Delft University of Technology
Master's Thesis in Embedded Systems

Integration of V2H/V2G Towards Effective Demand-Response Programs

Duncan Lew

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Master's Thesis in Embedded Systems

Embedded Software Section
Faculty of Electrical Engineering, Mathematics and Computer Science
Delft University of Technology
Mekelweg 4, 2628 CD Delft, The Netherlands

Duncan Lew
d.w.o.lew@student.tudelft.nl

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Author

Duncan Lew (d.w.o.lew@student.tudelft.nl)

Title

Integration of V2H/V2G Towards Effective Demand-Response Programs

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Graduation Committee

Prof. dr. K. G. Langendoen	Delft University of Technology
Dr. RangaRao Venkatesha Prasad	Delft University of Technology
Dr. Ir. Arjan van Genderen	Delft University of Technology

Daily Supervisor

Dr. Akshay Uttama Nambi	Microsoft Research India

Abstract

Increasing adoption of EVs in the next few decades is going to present new challenges such as EV charging creating a new and significant demand on the grid. The purpose of this thesis is to create a system that intelligently schedules the charging of EVs while considering the cost of energy and the discomfort of the user. At any given moment, 90% of vehicles are parked and have a huge energy source left unused. EVs could also be used as power sources for vehicle-to-home/vehicle-to-grid (V2H/V2G) to benefit from them during high demand of energy. This way the power plants would see almost a constant demand and usage, in the long run, making them more efficient.

This thesis uses a non-intrusive data-driven technique to create a occupancy and EV charging model of the household. Smart meters in each household collect power usage data. From this power usage data we determine occupancy and EV charge sessions. The next step is to determine temporal metrics for occupancy and EV charge sessions. The temporal metrics study the likelihood for occupancy or an EV charge session to occur or to switch from one state to another. Because there are differences between weekday/weekend and seasonal power usage, we have decided to create temporal metrics for each time period.

The next step is to create the EV charging algorithm and V2H/V2G algorithms. These algorithms require a flexibility window. This window indicates in which hours the EV can be charged. Which hours of the flexibility window are chosen, depends on the type of objective. We have created three objectives: cost minimization, comfort maximization and joint objective. The V2H/V2G algorithm is executed when the state of charge (SoC) of the EV is higher than the SoC boundary.

In order to measure the performance of the algorithm, we have created two metrics: relative savings and miss rate. The miss rate measures how an hour was scheduled for EV charging but failed. During the testing of the algorithm, we found that only the objective cost minimization was deemed useful. Each objective uses a flexibility window and we conclude that the user's preferences are already taken into account during the creation of this window. For the execution of the EV charge scheduling algorithm, a maximum relative savings can be achieved of 27% and a maximum miss rate of 11.1%. By choosing the SoC boundary value of 60% for V2H, maximum relative savings of 9.9% and a maximum miss rate of 5.2% can be achieved. V2G execution had a negligible effect on the relative savings and miss rate because the pricing dataset did not contain many price surges.

Preface

This Master of Science thesis is my final part of the curriculum at the department of Embedded Systems at EWI. This project is done at TU Delft as part of the Embedded Systems curriculum. In this thesis, I propose an algorithm for intelligently charging EVs during hours of low energy usage and to also use the battery of EVs for other V2H/V2G purposes.

I would like to express my sincere gratitude to Akshay and Mr. VP. They made time for me in during their busy professional life to advice, guide and support me in this thesis. Also, I would like to thank my parents and my friends for their support.

Duncan Lew
Delft, The Netherlands
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Contents

Chapter 1

Introduction

1.1 Background

The first electric vehicles (EVs) were produced in the late 19th century [1]. They were popular in the early 20th century until advancements in combustion engines and mass production of fossil-fuel vehicles caused a sharp decline in the usage of EVs. However, since 2008 there is a resurgence in the production of EVs due to advancements in battery technology, increasing oil prices and the importance of decreasing amount of greenhouse gases in the atmosphere [2].

Moreover, according to the Intergovernmental Panel on Climate Change (IPCC), 14.3% of the total worldwide green-house emissions were contributed by burning fossil-fuel for transportation [3]. Of all the transportation modes, road transportation contributed a total of 72% of greenhouse gases worldwide. If all these vehicles on the road were to be replaced with vehicles that produce zero emissions, this could drastically reduce the amount of emissions produced.

The transition to clean and renewable energy sources (RES) has been growing in the past couple of years. An alternative for traditional fossil-fuel cars are EVs. They produce zero emissions. Depending on government policies to incentivize the usage of EVs, the adoption rate will increase more rapidly in some countries. One of the big transitions in the coming years will be the transition from fossil-fuel based vehicles to fully electric vehicles. However, this rapid adoption of EVs is going to present new challenges. EV charging is going to create a new and significant demand on the grid[4]. EV users want to save money while charging their EVs. Electricity companies, on the other hand, want their power plants to operate at maximum efficiency, since turning the knobs to increase/decrease electricity production is a slow process and lowers efficiencies [5]. Having a variable pricing scheme for electricity is a way for both users and electricity companies to benefit.

In Figure 1.1, there are three hourly pricing levels. In order to incentivize customers to use electricity during midnight, the prices during these hours are the lowest. This helps in utilizing the power generated during the night hours. If an EV user charges their EV during midnight, they are saving money and they are helping the company to reduce its losses from over-capacity at midnight. The goal is to shift the charging of EVs to other time periods where it is cheaper and that benefit both the customer and the electricity companies.

Figure 1.1: Example of hourly pricing levels

Usually, the EVs contain a battery with a capacity ranging from 24 kWh to 90 kWh [6]. At any given moment, 95% of cars are parked [7]. If all these cars were EVs, a huge energy source would be left unused. A use-case for these batteries is to store the excess energy produced by RES. Another use-case can be to power a house with an EV battery, which is called vehicle-to-home (V2H). These parked EVs can be used to alleviate power demand in the house. An instance in which the usage of V2H is desirable is when the energy prices are very high during certain periods of a day.

EVs can also be used to sell the energy back to the grid when there is a shortage of energy. The action of transferring energy from the EV to the grid is called vehicle-to-grid (V2G). Users who sell their energy from the battery back to the grid get a monetary compensation, while the electricity companies benefit from keeping the stability of the grid.

Charging the EV battery is called home-to-vehicle (H2V) or grid-to-vehicle (G2V), but there is no special jargon to refer to this action and it will be called EV charging for the rest of this thesis.

The usage of RES and EVs poses new problems that need to be solved in order to intelligently make use of the energy of EVs to optimize or lower the demand and the load on the grid and household energy usage. The change in altering the power consumption to better match the power demand or supply is called demand response (DR). The goal of this thesis is to make use of intelligent scheduling methods in order to use the untapped energy source of the parked EVs.

1.2 Problem statement

In the coming years, as the adoption rate of EVs and more decentralized renewable energy sources increases, it will also provide an increasing amount of methods with which users can reduce their CO_2 footprint [8][9]. EVs and RES create new challenges. EV charging can create sudden demand spikes on the grid. RES, on the other hand, does not provide a constant supply of energy. A new method has to be thought out to connect the demand and supply in such a way that both the user and the electricity companies can benefit.

EVs have an energy source of 20-80 kWh depending on the model. The energy in these batteries can also be used for other purposes than driving: V2H and V2G. New algorithms have to be created for the decision making of when to use the EV's battery to power the house or send the energy back to the grid.

Not much research has been done to satisfy both the preferences of the users and the electricity companies while integrating V2H/V2G into one home ecosystem in order to alleviate power demand in the grid and in the household by shifting the timing when energy is consumed. Users have certain constraints on when they would want their EV to get charged and electricity companies have their own constraints regarding how much power demand they can handle. The problem statement (summed up in one sentence) is: **How can EV charge scheduling and V2H/V2G be integrated into the home ecosystem while taking other constraints into account?**

The problem statement, studied in this thesis, consists of three major challenges which are as follows:

- Charging EVs create a significant load on the grid
  If everyone comes home at 18:00 after work and charges their EV at exactly the same time, it will create a significant power load on the electricity grid. This situation is especially exacerbated when each EV owner uses a high power output charger of more than 22 kW.

- Aiding the household/grid with V2H/V2G
  If the electricity prices are very high during certain periods of time, this indicates that there is a scarce supply of electricity available. The high prices discourage people from using too much electricity. EV batteries contain a lot of energy that can be used to power appliances in the house. This V2H operation is ideal for time periods when electricity prices are higher. Parked EVs can also be used to sell their excess energy back to the grid. This V2G operation can thus help the grid

to reduce its scarce supply. Intelligent scheduling algorithms will have to be implemented in order to optimize the operations of V2H/V2G.

- Users' preferences
  Shifting the charging time of EVs can create an inconvenience to the user. Scheduling an EV to be charged during hours that a user is most likely not at home is not ideal. The algorithms that shift charging time cannot be run unrestrained without taking other constraints into account. A constraint that is important is users' preferences. Users have a predictable pattern in which they are most likely to be at home and most likely to charge their car. This will vary from user to user. The execution of all these scheduling algorithms should also take these preferences into account. The first question that would have to be answered is how to define the preferences of the user.

1.3 Methodology

The methodology which will be followed to execute this project can be seen in Figure 1.2. The first step is to create a model of the household's behavior. The behavior will be studied using the dataset of household energy usage and EV charging usage. From these two datasets, the household occupancy and EV charging behavior can be extracted for the model. The household occupancy and EV behavior form the basis of the user's preferences.

The next step is to create demand-response programs based on the input data of household energy and EV charging. The model from the previous step is used to determine a charging window of the EV. Each time slot of the charging window contains a value based on the user's preferences. Using this charging window, an EV charging and V2H/V2G algorithm will be run to determine what operations are the most beneficial for each situation.

1.4 Contributions

The contributions of this thesis are summarized here:

- Non-intrusive data-driven technique is proposed to create a model for household and EV usage
  The household energy usage and EV charging behavior of households have to be analyzed first. A system model is made of the behavior of a household and EV energy usage, which can be used later on for scheduling purposes.

- New metrics to define measure of comfort of a household is proposed.

- Algorithm for EV charge scheduling and V2G/V2H is developed
  These algorithms also take into account users' preferences, battery

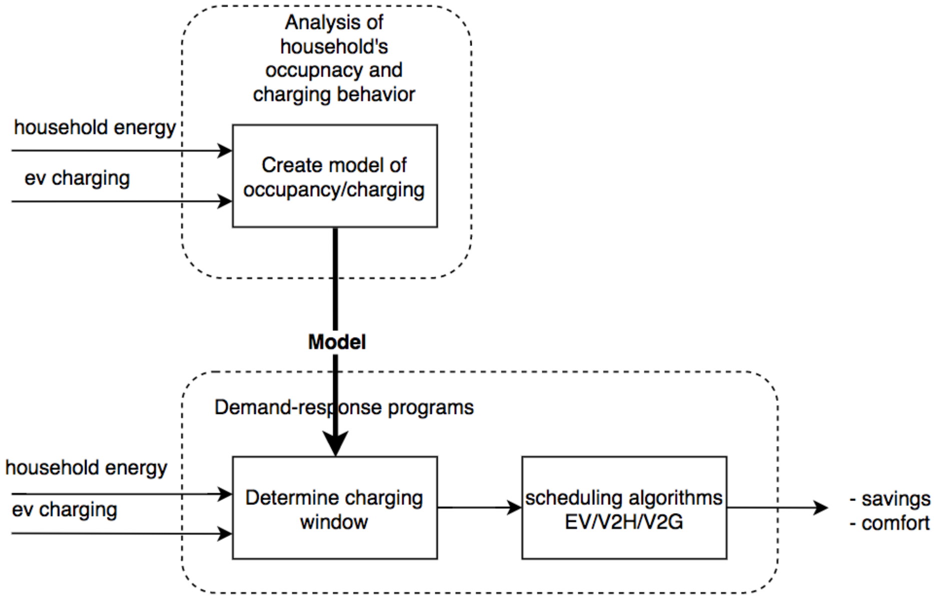


Figure 1.2: Methodology for executing the project

percentage and hourly electricity pricing scheme. EV scheduling and V2G/V2H are closely related to each other since a trade-off has to be made when to charge the EV and when to use it for V2H/V2G.

- Implementation study of the algorithm.
  The results show the effects of taking users' preferences into account when it comes to these algorithms. We will also show the optimum solutions for different objectives.

- Compare the relative savings and discomfort of using algorithms and not using algorithms for different configurations

1.5 Structure of thesis

The structure of the thesis is as follows: Chapter 2 gives an overview of the different research topics that have been conducted in this field of study. Chapter 3 elaborates in depth on the techniques used to create a system model. Chapter 4 discusses the algorithms created for the demand-response programs.

Chapter 2

Literature review

In this chapter works from other research teams are discussed in depth to identify how the topic of this thesis is related to these projects and what can be improved. There are different topics that are of importance to see what has been done and what can be improved. The users are the ones who have to adopt these new scheduling policies and therefore it is important to see what the main barriers are for users in terms of new technology adoption. A hardware implementation for V2H/V2G done by different research teams will also be discussed. These hardware implementations require some form of scheduling algorithms to make a decision between whether to charge the EV batteries or to use the batteries for V2H/V2G. How other research teams implemented these algorithms will be studied in this literature review. The topics that will be discussed are:

- Users' adaptability
- Hardware platforms
- Shifting EV charging
- V2H/V2G
- Window of opportunity

This chapter will be concluded with a discussion of all these different works and what improvements can be made upon all these works.

2.1 Users' preferences and behavior

Before adopting new ways of saving energy and using the EV battery for V2H/V2G purposes, it is also important to take the preferences of the users into account. They will be the ones using these new energy management systems and will be the main factor in how successful the adoption is thereof.

