Design directions for reducing the peak load on the residential grid using electric vehicles

Simulating the behaviour of electric vehicle owners using the concepts of Social Acceptance and Moral Acceptability in an Agent-Based model.

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Acknowledgements

I wrote this thesis in the context of the Complex System Engineering and Management master at the faculty Technology, Policy and Management of the TU Delft. I'm proud to present you this thesis as it discusses a subject which is close to my heart. Since I was a child I have been interested in the energy transition. During my bachelor I noticed that I enjoyed building Agent-Based models and therefore I looked for a graduation project related to both. Emile Chappin challenged me to research the difference between moral acceptability and social acceptance using ABM.

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Executive summary

Different countries have introduced policies to decrease the use of Internal Combustion Engine (ICE) cars. These cars are fossil fuel based and this is the reason why a transition to another type of car is necessary. A growth of the share of electric vehicles can be expected in the near future. The capacity of the grid is based on the peak load of the electricity demand and if the cars would increase this peak load significantly, the capacity will be insufficient. One of the solutions to reduce the peak load on the grid is to use smart grid technology for the charging process of electric vehicles: a smart electric vehicle system.

A smart electric vehicle (EV) system is a combination of hardware and software (smart grid technology) which can control the charging progress of the electric car. The smart EV system has potential benefits for peak reduction, grid reliability, environmental improvements and cost reduction. The disadvantages of the smart EV system are privacy and security problems. Furthermore, the EV owners are scared that due to the smart EV system, the car will not always be sufficiently charged. The smart EV system can be divided in two different charging modes. One directional charging from the grid to the vehicle (V1G) or bidirectional, from the vehicle to the grid as well (V2G). There is also the trade off between cost, renewables or grid optimization. A more advanced algorithm has a higher potential for privacy problems.

The most important difference with the current electricity system is that with the smart EV system the EV owners have a choice to participate in balancing the electricity network. If the electricity system depends on the electric vehicles to decrease the peak load, and EV owners will not use the smart EV system, the capacity of the grid will be insufficient. It is therefore not only important that the EV owners use the smart EV system, it might be even more important that they will not suddenly quit. Research has shown that 32% of the people have never heard of a smart grid and 48% have no knowledge of the functions of a smart grid. Therefore the choice does not only have a large impact, it also is uncertain what the EV owners will choose.

The design of the smart EV system has to decrease the peak load on the electricity grid to an extent where capacity increments would not be necessary, on the short and long-term. The research objective is to find design directions for the smart EV system which reduce the expected electricity grid problems sufficiently in the long-term. Design directions could be technical, political or institutional. Design directions are defined in this thesis as high-level design choices which lead to directions for future research, an example could be to change the ownership of the EV battery.

In this thesis a highly abstract case study is used as this thesis analyses a possible futuristic solution for a problem that might occur in the future. The model has to include heterogeneous persons, as every EV owner has its own behaviour, experience and morals. Secondly, the EV owners make decisions based on their experiences with the smart EV system. Based on these properties of the model, an Agent-Based model is used.

The literature review shows that the persons morals and their actual behaviour do

not necessarily align. To understand the decision of the EV owners different concepts are used. The concept 'Social Acceptance' discusses if a technology gets accepted by a community. The concept 'Moral Acceptability' describes if a technology should get accepted by the community. The Value-Belief-Norm theory argues that personal values determine the attitude towards a new technology. These concepts are combined in the 3-level conceptual model. In the 3-level concept, a person chooses whether he continues using the smart EV system based on his personal experiences combined with his individual acceptability judgment of the smart EV system.

In the 3-level conceptual model the person decides based on two things, what he expects (values) and what he experiences. Important personal values concerning the smart EV system are economic development, environmental sustainability, privacy and autonomy. The 3-level conceptual model is used to understand how the person makes his decision and if his decision will stay the same in long-term. The acceptance level is therefore a measure of long-term stability. Moral Acceptability is based on values of the society. In this model, the individual acceptability is used, however it is possible to make the assumption that if the majority of the society thinks the smart EV system is acceptable, the EV smart system is acceptable. The analysis show that if the majority is in favor of the system (75%), there is still a 12 percent chance that the smart EV system is not accepted. On the other hand, if a majority is negative, so thinks the system is unacceptable, the system is only accepted in 1 percent of the cases.

The technical infrastructure which is modelled in the model is the electricity grid. The electricity grid is scoped down to the local residential grid, the connection between the transformers and the households. The households demand power from this grid, as do the electric cars. The cars are connected when the owner is home. The smart EV system is used by default at first. The smart EV system signals the car what to do, charge, discharge or do nothing. The EV owner develops an opinion on the application based on the experience he has with the smart EV system. The EV owner chooses whether he wants to use the smart EV system or not.

For the design, the first criterium of the design of the smart EV system was that it would indeed be sufficient to prevent residential capacity upgrades. In that regard should system design focus on the combination of Vehicle to Grid-technology and a network optimal algorithm. Advantages of this design direction is the option to decrease the current electricity peak as well with vehicle to grid technology, making more profit for the owners in the process as well. The advantage of a network optimal algorithm is that the peaks caused by electrical cars at moments with low electricity cost are minimized. The main disadvantage of this combination is the extra data and control required in the charging process, causing this combination to be less accepted. An analysis of a technical system, where the vehicles are charged at a central point during the day and discharged during the peak hours in the evening with V2G, could be promising. With this procedure, the capacity of the residential grid network does not have to be increased, which would save costs, time and labour.

Secondly, an important criteria of the design of the smart EV system was that it would be a solution in the long-term. In that regard system design should focus on decreasing the uncertainty of the electrical vehicle owner behaviour by creating contracts. The purpose of this contracts should be to know which EV owners will use the smart EV system. A possible option is to include the smart EV system in the purchasing process, offering a discount for EV owners which will use the smart EV system. In the current labelling of cars, the electric cars have an A label, while in reality this would depend on the composition of electricity used by the cars. A second option is to make contracts between different parties, where the EV owner benefits from the use of smart EV technology by for example payments, free electricity or better parking spots. A hazard of these options is that it a party has to actively monitor if the EV owners actually use their smart EV system, which could give privacy problems. A solution which causes more privacy problems might be bad.

To conclude, the next steps in research for the system design of the smart EV system should be to involve the actors which could play a role in the smart EV system. A technical analysis from the Distribution System Operators into the required capacity, profits and technical errors should be done. Based on these facts business models can be discussed with the concerned actors and policy measures can be discussed with the concerned ministries.

Reading guide

If you are interested in the analysis of the the smart EV system design the following chapters could be interesting:

- In chapter 3.1 the advantages and disadvantages of the smart EV system are discussed.
- If you are interested in the algorithm for the smart grid which is used in the model, take a look at chapter 4.3.2.
- For a discussion of the possible design choices of the smart EV system based on the outcomes of the model, chapter 6 and 7 are recommended.
- Limitations of this research concerning the technical system design are discussed in chapter 7.3.3, as well as the possible ideas to expand the model.

If you are interested in the Agent-Based Modelling method:

- In chapter 2.4.2 the choice for Agent-Based Modelling is discussed, based on the characteristics of the problem and ABM.
- If you are interested in the choices made during the modelling procedure, in chapter 4 the model is formalized. In this chapter a description of the model can be found.
- In chapter 5 the ABM model is validated using the evaludation method.
- In chapter 7.1 it is briefly explained how the design choices are implemented in the model.
- In chapter 7.3 the limitations of the model are discussed and possible expansion ideas are discussed.

If you are interested in the analysis of Social Acceptance and Moral Acceptability

- The background of the discussion between Social Acceptance and Moral Acceptability can be found in chapter 3.2. In this chapter the conceptualization of these theories into the 3-level conceptual model is discussed as well.
- If you are interested in the equations which let to the decision behaviour of the EV owners. In 4.3.3 and 4.4.2 the concepts discussed in chapter 3 are formalized to equations which are used in the model.
- Conclusions about the use of Agent-Based Modelling for simulating the difference between Social Acceptance and Moral Acceptability are discussed in chapter 9.2. Recommended is to read the paper associated with this thesis, as this is the main topic of the paper.
- In chapter 7.3.2 ideas for the expansion of the model based on the 3-level conceptual model are discussed.

List of Abbreviations

EV	Electric Vehicle
ABM	Agent-Based Modelling
V1G	One directional electricity flow from the grid to the vehicle
V2G	Two directional electricity flow between the grid and the vehicle
V2B	Vehicle to building
CAS	Complex Adaptive System
EMA	Exploratory Modeling and Analysis
DSO	Distribution System Operator
KPI	Key Performance Indicator

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Chapter 1

Thesis Introduction

1.1 Expected growth of the share of electric vehicles

A growth of the share of electric vehicles can be expected. One of the biggest challenges of the 21st century we face as mankind is the battle against climate change. The average global temperature is rising and as agreed in Paris in 2015, a temperature increase of more than 2 degrees is likely to have catastrophic consequences. The use of fossil fuels and the consequences for the carbon dioxide level in the atmosphere are the main causes of climate change and the rise of temperature (Anderegg et al., 2010). The agreement has been made to decrease the amount of fossil fuels used, to ensure that the temperature increase will not exceed this important limit of 2 degrees Celsius (United Nations, 2015).

Transport is one of the main causes of CO_2 emissions in the society. One of the alternatives to decrease the emissions is to decrease the CO_2 related to transport significantly towards 2050 (IEA, 2017). The current Internal Combustion Engine (ICE) cars are fossil fuel based and this is the reason why a transition to another type of car is necessary. Different countries have introduced policies to forbid the sale of new ICE vehicles in a few years, like Norway, France and Great Britain. Expected from these policies is an exponential growth of the electric vehicle (EV), towards 90 percent in 2060 (IEA, 2017). An example is shown in a study of the TU Eindhoven (figure 1.1). The electric vehicle has the potential to be fully emission neutral. However, charging the vehicles will have a significant impact on the distribution grid (Clement-Nyns, Haesen, and Driesen, 2010) and to achieve carbon neutral vehicle transport, the electricity used to charge the car must be renewable.

1.2 Expected grid problems

The growth of the share of electric vehicles has an impact on the electricity grid. The ICE vehicle charges at a central point, a fuel station, in a couple of minutes. An electric car occupies an electric charging spot for a few hours to charge. Furthermore, this charging spot is probably in the residential area where the person lives. The capacity of the residential electricity grid is not built for the amount of electricity these cars will need. The capacity of the grid is based on the peak load of the electricity demand and if the cars would increase this peak load significantly the capacity will be insufficient. Studies have shown that with just 30% electric cars there will be an increment in peak load of 54% in the Netherlands (Habib, Kamran, and Rashid, 2015). Different Dutch Distribution System Operators (DSO's) address the rise of electric vehicles as one of the main challenges for the future electricity grid (Stedin, 2017; Enexis, 2017). One of the solutions would be to create more capacity on the

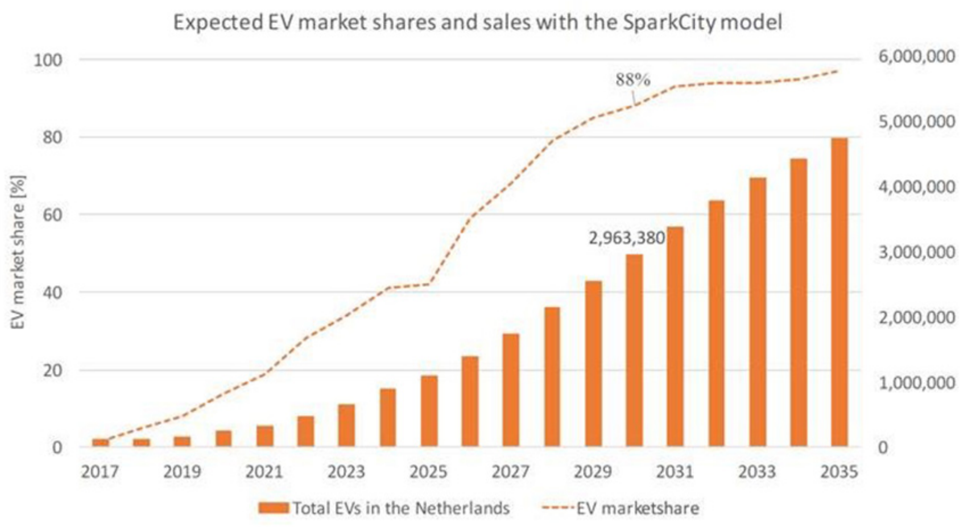

FIGURE 1.1: Possible scenario of growth of EV's towards 2035

electricity grid.Increasing the capacity it done by replacing or adding electricity cables in the ground. This is not only a costly matter, it also requires extensive labour and the DSO's expect that they will not have enough human capital to expand the capacity of the grid sufficiently (Stedin, 2017; Enexis, 2017). One of the other, less human capital intensive, solutions is to use smart grid technology for the charging process of electric vehicles: a smart electric vehicle system.

1.3 Smart grid technology as proposed solution

A smart electric vehicle (EV) system is defined in this paper as a combination of hardware and software (smart grid technology) which can control the charging progress of the electric car. The idea is to charge the cars when the load on the electricity grid is low to decrease the impact of the cars on the increase of peak demand. Another option to use the cars at peak load moments to deliver energy back to the either the grid (vehicle to grid (V2G)) or the building (Vehicle to building (V2B)) to decrease the peak load on the grid even further (Richardson, 2013). To decrease the load an algorithm is used, which signals the car to charge, discharge or do nothing.

The batteries in the vehicles in combination with smart grid technology offers options to charge and discharge the batteries in such a way that the battery will be an asset for the owner and the DSO at the same time. For instance, an algorithm which optimizes on charging costs for the owner could decrease the peak load as well, as the peak load is often correlated with high electricity prices. The algorithm uses the data of the electricity grid and the owner to optimize the charging process, the owner will have to agree with the use of his data. These are the basic principles of smart grid technology for electric cars, in chapter 3 this technology is discussed more extensively. Currently smart meters are being installed and soon the option will be available to use this technology. This is an option, as every household can decide to shut off the smart meter and use it as a regular meter, which means that the meter does not analyze and sends data. If the owner of the electric vehicle does want to use the smart grid technology for his car he has to install an app of a smart charging company, such as Jedlix or Mountox. The most important difference with the current electricity system is that in with the smart EV system the EV owners have a choice to participate in balancing the electricity network.

1.4 Uncertain EV owner behaviour

The EV owners can choose to use the smart EV system and thereby decrease the peak load on the system. It used to be that if the capacity of a local network was insufficient, the DSO could decide to expand the capacity, without the approval of the local citizens. In this new electricity system, the choice whether to use or not to use the smart EV system is critical as the impact on the electricity system could be significant, in the most extreme case even fatal. If the electricity system depends on the electric cars to decrease the peak load, and EV owners will not use the smart EV system, the capacity of the grid will be insufficient. An insufficient network capacity leads to high balancing cost and black-outs. It is therefore not only important that the EV owners use the smart EV system, it might be even more important that they will not suddenly quit. If the smart EV system is not the solution for the extra peak load, other investments in the residential grid capacity have to be made know. It is therefore important that, if the smart EV system is chosen as the solution, the smart EV system will indeed be used and will be sufficient to reduce the extra peak load. A survey of Raimi and Carrico (2016) showed that 32% of the respondents had never heard of a smart grid and 48% had no knowledge of the functions of a smart grid. Therefore the choice does not only have a large impact, it also is uncertain what the EV owners will choose.

1.5 Literature review: The choice of the smart EV system

A literature review shows that an understanding of this choice of the EV owners is lacking. Lampropoulos, Vanalme, and Kling (2010) is the closest research found. The scope of that research is "to stress the importance of including the behavior of small size prosumers in power system planning". A prosumer is someone who does not only consumer electricity, but produces electricity as well. In the article the electric car is used as the device to consume and produce electricity, so the prosumer is in this case the owner of the electric vehicle. The aim of the research is to understand the influence of the behaviour of the EV owner on the load on the electricity system. This is also an objective of this thesis. In the article of Lampropoulos, Vanalme, and Kling (2010) the behaviour of the EV owner is based on the work distances. This thesis goes a step further, taking into account the personal beliefs, for instance on privacy, to understand the more fundamental choice if the EV owners would use the smart EV system or not. The conclusion of the article is that it would be beneficial to charge the cars at work, which would result in less cars which have to charge when they get home. This conclusion is interesting and is used in this thesis. In this thesis more design directions, not only technical directions, also institutional and policy design directions, are discussed. For instance the allocation of property rights and the possibility of subsidies.

The step further, to understand if the EV owner would use the smart EV system is based on a critical assessment of acceptance of the smart EV system, which has not yet been done. Wüstenhagen, Wolsink, and Bürer (2007) introduced a special issue on the topic of 'Social Acceptance of Renewable Energy Innovation' in 2007, which was a collection of the best papers around acceptance of renewable innovations. Recently Gaede and Rowlands (2018) did this as well. They counted the number of articles in different topics and showed that research into electric vehicles/hydrogen is still lacking. Research about the combination between electric vehicles and smart grid is not mentioned in both articles.

Most smart grid related articles discuss the technological part of the system, discussing the possible data algorithms and importance of cyber-security(Mwasilu et al., 2014). Some articles have identified the importance of the choice of the EV owners. For example Baloglu and Demir (2017), which discuss that the electricity grid would depend on the EV owners, which means that "an incentive mechanism is needed to involve the owners and users of the electric vehicles". Wolsink (2012) have created a research agenda on the acceptance of smart-grid technologies as they identified the lack of research into this subject. Raimi and Carrico (2016) have done a survey on the understanding and beliefs of the citizens around smart grid technology. The conclusion is that the respondents are generally negative, they are expecting problems with their privacy and security. This survey is not in combination with the electric vehicles, where more problems can be identified, discussed in chapter 3.

1.6 Structure of this thesis

In chapter 2 the research objective and scope are discussed, as well as the research questions and methods. In chapter 3 the technical implications of EV smart grid technology are discussed first and the behaviour of the EV owners second. This is the basis for the model described in chapter 4. In chapter 5 this model is validated for the analysis of the results in chapter 6. The analyzed results are discussed and used to describe design directions in chapter 7. In this chapter the limitations of this thesis are discussed as well. Chapter 8 addresses the research questions of chapter 2 and concludes this research. In chapter 9 a reflection on this research from the authors perspective can be found.

Chapter 2

Research Problem

The goal of this chapter is to explain the research problem and the methods which are used to analyze this problem. In the first section the research gaps are summarized in a research statement. In the second section the objective and scope of this research are explained using the most important assumptions which are the basis for this research. In section 3 the research question are divided into different sub-questions. Finally the different research methods are discussed.

2.1 Research Statement

The growth of the share of electric vehicles will have a significant impact on the peak load on the electricity grid. A smart electric vehicle system is proposed as a solution. However, in this solution the electric vehicle owners EV owners have a choice to participate in balancing the electricity network. This new role for the EV owners is not only very important, it is also an uncertain factor for the electricity network.

Which design directions for a smart EV system will reduce the expected electricity grid problems sufficiently in the long-term?

This question has two important parts. Firstly, the smart EV system is sufficient to prevent residential capacity upgrades. Insufficiently would mean that the smart EV system would reduce the peak load, however, the same capacity expansion activities are required.

- The smart EV system has the technical potential to reduce the peak load sufficiently.
- The smart EV system is used sufficiently, there are enough users that the smart EV systems in use reduce the accumulated peak load on the grid sufficiently.

Secondly, the smart EV system is used on the long-term.

- The owners will not change their decision frequently, the DSO's have to know that the capacity of the residential grid will be sufficient at every moment.
- The smart EV system is used on the long-term, the owners will not stop using the smart EV system after a period of time. The DSO's have to be certain that it is not a temporary solution. As, if it would be, investments are necessary right now.

Given these criteria for the smart EV system and given the literature review in chapter 1.4 the following research gaps are identified:

- It is unknown which factors are involved in the decision of the EV owner to use the smart EV system and how the amount of users is related to the potential of the smart EV system.
- It is unknown which high-level conceptual choices, such as profit and ownership distribution, will increase the chance that the smart EV system will be sufficient in the long term. These choices lead to design directions or design guidelines for the smart EV system to increase the usage on a long-term basis.

2.2 Objective and Scope

The research objective is to find design directions for the smart EV system which reduce the expected electricity grid problems sufficiently in the long-term. Design directions could be technical, political or institutional. Design directions are defined in this thesis as high-level design choices which lead to directions for future research, an example could be to change the ownership of the EV battery. How to do this, for instance by smart contracts with private companies or giving ownership to DSO's by law, will be discussed. However, finding these options are not the main objective of the study as first general higher conceptual level choices have to be made. The main objective of this study is also not to find, for instance, the exact peak reduction that the smart EV system could have in a residential area, or the exact profit the EV owner earns when he uses the smart EV system.

These directions have an effect on the choices of people involving a solution for a problem in the future. The share of electric vehicles is currently growing, which means that the expected problem with the electricity grid is in the future. In addition, the proposed solution, the smart EV system, is still in progress as well. In essence, this thesis analyses a possible futuristic solution for a problem that might exist in the future. For this analysis different knowledge gaps can be identified. The case is therefore highly abstract.

The scope is limited to the scale of a neighborhood where charging at work or other spots is not part of the research, as the electricity grid of this neighborhood is the central point. The energy market is used as an input which is a limitation as well, in reality electricity demand shifts will change the electricity market and price accordingly. However, this study focuses on behavior, so calculating the exact changes to the energy market falls out of the scope. The model is designed to be used for different neighborhoods in different countries under different circumstances, as example this research scopes down on an average neighborhood in the Netherlands because the data is more accessible for the author. The technical electricity system is limited by the simplified algorithms used in the model, as improving these algorithms is time consuming and makes the model unnecessary complicated since the focus is on the choices of the EV owners.

2.3 Research Questions

To reach the research objective the main question will be answered using the following sub research questions. Question 1 and 2 address the first research gap discussed in chapter 2.1 and question 3 addresses the second research gap.

Question 1: How will the use of the smart EV system impact the residential electricity grid and the owners of electric vehicles?

The purpose of this question is to understand how the smart EV system will influence the current residential electricity system and the owners of electric vehicles. How does the technology work, what is possible and how will this affect the owners of electric vehicles.

Question 2: How do the EV owners decide to use the smart EV system?
The purpose of this question is to understand how the users of the smart grid electricity system choose to use the smart EV system and if they will use the system in the long term.

Question 3: Which design choices increase the chance that the smart EV system is sufficient for load reduction in the long term?
The purpose of this final question is to find design directions to prevent the cases found in question 3 and increase the use of the smart EV system.

2.4 Research Methods

The research objective is to find design directions for the smart EV system which reduce the expected electricity grid problems sufficiently in the long-term. The first step is to understand the implications of the smart EV system and to understand the behaviour of the EV owners. This is done with the literature review discussed in section 2.4.1. The second step is to conceptualize this into a model. This is discussed in section 2.4.2. Using this model, different scenario's have to be analyzed to understand the best and worst case scenarios and to find design directions. This will be explained in paragraph 2.4.3.

2.4.1 Literature Review

The goal of the literature review is to find an answer for the sub-questions 1 and 2. First the technological implications of the smart grid are analyzed. In this section the influence of smart grids are discussed on the grid operation, but also on the renewable potential of smart grids. The literature review is based on multiple articles on the technical implications of smart grids. For the second sub-question, 3 different academic research concepts are used. The concepts of social acceptance, moral acceptability and value-norm-belief are discussed and used to understand the decision process of the EV owners.

2.4.2 Modelling

As discussed in the chapter 2.3, the case is highly abstract. As the choices of the EV owners is a central focus of the research a questionnaire could be logical. However, a questionnaire about a proposed solution which does not yet exist for a problem that people do not yet experience is challenging. Furthermore, real-life behaviour can diverse from the statements made in a questionnaire Gangale, Mengolini, and Onyeji (2013). How people respond in surveys and how they behave in real life are often two different things. In this research a simulation is therefore used instead. Simulation does takes into account the randomness and interdependence which characterize the behavior of the EV owners. A simulation has different limitations. A simulation is a demarcation of the reality and therefore in principle never complete. In this case it is a demarcation of future reality, which makes the simulation even more uncertain. There is no real world counter part to compare the simulation with. These limitations are important with the interpretation the results.

Complex Adaptive Systems

The smart EV system described in the first chapter is not just a linear system based on physical processes. It is a Complex Adaptive System (CAS) (Holland, 1992). The EV owners do not just react to an input and then produce an output, they also react to the consequences of their own behaviour. The smart EV system shows 3 general characteristics of a CAS (Gell-Mann, 1994):

1. The inputs often include system behavior and the outputs often include effects on the system.
2. It is unclear which dynamics in the system are random and which are regularities.
3. The dynamics are not based on a look-up table, they are based on a combination of description, prediction and prescriptions for action.

These three general characteristics can be found in the smart EV system. Firstly, the proposed smart EV system is an example of a system where patterns at higher levels emerge from local interactions. The patterns which influence the electricity grid will emerge from the local choices to use the smart EV system. The choices that the EV owners make, have an impact on the electricity grid of the country, however why they make these choices is unclear. These owners make decisions on their local level, based on their experience and the interaction with other agents on their level. An essential aspect of such systems that there are multiple possible outcomes of the system with the same input parameters(Levin, 1998).

Agent-Based Modelling

The system which has been simulated with the model is a Complex Adaptive System, so the model had to be able to include the characteristics of a CAS. The model has to include heterogeneous persons, as every EV owner has its own behaviour, experience and morals and these behavior, experience and 'morals' influence an outcome of interest. Secondly, the EV owners make decisions based on their experiences with the smart EV system. Based on these properties of the model, an Agent-Based model (Railsback and Grimm, 2012) is used. Agent-based modelling is a good tool to simulate diffusion in a society (Bonabeau, 2002). Agent based models are usually used when a system (Williams, 2018):

- Has heterogeneous entities
- The entities have interaction between themselves and the system
- Is an evolutionary system in which the agents determine the development by their choices (emergent system patterns)

Agent-based modelling is often used in similar projects. El-Amine et al. (2017) argue in their article that ABM is suitable for studying shifting behaviour of people, bridging the gap between rhetoric and reality. Kraan, Kramer, and Nikolic (2018) use ABM to study investor behaviour in renewable technology, Kangur et al. (2017) studies electric vehicles diffusion using ABM and Tong et al. (2018) studies the post-consumer recycling in neighborhoods. These are a few examples of articles which are similar of interest en with similar methods used.

ODD Framework

The description of an agent based model can be complicated and therefore Grimm et al. (2006) have developed the ODD framework(Grimm et al., 2010). The primary objectives of the ODD framework is to make ABM model descriptions more understandable and complete, making ABM models more reproducible Grimm, Polhill, and Touza (2017). Examples can be found in Polhill et al. (2008) and Matthews et al. (2007).

Müller et al. (2013) has improved his ODD framework to the ODD+D framework to also describe the human decisions in the model, which is important for the model in this thesis. The ODD+D framework of this model can be found in appendix D. Difficulties with the Agent-Based model are that it is sometimes difficult to find in- and output data to validate the model, as it is mostly focused on the theoretical behaviour of agents. A case study is one of the ways that an Agent-Based model can be empirically tested (Janssen and Ostrom, 2006). However, the case study of this thesis is highly abstract and has no real counterpart, therefore a different validation method is used.

Validation method

To test the model the 'evaludation' method of Augusiak, Brink, and Grimm, 2014 is used. The difference between 'normal' validation and this method is that normal validation focuses on the comparison with empirical data. Augusiak, Brink, and Grimm (2014) argue that the normal method is too limited for ecological and environmental models. The fact that the output of a model matches the empirical data does not necessarily mean that the model is valid, as a combination of wrong input and parameters could still give a match. Furthermore, empirical data for these kinds of models are difficult to find.

This second argument is important for the validation of the model used in this research. The model simulates a reality in the future, therefore it is impossible to compare the model outcomes with its real world counterpart or empirical data. The 'Evaludation' method exists of six steps, discussed in chapter 5.

2.4.3 Exploratory Modeling and Analysis

The model depends on assumptions which are made based the articles and theories discussed in chapter 3. As it is difficult to validate these choices with a real world counterpart, it is an uncertain factor for the model outcomes.

To deal with this uncertainty, Exploratory Modeling and Analysis (EMA) is used. This gives the solution to the problem of an immature underlying theory (Hodges, Dewar, and Others, 1992). EMA is a research methodology that uses computational experiments to analyze complex and uncertain systems (Bankes, 1993). Kwakkel, 2017 presents an open source library which is used in this research. It is designed to "(i) support the generation and execution of series of computational experiments; and (ii) support the visualization and analysis of the results from the computational experiments." The method Exploratory Modelling and Analysis fits the Agent-Based model to study the transition dynamics in the electricity sector (Kwakkel and Pruyt, 2013).

Chapter 3

Conceptualizing the choice for the smart EV system

The goal of this chapter is to answer sub-questions 1 and 2 (see chapter 2). First the technological implications of the smart EV system are analyzed in section 1. The purpose of this section is to understand how the smart EV system will influence the current electricity system and the owners of electric vehicles. In section 2 the second sub-question is answered. The purpose of this question is to understand how the EV owners choose to use the smart EV system. The outcome of this chapter is the basis for the conceptualizing of the model discussed in chapter 4.

3.1 Impact of the smart EV system

The first sub-question is: *How will the use of the smart EV system impact the residential electricity grid and the owners of electric vehicles?*. In 3.1.1 it is explained what smart grid technology is and how it works. In paragraph 3.1.2 and 3.1.3 the advantages and disadvantages of the smart EV system are discussed. In chapter 3.1.4 different optimization algorithms are analyzed.

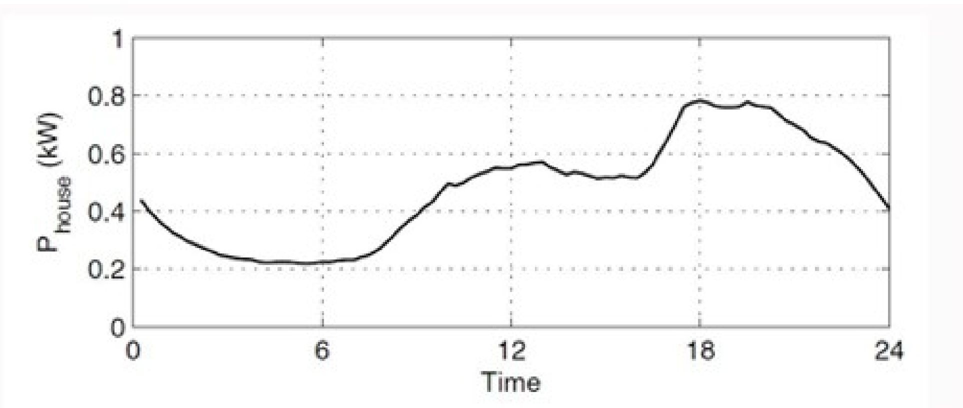

FIGURE 3.1: Average household load Netherlands (energieoverheid.nl)

3.1.1 Properties of smart grid technology

A smart grid is understood in this research as a grid where it is possible to control the energy flow at different points in the electricity network based on data. This requires a combination of hardware and software. This research focuses on the residential area and electric vehicles. Hardware is the smart meter installed in the houses which is able to gather and process the electricity data. The smart meter can connect to the DSO and sends and receives information. With software it is possible to analyze different factors as the electricity use of the house, the electricity price and the load on the residential grid. Using this analyzes the software can give a command to the electric vehicle to stop using electricity. To stop and start charging the car a special contact is necessary, so another piece of hardware.

The general load of a household is shown in figure 3.1. Normally the cars would charge when the owners get home from work which corresponds with the household peak moment at 18.00. Using smart grid technology it is possible to delay the charging of the cars to the night when the grid is not as heavily loaded. Changing the demand to optimize for the electricity system is also called demand side management. As mentioned in chapter 1, there is the option to use this battery as a storage to deliver electricity back to the grid (Paterakis et al., 2016). In that case there is a bidirectional energy flow possible from the grid to the vehicle. This principle is called vehicle to grid (V2G) integration. In this thesis the V2G option is analyzed separately from the the option where there is a one-directional energy flow from the grid to the vehicle, the charge only (V1G) option (Su et al., 2012).

There are different ways to optimize the charging process of the electric vehicle (Siano, 2014), namely optimization on:

- Costs, charging at lowest costs possible
- Renewables, charging as renewable as possible
- Network Capacity, charging without overloading the grid

Combining the optimization options with different smart grid technology options creates different smart charging algorithms. As an example some different options are discussed (Mwasilu et al., 2014).

The simplest option is to only change the charging process of the vehicle with V1G. In this option the battery will only demand energy and will not supply energy. For the optimization of costs and renewables the only data needed for this operation is the current state of charge of the battery and external data concerning the electricity price and available renewable energy. For network optimization more data is necessary and this makes it more complicated.

The most common option explored in literature is the use of an aggregator for charging the electric vehicles (Mwasilu et al., 2014). In this option all the EV's are seen as one and one aggregator controls the charging process of the EV's to avoid peaks. In this option the battery will also supply energy when needed to balance the grid, which means that the DSO's will have more control over the battery.

Another option is to involve the owners of the vehicles directly in the charging process with the electricity prices as an indicator, the owners can see the prices on an app and influence their own charging process accordingly. Research shows that if this could work, the owner saves around 10 percent and the peak load on the grid is decreased with 56 percent (Mwasilu et al., 2014).

3.1.2 Advantages of the smart EV system

A smart electric vehicle (EV) system is defined in this paper as a combination of hardware and software (smart grid technology) which can control the charging progress of the electric car. The smart grid has the potential to play an important role in the energy transition and the technology is currently under fast development, the technology can probably soon be implemented and tested(Blumsack and Fernandez, 2012).

