expected to take within the perspective. This perspective is also a representation of the current practice in which local policy makers have an active role.

The fact that there is not clear relationship between the industry the respondents worked in and on which perspective they loaded, supports the idea that perspectives are shared across different stakeholders and their ideas are mutually exclusive to the interests of the parties these persons work for. These findings support the idea from Cuppen (2012) that visions are shared across stakeholders. For policy makers this implies that a straightforward stakeholder analysis in which all interests are noted and compared does not necessarily imply that all visions are correctly represented.

7.6 Conclusions

This study has presented a systematic overview of stakeholders' perspectives on electric vehicle infrastructure development and has stipulated how these perspectives are aligned or are in disagreement. Q-methodology was used to identify different perspectives on the development of electric vehicle charging infrastructure. 39 respondents from nine different industries related to electric vehicle charging infrastructure participated in the Q-experiment. Factor analysis revealed four different perspectives on how charging infrastructure should be developed in the future. These perspectives are (A) EV drivers first by policy, (B) An open, smart and fast charging network, (C) Smart charging priority and (D) Wired electric only and open markets. These perspectives are shared across the different stakeholders with no clear relationship between the perspectives and respondents' affiliation to various stakeholder groups in practice. The analysis of these perspectives showed that three dominant issues divide the four perspectives. These are (i) the role of fast charging, (ii) the degree smart charging should be the standard option and (iii) the role of government. Fast charging is either seen as a dominant option in the future or found to be in conflict with 'smart charging' strategies. The analysis also showed that those in favour and those that oppose fast charging as main charging mode, use very different arguments in the debate. The perspectives agreed that smart charging plays a vital role in the future to incorporate charging stations in the electricity grid but disagreed on the degree smart charging should be the standard in charging. The dilemma at hand is the choice between a system with smart charging by design or an user-controlled version. On the role of the government multiple ideas existed, which varied in extent from nearly full government control to only standard setting practices. Perspectives took C & D contained a viewpoint with a government that should aid the transition but should slowly retreat as the market takes over.

The main policy implication is that Q-methodology aids policy makers to better able to steer on the most important issues of debate instead of trying to make policy for all aspects that are relevant for the stakeholders. The analysis showed very specific differences in opinion that were not identified by other studies such as the debate on whether smart charging should be standard or user controlled. The combination between the quantitative features of Q-methodology, which allowed to specify the most important areas of conflict, and using the comments from the respondents allows policy makers to focus on the important issues at hand. The finding that perspectives are not mutually exclusive with the stakeholders' interests, implies for policy makers that only looking at the stakeholders' interests is not the most effective way to manage stakeholders. Moreover these results show that multiple perspectives can exist within and across industry partners. The Q-methodology approach entails that participants have to choose which topics they prioritize, revealing more common ideas about the future than a classical stakeholders analysis might provide. Inviting all stakeholders for participation sessions to express their interests, could leave points of conflict and consensus unexplored. This analysis shows that stakeholders could be interested to look beyond their current interests and have similar visions as other industries despite differences in the stakes they pursue.

For charging infrastructure as a case this study has provided several starting points to rethink their policies for the coming years. A major issue is the fast versus slow charging conflict, which needs more alignment across stakeholders as they focus on different arguments in the debate. For smart charging it was generally recognised that it has a prominent future, but the focus should go towards the extent the user should be involved. Also the role of policy makers themselves and the extent to which they should intervene needs more discussion in the future as the market is becoming more mature. These results show that policy should not only be aimed at technical and social processes, but that critical reflection of the policy makers' own role in transitions should remain at the forefront. In this way the Q-methodology approach has identified three major issues that should receive more attention as they are the most prominent across the different stakeholders.

In comparison to previous studies in this field this study has revealed new areas of conflict and confirmed others. This study confirmed the importance of smart charging technologies to able to facilitate with the current electricity network as also found by Bakker et al. and Wirges. In addition to their analysis this research has found that the type of smart charging implementation, by design or user controlled, is the most relevant in this debate. Although the initial review of sources revealed integration into parking services as an important topic, in line with Bakker et al., it did not show as a top priority in one of the four perspectives. In addition to previous research, this study has found that the conflict between fast or level 2 charging as dominant charging mode is considered very important. From a technological perspective this debate is expected to be the most important for policy makers in the coming years. Furthermore, the role of policy makers themselves is considered relevant. In stakeholder analysis the role of policy makers themselves is often overlooked and also how other stakeholders look at them. There are substantial differences in the degree that policy makers should be pro-active or only facilitating in this field.

A limitation of this study is the focus on the Dutch industry. It should be noted, however, that the Dutch situation resembles one of the front-runners on public charging infrastructure. As such, it is likely that the topics of conflict identified in this study will also arise in many other countries across Europe and outside. The Dutch situation can be regarded as an exemplary case for the conflicts that will likely arise in dense urban areas that exist across the world. Nevertheless, the Dutch case also has several peculiarities, such as the high number of on-street parking at home and the active role of local municipalities. A recommendation would be to repeat a similar experiment in comparable cities in Europe such as Oslo and Stockholm, but also to compare it other frontrunner areas such as California or several Chinese cities such as Shenzhen. Diverging ideas could exist depending on the local context. Another limitation is that this study provides a view on how these stakeholders view the future on this moment. The rapidly changing technology might change their opinions despite their expertise. A repetition of this study in a few years could provide more insights on how technology developments influence the perspectives. Despite these limitations this paper provides better insights on the perspectives shared among stakeholders on how to develop future charging infrastructure.

7.7 References

Bakker, S., Maat, K., & van Wee, B. (2014). Stakeholders interests, expectations, and strategies regarding the development and implementation of electric vehicles: The case of the Netherlands. *Transportation Research Part A: Policy and Practice*, *66*(1), 52–64. https://doi.org/10.1016/j.tra.2014.04.018

Brown, S. R. (1980). *Political Subjectivity: Applications of Q Methodology in Political Science*. New Haven and London: Yale University Press. https://doi.org/10.2307/3151542

Brugha, R., & Varvasovszky, Z. (2000). Stakeholder analysis : a review. *Health Policy and Planning*, *15*(3), 239–246.

Burnham, A., Dufek, E. J., Stephens, T., Francfort, J., Michelbacher, C., Carlson, R. B., … Tanim, T. R. (2017). Enabling fast charging – Infrastructure and economic considerations. *Journal of Power Sources*, *367*, 237–249. https://doi.org/10.1016/j.jpowsour.2017.06.079

Collantes, G. O. (2007). Incorporating stakeholders ' perspectives into models of new technology diffusion : The case of fuel-cell vehicles, *74*, 267–280. https://doi.org/10.1016/j.techfore.2006.02.001

Cuppen, E. (2012). Diversity and constructive conflict in stakeholder dialogue : considerations for design and methods. *Policy Science*, *45*, 23–46. https://doi.org/10.1007/s11077-011-9141-7

European Alternative Fuel Observatory. (2018). Electric vehicle charging infrastructure: Total number of PEV charging positions. Retrieved July 1, 2018, from http://www.eafo.eu/electric-vehicle-charging-infrastructure

Exel, J. Van, & Graaf, G. de. (2005). Q methodology : A sneak preview. *Social Sciences*, *2*, 1–30. Retrieved from http://qmethod.org/articles/vanExel.pdf

Gnann, T., Plötz, P., Kühn, A., & Wietschel, M. (2015). Modelling market diffusion of electric vehicles with real world driving data – German market and policy options. *Transportation Research Part A*, *77*, 95–112. https://doi.org/10.1016/j.tra.2015.04.001

Hajer, M. (2006). Doing Discourse Analysis : Coalitions , Practices , Meaning. In M. Van den Brink & T. Hetze (Eds.), *Words matter in Policy and Planning: Discourse theory and method in the social sciences* (pp. 65–74). Utrecht: Netherlands Geographical Studies.

Harrison, G., & Thiel, C. (2017). Technological Forecasting & Social Change An exploratory policy analysis of electric vehicle sales competition and sensitivity to infrastructure in Europe. *Technological Forecasting & Social Change*, *114*, 165–178. https://doi.org/10.1016/j.techfore.2016.08.007

Hop, G., & Welleweerd, H. (2013). *Gratis laadpalen zonder overlast voor de omgeving*. Ede. Retrieved from http://overmorgen.nl/wp-content/uploads/2014/02/Gratis-Laadpalen.pdf

International Energy Agency. (2017). *Global EV Outlook 2017: Two million and counting. IEA Publications*. https://doi.org/10.1787/9789264278882-en

Madina, C., Zamora, I., & Zabala, E. (2016). Methodology for assessing electric vehicle charging infrastructure business models. *Energy Policy*, *89*, 284–293. https://doi.org/10.1016/j.enpol.2015.12.007

Maia, S. C., Teicher, H., & Meyboom, A. (2015). Infrastructure as social catalyst: Electric vehicle station planning and deployment. *Technological Forecasting and Social Change*. https://doi.org/10.1016/j.techfore.2015.09.020

Munir, K. A., & Phillips, N. (2005). The birth of the "Kodak moment": Institutional entrepreneurship and the adoption of new technologies. *Organization Studies*, *26*(11), 1665–1687. https://doi.org/10.1177/0170840605056395

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, *5*, 329–332.