In [10] consumers' interests and willingness to adopt new policies concerning energy management have been studied. A number of observations have been made. The key drivers to acquisition of new energy policies are electricity savings, less emissions and environment friendly. Users also want to be able to see immediately from a display inside or outside the car how much battery percentage is left. Consumers are not willing to pay a premium to charge vehicles during peak hours. It defeats the purpose of having an environmentally friendly car and then having to charge it during peak hours. Furthermore, users are willing to use night time charging or off-peak hour charging to save money, but would like the option to charge whenever needed when they suddenly need to make an unexpected trip. Controlled or interrupted charging is tolerable for consumers only if the interruption does not take too long and there is enough charge left to make an unexpected trip. Around 50% of consumers of EVs expect their EV to be charged up fully in the hour range from 4 to 8 hours. Consumers' preferred charging location is at home. This can be confirmed with a different study [11] that EV charging occurs more than 90% of the time at home.

The conclusion of these studies show that users are open to new EV charging policies. Users prefer an unobtrusive implementation of these policies with minimum involvement from them. However, they do want to be in control of these policies if their preferences change, and do not want these policies to disrupt their normal EV usage too much.

2.2 Profiling energy behavior

In [12], [13], the increasing usage of smart meters in households is discussed. These smart meters collect massive amounts of fine-grained usage data of households. [13] proposes that the analysis of this data can lead to better demand-response programs.

The data collected from the smart meters are placed into clustering algorithms in order to find demand states of user's energy consumption. The clustered results can be used to determine other kinds of temporal metrics. Different kinds of temporal metrics are described in [13]. These temporal metrics describe certain energy usage characteristics of households over certain periods of time. Most important temporal metrics that are of relevance are transient probability and temporal membership.

Transient probability describes the probability to move from one state to another state. The formula for the transient probability $T^u_{a\to b}$ from demand state a→b for a quality feature u is given by:

$$T^u_{a\to b} = \frac{1}{l-1}\sum_{j=1}^{l-1}\beta_j \tag{2.1}$$

where β_j is equal to 1 if the transition a→b takes place, otherwise 0. The

l in this situation denotes the total amount of time periods in which this transition is looked at. This transient probability can show how big the chances are for a household to move from a low energy state to a higher energy state. The equation only shows the transition a→b, but other kinds of transitions, including downwards transition, can be studied.

Temporal membership describes to preference to be in a certain demand state. These demand states indicate the intensity of the energy usage for a specific time period in which the measurement is made. The equation for temporal membership M_0^u for demand state 0 for feature u is as follows:

$$M_0^u = \frac{1}{l} \sum_{j=1}^{l} \gamma_j \tag{2.2}$$

where γ_j is equal to 1 if the demand state at time j is equal to 0, otherwise it is equal to 0. Temporal membership provides a better understanding of energy behavior by giving a value between 0 and 1 which indicates the likelihood for a demand state 0 to occur.

The thesis will need metrics on which the model of the household energy usage will be based on. The metrics introduced in [13] can be used as a steppingstone to look at the dynamics of energy states in a household. We can look at the probability to be in a demand state and the probability to switch from one demand state to another demand state.

2.3 Hardware platforms

Hardware architectures and communications platforms are proposed by [14], [15] and [16]. The focus is on the implementation of an energy management system with the help of communication protocol. The energy management system acts as a mediator. The house and EV communicate with this energy management system in order to sense in what kind of power consumption state each party resides in. These hardware and communication platforms require specific power electronics to make the execution of V2H/V2G successful. The proposed concept of making every part of the power delivery bidirectional can be seen in Figure 2.1.

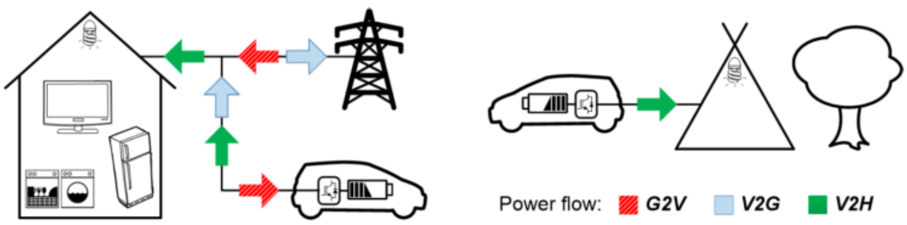


Figure 2.1: Concept of bi-direction architecture for V2H/V2G and G2V [16]

In [17] the power output of an EV battery during the execution of V2H is studied. The execution of V2H requires a DC to AC converter and this comes with some losses that have to be accounted for. The calculated efficiency for this conversion is 93% and this research team measured an efficiency of 88%. The 5% loss is probably attributed to the cooling system of the battery to keep the battery from overheating during a discharge.

We see that much work has been done to design a hardware architecture to make bi-direction power delivery possible. These architectures have been tested and their efficiencies have been measured. This thesis will have to take inefficiencies and other intricacies of the architectures into account and the preliminaries that have been performed by these research teams are beneficial.

2.4 Shifting EV charging

EV charging consumes a considerable amount of power depending on how depleted the battery is. Shifting the charging time of EV to other hours when electricity prices are lower can reduce the EV charging bill significantly. In [18] EV charging is completely shifted to midnight. No other users' preferences are taken into account in terms of SoC and whether the user might need to suddenly make an emergency trip. The assumption in [18] is that electricity prices are the lowest during midnight. No consideration is taken into account concerning hourly pricing schemes in which certain hours of midnight the prices can be lower. By shifting everything to midnight, the relative savings on the EV bill which can be saved is 12.5%. Another research team attempted to schedule EV charging based on past data on EV charging demand [19]. Past charging behavior is used to determine how to distribute EV charging in a neighborhood.

In [20] EV charging is approach from a game theory standpoint with a focus on energy sharing [21], [22]. The situation if of that of a neighborhood in which many EVs want to charge their batteries. There is, however, only one electricity company available to facilitate the charging of these EVs. Cooperative and non-cooperative scheduling is used to schedule EV charging for all these vehicles. A note has to be made that these scheduling algorithms do not take the users' preferences into account, no minimum amount of SoC is required which could lower the comfort level of the EV user if EV is suddenly needed. Other research teams attacked this problem of multiple EVs charging at the same time with linear programming and a data-driven queuing model [23], [19]. In this case, an optimal charge rate of each EV is determined in order to maximize the power that can be outputted by the grid.

We see that the maximum amount of relative savings that can be achieved for one research time when shifting EV charging to midnight is 12.5%. We will use this as our reference value during the development of algorithms for EV charging to which we want to improve our design. Furthermore, we have seen that many research teams have approached the interactions between home, EV and grid as a game theory problem. The resource that has to be shared among all three actors in this game is the EV battery. The research teams have looked into optimizing this problem, but do not take user's preferences into account for the decision making in how the EV battery should be shared.

2.5 V2H/V2G

The purpose of V2H is to alleviate the power demand in the household during peak electricity prices. In [24] methods for V2H systems are proposed. This system would allow a user to input their preferences in terms of what they would like the minimum SoC to be and what the usual departure times are of the user. This paper only introduces a conceptual approach and strategy to handle this problem. There is no actual implementation. This research team, however, did look at how constant discharge and charge at specific depth of discharge (DoD) levels affect the age of the battery. This can be seen in Figure 2.2. The more the battery is depleted constantly to a specific DoD, the faster the battery is going to age.

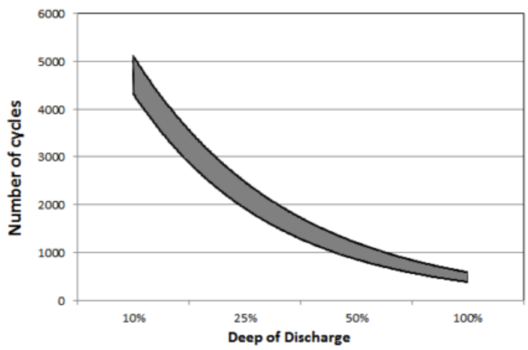


Figure 2.2: Cycle aging for different DoD [24]

In [25] a simulation is run on the execution of V2H. An EV battery with various SoCs is used for the simulation to study how the electricity demand in the house can be lowered. The assumption in these simulations is that the EV is always at home. No other considerations are taken into account in terms of availability of the EV and users' preferences. The goal of research team was to reduce peak power demand on the grid from charging EVs. The simulation for V2H execution was unfortunately not successful and the results of the optimizations for V2H execution could not be reported.

In [26], V2G is implemented based solely on the SoC, while in [27] V2G this is only done based on off-peak pricing. The two elements that influenced the design are the SoC and the off-peak pricing. If the SoC drops below a threshold value, only EV charging is allowed. If the SoC is higher than a specific threshold value, it may be used for V2G purposes. The flow of the decision making process of [26] can be seen in Figure 2.3. In [27], V2G and EV charge scheduling is combined into one algorithm and their achieved relative savings is 7%.

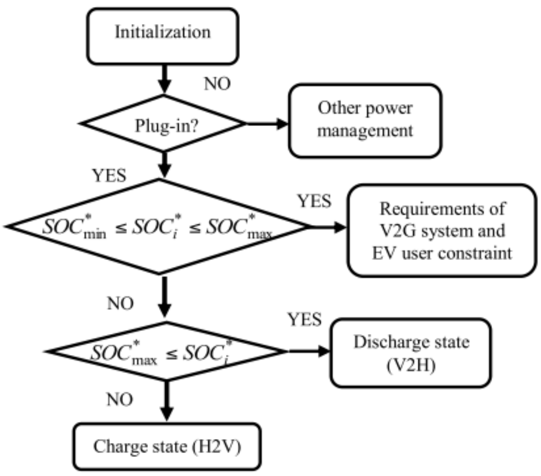


Figure 2.3: Management control for V2G [26]

V2H and V2G are methods introduced to alleviate power demand from the household on the grid. The work of the research teams shed light on different topics regarding the implementation of V2H and V2G. There were no results in terms of relative savings that could be achieved for V2H. Luckily, there was result of relative savings of V2G combined with EV charge scheduling.

2.6 Window of opportunity

In order to shift EV charging scheduling, we need to be able to create time periods in which we are able to charge the vehicle. The first thing that should be done before looking at time windows is looking at the preference of the user to charge during certain periods of time. In [28] real-world data is used to study the flexibility of charging behavior of EV users. First the charging behavior of the users was analyzed. Afterwards, the different charging behaviors which could be extracted from the data were put into categories of how flexible they are for the execution of demand-response programs. The key findings from this research team pointed out that charging times during evening and weekend were the most flexible in the sense that those times could easily be used for demand-response programs. Charging times that were executed at public spaces were the least flexible. This was probably due to the fact that people usually do not stay long at those public spaces to charge their car, thus rendering the usage of demand-response programs negligible.

In [29] a flexibility window is introduced. This flexibility window is defined as the window in which the EV can be charged. This is done on basis of the SoC. The time periods in which the SoC does not change or increases are windows in which the EV can be charged. Time slots in this flexibility window are created and a set of constraints is made to determine in which time slot to charge the EV. These time slots are filled with values based on discomfort level. This discomfort level is based on the SoC and the likelihood to use the vehicle. Historic data is used to determine how likely the user is to use their car in the time slot. Higher values in these time slots thus mean that the likeliness to use the car is higher, which means that it is not the most ideal time slot to schedule EV charging.

This prior research on the window of opportunity for charging EVs shows at which time periods shifting EV charging can benefit the users the most. This is mainly in the evening hours and in the weekends when the usage rate of the vehicle is lower. A flexibility window, which contains time slots, is of great value to this thesis. The algorithm for determining this window and the decision making for choosing specific time slots are of importance when implementing shifting EV charge scheduling and V2H/V2G execution.

2.7 Conclusion

Many different hardware implementations have already been realized to make V2H/V2G possible. The user behavioral study [10] also points out that users are open to change their EV charging behavior in order to save money, but would still like to be in control when necessary in cases of emergencies or unexpected trips. Intelligently shifting EV charging and V2H/V2G applications to save money or to adapt to the grid's supply has been done in one form or another.

The main focus of this thesis is to fill in the blanks to find out what can be improved upon all these introduced methods. An overview of the different subjects covered by the papers can be seen in Table 2.1. As can be seen from this table, there are a lot of different subjects which have been studied separately, but there is no integrated package that takes everything into account. An example of this is the study of user's preferences and behavior. A lot of the implementations of these papers study the EV usage behavior by putting bluetooth beacons or GPS trackers in the vehicles. This is a quite intrusive way to track vehicle usage.

Furthermore, a form of user preference that can be tracked is EV usage analysis, but this does not paint the whole picture. Looking at household occupancy to determine whether an EV is at home or able to charge is an example of user's behavior analysis. From this data user preferences can be deduced. The main focus of this paper is to integrate shifting of EV charging and V2H/V2G applications with constraints of user's preferences.

Topics	[10]	[14]	[15]	[16]	[17]	[18]	[19]	[23]	[26]	[27]	[24]	[25]	[28]	[29]
user preferences and behavior	x													
hardware		x	x	x	x					x				
shift EV charging						x	x	x						
V2H					x				x		x			
V2G										x	x	x		
save money						x								
window of opportunity													x	x
EV usage analysis							x	x					x	x
demand response								x					x	x

Table 2.1: Topics that are covered by different papers

Chapter 3

System model

This chapter goes in depth about the dataset and the methods which are used to create a system model. The workflow that is followed can be seen in Figure 3.1. The first step in the workflow is to check what kind of data can be collected from the database. The assumption is that sensors are used in conjunction with smart meters in households to extract fine-grained power usage data of household and (hybrid) electric vehicles (HEV). The second step is to analyze the data to know which characteristics of the households can be extracted. This is done by using a clustering algorithm. The results of the clustering algorithm are used to determine the occupancy and active EV charge sessions of the households. The last step is to create models based on the extracted information by using temporal metrics.