There is a potential as an average US car is parked 95 percent of the time (Pearre et al., 2011). The battery technology gets better and cheaper (Nykvist and Nilsson, 2015) and there are indications that smart grid technology would actually increase the battery lifetime (Uddin et al., 2017) (Baloglu and Demir, 2017). It is therefore assumed that vehicle to grid is a viable option to use in the smart grid system. New algorithms for the smart grid technology charge plans are developed (Paterakis et al., 2016)(Khamphanchai et al., 2015), but even a rather simple charging strategy can be sufficient for the integration of large scale charging processes (Blasius and Wang, 2018). Given this information, it is assumed in this thesis that smart grid technology will be available and developed in the next ten years (Kester et al., 2018). The technological and institutional feasibility of the smart grid is still under discussion, as the distributed storage in electric vehicles requires self-governance and flexible overall regulation (Wolsink, 2012). Controlling the charging process using the smart EV system has different benefits(Moslehi and Kumar, 2010) (Aghaei and Alizadeh, 2013)(Gelazanskas and Gamage, 2014), figure 3.2 (Gorguinpour, 2014).

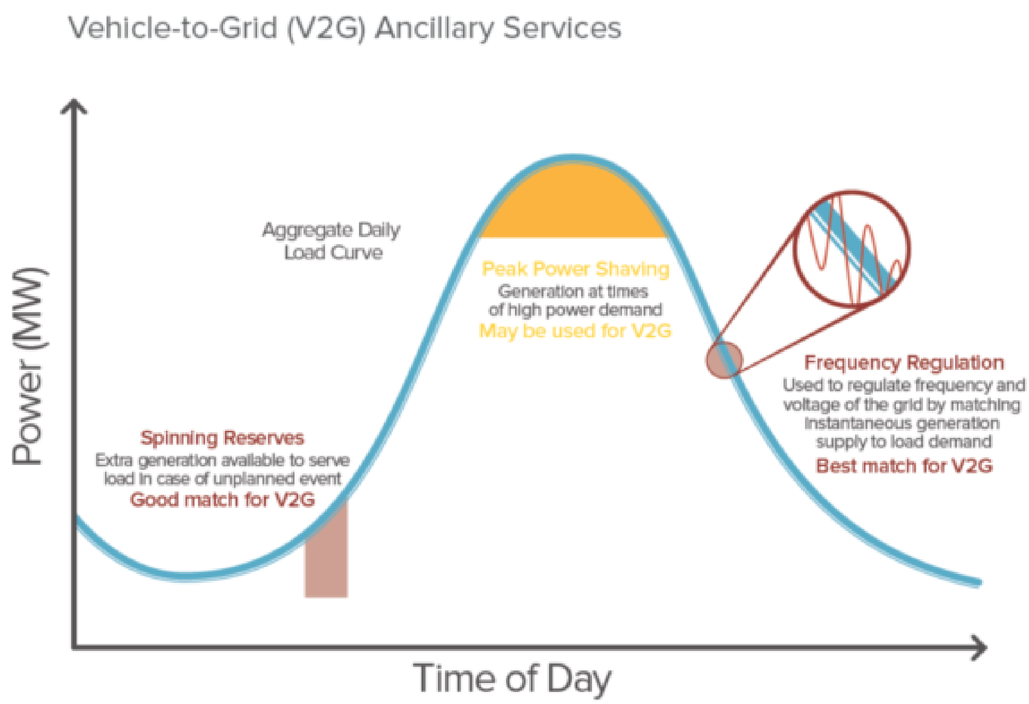

FIGURE 3.2: V2G options during the day

Peak reduction The first advantage is the reduction of the peak load (Richardson, 2013). The reduction depends on the amount of electric vehicles, the household loads and the grid capacity. With demand management without electric vehicles a reduction of 17% is reached by Ramchurn et al. (2011), with electric vehicles a reduction is calculated of 50% (Lopes et al., 2009).

Reliability The second advantage is that the smart EV system has the potential to improve the reliability, efficiency, losses and stability of the grid (Habib, Kamran, and Rashid, 2015). With V2G it is possible to use the cars for regulation of active power, support for reactive power, load balancing and current harmonics filtering (Kempton and Tomić, 2005).

Environment The third advantage is that the smart EV system could be used to balance the flexible energy production of renewable energy sources (Richardson, 2013). Calculations of Habib, Kamran, and Rashid (2015) suggest that V2G could stabilize large-scale wind power with 3 percent of the fleet dedicated to regulation for wind, plus 8–38 percent of the fleet providing operating reserves or storage for wind. Furthermore, reports suggest that, considering the current energy policy, the emissions of electric vehicles could be higher than ICE vehicles. Jochem, Babrowski, and Fichtner (2015) predicts that, based on an hour to hour model over the year, the CO2 emissions of electric vehicles in Germany will be 110 g/km, this is higher than a current fossil fuel based car. This is mainly caused by the periodic demand of the electric vehicles. However, with smart grid technology the emissions could go down with 30 percent.

Cost savings The EV owner can reduce the costs of their electricity bill. Mwasilu et al. (2014) mention in their article that most research of V2G reports a profit of around 100-300$ per year. Furthermore, balancing the electricity grid is a costly matter for the network operators and it is possible that the EV owner will get rewarded.

3.1.3 Disadvantages of the smart EV system

There are also disadvantages of the smart EV system identified in the literature.

Privacy and security Smart grid technology introduces many new security and privacy issues (Aghaei and Alizadeh, 2013). More advanced smart grid algorithms, for instance the algorithms which use V2G and a network optimization, need a more intensive communication between the charger and the grid (Su et al., 2012). When the algorithms get more complicated more data is required. The more data the EV owner shares the smarter the decisions of the smart EV system. However, more accessible information leads usually to more privacy leaks Fang et al. (2012).

The electricity usage data stored is an information-rich side channel, exposing customers' habits and behaviors (Yan et al., 2012). Certain activities, such as watching television, have detectable power consumption signatures. Due to the differences between city's, neighbourhoods and houses it is impractical to uniformly deploy strong security over the smart EV systems (Wang and Lu, 2013). History has shown that if the information is interesting for third parties, such as advertising companies, burglars or even foreign countries or cyber terrorists, the techniques for mining this data evole quickly (Yan et al., 2012). So even though the system could be secure now, does not mean that it will be secure forever.

Range anxiety The second disadvantage is the different charging process. Research into electric vehicles shows that range anxiety and long charging time are the two largest concerns for buying an electric car (Egbue and Long, 2012)(Hidrue et al., 2011). Range anxiety is the fear of being stranded in a BEV because it has insufficient range to reach its destination. By delaying the charging there is a chance that the car will not be fully charged in the morning. As this chance might be small, it is a significant concern to the owner of the EV. Research showed that the concerns of the EV owners where unrealistic at first and only after a few months the concerns were less urgent and more realistic (Franke and Krems, 2013). This indicates that even though the chance might be small that the car will not be charged due to the smart EV system, the concern of the person could still be significant. With V2G the car also gets discharged so the perceived chance is even higher that the car will not be charged sufficiently.

3.2 Understanding the decision

There were three important criteria of the design of the smart EV system which depend on the decision of the EV owner.

- The smart EV system is used sufficiently, there are enough users that the smart EV systems in use reduce the accumulated peak load on the grid sufficiently.
- The owners will not change their decision frequently, the DSO's have to know that the capacity of the residential grid will be sufficient at every moment.
- The smart EV system is used on the long-term, the owners will not stop using the smart EV system after a period of time. The DSO's have to be certain that it is not a temporary solution. As, if it would be, investments are necessary right now.

As discussed in chapter 2 a questionnaire is not applicable due to the abstract case and that real-life behaviour can diverse from the statements made in a questionnaire Gangale, Mengolini, and Onyeji, 2013. If people respond different in surveys than how they behave in real life what can be said about the decision of the person. Therefore the second sub-question is: *How do the EV owners decide to use the smart EV system?*.

To answer this sub-question a literature review has been performed. The objective of this literature review is to understand which factors play a role in using the smart EV system. It is not just about adoption of technology. If the EV owners starts using the smart EV system and stop after a while, this could bring more harm to the system than not introducing the smart EV system at all. The capacity of the grid depends on the peak moments. If the EV owners will not use the technology anymore it could bring harm to the system. If the electricity system depends on the electric cars to decrease the peak load, and EV owners will suddenly not use the smart EV system the capacity of the grid capacity will be insufficient. An insufficient network capacity could lead to high balancing cost or black-outs. The initial adoption of innovation is therefore not the focus of this literature review. This literature review is performed to understand the use and not the adoption of the system. The result of the literature review is a conceptual model which:

- Explains how the EV owners decide to use the smart EV system based on the impact of the smart EV system discussed in chapter 3.1.
- Explains how this decision can be evaluated on its long-term stability.

This literature review begins with the consumer behaviour and the concept of Social Acceptance, continued by the concept of Moral Acceptability and the Value-Belief-Norm concept. Finally these theories are used to develop a new theoretical conceptual model, the 3-level model, in chapter 3.3.

3.2.1 Consumer Behaviour

This literature review begins with the difference between what people say and what they do (Gangale, Mengolini, and Onyeji, 2013). Consumer behavioural science discusses this difference. Solomon, Russell-Bennett, and Previte, 2012 says that consumers are predictable, perform habits and routine decisions, yet also change their behaviour in a single day. It is a combination of the principles someone has and the situation he or she is in, which determines what a person does. Sometimes morals and actions are correlated, for instance in a research into choosing environment-friendly packaging Thvarphigersen, 1999. Sometimes a system would be expected, based on moral values, to be used and is not. Sometimes a system which is not expected to be used as it is unethical, is used regardless.

The persons morals and their actual behaviour do not necessarily align

The theory of planned behavior (TPB) by Ajzen, 1991 explains the factors influencing consumer behavior. This theory is used more often in research towards green technologies (Paul, Modi, and Patel, 2016). According to these theory the choices people make are based on three factors: (1) their attitude towards the technology, (2) the subjective norm of their surroundings towards the technology and (3) the perceived behavioural control, if they can use this technology. In general, media and social networks often influence values that affect consumer choices (Rogers, 2003)(Lane and Potter, 2007). The main reasoning of the TPB is that actions are chosen based on an analysis of the alternatives through which the optimum outcome is achieved Lane and Potter, 2007, so there is a trade-off for the costumer to accept one alternative instead of the other. In this context, consumer acceptance or social acceptance of technology is considered the choice to use the smart EV system. Social acceptance theory is a frequently used theory for the acceptation of green technologies.

The theory of Planned Behaviour describes how a person decides to use a a technology on the individual preferences of an actor.

3.2.2 Social Acceptance

The literature of Social Acceptance of green technologies has been growing since the introduction of climate policies in the 20th century. Otway and Von Winterfeldt, 1982 discuss that the resolution of conflicts about technology's is more than just an equation between benefit and risk for the society . Wüstenhagen, Wolsink, and Bürer, 2007 introduced a special issue on the topic of 'Social Acceptance of Renewable Energy Innovation' in 2007, which was a collection of the best papers around this subject. Different studies have been done previously into the social acceptance of energy technologies. Gaede and Rowlands, 2018 have made a bibliometric analysis of 857 articles representing the knowledge domain for the social acceptance of energy technology and fuels, which is discussed in chapter 3. Recent examples are wind and solar energy Sposato and Hampl, 2018, geothermal energy (Vargas Payera, 2018), bio-energy (Fytili and Zabaniotou, 2017), nuclear power (Yuan et al., 2017) and off grid solar power (Aklin, Cheng, and Urpelainen, 2018). The concept of Social Acceptance has the potential to explain and predict how the Ev owners will use the smart grid technology in different circumstances. Taebi, 2017 defines Social Acceptance as follows: "Social acceptance refers to the fact that a new technology is accepted by a community.

The concept 'Social Acceptance' discussed if a technology gets accepted by a community.

Social acceptance theory is a frequently used theory for the acceptation of green technologies, but lately critics argue that the concept of social acceptance is too narrow to grasp the problem. The concept of social acceptance is misunderstood too often as a barrier which has to be removed (Poel, 2016). Batel, Devine-Wright, and Tangeland, 2013 argue that it will be relevant for the literature to adopt a more critical perspective on the word 'acceptance' and to stop focusing on top-down policies and their social responses. In response to the article of Poel, 2016, Taebi, 2017 argues as well that the concept of 'social acceptance' is too narrow and needs an extension, the concept of Moral Acceptability (Poel, 2009).

3.2.3 Moral Acceptability

This concept approaches technology in a broader view over the whole system with the positive and negative values the technology entails for the system. The society has to determine what the best solution is between an optimal working electricity system and the right for their own privacy and control over their property, which is a conflict between values of the society as described in the article of Künneke et al., 2015. To include the impact of value conflicts in system designs, the concept of moral acceptability of the technology (Künneke et al., 2015)(Poel, 2009) is used in this thesis as well. This concept approaches technology in a broader view over the whole system with the positive and negative values the technology entails for the system. Although these two concepts have been used separately in the past, recent articles argue how combining these two theories might be crucial in understanding social adoption of technology (Taebi, 2017)(Poel, 2016).

Social acceptance and moral acceptability are two different views on social adoption of technology. Taebi, 2017 makes the distinction as follows: "Social acceptance refers to the fact that a new technology is accepted by a community and Moral Acceptability refers to the reflection on a new technology that takes into account the moral issues that emerge from its introduction." Künneke et al., 2015 define the difference between acceptance and acceptability as the difference between studying the short term in individual preferences of stakeholders against looking at the moral and societal values that are shared by all members of society.

The concept 'Moral Acceptability' describes if a technology should get accepted by the community.

Combining the concepts of Social Acceptance and Moral Acceptability responds to their strengths and weaknesses, for instance the fact that a technology is accepted does not mean that the technology is also morally right (Poel, 2016). On the other hand, the theory of moral acceptability is predominately conceptual without empirical input (Taebi, 2017). By combining these two concepts they complement each other for a thorough ethical evaluation of a technology, Taebi, 2017 argues that "good governance of risky technology requires the two concepts of acceptance and acceptability to be addressed in conjunction".

3.2.4 Acceptable and/or accepted systems

Taebi gives a few examples where acceptance is not in line with acceptability. First, acceptance is sometimes based on incomplete or false information. An example is a case study where the local communities were asked to choose possible sites for a chemical plant, not knowing that it was a radioactive plant. Secondly, acceptance is not universal for every actor, Walker, 1995 shows that local communities are often against wind parks, while the public would accept these wind parks. Thirdly, a technological project could be accepted on the basis of a wrong procedure. An example could be the diesel car, where initially the public thought that the car was more sustainable than the gasoline car, but recently it was discovered that car manufacturers where just better in manipulating the tests of the car.

Another present day example of a system which is accepted but not acceptable could be the use of the Facebook platform: on a principle level, the majority of the users might disagree with the data policy and the impact on their privacy, but on the other hand the benefits of using the system are apparently too high due to social influence and network effects. However, the fact that on a principle level people reject Facebook, makes the platform vulnerable: if there are problems with the privacy, such as data leaking, or there is another platform available where there are no principle issues, people will leave. Like in the spring of 2018, when data was leaked to a private company, which might have used it to influence the elections in USA. On the other hand for example, a system as the separation of waste, which in theory looks like a morally right system where everyone takes responsibility for their waste without a lot of effort, is not used as expected. To analyze the proposed system, the principles behind this system should therefore be taken into account, combined with the empirical situations the users of this system could face, which might deflect them from their principles.

Empirical examples show that a system that is acceptable does not always get accepted and the other way around.

The main message of these examples is the fact that when a system would be acceptable based on ethical values, it does not necessarily mean that the system is also accepted and the other way around.

To understand this combination of values versus behaviour the Value-Belief-Norm theory is discussed as well.

3.2.5 Value-Belief-Norm concept

The Value-Belief-Norm concept (Stern et al., 1995) considers values as the key to understanding behaviour (Kaiser, Hübner, and Bogner, 2005). It is therefore an interesting theory to discuss as the theory recognizes the values of moral acceptability and the theory does discuss behaviour like the theory of planned behaviour. It is developed for understanding pro environmental actions, which fits with the smart EV system.

> The Value-Belief-Norm theory argues that personal values determine the attitude towards a new technology

The link to values is important for the Value-Belief-Norm theory because attitudes toward new objects should be build on values (Stern et al., 1999). Personal values are seen as general guiding principles in life, and are guidelines for attitudes about new social objects. In this case the attitude is the choice that is made by the EV owner. The choice comes from the personal values, from beliefs that things important to those values are at risk, and from beliefs that actions initiated by the individual can restore the values Oreg and Katz-Gerro, 2006. The values which are used in the concept of Moral Acceptability differ from the values which are used in the Value-Belief-Norm concept. The values which are used in the concept of Moral Acceptability are for the society as a whole, in the Value-Belief-Norm concept the values reflect these values on an individual level.

3.3 3-level conceptual model

These theories are combined the 3-level conceptual model, shown in figure 3.3.

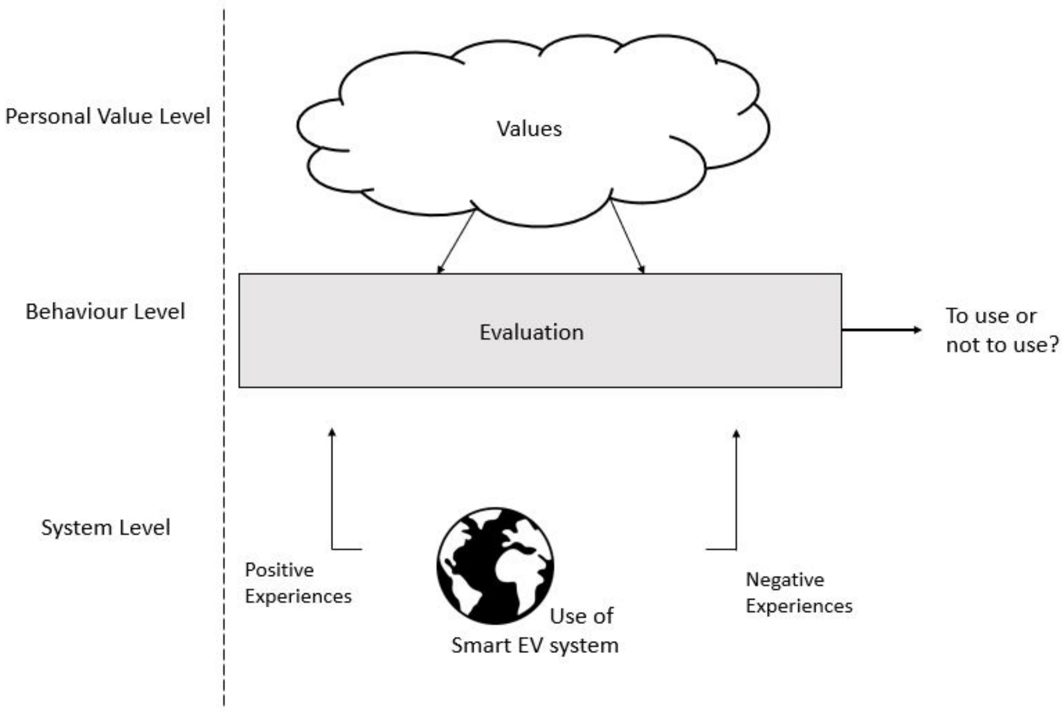

FIGURE 3.3: 3-level conceptual model

3.3.1 1st level: Personal Values

In the article of Künneke et al., 2015 the system is analyzed upfront based on values of Ligtvoet et al., 2015. The Value-Belief-Norm theory argues that these values influence the behaviour of the EV owner. These values are the guidelines of how the agent will react towards his new experiences. Value conflicts from the Moral Acceptability theory be used to explain the principles of the agents upfront. The personal value conflicts can be seen as an individual acceptability assessment of the smart EV system.

It is important to emphasize the difference between moral acceptability and individual acceptability. Individual acceptability is heterogeneous and different for every person, while for moral acceptability, in the ideal case, the moral values should be the same for everyone. If a person thinks a system is acceptable this means that the system is acceptable in the light of the personal values of an actor. In this thesis a simplification is made where a system is acceptable if the majority of the society thinks the system is acceptable. This does not have to be necessarily true as this is based on the individual acceptability of the EV owners and not on common moral values. This has to be considered in the reflection of the results of this project.

Using the values of Ligtvoet et al., 2015, the descriptions can be found in Appendix A, the most important values concerning this system are as follows:

Economic Development One of the main incentives for the owner of the electric vehicle is the possibility to earn money by charging at cheaper electricity prices (Gangale, Mengolini, and Onyeji, 2013). Furthermore, the extra investments into the electricity system without smart grid technology would have been payed by DSO, which could lead to an extra profit for the owner with for instance a contract.

Environmental Sustainability Another motivational factor for the use of the smart EV system is the environmental concern Gangale, Mengolini, and Onyeji, 2013. A second objective of the proposed system is to enhance the amount of renewable energy the electric cars use to charge their batteries.

Privacy To reach optimal efficiency of the system the data of the users is needed in the algorithm. This data is privacy sensitive as it contains personal information as discussed in the previous section.

Autonomy When the algorithm determines when the car will be charged there will be a chance that the car will not be charged sufficiently or that the charging process will be the victim of errors. Due to the algorithm, the owner might not be able to leave or drive the distances he desires and he loses his autonomy.

Ownership In a situation where the user would sell or rent his battery to the DSO, they will lose control over their car and ownership of their property. They have to give up the control and security they have over their property to reach the economic development and environmental sustainability desired.

Safety Using vehicle to grid operations on the battery might endanger the safety of the battery (Doughty and Roth, 2012), however this is not a well researched topic for smart grid operations. Moreover, in the survey of Egbue and Long, 2012 was safety the least concerns of the respondents for electric vehicles.

The choice has been made to involve the first four values: economic development, environmental sustainability, privacy and autonomy as these are the most discussed in V2G articles (Mwasilu et al., 2014). Gangale, Mengolini, and Onyeji, 2013 identifies the most important motivational factors for the use of a smart grid, which are the reduction of bills, environmental concerns and better comfort. Therefore economic development and environmental sustainability are chosen. Comfort for electric vehicles is seen in this thesis as the possibility to always complete your journey, one of the main concerns of electric vehicle drivers as discussed in chapter 3.1, so the value autonomy. The second important disadvantage discussed is privacy and security of the data collected in the smart EV system, hence the value privacy. Ownership is a value which only plays a role in one particular solution direction and the issue of safety is not yet researched enough to identify it as a real concern.

3rd level: System Performance

The experiences of the EV owner with the smart EV system influence their decisions. If there are changes to what a person values he will adjust his behaviour, in this case his choice. The person gets his experiences from using the smart EV system. Conversing the four values to experiences has been done as follows. Economic development is translated into the profit the person makes when using the smart EV system. Environmental sustainability is measured in the percentage of extra renewable energy the car uses with the smart EV system. Privacy is measured in the times that the person encounters a problem with his privacy due to an exposure of his data. Autonomy is measured in the times that the person is not able to drive to his desired distance with the charging level of the car.

2nd level: Behaviour

The information of these two levels are combined in the second level (figure 3.3. These values in level 1 reflect the principles the actors have. If people disagree on a principle level, they will react more strongly to information that confirms their principles regarding this system. This could be an experience they have with the system in level 3, but also an experience which their friends or neighbors have in level 3, as social influence is an important factor. These experiences are weighted against each other. Profit and increase in renewables are positive experiences and problems with privacy and autonomy are negative experiences. The literature notices that social context and media are an important factor in individual decision making. They will also react to information from the media. Using the information they get from the system they will make a decision in level 2: using the technology or rejecting it. This decision is conceptualized in this thesis project based on how much positive experiences and how much negative experiences they encounter using the smart EV system and how important the person thinks these experiences are based on the values from level 1. This leads to an acceptance level. If the the EV owner has a positive acceptance level he will use the smart EV system, if he has a negative acceptance level he will not use the system.

In the 3-level conceptual model the persons chooses if he continues using the smart EV system based on his personal experiences combined with his individual acceptability assessment of the smart EV system.

Difference between accepted and acceptable systems

The 3-level conceptual model should explain how the person decides and when his decision would be for the long-term. This 3-level conceptual model is used to analyze the long-term use of the smart EV system using the following assumptions:

- An acceptable system which is always accepted will be used on the long-term.
- If a person acts according to his values his behaviour will be more resilient.
- A system with a higher acceptance level is more robust than a system with a low acceptance level.

If the positive experiences are equal to the negative experiences, but the person values the negative experiences more, for instance he thinks privacy is more important than economic development, he will choose to quit the system. However, even if the person values privacy more and thinks the system as unacceptable, if he has no negative experiences he will still use it. This is how the difference between what a person says and does comes back in this conceptual model. In this conceptual model a system in its total is accepted when it is used by a majority of the population. An system, as discussed previously, is acceptable when a majority thinks the system should be used upfront.

3.4 Conclusion

The smart EV system has potential benefits for peak reduction, grid reliability, environmental improvements and cost reduction. The disadvantages of the smart EV system are privacy and security problems. Furthermore, the EV owners are scared that due to the smart EV system the car will not always have sufficient charge. The smart EV system can be divided in two different charging modes. One directional charging from the grid to the vehicle (V1G) or bidirectional, from the vehicle to the grid as well (V2G). There is also the decision between cost, renewables or grid optimization. A more advanced algorithm has a higher potential for privacy problems. Important personal values concerning the smart EV system are economic development, environmental sustainability, privacy and autonomy. These values influence the decision based on the experiences of the EV owner with the smart EV system. This decision process is conceptualized in the 3-level conceptual model. In chapter 4 this concept is formalized to agent behaviour in the agent-based model.

Chapter 4

Formalization and specification

The goal of this chapter is to build a model to answer sub-question 3 (see chapter 2). This will be done based on the answers on the sub-questions 1 and 2 (see chapter 3). The modelling objectives and key performance indicators to measure model behaviour are identified in section 1. In the second section the most important aspects of the model are formalized using a system diagram. In section 4.3 the model itself is formalized. This means that the model narrative is explained. The most important procedures, the smart grid algorithm and the decision-making process are elaborated on. In the last section the model is specified, which means that the relevant input data is selected and adjusted to fit for the Netlogo model. The outcome of this chapter is a model that will be ready for verification and validation in chapter 5. The model is shown in appendix B.

4.1 Objectives and KPI's

The research objective is to find design directions for the smart EV system which reduce the expected electricity grid problems sufficiently in the long-term. As discussed in chapter 2, this objective has two important parts. Firstly, the smart EV system is sufficient to prevent residential capacity upgrades. Insufficiently would mean that the smart EV system would reduce the peak load, however, the same capacity expansion activities are required.

- The smart EV system has the technical potential to reduce the peak load sufficiently.
- The smart EV system is used sufficiently, there are enough users that the smart EV systems in use reduce the accumulated peak load on the grid sufficiently.

Secondly, the smart EV system is used on the long-term.

- The owners will not change their decision frequently, the DSO's have to know that the capacity of the residential grid will be sufficient at every moment.
- The smart EV system is used on the long-term, the owners will not stop using the smart EV system after a period of time. The DSO's have to be certain that it is not a temporary solution. As, if it would be, investments are necessary right now.

To asses if the smart EV system is sufficient the peak reduction is measured is measured in three different ways:

- Average peak load per day per transformer
- Amount of times a transformer is overloaded during a year

- Percentage of transformer which is frequently overloaded in a short period of time and therefore broken

To asses the long term use of the smart EV system the smart EV system is measured based on the use and the acceptance level.

- Usage is measured in how many EV owners use the technology. The lowest amount of users in a year is the best indicator because the capacity of the grid has to be sufficient at that moment.
- The acceptance level is measured based on the average, median and variance of the EV owners. The acceptance level is important, if the average/median acceptance level is high it means that there is a small chance that the smart EV system will be rejected in the future as it would take more negative experiences to stop the average person. The acceptance level is therefore a measure of long-term stability.

As it is critical that the smart EV system is a certain solution for the problem, the system designs are tested on their robustness, which is also measured in two ways.

- In the model different scenario's are simulated. If the results of the system design are uncertain, for instance if the peak reduction could be very high or very low in different possible scenarios the risk of choosing this system is too high.
- In the model a scenario is simulated multiple times to deal with the randomness of the model. If in one possible scenario the system design scores high and low on the feasibility the design has a higher risk. The measurement for this uncertainty is the variance of the KPI's.

Renewable energy increase A second tier objective is to increase the percentage of renewable energy used to charge the electric vehicles. The electric vehicles measure the amount of green energy and the amount of total energy they use. The total increase is measured in comparison to the base model without the smart EV system.

4.2 Concept formalization

The model simulates the use of the smart EV system for one year. The model simulates the use in one neighborhood. This neighborhood is represented by a number of households in a Netlogo Model. The households will be randomly distributed in the model. The exact location of the houses would be specific for every neighborhood and does not play a role in this model, as the exact distance between the houses and number of household in every street does not have significant influence on the amount of energy they consume or amount of kilometers they drive. In this model a city is represented by detached houses, where in real life there are of course also flats and shops for instance in a neighborhood.

The technical infrastructure which is modelled in the model is the electric grid, as the impact of the EVS on the balance of the grid is one of the most important technical factors investigated in this research. The electric grid is scoped down to only the local grid, the connection between the transformers and the households. On average eighteen houses are connected to one transformer (Enexis, 2017), see figure 4.1. The households are connected to this grid. Some households have an

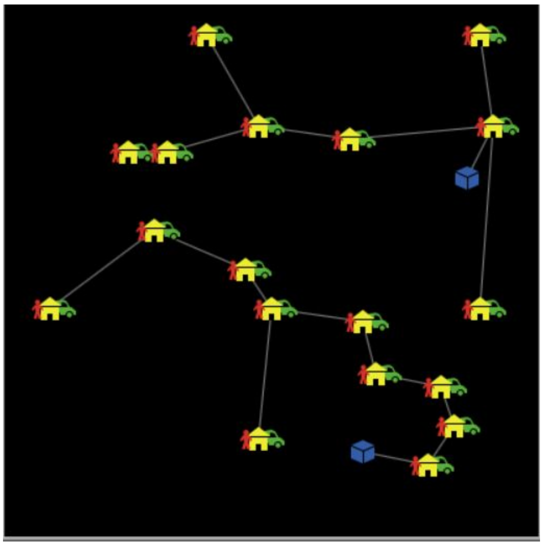

FIGURE 4.1: Layout Model

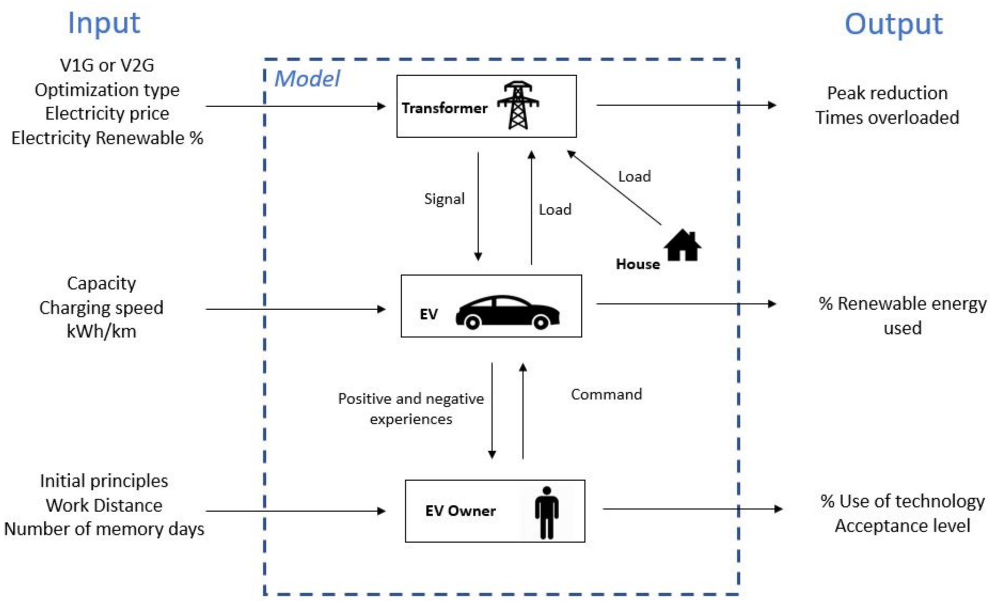

FIGURE 4.2: System Diagram

electric car, how many households is a choice in the model to analyze the difference between the amount of EV's available. The households demand power from this grid (3), just like the electric cars (2). The cars are connected when the owner is at home. The smart EV system is used by default at first. The smart EV system signals the car what to do, charge, discharge or do nothing (1). The transformer also tells the EV how much the costs are and how much of the energy he charges is renewable. The EV owner develops an opinion on the application based on the experience he has with the smart EV system (4). The EV owner chooses if he want to use the smart EV system and commands the car to (not) use it (5). (figure 4.2). As such the desired outputs are generated.

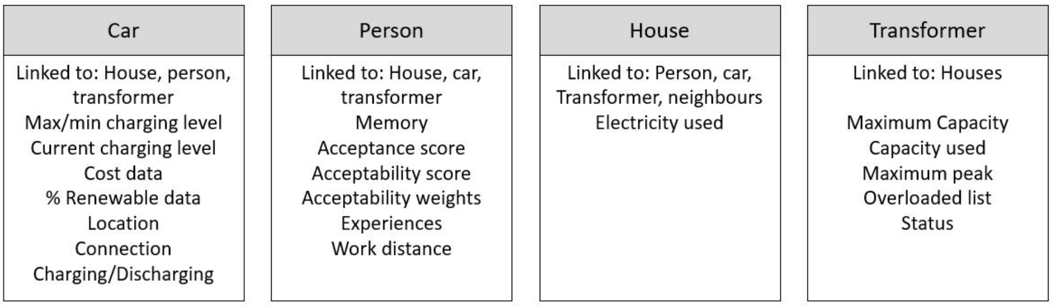

FIGURE 4.3: Entities

Persons In this model an average day-to-day routine of the vehicle drivers will be used. This means that the cars will leave in the morning around 8 AM and come back around 5 PM as shown in figure 4.4. The distance they have to drive differs depending on the distance to their work and therefore the electricity used will differ between the cars. Sometimes they will have to drive more due to appointments, but sometimes they also work home. In this model the activities outside the day-to-day routine such as holidays are not modelled.