Nykvist, B., Sprei, F., & Nilsson, M. (2019). Assessing the progress toward lower priced long range battery electric vehicles. *Energy Policy*, *124*(September 2018), 144–155. https://doi.org/10.1016/j.enpol.2018.09.035

Risdon, A., Eccleston, C., Crombez, G., & Mccracken, L. (2003). How can we learn to live with pain ? A Q -methodological analysis of the diverse understandings of acceptance of chronic pain, *56*, 375–386.

Schroeder, A., & Traber, T. (2012). The economics of fast charging infrastructure for electric vehicles. *Energy Policy*, *43*, 136–144. https://doi.org/10.1016/j.enpol.2011.12.041

Shafiei, E., Thorkelsson, H., Asgeirsson, E. I., Davidsdottir, B., Raberto, M., & Stefansson, H. (2012). An agent-based modeling approach to predict the evolution of market share of electric vehicles : A case study from Iceland. *Technological Forecasting & Social Change*, *79*, 1638–1653. https://doi.org/10.1016/j.techfore.2012.05.011

Steinhilber, S., Wells, P., & Thankappan, S. (2013). Socio-technical inertia: Understanding the barriers to electric vehicles. *Energy Policy*, *60*, 531–539. https://doi.org/10.1016/j.enpol.2013.04.076

Sweda, T. M., & Klabjan, D. (2015). Agent-Based Information System for Electric Vehicle Charging Infrastructure Deployment. *Journal of Infrastructure Systems*, *21*(2), 04014043. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000231

Torres, O., Bader, B., Romeral, J. L., Lux, G., & Ortega, J. a. (2013). Multiobjective optimization of a Parallel Plug-in Hybrid Electric Vehicle considering the fuel consumption , acceleration and elasticity on the vehicle performance, 1–16. https://doi.org/10.1109/EVS.2013.6914950

Warth, J., Gracht, H. A. Von Der, & Darkow, I. (2013). Change A dissent-based approach for multi-stakeholder scenario development — The future of electric drive vehicles. *Technological Forecasting & Social Change*, *80*(4), 566–583. https://doi.org/10.1016/j.techfore.2012.04.005

Wirges, J. (2016). *Planning the Charging Infrastructure for Electric Vehicles in Cities and Regions (Doctoral dissertation)*. Karlsruher Institut für Technologie.

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. G. (2018). Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments. *Transportation Research Part D: Transport and Environment*, *62*. https://doi.org/10.1016/j.trd.2018.03.012

Wolbertus, Rick, & van den Hoed, R. (2017). Managing parking pressure concerns related to charging stations for electric vehicles : Data analysis on the case of daytime charging in The Hague. In *European Battery, Hybrid & Fuel Cell Electric Vehicle Congress* (pp. 1–8). Geneva, Switzerland.

Zimmermann, M., Darkow, I., & Gracht, H. A. Von Der. (2012). Technological Forecasting & Social Change Integrating Delphi and participatory backcasting in pursuit of trustworthiness — The case of electric mobility in Germany. *Technological Forecasting & Social Change*, *79*(9), 1605–1621. https://doi.org/10.1016/j.techfore.2012.05.016

Appendix 7.A: Glossary

Concept	Description
Level 2 charging	Charging by cable with powers from 3-11kW mainly used for charging at home or the office while car is parked
Fast charging	Charging by cable with powers greater than 50kW.
Dynamic charging	Charging while the car is driving
Wireless charging	Charging without cable, but static as dynamic
Battery swapping	Replacing the car battery with a fully charged new one
Tender	Formal offer to operate charging stations for a stated price
Open market model	Allow multiple operators to place charging stations and determine their own prices
Open Charge Point Interface protocol	Open protocol that supports connections between any Mobility service Provider and Charge Point operator
Charging Standard	
Combined Charging standard	Fast charging standard mainly used by European OEMs
ChaDeMo	Fast charging standard mainly used by Japanese OEMs
GB/T	Fast charging standard mainly used by Chinese OEMs
Tesla connector	Fast charging standard used by Tesla Motors
Private charging	Parking and charging at home on own driveway or garage
On-street/Curbside	Parking and charging on the street or parking ground that is public
Semi-public	Parking and charging that are available to those with access but are shared, e.g. parking garages, company specific parking
Smart Charging	Alternate charging speed in order to prevent electricity grid overload or optimise use of renewable energy
Vehicle-2-Grid	Alternate charging speed and option to provide power back into the grid from EV battery
Storage solutions	Energy storage not in vehicles to temporarily store excess electricity

Appendix 7.B: List of sources used for statements

ABB- White Paper: Towards Winning Business Models for the EV-Charging Industry. Who plays this game, what are the rules and why IT is one of the most important competences in this industry
ABB – White Paper: Electric Vehicle Charging Infrastructure An evaluator's guide to DC fast charging stations
AgentschapNL (2012) De stekker in elektrisch vervoer, maar hoe?
Allego – White Paper: Urban Mobility in de toekomst visie of realiteit?
Bakker, S., Maat, K., & van Wee, B. (2014). Stakeholders interests, expectations, and strategies regarding the development and implementation of electric vehicles: The case of the Netherlands. Transportation Research Part A: Policy and Practice, 66(1), 52–64.
CE Delft: Uitbreiding publieke laadinfrastructuur tot 2020
Connolly, D. (2017). Economic viability of electric roads compared to oil and batteries for all forms of road transport. Energy Strategy Reviews, 18, 235–249. http://doi.org/10.1016/j.esr.2017.09.005
Dutch Incert - Werkdocument: Verkenning Elektrisch rijden
Ecofys – Eindrapport Toekomstverkenning elektrisch vervoer
Fastned- The Fastned story
Hardman et al. (2017) Considerations for the development of plug-in electric
IAE – Global EV Outlook 2017
IAE – Global EV Outlook 2018
AIP E-mobility- Roadmap Elektrische Mobiliteit in Nederland, November 2017
ICCT- White Paper: EMERGING BEST PRACTICES FORELECTRIC VEHICLE CHARGING INFRASTRUCTURE
Master's thesis
Ministry of Economic affairs: Vision on the charging infrastructure for electric transport
Municipality of Rotterdam (2015): Kader voor de plaatsing van laadinfrastructuur voor elektrische auto's
Municipality of The Hague (2014) Plan van aanpak laadinfrastructuur elektrische auto's
Municipality of Utrecht: Elektrisch rijden in de G4
Municipality of Utrecht (2017): Plaatsingsleidraad en inrichtingskader publieke laadinfrastructuur
Netbeheer Nederland: Laadstrategie Elektrisch Wegvervoer
NKL – Benchmark kosten publieke laadinfrastructuur 2016
NKL – Benchmark kosten publieke laadinfrastructuur 2017
NKL – Benchmark kosten publieke laadinfrastructuur 2018
NKL – Kencijfers Openbare Laadinfrastructuur Elektrisch Vervoer
Noel, L., & Sovacool, B. K. (2016). Why Did Better Place Fail ?: Range anxiety , interpretive fl exibility , and electric vehicle promotion in Denmark and Israel. Energy Policy, 94, 377–386. http://doi.org/10.1016/j.enpol.2016.04.029

PWC (2017) Smart Charging van elektrisch voertuigen. Institutionele knelpunten
Roland Thorensma: The future of public charging infrastructure in the Netherlands
RVO (2015) Green Deal “Openbaar Toegankelijke Elektrische Laadinfrastructuur”
Smart E-Mobility Magazine – December 2017
Smart E-Mobility Magazine – June 2017
Smart E-Mobility Magazine – March 2017
Smart E-Mobility Magazine – September 2017
Steinhilber, S., Wells, P., & Thankappan, S. (2013). Socio-technical inertia: Understanding the barriers to electric vehicles. Energy Policy, 60, 531–539. http://doi.org/10.1016/j.enpol.2013.04.076

Appendix 7.C Number of respondents loading on two or no factors for different cut-off points in the 4-factor solution

Cut-off point	Respondents loading on two factors	Respondents loading on zero factors
0.36	16	0
0.37	14	0
0.38	14	0
0.39	13	0
0.40	11	1
0.41	11	1
0.42	11	1
0.43	9	1
0.44	6	2
0.45	2	4
0.46	2	5

8 Conclusions and policy implications

This thesis has empirically tested the impact of operational measures on the goals set in tactical plans and strategic policies by municipalities for EV charging infrastructure. The main research question is: *How and to what extent do operational measures for electric vehicle charging infrastructure influence the goals set in tactical plans and strategic policies for public charging stations in dense urban areas?* In Chapter 2 the case study of EV development the Netherlands is introduced and analysed, followed by explanatory research on the factors that influence charging behaviour in Chapter 3. In Chapters 4 and 5 the effect of operational measures, which include free parking, daytime charging and time-based charging tariffs, on charging behaviour and the purchase intention of electric vehicles is tested. In Chapter 6 an integral simulation of the effect of policies on the EV charging system is performed. Finally, in Chapter 7 the normative perspectives on EV charging infrastructure of stakeholders are analysed. Below, the results of the thesis are summarised in relation to the formulated research questions.

8.1 Conclusions for Study 1: Plug-in (hybrid) electric vehicle adoption in the Netherlands: Lessons learned

How has national and local electric vehicle and charging infrastructure policy shaped electric vehicle adoption and charging behaviour in The Netherlands?