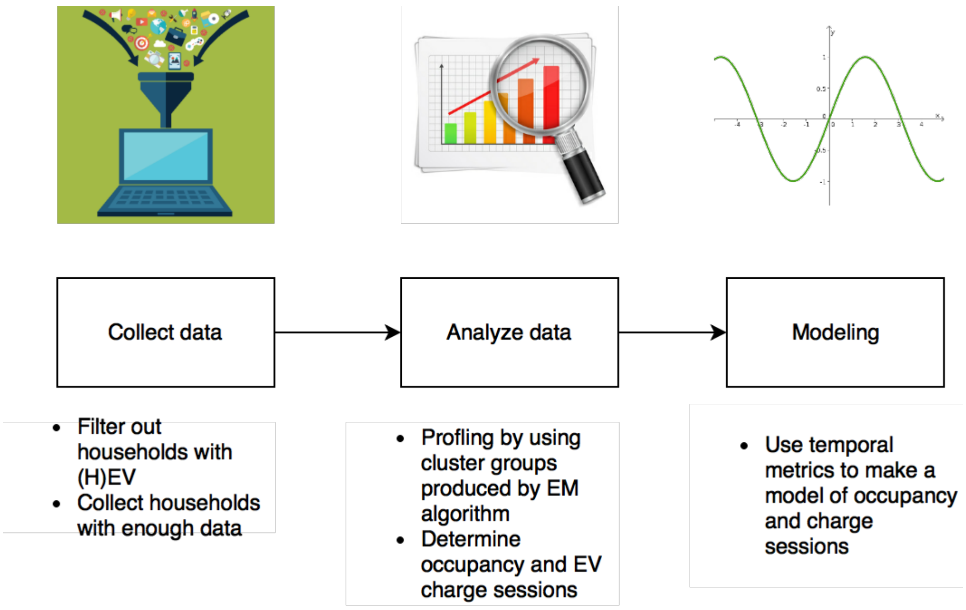


Figure 3.1: Workflow for system model

3.1 Analysis of dataset

The database which is used for this thesis project is Pecan Street [30]. Pecan Street contains numerous households and their daily energy usage data. All this data is collected from households in the state of Texas in the USA. The energy usage data is split up according to the available rooms and appliances which are available in the household. Households also have metadata concerning the number of occupants and which days they spend a significant portion of the workday at home. This database thus contains a multitude of data which can be used to create the system model.

In the database provided, there are households that own a hybrid electric vehicle (HEV) or EV. The intention is to filter households that have an (H)EV. The other intention is to make sure that there is sufficient data from the database to work with. After careful examination of the different types of data that are available from the database, two sets of data are of the most importance and will be used for further analysis in the next steps. The two data sets which were the most interesting were the EV charging data and the household energy usage data. The household energy usage data does not include the charging of the EV. The database provides two ways to represent this power usage data. The data can be represented in time intervals of hours or minutes.

For a specific household (with dataid 26), the household and EV charging usage of January 9, 2014 using minute by minute data can be seen in Figure 3.2. The same representation in hourly data can be seen in Figure 3.3. The horizontal axes in both these figures represent the hours of the day and the vertical axes represents the average power usage. The minute data shows the raw data of the overall average power usage from minute to minute. It can be clearly seen where home power consumption suddenly spikes, namely around 6:00 and 16:00. Those periods correspond to an increase of activity in the household, which indicates that someone is at home using electricity. The precise moment of the start and end of charge sessions can also be observed in the minute data figure. Figure 3.3, shows a rough sketch that also corresponds to hourly periods in which increased activity in the household occurs.

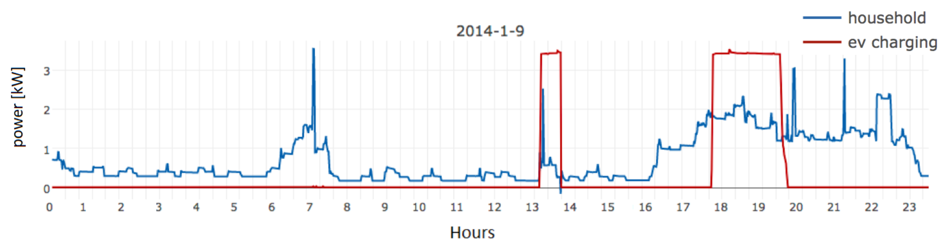


Figure 3.2: Minute by minute data of the energy usage

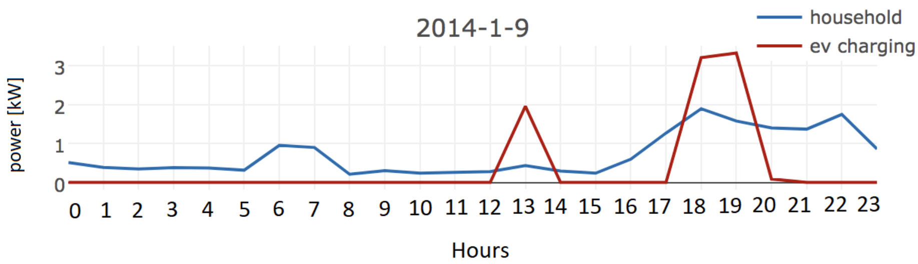


Figure 3.3: Hour by hour data of the energy usage

3.2 Profiling households

From the previous section, we can see graphs in which time periods of increased electricity usage in the house can be observed. Time periods of EV charging can also easily be found. There are two ways to represent this data. Since the goal of the project is to look at changes from hour to hour and not zoom in on a minute to minute basis, the focus will be placed on the hourly data of the dataset. The model that will be created is not concerned with what happens on a minute to minute basis, but will extrapolate to what happens on an hourly basis.

Now that we know what type of data is used, the next step is to find out how households can be profiled from the data. For the household energy usage, the question that has to be answered is: How do you determine when someone is at home? For the EV charging usage, the question is to determine when EV charging takes place. In order to determine this, various groups are going to be made for the energy usage of the household and EV charging. This is achieved by using a clustering algorithm. Afterwards, we are going to use temporal metrics to be able to create models of the households' energy usage and EV charging behavior.

3.2.1 EVs and charge rate

Using the dataset, the model of EV that each household owns can be found very easily. The battery capacity for each EV in the household can be found using the model of EV. However, the type of charger that the household uses to charge their EV is not known. There are different kinds of chargers available for EVs and each type charges at its own rate. The metadata of the database does not provide information of the type of charger used. The best way to find out what the charge rate is, is to look at a minute by minute data of the charge session. Figure 3.2 illustrates nicely that when the EV is charged, it charges immediately at its maximum rate. The household in this figure uses a 3.3 kW charger.

3.2.2 Clustering

Clustering is the task of placing objects in the same group that are similar to each other. In this case, the hourly energy usage of households will be placed in different cluster groups according to their levels. This will also be done for EV charging. An unsupervised machine learning algorithm is used to make this classification. The main benefits of using clustering is that it does not require the data to be labeled. The other reason is that clustering can indicate the possible states the energy usage of a household can reside in. If for example clustering produces three clusters, the clusters could indicate low, medium and high level states.

For this thesis, Expectation-Maximization algorithm [31] is used for the clustering. This algorithm takes as input the hourly energy usage values and outputs the cluster values. The cluster values represent a specific group that the hourly usage value belongs to for a specific hour. Each cluster value contains a centroid, which represents a central value for a specific cluster. Energy usage values that are close to a cluster's centroid are going to be placed in that cluster. These clustered values only hold for hourly time intervals since this is being used as input.

All the relevant data of the households regarding the household energy usage and EV usage is collected with hourly intervals in a time period of one year. A time period of one year is ideal since this includes all the seasonal changes and energy shifting behavior during a year. All this data is put into the clustering algorithm to produce the clustering characteristics for each household.

An simple illustration of the input and output of the EM clustering algorithm can be seen in Figure 3.4. The input of all households with their corresponding energy usage values of either household or EV charging is inputted into the algorithm in hourly intervals. The output of the algorithm is the clustered values for their corresponding hourly interval.

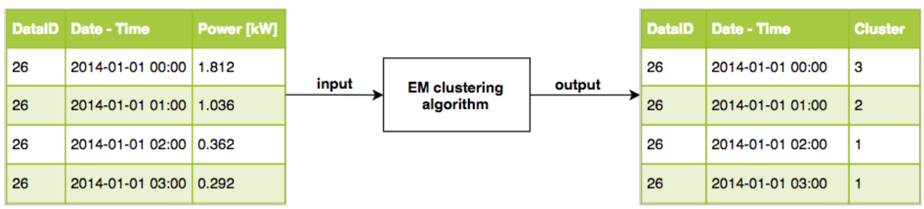


Figure 3.4: Input and output of EM clustering algorithm

3.2.3 Determination of characteristics

There are two datasets which have been retrieved from the dataset: household energy usage and EV charging usage. Two specific characteristics have to be distinguished for the households, namely, we have to be able to determine the occupancy of the household. Of the EV charging usage, we have to be able to determine when a charging session occurs. Since the data is collected in hourly intervals, the determination of occupancy and active charge session is also done on an hourly basis. The determination of these occupancy and charging states will be done by means of clustering data.

Occupancy

Putting the household energy usage data through the clustering algorithm will produce a certain amount of cluster values. Each cluster value represents a different level of energy usage. The higher the cluster value, the higher the energy usage for that particular hour. From these cluster values, the occupancy has to be determined. The occupancy is either True or False. The lowest cluster value will have a centroid of around 0, which may represent that there are no occupants at that hour. All the cluster values higher than the lowest value can indicate that there are occupants in the home. This cluster value of 0 can be used as a boundary value. However, this boundary value may not always be valid for all households.

We need a boundary value to determine whether there is occupancy in a household. Finding this boundary can be done by considering different factors. Looking at the centroid values of the clusters can be one of the things that can be used. Looking at whether there is enough separation between the two lowest clustered values, can be an indication of a valid boundary value.

Another way of making this distinction of occupancy based on cluster values is to use metadata of the households. If there are more occupants in the house, the assumption can be made that a higher cluster value might be needed to indicate occupancy. If a household indicates that they are often at home on certain days of the week, a higher cluster value might also be needed to indicate that the residents are at home, since the energy usage on those indicated days can be higher.

In order to extract this occupancy property properly, three assumptions are made and each assumption will be tested to see whether they hold up in all conditions. Occupancy for hour h is occupancy_h. The assumptions are as follows:

- Assumption 1
  There is sufficient separation between the two lowest clustered values that cluster 0 can be used as boundary value to map True/False occupancy

$$\text{occupancy}_h = \begin{cases} \text{False}, & \text{if clustered value} = 0 \\ \text{True}, & \text{otherwise} \end{cases} \tag{3.1}$$

- Assumption 2
  The days on which households have indicated that they are at home, requires higher boundary values since their baseline electricity usage on these days is higher

$$\text{occupancy}_h = \begin{cases} \text{False}, & \text{if clustered value} <= \text{boundary value} \\ \text{True}, & \text{otherwise} \end{cases} \tag{3.2}$$

- Assumption 3
  The higher the number of occupants in the household, the higher the boundary value has to be set to determine occupancy.

$$\text{occupancy}_h = \begin{cases} \text{False}, & \text{if clustered value} <= \text{boundary value} \\ \text{True}, & \text{otherwise} \end{cases} \tag{3.3}$$

The boundary values as seen in these equations are not defined yet. Validation will have to be done to see what boundary values can be used in these equations of the three assumptions. These assumptions will also have to be validated to see whether they are valid in all situations. The validation will be done in Chapter 5.

EV charge session

The determination of active EV charge sessions is more straightforward than that of occupancy. When an EV is not charging, it draws 0 kW from the grid. This 0 kW is represented with the lowest clustered value. All cluster values higher than the lowest cluster value indicate that there is a charge session active. The boundary for the determination of EV charge sessions is thus easily found.

The method for determination of occupancy and EV charge session is to use the clustered values and determine from these values a True or False state for each hour. Concerning the EV charge sessions, we are not concerned about the intensity of the energy usage but solely on whether a charge session is active or not. We declare a variable called **active charge**. This variable represents a True or False value depending on whether a charge session is active or not. The **active charge** at hour h is defined as follows:

$$\text{active charge}_h = \begin{cases} \text{False}, & \text{if clustered value} = 0 \\ \text{True}, & \text{otherwise} \end{cases} \tag{3.4}$$

3.3 Modeling of the households

In order to model the households depending on a specific property, metrics are needed. These metrics are temporal metrics, which are based on previous studied papers. These temporal metrics will have to be tweaked a bit in order to make them compatible with the True/False state of the properties. In the end, a distinction will be made between weekdays/weekend and seasonal metrics, since the energy usage between these time periods can differ considerably.

3.3.1 Temporal metrics

In order to create models for the households based on their energy usage and EV charging, two metrics are going to be used: temporal membership and transient probability. These are metrics which are based on [13].

Temporal membership for hour h is defined as the probability of a household to be in a certain cluster c over a time period n. Temporal memberships are created for each hour h over a time period of n days. This is expressed as follows:

$$M_c^h = \frac{1}{n}\sum_{i=1}^{n} b_i^h; \quad b_i^h = \begin{cases} 1, & \text{if cluster } c \text{ occurs} \\ 0, & \text{otherwise} \end{cases} \tag{3.5}$$

Since there are 24 hours in a day, 24 temporal memberships are created to asses the likelihood to be in a certain cluster at hour h.

Transient probability from hour h to $h+1$ is defined as the probability of moving from one cluster value (a) to a different cluster value (b) over a period of time n

$$T_{a\to b}^{h\to h+1} = \frac{1}{n}\sum_{i=1}^{n} c_i^{h\to h+1}; \quad c_i^{h\to h+1} \begin{cases} 1, & \text{if } s_i^h = a \wedge s_i^{h+1} = b \\ 0, & \text{otherwise} \end{cases} \tag{3.6}$$

where $c_i^{h\to h+1}$ is a binary value that is either 1 or 0 depending on whether the cluster values of s_i^h and s_i^{h+1} satisfy the condition. A cluster transition from a to b can either mean that there is a cluster transition upwards or downwards. If for example the transition is from cluster value 1 to cluster value 2, this means that in that hour transition, the energy level also goes up. The downward transition can also be studied with this equation.

These temporal metrics are expressed in percentages in order to asses whether a household is more likely to be a member of a certain cluster or whether a certain cluster transition is more likely to happen.

The temporal metrics as described in Equation 3.5 and 3.6 are only valid for a specific household. Since the data differs for each household, these metrics have to be calculated separately for each household.

3.3.2 Consequence of mapping clusters to True/False states

As discussed in Section 3.2.3, cluster values will be mapped to either a True or False state for both occupancy and EV charging states. This entails that there is no variation anymore in the energy intensity level of the energy usage expressed cluster values. Temporal metrics discussed above look at cluster values and not at True/False states. The equations have to be tweaked slightly to only look at True/False states.