Houses The household usage is the combined power usage of an average household and the power used when charging the electric vehicle. The power usage of the household itself is based on the typical load curve of a household with a little bit of variance just as in the real world. This means that every day and every season the households will have the the (almost) the same electricity demand, which is a simplification of the real world.

Electric vehicle In the model different cars will be used. The normal connection of a household has a charging speed of 3.6 KwH per hour. The car uses around 0.2 KwH per km. To represent different fleets it is possible to change the fleets with a different percentage of 30 kWh, 60 kWh and 90 kWh batteries. The reasoning of these numbers and other input values can be found in appendix C.

Transformers The capacity of the transformer is the total sum of the electricity used by the houses connected with a safety percentage of 75. This is an assumption without data and therefore it should be kept in mind for the interpretation of the results.

The electricity available is based on a model of the electricity sector in 2015, which is explained in section 4 of this chapter. In this model the electricity is used as an input, so the electricity used in the model does not impact the amount of power stations that have to be active or the cost of electricity.

There are 2 options one-directional (V1G) and bi-directional charging (V2G) and 3 different ways to optimize the charging process of the car as discussed in chapter 3.1.

Cost optimal charging The way to charge at the lowest cost possible is simplified in this model. Assumed is that the average electricity costs are known and the car will be charged when the cost are below average. An option would be to include an option where the person can choose to charge when the costs are below halve of average. With a more advanced algorithm you could use the day-ahead market to plan ahead.

Renewable optimal charging The way to charge at the most renewable way possible is simplified in this model. Assumed is that the average renewable percentage of the electricity mix is known and the car will be charged if the percentage is above average. An option would be to include an option where the car will be charged when the percentage is above a certain threshold. In reality a more advanced algorithm would look at the merit order in use of the electricity mix and calculate when a non-renewable plant would be active due to the charging process of the cars.

Network optimal charging In this model there is also the option to use an algorithm next to either the cost or renewable algorithm to optimize the load on the electricity network. This algorithm is based on the maximum capacity of the transformers and overwrites the other algorithms if the load on the transformers is too high.

4.3 Model formalization

In this section the model narrative and the most important procedures will be explained. Before the model can start, the setup procedure has to be done first. In the setup procedure the entities are linked, the random parameters for the entities are generated and the electricity price, renewable generation and household load is loaded for the whole year from an Excel file. This yearly data has to be loaded into the model in the setup as the input data has to be known for the EMA workbench, used for the exploration, to work.

In figure 4.4 the walk-trough of the model is shown. The car drives to work and back, there is a chance that the person will work from home and this is taken into account. Sudden unexpected drives are also taken into account when a car is home. When the car is at home, it will be connected and the smart EV system will take a decision what to do with the car, which will be further analyzed in paragraph 4.3.2. Based on the decision, the car will act accordingly and do either nothing or charge/discharge the car. Every day there is a chance for problems to occur and every day the person will evaluate how he experienced the smart EV system. This evaluation will be discussed in paragraph 4.3.3.

4.3.1 Procedures

There are different procedures, some procedures happen every hour and some procedures happen daily. In this subsection the difference will be indicated and some of the procedures which are not further analyzed in other sections will be explained.

Hourly procedures

- **Household electricity use** The electricity use of a household is calculated based on the average household load at a certain moment with a given variance for the household and whether the car is charging or discharging using V2G. In this case V2G is not really calculated as a real V2G connection, but as a combination of V2G and V2B (vehicle to building). This means that the electricity is first used for the house and then the residual is fed back to the grid.

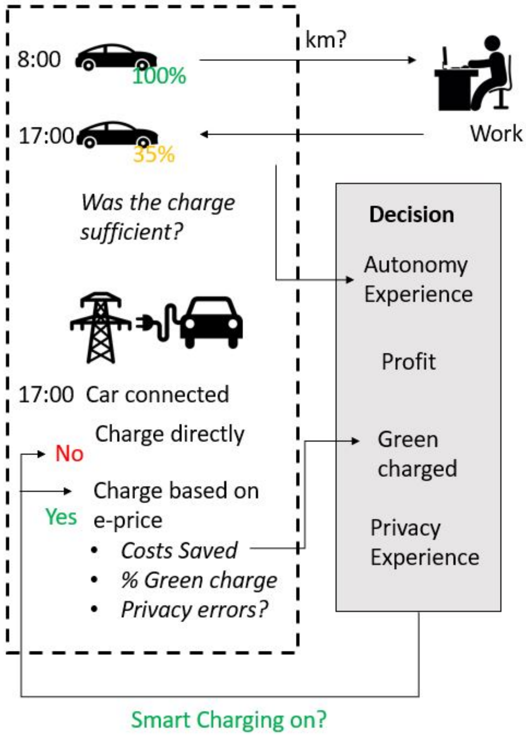

FIGURE 4.4: Day of an Agent Walk-trough

- **Network capacity update** The capacity of the transformers is the sum of the households connected to the transformer. The transformers have a maximum capacity of two times the expected summarized household load.
- **Smart-grid decision** The smart grid decision is analyzed in paragraph 4.3.2.
- **Charging/Discharging** If the car gets the order to charge from the grid, the car will first check if the battery is almost full and can be fully charged at that moment. If that is not the case, the car will charge with the given charging speed and calculate the costs of that charge and the percentage renewable energy it uses. If the car can be set full, the car will charge the amount necessary and calculate the costs over that amount. If the car gets the signal to discharge the battery, it will discharge the car with the given charging speed and calculate the profit that it makes with the current electricity price.
- **Unexpected driving** One of the fears of using the smart EV system is that when a person has to leave unexpected the car does not have a sufficient charging level as it is not charged immediately. In this model these unexpected drives are not just picking a kid up from school, but drives with more than 50 km in total, up to 150 km.
- **Update color** The color adapt to the state the persons and cars are in. Persons are green (acceptance high), yellow (acceptance neutral) or red (acceptance negative). The cars are green (full capacity), yellow (above minimum charging capacity) and red (below minimum charging capacity).

Daily procedures

- **Driving to work and back** The cars will either drive to work at 8 AM or stay at home, depending on the chance that their owner will work from home. The battery costs are the drive to work and home multiplied by the kWh cost per km. If the battery would be empty after deducting this cost it means that the battery would be empty and assumed is that the owner would have charged somewhere else for a high cost. The current level of charging is then set randomly. The car running empty on its way to work is also a problem for the owner so his autonomy experience goes down.

- **Causing problems** In this model it is assumed that there is a chance that errors occur when using technology. Every day there is chance for every car that an error will occur. A privacy error sets the privacy experience -1 and an autonomy error sets the autonomy experience -1 if the car has to be used. If it is a weekend or the person works from home the owner does not notice that an error occurred. When more data is used and the algorithms get more advanced, the risk for an error to occur gets higher.

- **Media** The media does nothing in this model except when in a certain day some people (20% of the population) are extremely happy, this means that their acceptance for the day is more than 10, or when some people are extremely unhappy, their daily acceptance is lower than -10. If this is the case, all the persons will take this into account in their daily acceptance the next day.

- **Updating Acceptance level** This procedure will be discussed in chapter 4.3.3.

- **Update daily data** The daily data collected, such as the daily costs, daily green energy used and daily charged, will be set to zero. But first this data will be aggregated in the yearly data variables.

4.3.2 Smart-grid decision procedure

This section explains the algorithm behind the smart grid procedure (figure 4.5. The smart grid procedure only occurs when a car is connected to a charging point. The procedure signals the car what to do, there are three signals: Charge, discharge and explicitly signaling the car to do nothing.
Based on chapter 3.1 there are three choices for the technology: No technology, a smart charging with V1G and smart charging with with V2G (pink in figure 4.5). There are also three optimization choices: Optimizing on costs, renewables and the network (green in figure 4.5).
If the smart EV system is not available, the car will automatically try to charge when connected. If it is available, but the owner does not accept the use of the technology, the car will also automatically charge.

The next steps in the procedure depend on the optimization which is chosen. It is possible in this procedure to make a combination between network (transformer) optimal and an optimization on cost or renewables. Network optimization has the highest priority by default, as the idea behind this optimization is to not overload the transformers and this can only be done when this has the highest priority.

If the procedure should be optimized on network capacity the smart technology will check if the transformer providing electricity to the car will be overloaded if the car will charge. For this check there has to be more data available than only the data of the car itself. If the transformer is indeed overloaded the car will try to decrease the load on the transformer by using V2G if it is available.

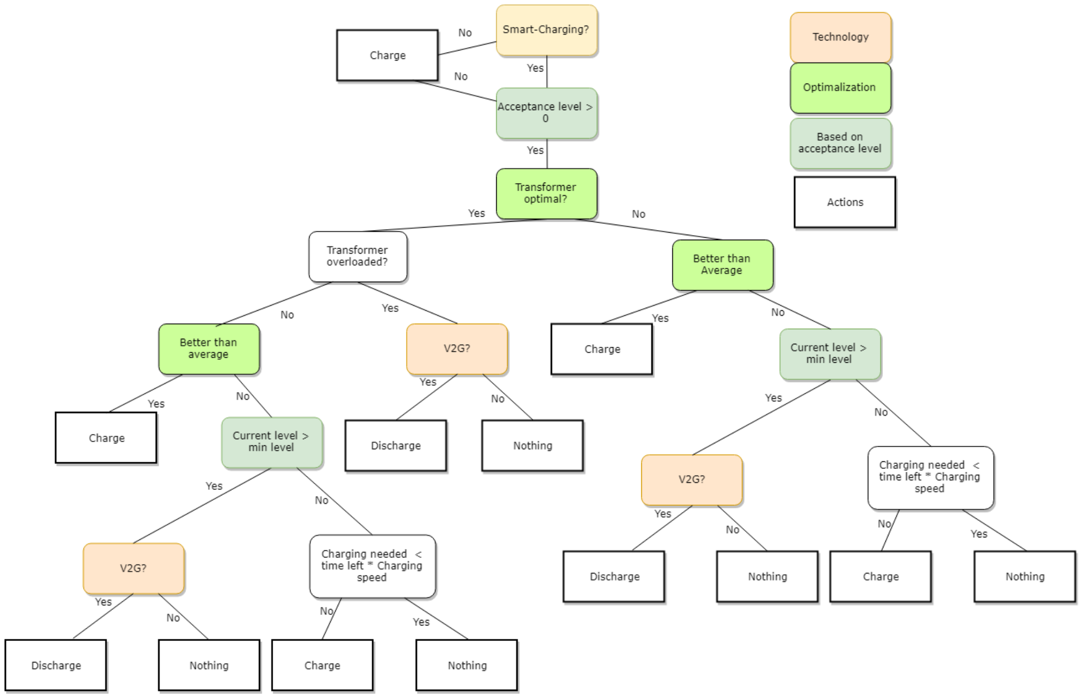

FIGURE 4.5: The way the smart EV system determines what an EV has to do

If the transformer is not overloaded the smart grid will check the second optimization, either the price of the percentage of renewable energy in the electricity mix. If the price is lower than average or the percentage renewable energy is higher than normal, the car will charge. If this is not the case the car will check if it has reached its minimum charging level. This minimum charging level is based on the acceptance level of the person, if the person has a higher acceptance level he has more trust in the system and will take a higher risk. If the charging level is sufficient it will try to sell the electricity it has in surplus to the grid for a high price. If the charging level is not sufficient, the smart grid will check if the car has to start charging now to reach the minimum level before 8 AM, where it will probably leave.

If the smart grid procedure does not have to optimize on the network capacity it will skip this step and start with the second optimization step and go through the same procedure.

4.3.3 Updating Acceptance level

The acceptance level calculation happens at the end of every day. The acceptance level procedure is based on three different layers as is shown in figure 4.6 in chapter 3: The acceptability level, acceptance level and the model level. The acceptability level has the initial scores that the person gives to a value (X_{score}). There are four values used in this model. On a model level the values reflects how the system scores on the different values in real life (X_{model}). On the acceptance level, the weights reflect how the person thinks the system scores would be in balance (X_{exp}). The four values used in this model are Economic Development, Environmental Sustainability, Privacy and Autonomy. These are used as followed:

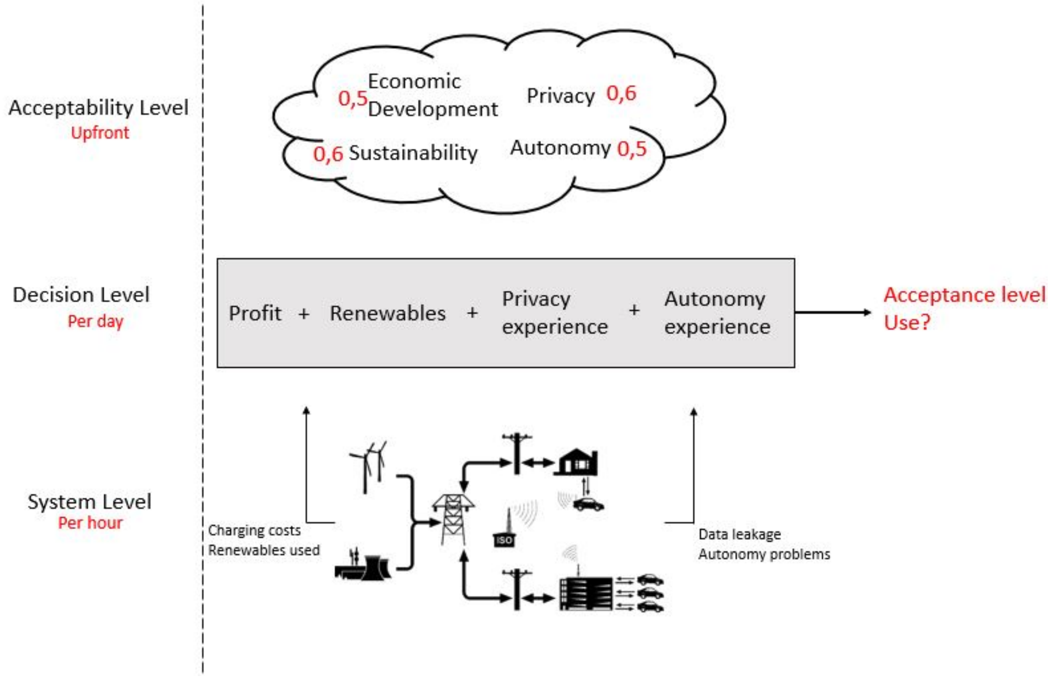

FIGURE 4.6: 3-level conceptual model, formalized

PT_{score}	PT_{model}	PT_{exp}	Economic Development
R_{score}	R_{model}	R_{exp}	Environmental Sustainability
PY_{score}	PY_{model}	PY_{exp}	Privacy
A_{score}	A_{model}	A_{exp}	Autonomy

Every day the person calculates his acceptance level (Acc_{day}). However, the acceptance level the person uses to determine if he will use the technology is based on his previous experience as well (Acc_{total}).

$$Acc_{total} = \frac{\sum_{d=1}^{Memory} Acc_{day}}{Memory} \tag{4.1}$$

Daily acceptance

The acceptance level per day is calculated based on the three layer model. The equation is based on the ratio between the expected value and the real (or in this case model) value multiplied with the score of the value in the acceptability level.

$$Acc_{day} = \frac{PT_{model}}{PT_{exp}} * PT_{score} + \frac{R_{model}}{R_{exp}} * R_{score} - \frac{PY_{model}}{PY_{exp}} * PY_{score} - \frac{A_{model}}{A_{exp}} * A_{score} \tag{4.2}$$

This equation is based on zero acceptance. This means that a neutral person would reach zero acceptance if the reality would be exactly as he expected. A neutral person would have the sum of the positive scores the same as the negative scores.

$$PT_{score} + R_{score} = PY_{score} + A_{score} \tag{4.3}$$

If the reality would be as he expected, it means that the ratio between model and expected is equal to zero.

$$\frac{PT_{model}}{PT_{exp}} = \frac{R_{model}}{R_{exp}} = \frac{PY_{model}}{PY_{exp}} = \frac{A_{model}}{A_{exp}} = 1 \tag{4.4}$$

This means that the acceptance of a person will be 0 after a day where the reality gives the results as expected. However, the reality (the model) does not always give the results expected upfront, which will be explained in the next paragraph.

Model values

The profit made in the model is the profit in comparison with the base model, which means without the smart EV system. The profit per day is calculated based on the average costs of charging the car multiplied with the amount of kWh charged (4.5).

$$PT_{model} = (C_b - \frac{\sum_{t=1}^{24} C_t}{\sum_{t=1}^{24} CH_t}) * \sum_{i=1}^{24} CH_t \tag{4.5}$$

C_b	Cost base (constant)
C_t	Cost at time t
CH_t	Charged at time t

The improvement on environmental sustainability is measured based on the percentage of energy charged with green electricity. The ratio between the percentage with the smart EV system and without the technology is the renewable profit that is made.

$$R_{model} = (\frac{\sum_{t=1}^{24} G_t}{\sum_{t=1}^{24} Ch_t})/G_b \tag{4.6}$$

G_b	Green percentage base
G_t	Green percentage charged at t

The privacy experience calculation is relatively simple, if an error happens, the privacy experience is set to -1 and if nothing happens during the day it is zero.

$$PY_{model} = \begin{cases} 1, & \text{if error?} \\ 0, & \text{otherwise} \end{cases} \tag{4.7}$$

The autonomy experience calculation is the same, except that there is a chance that the person does not experience an error if he won't use the car that day.

$$A_{model} = \begin{cases} 1, & \text{if charging level} < 0 \\ 0, & \text{otherwise} \end{cases} \tag{4.8}$$

Social influence

Social influence could come from either the friends of the person or a media coverage. Social influence from friends is based on the value that the person gives to the information he gathers from his friends. This means that the persons does not necessary get influenced by the opinion of his friends, he only gathers more information about the smart EV system. This value he gives to the information is called Friends Importance (FI). This is a value between 0 and 1, where 0 means that the person does not take the info into account and 1 means the person will act entirely on the information of his friends. The social influence changes the model value, which will be used in equation 4.2. For example, the formula for the new model value for profit will be:

$$PT_{model-new} = (1 - FI) * PT_{model-old} + FI * avgPT_{model-friends} \tag{4.9}$$

For example, if the person does not experience any privacy problems, but a friend of him does he will value this information in his trade-off. If only one of his friends uses the smart EV system, he will also take into account the fact that his other friends don't use the smart EV system, as it is an average of his friends who have an electric car.

Acceptance of non-users

The daily acceptance of the non-users is automatically zero, as they don't use the system they should not expect any positive or negative experiences. However, they will still be influenced by the media and their friends. Furthermore if the total acceptance is zero, it is assumed that the EV owner will start using the smart EV system again.

4.4 Model specification

In this section of chapter 4 the data which is used as input for the model is discussed. The goal of this model is to function for different countries and different scenarios. However, to use and test the model for this research, an example country is chosen, which is the Netherlands. In chapter 7, section 3, there will be explained how to change the model to fit for other countries or scenario's. In appendix C the default values of the model are shown.

4.4.1 Energy mix input

In this model the electricity price in combination with the amount of renewable energy is an important factor for the smart grid algorithm. As the scope of this model is at least ten years from now, the energy mix will have changed in comparison to today. This energy mix will also be different for every country. As an example country the Netherlands is chosen as the data is accessible and understandable. The input for this model should be an hourly electricity price and the percentage of the energy which is green. This input is reached in three steps (figure 4.7).

First a renewable energy scenario is chosen using the energy transition model. The future amount of renewable capacity is important to calculate the electricity price and renewable percentage of the energy. To analyze different possible scenarios three default scenario's are loaded in the model.

Second, the renewable energy capacity is used in combination with the current data on the power plants in the Netherlands to build the merit order of the Netherlands. Using expected wind and solar data, the merit order of the full year can be

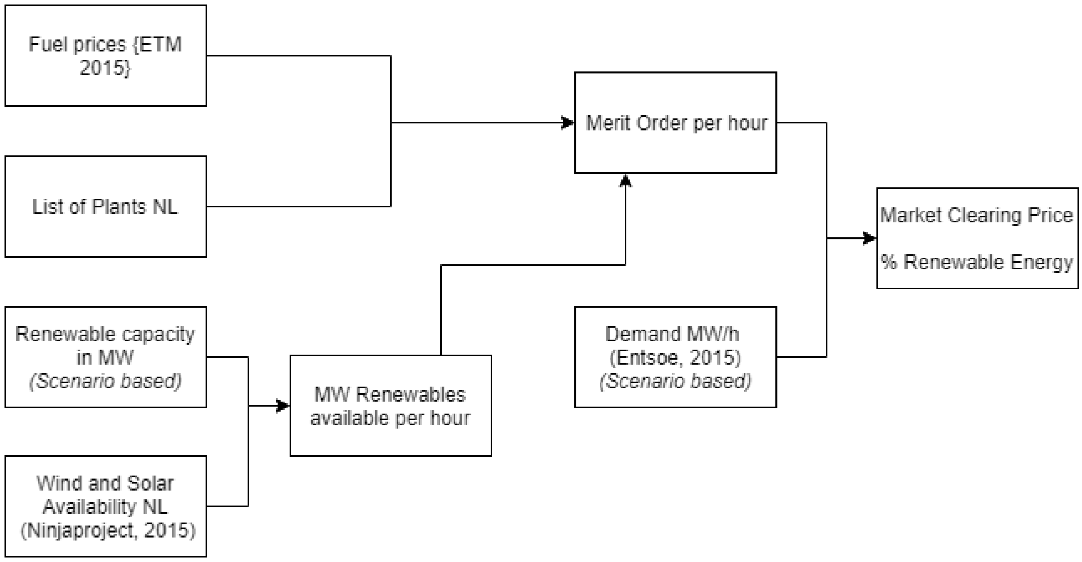

FIGURE 4.7: Calculation of hourly prices and renewables

	Scenario 1	Scenario 2	Scenario 3
Renewable Perc	13	25	50
Percentage EV	15	25	50
Hload factor	1	1.1	1.2

TABLE 4.1: Default Scenario's

generated. With the hourly demand of energy of 2015, the highest power plant in use can be calculated. This leads to an electricity price given the amount of wind and solar energy available with the percentage of green energy.

The third step is to take this information and convert it to an csv or txt file so the data can be used in the Netlogo model.

With this method a simplified version of the electricity market is approached, which is not accurate for scenario's for 2030 as the composition of the power plants and fuel prices will differ. However for this model, where the focus is on behaviour, the exact amount of profit they will not make a lot of difference. The weights that the agents give to profit they make is what matters for the model. And the weights can be adjusted to the current data input, as will be shown in the next section.

4.4.2 Weights and ratio

The values are personal and different for each person. The weights for the two positive values (economic development and environmental sustainability) and the two negative values (privacy and autonomy) are taken randomly from 0.00 to 1.00. If the sum of the weights of the positive values are higher than the negative values, a person is called principally positive.In the base case the average person will be principally neutral. This means that on average there are as many persons which have a positive acceptability level as a negative acceptability level. This can be adjusted by changing the average person to a positive or negative person using the initial acceptability slider. If this slider is is set to 1 the persons will have a 20% higher chance to take a higher number for the positive values and a lower number for the negative value. This chance increases with 20% as the initial principles slider is set higher. The same counts for a setting the principles slider lower.

The acceptance weights are based on an average zero acceptance model for a simple smart grid. This means that the goal of the initial weights is to have on average an acceptance level of 0. To do this the yearly profit is calculated using the model, based on a technological system with a smart grid, but without social interaction and acceptance playing a role, this is around 4600 ct/year. On average the energy percentage doubles. The default error values are one privacy error per year and four autonomy errors a year so the weights should reflect an average zero acceptance principle. To get a better understanding of the mathematical consequences, some examples are shown in table 4.2.

$$PT_{exp} = 4600 \text{ (ct/year)}$$
$$R_{exp} = 0.75 \text{ (times more renewable)}$$
$$PY_{exp} = 1 \text{ (incidents/year)}$$
$$A_{exp} = 4 \text{ (incidents/year)}$$

Example	1	2	3	4
PT_{model}	4600	4600	*2300*	4600
R_{model}	0.75	0.75	0.75	0.75
PY_{model}	1	1	1	2
A_{model}	4	4	4	4
PT_{score}	0.5	*1*	0.5	0.5
R_{score}	0.5	0.5	0.5	0.5
PY_{score}	0.5	0.5	0.5	*0.25*
A_{score}	0.5	0.5	0.5	0.5
Acc_{total}	0	0.5	-0.5	0

TABLE 4.2: Example of the zero acceptance principle

Example 1 shows the zero acceptance principle if the person would have the exact model outputs as expected and an all acceptability scores equal. The second example shows what happens when an acceptability score would change, for instance profit. Example 3 shows what happens if the profit is not as much as expected, so an Acc_{total} of -0.5 means that on one of the targets the real life was half as good as expected. Example 4 shows that trade-off between positive and negative targets, if both the positive and a negative target improves but the person didn't really value that target as important in the first place, the acceptance will still be zero. An acceptance level of 1 means that the positive experiences are twice as high as expected or that the positive experiences are the same as expected but the person values these values more.

4.5 Conclusion

The purpose of this chapter is to design a model based on chapter 3. The technical algorithms of chapter 3.1 are implemented in a simplified way. The most important KPI's are the peak reduction and the use of the smart EV system. The acceptance level is the measure of long-term stability. The 3-level conceptual model is formalized in such a way that theoretically a person with a positive acceptability will also have a positive acceptance level. Whether this actually happens, depends on the characteristics of the persons which are heterogeneous, the interaction between the persons and the stochastic behaviour of the model.

Chapter 5

Model validation

The goal of this chapter is to verify and validate the model build in chapter 4. This is done based on the 'evaludation' method. In the first step uncertainties in the input data are discussed. In the second step the conceptual model is evaluated. In 5.3 the procedures are tested. In section 5.4 the model output is verified. In section 5 the sensitivity of the model is tested and in the last step of the evaludation method the model is evaluated based on the validation and verification. This 'evaludation' of the model will be the basis for the interpretation of the results of the experiments in chapter 6.

5.1 Step 1: Data evaluation

Augusiak, Brink, and Grimm (2014) define the data evaluation step as "the assessment of the quality of numerical and qualitative data used to parameterise the model, both directly and inversely via calibration, and of the observed patterns that were used to design overall model structure, whereby not only the measurement protocols need to be evaluated but conclusions drawn from the data should be challenged as well".

In other words, the question is if the input data used in model 4 is uncertain. The quality of the numerical and qualitative data of this model for the basis of the technological system should be high as for the technical assessment of the system it is important to make the right calculations which can not be questioned. The quality of the input data of the social system can be lower as the social theories which are the basis of the model are relatively open to the interpretation of the modeller. It is important to discuss which input variables are based on sources and which are based on assumptions and what this could mean for the output of the model. In appendix C.1 the input variables which are chosen in this model are named and explained why the a certain default value is chosen. Some of the most uncertain factors are discussed in the next paragraphs.

Energy mix input The assumptions made for the calculation of the electricity price and percentage renewable energy described in section 4.4.2 are debatable. The data used is out dated in comparison with the time scope of this model, as the active use of smart EV system is still a few years away and the data is from 2015. The electricity price and percentage renewable energy will therefore be different in reality. This means for the analysis of the model that the exact calculated profits and green percentages should not be the main focus and the results should be analyzed on a higher level. Figure 5.1 shows how the electricity price which is used as input looks like. There are three different renewable scenarios available to use in this model with a share of respectively 15, 25 and 50 percentage of renewables, these scenarios also

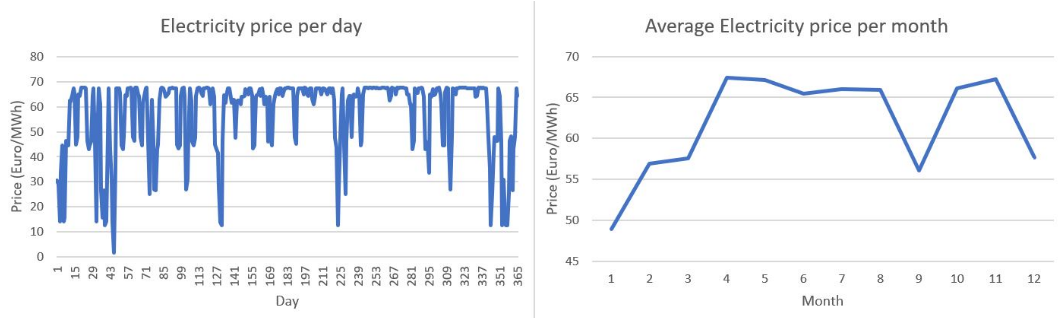

FIGURE 5.1: Electricity prices input

have a different electricity cost. The results show that the green charging percentage is almost equal to the input of the scenarios. Interesting is the profit which is made with a higher percentage renewables, as it is the relative profit, so the cost for normal charging are also lower. However with a higher renewable percentage the prices fluctuate more and more money can be made with the V2G option. This should be kept in mind that with a higher renewable energy percentage the fluctuation in price will be higher and the users will make more profit.

Renewable input perc	15	25	50
Users	42	57	61
Mean Acceptance	0.26	0.19	0.43
Median Acceptance	0.22	0.16	0.33
Variance Acceptance	1.05	0.82	1.31
Mean Peak per day (kWh)	20.0	21.5	19.6
Times overloaded	41	55	39
Percentage Renewable	16.4	33.7	51.2
Fuel cost (ct/kWh)	6.66	5.33	5.34
Yearly profit (ct)	507	2829	1939
Autonomy problems	1.94	2.05	2.21
Total charged (kWh)	2293	2300	2280

TABLE 5.1: V1G, Renewable input percentages, based on 100 runs each

Renewable input perc	15	25	50
Users	33	41	49
Mean Acceptance	-0.01	0.54	0.73
Median Acceptance	-0.16	-0.04	0.11
Variance Acceptance	1.6	3.3	4.1
Mean Peak per day (kWh)	21.3	23.1	21.6
Times overloaded	71	117	93
Percentage Renewable	16.7	37.4	54.8
Fuel cost (ct/kWh)	4.01	2.65	0.44
Yearly profit (ct)	9554	12709	20140
Autonomy problems	5.3	5.3	5.7
Total charged (kWh)	3537	3567	4463

TABLE 5.2: V2G, Renewable input percentages, based on 100 runs each

Charging Speed The charging speed is based on the average charging speed of a normal household wall outlet, however currently there are a technical improvements where for instance Tesla and BMW develop an special wall plugs which increase the charging speed significantly. Charging level has a high impact on the KPI's of the system. This can be explained by the possibility to charge and discharge quickly and effective. For instance if the price is low the car can charge a larger amount and if the price is high the car can sell a larger amount. The car has also less change to be empty as it needs less time to charge. However, if the cars can charge more it means that the load per hour is also higher.

Problems The input variables for the amount of problems that occur are based on assumptions. As the use of smart grid technology in combination with the electric vehicle is a new field of research it is difficult to say how often errors could occur. The assumption that with more difficult algorithms more errors occur is based on general technical knowledge that more difficult tasks are vulnerable for mistakes, but how this translates into data analysis steps is difficult to tell. To keep the model simple to understand the initial errors in the model are equal to what the owners would expect.

Transformer Capacity On average a transformer is connected to 18 houses, however the exact capacity of a transformer is unknown and therefore assumed in this model. This means that the number of times a transformer is overloaded should be compared to other scenario's and not be interpreted on its own output of the model.

Distance to work The distance to work shows an interesting dynamic as the EV owner has a trade-off between profit and the problems he might have. If the person does not have a large driving distance this means that he does not have to charge a lot and will make less absolute profit. He has the same chances of problems as someone with a larger driving distance and more absolute profit, therefore it would make sense that this person would reject V1G earlier. On the other hand, someone who does not have to drive far does not need a high minimum charging level and therefore can make more profit with a V2G technology than someone with a higher driving range.

Memory The concept of memory for agents is difficult to grasp. How long does someone remember the fact he made 5 euro's last month using the smart EV system and how long does someone remember that he had to wait before his car was charged to drive to a surprise birthday party? It is difficult to value these kind of experiences on a memory scale.

Conclusion of step 1

- Scenario's: higher renewable percentage means higher fluctuation and higher profit for the V2G option.
- With a higher charging speed the load on the grid can be higher, however the cars can also react faster and better to profitable situations.

5.2 Step 2: Conceptual Model Evaluation

Augusiak, Brink, and Grimm (2014) define the conceptual model evaluation step as “the assessment of the simplifying assumptions underlying a model’s design and forming its building blocks, including an assessment of whether the structure, essential theories, concepts, assumptions, and causal relationships are reasonable to form a logically consistent model”.

What they intend with this step is that several conceptual models should be considered and tested during the creation of the model. The first important conceptual model is the 3-level conceptual model explained in chapter 3 and formalized in chapter 4. Examples of models with the combination of the two theories are not available as that is one of the research gaps was the understanding of the choice of the EV owners and therefore it is difficult to compare the conceptualization. However, as mentioned in chapter 3, this conceptual model is based on one interpretation of the theories and other interpretations are also possible. Input data for the social part of the model is difficult to value. How important is the role of their friends for the owner in the model? It is difficult to put a value on a relationship. Therefore the influence of the friends and media has been analyzed using the regression analysis.

The smart grid algorithm is simplified as mentioned in chapter 4. This has to be kept in mind when analyzing the results. With a more difficult algorithm the charging speed could be altered and a charging plan for a couple of hours could be made. Instead the charging speed is the same in this model and the algorithm only plans ahead based on the time it takes to charge to the minimum charging level. With an algorithm that plans ahead on costs and renewables as well, altering the charging speed accordingly, the profit could be higher and the peak load lower.