The first study has looked at how Dutch fiscal incentives at the national level and charging infrastructure development at the local level have contributed to shaping the Dutch electric vehicle market. The electric mobility history in the Netherlands provides interesting material to reflect on the interplay between regulation, uptake of EVs by consumers and the utilization of charging infrastructure by EV drivers. It can be concluded that the fiscal incentives have played a decisive role in the Dutch uptake of EVs in general and has led to largely favouring PHEVs up to 2016 in particular. The shift in available subsidies for PHEVs between 2013 and 2018 and subsequent dramatic reductions in PHEV sales illustrate the role which the benefit-in-kind subsidy schemes played in driving adoption.

The increase in sales of PHEVs sparked the need for public charging infrastructure. Grid operators and municipalities facilitated the roll-out of early charging infrastructure. This mainly catered the needs of those that rely on on-street parking and therefore public charging at home and workplace locations. The programs are considered a success as the Netherlands developed an infrastructure with a low EV to charging station ratio and therefore and abundantly available infrastructure. The demand driven roll-out strategy also resulted in potential EV drivers not having to worry there would be no charging opportunity near their home, which potentially accelerated the adoption of EVs. Additionally the roll-out has supported the adoption of other modes of electric transport such as free floating car sharing services.

The combination of fiscal incentives and a demand-driven roll-out strategy for charging infrastructure however resulted in an ineffective utilization of the charging infrastructure. Occupation rates of charging stations were low compared to regular parking spots as they were mainly placed to service only a few users. Despite this relatively low utilisation their occupation is high compared to other countries. The high number of PHEVs also resulted in a lower turnover in kWh, making business case development for charging point operators problematic. This also implied that, on average, EVs connected to charging stations used only 15-25% of the time connected to actually charge, resulting in an effective utilisation of merely 5-10%. All in all, these developments have resulted in new challenges for local policy makers especially in which they have to balance over- and underutilisation of charging infrastructure to optimise the utilisation of charging infrastructure.

8.2 Conclusions for Study 2: Fully charged: An empirical study into the factors that influence connection times at EV-charging stations

Which factors and to which extent do these factors influence electric vehicles' connection times at charging stations?

This study systematically and empirically analysed the factors that influence connection times of EVs at charging stations. So far studies that try to optimize charging infrastructure roll-out strategies, treat EV charging demand as a spatial-temporal issue. However due to the rival nature of charging stations, predicting the charging sessions duration is crucial. To assess which factors have an impact on these connections a large empirical database with over 2.6 million charging sessions from public charging infrastructure was analysed. The analysis showed that the duration of charging sessions could be categorised in five different time bins that could be classified.

In an urban context charging stations are not solely used for charging but for a combination of parking and charging. Different types of users such as inhabitants, commuters, visitors, taxis and new modes such as shared electric free floating cars are all competing for the same charging stations. Results show that the time-of-day and the type of charging station (level 2 vs. fast) have the most substantial effect on the duration of the connection to the charging station. More specifically, for level 2 charging stations connection duration is very much aligned with parking behaviour and preferences: due to the lower charging speed at these stations, EV-drivers tend to leave their vehicle parked at a charging station for a longer time while they are (for example) at work or sleeping.

Combining the right parking policies with EV charging could prove to be difficult. Especially with the growing battery sizes of vehicles, cars may possibly not fully charge if parking times are limited. On the other hand, our analysis shows that in a significant amount of sessions cars are connected longer than 24 hours, keeping valuable charging spots unnecessarily occupied. To design the right policies to tackle this problem, policy makers also need to combine insights from both the charging and parking literature.

8.3 Conclusions for Study 3: Improving electric vehicle charging station efficiency through pricing

How and to what extent can time-based fees help to reduce idle time at electric vehicle charging stations?

The second study found that connection times at EV charging stations are strongly related to parking behaviour. This also results in possible unnecessary occupancy of charging stations preventing other EV users to charge. The third study has examined the influence of a time-based fee on the decision to remove an EV from a charging station once fully charged. A stated choice survey was conducted among EV drivers to see the influence of such a fee in different circumstances. A binary logit model shows that such a fee can be effective and can result in more efficient use of charging stations. Other factors influencing the choice, such as parking pressure, time until next drive and the time of day were also found to be relevant, although straightforward interpretation was not always possible.

To assess the heterogeneity among EV drivers regarding the time-based fee, a discrete choice latent class model was estimated. Additional variables about the type of EV and charging behaviour of the respondents were added to the model as predictors of class membership. Results show that three types of users could be distinguished; those that responded to the fee, users that always moved their car once fully charged independent of the fee and those that refused to move, regardless of the set fee level. Membership variables showed that members of the second class indicated that indeed this behaviour belonged to their normal charging behaviour. Members of the third class were more likely to experience parking pressure when parking at home. These drivers do not see the opportunity to park their car elsewhere once fully charged. Such distinctions are important for policy makers because those that experience parking pressure are mostly drivers who rely on curb side charging and parking because they make use of public charging infrastructure on a daily basis.

8.4 Conclusions for Study 4: Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective owners: Natural and stated choice experiments

How and to what extent do parking policies influence charging behaviour and electric vehicle purchase intention and how are they interrelated?

In the fourth study case studies on operational measures by local policy makers were used to investigate cross-links (see *Figure 8.1*) between EV purchase measures and EV charging measures. The case study concerning the free parking measure shows that, on the one hand, it has a positive intended effect on purchase intention, while, on the other hand, it results in a longer connection duration of charging sessions, which could lead to inefficient use of charging stations. Vice versa, a case study of daytime charging shows that controlling charging behaviour is effective but that such a restrictive policy negatively influences EV-purchase intentions. Studying the impact of operational measures on their non-intended effects is a relevant subject of study, as these cross-effects may be non-trivial.

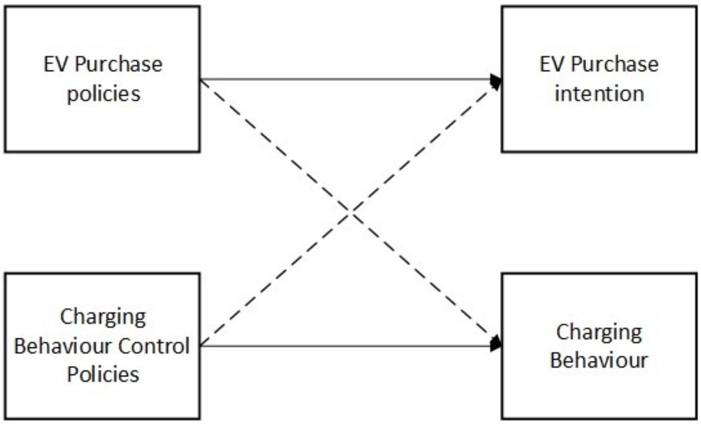


Figure 8.1 Cross-pollination between operational measures

Although the cross-effects of such policies do not appear to be dominant in either determining charging behaviour or purchase intention, they are too important to ignore by policy makers who aim to design policies that are effective at one level (e.g. stimulating EV-ownership) without having a negative side effect at another level (e.g. parking pressure). The interactions in the EV charging system are complex and can lead to opposite and undesired results. Policy makers should not only focus on the direct effects on the intended policy but also take into account possible (negative) side effects. The presented case studies, each evaluated with an unique database on charging behaviour, show that these side effects do exist and therefore should be taken into account when evaluating the effect of proposed or implemented policies.

8.5 Conclusions for Study 5: Scaling electric vehicle charging infrastructure: An agent based model approach

Which roll-out strategy for charging infrastructure can optimize tactical plans and why?

Planning charging infrastructure requires knowledge on long term effect as upfront costs are high and rewards can only be expected after several years. The fifth study provides insight into long term effects of different roll-out strategies using a data driven agent based model approach which was used to explore three different roll out strategies. The results of the first study, in which single charging stations were placed, has shown that positive reciprocal effects can be expected. A low ratio of EVs and charging stations resulted in exponential growth of new EV owners as purchase intention increases when sufficient charging infrastructure is available. A higher ratio, and therefore a lower number of stations, resulted in more linear growth. Investing in sufficient charging stations for those that rely on on-street charging facilities results in an increased adoption pace.

If the ratio between EVs and charging stations was kept at slightly higher levels than observed levels (approximately three EVs to one station), EV drivers were still able to find available charging stations. Due to return to scale effects, in which a network of charging stations results in more alternatives becoming available, the share of failed sessions declines in time even though the ratio between EVs and charging stations is kept equal. This proves that policy makers and charging point operators can in time increase the threshold for placing a charging station without effecting service levels. This increases efficiency with lower impacts on the grid and public space and has a positive impact on the business case due a higher number of sessions per charging station.

A comparison between different roll-out strategies such as placing charging hubs instead of single charging stations or adding fast charging stations shows that trade-offs in roll-out strategies are inevitable. Reaching all tactical plans is not possible. There are distinct trade-offs between charging availability, convenience (in terms of cruising traffic) and public space and grid integration. Results of the simulation show that a charging hub strategy in which charging stations were clustered provides more convenience in terms of charging without searching for available stations for drivers. However it results in lower charging availability, as the network effect and therefore positive return to scale effects are missing. Fast charging stations do provide network effects but provide additional EV drivers have an additional inconvenience as they have to wait while charging the car. At lower 'fast charging speeds' such as 50 and 150kW this was especially problematic. Providing the same charging availability at similar investments costs was not possible.