Each temporal metric represents a specific property of the household. This property can either be the occupancy or the charge session of the household.

Temporal membership measures the likelihood for a household to be a member of a certain cluster. Since there are only two states, it is easier to use a different terminology to define temporal membership. After tweaking the temporal membership equation, we are left with a property probability. The probability for a household to be in a positive state at a certain hour h over a period of days n is expressed as follows.

$$P^h_{\text{property}} = \frac{1}{n}\sum_{i=1}^{n} b^h_i; \quad b^h_i = \begin{cases} 1, & \text{if state} = \text{True} \\ 0, & \text{otherwise} \end{cases} \tag{3.7}$$

where b is a binary value that is 1 if the occupancy for hour h is True. This property probability can be either an occupancy probability ($P_{\text{occupancy}}$) or an EV charge session probability (P_{charge}).

Transient probability can study both the upwards or downwards cluster transitions. In the case of only having two states, the following 4 transitions can be studied:

- False → False
- True → True
- False → True
- True → False

The las two transitions in which a state change occurs are interesting to study, since they measure the probability for a specific state transition. If, for example, a person in a specific household always arrives home at 5 PM, the positive transition from 4 PM to 5 PM is going to occur a lot more frequently, since the household energy usage most likely is going go up from 5 PM onwards.

Transient probability for a property is defined as the probability of transition $(0 \rightarrow 1)$ [1] to occur from hour h to $h+1$ over a period of time n:

$$T^{h\rightarrow h+1}_{\text{property},0\rightarrow 1} = \frac{1}{n}\sum_{i=1}^{n} c^{h\rightarrow h+1}_i; \quad c^{h\rightarrow h+1}_i \begin{cases} 1, & \text{if } s^h_i = False \wedge s^{h+1}_i = True \\ 0, & \text{otherwise} \end{cases} \tag{3.8}$$

[1]The notation of $0 \rightarrow 1$ is used instead of False→True to make the equation more organized since it needs less space

where $c_i^{h\rightarrow h+1}$ is a binary value that is either 1 or 0 depending on whether the upwards state transition occurs. This upward transition is denoted by s_i^h and s_i^{h+1}. Note that in this equation only the upwards transition is taken into account.

The other transition that we also studied is the downwards transition of $1 \rightarrow 0$. This state transition of $1 \rightarrow 0$ can be denoted by the following formula:

$$T_{\text{property},1\rightarrow 0}^{h\rightarrow h+1} = \frac{1}{n}\sum_{i=1}^{n} c_i^{h\rightarrow h+1}; \quad c_i^{h\rightarrow h+1} \begin{cases} 1, & \text{if } s_i^h = True \wedge s_i^{h+1} = False \\ 0, & \text{otherwise} \end{cases} \tag{3.9}$$

The transient probability can either be an occupancy transient probability ($T_{occupancy}$) or a charge session transient probability (T_{charge}).

3.3.3 Splitting properties into weekdays/weekends and seasons

The two metrics which we use are property probability and transient probability. Each metric studies two properties. These properties are occupancy and EV charging. The behavior of the occupancy of a household during weekdays and weekends can vary significantly. If there are two people in a household and both of them work each day during the week except for the weekends, their occupancy pattern is going to be different during the weekends. The same also holds for the EV charging property.

The dataset contains households from Texas. Texas has 4 seasons with the two extremes of summer and winter. People's energy usage is going to change depending on the season. Therefore, having separate metrics for each season will also be more representative for the model.

Since each property's behavior during weekdays and weekends can vary, it is better to have separate probabilities for each case. Furthermore, there are 4 seasons, resulting in 4 property probabilities for each week/weekend period. The visualization of this binary tree can be seen in Figure 3.5.

A binary tree can also be created for the transient probability. There are also two properties for transient probability. Each property can be split into weekdays and weekends. There are also 4 seasons, which results in the weekday and weekend having their separate 4 seasons probabilities. The visualization of this binary tree can be seen in Figure 3.6. The two state transitions of interest ($1 \rightarrow 0$ and $0 \rightarrow 1$) are not denoted in this figure.

3.4 Conclusion

With the help of data collection and data analysis, a model can be made of the occupancy and EV charging behavior of each household. The model will use the clustered values of each dataset for the determination of occupancy

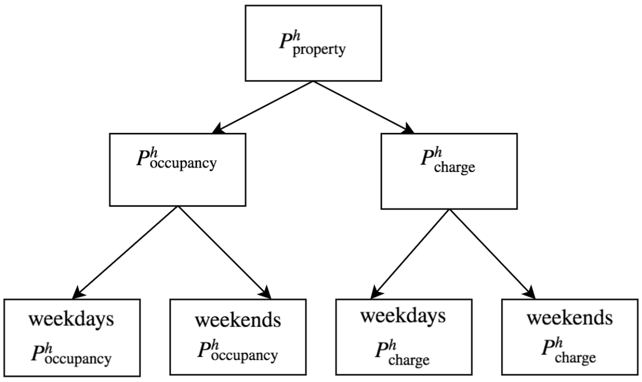


Figure 3.5: Tree for $P^{\text{h}}_{\text{property}}$

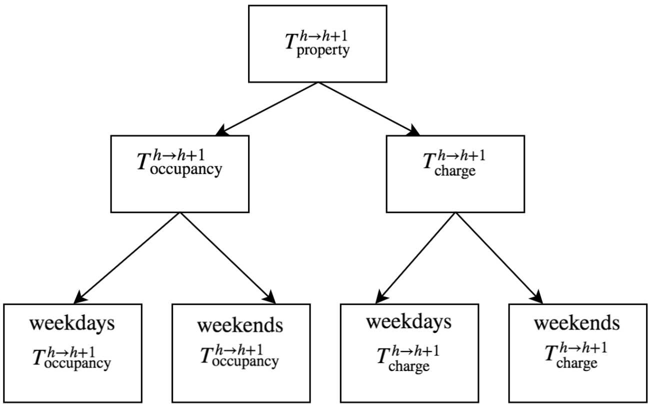


Figure 3.6: Tree for $T^{h\to h+1}_{\text{property}}$

and active EV charge sessions. Based on this model, temporal metrics are introduced. They are as follows:

- Occupancy probability
- EV charge probability
- Occupancy transient probability for state transition $0 \to 1$
- Occupancy transient probability for state transition $1 \to 0$
- EV charge transient probability for state transition $0 \to 1$
- EV charge transient probability for state transition $1 \to 0$

These temporal metrics will determine the behavior of the algorithms which will be discussed in the next chapter.

Chapter 4

Algorithms

In this chapter, we first discuss the preparation steps that were done for the algorithms. The actual algorithm will also be discussed. The preparation steps consist of the definitions of EV charge sessions, pricing scheme and flexibility window. These are all elements that are of importance before the actual design of the algorithms can be started. In order to implement these elements, metrics of Chapter 3 are used. Furthermore, we created two algorithms. The first one is the EV charge scheduling algorithm. The second algorithm is the V2H/V2G algorithm.

4.1 EV charge session

We need to be able to define what an EV charge session is. From the previous results, using the clustered results, the specific hours at which an EV charge session is running can be found easily. We may know at each hour whether an EV session is active, but we may not necessarily know when the session began and when it ended. There are also other properties of each EV session that we have not uncovered yet from the clustered results.

In Figure 4.1 the hourly power usage and clustered values can be seen for EV charge sessions. If for an hour the EV cluster value has a value larger than 0, that means that at that hour there is an active charge session. In this Figure, the hours in which there are active charge sessions are hours 18:00 and 19:00. We can clearly see that this is a continuous charge session which started at hour 18:00 and ends at hour 20:00. The figure thus illustrates one charge session. In order to identify each charge session, a finite-state machine (FSM) is made. This FSM uses the EV clustered values to identify the start and end of each charge session. This FSM can be seen in Figure 4.2. An EV charge session that starts for example at 23:00 and ends at 02:00 counts as one charge session and not two separate sessions.

Now that each EV charge session can be identified, we can easily retrieve how much energy is charged during each session. Using this data, we can

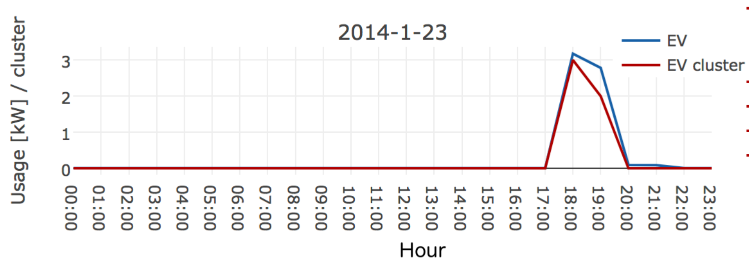


Figure 4.1: Graph in which an EV charge session can be seen

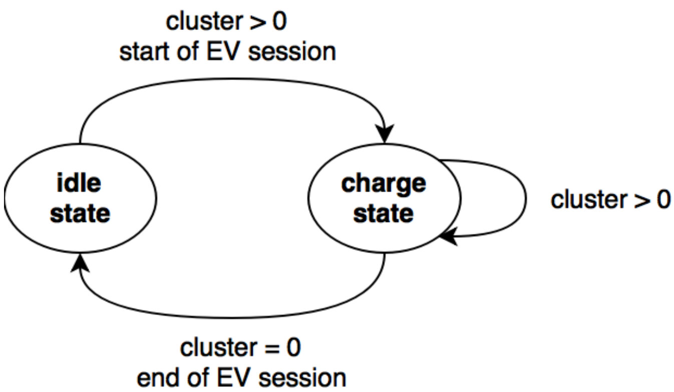


Figure 4.2: Finite-state machine for identifying each charge session

calculate depending on the EV model the battery percentage when the session started. This battery percentage is called state of charge (SoC). The assumption is that each EV charge session charges the battery to 100%. For each charge session, the following properties can be extracted:

- start hour
- end hour
- energy used
- SoC prior to session

4.2 Pricing scheme

A pricing scheme is needed to know how much has to be paid for an amount of kWh used for a specific hour. For this thesis, an hourly pricing scheme from the US electricity company ComEd is used [32]. Using this pricing scheme, customers can decide to shift their energy usage to a specific hour or time period in which the prices are the lowest.

ComEd provides an API to access historical electricity prices. All the modeling of the previous chapters is based on the year 2014. The year 2014 is also included in the historical electricity prices of ComEd.

4.3 Flexibility window

Before we move on to algorithms, it is important to discuss what a flexibility window is. For each charge session a flexibility window is created. The flexibility window consists of hourly time slots. Each time slot contains a value which indicates whether charging in this hour is preferable.

The flexibility window gives a time period in which the charging of the EV can be scheduled. Which hours are chosen for charging the EV depends on the type of objective. The creation and the decision making based on certain objectives will be discussed in the next few sections.

4.3.1 Requirements

To create the flexibility window, we need a set of requirements. These requirements dictate the length of the window and what rules are applied to create the flexibility window. The requirements and their explanation are as follows:

- The window's minimum length is the minimum hours needed to charge

$$\text{minimum length} = \left\lceil (1 - \text{SoC}) \cdot \frac{\text{battery capacity}}{\text{charge rate}} \right\rceil \tag{4.1}$$

- The window's maximum length is equal to 6 hours
  We have set the maximum length of the window to 6 hours. The reasoning for this is that one would want their car to be charged fully in the next 6 hours. Anything longer than 6 hours or a quarter of a day could be experienced as an inconvenience.

- The window expansion is based on boundary value of transient probability
  Occupancy transient probability is used with the state transition of $1 \rightarrow 0$. We are checking the probability for the occupants to leave the house. If the probability to leave the house is lower than the boundary value, the window may be expanded. If the transient probability crosses the boundary value, this implies that there is a big probability that there will be no people at home in the next hour. There is no need to expand the window. If the probability to leave the house is lower

than the boundary value, people will stay home and we can expand the window because they are not going to need the vehicle.

- During midnight the window may be expanded to maximum length
  The midnight hours are defined as the period of 00:00 till 05:00. If the next hour to which the window can be expanded happens during this midnight period, the window may be expanded to this extra hour without considering the boundary value expansion of the previous requirement. These midnight hours are usually hours when someone is asleep and the energy usage activity is at its lowest.

During midnight the window may be expanded to maximum length
The midnight hours are defined as the period of 00:00 till 05:00. If the next hour to which the window can be expanded happens during this midnight period, the window may be expanded to this extra hour without considering the boundary value expansion of the previous requirement. These midnight hours are usually hours when someone is asleep and the energy usage activity is at its lowest.

4.3.2 Creation of the flexibility window

The creation of the flexibility window takes all the requirements of the previous section into account. The process of creating the flexibility window can be seen as an FSM in Figure 4.3. The following variables are used in the FSM:

- length
  This is the length of the window.

- min_length
  This is the minimum length of the window which is defined as the minimum hours needed to charge EV to 100%.

- max_length
  This is the maximum length of the window which is defined as 6 hours.

- trans_prob
  This is the transient probability of the occupancy for transition $1 \rightarrow 0$. It is the probability that measures the likelihood of leaving the house for a certain hour transition.

- boundary
  This is the occupancy boundary value which is used for the conditional statements of the **check boundary/midnight** state. If the trans_prob is lower or equal to the occupancy boundary value, the window may be expanded with one hour extra. Otherwise, the expansion of the window is halted.

Creation process

The creation of the window is started when there is a new charge session. The window length is immediately set to the minimum length. As long as the length is smaller than max_length, the expansion process will continue. The next hour beyond outside the window is checked for its transient probability and whether it is a midnight hour. If the transient probability of that hour is lower or equal to the occupancy boundary value or it is a midnight hour, the window may be expanded with that hour. The window will constantly be expanded until the condition **trans_prob** > **boundary** is satisfied or if the length of the window is 6 hours.

A higher occupancy boundary value will result in bigger flexibility windows, but there will be a risk of the EV not having a high enough SoC for the user in case of an emergency. Varying the boundary values will be done in the next chapter to find the optimum values for **boundary**.