Conclusion of step 2

- Conceptualization of 3-level model should be reflected on as it is new and can not be validated.
- Smart grid algorithm is simplified and this will decrease the performance of the smart EV system, in reality the smart EV system will perform better on the peak reduction.

5.3 Step 3: Implementation verification

Augusiak, Brink, and Grimm (2014) define the implementation verification step as “the assessment of (1) whether the computerised implementation the model is correct and free of programming errors and (2) whether the implemented model performs as indicated by the model description. The aim is to ensure that the modelling formalism is accurate”. In appendix E an overview of the different procedures and their tests can be found. The only problem found was the smart grid algorithm of the V2G. Expected was a higher peak reduction. This problem also arises when the combination with the network optimal algorithm is used. The smart grid algorithm for the combination of V2G and transformer optimal does not work as intended as the peak load is sometimes still higher than the capacity of the transformer. The peak is however significantly reduced.

Conclusion of step 3

- The smart grid algorithm for the combination of V2G and transformer optimal does not work as intended as the peak load is sometimes still higher than the capacity of the transformer. The peak is however significantly reduced.

5.4 Step 4: Model output verification

Augusiak, Brink, and Grimm, 2014 define the model output verification step as "the assessment of (1) how well model output matches observations and (2) to what degree calibration and effects of environmental drivers were involved in obtaining good fits of model output and data. The aim is to ensure that the individuals and populations represented in the model respond to habitat features and environmental conditions in a sufficiently similar way as their real counterparts".

In this section the basic outcomes of the model which are the peak reduction, renewable energy increase and profit are discussed. In addition some of the advantages and disadvantages of the smart EV system from chapter 4 are discussed as well. In the first paragraph the technical outcomes are discussed and in the second paragraph the same results are shown when the EV owner have a choice.

5.4.1 Technical Outcomes

In the tables 6.1 and 6.1 the technical potential are shown. The results are shown when every EV owner would use the smart EV system.

	Base	V1G Cost	V1G Ren	V1GTrans
Mean Peak per day (kWh)	24.8	20.4	21.5	20.2
Times overloaded	138	54	78	0
Percentage Renewable	23.0	40.5	34.9	40.9
Fuel cost (ct/kWh)	6.4	4.7	6.0	5.3
Yearly profit (ct)	46	4535	1324	4148
Autonomy problems	0.1	3.5	3.0	8.7
Total charged (kWh)	2251	2311	2353	2447

TABLE 5.3: Basic Technical Outcomes V1G, without choice

	Base	V2G Cost	V2G Ren	V2G Trans
Mean Peak per day (kWh)	24.8	24.0	24.6	23.0
Times overloaded	138	172	220	35
Percentage Renewable	23.0	44.6	35.5	44.0
Fuel cost (ct/kWh)	6.4	1.1	2.3	2.1
Yearly profit (ct)	46	24306	15821	21450
Autonomy problems	0.1	11.4	10.2	26.0
Total charged (kWh)	2251	4647	5176	4796

TABLE 5.4: Basic Technical Outcomes V2G, without choice

Peak reduction with the smart EV system The main goal of smart EV system was to reduce the peak load on the network. The technology does indeed decrease the peak load on the transformers as is shown in the table. Interesting is the outcome that using vehicle to grid technology does not decrease the peak load as much as the V1G option. This could be caused by the simplification of the algorithm as prediction is not as precise as in the real world. With the V2G option the amount of electricity charged almost doubles in the model, which means that the simplification of the algorithm has more impact on the V2G option as it is more dependent on the algorithm. However, the result that with the V2G option the demand of electricity almost doubles still indicates that in total there will be more demand on the grid, debatable is if the peak demand would also increase as in this model with a better algorithm .

Increasing green percentage The second advantage of using the smart EV system was to increase the percentage of renewable energy the cars use. Using V1G the percentage of green electricity indeed almost doubles. V2G has a slightly higher green percentage, this can be explained by the increased amount of electricity which is charged, V2G has the option to charge more at better spots than without V2G where the car is full more often.

Profit One of the incentives for the owners of the electric vehicles is the decrease of charging costs. As expected is the profit of V2G significantly higher as the option of V2G gives the possibility to also sell electricity at high prices. The total profit of the basic model is almost zero (44 ct), which is correct as the profit of the technologies is based on the basic model.

Optimization with network optimal algorithms Using a network optimal algorithm the percentage of overloaded transformers is significantly lower, which should be the case. A transformer optimal algorithm would decrease the overloaded transformations drastically, but does not increase any of the main objectives for the persons themselves, so a DSO has to look for more incentives for the persons, this is discussed in chapter 6.

Optimization with renewable optimal Using a renewable optimal charging algorithm does not make a significant difference with a cost optimal algorithm. This was expected as there is a correlation between the amount of renewable energy available and the electricity price as discussed in chapter 4. Therefore the output of both cost and renewable optimal charging are alike. The renewable optimization algorithm is therefore not used in further analysis.

Variance of peak reduction The variance over all the difference runs is shown in appendixI. The variance of the outcomes increases when the technology is introduced. The times the transformers are overloaded on average each year has the highest variance. This variance is important as peak reduction is the main objective of implementing the smart EV system. If the peak reduction can not be guaranteed, which is the case with a high standard deviation, then the smart EV system is not a robust and therefore viable solution for reducing the peak load. The variance of the peak reduction is reduced significantly when the network optimal algorithm is used.

5.4.2 Social outcomes

On a technological basis the the smart EV system shows promising improvements for the electricity system, reducing the load on the network, improving the amount of green energy used, while giving profit to the owners. From a technological standpoint this could be the end for designing a system, but as discussed in the previous chapters different technological and social factors play a role due to the participation of the EV owners. Using the acceptance level calculation generated in chapter 4, the owners are given an option to actually stop using the smart EV system. The outcomes change and are shown in table **??**.

	V1G Cost	V1G Cost choice	V1GTrans	V1G Trans choice
Mean Peak per day (kWh)	20.4	21.5	20.2	22.9
Times overloaded	54	55	0	75
Percentage Renewable	40.5	33.7	40.9	28.8
Fuel cost (ct/kWh)	4.7	5.33	5.3	6.00
Yearly profit (ct)	4535	2829	4148	1357
Autonomy problems	3.5	2.05	8.7	2.53
Total charged (kWh)	2311	2300	2447	2341
Users		57		28
Mean Acceptance		0.19		-0.25
Median Acceptance		0.16		-0.12
Variance Acceptance		0.82		0.70

TABLE 5.5: Basic Technical Outcomes, with acceptance

	V2G Cost	V2G Cost choice	V2G Trans	V2G Trans choice
Mean Peak per day (kWh)	24.0	23.1	23.0	23.6
Times overloaded	172	117	35	111
Percentage Renewable	44.6	37.4	44.0	30.5
Fuel cost (ct/kWh)	1.1	2.65	2.1	4.66
Yearly profit (ct)	24306	12709	21450	4689
Autonomy problems	11.4	5.35	26.0	4.46
Total charged (kWh)	4647	3567	4796	2858
Users		41		12
Mean Acceptance		0.54		-0.29
Median Acceptance		-0.04		-0.20
Variance Acceptance		3.30		1.19

TABLE 5.6: Basic Technical Outcomes, with acceptance

The acceptance and use of the smart EV system The amount of users is on average around the 50%. The V1G option is more used than the V2G option. V2G technology and the transformer optimal algorithms have a lower social acceptance, this can be explained by the higher risk for privacy and autonomy problems. Important is to note the difference between the mean and the median acceptance level for the V2G option with cost optimization. If in this model the average acceptance was the only measure for the KPI of acceptance it might have resulted in a wrong result, as the average is positive, however the median is not. This means that there is a small percentage with a relatively high acceptance level.

Smaller impact on KPI's of smart EV system When the owners stop using the technology the benefits described in the previous paragraph of the smart EV system are not as significant overall. This is logical as a smaller part of the population uses the technology.

Conclusion of step 4

- The model is able to create circumstances in which the owners of the cars can and will choose to reject the technology.
- The results show that the zero acceptance model choice in chapter 4 works.
- The extensions of V2g and network optimal algorithms have a different impact on the KPI's than just the V1G option and should be analyzed separately in chapter 6.

5.5 Step 5: Model analysis

Augusiak, Brink, and Grimm (2014) define model analysis as "the assessment of (1) how sensitive model output is to changes in model parameters (sensitivity analysis), and (2) how well the emergence of model output has been understood. The aim is to understand the model and be able to find out why which output is being produced to avoid drawing the wrong conclusions from model output".

5.5.1 Regression analysis

This step exists out of two parts. The purpose of the first part of the step is to find unexpected change of outputs in comparison with a change of input. The conclusion is drawn in step 2 that there are different dynamics between V1G and V2G. Therefore a regression analysis is ran for both options. Secondly, in step 3 it was concluded that the 3-level conceptual model is new and therefore should be analyzed further. Therefore the initial acceptability and acceptance coefficients are analyzed separately. The sensitivity analyses are executed with the EMA workbench, based on the experiment in table G.1 an can be found in appendix F.

Variable	Lower	Upper
Initial acceptability	-4	4
Profit coefficient	2600	6600
Ren coefficient	0.5	1
Privacy coefficient	0.5	1.5
Autonomy coefficient	2	6

TABLE 5.7: Regression experiment setup 1

Regression analysis results experiment 1 For the V1G and V2G option the correlations are roughly the same. The initial acceptability has the highest correlation with the acceptance as expected. It is interesting to notice the S-curve in the correlation between the acceptability and the amount of users. After a certain initial acceptability (more than 3) the chance is high that everyone will use the smart EV system. The renewable coefficient and privacy coefficient have a high coefficient as well. These are the smaller acceptance coefficients and therefore this was expected. As shown in figure **??** there is a positive relationship between the users, average acceptance, median acceptance and the individual acceptability. As shown in regression analysis in

Variable	Lower	Upper
Friends	2	8
Stay at home	7	21
Mean work distance	11.5	34.5
Charging speed initial	1.8	5.4
Friends importance	0.125	0.375
Percentage EV	12.5	37.5
Memory days	45	135
Stay at home	7	21
Privacy error chance	1	3

TABLE 5.8: Regression experiment setup 2

appendix F the regression coefficient between moral acceptability and social acceptance is high and significant. This fits the hypothesis of moral acceptability. Using prim analysis the interesting cases of the model are identified, for instance the cases where the acceptance is below zero. The prim analysis (Appendix **??** shows that the only variable which determines these cases is the moral acceptability.

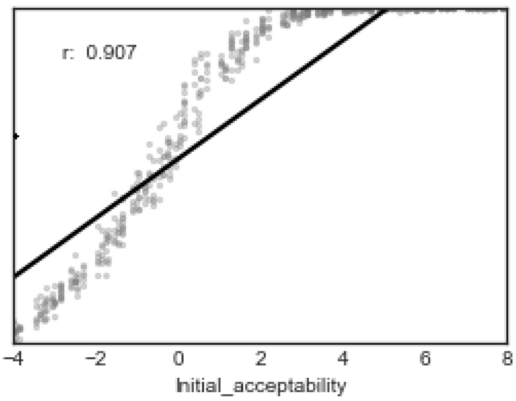

FIGURE 5.2: Correlation between users and initial acceptability

Regression analysis results experiment 2 The acceptance is positively influenced by the memory days and the charging speed, although it has to be noted that the coefficient is not high. The charging speed has a correlation on the peak reduction on the electricity system as already noticed. This is confirmed by the sensitivity analysis for the V1G option, for the V2G option only the distance to work has a significant impact on the peak reduction. The share of renewable energy is correlated with the memory days and the charging speed.

5.5.2 Emergent patterns

The second step is to look at emergent patterns. The model runs for default for a year. If the model is extended to 4 years the patron for social acceptance and users is shown in figure 6.7. This figure shows that at the end of year 1 the all time low is reached and therefore it is a plausible indicator for long term stability as it will not be worse than at the end of year 1. In step 2 the conclusion is made that with a higher renewable intensive energy mix, which due to the energy transition can be expected, will increase the acceptance. Therefore the conclusion is made that if the goals are

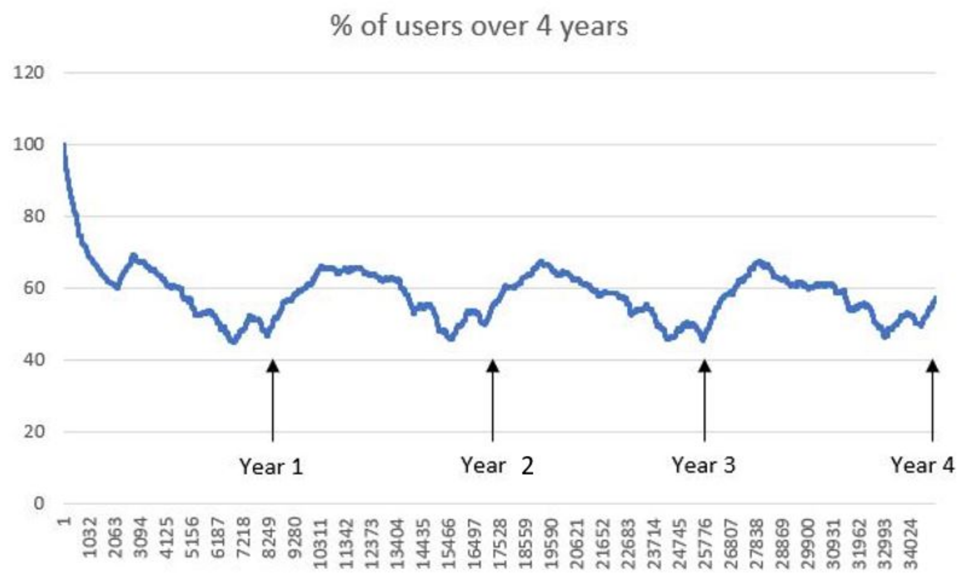

FIGURE 5.3: Average use of smart EV system, V1G, 100 runs of 4 years

reached after year 1 the goals will be reached in the coming years and therefore on long term. However, when taking averages, for instance the average peak load over the first year, it gives a more positive result than it should give in the long=term as at the start the smart EV system is used more than over long-term.

Conclusion of step 5

- Higher charging speed chargers have a positive influence on the acceptance of the users of the system but a negative influence on the load on the system.
- 1 year gives enough indication for long term stability.

5.6 Step 6: Model output corroboration

Augusiak, Brink, and Grimm (2014) define the model output corroboration as “the comparison of model predictions with independent data and patterns that were not used, and preferably not even known, while the model was developed, parameterised, and verified. This step strengthens a model’s credibility by proving that the model is capable of predicting/reproducing pattern and data that could not have influenced the model development”.

There is little independent data and patterns found to use for the corroboration. However, to still do a comparison the data which was found in advance of modelling is used. Mwasilu et al. (2014) mention in their article that most research of V2G reports a profit of around 100-300$ per year, so 253 euro per year in this model seems acceptable. Jochem, Babrowski, and Fichtner (2015) reports a 30% increase of renewable charging with a smart grid. These results indicate that the profit per year and increase renewables give a decent indication compared to other research. This is important as these variables are two important building stones of the 3-level conceptual model.

Conclusion of step 6

- Independent data not found
- Profit and renewable improvements per year plausible outcomes

5.7 Conclusions

The purpose of this validation is to understand how the choices made in chapter 3 and 4 will influence the results of the model. The following conclusions have been made and should be used when analyzing the results:

- A higher initial renewable percentage means a higher fluctuation and higher profit for the V2G option.
- With a higher possible charging speed the load on the grid can be higher, however the cars can also react faster and better to profitable situations. Therefore higher charging speed chargers have a positive influence on the acceptance of the users and a negative influence on the load on the system.
- The smart grid algorithms are simplified and this will decrease the performance of the smart EV system, in reality the smart EV system will perform better on the peak reduction.
- The vehicle to grid algorithm combined with the network optimal algorithm does not work as expected, the peak load is higher than it should be.
- The results show that the zero acceptance model choice designed in chapter 4 works as intended.
- V2g has a a different impact on the KPI's than the V1G option and should be analyzed separately in chapter 6.
- The network optimal algorithm has a different impact on the KPI's than the cost optimal algorithm, the renewable algorithm does not performs worse on all KPI's than the cost algorithm.
- Running the model for 1 year gives enough indication of the long term stability of the system, however averages over the first year are too positive.
- The calculated profit which is generated by the owners is a plausible outcome.
- The amount of errors per technology and algorithm is not based on any scientific data and should be treated carefully.

Chapter 6

Model outcomes

In this chapter the verified results of the model are analyzed. In section 6.1 the technological results are analyzed. In section 6.2 the long-term use of the smart EV system is discussed. In section 6.3 the dynamics of the model are analyzed, identifying circumstances which influence the use of smart EV system in a negative way.

6.1 Analysis of results

6.1.1 Technological results

In chapter 2 the first criteria of the smart EV design has been discussed: *The smart EV system is sufficient to prevent residential capacity upgrades. Insufficiently would mean that the smart EV system would reduce the peak load, however, the same capacity expansion activities are required.*

- The smart EV system has the technical potential to reduce the peak load sufficiently.
- The smart EV system is used sufficiently, there are enough users that the smart EV systems in use reduce the accumulated peak load on the grid sufficiently.

	V1G Cost	V1GTrans	V2G Cost	V2G Trans
Mean Peak per day (kWh)	20.4	20.2	24.0	23.0
Times overloaded	54	0	172	35
Percentage Renewable	40.5	40.9	44.6	44.0
Fuel cost (ct/kWh)	4.7	5.3	1.1	2.1
Yearly profit (ct)	4535	4148	24306	21450
Autonomy problems	3.5	8.7	11.4	26.0
Total charged (kWh)	2311	2447	4647	4796

TABLE 6.1: Basic Technical Outcomes

Based on the technological results a transformer optimal algorithm combined V1G is sufficient to decrease the peak load. However, the autonomy problems are increased for the users of the cars.

Difference between V1G and V2G The amount of users is on average around the 50%. The V1G option is more used than the V2G option. V2G technology has a lower social acceptance, this can be explained by the higher risk for privacy and autonomy problems. In the model it is assumed that the chance for problems is three times as high for V2G than for V1G. If the chance would be lower, for instance twice as

	Base	V1G	V2G
Users		57	41
Mean Acceptance		0.19	0.54
Median Acceptance		0.16	-0.04
Variance Acceptance		0.82	3.3
Mean Peak per day (kWh)	24.79	21.5	23.1
Times overloaded	138	55	117
Percentage Renewable	23.00	33.7	37.4
Yearly profit (ct)	46.43	2829	12709
Autonomy problems	0.07	2.05	5.3

TABLE 6.2: Comparison results V2G and V2G

Higher chance of errors	3	2
Users	41	56
Mean Acceptance	0.54	1.06
Median Acceptance	-0.04	0.40
Variance Acceptance	3.3	4.1

TABLE 6.3: Comparison of higher error chance of V2G to V1G

high, V2G would be as acceptable as V1G (table 6.3. The higher chance of errors is therefore important and should be further analyzed in the future.

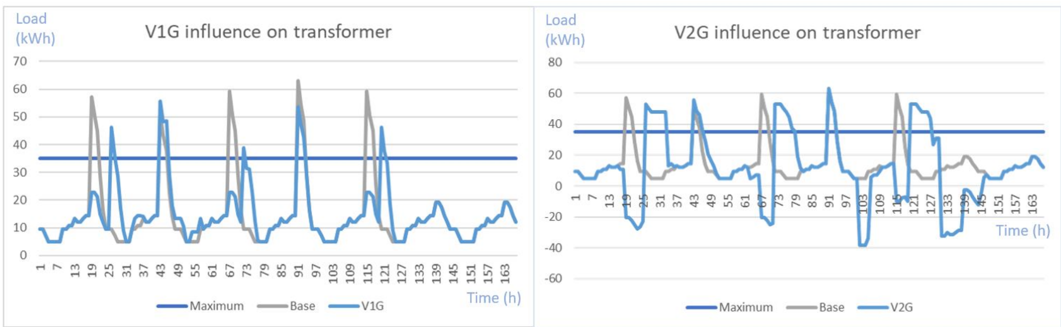

FIGURE 6.1: The different effect on a transformer with V1G and V2G

The peak load for the V2G is higher which is based on the choice for the smart grid algorithm in chapter 4. The algorithm is simplified as the charging speed is the same and the algorithms capability to plan ahead is limited. With an algorithm that plans ahead on costs and renewables as well, altering the charging speed accordingly, the profit could be higher and the peak load lower. In figures 6.1 the difference between the two options is shown. These results are on one transformer for 1 week. A week has been chosen where the influence of the smart grid technologies is significant, there are also weeks where the smart grid technologies have less influence. Both options decrease the peak load on the transformer around 6 pm. However, both options also cause peaks at later moments. With the V2G option it is possible to deliver electricity back to the grid when the peaks would normally be high. The V2G option has the potential to decrease the required flexible energy production options on a national scale.

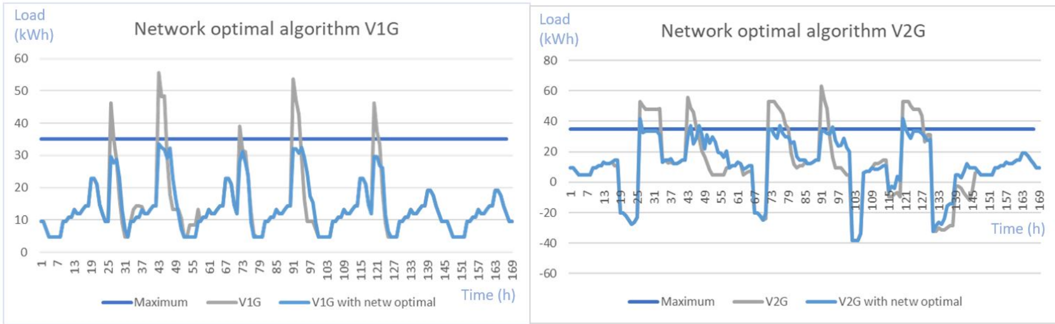

FIGURE 6.2: The different effect on a transformer with a network optimal algorithm

Cost vs Network optimal algorithm As discussed in chapter 5, the times the transformers are overloaded on average each year have the highest variance. This variance is important as peak reduction is the main objective of implementing the smart EV system. If the peak reduction can not be guaranteed, which is the case with a high standard deviation, then the smart EV system is not a robust and therefore viable solution for reducing the peak load. The variance of the peak reduction is reduced significantly when the network optimal algorithm is used. Using the network optimal algorithm should therefore be the optimization tool.

The network optimal algorithm has the potential to decrease the peak load significantly, however the positive experiences for the users are the same and the negative experiences are higher. This is based on the assumption that a network optimal algorithm increases the errors as it is a more complicated algorithm with a higher dependence on data. The second underlying assumption is that the EV owners will focus on their personal experience. From a system level view the overall system costs would be much lower due to the decrease of peak load, which eventually would also be paid be the owners trough taxes. In figure 6.2 the difference between the cost optimal and the network optimal algorithm is shown, the difference is significant and is required for the smart EV system to work.

For the network optimal algorithm to work optimally, everyone with an electric vehicle should use the smart EV system. At 100% the network optimal algorithm can ensure that a transformer never gets overloaded. If 75% of the EV owners use the smart EV system, the network algorithm only reduces the times overloaded under the 10 times a year in 50% of the simulations.

Robustness The times the transformers are overloaded on average each year has the highest variance. This variance is important as peak reduction is the main objective of implementing the smart EV system. This means that the peak reduction can not be guaranteed, due to the high standard deviation. This means that the smart EV system is not a robust and therefore viable solution for reducing the peak load. However, the variance of the peak reduction is reduced significantly when the network optimal algorithm is used.

6.1.2 Reflection on the model outcomes for system design

The purpose of this section was to answer if there is a smart EV system design which is sufficient to prevent residential capacity upgrades.Regarding this objective the contribution of the model are discussed in this section. The first part of this answer is if there is a smart EV system design with the technical potential to reduce the peak load sufficiently.

1. V1G decreases the peak load more than V2G. There are two main causes of the higher peak load reduction. Firstly, with V1G the electricity charged is lower than with V2G, this reduces the load in general and causes less peak moments, which is a valid argument. Secondly, the algorithm which is used for V2G in the model is not as advanced as it should be. Therefore the peak load reduction is not as high as it should be. The conclusion can be drawn that V1G creates less load on the electricity system.

2. Network optimal algorithm is preferred. In this model general capacities are used as it is an abstract case. Real world capacities are required to analyze the impact on the capacities further. However, it can be concluded, based on the model results, that with a cost optimal algorithm still peaks occur which are higher than the capacity. Therefore, from this model, it can be concluded that a network optimal algorithm is preferred.

3. V2G has a higher national influence. Due to the option to supply electricity on the peak moments the V2G option decreases the base peak moments significantly. In some cases the net electricity on the transformers is negative, which means that electricity flows into the national electricity grid. This means that this electricity can be used to reduce the peak supply plants or to sell electricity to other countries.

The second part of the answer is if there is a smart EV system design which is is used sufficiently, there are enough users that the smart EV systems in use reduce the accumulated peak load on the grid sufficiently.

1. V1G has a higher acceptance This is namely caused by the extra errors of V2G. These extra errors are uncertain as discussed in chapter 5. Therefore the conclusion that V1G is more accepted can not be made.

2. V2G makes more profit than V1G. Due to the option to sell electricity at high electricity prices the V2G option generates more profit than the V1G option. In reality this would happen as well, however, due to the fact that the electricity prices is not influenced by the demand or supply of the electric cars, the amount of profit would be lower in reality.

Conclusion The question if there is a smart EV system design which is sufficient to prevent residential capacity upgrades can not be answered with this model. The capacity of the residential grid is different for every neighborhood and therefore none of the design are certainly sufficient. In general reduces the V1G the load on the residential grid more, but the V2G has more potential nationally. The network optimal algorithm is required for a design to be sufficient, however more autonomy problems arise. This shows a trade-off between problems for electricity grid or the transport sector. Based on the characteristics of the technical components used in this model the smart EV system is not used sufficiently to prevent residential capacity upgrades.

6.2 Use in the long-term

In chapter 2 the second criteria of the smart EV design has been discussed: *The smart EV system is used on the long-term.*

- The owners will not change their decision frequently, the DSO's have to know that the capacity of the residential grid will be sufficient at every moment.
- The smart EV system is used on the long-term, the owners will not stop using the smart EV system after a period of time. The DSO's have to be certain that it is not a temporary solution. As, if it would be, investments are necessary right now.

Regarding this criteria, first an important feature of the model conceptualization is highlighted. The EV owner decides based on two things, what he expects (values) and what he experiences. An important feature of the model is that in the model an average EV owner receives what he expected upfront from the smart EV system. How this exactly works is explained in chapter 4.4.2, the key point is that a person with a neutral acceptability, he does not value any of the positive experiences more than the negative experiences, would have an acceptance level of zero. This means that the person is indifferent about using the smart EV system. This means that if a person would have a positive individual acceptability he will eventually accept and use the smart EV system and the other way around. Whether this actually happens, depends on the characteristics of the persons which are heterogeneous, the interaction between the persons and the stochastic behaviour of the model.

The first part of the criteria is that the owners will not change their decision frequently, the DSO's have to know that the capacity of the residential grid will be sufficient at every moment. To understand how the EV owners decide to use the technology and to understand when the EV owner will use the technology in long term the 3-level conceptual model has been developed in chapter 3. Some parts of the theory can be identified in the model. For instance that what a persons values and their actual behaviour does not necessarily align. There are cases in which there are more people positive upfront and still don't use the technology at the end. On individual basis there are sometimes persons who should, based on their morals, use the technology and don't and the other way around as shown in table 6.4. This fits the examples given in chapter 3 where a person does not act to his moral values, so this was expected. The majority of the EV owners act accordingly to their values, as was argued in the Value-Belief-Norm theory.

Positive upfront	Acceptable to unaccepted	Unacceptable to accepted	Act accordingly
10	3	32	65
25	9	32	59
50	16	22	62
75	20	12	68
90	20	4	76

TABLE 6.4: Values and behaviour, V1G based on 1000 runs

Positive upfront	Acceptable to unaccepted	Unacceptable to accepted	Act accordingly
10	5	16	79
25	13	17	70
50	21	13	66
75	24	9	69
90	21	3	76

TABLE 6.5: Values and behaviour, V2G based on 1000 runs

In the 3-level conceptual model it was assumed that a person who acts according their values would be more resilient. Looking at the difference between V1G and V2G there is a small difference. In V2G more people will use according to their values. So given this assumption, V2G would be a more certain choice in the long-term.

The second part of the criteria was that the smart EV system is used on the long-term, the owners will not stop using the smart EV system after a period of time. To answer this another assumption in the 3-level conceptual model is that an acceptable system which is always accepted will be used on the long-term. This assumption was made out of the theories of Social Acceptance and Moral Acceptability. If a system should get accepted and is accepted in every scenario, the system will probably be used in the long-term. In chapter 3 there where examples given that acceptable systems are sometimes not accepted and the other way around.

Acceptable (%)	Accepted%
10	12
25	45
50	81
75	100
90	100

TABLE 6.6: Acceptable and accepted systems, V1G based on 1000 runs

Acceptable (%)	Accepted%
10	0
25	1
50	16
75	88
90	100

TABLE 6.7: Acceptable and accepted systems, V2G based on 1000 runs

In this model, the individual acceptability is used, however it is possible to make the assumption that if the majority of the society thinks the smart EV system is acceptable, the EV smart system is acceptable. The tables 6.6 and 6.7 show that V1G is a better choice in the long term. With an acceptable system where 75% of the society is in favour of the system the system always gets accepted. In contrast to V1G, with V2G the system is only accepted in 88% of the cases. If a majority is negative, so thinks the system is unacceptable, the system is only accepted in 1% of the cases. This is also based on the definition of when a system is accepted, above 50% users. If the majority is higher, the chance is lower, however there is still a chance. This fits with the empirical examples that sometimes systems which are acceptable, are not accepted.

The assumption that, if a majority of the society from an individual perspective thinks the system is acceptable, the system is acceptable should be treated carefully. From a system level view, the overall system costs would be lower in case a network optimal algorithm would be used, however the peak reduction is not an issue for the EV owners which they use in their individual assessment of the system acceptability. This is a choice which is made in this model concept because the EV owners don't experience the peak reduction directly. This could change in case peak reduction would be rewarded with money by for instance contracts with the DSO or if the EV owners would experience black-outs as discussed in section 7.3.

Conclusion On the basis of the results it can be concluded that for system design on the long-term V2G would be a better option as the EV owners act more accordingly to their values. On the other hand, V1G would be a better option because when the V1G design is acceptable it will get accepted more often than the V2G option. In reflection on the theories there is a discrepancy between the individual and general assessment of the acceptability of the system.

6.3 Analysis of model dynamics

In chapter 5 uncertain concepts are identified. The goal of the experiments here is to analyze the model dynamics these uncertain concepts cause and which conclusions can be drawn given the choices and assumptions made in this model. These experiments are done with the EMA workbench using Latin hypercube sampling (LHS). LHS is a statistical method for generating a near-random sample of parameter values from a multidimensional distribution.

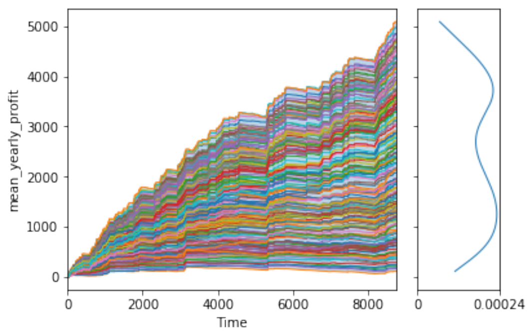

FIGURE 6.3: Profit over the year (V1G)

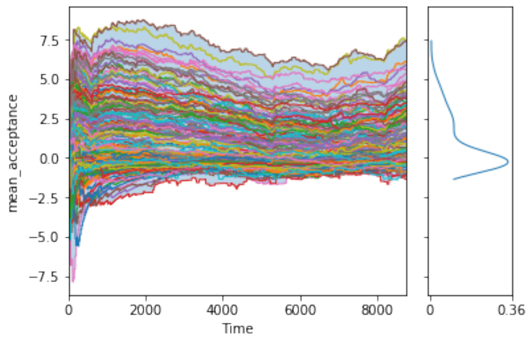

FIGURE 6.4: Acceptance over the year (V1G)

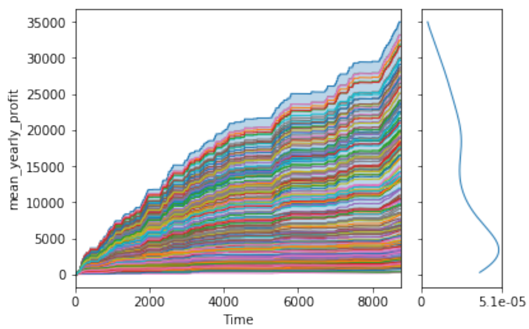

FIGURE 6.5: Profit over the year (V2G)

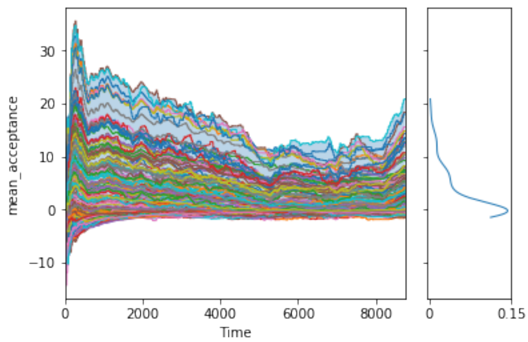

FIGURE 6.6: Acceptance over the year (V2G)

Figure 6.7 shows fast decline at the beginning of the model, this is caused by the EV owners who have a negative experience when they do not have the positive

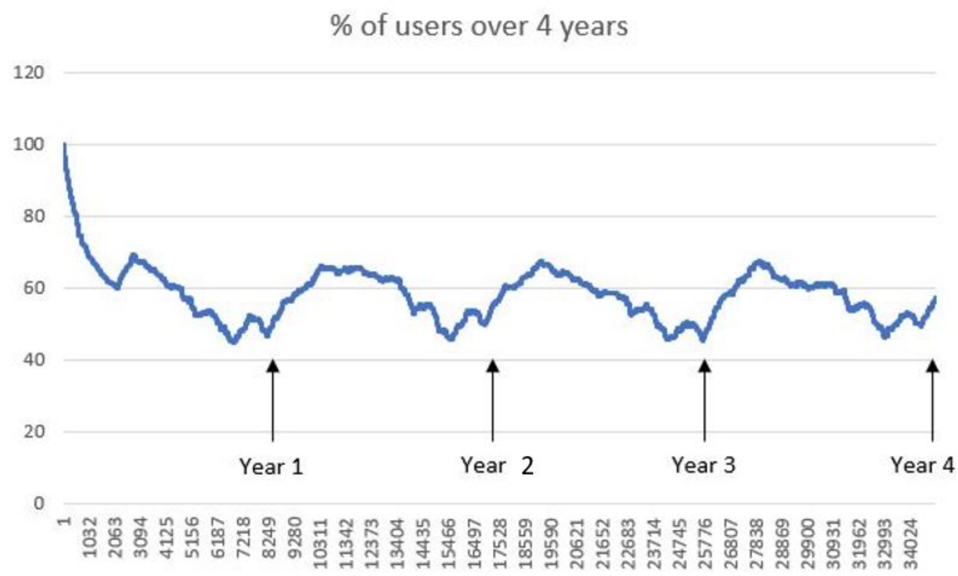

FIGURE 6.7: Average use of smart EV system, V1G, 100 runs of 4 years

experiences yet to compensate. As shown in figure 6.4 the acceptance goes down during the year when using a V1G. This is caused by the uneven distribution of positive experiences the person has during the year. As can be seen from picture 6.3 the profit will stagnate during the model. This is probably caused by the high electricity prices during the summer as discussed in chapter 5. These high electricity prices are caused by the lack of wind during the summer and wind energy is the main renewable and cheap energy source of the Netherlands. This dynamic is also visible if the model is ran for a few years as in 6.7, when the prices go up again the persons start using the technology again due to the positive experiences of their friends. Due to the memory which the persons have (3 months) the high profits and extra renewable energy at the beginning of the year will be forgotten and the social acceptance declines. They forget the positive experiences which balance the negative experiences and their social acceptance will fall below zero. When the social acceptance goes down the people stop using the smart grid. This is an important dynamic as it is based on different assumptions used in the model.