8.6 Conclusions for Study 6: Stakeholders' perspectives on future charging infrastructure developments

What perspectives do stakeholders have on future tactical plans for electric vehicle charging infrastructure and how are they (dis-)aligned?

The fifth study provides evidence that building a charging infrastructure will be a trade-off between several tactical plans. Stakeholders might be willing to put the tactical plan that suits their interests most first. The sixth study has examined the normative perspectives of stakeholders on the EV charging infrastructure. The study found, using Q-methodology, that four different perspectives on the development of charging infrastructure on the future could be categorised. These four perspectives are (A) EV drivers first by policy, (B) An open, smart and fast charging network, (C) Smart charging priority and (D) Wired electric only and open markets.

These four different perspectives are divided across three main issues which are the share of fast charging, the degree to which smart charging should be the standard option and which role governments should play. Fast charging is either seen as a dominant option in the future or found to be in conflict with 'smart charging' strategies. The analysis shows that those in favour and those that oppose fast charging as main charge mode, use very different arguments in the debate. The perspectives are aligned in the idea that smart charging plays a vital role in the future to incorporate charging stations in the electricity grid but are in conflict with each other on the degree smart charging should be the standard in charging. The dilemma at hand is the choice between a system with smart charging by design or an user-controlled version. On the role of the government multiple ideas existed, which varied in extent from nearly full government control to only standard setting practices. Perspectives took C & D contained a viewpoint with a government that should aid the transition but should slowly retreat as the market takes over.

The study found that perspectives are not one-on-one associated with the stakeholders' interests. This implies that only looking at the stakeholders' interests is not the most effective way to manage the tactical interests. Moreover these results show that multiple perspectives can exist within and across industry partners. The Q-methodology approach entails that participants have to choose which topics they prioritize, revealing more common ideas about the future than a classical stakeholders analysis might provide. Inviting all stakeholders for participation sessions to express their interests, could leave points of conflict and consensus unexplored. This analysis shows that stakeholders could be interested to look beyond their current interests and have similar visions as other industries despite differences in the stakes they pursue.

8.7 Policy implications

Policy recommendations that use the results from this thesis are relevant for decision makers both at the operational and tactical or strategic level. At the operational level results show that financial incentives have a very strong impact on the EV landscape and charging infrastructure utilisation. To steer purchases of company lease cars, adjustment of the addition (or benefit-in-kind) tax is effective but policy makers at the national level should also take into account how this impacts charging infrastructure developments and utilization. Rapid changes in financial incentives result in peak demand for public charging infrastructure which is difficult to manage on the short term. The sales stimulation of PHEV has resulted in a lower than desired charge time to connection time ratio, which makes business case development for CPOs difficult. As attention has shifted to FEV, policy makers now have to make choices if they only want to stimulate cheaper medium-ranged cars or all EVs. The stimulation of medium- instead of long-ranged FEVs requires more charging infrastructure to facilitate all charging needs. Financially, results suggest that charging infrastructure investments are much cheaper than purchase incentives in order to reach the same impact on purchase intention, but the impact on public space, parking and the electricity grid also have to be considered. Moreover, a combination of the two most likely yields the best results. Policy makers should therefore push the development of charging infrastructure at semi-public areas such as parking garages and workplace charging. Investments at these places are cheaper and have less impact on the public space.

Several policy implications for operational measures for charging infrastructure have been derived. Sufficiently available charging infrastructure for potential EV drivers is important when they consider a purchase. Policy makers should therefore ensure that those that rely on on-street parking facilities have sufficiently available charging stations around. In a lot of urban areas these are the majority of inhabitants. For effective utilisation of this charging infrastructure policy makers should not implement free parking, as it results in longer connection times, while a fee structure that includes a payment per hour model increases efficiency. Yet, straightforward implementation is not sensible without including the surrounding parking situation in each case; increasing utilisation might also lead to unnecessary parking pressure for non-EV drivers which on the longer term this might increase resistance to additional charging stations. Implementation of a time-based fee in areas with high parking pressure is therefore not recommended. To relieve this additional parking pressure, window times in which non-EV drivers may make use of the parking spot next to charging station are to be used. Results from this thesis show that when policy makers implement such measures cross-pollination to other domains is relevant and should always be considered by policy makers. The operational measures discussed are effective in their own domain but can result in inefficiencies for other policy goals. Active monitoring and evaluation of charging infrastructure utilisation is important to track the effect of measures taken.

On a tactical level the thesis has provided the insight to policy makers that the development of a charging network not only entails to facilitate the EV driver in its charging needs. Mathematical optimisations based upon travel patterns to optimize charging infrastructure roll-out are not sufficient for three main reasons. First, charging behaviour is not only a result of charging needs, but is an interplay between parking and refuelling needs. To plan charging infrastructure there where cars park is a good start, but overinvestments at these locations leads to inefficient use available infrastructure. It is key to balance the ratio between EVs and charging stations. A high ratio implies possible limited access, a low ratio overinvestment by CPOs leading to a failing business case. Yet, with technological developments on both the battery and charging side, policy makers should look at the possibilities of fast charging. This could provide a more cost and space efficient solution for charging needs of urban residents in the future. Secondly, charging infrastructure management is not only about charging needs fulfilment but also about government of public concerns on e.g. parking, building a business case for charging point operators and the expectations of other stakeholders (i.e. grid operators, automobile manufacturers). Not each stakeholder only pursues their own short term goals, but their perspectives on a future charging infrastructure are often shared. Focus on the key issues, such as the debate between level 2 and fast charging, in these perspectives results in more alignment in the development of an operational charging infrastructure. Policy makers are encouraged to critically think about their roll-out strategies. Despite the success of the Dutch roll-out approach, policy makers should not think this the silver bullet when scaling to a complete electric fleet. Finally, the results have shown that a perspective of charging infrastructure as a complex network in which EV drivers compete for available resources provides new insights. This allows policy makers to think about how different users and types of users can make use of the same infrastructure. Additionally, this approach allows to see how charging infrastructure will be used in the coming years in which the number of EVs will be a multitude of the limited number of EVs that are currently on the road. Due to network effects a (limited) return to scale effect can expected. It is recommended to policy makers to invest in a charging network with optimal coverage in the coming years to create a minimum network across the city. In later years this network can be strategically reinforced at locations at where demand concentrates. This leads to a charging network in which the EV to charging station ratio can be relatively high and investments in the later years can be limited.

8.8 General reflections

The research for this thesis has been performed in a time (2015-2019) in which the EV industry has transformed in a very rapid pace. While in 2015 the total stock of EVs surpassed 1 million for the first time, in 2018 alone more than 2 million EVs were sold (International Energy Agency, 2019). Sales have considerably increased due to strong policies. EV markets have therefore been rather concentrated in certain countries, states and cities. This research has also focussed on one of those frontrunner countries, The Netherlands. The Netherlands can be characterised an area with high urban density and a large demand for on-street parking and charging. The results of thesis should be placed within the frame of that context although generalisations for urban areas are possible.

Much of the research has focussed on level 2 charging stations, which facilitate slower charging that is mostly sufficient to charge an EV overnight. This mode of charging is the dominant mode of charging not only in the Netherlands but globally, although there are substantial differences between cities (Hall, Cui, & Lutsey, 2018). Ironically, this type of slow charging is both a key reason for the success of EVs as a potential pitfall to future growth. As early EVs had limited fast charging speeds and opportunities, level 2 charging at convenient places was necessary for an acceptable driving experience among early adopters. In many cases these early adopters had the possibility to install these charging stations at locations such as at home or the workplace. Additionally, this could be supported by regular electricity outlets already available. A comparison could be drawn here with early gasoline refilling in which cars made use of an already abundant available infrastructure of oil lamp shops at which gasoline could be bought to fill the car at home. In contrast to other alternative fuels such as hydrogen or CNG, the EV transition is much more a result of a bottom-up process, mainly facilitated by drivers themselves and by available electricity networks that can provide charging power. Other alternative fuels would have to rely on large investments on filling stations, creating a chicken-or-egg dilemma which has proven hard to crack. It is well worth to think about the history of traditional filling stations a draw comparison with charging stations. Can it be expected that EV charging stations will also evolve to a more centralised model with fewer fast charging stations? Although it might be hard to predict which direction charging infrastructure will develop, I agree with Kanger et al. (2019) that the result is part of a social embedding and technological features. The choices currently made by stakeholders and policy makers affect the path that this technological development will take.

The studies presented, especially studies 2 to 4, should be evaluated in the light of the trajectory in which EV charging infrastructure has been developed. Many of the formulated tactical plans, such as integration into parking policies and facilitating the business case, only relate to a large level 2 charging network. Despite level 2 being the dominant charging mode, it is not the only mode that is considered. The results of study 7 show that multiple trajectories are considered by stakeholders involved. In study 6 alternative trajectories such as those in with centralised charging hubs and fast charging stations are simulated. Charging choices of these new modes however cannot be determined from observing current charging patterns. A discrete choice experiment among EV drivers was used to determine 'charging rules' for the fast charging mode. Although it is my belief that current EV drivers are better suited to estimate their preferences for charging modes than non-EV drivers, it is worth reflecting on how the current trajectory has shaped these preferences. They might prefer level 2 charging over fast charging as they have experienced the convenience of charging while parking and could as well associate charging with certain parking benefits. Non-EV drivers might be more oriented to a charging infrastructure that resembles the current gasoline stations as they are used to this. When asked their preferences on charging infrastructure, the results might well be very different from EV drivers. If technological developments allow a scenario with nearly only fast charging, should we then shape the infrastructure with preferences from EV drivers or only potential EV drivers?