We are going to discuss one boundary condition of the flexibility window creation process. What if there is a new charge session and the minimum length of the window is set to 7. The expansion process is not run at all and the window creation process is completed with a length of 7 hours. This boundary condition is taken into account in the FSM with the conditional transition: length $\geq$ max_length.

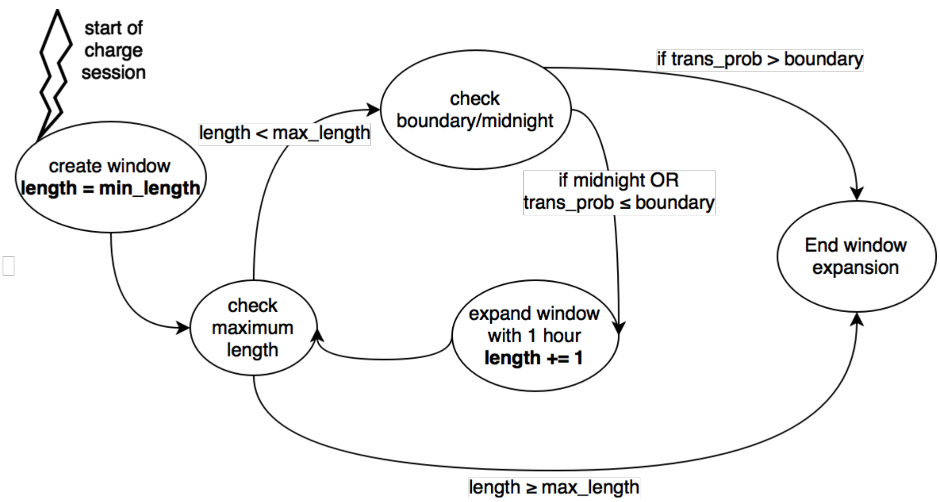


Figure 4.3: FSM for the flexibility window

4.3.3 Decision making

Let's say that a flexibility window containing 3 hours is created for a charge session with start hour 12:00 as seen in Figure 4.4. Since hour 15:00 does not satisfy the boundary condition, it will not be added to the flexibility window and the expansion has been halted. Let's assume that 2 hours are needed to charge the EV to 100%. Which of these 2 hours of the 3 hours will be chosen to charge the EV? This decision making will depend on the objective. We introduce two types of objectives: *cost minimizing*, *comfort maximizing* and *variable comfort*.

Figure 4.4: Flexibility window created with a length of 3 hours

Cost minimizing

Cost minimizing as objective entails that in the decision making the cheapest hours of the flexibility window will be chosen to charge the car. The chosen hours may not make up a continuous charge session. Looking at Figure 4.5, we can see the electricity price for each hour in the flexibility window. Let's continue with the previous example that the EV needs 2 hours to be charged fully. 2 of the 3 hours have to be chosen to charge the EV. The hours that are the cheapest are 12:00 and 14:00. These hours will be chosen to charge the EV, leaving an idle hour 13:00 in between.

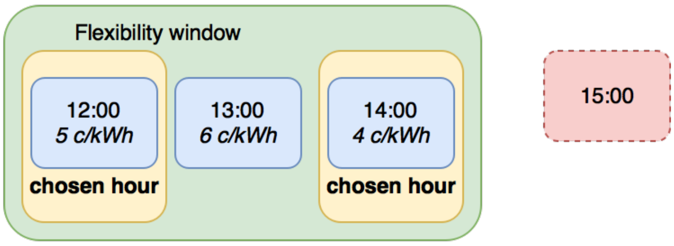


Figure 4.5: Chosen hours of flexibility window based on prices

Comfort maximizing

The other objective used for the process of decision making is comfort maximizing. The main question is how to define comfort in terms of users' preferences. The definition of comfort for the user depends on what comfort entails. This comfort should be based on the user's preferences and past behavior. We need a way to express the comfort level, (comfort^h), for a given hour h. Four parameters are introduced to measure the comfort level. These four parameters contain values ranging between 0 and 1. The four parameters with their explanations how they contribute to comfort are as follows:

- Occupancy probability: P^h_{occ}
  If there is a high probability for someone to be at home at hour h, this will be reflected in the value of P^h_{occ}. Otherwise, P^h_{occ} will be lower. If the probability is lower, the chances are bigger that the EV cannot be charged, since no one is at home. Higher probability contributes to higher comfort level, since there is a higher chance that the EV can be charged successfully during those hours.

- Charge probability: P^h_{charge}
  If the occupant is very likely to charge at hour h, the value of P^h_{charge} will be higher. The EV owner may have their own preferences when they would like to charge their car normally. Choosing hours in which the charge probability is higher contributes more to the level of comfort.

- Price comfortability: price_comfort^h
  The price comfortability is a value expressed between 0 and 1. Normalized prices of the year 2014 are used to calculate price_comfort^h. price_comfort^h is calculated using the following formula:

$$\text{price\_comfort}^h = 1 - \text{normalized\_price}^h \tag{4.2}$$

  If price_comfort^h has a value of 1, this entails that the comfort is at its highest and therefore the prices are at their cheapest. On the other end of the spectrum, price_comfort^h having a value of 0 entails that the prices are at their most expensive. A visualization of the range of price_comfort^h can be seen in Figure 4.6.

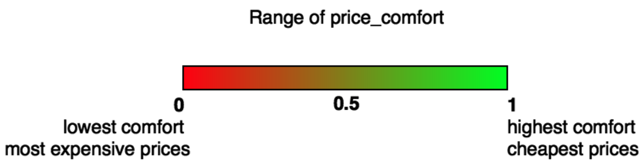


Figure 4.6: The range of price_comfort

- Midnight boolean: B^h_{midnight}
  The midnight hours are defined as the time period of 00:00 to 05:00. These are normally hours in which people are at home sleeping and not using their car. These hours are thus ideal from a user's preferences perspective to charge their EV.

The four parameters are all specific to an hour and season. Each parameter has a value ranging between 0 and 1 except for B^h_{midnight}. These four parameters are defined as components that measure the comfort level. The occupancy and charge probability are the likelihood of users to be at home and charge their car, respectively. They are considered as contributors of comfort, since the user's preferences are taken into account. Choosing hours with higher chances of being home and chances of charging the car, will result in a higher success rate of the charge plan. A higher success rate means that the comfort is higher for the user.

These 4 parameters each contain a weight that decides how much they contribute to the comfort level. The formula for the level of comfort for hour h is as follows:

$$\text{comfort}^h = \frac{1}{\sum_{i=1}^{4} c_i} \cdot \left[c_1 \cdot \text{price\_comfort}^h + c_2 \cdot P^h_{\text{occ}} + c_3 \cdot P^h_{\text{charge}} + c_4 \cdot B^h_{\text{midnight}}\right] \tag{4.3}$$

This equation for the level of comfort produces a value between 0 and 1. The weights of each parameter expressed by c_i are used to determine how much they can contribute to the comfort level. The determination of the weights can be done from the user standpoint. If the user has a very high preference for cost minimizing (price_comfort) but also to occupancy probability, they can appoint higher weights to these two parameters.

Joint comfort

In the objective "comfort maximizing", we defined the level of comfort in which the weights for each parameter are fixed. They can be set beforehand, but afterwards there is not much flexibility. What if we want the weights to change dynamically according to certain conditions? In this case, we introduce a new objective: joint comfort. In joint comfort the weights are going to change depending on certain conditions.

If the electricity prices are low, it may not matter so much which hour you choose to charge the EV. It may be more relevant to then pick the hours in which someone is most likely to be at home or to charge the car. So we want to put more emphasis on user's preferences when the electricity prices are low. If the prices are high, we may want to prioritize the hours according to the prices instead of user's preferences.

We use the price comfort boundary of 0.8 for deciding what to prioritize. This value of 0.8 corresponds to the electricity price of 32 c/kWh. If the prices are lower than 32 c/kWh, higher weights are given to the user's preferences. Otherwise, the weight for price_comfort will be given a higher weight.

4.4 EV charge scheduling algorithm

Now that we have a thorough understanding of how the flexibility window works and how it is created, we can move on to the next step: EV charge scheduling algorithm. This algorithm has as input the start hour of an EV charge session and schedules the charging time according to a certain objective. Using this objective, a charging schedule is made to charge the EV to 100%. After having made a schedule of when to charge the car, this new charging schedule has to be checked against the real occupancy data to see whether the scheduled charge time can actually be completed. If the EV cannot be charged during the scheduled hour, the algorithm tries to schedule this missed hour in the remaining hours if possible.

4.4.1 Requirements

We introduce two requirements for the EV charge scheduling algorithm. The first requirement is that the EV can only be charged when the occupants are at home. If there is no one at home, the EV cannot be charged, since the assumption is that the occupants left the house with the EV. The second requirement is that the hourly average power usage from the grid may not exceed 10 kW. This requirement is made to ensure grid stability and to prevent too big of a strain on the grid. This value of 10 kW to ensure stability in the grid will vary depending on the neighborhood and the electricity company. We start with an average hourly power of 10 kW as a boundary that may not be exceeded. Using both a washing machine and a dryer at the same time will constitute an average power usage of 3 kW. Most home EV chargers are of the 3.3 kW type [1]. There is still 3.7 kW of power left that can be used for household purposes. A boundary value of 10 kW seems reasonable as a starting point for the boundary value.

4.4.2 The steps of the algorithm

The flow diagram of the EV scheduling algorithm can be seen in Figure 4.7. Each step of the algorithm is clearly highlighted in this figure. One new variable is introduced in this algorithm: deficiency. The deficiency is defined as the amount of kWh left to charge the EV to 100% during the previous charge session. A deficiency can occur when during a previous charge session the EV could not get charged to 100% due to certain requirements as discussed in the previous section. The following steps in the algorithm are undertaken:

1. Create flexibility window
   The input of start hour, SoC and the deficiency of the start of the

[1] From all the households used for this thesis, 83% of them have a 3.3 kW charger.

charge session are used to create a flexibility window. The flexibility window is expanded up to the maximum length depending on the boundary value. This flexibility window is that given as input to the next step.

2. Schedule which hours to charge
   The flexibility window contains the hours that are available to charge the EV. Depending on the objective of either cost minimizing or comfort maximizing, certain hours will be chosen to charge the EV. These chosen hours are given to the next step.

3. Check whether charge successful
   An input is received of which hours are chosen to schedule the charging of the EV. In this step, the verification is done whether it is possible to charge the EV during those scheduled hours. This is done for each hour from the beginning to the end. If it is not possible to charge the EV during a specific hour due to the requirements, the algorithm goes back to step 2 and tries to reschedule in the remaining hours of the flexibility window, if possible. It is only possible to select the hours after the failed scheduled hour. After all the scheduled charging hours are verified, one of the following two scenarios are possible before continuing step 4: the EV could be charged fully to 100%, or there were no more hours left in the flexibility window to charge EV to 100%. Regardless of either scenario, step 4 is entered.

4. Check deficiency
   In step 4, we are going to verify whether the EV could be charged to 100% during the previous step. If the EV could not be charged to 100%, there is a deficiency. This deficiency is given as input to step 1 and will be corrected the next time when the EV is charged again. If there is no deficiency, there is nothing els to do and the algorithm can be exited.

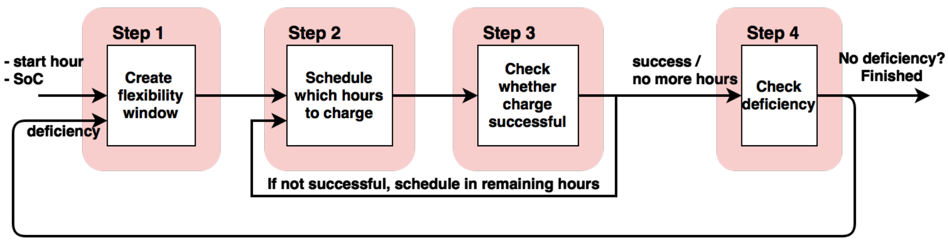


Figure 4.7: Flow diagram of the EV charge scheduling algorithm

4.4.3 Special scenario for midnight

We have created two special scenarios in which the algorithm behaves differently. The first scenario concerns step 3 of the algorithm. Each hour of the flexibility window is checked whether there is a scheduled charge session and this scheduled hour is checked whether occupancy is true at that hour. However, according to the model, there are certain hours when the occupancy is always false, but people are at home. These are the midnight hours when people are asleep. The midnight hours are defined as the hours from 00:00 to 05:00. During these hours, the assumption is made that the occupants are at home. The EV can thus always be successfully charged during midnight hours.

The second scenario concerns the deficiency. We always want the car to be charged to 100% by 5 AM so that it is ready to be used for the day. What if there was a deficiency created during one of the charge sessions and that has not been corrected by 00:00? In this case, we are going to run the algorithm again with the input of start hour at 00:00. By doing this, the EV can be charged to 100% by 5 AM.

4.5 V2H/V2G scheduling algorithm

In this section, the algorithm for V2H/V2G scheduling is introduced. Its starting point is the start of the EV charge session. At this point in time, the SoC of the EV and the starting time of the session are known. Using this preliminary information, the algorithm is run for the next consecutive hours until the EV is charged to 100% at 05:00 or the EV is used again. This algorithm introduces a couple of intermediary steps that have to be finished before executing V2H/V2G. These intermediary steps are all checks to make sure that certain requirements are met first before actually doing V2H/V2G execution. If a requirement is not met, the algorithm falls back on the EV charge scheduling algorithm that has been discussed in the previous section.

4.5.1 Requirements

We have created requirements for the V2H/V2G algorithm. These requirements have to be met first before the V2H/V2G execution can actually be done. They are as follows:

1. Algorithm started when SoC is known
   An important element of the V2H/V2G algorithm is knowing the SoC of the EV. The SoC is not known for every hour of the day. We know what the SoC is of the EV at the beginning of a charge session. The V2H/V2G will be started precisely at the beginning of the charge session.