This dynamic is different with a vehicle to grid technology. As the profit which can be made is less dependent on the height of the electricity prices and more on the volatility of the electricity price persons with vehicle to grid technology are able to make an even profit during the year. However, the problem with vehicle to grid technology is the extra peak load on the system. The network optimal algorithm could fix this, as the electricity system the network optimal algorithm decreases the number of times that the transformers are overloaded. However for the individual the profit and renewable energy increase will be the same, but the privacy and especially the autonomy problems increase (as the cars are sometimes not allowed to charge if they need to). The balance between the positive values and negative values is therefore disturbed and the chance of dissatisfied owners is higher. This while for the overall system the costs would be much lower, which eventually would also be paid be the owners by taxes.

Rejection at the start In the model the decline at the beginning is caused by EV owners who have a negative experience and the lack of memory of positive experiences. This is based on the assumption that everyone just starts using the technology at a certain point and have no knowledge of what will happen and react to what they experience. In reality different pilots will have been done and the technology will slowly be introduced. However, it is not unlikely that if the EV owners experience a problem in the early stages of the introduction of the technology they will reject it immediately. It can be concluded that in the early stage of introducing the technology people will stop when they experience problems.

Uneven distribution of positive experiences The uneven distribution of positive experiences is caused by different assumptions and model choices in this model. Firstly, the amount and type of renewable energy sources used to calculate the electricity market price in chapter 4.4.1 which cause a different electricity price during the year. The second cause is the way the positive experiences are calculated in chapter 4.3, a positive experience is calculated based on the comparison to the average cost of a year of the base model without smart grid technology. A comparison with the average cost per day would make the distribution less uneven. This trade-off is also based on the experiences they actually have, which means that the person does not take into account the experiences he does not have. If he would value every day he does not have a privacy or autonomy problem the distribution would also be less uneven. Despite the assumptions made, what can be concluded is: if the electricity prices are uneven distributed in a year and he compares his profit to an average over the year he will experience an uneven distribution of experiences.

Memory As already discussed in chapter 5, the memory of the agents in this model is not based on scientific literature and the default value is therefore uncertain. In this model a memory of 3 months is used and therefore the only conclusion that can be made is: if persons have short term memory and there is an uneven distribution over the year of positive and negative experiences the technology will get probably rejected.

6.4 Conclusions

The question if there is a smart EV system design which is sufficient to prevent residential capacity upgrades can not be answered with this model. The capacity of the residential grid is different for every neighborhood and therefore none of the design are certainly sufficient. In general reduces the V1G the load on the residential grid more, but the V2G has more potential nationally. The network optimal algorithm is required for a design to be sufficient, however more autonomy problems arise. This shows a trade-off between problems for electricity grid or the transport sector. Based on the characteristics of the technical components used in this model the smart EV system is not used sufficiently to prevent residential capacity upgrades.

On the basis of the results it can be concluded that for system design on the long-term V2G would be a better option as the EV owners act more accordingly to their values. On the other hand, V1G would be a better option because when the V1G design is acceptable it will get accepted more often than the V2G option. In reflection on the theories there is a discrepancy between the individual and general assessment of the acceptability of the system.

Chapter 7

System Design Directions

Section 7.1 design choices regarding the model dynamics analyzed in chapter 6.3 are discussed. In section 7.2 the results of chapter 6 and 7.1 are used to identify design directions for technical, institutional and policy research. In chapter 7.3 the limitations of this project are discussed concerning the scope, the 3-level conceptual model and the technical system modelled.

7.1 Analysis of design choices

In this section design options will be discussed based on the conclusions of the previous chapter. The results can be found in appendices K and L. The following choices are discussed:

- Choice 1: Creating a standard profit during the year
- Choice 2: Creating a system where the number of users is fixed
- Choice 3: Create a longer memory
- Choice 4: Increasing initial moral acceptability
- Choice 5: Positive media output
- Choice 6: Try-out phase
- Choice 7: Charging at the office

These choices are each discussed based on the hypothesis, model implementation, results and application in the real world. First the idea behind the design option, the hypothesis is designed. Secondly it is explained how this is implemented in the model. Thirdly, the results are discussed and finally the application of this direction is discussed in the real world.

7.1.1 Choice 1: Standard profits

Hypothesis The purpose of using standard profits is to have a more even profit distribution. A more even distribution would decrease the impact of seasonal differences and would result in a more evenly distributed use of the smart EV technology.

Model implementation This Choice is modelled by taking away the profits the persons would make during the year and distributing them evenly over the year. The average profit which will be made with V1G is 4600 and with V2G technology 25000 (table **??**).

	V1G	1	V2G	1
Users	57	61	41	46
Mean Acceptance	0.19	0.18	0.54	0
Median Acceptance	0.16	0.24	-0.04	0.0
Variance Acceptance	0.82	0.81	3.3	2.7
Mean Peak per day (kWh)	21.5	21.4	23.1	23.1
Times overloaded	55	58	117	115
Percentage Renewable	33.7	34.1	37.4	37.1
Fuel cost (ct/kWh)	5.33	5.30	2.65	2.82
Yearly profit (ct)	2829	2880	12709	11799
Autonomy problems	2.05	2.13	5.3	5.2
Total charged (kWh)	2300	2270	3567	3444.2

TABLE 7.1: Results, Choice 1, based on 100 runs

Results The results are shown in table 7.1. The amount of users is increased, however not significantly. The variance of the acceptance is lowered in the case of V2G which is logical as the profit is based on less randomness and therefore the score of the acceptance level is more evenly distributed, also shown in the decrease of the mean acceptance and a slight increase of the median acceptance.

Real world application For creating a standard profit during the year there are different alternatives. An option is for instance to have feed-in tariffs, extra subsidy when charging at favorable times, which is standardized. A second option could be to have a contract with the DSO or an energy company, where the EV owner does not earn anything daily but gets a monthly payment and the DSO or energy company has the fluctuating daily income.

7.1.2 Choice 2: Fix the amount of users of the smart EV system

Hypothesis The idea is to fix the number of users, for instance on 100%. The idea is that if a persons stops he will not have the positive experiences he would have had if he would have continued. This profit which he misses out on could have compensated the negative experiences he has now. However as they don't use these future profits in their calculation the EV owners stop using the smart EV system. However, if he had no choice he would benefit from these profits and this might make him accept the technology.

Model implementation Every EV owner is a user, regardless their acceptance level.

Results The results of this option are shown in table **??**. The average acceptance is not increased, however the median acceptance is, which means it can be assumed that absolutely more people would accept the technology than without the policy. This means that the hypothesis is confirmed.

Real world application Creating a system where the persons will not stop using their smart grid technology is difficult as the persons who does stop wants to stop at that moment. This means that at the moment the person wants to stop there has to be something binding him. The most extreme solution is to prohibit persons to stop by law, which is questionable as negative experiences might be taken more seriously

	V1G	2	V2G	2
Users	57	100	41	100
Mean Acceptance	0.19	0.18	0.54	0.52
Median Acceptance	0.16	0.43	-0.04	0.63
Variance Acceptance	0.82	1.62	3.3	7.9
Mean Peak per day (kWh)	21.5	20.5	23.1	24.1
Times overloaded	55	53	117	164
Percentage Renewable	33.7	40.6	37.4	44.5
Fuel cost (ct/kWh)	5.33	4.67	2.65	1.08
Yearly profit (ct)	2829	4549	12709	24277
Autonomy problems	2.05	3.43	5.3	11.4
Total charged (kWh)	2300	2304	3567	4658

TABLE 7.2: Results, Choice 2, based on 100 runs

when they are caused by an obligated technology. However, there are also other ideas possible involving contracts between parties. An idea could be that the DSOs would lease the ownership of the batteries from the EV owners or with another procedure. This idea still provides a lot of questions, for example how much will this cost and how will this contract look like. This could be an interesting institutional subject. Another option could be that the use of the EV system is obligated by a company. For example, the car company sells his electric vehicles with a obligated smart EV system. The car company could make a deal with the DSO's or the government for a small payment every vehicle they sell with the smart EV system and make the cars cheaper. This would mean that the initial positive EV owners would buy the car. However, how to enforce such a deal and how much this would cost is a difficult institutional question.

7.1.3 Choice 3: Memory

Hypothesis The idea behind creating a longer memory is to let the person make a decision based on the experiences of a longer period of time. This could work because the person would be less vulnerable to negative experiences. Positive experiences are relatively small but encountered on a more frequent basis than negative experiences and based on shorter period of time these negative experiences are not balanced by the positive experiences.

Model implementation The number of days that the EV owners remembers is set from 90 to 365.

Results The results show that the hypothesis is not true. The number of users goes down and not up. This might be explained by the assumption in this model that someone forgets his negative experience after 3 months and starts using the technology again. A privacy incident has a chance of once a year so there is a chance that this negative experience is forgotten and does not come back for the rest of the year.

Real world application Creating a longer memory is difficult as this is a basic human cognitive skill. However, increasing the amount of information they use in their decision. For example an app which will document the profits over a longer period

	V1G	3	V2G	3
Users	57	40	41	39
Mean Acceptance	0.19	0.18	0.54	0.60
Median Acceptance	0.16	-0.03	-0.04	-0.04
Variance Acceptance	0.82	0.32	3.3	1.8
Mean Peak per day (kWh)	21.5	21.9	23.1	23.2
Times overloaded	55	76	117	121
Percentage Renewable	33.7	33.1	37.4	38.0
Fuel cost (ct/kWh)	5.33	5.4	2.65	2.68
Yearly profit (ct)	2829	2684	12709	12871
Autonomy problems	2.05	1.83	5.3	5.5
Total charged (kWh)	2300	2287	3567	3552

TABLE 7.3: Results, Choice 3, based on 100 runs

of time. However, this means that more data has to be stored and this could cause more privacy problems.

7.1.4 Choice 4: Individual acceptability

Hypothesis As discussed in section 6.1 and 6.3 the initial moral acceptability has the largest influence of the variables on the outcome of the model. A positive moral acceptability will increase the chances of a positive outcome of the model.

Model implementation The individual acceptability is set to 1.

	V1G	4	V2G	4
Users	57	76	41	75
Mean Acceptance	0.19	0.78	0.54	2.53
Median Acceptance	0.16	0.88	-0.04	2.40
Variance Acceptance	0.82	1.00	3.3	6.8
Mean Peak per day (kWh)	21.5	20.9	23.1	23.3
Times overloaded	55	46	117	126
Percentage Renewable	33.7	36.8	37.4	41.5
Fuel cost (ct/kWh)	5.33	5.03	2.65	1.68
Yearly profit (ct)	2829	3621	12709	19066
Autonomy problems	2.05	2.66	5.3	8.6
Total charged (kWh)	2300	2293	3567	4182

TABLE 7.4: Results, Choice 4, based on 100 runs

Results This design option has indeed a positive influence as expected from the analysis in 3.2. The use of the smart EV system increases significantly.

Real world application Improving the individual acceptability is complicated, as these represent moral values of a person and changing these moral values takes time. For instance the importance of environmental sustainability has been growing in the last few decades due to climate change. Improving the individual acceptability is therefore difficult, however as the research into these theory is still developing options might be available in the future.

7.1.5 Choice 5: Extra positive experience

Hypothesis In the society media plays an important role. Using the media to focus on the positive experiences instead of the negative experiences could improve the acceptance of the EV owners as they use the opinion of the media in their consideration.

Model implementation In the model a standard positive output every day is used.

	V1G	5	V2G	5
Users	57	85	41	69
Mean Acceptance	0.19	1.19	0.54	1.54
Median Acceptance	0.16	1.37	-0.04	1.35
Variance Acceptance	0.82	1.24	3.3	5.1
Mean Peak per day (kWh)	21.5	20.6	23.1	23.1
Times overloaded	55	46	117	132
Percentage Renewable	33.7	38.0	37.4	40.4
Fuel cost (ct/kWh)	5.33	4.93	2.65	1.92
Yearly profit (ct)	2829	3904	12709	17219
Autonomy problems	2.05	2.98	5.3	7.7
Total charged (kWh)	2300	2304	3567	4019

TABLE 7.5: Results, Choice 5, based on 100 runs

Results The results show that this option does increase the amount of users of the smart EV system significantly. The acceptance is higher, as expected from the average extra positive experience every day.

Real world application The influence of the media is simplified in the model to an extra positive experience. A positive experience is for instance twice as much profit as expected that day. This simplification is not in line with the real world, as it is unlikely that the someone will let a positive news article influence his decision every single day. Moreover, the influence of the media might not be as high as an extra positive experience every day. As such, this result can not be used to draw a conclusion about the influence of the media. However, the fact that an extra positive experience each day can improve the use of the smart EV system does. An extra positive experience could be the increase of profit and renewable charging. Renewable charging is difficult to improve. However, the profit of the EV owner can be increased externally by for instance a contract with the DSO. If the DSO doubles the profit that the EV owner expects the same result will be reached as in the table shown above.

7.1.6 Choice 6: Try-out phase

Hypothesis If the EV owner has a negative experience when he just started using the technology, he will quit immediately, as he does not yet have any positive experiences to balance this negative experience. Using a try-out phase where the person will not stop using the technology in the first few months could help to bridge these first period without any positive experiences.

Model implementation In the first three months it is impossible for the EV owners to stop using the smart EV system.

	V1G	6	V2G	6
Users	57	57	41	41
Mean Acceptance	0.19	0.19	0.54	0.53
Median Acceptance	0.16	0.15	-0.04	-0.04
Variance Acceptance	0.82	0.83	3.3	3.1
Mean Peak per day (kWh)	21.5	21.3	23.1	23.5
Times overloaded	55	60	117	141
Percentage Renewable	33.7	35.3	37.4	39.7
Fuel cost (ct/kWh)	5.33	5.15	2.65	2.14
Yearly profit (ct)	2829	3283	12709	15681
Autonomy problems	2.05	2.32	5.3	6.4
Total charged (kWh)	2300	2301	3567	3890

TABLE 7.6: Results, Choice 6, based on 100 runs

Results This option does not increase the amount of users of the system on the long-term. Probably due to the short memory in the model the try-out phase has no influence on the long-term.

7.1.7 Choice 7: Charging at office

Hypothesis The idea behind this option is to decrease the electricity that the cars have to charge when they get back from work. This idea comes from Lampropoulos, Vanalme, and Kling (2010).

Model implementation The car is assumed to charge to full at work and will come back home with a full battery minus the electricity used from his work to his house. The charge at their work is not used in cost or renewable calculation.

	V1G	7	V2G	7
Users	57	80	41	80
Mean Acceptance	0.19	0.36	0.54	2.94
Median Acceptance	0.16	0.55	-0.04	2.67
Variance Acceptance	0.82	1.00	3.3	9.8
Mean Peak per day (kWh)	21.5	18.5	23.1	17.2
Times overloaded	55	11	117	41
Percentage Renewable	33.7	38.0	37.4	49.0
Fuel cost (ct/kWh)	5.33	4.75	2.65	-16.16
Yearly profit (ct)	2829	1259	12709	29649
Autonomy problems	2.05	0.11	5.3	1.6
Total charged (kWh)	2300	742	3567	2477

TABLE 7.7: Results, Choice 7, based on 100 runs

Results The results show that this design has a positive benefit on the use of the smart EV system for both V1G and V2G. The cause however is different for the two options. For the V1G the cause is the decrease of autonomy problems. The car is

	V1G	4 7	V2G	4 7
Users	57	88	41	92.9
Mean Acceptance	0.19	0.85	0.54	5.50
Median Acceptance	0.16	0.98	-0.04	5.53
Variance Acceptance	0.82	0.79	3.3	11.35
Mean Peak per day (kWh)	21.5	18.1	23.1	17.63
Times overloaded	55	12	117	59
Percentage Renewable	33.7	40.4	37.4	51.06
Fuel cost (ct/kWh)	5.33	4.50	2.65	-18.13
Yearly profit (ct)	2829	1366	12709	34387
Autonomy problems	2.05	0.12	5.3	1.97
Total charged (kWh)	2300	702	3567	2660

TABLE 7.8: Results, Choice 4 and 7, based on 100 runs

almost full when it gets home and therefore the chance is lower that when the EV owner has to go anywhere suddenly the car is not charged sufficiently. The profit that the EV owner makes is lower, this is caused by the fact that the car ha to charge less when he gets home and therefore can make less profit.

In contrast to V1G, with V2G the EV owner makes a lot more profit. This is caused by the fact that with V2G the car has a lower charging level when he goes to work and is almost full when it gets back. All this extra free electricity can be sold at very high prices during the peak hours when he gets home. In reality the electricity might not be free, however it is not unthinkable that companies would offer their employees free electricity.

Both V1G and V2G have with design 7 a significant impact on the peak reduction. The times that the transformers are overloaded decreases significantly. This is caused by the fact that the vehicles don't have to charge that much, as shown in the table. With V2G it is also possible to feed back the extra energy they got from their work on peak hours to their local grid and decrease the peak.

Real world application In the real world this design would also be applicable, under certain conditions. Free charging at the office is perhaps not realistic, however there are already certain companies who provide their employees with free electricity for their travel costs. Second condition is that the network capacity at the offices is probably also not enough to support charging all the electric vehicles.

As such, it is still an interesting idea to increase the network capacity at certain central locations, charge the cars there and use the cars to decrease the peak load in the residential neighborhoods. The capacity of the residential grid network does not have to be increased. which would save costs, time and labour.

Combination of choices A combination of these choices is possible as well. Choices 4, 5 and 7 scored the best, combining them gives the following results.

Combining the options shows that a very high percentage of users can be achieved. In the V2G scenario the users have an average acceptance of 3.5 which is high. These options should therefore be the objective for the research directions in chapter 7. In section 6.1 it has been concluded that for the network the best option would be to use V2G and a network optimal algorithm. The results of the network optimal algorithm with choice 7 is shown in the following table.

	V1G	5 and 7	V2G	5 and 7
Users	57	89.032	41	85.5
Mean Acceptance	0.19	1.35	0.54	3.56
Median Acceptance	0.16	1.55	-0.04	3.33
Variance Acceptance	0.82	1.11	3.3	9.93
Mean Peak per day (kWh)	21.5	18.05	23.1	17.39
Times overloaded	55	10.77	117	43
Percentage Renewable	33.7	40.56	37.4	49.93
Fuel cost (ct/kWh)	5.33	4.49	2.65	-17.04
Yearly profit (ct)	2829	1368	12709	31707
Autonomy problems	2.05	0.12	5.3	1.76
Total charged (kWh)	2300	698	3567	2558

TABLE 7.9: Results, Choice 5 and 7, based on 100 runs

	V1GTrans	Choice 7	V2GTrans	Choice 7
Users	28	49	12	52
Mean Acceptance	-0.25	-0.27	-0.29	1.11
Median Acceptance	-0.12	0.0	-0.20	0.21
Variance Acceptance	0.70	0.8	1.19	7.3
Mean Peak per day (kWh)	22.9	21.3	23.6	23.1
Times overloaded	75	59	111	41
Percentage Renewable	28.8	48.3	30.5	57.8
Fuel cost (ct/kWh)	6.00	4.08	4.66	-6.60
Yearly profit (ct)	1357	1522	4689	24622
Autonomy problems	2.53	0.1	4.46	0.8
Total charged (kWh)	2341	1133.22	2858	2956

TABLE 7.10: Results, 7, based on 100 runs

The use of the smart EV system is not that high, however the decrease of the times that the transformers are overloaded is still significant. This system is therefore preferred above a system where more EV owners use the smart EV system but the use fluctuates.

7.2 Design directions and research implications

The research objective is to find design directions for the smart EV system which reduce the expected electricity grid problems sufficiently in the long-term. Design directions are defined in this thesis as high-level design choices which lead to directions for future research. An example could be to change the ownership of the EV battery. Design directions could be technical, political or institutional.

On a technological basis, the smart EV system shows promising improvements for the electricity system, reducing the load on the network and improving the amount of green energy used, while giving profit to the owners. The times a transformer is overloaded each year can be reduced by 60% and the used renewable energy can be improved with 80%. Using a network optimal charging algorithm could reduce the amount of times the transformers are overloaded with 70 to 100%. These are the results from a highly abstract case and therefore should be interpreted as an indication for the possibilities of the smart EV system.

7.2.1 Technological Directions

For the technical design, it is important to understand the advantages and disadvantages of the different smart technology options, V1G and V2G. With V2G, the EV owner makes more profit, but the chance of privacy and autonomy problems are higher. How much higher is an important factor. According to the model, V2G is better in case the chance of problems is twice as high as with V1G. However, if the chance for problems is three times as high, the V1G option is better. For the network it would be better when the network optimal algorithm is used as there is less variance in the results of the peak reduction.

In the technical design it is important to take the charging speed into account. When charging speed increases, this could increase the privacy and autonomy problems. But this also provides more possibilities with the algorithm. Charging level has a high impact on the KPI's of the system. This can be explained by the possibility to charge and discharge quickly and effective. For instance if the price is low, the car can charge a larger amount and if the price is high the car can sell a larger amount. The car has also less chance to be empty as it needs less time to charge. However, if the cars can charge more it means that the load per hour has the potential to be higher as well.

For a technical design it would be interesting to analyze a technical system where the vehicles are charged at a central point during the day and discharged during the peak hours in the evening. The results show that this design has a positive benefit on the use of the smart EV system for both V1G and V2G. The times that the transformers are overloaded decrease significantly. This is caused by the fact that the vehicles have to charge less. With V2G it is also possible to feed back the extra energy they got from their work on peak hours to their local grid and decrease the peak. As such, the idea is to increase the network capacity at certain central locations, for example offices. Charging the cars there enables using the cars to decrease the peak load in the residential neighborhoods. The capacity of the residential grid network does not have to be increased, which would save costs, time and labour.

Research has to be done to explore this idea. Uncertainties are how high the network capacity should be at the this central point and if this investment would be profitable. Thereby, it is important that the EV owners will actually use the smart EV system when they get home. If in some streets all the cars use the smart EV system, but in other streets none of the cars use the smart EV system, problems with the capacity are still critical. To take away this uncertainty, institutions have to be made.

7.2.2 Institution Directions

Decreasing the uncertainty is important. Ideally, there is as little fluctuation as possible, as the capacity has to be built for the lowest use of the smart EV system. A way to increase certainty is to take away the choice of the EV owners. Legislation is an option, but obligating the use of the smart EV system could result in public dissatisfaction, so it is probably better to find an option which would benefit more parties. An option would be a contract with the DSO where, in exchange for compensation, you would use the smart EV system.

Another option would be to include the use of the smart EV system in the purchase process of the electric car. Car companies could provide an offer such that the car would be cheaper if you use the smart EV system. The car company then has a deal with the DSO or the government for compensation. The government could also subsidize the electric vehicle if you use the smart EV system, solving the high upfront costs of the electric vehicle as well.

Companies could also decrease the lease costs of a car. This could also be combined with free electricity if you use the smart EV system. Free charging at the office is perhaps not realistic, however, there are companies that already compensate their employees for their travel costs. This means there might be possibilities to negotiate other arrangements. This could also be a DSO, instead of a private company, providing free electricity if you can prove you use the smart EV system.

Another option could be to not use money as an incentive, but comfort, as this was one of the main problems of the EV owners. It is possible to have certain public parking spots, close to malls or city centers, only for EV owners which use the smart EV system. It is also possible to have a discount on public charging for smart EV owners.

A hazard of these proposed solutions is that it has to be actively monitored whether the EV owners actually use their smart EV system. This should be possible, as for every house the data is already there to check if they use the smart EV system. It is possible to register everyone who should use the smart EV system in a database and compare it with the data of the DSO. However, this would mean more data collection and this would require legislation for fines, supervising authorities and other rules. This would require policies.

7.2.3 Policy Directions

The problem with the previously discussed options is that multiple actors are involved and it is uncertain which actor can offer what. The DSO's and therefore the government are the initial actors and should take the lead in increasing the use of the smart EV system. Peak reduction is the most important problem, which the smart EV system solves. The DSO's are the main actors who profit from this peak reduction. An actor analysis is necessary to understand which companies are interested and prepared to play a role. It might be interesting to try to limit the number of actors involved to reduce the time to get to a solution. A technical analysis from the DSO's into the required capacity, profits and technical errors should be done. Based on these facts the business models described could be investigated.

It is also a question of legislation. Currently the electric vehicle is seen as a fully green car, while this is not true, as part of the electricity is not renewable produced. Using the smart EV system, the amount of renewables is increased, but this is not taken into account in the current legislation and labelling of the car. In the current labelling of cars the electric cars have an A label, while in reality this would depend on the composition of electricity used by the cars. If the labelling would differentiate between an electric vehicle with an without a smart EV system, this can be taken into account in the buying process of an EV.

Important for policies is the framing of the smart EV system. Taking away the uncertainty by legislation and using fines to ensure the use of the smart EV system, frames the smart EV system as something which is the users should not want and therefore it is obligated. However, there are enough benefits for the EV owner, he makes money and improves the share of renewable energy he uses. It is important that in the design of the policies for the smart EV system these positive experiences are highlighted. Using subsidies instead of fines could frame the smart EV system differently. This should be taken into account when designing policies for the use of the smart EV system.

7.3 Limitations of the research

While scoping down in chapter 2, conceptualizing in chapter 3 and formalizing in chapter 4, choices are made which shape this research. However, different choices could have been made. This section discusses which choices could have been made differently and how this could improve the model. Options for future research are discussed as well.

7.3.1 Model scope

In this section the choices for the research scope and model environment will be discussed.

Broader geographical scope In the model, the scope is limited to a neighborhood; consequence is that only the local electricity grid is modelled. The impact on the national electricity grid is important as well and the behaviour of the EV owners also has an important emergent impact on this system, which would be interesting as well. This model could be a part of a larger model analyzing the influence on the national electricity grid.

Driving In the model, it is assumed that the persons drive exactly to their work at 8 and come back at 5. However, working from 9 to 5 is getting less standard and this could have an influence on the peak loads of the electricity system. Differences could be the time when the cars leave, come back or how often a person works at home. In this model, the driving procedure is relatively abstract as the cars disappear and electricity is used. Modelling the driving behaviour, for instance traffic, could make the model more realistic.

Different country In this research, the Netherlands is used as an example. A different country would be interesting to analyze as well. Countries differ for instance on electricity prices, share of renewables and average home-work kilometers, which can change the dynamics of the model.

Longer running time In this model, long term acceptance is based on a run of 1 year and running more years will just reproduce the year with the same input electricity price and renewable input. It would be interesting to see what happens if the electricity prices change over the years, which they probably will, due to the energy transition. Furthermore, it would be interesting to use different wind and solar data, to analyze if there are difference between sunny summers and less sunny summers.

7.3.2 Conceptual model

This subsection discusses the choices in the conceptualization steps in chapter 3.2.

concepts for conceptualizing behaviour In this project, the concepts of Moral Acceptability, Social Acceptance and Value-Norm-Belief are used to conceptualize the behaviour of the EV owners. Other concepts could also have been used to explain the behaviour in a different way. There are more concepts in economics, sociology and psychology which could describe the behaviour of the EV owner. Examples are the Diffusion of Innovations Theory (Rogers, 2003), the Expected Utility Theory (Rabin, 2013) and the normative, gain and hedonic goal frames from Lindenberg and Steg (2007) guiding environmental behavior. It would be interesting to use these other concepts and analyze the similarities and differences between the results.

Different combination of social acceptance and acceptability In the conceptualization steps in chapter 3, different parts of the applied theory are used for the 3-level conceptual model. Values are analyzed upfront, the environment influences decisions and social influence is important. This combination could also be approached differently by for instance not combining the two theories and creating two models based on the two different theories which can be compared. Another approach could be to define the conceptual model in a different way, using other definitions of concepts of Social Acceptance and Moral Acceptability. It would be interesting to conceptualize the combination in different ways and analyze if an agent-based model would still give the same outputs.

Experiences In the conceptualization, the trade-off is made between positive and negative experiences. This trade-off is based on the experiences they actually have, which means that the person does not take into account the experiences he does not have. He does not enjoy every day he has no privacy error for example. Changing the way the trade-off is calculated influences the behaviour of the person. If he is extra happy he does not have any privacy errors, as he values them highly, he will still use the smart EV system even when he might not make any profit. Therefore he will more likely accept the smart EV system.

Involving more values In the conceptualization of level 1, individual acceptability, there are 4 values chosen which are used in the model, economic development, environmental sustainability, privacy and autonomy. It is possible to choose different values which can be experienced in the model. An example could be to choose for safety as well involving for instance overheating problems. By involving more values the decision of the people becomes more complicated, which is a choice that can be made.

Memory In this conceptualization, memory plays an important role which is not based on any strong scientific evidence. Research into the impact of the role of memorization in these kind of models could improve the model. As in reality, choices are not always made based on the experiences they encounter in the last period of time, but also the experiences they have had a long time ago or just based on for instance their normal habits that they do not want to change.

Media and social influence The impact of friends and social media is conceptualized as an information source which the persons use to make their decision. However, in the applied theoretical concepts of social acceptance and moral acceptability the social influence goes further, where the persons would react to what others think about their personal actions. This social pressure is not used in this research and could improve the model.

7.3.3 Technical system

This subsection will discuss the assumptions for the technical system made in chapter 3 and 4.

Improved algorithm The smart grid algorithm is simplified as mentioned in chapter 4. With a more difficult algorithm, the charging speed could be altered and a charging plan for a couple of hours could be made. Instead the charging speed is the same in this model and the algorithm only plans ahead based on the time it takes to charge to the minimum charging level. With an algorithm that plans ahead on costs and renewables as well, altering the charging speed accordingly, the profit could be higher and the peak load lower.

Electricity market In the model the imbalance market is outside the scope. However, the imbalance market could be an important source of income for the persons. The profits are now based on the day-ahead prices and calculated each hour. The imbalance market shows great potential as the prices for short term imbalance are high in comparison to the day-ahead prices and this could be an important extra source of income. On the other hand, in reality the extra energy demand of the EVs will have an influence on the electricity price. More demand means a higher price and this could limit the profits the person could make if other EVs start charging as well and the electricity price will get higher.

Electricity black-outs Electricity black-outs could have added an interesting dynamic to the model. If the EV owners do not use the technology and the transformer is overloaded, they might start using the technology again to prevent this. This will be a tough decision as the EV owner might be against the technology and hopes his neighbours will solve the problem. However, if every owner would try to be a 'free rider' they will not be happy either. This could add an interesting dynamic in the agent-based model with more interaction between the neighbours.

7.4 Conclusions

Further research has to focus on increasing the use of the smart EV system and removing the uncertainty of the use of the smart EV system. This research has shown that Agent-Based modelling has the potential to contribute to the academic discussion concerning acceptance and acceptability, which explains some of the uncertain behaviour. A way to decrease the uncertainty is to take away the choice of the EV owners. A possible option is to include the smart EV system when the cars are purchased for a discount. A second option is to make contracts between different parties, where the EV owner benefits from the use of smart EV technology by for example payments, free electricity or better parking spots. A hazard of these proposed solutions is that it has to be actively monitored if the EV owners actually use their smart EV system. For these options it has to be clear which actors could play a role in the smart EV system. A technical analysis from the DSO's into the required capacity, profits and technical errors should be done. Based on these facts the business models described could be investigated. In the current labelling of cars the electric cars have an A label, while in reality this would depend on the composition of electricity used by the cars. Important for policies is the framing of the smart EV system. Taking away the uncertainty by legislation and using fines to ensure the use of the smart

EV system, frames the smart EV system as something which is the users should not want and therefore it is obligated.