Not only might potential EV drivers have different preferences due to a lack of experience, current EV drivers are also early adopters which are a substantially different group than the entire population of car owners (Hoekstra & Refa, 2017) in different aspects. Many of the EV drivers are driving company lease cars which are known to drive much more on an annual basis. Future drivers, especially second hand car owners, are known to drive less (CBS, 2018). They could therefore stay connected to charging stations longer, which will increase the inefficient use of charging stations. Lease drivers often do not have to pay for fuel costs, making them rather insensitive to price differences. Future drivers might be much more price sensitive in which case price transparency becomes more important. In retrospect, this work could have paid more attention to such systematic differences when it comes to scaling up charging infrastructure for the future. Changing preferences over time due to the inclusion of new user groups has lacked.

This thesis has proceeded from the idea that the behaviour and thus preferences of the EV driver should be analysed to shape the charging infrastructure accordingly. This should be done within the constraints of for example public space and the electricity grid. Yet, as with many technological developments, the preferences of users are not set but are actively shaped through their interactions with the technology. As mentioned above, users prefer level 2 charging near home as they encountered as the most viable option early on. Problems such as grid overload are caused because of charging behaviour that is enabled by this infrastructure. Techniques such as smart charging and Vehicle-2-X are employed to 'correct' this behaviour once it has already taken place. Yet, as preferences are shaped in the early phase of the transition, this allows policy makers to shape these in line with other policy goals. Why should policy makers not stimulate charging during the day at work? This is often in the semi-public space, with less implications for public space and parking. It allows users to charge when most solar energy is provided and during these times electricity grids have more available capacity. Rethinking roll-out strategies by already looking at the implications of location choice in terms of expected behaviour could be a much more cost efficient solution.

With respect to management of charging infrastructure this thesis has made a contribution in the knowledge of current charging behaviour and how operational measures influence this behaviour. Results have shown that charging behaviour is much more than simply fulfilment of refuelling needs but is an interplay between refuelling and parking behaviour. This complex interaction between EV drivers and the available charging stations makes that operational measures do not always only reach the desired effect but that cross-pollination between operational measures for different tactical plans exist. The integral simulation of the EV system provided new insights into the effects of different roll-out strategies and this approach showed that viewing charging stations as a rival good for which there is competition among EV drivers is a valuable approach for further research. Despite the limitations of not including possible important differences between early adopters and future EV drivers, the approach is considered valuable for policy makers to see how their operational policies could influence the electric car is charged.

8.9 Future research directions

The second chapter of thesis has shown that financial stimulation has resulted in a large number of Plug-in Hybrid EV drivers. At the same time full battery electric vehicles were stimulated in a similar matter or received in more stimulation. Yet, the majority of drivers chose the PHEV, possibly due to range anxiety. Given that PHEVs in the Netherlands no longer receive substantial stimulation it is interesting to research which drivers are willing to switch to FEVs. A potential comparable group is those of diesel drivers that also received financial stimulation to drive ‘cleaner’ diesel vehicles. How has the experience of PHEV drivers shaped their idea about FEVs and the available charging infrastructure? Does this experience of driving a partly electric vehicle result in a higher willingness-to-purchase a full electric vehicle? Which experiences have shaped their perspectives on EVs?

This thesis has mainly focussed on public charging infrastructure in the urban area. Although a large amount of data on charging transactions was gathered, the data did not provide all charging sessions of individual drivers. Data on private charging infrastructure, fast charging along highways and charging at semi-public locations such as the workplace or parking garages was missing. Additionally, barely any data was collected of those drivers with a private charging station. Obtaining additional data on these other modes of charging could result in a full picture of a charging profile and this information can be used to develop a charging infrastructure. This will result in better integration with parking policies, which often tend to focus on removing parking spots from the street and into parking garages while in current infrastructure policies on-street charging dominates. The dynamics in these areas is currently unknown and shows to be promising field of research. Additional modes of transport that will be electrified in the future such as (city) logistics are also more likely to make use of private or semi-public charging infrastructure. These modes therefore have to be included to provide a complete overview of the required charging infrastructure in the urban area.

A topic mostly disregarded in this thesis is the grid integration of electric vehicle charging stations. Although the topic is widely discussed in literature and in practice, the simulation model used in *chapter 7* is useful to further develop the knowledge on optimisation of grid integration of charging stations. Due to the unique database on charging infrastructure roll-out strategies these optimisation strategies can better be informed with actual charging patterns. With the growth charging infrastructure and the differences in charging patterns, due to e.g. EVs with larger batteries, the impact on the grid can better be assessed. Little is yet known about how the charging capacities of cars influence the charging behaviour and how this impacts grid congestion. The agent based model allows to further develop this kind of knowledge in combination with the differentiation in roll-out strategies.

8.10 References

CBS. (2018). *Jaarmonitor Wegvoertuigen: Kilometers 2017*. Retrieved from https://www.cbs.nl/nl-nl/achtergrond/2018/45/jaarmonitor-wegvoertuigen-kilometers

Hall, D., Cui, H., & Lutsey, N. (2018). *Electric vehicle capitals: Accelerating the global transition to electric drive*. Retrieved from https://www.theicct.org/publications/modernizing-regulations-electrification

Hoekstra, A., & Refa, N. (2017). Characteristics of Dutch EV drivers. In *Electric Vehicle Symposium 30* (pp. 1–13). Stuttgart.

International Energy Agency. (2019). *Global EV Outlook 2019*. Retrieved from https://webstore.iea.org/download/direct/2807?fileName=Global_EV_Outlook_2019.pdf

Kanger, L., Geels, F. W., Sovacool, B., & Schot, J. (2019). Technological diffusion as a process of societal embedding : Lessons from historical automobile transitions for future electric mobility. *Transportation Research Part D*, *71*(June 2018), 47–66. https://doi.org/10.1016/j.trd.2018.11.012

Summary

Climate change and air pollution are considered major health threats. CO_2, NO_x, SO_x and PM emissions from the combustion of fossil fuels in road transport are a major contributor to these problems. Electric Vehicles (EVs) show great promise to reduce these emissions. Governments therefore strive to replace fossil fuel driven vehicles with electric versions as soon as possible. Cities are frontrunners in implementing policies to promote EVs as they feel the burden of air quality the most. Despite a number of ambitious goals by leading cities aiming to ban the sales or city access of gasoline vehicles by 2030/2040, the number of EVs on the road is still small in most countries. Three main barriers have been identified that hamper the large scale introduction of EVs. These barriers are the high purchase costs, the limited driving range and a lack of public charging infrastructure. The continuous developments in battery technology has driven down costs and has increased energy density of batteries, in turn allowing larger driving ranges. As these developments are expected to continue, the first two barriers are expected to be overcome in the years ahead.

The third barrier, a sufficient charging infrastructure is therefore what policy makers focus on to accelerate the transition to EVs. So far, in many cases the development of charging infrastructure has followed the number of EVs on the road, which leaves potential buyers with doubts about their recharging options. Especially in urban environments in which EV drivers cannot charge on their own driveway but rely on on-street parking and charging facilities supplying sufficient charging options is vital. In these urban environments other modes of transport such as taxis, car sharing services and city logistics compete for the same charging infrastructure, which creates a unique and complex dynamic of optimizing assets as well as competition and synergy effects. Additionally, policy makers need to consider the interests of multiple stakeholders such as charging point operators, non-EV drivers, city departments such as parking and local grid operators. Hence, management of charging infrastructure requires planning at the strategic, tactical and operational level.

To understand the effects of policies and measures at all level requires a thorough understanding of the EV charging system and its interactions. This thesis focusses on the EV charging system and specific how operational measures influence goals set in tactical plans and strategic policies. To assess this influence a mixed method approach is used. A research opportunity was provided to study one of the frontrunners in the world, the public charging network in the Netherlands and especially in its four major cities: Amsterdam, Rotterdam, The Hague, Utrecht and the metropolitan region of Amsterdam. These areas have one of the most densely operated charging networks globally. A unique dataset with millions of records of charging sessions at public charging stations and natural experimental conditions enabled an assessment of the effects of operational measures. Combined with stated choice experiments, Q-methodology for a qualitative perspective on infrastructure developments and agent based modelling to address scaling up into the future, this thesis provides a comprehensive overview of the EV charging system.

Chapter 2 introduces the case study of the Netherlands and shows how the reduction in addition tax for plug-in hybrid vehicles spurred the sales of these vehicles. A subsequent reduction of this tax benefit implied that sales dramatically decreased and shifted towards full electric vehicles. Generally, the scheme is widely considered a success, as EV sales shares even peaked over 10% of all sales by 2015. Yet, the tax incentive also received much critique. Plug-in hybrid vehicles drove far less on the battery than emission cycle tests would expect, mainly because company car drivers lacked the financial incentive to charge. And thus, the fiscal measures resulted in less emission reduction than expected on beforehand. Large sales names number spurred the development of a public charging network, as many of the drivers relied on on-street parking. Due to small battery sizes of plug-in hybrid vehicles these charging stations are used rather inefficiently. Data analysis shows that charging stations were used only 30-40% of the time and of this actual connection time only 15-20% was used for charging. This results in an actual effective utilisation of only 5-10%. The low utilisation was mainly due to the small battery packs of PHEVs which proved that there is a strong link between purchase incentives and charging infrastructure utilisation.