2. EV discharge efficiency
   The discharge efficiency (η) of the EV battery is set to 88%. This discharge efficiency is a value that has been achieved by [17] in their hardware architecture for discharging the EV for V2H usage. The discharge rate of each EV is dependent on its charge rate:

$$\text{discharge\_rate} = \eta \cdot \text{charge\_rate} \tag{4.4}$$

3. Prevent EV charging when electricity prices are too high
   The average electricity price used from the dataset is 4 c/kWh. We define 8 c/kWh as the threshold when the grid's supply does not meet the demand. When the price is higher than this boundary, EV charging is prohibited. We want to prevent the EV from charging during expensive hours and then executing V2H/V2G during cheap hours.

4. Algorithm run when occupancy is true
   The algorithm can only be run when the occupancy is true. If the occupancy is false, the occupants have left the house with the EV. As with the EV charge scheduling algorithm, the assumption is made that during the midnight hours of 00:00 to 05:00 occupancy is always true.

5. Time period restriction [17:00 - 05:00]
   We have made the decision to restrict the execution of V2H/V2G algorithm only in the time period of 17:00 to 05:00. If a car is charged in the morning or in the afternoon, the chances are much higher that the car will need to be used again. It is in these instances very inconvenient for the user to have the battery of the EV used for other purposes than driving. During the restricted time period, the chances are much smaller that the user leaves the house in that time period.

6. EV charged fully by 05:00
   The V2H/V2G algorithm cannot be run forever, since the car still has to be used during the day. We decided that V2H/V2G may be run unrestricted during the restricted time period, but the EV has to be fully charged by 05:00. The car needs to be fully charged up in the morning when the user needs it.

7. SoC threshold
   During the execution of V2H/V2G, the battery of the EV is discharged for powering the home or sending the energy back to the grid. However, it can be inconvenient for the user if the battery is depleted too much to make an emergency ride if needed. That is why it is important to have a SoC threshold. The EV battery may not be depleted more than the threshold.

4.5.2 Fallback methodology

Requirement 4 to 7 are requirements that are checked during the execution of the V2H/V2G algorithm. If one of these requirements are not met, the V2H/V2G resorts to either one of the two types of EV charge scheduling. The first one is the normal EV charge scheduling as defined in the previous section. The second one is the modified EV charge scheduling.

Modified EV charge scheduling is executed when the SoC threshold was too low to be used for V2H/V2G execution. The biggest difference between modified EV charge scheduling and normal EV charge scheduling is that in the modified version, the goal is to charge the car as quickly as possible so that SoC is above the SoC threshold. The modified version is not going to try to charge it to 100%. The max length of the flexibility window is set to 4 in this case. With a window of 4, the V2H/V2G execution is postponed up to 4 hours when the SoC does not satisfy the threshold value.

The flow diagram of the modified EV scheduling can be seen in Figure 4.8. The steps of the modified version are as follows:

1. Check length of window
   The first step is to check whether there is a flexibility window with a sufficient length created. This flexibility window can be created during a previous session of modified EV charge scheduling. All hours that are less than the start hour are removed from the window. If the resulting length of window is equal to zero, continue to step 2. Otherwise, continue to step 3.

2. Create flexibility window
   A flexibility window is created with a length of 4 and with the start hour as starting hour of the window.

3. Schedule in first hour if possible
   Depending on the objective, check whether it is possible to schedule in the first hour. If it is possible to schedule charging of the car of the car in the first hour, this will be executed.

4. Remove first hour from window
   Regardless of whether it was possible to schedule anything in the first hour of the flexibility window, the first hour will be removed from the window, since this hour will not be relevant anymore when the modified EV charge scheduling is rerun in the next hour.

4.5.3 Steps of the algorithm

Knowing all the requirements of the V2H/V2G scheduling algorithm and the fallbacks when the requirements are not met, the steps of the V2H/V2G

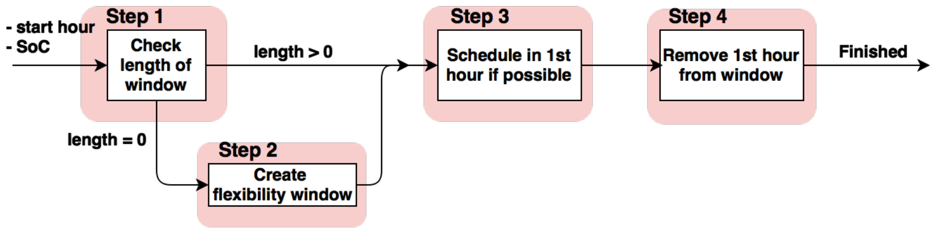


Figure 4.8: Flow diagram of the modified EV charge scheduling

algorithm can finally be introduced. The flow diagram of this algorithm can be seen in Figure 4.9. The variable **current_hour** is used in this flow diagram. This algorithm is an iterative process that checks the requirements at **current_hour**. After each hour, **current_hour** will be incremented to repeat the process for the next hour. The steps are as follows:

1. Check time period restriction
   The algorithm is started when a charge session starts. The first thing that has to be checked is whether the V2H/V2G scheduling algorithm may be continued. If the time period is in the time range of 17:00 to 05:00, the algorithm may continue to step 2. Otherwise, it resorts to normal EV charge scheduling.

2. Check occupancy
   In this step, verification is done whether occupancy is True for **current_hour**. If this is True, the algorithm may proceed to step 3. Otherwise, the iterative process is exited and we check what the deficiency is according to the current SoC. This deficiency is given as input to step 1 so that this deficiency can be corrected during the next charge session. Afterwards, the algorithm is terminated.

3. Check hours needed to fully charge
   According to the requirements, the EV needs to be fully charged by 05:00. In this step we check how many hours are needed to charge the EV to 100%. This is expressed as **hours_needed**. If the sum of **current_hour** and **hours_needed** is greater or equal to 05:00, the iterative process is exited and normal EV charge scheduling will be started. This is done in order to avoid the EV having a SoC lower than 100% by 05:00. Otherwise, step 4 may be entered.

4. Check SoC threshold
   A SoC threshold is a threshold which the SoC of the EV may not cross. The EV must always have a sufficiently charged battery, so the driver can always make unexpected trips if possible. If the SoC is lower than

the SoC threshold for **current_hour**, the EV needs to be charged. This is done in modified EV charge scheduling. If the SoC is higher than the threshold, the V2H/V2G step may be entered.

5. V2H/V2G
   V2H operation is executed when all the above checks have been met. The amount of energy sent from the battery to the household may not deplete the EV's battery to a percentage lower than SoC threshold.

   V2G is operated when there is a mismatch between the supply and demand of electricity. V2H will not be operated. When the demand is higher than the supply, the electricity prices will increase. In order to aid the grid with its supply, V2G will be executed. The monetary compensation for the EV owner will be 20% of the current price at which V2G is operated.

6. Next hour preparation
   In this step, we check how much has been charged or discharged of the EV's battery and calculate the new SoC. Since the current iterative process is completed for **current_hour**, we increment this variable with 1, so that step 2 can be re-entered for the next hour.

4.5.4 Special scenario for midnight

The V2H/V2G algorithm also has two special scenarios that have to be accounted for. The first scenario concerns the midnight occupancy. In Step 2 of the V2H/V2G scheduling algorithm the occupancy is checked for **current_hour**. During the midnight period of 00:00 to 05:00, the occupancy is always True.

For the second scenario, the algorithm checks whether there is a deficiency of the SoC at midnight. If there is a deficiency, the EV needs to be charged to 100% so that it can be used again the next day. In the case that there is a deficiency by midnight, the normal EV charge scheduling will be run to ensure that the battery is fully charged.

4.6 Metrics

In order to measure how well we are predicting when to charge the EV, we introduce the metric of miss rate of scheduled hours. Using the flexibility window, the algorithm chooses to schedule the EV during certain hours according to certain objectives. If the EV is scheduled to charge at an hour in which there are no occupants in the house, this scheduled charge session cannot occur. In this case, rescheduling needs to take place to correct for

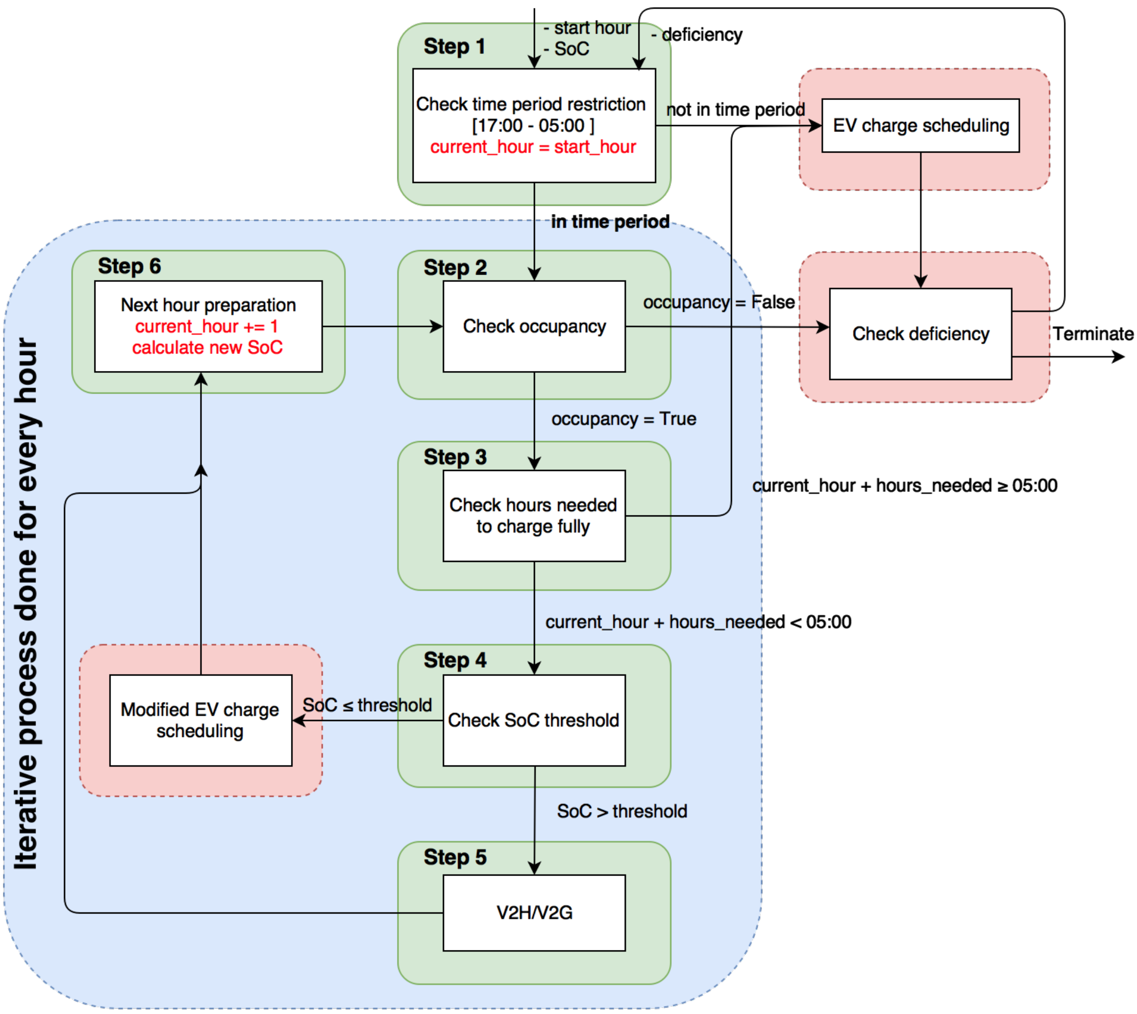


Figure 4.9: Flow diagram of the V2H/V2G algorithm

this missed scheduled hour. The miss rate is defined as:

$$\text{miss rate} = \frac{\text{missed hours}}{\text{scheduled hours}} \tag{4.5}$$

Another metric that will be used to measure how well the algorithm is performing is: relative savings. We define two types of relative savings: one is the savings on the EV charging bill, and the other is the savings on the overall electricity bill (including EV charging). These relative savings are calculated as follows:

$$\text{relative savings} = \frac{\text{bill}_{\text{original}} - \text{bill}_{\text{new}}}{\text{bill}_{\text{original}}} \tag{4.6}$$

where $\text{bill}_{\text{original}}$ is the bill without the implemented algorithms and bill_{new} is the bill with the implementation of the algorithms.

4.7 Conclusion

We have defined a flexibility window which contains hours in which the EV can be charged. The determination of which hours of the flexibility window is chosen, depends on the objectives. We have defined three objectives: cost minimization, comfort maximization and joint comfort. These objectives can be chosen by the user to prioritize the comfort, the cost savings or a combination of these two. The two algorithms that we have designed are EV charge scheduling algorithm and V2H/V2G algorithm. These two algorithms use the flexibility window in order to make a decision when to charge the EV depending on the objectives. The V2H/V2G algorithm has the variables SoC boundary and price boundary that determines when V2H/V2G gets executed. These two algorithms give the users the freedom to prioritize their preferences: extra savings that can be achieved or the security that they can use their EV in an emergency.

Chapter 5

Results and evaluation

This chapter discusses the results of the modeling and the results of the algorithms. Based on these results, certain decisions are going to be made how to tweak the model and which optimum configurations can be selected for the algorithms.

5.1 Results of system modeling

This section describes all the steps that have been taken to achieve the end result for the modeling of the system. First, the dataset has been studied to see what kind of information can be retrieved. The next step is to put all the information through a clustering algorithm to get clustered results. Depending on the clustered results, the occupancy and EV charge sessions property are extracted. Afterwards, using these two properties a model is created based on two temporal metrics.

5.1.1 Results from Pecan Street dataset

The dataset of Pecan Street provides a lot of granular data of households and their electricity usage. Data from the year of 2014 was collected for all these households. However, not all the available households can be used for this project. We made the following two requirements when selecting households out of the database:

- Households must own an (H)EV
- More than 250 days of EV charging data must be available

Accounting for these two requirements to ensure that only households with an EV were chosen and that there is enough EV charging data to work with, a total of 65 households were selected for this thesis.