Chapter 8

Conclusions

In this chapter the research is concluded on the basis of the sub-questions of chapter 2. The research objective is to find design directions which would increase the use of the smart electric vehicle system and secondly reduce the fluctuation of the use of the smart electric vehicle system. Design directions are defined in this thesis as high-level design choices which lead to directions for future research.

Question 1: How will the use of the smart EV system impact the residential electricity grid and the owners of electric vehicles?
A smart electric vehicle (EV) system is a combination of hardware and software (smart grid technology) which can control the charging progress of the electric car. The smart EV system has potential benefits for peak reduction, grid reliability, environmental improvements and cost reduction. The disadvantages of the smart EV system are privacy and security problems. Furthermore, the EV owners are concerned that due to the smart EV system, the car will not always have a sufficient charging level. The smart EV system can be divided in two different charging modes. One directional charging from the grid to the vehicle (V1G) or bidirectional, from the vehicle to the grid as well (V2G). There is also the decision between cost, renewables or grid optimization. A more advanced algorithm has a higher potential for privacy problems. The algorithms have therefore different impact on the owners of electric vehicles.

Question 2: How do the EV owners decide to use the smart EV system?
The persons morals and their actual behaviour do not necessarily align. The concept 'Social Acceptance' discusses if a technology gets accepted by a community. The concept 'Moral Acceptability' describes if a technology should get accepted by the community. The Value-Belief-Norm theory argues that personal values determine the attitude towards a new technology. In the 3-level concept, a person chooses whether he continues using the smart EV system based on his personal experiences combined with his individual acceptability judgment of the smart EV system. The person decides based on two things, what he expects (values) and what he experiences. Important personal values concerning the smart EV system are economic development, environmental sustainability, privacy and autonomy. If a person has a positive individual acceptability he will accept and use the smart EV system and the other way around based on the conceptual model. Whether this actually happens, depends on the characteristics of the persons which are heterogeneous, the interaction between the persons and the stochastic behaviour of the model.

The acceptance level is important. If the acceptance level is high, it means that there is a smaller chance that the smart EV system will be rejected in the future. The acceptance level is therefore a measure of long-term stability. Moral Acceptability is based on values of the society. In this model, the individual acceptability is used, however it is possible to make the assumption that if the majority of the society thinks the smart EV system is acceptable, the EV smart system is acceptable.

Question 3: Which design choices increase the chance that the smart EV system is sufficient for load reduction in the long term?
First of all, the main criteria of the design of the smart EV system was that it would indeed be sufficient to prevent residential capacity upgrades. In that regard should system design focus on the combination of Vehicle to Grid-technology and a network optimal algorithm. Advantages of this design direction is the option to decrease the current electricity peak as well with vehicle to grid technology, making more profit for the owners in the process as well. The advantage of a network optimal algorithm is that the peaks caused by electrical cars at moments with low electricity cost are minimized. The main disadvantage of this combination is the extra data and control required in the charging process, causing this combination to be less accepted. An analysis of a technical system where the vehicles are charged at a central point during the day and discharged during the peak hours in the evening with V2G. With this procedure, the capacity of the residential grid network does not have to be increased, which would save costs, time and labour.

Secondly, an important criteria of the design of the smart EV system was that it would be a solution in the long-term. In that regard should system design focus on decreasing the uncertainty of the electrical vehicle owner behaviour by creating contracts. The purpose of this contracts should be to know which EV owners will use the smart EV system. A possible option is to include the smart EV system in the purchasing process, offering a discount for EV owners which will use the smart EV system. In the current labelling of cars the electric cars have an A label, while in reality this would depend on the composition of electricity used by the cars. A second option is to make contracts between different parties, where the EV owner benefits from the use of smart EV technology by for example payments, free electricity or better parking spots. A hazard of these options is that it a party has to actively monitor if the EV owners actually use their smart EV system, which could give privacy problems. A solution which causes more privacy problems might be bad.

To conclude, the next steps in research for the system design of the smart EV system should be to involve the actors which could play a role in the smart EV system. A technical analysis from the DSO's into the required capacity, profits and technical errors should be done. Based on these facts business models can be discussed with the concerned actors and policy measures can be discussed with the concerned ministries.

Chapter 9

Reflection

In this chapter, I will reflect on this thesis project. The goal of this reflection is to identify which lessons can be drawn from the project. Identifying these lessons is important to prevent the same errors in similar projects. In this chapter a reflection is executed on the model, the methodology and the process.

9.1 Reflection on the model

In this project a highly abstract case is used. In my opinion this fits the use of an Agent-Based model. However, as more often in my experience with Agent-Based modelling, it is difficult to draw exact conclusions. I already expected this due to my experience with Agent-Based Modelling and therefore the purpose of this research is to find design directions, not actual designs.

The results of the model are interesting and fit this purpose. A research objective of this model was to simulate the difference between acceptability and acceptance and the model is able to do this. The model is generic as different cases can be investigated using different input data. A generic model for an abstract case is in principle logical, however, in my opinion it would have been interesting to focus more on a specific neighborhood. I think this model misses more input data, especially on the network data. How the network looks like, how much capacity each city has is different. It would be interesting to have a specific city or neighborhood where the capacities are known. I have chosen to make this neighborhood more abstract, due to the lack of data and to have a simpler, more generic model. However, I think it would have added value to the technical outcomes if the electricity infrastructure in the model would be based on an existing infrastructure.

Looking back on the model I could have included more interaction between the agents in this model. One of the perks of agent-based modelling is that it offers possibilities to include interactions and more interactions would have caused more emergent behaviour. Secondly it would have been interesting to broaden the model, for instance by including roads and offices. More dynamics could have been analyzed and the model would have more visual impact. In this model the cars disappear when they leave and the colors of the entities change which has not much added value for the interface of the model. It would be an interesting future addition to the model.

9.2 Reflection on the methodology

The methodology had to fit the abstract case which was used in this research. Analyzing the literature about the smart grid technology itself was not difficult. However, analyzing the decision of the EV owners was challenging. Going into the difference between values and behaviour can be abstract and even vague. To understand the different concepts and use parts of these concepts in a logical way was difficult. Eventually, the interpretation of these concepts will be different for every individual. In my opinion the way I used the literature for this subject is logical, however it is plausible that a completely different way can also be defended.

In reflection on the theories used it can be concluded that modelling moral acceptability is difficult in an Agent-Based model. An ABM model is focused on the behaviour and decisions of individual agents. The emergent behaviour of the ABM method is actually a problem for modelling moral acceptability. The macro outcomes, in this case the peak reduction of the system, are outcomes of the combined behaviour of the agents. The agent himself can not value his personal contribution to certain outcomes of the system. As moral acceptability is based on the values of a system itself it is difficult to conceptualize this in a model which is based on decisions of individual agents. Agents in ABM modelling are self-focused and optimize for themselves.

This does not mean in my opinion that moral acceptability is useless in research with an agent-based model. Combining the outcomes of an agent-based model with the theory of moral acceptability actually shows where problems will arise between the acceptability and the acceptance of a system. This can be used in the design of the system. For example, a network optimal algorithm decreases the peak reduction significantly and this makes the system more acceptable. However, it does not make the system more accepted as the individual person does not directly values this effect in his decision making. In system design this has to be taken into account, for instance by designing the system in such a way that the individual agents will take this into account (e.g. black outs) or by changing the decision of the individual agent (e.g. contract offers). These system designs, based on the problems identified with the theory of moral acceptability, can be modelled in the agent-based model.

A second benefit of the use of combination of the theories, in comparison with for instance the theory of diffusion of innovation (Rogers, 2010), is that it goes further than the adoption of the smart EV system. The average acceptance of the different technological designs gives an indication on how long this technology will be used by the EV owners. This feature is important as the smart EV system will only be a solution for the peak load problem if the smart EV system is indeed consistently on the long term.

ABM is in my option the tool to understand these kinds of choices between centralizing and decentralizing. The creation of local communities in the energy transition is a topic of discussion and I think ABM can contribute to the research into this subject. However, this could be a biased opinion as I already decided I would like to use ABM in advance of the project. Due to the abstractness of the case and the lack of data the validation was difficult. I think the evaludation method was helpful for this problem. Due to the evaludation method I am confident that my model does what it was intended to do in chapter 4.

In the use of the EMA workbench I noticed that I lacked basic knowledge about

Python. The idea of using the EMA workbench for uncertainty caused by the conceptual choices in chapter 3 and 4 is good, however not implemented enough in this Thesis. Further analysis into the cases where system acceptability and acceptance don't align would have an added benefit for the project.

9.3 Reflection on the process

Due to the abstract case the most challenging part of this thesis was the academical writing. Academic writing, being clear in what I have done and why, was challenging as the subject was abstract. Especially the concepts of Social Acceptance and Moral Acceptability are difficult to grasp and ambiguous. It was difficult to find a way to combine these concepts into the Agent-Based model as was the challenge given at start of my thesis. In my opinion is the case I used to simulate these two concepts, the smart EV system, important and a challenging problem for the future.

I made the conscious decision to write my thesis at the university to find more support for the academic writing. However, the design directions of the smart EV system would have been interesting for DSO's as well and it might have been a missed opportunity that I did not involve the DSO's in my project. DSO's would have added more input data and maybe other concerns or options that I did not consider.

Another missed opportunity might be the use of the EMA workbench. Due to the time-line I used a very limited number of features of the EMA workbench and there are more possibilities which would have been interesting. Exploring the possibilities of the workbench took a lot of time and if I had more experience in Python I could have used more extensive analysis.

Overall, I am pleased with the research that I did in this project. The model is able to show the difference between Social Acceptance and Moral Acceptability, which was the initial research objective given at the start of the project. Furthermore the dynamics of the model show interesting guidelines for future research, which were not yet identified in previous literature. The knowledge I gained during this project is important for me personally as well. After my graduation I will start my job in the electrical infrastructure and mobility and the lessons learned from this thesis will help me in my further career.

Appendix A

Value description of Ligtvoet et al.

Table 8.2 Overview of 23 values that we found in the value sensitive design literature

Value	Description
Accountability	The system allows for tracing the activities of individuals or institutions
Autonomy	The system allows for its users to make their own choices and choose their own goals
Calmness	The system promotes a peaceful and quiet state
Cooperation	The systems allows for its users to work together with others
Correctness	The systems processes the right information and performs the right actions
Courtesy	The system promotes treating people with politeness and consideration
Democracy	The system promotes the input of stakeholders
Economic development	The system is beneficial to the economic status/finances of its users
Efficiency	The system is effective given the inputs
Environmental sustainability	The system does not burden ecosystems, so that the needs of current generations do not hinder future generations
Freedom from bias	The system does not promote a select group of users at the cost of others
Identity	The system allows its users to maintain their identity, shape it, or change it if required
Informed consent	The systems allows its users to voluntarily make choices, based on arguments
Legitimacy	The system is deployed on a legal basis or has broad support
Ownership	The system facilitates ownership of an object or of information and allows its owner to derive income from it
Participation	The system promotes active participation of its users
Privacy	The system allows people to determine which information about the is used and communicated[a]
Reliability	The system fulfils its purpose without the need to control or maintain it
Safety and health	The system does not harm people
Tractability	The functioning of the system can be traced
Trust	The system promotes trust in itself and in its users
Universal usability	The system can be easily used by all (foreseen) users
Welfare	The system promotes physical, psychological, and material well-being

[a] We acknowledge that this is a limited definition of privacy

FIGURE A.1: Value descriptions of Ligtvoet et al., 2015

Appendix B

Model layout

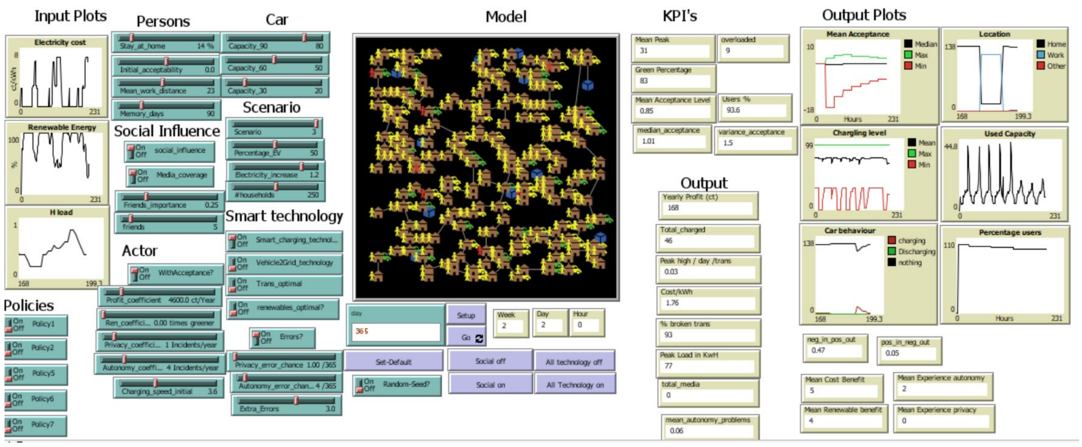

FIGURE B.1: Model layout - overview

In this appendix the model is shown. In figure B.1 the whole model is shown. On the left it is possible to change the input parameters and make different experimental setups (figure B.2. In the middle the representation of the neighborhood is shown (figure B.3. On the right the results of the model are shown (figure B.4. The KPI results can be found on top and the other outputs are used for the understanding of the model.

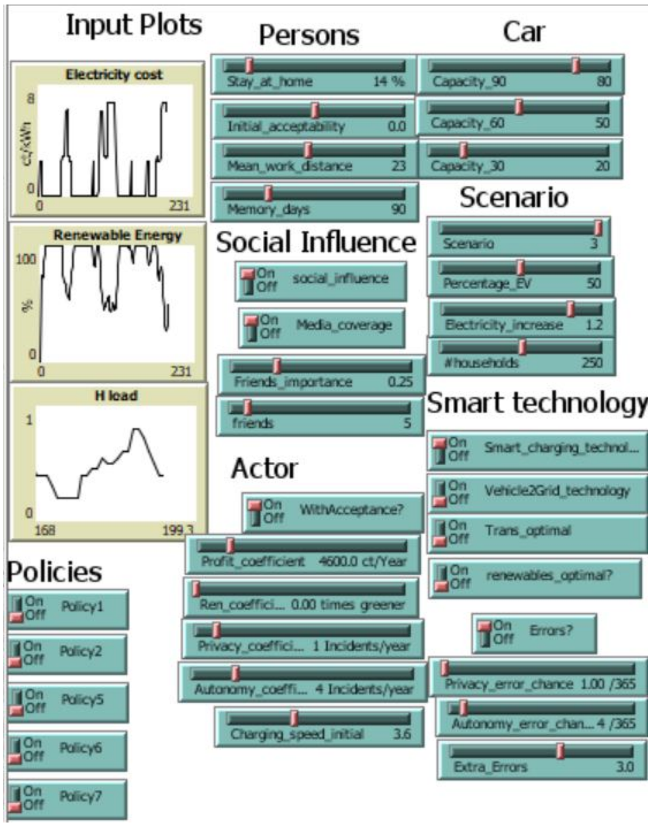

FIGURE B.2: Model layout - Input

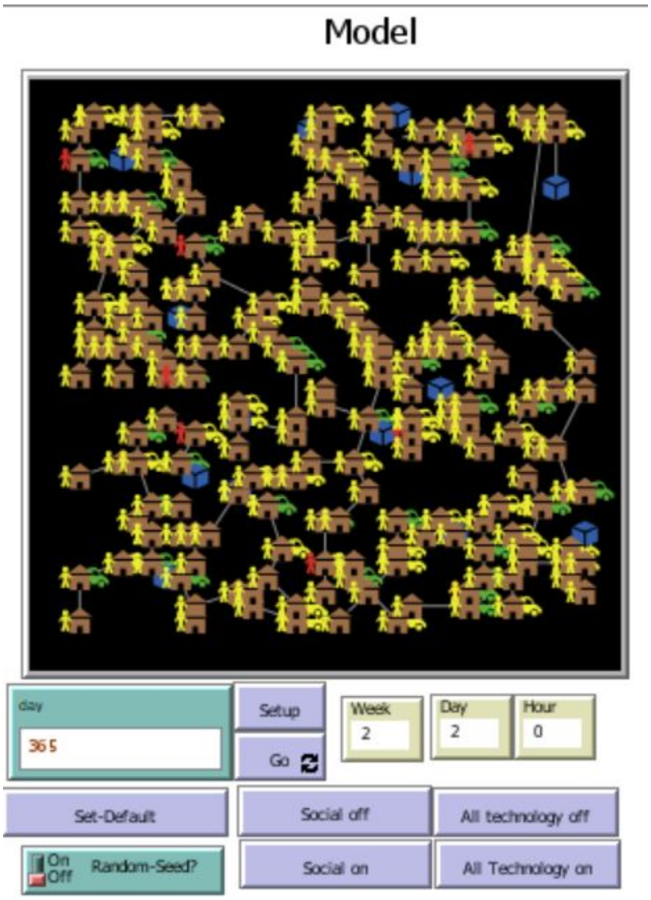

FIGURE B.3: Model layout - Model

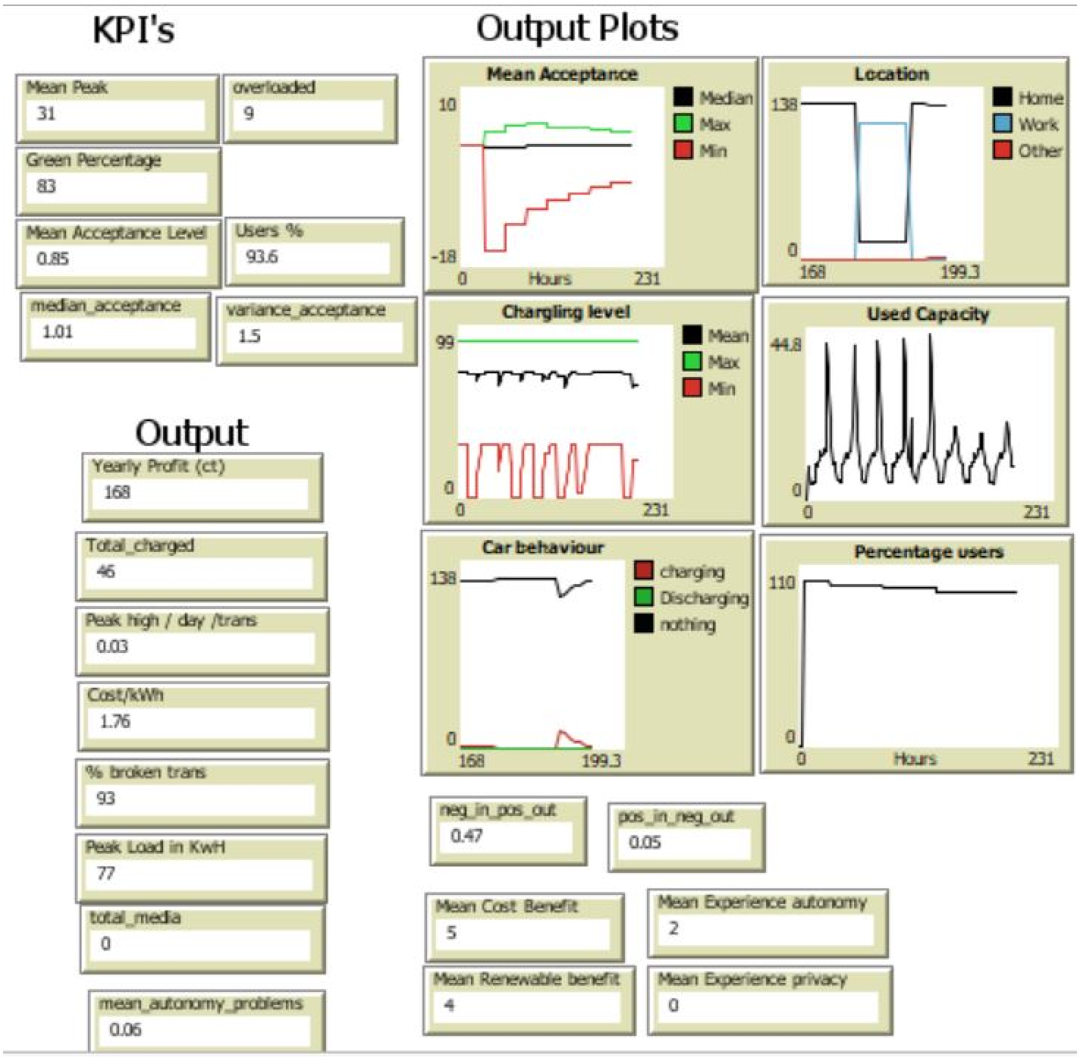

FIGURE B.4: Model layout - Output

Appendix C

Default values

This appendix shows the default values which are used in the model. Furthermore it is shortly explained why they are chosen.

Input	Default	Why	Source
Initial Acceptability	0		
Scenario	2	This is the default scenario as it is the most interesting (more cars than scenario 1), but also more realistic than scenario 3.	
Memory days	90		
Stay at home chance	14%	Average in the NL	(Rameakers, 2017)
Percentage EV	15%	Currently 0.25% which is not interesting for the model. 50% in 2030?	Evrijders.nl
#households	250		
Capacities	20 – 30kWh 50 – 60kWh 80 – 90kWh	Currently top BEV in nl: 2000 BWM i3 (28 kWh) 5000 Nissan Leaf/Renault Zoe (60 kWh) (new ones) Tesla model S (90 kWh)	(RVO, 2017)
Error chance	1 privacy incident and 4 autonomy incidents per year with a multiplier of 3 for more functions (v2g and transoptimal)	It is assumed that problems with charging the car occur more often as it is more dependent of the customer. Thereby, it is assumed that as the smart grid has more functions, more errors will occur.	
Coefficients	4000 profit 1 renewable 1 privacy incident 4 autonomy incident	Based on a zero final acceptance model	
Charging speed	3.6 kWh/h	Standard house connection	Groen7.nl
kWh/km	0.2 kWh/km	Average of 0.08-03	Gaslicht.com
Friends	5		
Friend_importance	0.25		
Work Distance	Random 45 km	Average of nl = 22.5	(autorai.nl)

FIGURE C.1: Default Values

Appendix D

ODD + D Protocol

Outline (→ template)		Guiding questions	Own ODD+D Model description
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	The purpose of this research is to design a robust electricity system in the future when electric vehicles are the norm and a solution is found for the capacity problems of the grid by using smart grid technology.
		I.ii.b For whom is the model designed?	Scientists, Decision makers
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	Cars, Houses, Persons, Transformers
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	Figure 4.3, chapter 4.2.3
		I.ii.c What are the exogenous factors / drivers of the model?	Available Electricity, Smart grid algorithm
		I.ii.d If applicable, how is space included in the model?	Not included
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	One-time step represents one hour, and the simulation is run for 1 year.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	Transformers provide the cars and houses with electricity. Cars drive the person to their destination and charge their battery. Persons decide to use the technology.
II) Design Concepts	II.i Theoretical and Empirical Backgroun d	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	Social Acceptance, Moral Acceptability, Consumer behavior
		II.i.b On what assumptions is/are the agents' decision model(s) based?	3-level acceptance concept, which is developed in this thesis, based on the theories of social acceptance and moral acceptability.
		II.i.c Why is a/are certain decision model(s) chosen?	The concept is developed such that the difference between social acceptance and moral acceptability can be found.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	-
		II.i.e At which level of aggregation were the data available?	-

FIGURE D.1: ODD part 1

Outline (→ template)		Guiding questions	Own ODD+D Model description
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	The purpose of this research is to design a robust electricity system in the future when electric vehicles are the norm and a solution is found for the capacity problems of the grid by using smart grid technology.
		I.ii.b For whom is the model designed?	Scientists, Decision makers
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	Cars, Houses, Persons, Transformers
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	Figure 4.3, chapter 4.2.3
		I.ii.c What are the exogenous factors / drivers of the model?	Available Electricity, Smart grid algorithm
		I.ii.d If applicable, how is space included in the model?	Not included
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	One-time step represents one hour, and the simulation is run for 1 year.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	Transformers provide the cars and houses with electricity. Cars drive the person to their destination and charge their battery. Persons decide to use the technology.
II) Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	Social Acceptance, Moral Acceptability, Consumer behavior
		II.i.b On what assumptions is/are the agents' decision model(s) based?	3-level acceptance concept, which is developed in this thesis, based on the theories of social acceptance and moral acceptability.
		II.i.c Why is a/are certain decision model(s) chosen?	The concept is developed such that the difference between social acceptance and moral acceptability can be found.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	-
		II.i.e At which level of aggregation were the data available?	-

FIGURE D.2: ODD part 2

	Outline (→ template)	Guiding questions	Own ODD+D Model description
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	The purpose of this research is to design a robust electricity system in the future when electric vehicles are the norm and a solution is found for the capacity problems of the grid by using smart grid technology.
		I.ii.b For whom is the model designed?	Scientists, Decision makers
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	Cars, Houses, Persons, Transformers
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	Figure 4.3, chapter 4.2.3
		I.ii.c What are the exogenous factors / drivers of the model?	Available Electricity, Smart grid algorithm
		I.ii.d If applicable, how is space included in the model?	Not included
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	One-time step represents one hour, and the simulation is run for 1 year.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	Transformers provide the cars and houses with electricity. Cars drive the person to their destination and charge their battery. Persons decide to use the technology.
II) Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	Social Acceptance, Moral Acceptability, Consumer behavior
		II.i.b On what assumptions is/are the agents' decision model(s) based?	3-level acceptance concept, which is developed in this thesis, based on the theories of social acceptance and moral acceptability.
		II.i.c Why is a/are certain decision model(s) chosen?	The concept is developed such that the difference between social acceptance and moral acceptability can be found.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	-
		II.i.e At which level of aggregation were the data available?	-

FIGURE D.3: ODD part 3

Appendix E

Validation

In this appendix the results of the validation steps in chapter 5 are shown.

Input	Hypothesis	Test	Check	Cause	Solved
Hload	Hload every day same?	Visual comparison at 2 days	✔		
Ecost	E-cost > 0	Graph	✔		
Renewables	Renewable >0 and <1	Graph	X	Excess renewable energy	✔
Initial Acceptability	Acceptability influences acceptance	Difference -5 and + 5 in acceptance	✔		
Scenarios	Higher input green means higher output green	Comparing 1,2,3 scenario on green percentage	✔		
Memory days					
Stay at home chance	Selling more electricity with V2G	Lower cost at 90% than 10%	✔		
Percentage EV	Higher percentage means more overload	Comparing mean peak load at 10% to 70%	✔		
#households	More households shouldn't chance mean peak load	Comparing peak load at Households 100 – 250	✔		
Capacities	Lower capacity should encounter more autonomy troubles	Capacities to 30 kWh	✔		
Error chance	Higher error chance leads to higher number of problems	Autonomy chance 4-> 8, problems should double with stay at home 0%.	X	Errors are made, but not experienced. Car got charged before error was experienced. + Weekend no problem	✔
Coefficients	Lower profit expectation should lead to a higher acceptance, vice versa for incidents	Profit expectation from 4750 to 1000, higher acceptance?	✔		
Charging speed	Higher charging speed should lead to higher peaks	Charging speed to 15	✔		

FIGURE E.1: Verification input

Procedures	Hypothesis	Test	Check	Cause	Solved
(dis)Charging	Hload every day same?	Charging level >0 and <100%	✓		
Driving	E-cost > 0	Graph	✓		
	Random leaving	Printing x	✓		
Smartgrid decision	Switches work correctly	Printing x in the decision tree where it is not supposed to go			
	Improvement by technology	Smart grid: peak down V2G: cost down Trans: % dead trans down	✓		
Actor Decision	In basic model positive acceptance (as no errors)	Over 100 runs, acceptance positive with a memory of 12 months and no errors	✓		
	Zero acceptance at smart grid true	Over 100 runs, acceptance zero with a memory of 12 months, no errors and no quitting	✓		
Errors	Avg errors over year = input	Counting the errors per person	✓		
Update-colour	Colors should be as designed	Sample of agents	✓		
Connect Houses	Houses with 2 trans	Monitor of max of houses	✓		
	Trans with avg 15	Monitor of avg of trans	✓		

FIGURE E.2: Verification Procedures

Input	Uncertain?	Investigate?	Important?	Why
Hload	No			Average of the NL over the years
Initial Acceptability	Yes	Yes	Yes	Has the highest correlation with acceptance
Scenario	Yes	No		This variable is uncertain, however the output changes as expected based on the input.
Memory days	Yes	Yes	Yes	A larger memory in combination with design options shows potential
Stay at home chance	Yes	Yes	No	As flex working is becoming more popular this could influence the model, however not significant for acceptance
Percentage EV	Yes	Yes	No	Growth of EV cars is uncertain, however not significant for acceptance
#households	No			Will not change the output
Capacities	Yes	No		Shows as expected that more problems arise when there are more cars with a lower battery
Error chance	Yes	Yes		
Coefficients	Yes	Yes	Yes	Based on a zero final acceptance model
Charging speed	Yes	Yes	Yes	Standard house connection
kWh/km	No			Average of 0.08-03
Friends	Yes	Yes	No	Not significant
Friend importance	Yes	Yes	No	Not significant
Work Distance	Yes	Yes	No	Not significant

FIGURE E.3: Verification Procedures

Appendix F

Sensitivity analysis

This appendix shows the results of the sensitivity analysis in chapter 6.1. The experimental setup of the experiments is shown in table G.1.