Chapter 3 provides exploratory and explanatory research on the large database of charging sessions (in this research more 2.6 million sessions) in the Netherlands. A multinomial logit model is estimated to see which factors have the most impact on connection times of charging stations. The results show that charging behaviour with respect to connection times could be split into discrete bins which corresponded with different types of parking behaviour. The most important factors that determine connection times are the time of day (and also day of the week) and if the EV driver used a fast or level 2 charging station. Furthermore, data analysis revealed that a sessions longer than 24 hours are responsible for a considerable part of the occupancy of charging stations. These are far longer than what is necessary to fully charge. Parking behaviour dictates the connection time at level 2 charging stations in urban environments. Policy makers should focus on integration of these charging stations in their parking policies. Yet such integration could proof to be difficult, as it involves cooperation of non EV-drivers and effective utilisation of charging station is not directly aligned with parking behavior.

Chapter 4 continues with the notion that charging behaviour is mostly linked to parking and focusses on how to improve charging station efficiency given this behaviour. A stated choice experiment is used to estimate when a time-based fee is effective to reduce idle times at charging stations. EV drivers were faced with the choice whether they would move their vehicle once fully charged under certain conditions which included a fee per hour. A logit model reveals that a time-based fee can be effective to reduce the idle time. To address the heterogeneity across the respondents a latent class choice model is estimated. There are three types of respondents; those that are always willing to move regardless of a fee, those that are responsive to the size of the fee and those that are never willing to move. Those that are not willing to move experience more parking pressure compared to others and are afraid to move their car and not find a parking spot elsewhere.

Chapter 5 takes two other operational measures and estimates their effects and the cross-pollination between these measures. The chapter uses two natural experiments on free parking and daytime parking at public charging stations (which allows non-EV users to make use of the parking spot next to charging stations) and a stated choice experiment on the purchase intention of prospective EV owners. *Free parking* results in longer connection times at public charging stations but also provides a small incentive for prospective owners to choose an EV. *Daytime charging* can provide a relief in parking pressure for non-EV owners without compromising on charging station availability but does lead to a reduced likelihood of choosing an EV by prospective EV users. Reduced charging security near home has a negative effect on the purchase intention for EVs. These results show that cross-pollination effects between operational measures can be considerable. For example, measures aimed at purchase intent (e.g. free parking) can result in longer connection times (charging behavior) or vice versa, a measure aimed at charging behaviour (e.g. daytime parking for EV at a charging station) with negative effects on purchase intentions.

Chapter 6 provides an integral simulation of the charging system in the city of Amsterdam with various growth scenarios. It aims to provide answers to which roll-out strategy is most suited to scale up charging infrastructure up to 2025. The charging behaviour in the agent based simulation is based upon charging patterns observed and distinguishes itself from other studies that rely on travel data to estimate charging decisions. As part of modelling the EV charging system, the simulation includes both the purchase decisions of prospective owners (leading to a growing stock of EVs/agents) and the placement decision by charging point operators (leading to a growing charging network). In both decisions the charging infrastructure utilisation is considered. The developed model is used to study three different roll-out strategies (single, clustered and fast charging stations) at different intensities. Results show that when scaling up charging infrastructure, return to scale effects can be expected as long as there is sufficient network formation. Expanding networks increase charging opportunities for multiple users at once. This implies that in time the ratio between EVs and charging stations can come down as the options become more abundant. Simulation of the different roll-out strategies reveals that there is a trade-off between providing charging security (able to charge) and convenience (easily find an available spot), while taking into account the impact on public space and the business case of the charging point operator.

Chapter 7 investigates the normative perspectives of stakeholders on future charging infrastructure developments. Using Q-methodology stakeholders have to order statements about these developments to the extent they agree with them. Analysis of this ordering reveals that there are four perspectives that are shared across different stakeholders. These perspectives are mainly divided across three issues which are the importance of fast charging, the implementation of smart charging as a standard and the role of government. The four perspectives are shared across different stakeholder groups, implying that simply investigating the interests of stakeholders does not lead to the best management at the tactical level.

In conclusion, this thesis has provided new insights into charging behaviour at public charging stations in The Netherlands, one of the frontrunner countries on electric mobility. Using a large dataset on charging infrastructure and several experiments regarding operational measures on the ex-post operation of charging stations new insights have been gathered about the dynamics of charging behaviour on how this can be steered. A clear link between parking behaviour and charging station occupancy in the urban area has been proven, showing that policy makers should take into account integrating infrastructure deployment in their parking policies. Given this behaviour several roll-out strategies have been simulated allowing policies to make more informed decisions about their strategies, which turn out to be a trade-off between convenience and charging security. The simulation framework also provides the opportunity for policy makers to see how other modes than individual transport make use of the same charging infrastructure and provides future research opportunities to explore the consequences of policy choices on tactical goals of stakeholders involved.

Samenvatting

Klimaatverandering en luchtvervuiling worden als belangrijke gezondheidsbedreigingen beschouwd. CO_2-, NO_x-, SO_x- en PM-emissies van de verbranding van fossiele brandstoffen in het wegvervoer leveren een belangrijke bijdrage aan deze problemen. Elektrische voertuigen (EV) tonen grote beloftes om deze emissies te verminderen. Overheden streven er daarom naar om voertuigen die op fossiele brandstoffen rijden zo snel mogelijk door elektrische versies te vervangen. Steden lopen voorop bij het implementeren van beleid om EV te promoten, omdat steden het meest last hebben van slechte luchtkwaliteit. Ondanks ambitieuze doelstellingen van toonaangevende steden die de verkoop of toegang tot de stad van benzinevoertuigen tegen 2030/2040 willen verbieden, is het aantal EV op de weg in de meeste landen nog steeds klein. Drie belangrijke barrières zijn geïdentificeerd die de grootschalige introductie van EV's belemmeren. Deze barrières zijn de hoge aanschafkosten, de beperkte rijafstand en een gebrek aan openbare laadinfrastructuur. De voortdurende ontwikkelingen in batterijtechnologie hebben de kosten verlaagd en de energiedichtheid van batterijen verhoogd, waardoor grotere rijbereiken mogelijk zijn geworden. Omdat deze ontwikkelingen zich naar verwachting zullen voortzetten, zullen de eerste twee barrières naar verwachting de komende jaren worden overwonnen.

De derde barrière, voldoende laadinfrastructuur, is waar beleidsmakers zich op richten om de overgang naar EV's te versnellen. Tot nu toe heeft de ontwikkeling van laadinfrastructuur in veel gevallen het aantal EV op de weg gevolgd, waardoor potentiële kopers twijfels hebben over hun oplaadopties. Vooral in stedelijke omgevingen waar EV-eigenaren niet op hun eigen oprit kunnen opladen, maar afhankelijk zijn van parkeren en laden op straat, is het bieden van voldoende laadopties van vitaal belang. In deze stedelijke omgevingen concurreren andere vervoerswijzen zoals taxi's, autodeeldiensten en stadslogistiek om dezelfde laadinfrastructuur, wat een unieke en complexe dynamiek creëert voor het optimaliseren van de midellen, evenals unieke concurrentie- en synergie-effecten. Bovendien moeten beleidsmakers rekening houden met de belangen van meerdere belanghebbenden, zoals oplaadpunt exploitanten, niet-EV-bestuurders, stadsafdelingen zoals de sectie parkerem en lokale netbeheerders. Daarom vereist het beheer van laadinfrastructuur planning op strategisch, tactisch en operationeel niveau.

Om de effecten van beleid en maatregelen op elk niveau te begrijpen, is een grondig begrip van het EV-laadsysteem en de interacties ervan vereist. Dit proefschrift richt zich op het EV-laadsysteem en specifiek hoe operationele maatregelen doelen beïnvloeden die zijn vastgesteld in tactische plannen en strategisch beleid. Om deze invloed te beoordelen, wordt een gemengde methode benadering gebruikt. De onderzoeksmogelijkheid werd geboden om een van de koplopers op het gebied van elektrisch vervoer ter wereld te bestuderen, het openbare laadnetwerk in Nederland en vooral in de vier grote steden: Amsterdam, Rotterdam, Den Haag, Utrecht en de grootstedelijke regio van Amsterdam. Deze gebieden hebben wereldwijd een van de dichtst beheerde laadnetwerken. Een unieke dataset met miljoenen observaties van laadsessies bij openbare laadstations en natuurlijke experimentele omstandigheden maakte een analyse van de effecten van operationele maatregelen mogelijk. Gecombineerd met keuze-experimenten, Q-methodologie voor een kwalitatief perspectief op infrastructuurontwikkelingen en agent-gebaseerde modellering om op te schalen naar de toekomst, biedt dit proefschrift een uitgebreid overzicht van het EV-laadsysteem.