The dataset also provides metadata about the households. Part of the metadata can be seen in Figure 5.1. The most useful metadata that can be used later on in this research are the number of occupants in the household and on which days the occupants are at home. These can prove to be quite useful for the occupancy property. The metadata is not available for all households, since not all households have opted in to fill in their personal information.

dataid	status	spend_time	spend_time_	spend_time_	spend_time_	spend_time_	number_of_residents
35	Complete	Monday	Tuesday	Wednesday	Thursday	Friday	4
43	Complete	Monday	Tuesday	Wednesday	Thursday	Friday	1
59	Complete	Monday	Tuesday	Wednesday	Thursday	Friday	2
94	Complete						2
111	Complete	Monday				Friday	4
114	Complete				Thursday	Friday	4
121	Partial	Monday	Tuesday	Wednesday	Thursday	Friday	4

Figure 5.1: Partial metadata of the households

The households that were used from the database all owned either an EV or HEV. 33% of the cars were EVs and the other 66% were HEVs. All the EVs have their own battery capacity and their own charge rate depending on the type of charger that is installed in the household. The types of chargers and amount of households that have this charger can be seen in Table 5.1. The amount of (H)EVs that have a certain battery capacity can be seen in Table 5.2.

charger type [kW]	**household share [%]**
3.3	83
5	7
6.6	10

Table 5.1: Percentage of households that own a certain charger type

battery capacity [kWh]	**(H)EV share [%]**
7.6	3
17.1	69
24	21
70	7

Table 5.2: Percentage of EVs that have a certain battery capacity

5.1.2 Clustered results

The machine-learning software package Weka [33] was used to get the clustered results of the two datasets that were extracted from the database. In Figure 5.2 the clustered results of household power usage can be seen. The clustered results of the EV charging usage can be seen in Figure 5.3. Hourly data was used for both of these properties. The sample numbers seen in these figures represent each hour of the year for all households. The y axis represents household power usage. Each point corresponds to a certain cluster, determined by the clustering algorithm.

For the household power usage 6 clusters were identified, while for the EV charging usage 4 clusters were identified. The means of the first three clusters for each set can be seen in Table 5.3. From these clustered values, a mapping can be made to True/False states for the occupancy and charge session property. A boundary will have to be determined in order to distinguish cluster values will be mapped to a True/False state. The means for cluster 0 and cluster 1 for both datasets seem to be sufficiently separated that they can be used as the boundary states for the occupancy and charge session properties. This will be explored more in depth in further sections.

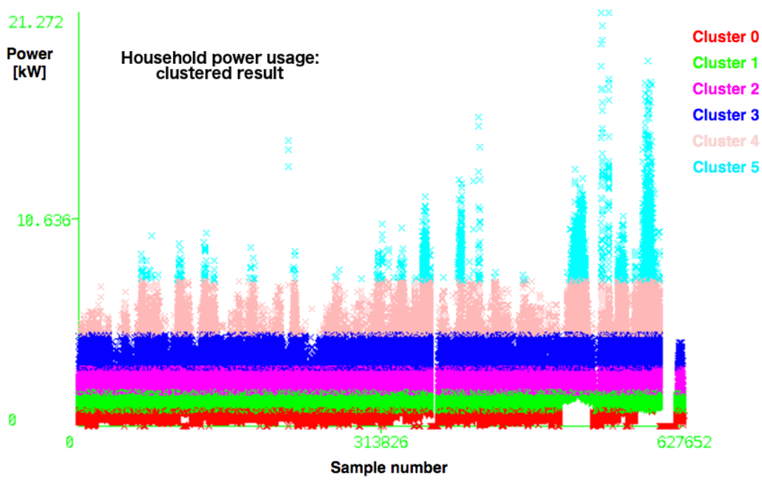


Figure 5.2: Clustered results of the household energy usage

cluster	mean(EV charge)[kW]	mean(household power)[kW]
0	0.01	0.37
1	1.29	1.17
2	2.51	2.25

Table 5.3: The means of each cluster value for the two datasets

5.1.3 Extraction of occupancy property

The two properties that have to be extracted from the clustered results are the household occupancy and the active charge sessions on an hourly basis. These two properties are True/False states. The clustered results of the

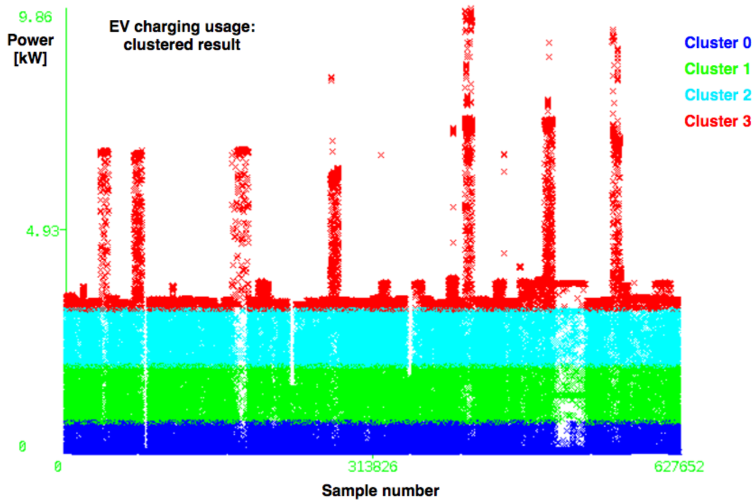


Figure 5.3: Clustered results of the EV charging usage

two datasets of household power usage and EV charge sessions have to be mapped to these True/False states of their respective properties. In this section, only the occupancy property will be discussed.

The means of clustered values of household power usage can be seen in Table 5.3. The means of cluster 0 and cluster 1 for household power usage seem to be sufficiently separated that they can constitute as a boundary value. Cluster 0 should then constitute the off state and everything higher than cluster 0 should then be the on state. However, this may not always be the case, since some households might use more power than others. These households could need a higher occupancy boundary value. In the previous section three assumptions were made in terms of the occupancy property. They will be tested to see whether they are valid in this section.

Assumption 1

A boundary value of 0 to map True/False occupancy satisfies all conditions

$$\text{occupancy}_h = \begin{cases} \text{False}, & \text{if clustered value} = 0 \\ \text{True}, & \text{otherwise} \end{cases} \tag{5.1}$$

The hourly power usage and clustered values of a household with dataid 114 for Jan 21 2014 can be seen in Figure 5.4. The household energy usage spikes up in the morning, around 13:00 and in the evening. This corresponds nicely with the clustered values. The clustered values of 0 indicate that there is no occupancy. Cluster values higher than 0 indicate that there is occupancy. In this instance, the assumption 1 does hold up.

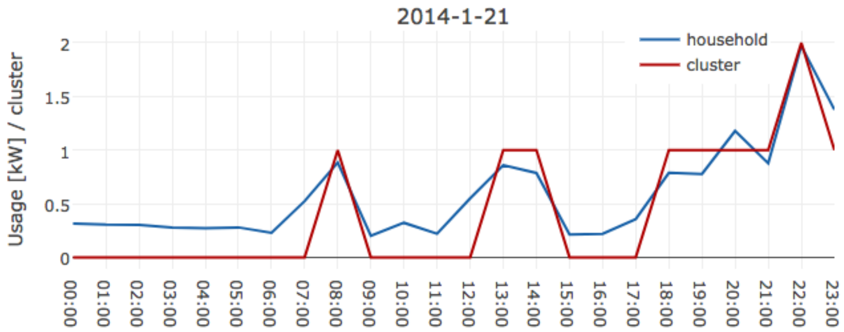


Figure 5.4: Household power usage and clustered result for dataid 114

In Figure 5.5, a different hourly power usage and clustered values of household 9776 can be seen for Jan 28 2014. In this figure we can see that the state of no occupancy is defined by cluster 2 and not by cluster 0. Everything higher than cluster 2 at a certain hour indicates there there is occupancy in the household. So assumption 1 that cluster 0 can be used as the boundary value to determine occupancy is not valid.

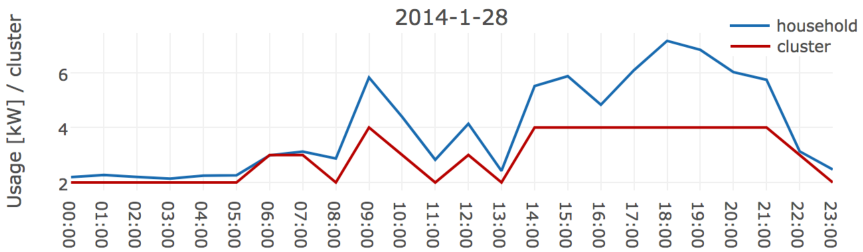


Figure 5.5: Household power usage and clustered result for dataid 9776

Assumption 2

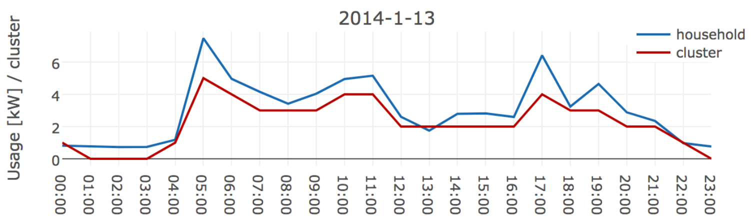
The days on which households have indicated that they are at home, requires higher boundary values since their baseline electricity usage on these days is higher.

$$\text{occupancy}_h = \begin{cases} \text{False}, & \text{if clustered value} <= \text{boundary value} \\ \text{True}, & \text{otherwise} \end{cases} \tag{5.2}$$

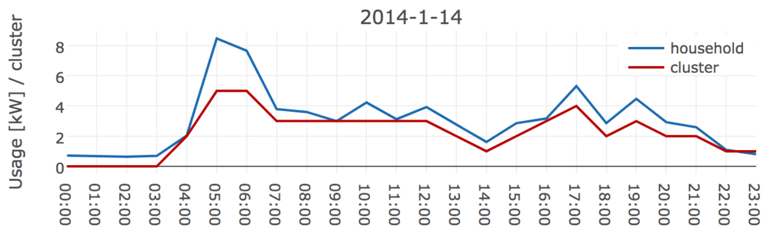
From the metadata extracted from the households, there are days on which some households are at home and some days on which they are not at home.

This is personal occupancy information that the people of the household have filled in for the survey. The occupancy boundary value should be higher on days that occupants have indicated that they spent a significant portion of the work day at home.

We are going to look specifically at household 5357. Household 5357 has indicated that they are at home on Monday, Wednesday and Thursday. In Figure 5.6 the hourly power usage and clustered values for Monday Jan 13 and Tuesday Jan 14 can be seen. Monday is the day on which someone is at home and Tuesday is supposed to be the day when no one is at home as indicated from the metadata. However, when carefully looking at the two days in Figure 5.6a and 5.6b both their baseline boundary values would be 0. Starting from the morning around 4 AM the household electricity usage goes up and the pattern for the whole day is more or less the same for both days. Since someone is supposed to be at home on Monday, we assumed that the baseline electricity usage would be higher. This would result in a higher occupancy boundary value. This assumption is not valid as we can see in this case.



(a) Monday Jan 13 2014



(b) Tuesday Jan 14 2014

Figure 5.6: Hourly household power usage and clustered values for household 5357

Assumption 3

The higher the number of occupants in the household, the higher the boundary value has to be set to determine occupancy.

$$\text{occupancy}_h = \begin{cases} \text{False}, & \text{if clustered value} <= \text{boundary value} \\ \text{True}, & \text{otherwise} \end{cases} \tag{5.3}$$

Another bit of information that can be extracted from the household metadata is the number of occupants in a household. The assumption is that the more occupants there are, the more electricity is going to be used. That would entail that the occupancy boundary value should be higher, since the baseline electricity usage is also higher.

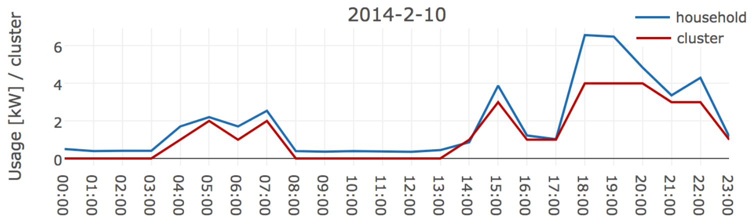
Let's take a look at the following two households and their respective number of occupants:

- Household 6941: 4 occupants
- Household 8197: 2 occupants

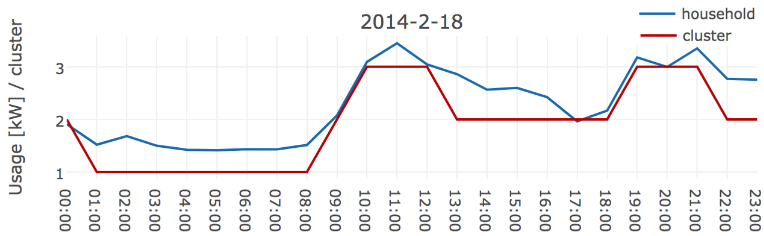
Looking at the number of occupants for those two households, the household with 4 occupants should have a higher electricity usage overall and thus have a higher occupancy boundary value. In Figure 5.7 two graphs can be seen. One for household with 4 occupants and the other one with 2. When we look at the graph with 4 occupants, we see that the overall electricity usage is low and that a boundary occupancy value of 0 can be used. For all clustered values above 0, there is occupancy in the household. This is not something we would expect, since the number of occupants is quite high. If we look at Figure 5.7b for the household with 2 occupants we see a different situation. The overall electricity usage is actually higher than that of the household with 4 occupants. In this instance, the boundary value would have to be set to 1 to accurately convey the household occupancy. We conclude that the assumption that more occupants result in a higher boundary value is not valid.

Baseline boundary value

We have seen that the three assumptions that were made concerning the occupancy boundary value are not valid. Every household differs a bit. There are household that use a lot of electricity and there are household that use less electricity. This electricity usage did not always depend on the number of occupants in the household, neither did specific days of occupancy play a significant role. So using metadata is not a good predictor to higher electricity usage on certain days. Thus, the occupancy boundary value has to be determined in a different way. One common characteristic of all households is that their electricity usage during night time all drop to their lowest



(a) Household 6941 with 4 occupants



(b) Household 8197 with 2 occupants

Figure 5.7: Power usage and clustered results for household 6941 and 8197

clustered values. The lowest clustered values for each household is different. The corresponding lowest clustered value during this time period can hence be used as the boundary value. Each household would have its own boundary value.