Uncertainty sampling	SOBOL
Uncertainties	Experiment design 1
Runs	1400
Particularities	None

TABLE F.1: LHS design

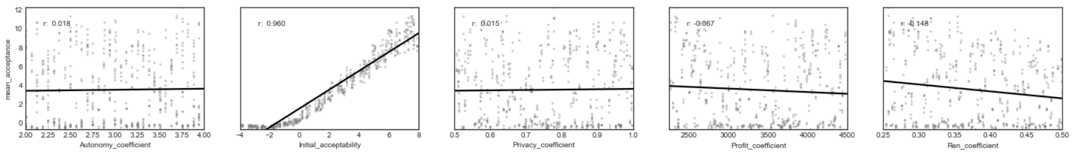

FIGURE F.1: Sensitivity plots acceptance (V1G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.943
Model:                            OLS   Adj. R-squared:                  0.943
Method:                 Least Squares   F-statistic:                     1645.
Date:                Thu, 19 Jul 2018   Prob (F-statistic):               0.00
Time:                        00:21:57   Log-Likelihood:                -755.77
No. Observations:                 600   AIC:                             1526.
Df Residuals:                     593   BIC:                             1556.
Df Model:                           6
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     4.5725      0.383     11.948      0.000       3.821       5.324
Autonomy_coefficient     -0.0287      0.061     -0.473      0.636      -0.148       0.090
Initial_acceptability     0.9955      0.010     97.878      0.000       0.975       1.015
Privacy_coefficient       0.7680      0.243      3.155      0.002       0.290       1.246
Profit_coefficient       -0.0003   5.42e-05     -6.285      0.000      -0.000      -0.000
Ren_coefficient          -6.2593      0.489    -12.811      0.000      -7.219      -5.300
scenario_id           -2.968e-05      0.000     -0.147      0.884      -0.000       0.000
==============================================================================
Omnibus:                       56.096   Durbin-Watson:                   1.192
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               69.433
Skew:                           0.807   Prob(JB):                     8.37e-16
Kurtosis:                       3.411   Cond. No.                     5.42e+04
==============================================================================
```

FIGURE F.2: Regression acceptance (V1G)

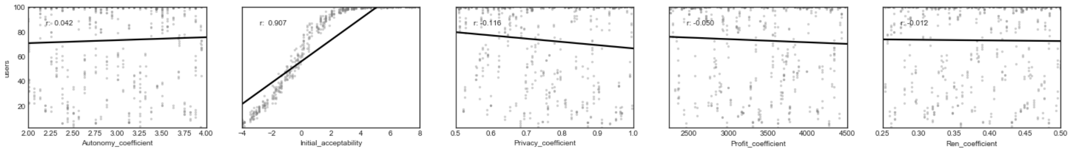

FIGURE F.3: Sensitivity plots users (V1G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.943
Model:                            OLS   Adj. R-squared:                  0.943
Method:                 Least Squares   F-statistic:                     1645.
Date:                Thu, 19 Jul 2018   Prob (F-statistic):               0.00
Time:                        00:22:07   Log-Likelihood:                -755.77
No. Observations:                 600   AIC:                             1526.
Df Residuals:                     593   BIC:                             1556.
Df Model:                           6
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     4.5725      0.383     11.948      0.000       3.821       5.324
Autonomy_coefficient     -0.0287      0.061     -0.473      0.636      -0.148       0.090
Initial_acceptability     0.9955      0.010     97.878      0.000       0.975       1.015
Privacy_coefficient       0.7680      0.243      3.155      0.002       0.290       1.246
Profit_coefficient       -0.0003   5.42e-05     -6.285      0.000      -0.000      -0.000
Ren_coefficient          -6.2593      0.489    -12.811      0.000      -7.219      -5.300
scenario_id           -2.968e-05      0.000     -0.147      0.884      -0.000       0.000
==============================================================================
Omnibus:                       56.096   Durbin-Watson:                   1.192
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               69.433
Skew:                           0.807   Prob(JB):                     8.37e-16
Kurtosis:                       3.411   Cond. No.                     5.42e+04
==============================================================================
```

FIGURE F.4: Regression users (V1G)

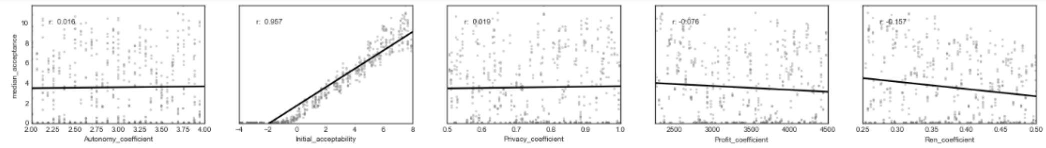

FIGURE F.5: Sensitivity plots median acceptance (V1G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.943
Model:                            OLS   Adj. R-squared:                  0.943
Method:                 Least Squares   F-statistic:                     1645.
Date:                Thu, 19 Jul 2018   Prob (F-statistic):               0.00
Time:                        00:21:40   Log-Likelihood:                -755.77
No. Observations:                 600   AIC:                             1526.
Df Residuals:                     593   BIC:                             1556.
Df Model:                           6
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                      4.5725      0.383     11.948      0.000       3.821       5.324
Autonomy_coefficient      -0.0287      0.061     -0.473      0.636      -0.148       0.090
Initial_acceptability      0.9955      0.010     97.878      0.000       0.975       1.015
Privacy_coefficient        0.7680      0.243      3.155      0.002       0.290       1.246
Profit_coefficient        -0.0003   5.42e-05     -6.285      0.000      -0.000      -0.000
Ren_coefficient           -6.2593      0.489    -12.811      0.000      -7.219      -5.300
scenario_id            -2.968e-05      0.000     -0.147      0.884      -0.000       0.000
==============================================================================
Omnibus:                       56.096   Durbin-Watson:                   1.192
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               69.433
Skew:                           0.807   Prob(JB):                     8.37e-16
Kurtosis:                       3.411   Cond. No.                     5.42e+04
==============================================================================
```

FIGURE F.6: Regression median acceptance (V1G)

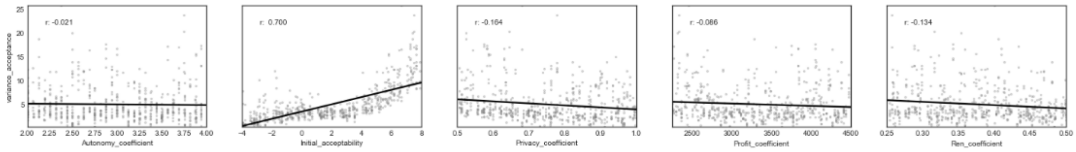

FIGURE F.7: Sensitivity plots variance acceptance (V1G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.943
Model:                            OLS   Adj. R-squared:                  0.943
Method:                 Least Squares   F-statistic:                     1645.
Date:                Thu, 19 Jul 2018   Prob (F-statistic):               0.00
Time:                        00:20:36   Log-Likelihood:                -755.77
No. Observations:                 600   AIC:                             1526.
Df Residuals:                     593   BIC:                             1556.
Df Model:                           6
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     4.5725      0.383     11.948      0.000       3.821       5.324
Autonomy_coefficient     -0.0287      0.061     -0.473      0.636      -0.148       0.090
Initial_acceptability     0.9955      0.010     97.878      0.000       0.975       1.015
Privacy_coefficient       0.7680      0.243      3.155      0.002       0.290       1.246
Profit_coefficient       -0.0003   5.42e-05     -6.285      0.000      -0.000      -0.000
Ren_coefficient          -6.2593      0.489    -12.811      0.000      -7.219      -5.300
scenario_id           -2.968e-05      0.000     -0.147      0.884      -0.000       0.000
==============================================================================
Omnibus:                       56.096   Durbin-Watson:                   1.192
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               69.433
Skew:                           0.807   Prob(JB):                     8.37e-16
Kurtosis:                       3.411   Cond. No.                     5.42e+04
==============================================================================
```

FIGURE F.8: Regression variance acceptance (V1G)

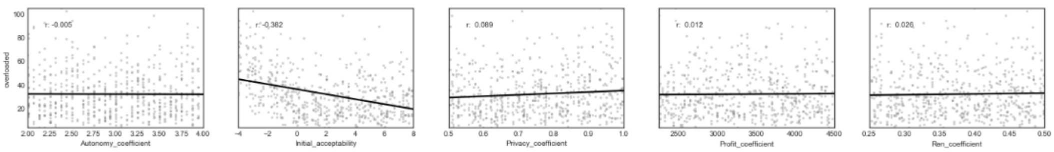

FIGURE F.9: Sensitivity plots overloaded (V1G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.943
Model:                            OLS   Adj. R-squared:                  0.943
Method:                 Least Squares   F-statistic:                     1645.
Date:                Thu, 19 Jul 2018   Prob (F-statistic):               0.00
Time:                        00:28:14   Log-Likelihood:                -755.77
No. Observations:                 600   AIC:                             1526.
Df Residuals:                     593   BIC:                             1556.
Df Model:                           6
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     4.5725      0.383     11.948      0.000       3.821       5.324
Autonomy_coefficient     -0.0287      0.061     -0.473      0.636      -0.148       0.090
Initial_acceptability     0.9955      0.010     97.878      0.000       0.975       1.015
Privacy_coefficient       0.7680      0.243      3.155      0.002       0.290       1.246
Profit_coefficient       -0.0003   5.42e-05     -6.285      0.000      -0.000      -0.000
Ren_coefficient          -6.2593      0.489    -12.811      0.000      -7.219      -5.300
scenario_id           -2.968e-05      0.000     -0.147      0.884      -0.000       0.000
==============================================================================
Omnibus:                       56.096   Durbin-Watson:                   1.192
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               69.433
Skew:                           0.807   Prob(JB):                     8.37e-16
Kurtosis:                       3.411   Cond. No.                     5.42e+04
==============================================================================
```

FIGURE F.10: Regression overloaded (V1G)

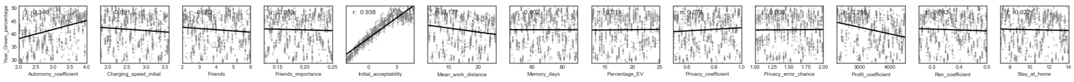

FIGURE F.11: Sensitivity plots green percentage (V1G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.943
Model:                            OLS   Adj. R-squared:                  0.943
Method:                 Least Squares   F-statistic:                     1645.
Date:                Thu, 19 Jul 2018   Prob (F-statistic):               0.00
Time:                        00:29:53   Log-Likelihood:                -755.77
No. Observations:                 600   AIC:                             1526.
Df Residuals:                     593   BIC:                             1556.
Df Model:                           6
Covariance Type:            nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
const                       4.5725      0.383     11.948      0.000       3.821       5.324
Autonomy_coefficient       -0.0287      0.061     -0.473      0.636      -0.148       0.090
Initial_acceptability       0.9955      0.010     97.878      0.000       0.975       1.015
Privacy_coefficient         0.7680      0.243      3.155      0.002       0.290       1.246
Profit_coefficient         -0.0003   5.42e-05     -6.285      0.000      -0.000      -0.000
Ren_coefficient            -6.2593      0.489    -12.811      0.000      -7.219      -5.300
scenario_id             -2.968e-05      0.000     -0.147      0.884      -0.000       0.000
==============================================================================
Omnibus:                       56.096   Durbin-Watson:                   1.192
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               69.433
Skew:                           0.807   Prob(JB):                     8.37e-16
Kurtosis:                       3.411   Cond. No.                     5.42e+04
==============================================================================
```

FIGURE F.12: Regression green percentage (V1G)

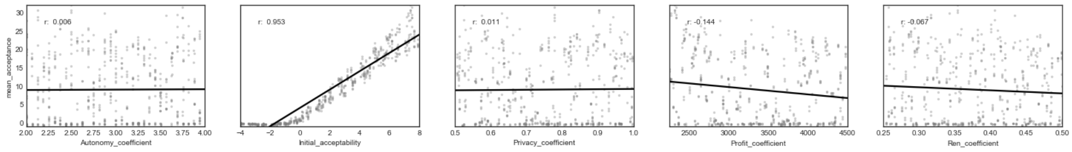

FIGURE F.13: Sensitivity plots acceptance (V2G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.931
Model:                            OLS   Adj. R-squared:                  0.930
Method:                 Least Squares   F-statistic:                     1334.
Date:                Thu, 19 Jul 2018   Prob (F-statistic):               0.00
Time:                        00:41:27   Log-Likelihood:                -1367.8
No. Observations:                 600   AIC:                             2750.
Df Residuals:                     593   BIC:                             2780.
Df Model:                           6
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                    11.6325      1.061     10.960      0.000       9.548      13.717
Autonomy_coefficient     -0.2209      0.168     -1.313      0.190      -0.551       0.110
Initial_acceptability     2.4872      0.028     88.180      0.000       2.432       2.543
Privacy_coefficient       2.0229      0.675      2.996      0.003       0.697       3.349
Profit_coefficient       -0.0019      0.000    -12.812      0.000      -0.002      -0.002
Ren_coefficient          -5.7127      1.355     -4.216      0.000      -8.374      -3.052
scenario_id               0.0002      0.001      0.349      0.727      -0.001       0.001
==============================================================================
Omnibus:                       49.618   Durbin-Watson:                   1.237
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               60.060
Skew:                           0.767   Prob(JB):                     9.08e-14
Kurtosis:                       3.219   Cond. No.                     5.42e+04
==============================================================================
```

FIGURE F.14: Regression acceptance (V2G)

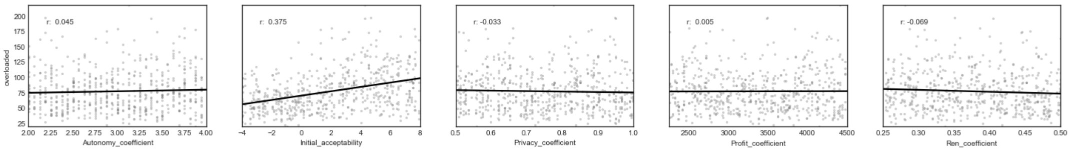

FIGURE F.15: Sensitivity plots overloaded (V2G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.931
Model:                            OLS   Adj. R-squared:                  0.930
Method:                 Least Squares   F-statistic:                     1334.
Date:                Thu, 19 Jul 2018   Prob (F-statistic):               0.00
Time:                        00:47:34   Log-Likelihood:                -1367.8
No. Observations:                 600   AIC:                             2750.
Df Residuals:                     593   BIC:                             2780.
Df Model:                           6
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                    11.6325      1.061     10.960      0.000       9.548      13.717
Autonomy_coefficient     -0.2209      0.168     -1.313      0.190      -0.551       0.110
Initial_acceptability     2.4872      0.028     88.180      0.000       2.432       2.543
Privacy_coefficient       2.0229      0.675      2.996      0.003       0.697       3.349
Profit_coefficient       -0.0019      0.000    -12.812      0.000      -0.002      -0.002
Ren_coefficient          -5.7127      1.355     -4.216      0.000      -8.374      -3.052
scenario_id               0.0002      0.001      0.349      0.727      -0.001       0.001
==============================================================================
Omnibus:                       49.618   Durbin-Watson:                   1.237
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               60.060
Skew:                           0.767   Prob(JB):                     9.08e-14
Kurtosis:                       3.219   Cond. No.                     5.42e+04
==============================================================================
```

FIGURE F.16: Regression overloaded (V2G)

Uncertainty sampling	SOBOL
Uncertainties	Experiment design 1
Runs	1400
Particularities	None

TABLE F.2: LHS design

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.162
Model:                            OLS   Adj. R-squared:                  0.144
Method:                 Least Squares   F-statistic:                     9.426
Date:                Thu, 19 Jul 2018   Prob (F-statistic):           3.71e-13
Time:                        00:56:30   Log-Likelihood:                 432.29
No. Observations:                 450   AIC:                            -844.6
Df Residuals:                     440   BIC:                            -803.5
Df Model:                           9
Covariance Type:            nonrobust
=============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                      -0.4486      0.065     -6.908      0.000      -0.576      -0.321
Charging_speed_initial      0.0435      0.009      4.962      0.000       0.026       0.061
Friends                     0.0081      0.004      2.050      0.041       0.000       0.016
Friends_importance         -0.0916      0.131     -0.702      0.483      -0.348       0.165
Mean_work_distance          0.0009      0.001      0.656      0.512      -0.002       0.004
Memory_days                 0.0023      0.000      6.682      0.000       0.002       0.003
Percentage_EV               0.0003      0.001      0.252      0.801      -0.002       0.003
Privacy_error_chance        0.0075      0.016      0.481      0.631      -0.023       0.038
Stay_at_home                0.0004      0.002      0.162      0.871      -0.004       0.005
scenario_id             -3.818e-05   3.45e-05     -1.107      0.269      -0.000    2.96e-05
==============================================================================
Omnibus:                        0.086   Durbin-Watson:                   2.154
Prob(Omnibus):                  0.958   Jarque-Bera (JB):                0.155
Skew:                          -0.027   Prob(JB):                        0.925
Kurtosis:                       2.927   Cond. No.                     8.08e+03
==============================================================================
```

FIGURE F.17: Setup 2 Regression users (V1G)

```
                           OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.162
Model:                            OLS   Adj. R-squared:                  0.144
Method:                 Least Squares   F-statistic:                     9.426
Date:                Thu, 19 Jul 2018   Prob (F-statistic):           3.71e-13
Time:                        00:58:34   Log-Likelihood:                 432.29
No. Observations:                 450   AIC:                            -844.6
Df Residuals:                     440   BIC:                            -803.5
Df Model:                           9
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                     -0.4486      0.065     -6.908      0.000      -0.576      -0.321
Charging_speed_initial     0.0435      0.009      4.962      0.000       0.026       0.061
Friends                    0.0081      0.004      2.050      0.041       0.000       0.016
Friends_importance        -0.0916      0.131     -0.702      0.483      -0.348       0.165
Mean_work_distance         0.0009      0.001      0.656      0.512      -0.002       0.004
Memory_days                0.0023      0.000      6.682      0.000       0.002       0.003
Percentage_EV              0.0003      0.001      0.252      0.801      -0.002       0.003
Privacy_error_chance       0.0075      0.016      0.481      0.631      -0.023       0.038
Stay_at_home               0.0004      0.002      0.162      0.871      -0.004       0.005
scenario_id            -3.818e-05   3.45e-05     -1.107      0.269      -0.000    2.96e-05
==============================================================================
```

FIGURE F.18: Setup 2 Regression overloaded (V1G)

```
                           OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.162
Model:                            OLS   Adj. R-squared:                  0.144
Method:                 Least Squares   F-statistic:                     9.426
Date:                Thu, 19 Jul 2018   Prob (F-statistic):           3.71e-13
Time:                        00:59:41   Log-Likelihood:                 432.29
No. Observations:                 450   AIC:                            -844.6
Df Residuals:                     440   BIC:                            -803.5
Df Model:                           9
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                     -0.4486      0.065     -6.908      0.000      -0.576      -0.321
Charging_speed_initial     0.0435      0.009      4.962      0.000       0.026       0.061
Friends                    0.0081      0.004      2.050      0.041       0.000       0.016
Friends_importance        -0.0916      0.131     -0.702      0.483      -0.348       0.165
Mean_work_distance         0.0009      0.001      0.656      0.512      -0.002       0.004
Memory_days                0.0023      0.000      6.682      0.000       0.002       0.003
Percentage_EV              0.0003      0.001      0.252      0.801      -0.002       0.003
Privacy_error_chance       0.0075      0.016      0.481      0.631      -0.023       0.038
Stay_at_home               0.0004      0.002      0.162      0.871      -0.004       0.005
scenario_id            -3.818e-05   3.45e-05     -1.107      0.269      -0.000    2.96e-05
==============================================================================
Omnibus:                        0.086   Durbin-Watson:                   2.154
Prob(Omnibus):                  0.958   Jarque-Bera (JB):                0.155
Skew:                          -0.027   Prob(JB):                        0.925
Kurtosis:                       2.927   Cond. No.                     8.08e+03
==============================================================================
```

FIGURE F.19: Setup 2 Regression mean acceptance (V2G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.032
Model:                            OLS   Adj. R-squared:                  0.029
Method:                 Least Squares   F-statistic:                     13.12
Date:                Thu, 19 Jul 2018   Prob (F-statistic):           7.65e-21
Time:                        01:00:35   Log-Likelihood:                -2507.6
No. Observations:                3600   AIC:                             5035.
Df Residuals:                    3590   BIC:                             5097.
Df Model:                           9
Covariance Type:            nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
const                       0.1719      0.115      1.494      0.135      -0.054       0.398
Charging_speed_initial      0.0216      0.016      1.381      0.167      -0.009       0.052
Friends                     0.0070      0.007      0.993      0.321      -0.007       0.021
Friends_importance         -0.1459      0.225     -0.648      0.517      -0.587       0.295
Mean_work_distance          0.0162      0.002      6.620      0.000       0.011       0.021
Memory_days               2.59e-05      0.001      0.042      0.967      -0.001       0.001
Percentage_EV               0.0021      0.002      0.938      0.349      -0.002       0.007
Privacy_error_chance       -0.2369      0.028     -8.431      0.000      -0.292      -0.182
Stay_at_home                0.0041      0.004      1.031      0.303      -0.004       0.012
scenario_id               6.46e-06   7.81e-06      0.828      0.408   -8.84e-06    2.18e-05
==============================================================================
Omnibus:                      727.946   Durbin-Watson:                   2.040
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1471.152
Skew:                          -1.197   Prob(JB):                         0.00
Kurtosis:                       5.019   Cond. No.                     5.91e+04
==============================================================================
```

FIGURE F.20: Setup 2 Regression users (V2G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.032
Model:                            OLS   Adj. R-squared:                  0.029
Method:                 Least Squares   F-statistic:                     13.12
Date:                Thu, 19 Jul 2018   Prob (F-statistic):           7.65e-21
Time:                        01:02:14   Log-Likelihood:                -2507.6
No. Observations:                3600   AIC:                             5035.
Df Residuals:                    3590   BIC:                             5097.
Df Model:                           9
Covariance Type:            nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
const                       0.1719      0.115      1.494      0.135      -0.054       0.398
Charging_speed_initial      0.0216      0.016      1.381      0.167      -0.009       0.052
Friends                     0.0070      0.007      0.993      0.321      -0.007       0.021
Friends_importance         -0.1459      0.225     -0.648      0.517      -0.587       0.295
Mean_work_distance          0.0162      0.002      6.620      0.000       0.011       0.021
Memory_days               2.59e-05      0.001      0.042      0.967      -0.001       0.001
Percentage_EV               0.0021      0.002      0.938      0.349      -0.002       0.007
Privacy_error_chance       -0.2369      0.028     -8.431      0.000      -0.292      -0.182
Stay_at_home                0.0041      0.004      1.031      0.303      -0.004       0.012
scenario_id               6.46e-06   7.81e-06      0.828      0.408   -8.84e-06    2.18e-05
==============================================================================
Omnibus:                      727.946   Durbin-Watson:                   2.040
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1471.152
Skew:                          -1.197   Prob(JB):                         0.00
Kurtosis:                       5.019   Cond. No.                     5.91e+04
==============================================================================
```

FIGURE F.21: Setup 2 Regression overloaded (V2G)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.032
Model:                            OLS   Adj. R-squared:                  0.029
Method:                 Least Squares   F-statistic:                     13.12
Date:                Thu, 19 Jul 2018   Prob (F-statistic):           7.65e-21
Time:                        01:03:13   Log-Likelihood:                -2507.6
No. Observations:                3600   AIC:                             5035.
Df Residuals:                    3590   BIC:                             5097.
Df Model:                           9
Covariance Type:            nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
const                       0.1719      0.115      1.494      0.135      -0.054       0.398
Charging_speed_initial      0.0216      0.016      1.381      0.167      -0.009       0.052
Friends                     0.0070      0.007      0.993      0.321      -0.007       0.021
Friends_importance         -0.1459      0.225     -0.648      0.517      -0.587       0.295
Mean_work_distance          0.0162      0.002      6.620      0.000       0.011       0.021
Memory_days               2.59e-05      0.001      0.042      0.967      -0.001       0.001
Percentage_EV               0.0021      0.002      0.938      0.349      -0.002       0.007
Privacy_error_chance       -0.2369      0.028     -8.431      0.000      -0.292      -0.182
Stay_at_home                0.0041      0.004      1.031      0.303      -0.004       0.012
scenario_id               6.46e-06   7.81e-06      0.828      0.408   -8.84e-06    2.18e-05
==============================================================================
Omnibus:                      727.946   Durbin-Watson:                   2.040
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1471.152
Skew:                          -1.197   Prob(JB):                         0.00
Kurtosis:                       5.019   Cond. No.                     5.91e+04
==============================================================================
```

FIGURE F.22: Setup 2 Regression mean acceptance (V2G)

Appendix G

LHS plots

This appendix shows the results of the experiments in chapter 6. The experimental setup of the following experiments is shown in tabel G.2.

Variable	Lower	Upper
Initial acceptability	-4	4
Profit coefficient	2600	6600
Ren coefficient	0.5	1
Privacy coefficient	0.5	1.5
Autonomy coefficient	2	6
Friends	2	8
Stay at home	7	21
Mean work distance	11.5	34.5
Charging speed initial	1.8	5.4
Friends importance	0.125	0.375
Percentage EV	12.5	37.5
Memory days	45	135
Stay at home	7	21
Privacy error chance	1	3

TABLE G.1: Sensitivity experiment setup

Uncertainty sampling	LHS
Uncertainties	Experiment design chapter 6.1
Runs	200
Particularities	None

TABLE G.2: LHS design

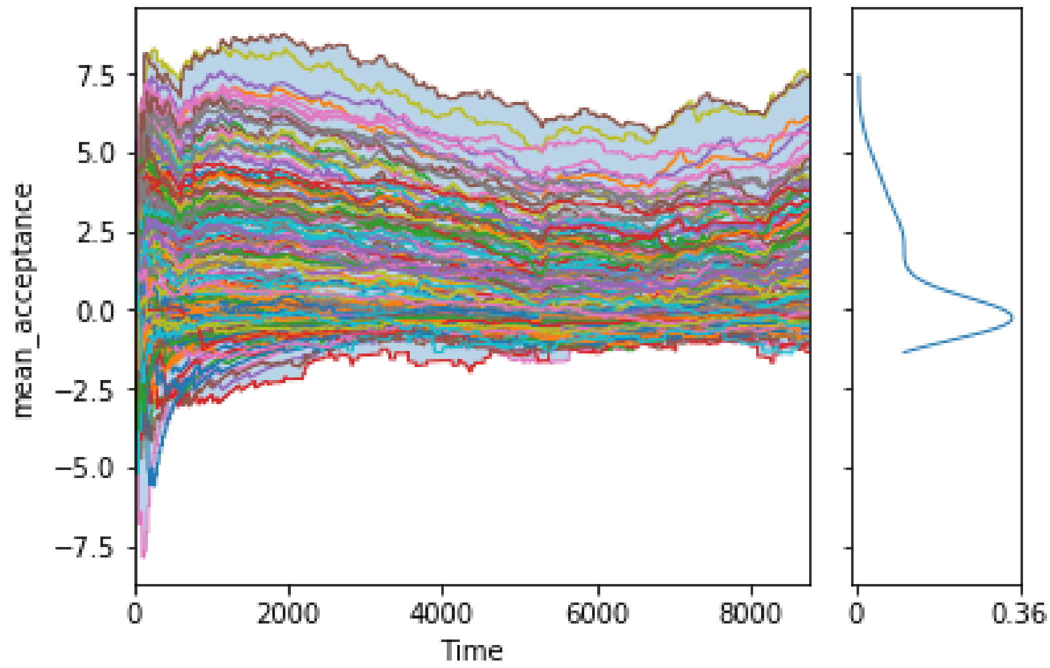

FIGURE G.1: Outcome experiment mean acceptance (V1G)

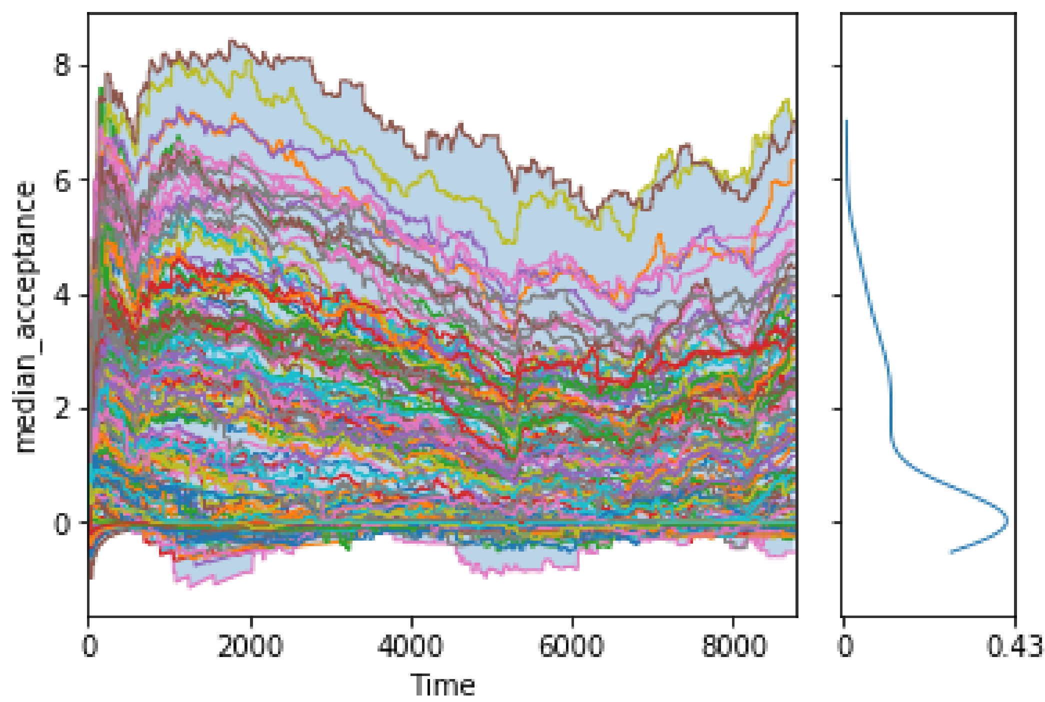

FIGURE G.2: Outcome experiment median acceptance (V1G)

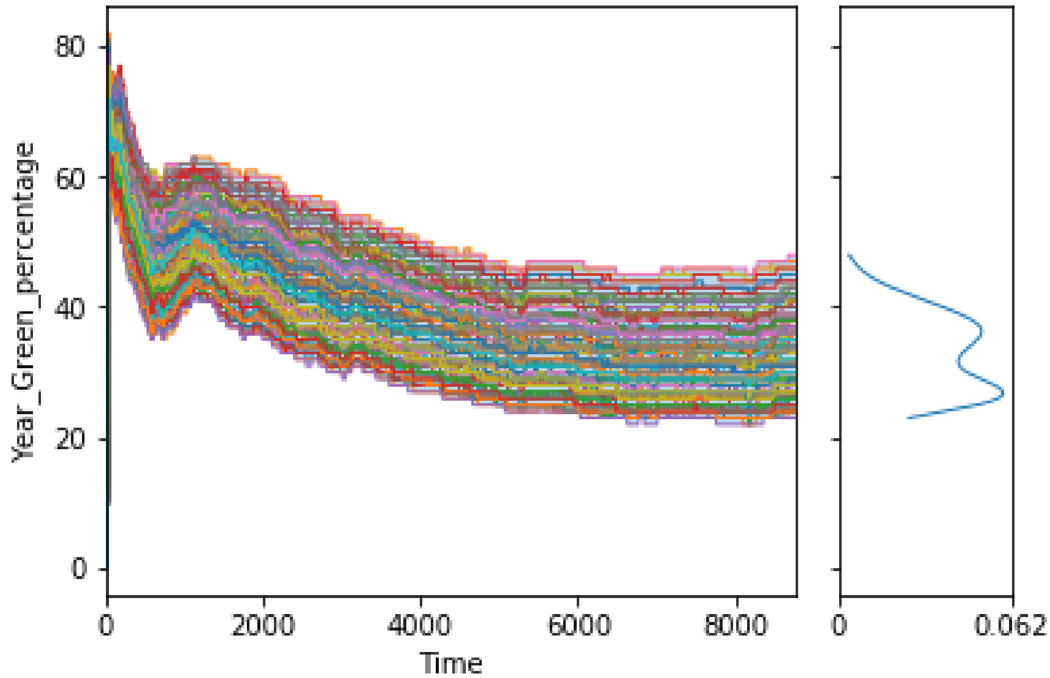

FIGURE G.3: Outcome experiment Green percentage (V1G)

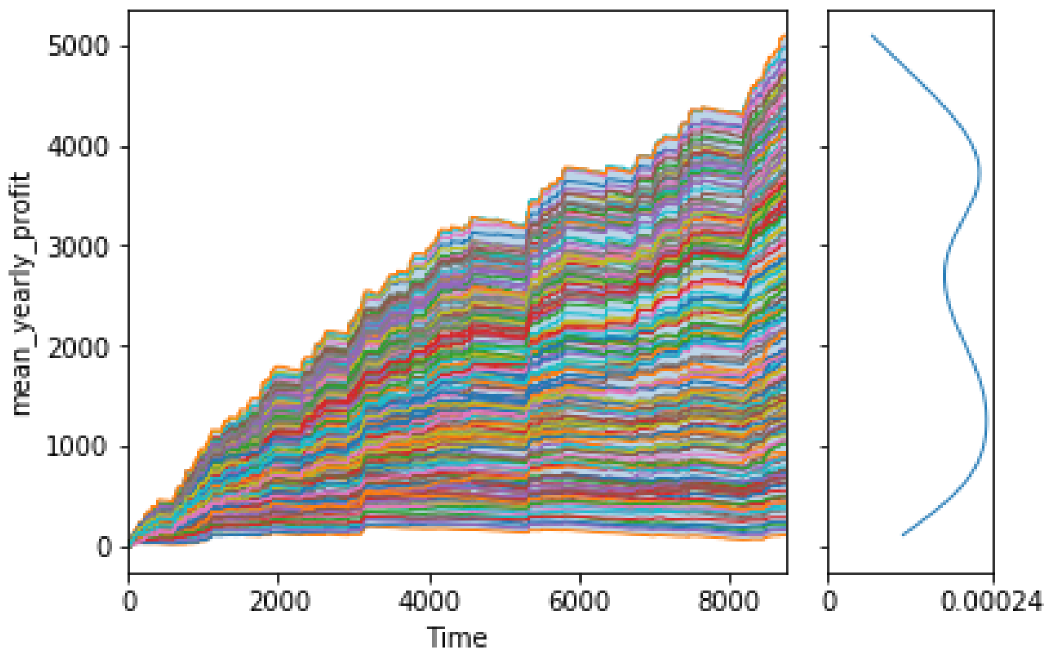

FIGURE G.4: Outcome experiment Profit (V1G)

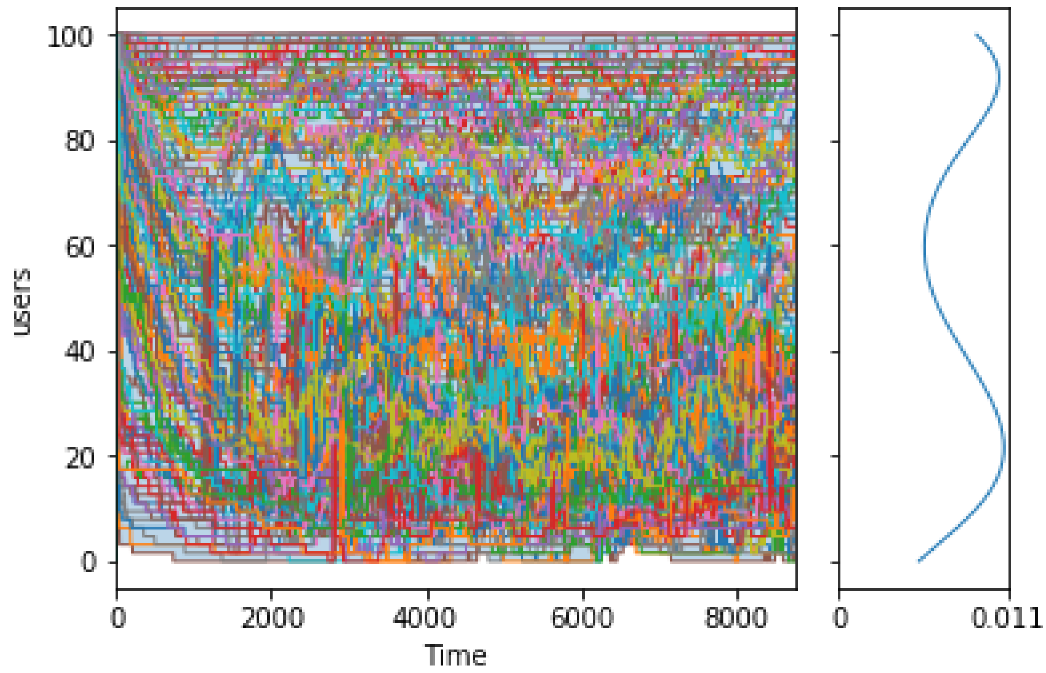

FIGURE G.5: Outcome experiment Users (V1G)