Hoofdstuk 2 introduceert de situatie in Nederland en laat zien hoe de verlaging van de bijtelling voor plug-in hybride voertuigen de verkoop van deze voertuigen heeft gestimuleerd. Een daaropvolgende vermindering van dit belastingvoordeel impliceerde dat de verkoop dramatisch daalde en verschoof naar volledig elektrische voertuigen. Over het algemeen wordt de regeling algemeen als een succes beschouwd, omdat EV-verkoopaandelen zelfs een piek bereikten van meer dan 10% van alle verkopen in 2015. Toch kreeg de fiscale stimulans ook veel kritiek. Plug-in hybride voertuigen reden veel minder op de batterij dan emissietests zouden verwachten, vooral omdat bestuurders van bedrijfsauto's niet de financiële prikkel hadden om te laden. En dus resulteerden de fiscale maatregelen in minder emissiereductie dan vooraf werd verwacht. Het grote aantal verkoopnamen stimuleerde de ontwikkeling van een openbaar laadnetwerk, omdat veel chauffeurs afhankelijk waren van parkeren op straat. Vanwege de kleine batterijafmetingen van plug-in hybride voertuigen worden deze laadstations redelijk inefficiënt gebruikt. Gegevensanalyse toont aan dat laadstations slechts 30-40% van de tijd werden gebruikt en van deze werkelijke connectietijd slechts 15-20% werd gebruikt voor het opladen. Dit resulteert in een effectief gebruik van slechts 5-10%. Het lage gebruik was voornamelijk te wijten aan de kleine batterijpakketten van plug-in hybride voertuigen en daarmee werd bewezen dat er een sterk verband bestaat tussen aankoopprikkels en het gebruik van de laadinfrastructuur.

Hoofdstuk 3 is een verkennend en verklarend onderzoek naar de grote database van laadsessies (in dit onderzoek meer 2,6 miljoen sessies) in Nederland. Een multinomiaal logit model wordt geschat om te zien welke factoren de meeste invloed hebben op de connectietijden van EV bij laadstations. De resultaten laten zien dat het laadgedrag met betrekking tot de connectietijden kan worden opgesplitst in discrete tijdsvakken die overeenkomen met verschillende soorten parkeergedrag. De belangrijkste factoren die de connectietijden bepalen, zijn het tijdstip (en ook de dag van de week) en of de EV-bestuurder een snel of niveau 2-laadstation heeft gebruikt. Bovendien bleek uit het onderzoek dat sessies van meer dan 24 uur verantwoordelijk is voor een aanzienlijk deel van de bezetting van laadstations. Deze sessies zijn veel langer dan nodig is om volledig op te laden. Kortom, parkeergedrag bepaalt de connectietijd op laadstations van niveau 2 in stedelijke omgevingen. Beleidsmakers moeten zich dus richten op de integratie van deze laadstations in hun parkeerbeleid. Toch kan een dergelijke integratie moeilijk blijken, omdat het samenwerking met niet-EV-bestuurders inhoudt en het effectieve gebruik van het laadstation niet direct is afgestemd op het parkeergedrag.

Hoofdstuk 4 gaat verder met het idee dat laadgedrag meestal gekoppeld is aan parkeren en richt zich op het verbeteren van de efficiëntie van het laadstation gezien dit gedrag. Een keuze-experiment wordt gebruikt om te schatten wanneer een op tijd gebaseerde vergoeding effectief is om de inactieve tijd bij laadstations, het zogenoemde laadplaalkleven, te verminderen. EV-eigenaren worden voor de keuze gesteld of ze hun voertuig zouden verplaatsen zodra het volledig opgeladen was onder bepaalde voorwaarden, waaronder een tarief per uur. Een logit-model onthult dat een op tijd gebaseerde tarief effectief kan zijn om de inactieve tijd te verminderen. Om de heterogeniteit onder de respondenten te bestuderen, wordt een latent keuzemodel geschat. Er zijn drie soorten respondenten; degenen die altijd bereid zijn hun voertuig te verplaatsen ongeacht het tarief, degenen die reageren op de hoogte van het tarief en degenen die nooit bereid zijn te veplaatseb. Degenen die niet willen verplaatsen, ervaren meer parkeerdruk dan anderen en zijn bang om hun auto te verplaatsen omdan nergens anders een parkeerplaats te vinden.

Hoofdstuk 5 neemt twee andere operationele maatregelen en schat de effecten ervan en de kruisbestuiving tussen deze maatregelen. Het hoofdstuk maakt gebruik van twee natuurlijke experimentele omstandigheden: Gratis parkeren, exclusief overdag parkeren bij openbare laadpalen (waarmee niet-EV-gebruikers de parkeerplaats naast laadpalen kunnen gebruiken in de avonduren) en een keuze-experiment met betrekking tot de aankoopintentie van potentiële EV-eigenaren. Gratis parkeren resulteert in langere connectietijden bij openbare laadstations, maar biedt ook een kleine stimulans voor potentiële eigenaren om een EV te kiezen. Het alleen overdag exclusief parkeren voor EV bij laadpalen kan de druk in het parkeren voor niet-EV-eigenaren verminderen zonder concessies te doen aan de beschikbaarheid van het laadstation, maar leidt wel tot een kleinere kans op het kiezen van een EV door potentiële EV-gebruikers. Lagere laadveiligheid in de buurt van huis heeft een negatief effect op de aankoopintentie voor EV. Deze resultaten laten zien dat kruisbestuivingseffecten tussen operationele maatregelen aanzienlijk kunnen zijn. Zo kunnen maatregelen gericht op de koopintentie (bijv. gratis parkeren) resulteren in langere connectietijden (laadgedrag) of andersom, een maatregel gericht op het gebruik van het laadstation (bijv. alleen exclusief overdag parkeren voor EV bij een laadpaal) met negatieve effecten voor aankoopintenties.

Hoofdstuk 6 biedt een integrale simulatie van het laadsysteem in de stad Amsterdam met verschillende groeiscenario's. Het beoogt antwoorden te geven op welke uitrolstrategie het meest geschikt is om de laadinfrastructuur op te schalen tot in 2025. Het laadgedrag in de agent-gebaseerde simulatie zijn ontleedt op waargenomen laadpatronen en onderscheidt zich daarmee van andere studies die op reisgegevens bouwen om het laadgedrag te simuleren. Als onderdeel van het modelleren van het EV-laadsysteem omvat de simulatie zowel de aankoopbeslissingen van potentiële eigenaars (leidend tot een groeiende voorraad EV/agenten) als de plaatsingsbeslissing door laadpaalexploitanten (leidend tot een groeiend laadnetwerk). In beide beslissingen wordt rekening gehouden met het gebruik van de laadinfrastructuur. Het ontwikkelde model wordt gebruikt om drie verschillende uitrolstrategieën (afzonderlijke, geclusterde en snellaadstations) met verschillende intensiteiten te bestuderen. De resultaten tonen aan dat bij het opschalen van laadinfrastructuur effecten op de schaalgrootte kunnen worden verwacht zolang er voldoende netwerkvorming is. Uitbreidende netwerken vergroten laadmogelijkheden voor meerdere gebruikers tegelijk. Dit betekent dat na verloop van tijd de verhouding tussen EV en laadstations kan dalen naarmate de opties overvloediger worden. Simulatie van de verschillende uitrolstrategieën onthult dat er een afweging bestaat tussen het bieden van laadveiligheid (kunnen opladen) en gemak (gemakkelijk een beschikbare plek vinden), rekening houdend met de impact op de openbare ruimte en de business case van de laadpunt operator

Hoofdstuk 7 onderzoekt de normatieve perspectieven van belanghebbenden op toekomstige ontwikkelingen in de laadinfrastructuur. Met behulp van de Q-methodologie moeten belanghebbenden uitspraken over deze ontwikkelingen rangschikken in de mate zij het daarmee eens zijn. Uit analyse van deze ordening blijkt dat er vier perspectieven zijn die worden gedeeld door verschillende belanghebbenden. Deze perspectieven zijn hoofdzakelijk verdeeld over drie kwesties: Het belang van snelladen, de implementatie van slim laden als standaard en de rol van de overheid zijn. De vier perspectieven worden gedeeld over verschillende industrieën, wat inhoudt dat het eenvoudigweg onderzoeken van de belangen van individuele partijen en industrieën niet leidt tot het beste management op tactisch niveau.

Concluderend heeft dit proefschrift nieuwe inzichten opgeleverd in laadgedrag bij openbare laadstations in een van de koplopergebieden van elektrische mobiliteit, Nederland. Met behulp van een grote dataset over het gebruik laadinfrastructuur en verschillende experimenten met betrekking op het effect van operationele maatregelen zijn nieuwe inzichten verzameld over de dynamiek van laadgedrag en over hoe dit kan worden gestuurd. Er is een duidelijk verband aangetoond tussen het parkeergedrag en de bezetting van het laadstation in het stedelijk gebied, waaruit blijkt dat beleidsmakers rekening moeten houden met de integratie van de infrastructuur in hun parkeerbeleid. Gegeven dit gedrag zijn verschillende uitrolstrategieën gesimuleerd, waardoor beleidsmaatregelen beter geïnformeerde beslissingen kunnen nemen over hun strategieën, die een afweging blijken te zijn tussen gemak en beveiligingszekerheid. Het simulatiekader biedt beleidsmakers ook de mogelijkheid om te zien hoe andere vervoerswijzen dan individueel personen vervoer zoals taxi’s, deelauto’s en stadslogistiek gebruik maken van dezelfde laadinfrastructuur en biedt toekomstige onderzoeksmogelijkheden om de gevolgen van beleidskeuzes op tactische doelen van de betrokken belanghebbenden te onderzoeken.