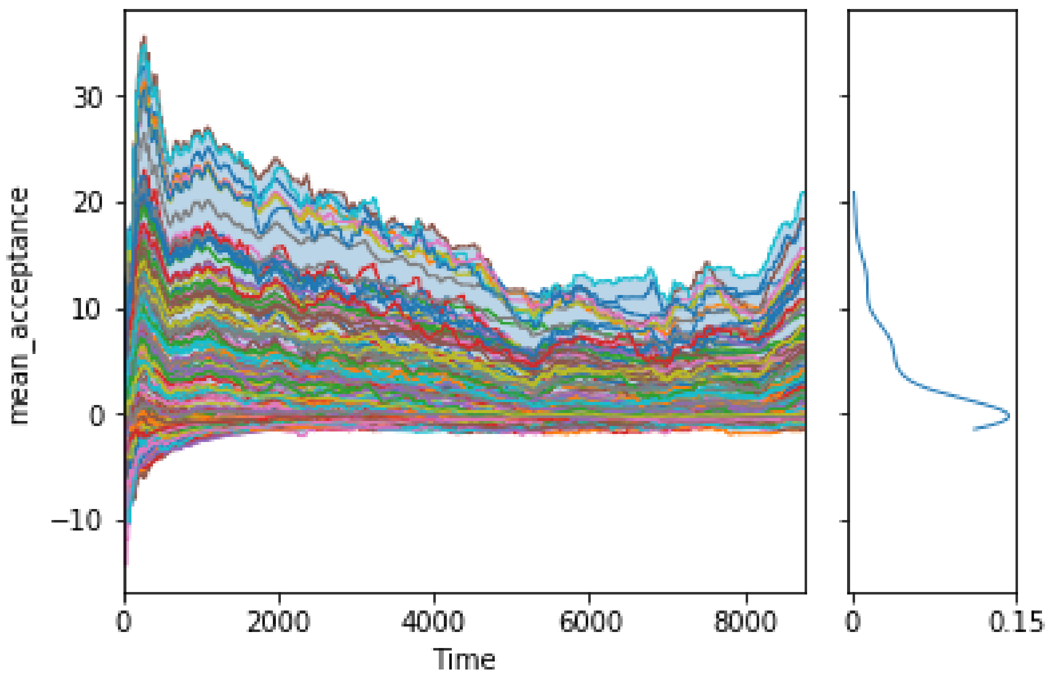

FIGURE G.6: Outcome experiment mean acceptance (V2G)

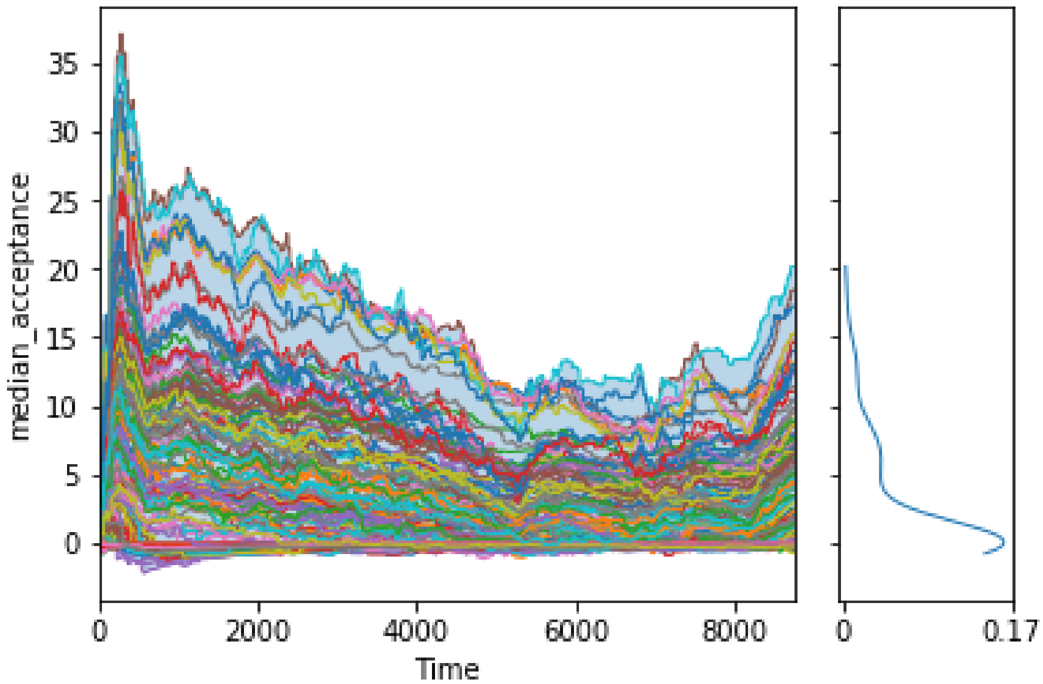

FIGURE G.7: Outcome experiment median acceptance (V2G)

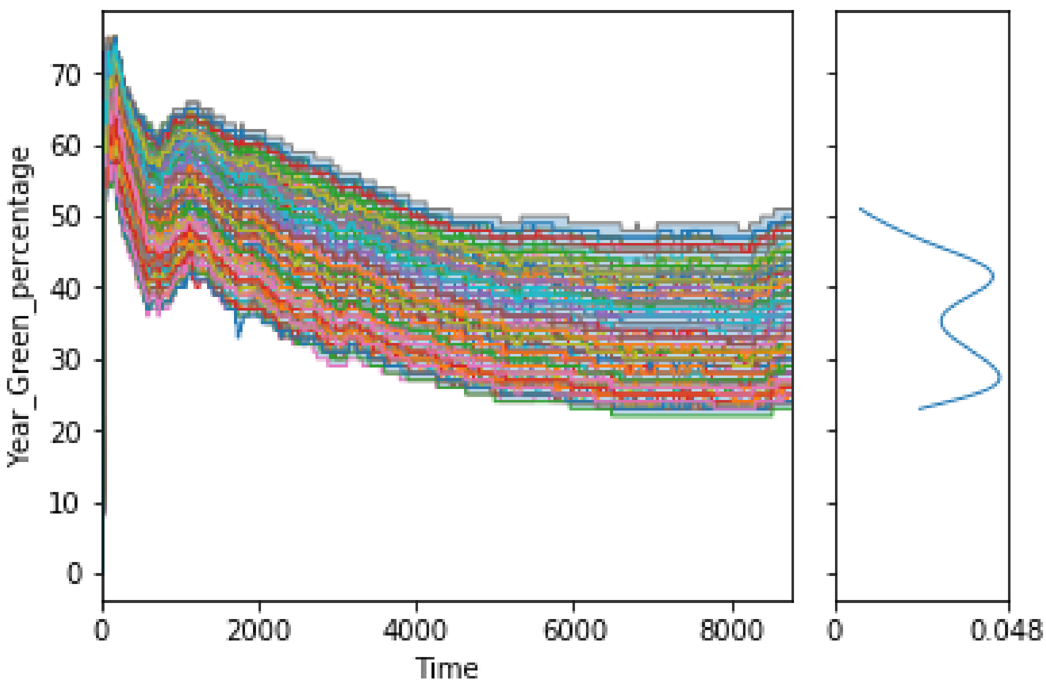

FIGURE G.8: Outcome experiment Green percentage (V2G)

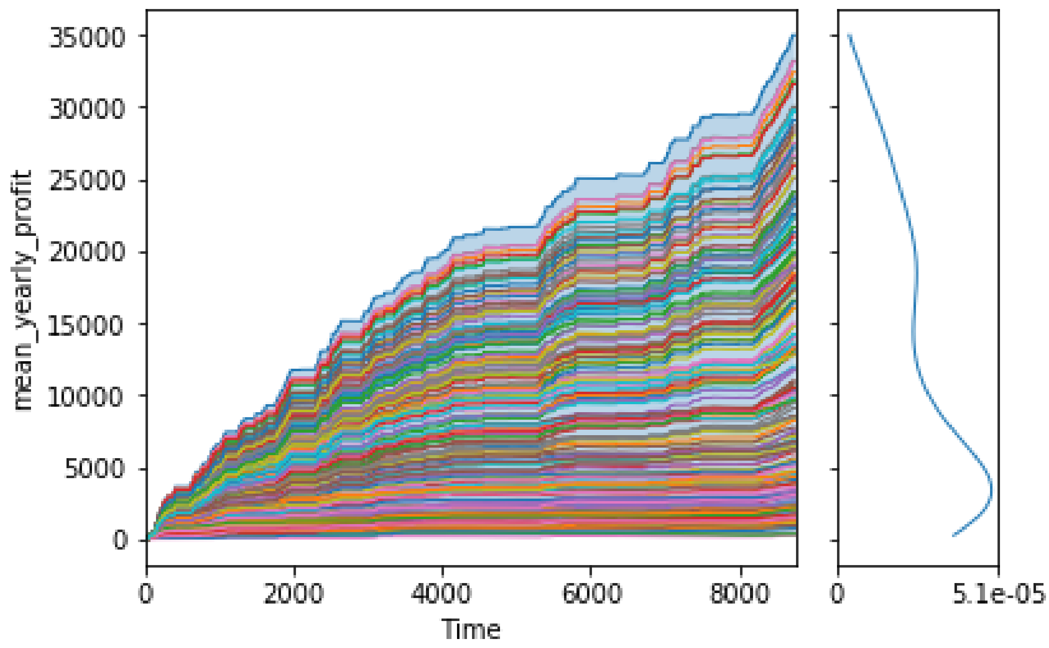

FIGURE G.9: Outcome experiment Profit (V2G)

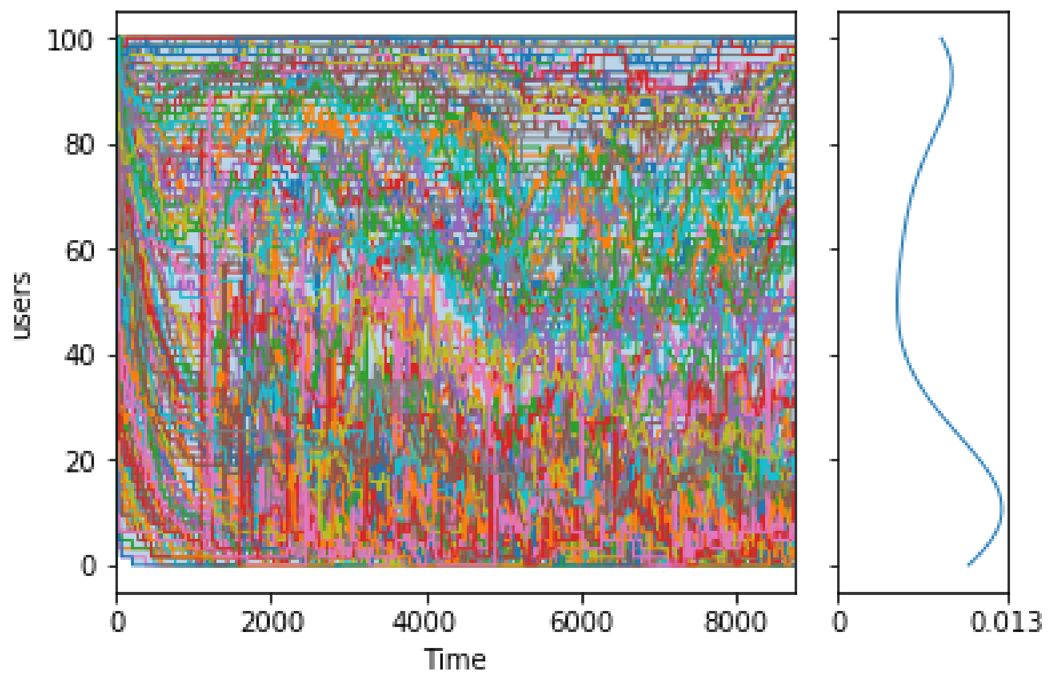

FIGURE G.10: Outcome experiment Users (V2G)

Appendix H

Prim Analysis

Using the Prim tool kit the most important factors which determine the outcomes are extracted from the sensitivity analysis.

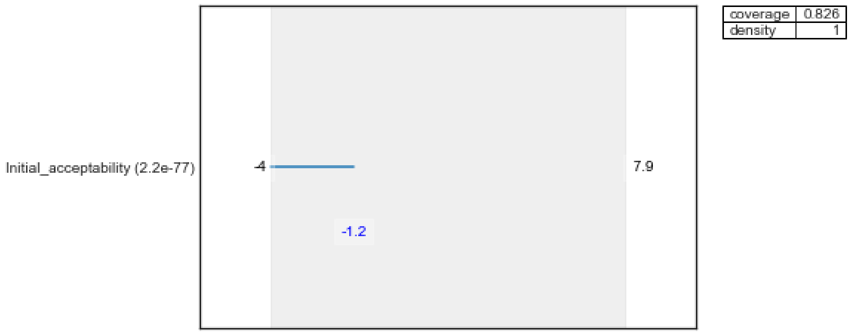

FIGURE H.1: Prim results for users below 50, V1G

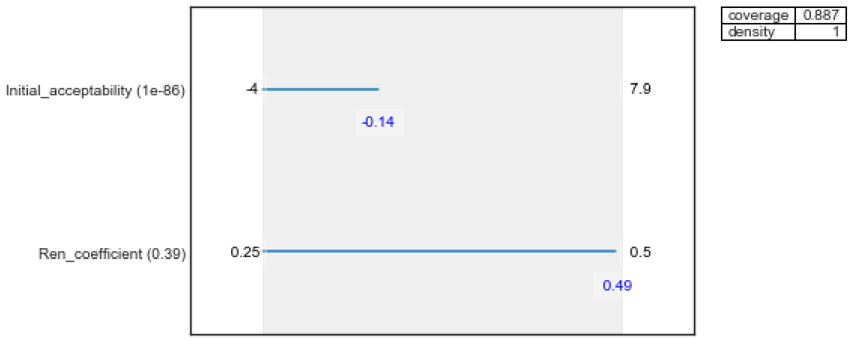

FIGURE H.2: Prim results for users below 50, V2G

The results of the Prim analysis shows that the initial acceptability is the only parameter which can be used significantly to predict when the number of users will be under the 50%.

Appendix I

Technical outcomes

	Avg	Max	Min	StDev
Users	100.00	100	100	0
Mean Acceptance	-0.38	-0.29	-0.46	0.03
Median Acceptance	-0.38	-0.24	-0.50	0.05
Variance Acceptance	0.05	0.07	0.04	0.01
Mean Peak per day (kWh)	24.79	27.15	23.69	0.47
Times overloaded	138	298	40	42
Percentage Renewable	23.00	23.00	23.00	0.00
Fuel cost (ct/kWh)	6.42	6.44	6.40	0.01
Yearly profit (ct)	46.43	94.52	-7.54	15.87
Autonomy problems	0.07	0.17	0.00	0.04
Total charged (kWh)	2251	2542	1950	131

TABLE I.1: Results without technology

	Avg	Max	Min	StDev
Users	100	100	100	0
Mean Acceptance	0.17	0.41	-0.05	0.11
Median Acceptance	0.26	0.63	-0.04	0.13
Variance Acceptance	0.90	1.38	0.52	0.17
Mean Peak per day (kWh)	20.45	22.06	19.61	0.44
Times overloaded	54	156	8	32
Percentage Renewable	40.50	42.00	39.00	0.69
Fuel cost (ct/kWh)	4.69	4.86	4.53	0.07
Yearly profit (ct)	4535	4943	4015	218
Autonomy problems	3.54	4.14	3.03	0.25
Total charged (kWh)	2311	2672	2020	127

TABLE I.2: Results without choice, V1G cost

	Avg	Max	Min	StDev
Users	100	100	100	0
Mean Acceptance	-0.18	0.03	-0.43	0.11
Median Acceptance	-0.07	0.20	-0.42	0.12
Variance Acceptance	0.69	1.12	0.33	0.16
Mean Peak per day (kWh)	21.46	23.20	20.73	0.42
Times overloaded	78	159	31	29
Percentage Renewable	34.92	36.00	34.00	0.58
Fuel cost (ct/kWh)	6.02	6.17	5.95	0.04
Yearly profit (ct)	1324	1567	1022	124
Autonomy problems	3.03	3.62	2.40	0.23
Total charged (kWh)	2353	2791	1899	172

TABLE I.3: Results without choice, V1G ren

	Avg	Max	Min	StDev
Users	100	100	100	0.00
Mean Acceptance	-1.51	-0.93	-1.97	0.21
Median Acceptance	-1.25	-0.72	-2.04	0.26
Variance Acceptance	2.91	10.65	1.46	1.14
Mean Peak per day (kWh)	20.19	22.05	19.50	0.40
Times overloaded	0.00	0.00	0.00	0.00
Percentage Renewable	40.92	43.00	39.00	0.84
Fuel cost (ct/kWh)	5.26	5.49	5.08	0.08
Yearly profit (ct)	4148	4648	3678	216
Autonomy problems	8.73	11.57	7.71	0.65
Total charged (kWh)	2447	2781	2087	151

TABLE I.4: Results without choice, V1G trans

	Avg	Max	Min	StDev
Users	100	100	100	0
Mean Acceptance	0.19	0.95	-0.48	0.31
Median Acceptance	0.20	1.18	-0.95	0.41
Variance Acceptance	6.09	9.46	4.27	1.13
Mean Peak per day (kWh)	24.00	25.65	23.38	0.32
Times overloaded	172	402	28	67
Percentage Renewable	44.57	47.00	43.00	0.81
Fuel cost (ct/kWh)	1.06	1.57	0.47	0.23
Yearly profit (ct)	24306	25940	22998	550
Autonomy problems	11.43	12.83	10.30	0.58
Total charged (kWh)	4647	4852	4382	105

TABLE I.5: Results without choice, V2G cost

	Avg	Max	Min	StDev
Users	100	100	100	0
Mean Acceptance	-0.65	0.20	-1.18	0.26
Median Acceptance	-0.56	0.33	-1.22	0.28
Variance Acceptance	4.21	7.04	2.18	0.85
Mean Peak per day (kWh)	24.57	26.43	23.96	0.36
Times overloaded	220	428	91	67
Percentage Renewable	35.45	37.00	34.00	0.54
Fuel cost (ct/kWh)	2.29	2.74	1.68	0.20
Yearly profit (ct)	15821	17170	14958	400
Autonomy problems	10.16	11.25	9.05	0.47
Total charged (kWh)	5176	5421	4966	95

TABLE I.6: Results without choice, V2G renewable

	Avg	Max	Min	StDev
Users	100	100	100	0
Mean Acceptance	-4.87	-3.53	-6.35	0.54
Median Acceptance	-4.62	-2.87	-6.51	0.69
Variance Acceptance	16.31	23.23	9.38	2.91
Mean Peak per day (kWh)	22.99	24.93	22.13	0.49
Times overloaded	35	111	6	19
Percentage Renewable	44.01	46.00	43.00	0.81
Fuel cost (ct/kWh)	2.08	2.55	1.50	0.23
Yearly profit (ct)	21450	23129	19702	670
Autonomy problems	25.97	27.71	24.17	0.70
Total charged (kWh)	4796	5072	4423	123

TABLE I.7: Results without choice, V2G trans

Appendix J

Model with choice outcomes

In this appendix the outcomes of the model are shown where the EV owners have a choice to use the technology. The runs are based on the default values and 100 replications each.

	Avg	Max	Min	StdDev
Users	56.762	73.02	34.92	7.48312
Mean Acceptance	0.19	0.56	-0.12	0.12
Median Acceptance	0.16	0.59	-0.08	0.13
Variance Acceptance	0.82	1.45	0.38	0.20
Mean Peak per day (kWh)	21.47	22.93	20.61	0.38
Times overloaded	55.25	147.00	16.00	28.01
Percentage Renewable	33.69	36.00	32.00	0.88
Fuel cost (ct/kWh)	5.33	5.51	5.13	0.09
Yearly profit (ct)	2829.28	3393.20	2227.06	249.52
Autonomy problems	2.05	2.51	1.71	0.17
Total charged (kWh)	2299.61	2833.00	1862.00	157.63

TABLE J.1: Outcomes with choice, V1G cost

	Avg	Max	Min	StdDev
Users	28	47.62	11.11	7.93
Mean Acceptance	-0.25	-0.05	-0.63	0.12
Median Acceptance	-0.12	0.00	-0.28	0.06
Variance Acceptance	0.70	1.27	0.36	0.20
Mean Peak per day (kWh)	22.91	24.72	22.07	0.45
Times overloaded	74.69	148.00	17.00	33.20
Percentage Renewable	28.77	30.00	27.00	0.72
Fuel cost (ct/kWh)	6.00	6.21	5.81	0.07
Yearly profit (ct)	1356.56	1911.17	806.61	200.11
Autonomy problems	2.53	3.25	2.05	0.24
Total charged (kWh)	2340.94	2769.00	2025.00	163.35

TABLE J.2: Outcomes with choice, V1G trans

	Avg	Max	Min	StdDev
Users	41.38	60.32	25.40	8.51
Mean Acceptance	0.54	1.30	0.08	0.23
Median Acceptance	-0.04	0.40	-0.23	0.10
Variance Acceptance	3.30	5.83	2.00	0.75
Mean Peak per day (kWh)	23.14	24.75	22.55	0.41
Times overloaded	116.94	252.00	43.00	45.87
Percentage Renewable	37.35	40.00	34.00	1.15
Fuel cost (ct/kWh)	2.65	3.43	1.91	0.30
Yearly profit (ct)	12709	16237	9783	1200
Autonomy problems	5.35	6.87	4.27	0.53
Total charged (kWh)	3566.87	4168.00	3167.00	163.37

TABLE J.3: Outcomes with choice, V2G cost

	Avg	Max	Min	StdDev
Users	11.90	30.16	1.59	5.15
Mean Acceptance	-0.29	0.13	-0.76	0.15
Median Acceptance	-0.20	-0.06	-0.48	0.08
Variance Acceptance	1.19	2.54	0.37	0.45
Mean Peak per day (kWh)	23.61	25.60	22.75	0.39
Times overloaded	110.91	229.00	40.00	40.70
Percentage Renewable	30.45	33.00	28.00	1.10
Fuel cost (ct/kWh)	4.66	5.22	4.10	0.24
Yearly profit (ct)	4689	6926	3130	740
Autonomy problems	4.46	6.48	3.11	0.71
Total charged (kWh)	2858	3276	2511	137

TABLE J.4: Outcomes with choice, V2G trans

Appendix K

Design outcomes V1G

	Base	1	2	3	4	5	6	7
Users	57	61	100	40	76	85	57	80
Mean Acceptance	0.19	0.18	0.18	0.18	0.78	1.19	0.19	0.36
Median Acceptance	0.16	0.24	0.43	-0.03	0.88	1.37	0.15	0.55
Variance Acceptance	0.82	0.81	1.62	0.32	1.00	1.24	0.83	1.00
Mean Peak per day (kWh)	21.5	21.4	20.5	21.9	20.9	20.6	21.3	18.5
Times overloaded	55	58	53	76	46	46	60	11
Percentage Renewable	33.7	34.1	40.6	33.1	36.8	38.0	35.3	38.0
Fuel cost (ct/kWh)	5.33	5.30	4.67	5.4	5.03	4.93	5.15	4.75
Yearly profit (ct)	2829	2880	4549	2684	3621	3904	3283	1259
Autonomy problems	2.05	2.13	3.43	1.83	2.66	2.98	2.32	0.11
Total charged (kWh)	2300	2270	2304	2287	2293	2304	2301	742

TABLE K.1: V1G Design comparison

	Avg	Max	Min	StDev
Users	60.98	79.37	39.68	8.34
Mean Acceptance	0.18	0.51	-0.15	0.13
Median Acceptance	0.24	0.59	-0.06	0.16
Variance Acceptance	0.81	1.34	0.38	0.21
Mean Peak per day (kWh)	21.37	23.52	20.49	0.49
Times overloaded	58	159	11	35
Percentage Renewable	34.06	36.00	32.00	0.98
Fuel cost (ct/kWh)	5.30	5.53	5.04	0.11
Yearly profit (ct)	2880	3586	2279	279
Autonomy problems	2.13	2.57	1.71	0.16
Total charged (kWh)	2270	2683	1928	148

TABLE K.2: V1G Design 1

	Avg	Max	Min	StDev
Users	100	100	100	0
Mean Acceptance	0.18	0.52	-0.33	0.17
Median Acceptance	0.43	0.74	-0.04	0.16
Variance Acceptance	1.62	3.85	0.75	0.55
Mean Peak per day (kWh)	20.47	22.15	19.57	0.50
Times overloaded	53	127	13	28
Percentage Renewable	40.57	44.00	39.00	0.81
Fuel cost (ct/kWh)	4.67	4.84	4.41	0.08
Yearly profit (ct)	4549	5035	3922	237
Autonomy problems	3.43	4.08	2.86	0.23
Total charged (kWh)	2304	2654	1911	150

TABLE K.3: V1G Design 2

	Avg	Max	Min	StDev
Users	40.2	57.14	19.05	7.17
Mean Acceptance	0.18	0.37	-0.02	0.07
Median Acceptance	-0.03	0.22	-0.11	0.06
Variance Acceptance	0.32	0.46	0.16	0.06
Mean Peak per day (kWh)	21.85	23.18	20.34	0.48
Times overloaded	75.50	186.00	11.00	34.42
Percentage Renewable	33.09	36.00	30.00	1.33
Fuel cost (ct/kWh)	5.37	5.63	5.03	0.14
Yearly profit (ct)	2684	3624	1854	363
Autonomy problems	1.83	2.30	1.27	0.21
Total charged (kWh)	2287	2745	1869	160

TABLE K.4: V1G Design 3

	Avg	Max	Min	StDev
Users	75.6	87.3	61.9	5.57
Mean Acceptance	0.78	1.08	0.43	0.13
Median Acceptance	0.88	1.29	0.47	0.17
Variance Acceptance	1.00	1.84	0.55	0.22
Mean Peak per day (kWh)	20.87	23.21	20.08	0.55
Times overloaded	46.14	168.00	6.00	26.78
Percentage Renewable	36.82	39.00	35.00	0.78
Fuel cost (ct/kWh)	5.03	5.25	4.80	0.08
Yearly profit (ct)	3621	4198	3084	276
Autonomy problems	2.66	3.38	2.22	0.20
Total charged (kWh)	2293	2705	1977	144

TABLE K.5: V1G Design 4

	Avg	Max	Min	StDev
Users	85.3	95.24	73.02	4.53
Mean Acceptance	1.19	1.58	0.84	0.14
Median Acceptance	1.37	1.83	1.11	0.13
Variance Acceptance	1.24	1.82	0.62	0.26
Mean Peak per day (kWh)	20.63	22.26	19.95	0.38
Times overloaded	46.46	119.00	4.00	25.41
Percentage Renewable	37.96	39.00	37.00	0.67
Fuel cost (ct/kWh)	4.93	5.07	4.76	0.07
Yearly profit (ct)	3904	4433	3261	233
Autonomy problems	2.98	3.56	2.40	0.22
Total charged (kWh)	2304	2783	1976	137

TABLE K.6: V1G Design 5

	Avg	Max	Min	StDev
Users	56.8	71.43	38.1	6.80
Mean Acceptance	0.19	0.48	-0.19	0.10
Median Acceptance	0.15	0.52	-0.10	0.14
Variance Acceptance	0.83	1.38	0.37	0.23
Mean Peak per day (kWh)	21.25	23.43	20.34	0.47
Times overloaded	59.98	194.00	7.00	34.83
Percentage Renewable	35.31	37.00	33.00	0.76
Fuel cost (ct/kWh)	5.15	5.33	4.93	0.08
Yearly profit (ct)	3283	3937	2570	261
Autonomy problems	2.32	2.65	1.78	0.16
Total charged (kWh)	2301	2652	1840	172

TABLE K.7: V1G Design 6

	Avg	Max	Min	Var
Users	80.30	90.48	66.67	5.28
Mean Acceptance	0.36	0.64	0.09	0.12
Median Acceptance	0.55	0.82	0.31	0.10
Variance Acceptance	1.00	1.81	0.53	0.24
Mean Peak per day (kWh)	18.48	19.86	17.76	0.36
Times overloaded	11.01	53.00	1.00	9.39
Percentage Renewable	37.98	42.00	35.00	1.35
Fuel cost (ct/kWh)	4.75	5.04	4.36	0.14
Yearly profit (ct)	1259	1523	1053	94
Autonomy problems	0.11	0.24	0.03	0.05
Total charged (kWh)	742	893	627	55

TABLE K.8: V1G Design 7

Appendix L

Design outcomes V2G

V2G Comparison policies

	Base	1	2	3	4	5	6	7
Users	41	46	100	39	75	69	41	80
Mean Acceptance	0.54	0	0.52	0.60	2.53	1.54	0.53	2.94
Median Acceptance	-0.04	0.0	0.63	-0.04	2.40	1.35	-0.04	2.67
Variance Acceptance	3.3	2.7	7.9	1.8	6.8	5.1	3.1	9.8
Mean Peak per day (kWh)	23.1	23.1	24.1	23.2	23.3	23.1	23.5	17.2
Times overloaded	117	115	164	121	126	132	141	41
Percentage Renewable	37.4	37.1	44.5	38.0	41.5	40.4	39.7	49.0
Fuel cost (ct/kWh)	2.65	2.82	1.08	2.68	1.68	1.92	2.14	-16.16
Yearly profit (ct)	12709	11799	24277	12871	19066	17219	15681	29649
Autonomy problems	5.3	5.2	11.4	5.5	8.6	7.7	6.4	1.6
Total charged (kWh)	3567	3444.2	4658	3552	4182	4019	3890	2477

TABLE L.1: V2G Design Comparison

	Avg	Max	Min	StDev
Users	46.1	65.1	27.0	6.7
Mean Acceptance	0.46	0.84	-0.11	0.22
Median Acceptance	0.00	0.50	-0.26	0.14
Variance Acceptance	2.69	3.77	1.72	0.49
Mean Peak per day (kWh)	23.12	25.11	22.48	0.42
Times overloaded	115	226	39	40
Percentage Renewable	37.09	40.00	35.00	1.06
Fuel cost (ct/kWh)	2.82	3.45	2.13	0.28
Yearly profit (ct)	11799	13928	9344	1074
Autonomy problems	5.21	6.24	4.11	0.48
Total charged (kWh)	3444	3788	3123	165

TABLE L.2: V2G Design 1

	Avg	Max	Min	StDev
Users	100	100	100	0
Mean Acceptance	0.52	1.29	-0.40	0.36
Median Acceptance	0.63	1.78	-0.38	0.46
Variance Acceptance	7.85	13.70	4.72	1.51
Mean Peak per day (kWh)	24.12	26.10	23.34	0.54
Times overloaded	164	329	38	58
Percentage Renewable	44.49	47.00	43.00	0.83
Fuel cost (ct/kWh)	1.08	1.58	0.26	0.24
Yearly profit (ct)	24277	25531	22869	539
Autonomy problems	11.36	12.46	10.17	0.53
Total charged (kWh)	4658	4911	4257	111

TABLE L.3: V2G Design 2

	Avg	Max	Min	StDev
Users	38.65	53.97	22.22	7.73
Mean Acceptance	0.60	1.10	0.19	0.20
Median Acceptance	-0.04	0.50	-0.15	0.09
Variance Acceptance	1.77	2.98	0.86	0.40
Mean Peak per day (kWh)	23.16	24.89	22.30	0.43
Times overloaded	120.93	262.00	40.00	43.10
Percentage Renewable	38.04	41.00	35.00	1.38
Fuel cost (ct/kWh)	2.68	3.48	1.89	0.37
Yearly profit (ct)	12871	16076	9297	1600
Autonomy problems	5.48	7.22	3.70	0.75
Total charged (kWh)	3552	3972	3117	176

TABLE L.4: V2G Design 3

	Avg	Max	Min	StDev
Users	75.0	85.7	61.9	5.01
Mean Acceptance	2.53	3.28	1.70	0.32
Median Acceptance	2.40	3.37	0.42	0.55
Variance Acceptance	6.85	9.50	4.48	0.87
Mean Peak per day (kWh)	23.33	24.76	22.62	0.33
Times overloaded	125.96	300.00	31.00	51.31
Percentage Renewable	41.47	44.00	39.00	0.95
Fuel cost (ct/kWh)	1.68	2.37	0.95	0.26
Yearly profit (ct)	19066	20882	16279	990
Autonomy problems	8.57	10.11	7.25	0.53
Total charged (kWh)	4182	4421	3777	133

TABLE L.5: V2G Design 4

	Avg	Max	Min	StDev
Users	68.73	82.54	57.14	4.64
Mean Acceptance	1.54	2.44	1.07	0.26
Median Acceptance	1.35	2.65	0.60	0.33
Variance Acceptance	5.10	7.12	3.28	0.85
Mean Peak per day (kWh)	23.11	24.91	22.50	0.33
Times overloaded	132.37	324.00	39.00	50.58
Percentage Renewable	40.37	42.00	39.00	0.82
Fuel cost (ct/kWh)	1.92	2.29	1.43	0.20
Yearly profit (ct)	17219	19769	14997	843
Autonomy problems	7.65	8.87	6.68	0.45
Total charged (kWh)	4019	4267	3761	122

TABLE L.6: V2G Design 5

	Avg	Max	Min	StDev
Users	41.2	65.08	22.22	8.87
Mean Acceptance	0.53	1.16	0.04	0.24
Median Acceptance	-0.04	0.46	-0.26	0.12
Variance Acceptance	3.09	4.78	1.14	0.77
Mean Peak per day (kWh)	23.53	25.59	22.91	0.51
Times overloaded	140.80	285.00	47.00	46.39
Percentage Renewable	39.67	42.00	37.00	0.90
Fuel cost (ct/kWh)	2.14	2.69	1.48	0.24
Yearly profit (ct)	15681	17590	13811	784
Autonomy problems	6.45	7.54	5.25	0.48
Total charged (kWh)	3890	4193	3498	150

TABLE L.7: V2G Design 6

	Avg	Max	Min	StDev
Users	79.8	90.48	63.49	5.21
Mean Acceptance	2.94	3.82	2.08	0.41
Median Acceptance	2.67	4.10	1.41	0.64
Variance Acceptance	9.85	14.39	6.93	1.42
Mean Peak per day (kWh)	17.20	18.57	16.79	0.31
Times overloaded	41.41	124.00	4.00	29.38
Percentage Renewable	48.98	51.00	47.00	0.75
Fuel cost (ct/kWh)	-16.16	-14.18	-17.93	0.80
Yearly profit (ct)	29649	33132	26496	1258
Autonomy problems	1.62	2.32	0.87	0.26
Total charged (kWh)	2477	2611	2321	55

TABLE L.8: V2G Design 7

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