About the author

Rick Wolbertus was born on the 24th of April 1989 in Venlo, the Netherlands. He obtained both a Bachelor and Master degree in Innovation Sciences from Eindhoven University of Technology. After graduating he worked as an innovation consultant at Craeghs Consultancy in 2015. In 2016 he started his PhD trajectory at Delft University of Technology while being employed at the Amsterdam University of applied Sciences. His work was part of the SiA Raak funded project IDOLaad. The project focused on analyzing and predicting the use of charging stations for electric vehicles. During his time in Amsterdam he worked at the Urban Technology department under the research group Energy and Innovation. In Delft he worked at the Transport and Logistics section under the Engineering Systems and Services department at the faculty of Technology, Policy and Management.

In September 2019 he started working as a teacher in Software Engineering at the Amsterdam University of Applied Sciences. He also continues his work on charging infrastructure as a researcher and project leader for the four year SiA Raak funded project Future Charging. With his research he aims to help policy makers and businesses to efficiently roll-out a charging infrastructure to accommodate a swift transition to zero-emission mobility.

Publication list

Peer reviewed journal

Wolbertus, R., van den Hoed, R., & Maase, S. (2016). Benchmarking charging infrastructure utilization. *World Electric Vehicle Journal*, *8*(4).

Wolbertus, R., Kroesen, M., van den Hoed, R., & Chorus, C. G. (2018). Policy effects on charging behaviour of electric vehicle owners and on purchase intentions of prospective

owners: Natural and stated choice experiments. *Transportation Research Part D: Transport and Environment*, *62*. https://doi.org/10.1016/j.trd.2018.03.012

Wolbertus, Rick, Kroesen, M., van den Hoed, R., & Chorus, C. (2018). Fully charged: An empirical study into the factors that influence connection times at EV-charging stations. *Energy Policy*, *123*(August), 1–7. https://doi.org/10.1016/j.enpol.2018.08.030

Wolbertus, Rick, & Gerzon, B. (2018). Improving electric vehicle charging station efficiency through pricing. *Journal of Advanced Transportation*, *2018*, 1–11. https://doi.org/doi.org/10.1155/2018/4831951

Wolbertus, Rick, & Van den Hoed, R. (2019). Electric Vehicle Fast Charging Needs in Cities and along Corridors. *World Electric Vehicle Journal*, *10*(2), 45. https://doi.org/10.3390/wevj10020045

Peer reviewed journal (under review)

Wolbertus, Rick, van den Hoed, R., Kroesen, M., & Chorus, C. G. (Under Review). Charging infrastructure roll-out strategies for large scale introduction of electric vehicles in urban areas: A simulation study. *Transportation Research Part A: Policy and Practice*.

Wolbertus, Rick, Jansen, S., & Kroesen, M. (Submitted). Stakeholders' perspectives on future electric vehicle charging infrastructure developments. *Futures*.

Book Chapter

Wolbertus, R., & van den Hoed, R. (Forthcoming). Plug-in (Hybrid) Electric Vehicle adoption in the Netherlands: Lessons learned. In M. S. . Contestabile, G. Tal, & T. Turrentine (Eds.), *Driving Electric Cars - Consumer adoption and use of plug-in electric cars*. Springer.

Conference papers

Wolbertus, Rick, & van den Hoed, R. (2017a). Charging station hogging : A data-driven analysis. In *Electric Vehicle Symposium 30* (pp. 1–14). Stuttgart.

Wolbertus, Rick, & van den Hoed, R. (2017b). Managing parking pressure concerns related to charging stations for electric vehicles : Data analysis on the case of daytime charging in The Hague. In *European Battery, Hybrid & Fuel Cell Electric Vehicle Congress* (pp. 1–8). Geneva, Switzerland.

Wolbertus, R, Helmus, J., Maase, S. J. F. M., & Van. (2018). Modes of fast charging : Rolling out fast chargers in cities and along corridors to meet the heterogeneity of needs among EV drivers. In *Electric Vehicle Symposium 31* (pp. 1–6).

Wolbertus, Rick, & Hoed, R. Van Den. (2019). Expanding charging infrastructure for large scale introduction of electric vehicles. In *Electric Vehicle Symposium 32* (pp. 1–15). Lyon, France.

TRAIL Thesis Series

The following list contains the most recent dissertations in the TRAIL Thesis Series. For a complete overview of more than 250 titles see the TRAIL website: www.rsTRAIL.nl.

The TRAIL Thesis Series is a series of the Netherlands TRAIL Research School on transport, infrastructure and logistics.

Wolbertus, R., *Evaluating Electric Vehicle Charging Infrastructure Policies,* T2020/4, February 2020, TRAIL Thesis Series, the Netherlands

Yap, M.D., *Measuring, Predicting and Controlling Disruptions for Urban Public Transport,* T2020/3, February 2020, TRAIL Thesis Series, the Netherlands

Luo, D., *Data-driven Analysis and Modeling of Passenger Flows and Service Networks for Public Transport Systems,* T2020/2, February 2020, TRAIL Thesis Series, the Netherlands

Erp, P.B.C. van, *Relative Flow Data: New opportunities for traffic state estimation,* T2020/1, February 2020, TRAIL Thesis Series, the Netherlands

Zhu, Y., *Passenger-Oriented Timetable Rescheduling in Railway Disruption Management,* T2019/16, December 2019, TRAIL Thesis Series, the Netherlands

Chen, L., *Cooperative Multi-Vessel Systems for Waterborne Transport,* T2019/15, November 2019, TRAIL Thesis Series, the Netherlands

Kerkman, K.E., *Spatial Dependence in Travel Demand Models: Causes, implications, and solutions,* T2019/14, October 2019, TRAIL Thesis Series, the Netherlands

Liang, X., *Planning and Operation of Automated Taxi Systems,* T2019/13, September 2019, TRAIL Thesis Series, the Netherlands

Ton, D., *Unravelling Mode and Route Choice Behaviour of Active Mode Users*, T2019/12, September 2019, TRAIL Thesis Series, the Netherlands

Shu, Y., *Vessel Route Choice Model and Operational Model Based on Optimal Control,* T2019/11, September 2019, TRAIL Thesis Series, the Netherlands

Luan, X., *Traffic Management Optimization of Railway Networks,* T2019/10, July 2019, TRAIL Thesis Series, the Netherlands

Hu, Q., *Container Transport inside the Port Area and to the Hinterland,* T2019/9, July 2019, TRAIL Thesis Series, the Netherlands

Andani, I.G.A., *Toll Roads in Indonesia: transport system, accessibility, spatial and equity impacts,* T2019/8, June 2019, TRAIL Thesis Series, the Netherlands

Ma, W., *Sustainability of Deep Sea Mining Transport Plans,* T2019/7, June 2019, TRAIL Thesis Series, the Netherlands

Alemi, A., *Railway Wheel Defect Identification,* T2019/6, January 2019, TRAIL Thesis Series, the Netherlands

Liao, F., *Consumers, Business Models and Electric Vehicles,* T2019/5, May 2019, TRAIL Thesis Series, the Netherlands

Tamminga, G., *A Novel Design of the Transport Infrastructure for Traffic Simulation Models,* T2019/4, March 2019, TRAIL Thesis Series, the Netherlands

Lin, X., *Controlled Perishable Goods Logistics: Real-time coordination for fresher products*, T2019/3, January 2019, TRAIL Thesis Series, the Netherlands

Dafnomilis, I., *Green Bulk Terminals: A strategic level approach to solid biomass terminal design*, T2019/2, January 2019, TRAIL Thesis Series, the Netherlands

Feng, Fan, *Information Integration and Intelligent Control of Port Logistics System,* T2019/1, January 2019, TRAIL Thesis Series, the Netherlands

Beinum, A.S. van, *Turbulence in Traffic at Motorway Ramps and its Impact on Traffic Operations and Safety,* T2018/12, December 2018, TRAIL Thesis Series, the Netherlands

Bellsolà Olba, X., *Assessment of Capacity and Risk: A Framework for Vessel Traffic in Ports,* T2018/11, December 2018, TRAIL Thesis Series, the Netherlands

Knapper, A.S., *The Effects of using Mobile Phones and Navigation Systems during Driving,* T2018/10*,* December 2018, TRAIL Thesis Series, the Netherlands

Varotto, S.F., *Driver Behaviour during Control Transitions between Adaptive Cruise Control and Manual Driving: empirics and models,* T2018/9, December 2018, TRAIL Thesis Series, the Netherlands

Stelling-Kończak, A., *Cycling Safe and Sound,* T2018/8, November 2018, TRAIL Thesis Series, the Netherlands

Essen, van M.A., *The Potential of Social Routing Advice,* T2018/7, October 2018, TRAIL Thesis Series, the Netherlands

Su, Zhou, *Maintenance Optimization for Railway Infrastructure Networks*, T2018/6, September 2018, TRAIL Thesis Series, the Netherlands

Cai, J., *Residual Ultimate Strength of Seamless Metallic Pipelines with Structural Damage*, T2018/5, September 2018, TRAIL Thesis Series, the Netherlands

Ghaemi, N., *Short-turning Trains during Full Blockages in Railway Disruption Management,* T2018/4, July 2018, TRAIL Thesis Series, the Netherlands

Gun, van der J.P.T., *Multimodal Transportation Simulation for Emergencies using the Link Transmission Model,* T2018/3, May 2018, TRAIL Thesis Series, the Netherlands