The methodology to do this is to extract two months of data for all the households and specifically look at time periods from 00:00 to 04:00. The two months that were chosen are January and February. In that time period of 4 hours we look at which clustered value occurs the most often. The clustered value that occurs the most often is then the occupancy boundary value of the household. The reason for choosing the months January and February is because in these two months the electricity usage is lower compared to the summer months. The higher electricity usage may skew the boundary value during the midnight hours, since during those hours the AC must be turned on to cause the electricity usage baseline to be higher during midnight. However, during the summer months when there is no occupancy, the clustered value does drop to the boundary value as determined.

5.1.4 Extraction of charge session property

Putting the hourly EV charge data through the clustering algorithm produced 4 clusters. The means of cluster 0 and cluster 1 are 0.01 and 1.29, respectively. They are sufficiently separated that cluster value 0 can be used as a boundary value to determine whether a charge session is active or not. The reason for this simplicity in determining this property is because the EV is either charging or it is not charging. When a charge session is active, the charger delivers immediately the maximum power output that is possible to the EV. This property **active charge** for hour h can be represented with the following equation:

$$\text{active charge}_h = \begin{cases} \text{False}, & \text{if clustered value} = 0 \\ \text{True}, & \text{otherwise} \end{cases} \tag{5.4}$$

In Figure 5.8, the EV charge usage and clustered results can be seen for household 545 on Jan 27 2014. The periods in which a charge session occurs can be clearly seen, and the clustered results also reflect this. Cluster 0 nicely represents periods of inactivity and all values above also reflect that the charge activity is active during the other periods. So Equation 5.4 is valid.

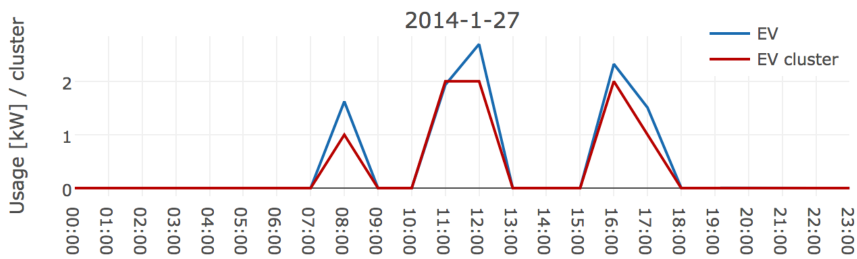


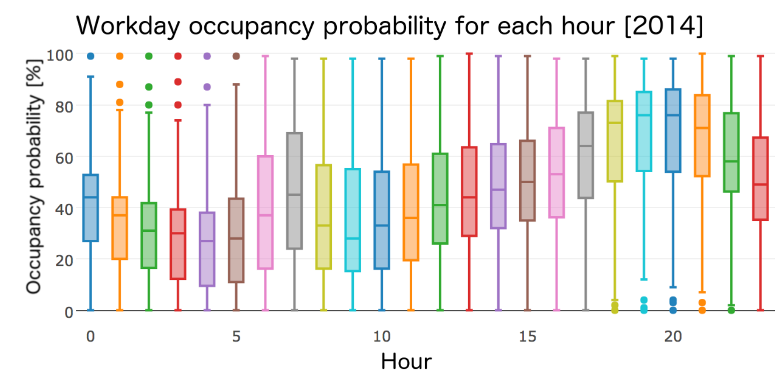
Figure 5.8: EV charge usage and EV clustered results for household 545

5.1.5 Modeling the household

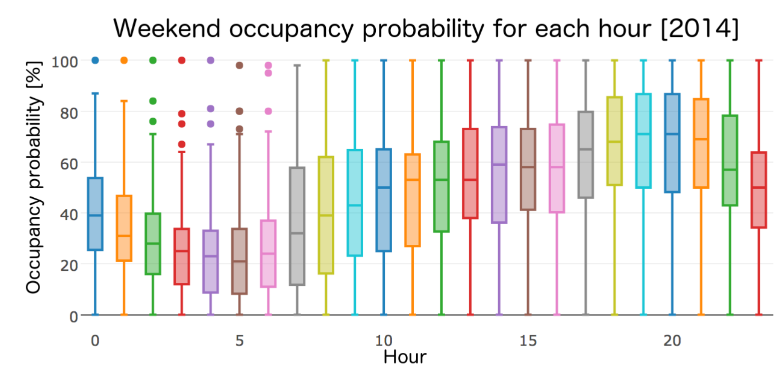
In order to discuss the results of the household modeling, this section will be split into two parts. The occupancy probability and charge probability are going to be discussed. Afterwards, the results of the transient probability will be discussed.

Occupancy probability

We are first going to discuss the occupancy probability. The occupancy probability is split up into two versions. One for the workday and one for the weekend. These two versions are calculated for the whole period of 2014. We first want to see the distribution of the occupancy probability for all households. We use box plots for this. The result of this can be seen in Figure 5.9. There is not a significant difference between the box plots of the occupancy probability of the workday and that of weekends. In both cases we see that the occupancy probability decreases during the midnight and during the day it increases again with a peak in the evening. The biggest difference between these two is that during the morning hours around 5 AM, the workday probability is higher than during the weekend. The increase in probability in the weekends occurs around 9 AM and 10 AM.



(a) Box plot for the occupancy probability during workdays



(b) Box plot for the occupancy probability during weekends

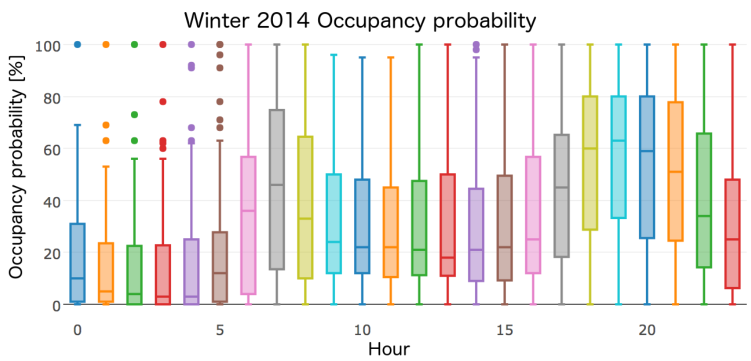
Figure 5.9: Box plots for the each hour of the occupancy probability during the year of 2014

We calculated the occupancy probability for all the households for a all of 2014. Since there can be seasonal differences between certain months, taking such a big period of one year can skew the occupancy probability. We want to see whether there is a significant difference between certain seasons in the occupancy probability. If this is the case, the occupancy probabilities may have to be split up into seasonal occupancy probabilities. The following 4 seasons were defined with the corresponding months:

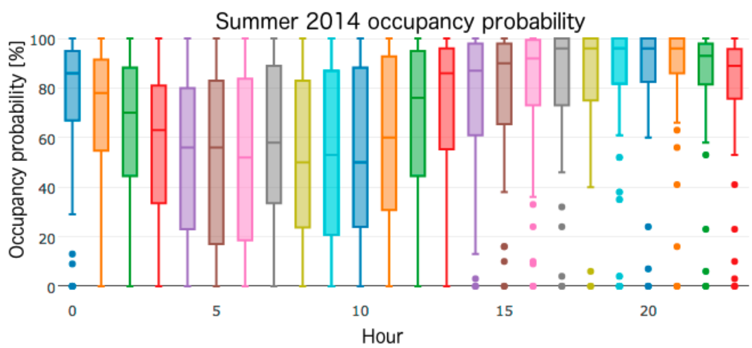
- Winter: Dec, Jan, Feb
- Spring: Mar, Apr, May
- Summer: Jun, Jul, Aug

- Fall: Sep, Oct, Nov

The two extremes would be winter and summer. In Figure 5.10 the box plots for the two extremes can be seen. We can see that the distribution of the occupancy probabilities move up during the summer months. The distribution of the probability to be at home during the evening hours is very much concentrated near 100%. During morning hours, the occupation distribution of the summer months is much more varied. There is considerable difference between these two seasons that it would be a good idea to further split the occupancy probability into 4 parts. One for each season. This step would make the occupancy probabilities for a specific month much more representative than having one occupancy probability that is represented for all the workdays/weekend of all months.



(a) Box plot for winter occupancy probability during workdays

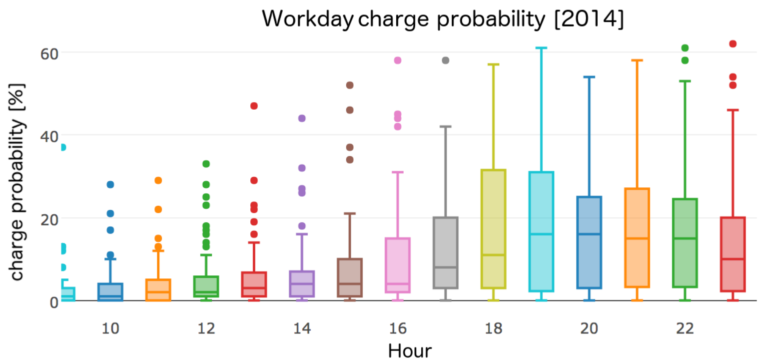


(b) Box plot for the summer occupancy probability during weekends

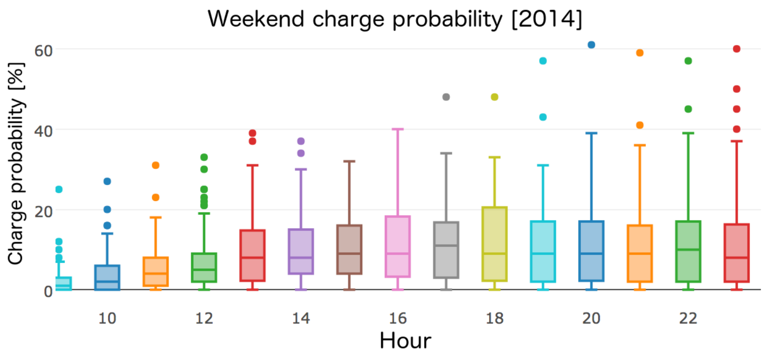
Figure 5.10: Box plots for the each hour of the occupancy probability for two extremes

Charge probability

We checked the charge probability for different periods. We have already defined a workweek and weekend charge probability. The period that is used for the calculation of these two probabilities is the whole year of 2014. In Figure 5.11, we can see only see the hourly box plots of the hours during daytime. During the midnight hours, the probability to charge the car is very low and is thus not of that much interest. When we compare the two figures we see that during the workdays the probability to charge the car is much higher than during the weekend. This is especially true during the evening hours. In the weekends, the overall probability to charge the car is lower. This is most probably attributed to the fact that EVs are not used that much during weekends.



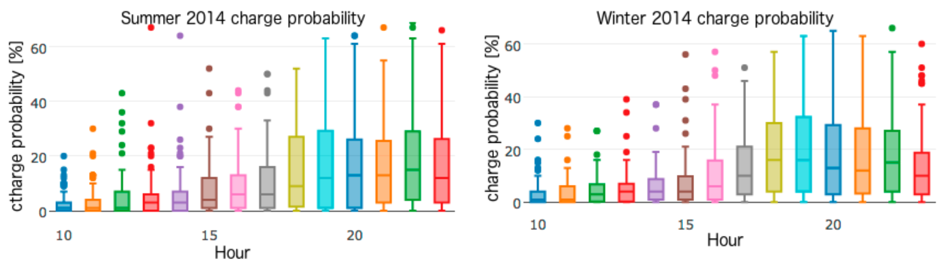
(a) Box plot for charge probability during workdays



(b) Box plot for charge probability during weekend

Figure 5.11: Box plots for specific hour of the charge probability for the year 2014

In Figure 5.11, the data of the whole year of 2014 is used. We would also like to look at whether there is a significant difference between the charging behavior of summer and winter. The box plots for the summer and winter periods of charge behavior can be seen in Figure 5.12. The time periods of 10 AM till midnight can be seen in this Figure. We can see that there is hardly any difference in the charging behavior between the summer and the winter. People's driving and thus charging behavior do not change depending on the season. The occupancy probability was split up into 4 seasons. It is not necessary to split up the charge probability into 4 seasons too. However, in this case, we made the decision to include the 4 seasons in the analysis of charge probability. This dataset does not show a discernible difference in the charging behavior between these two seasons at their extremes, but a different dataset that may be used in the future might have this difference. The distinction of 4 season is kept for the charge probability, in order to facilitate a better transition to a different dataset, if needed.



(a) Box plot for charge probability during workdays of summer 2014

(b) Box plot for charge probability during workdays of winter 2014

Figure 5.12: Box plots for specific hours of the charge probability for summer and winter 2014

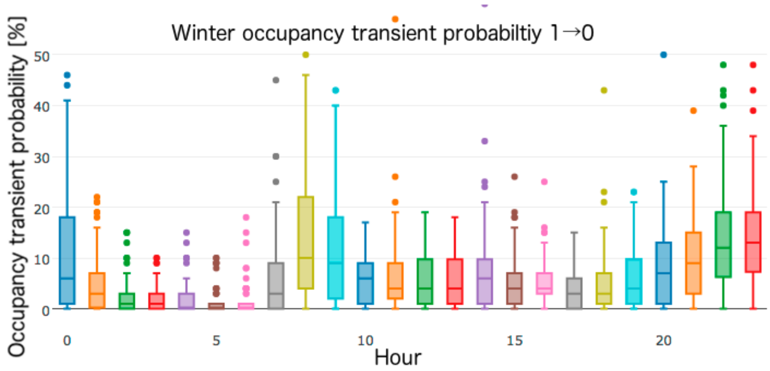
Transient probability for occupancy

There are two state transitions that can be studied for the transient probability for occupancy. The two state transitions are $0 \rightarrow 1$ and $1 \rightarrow 0$. In this thesis, we are only concerned with the state transition of $1 \rightarrow 0$ [1].

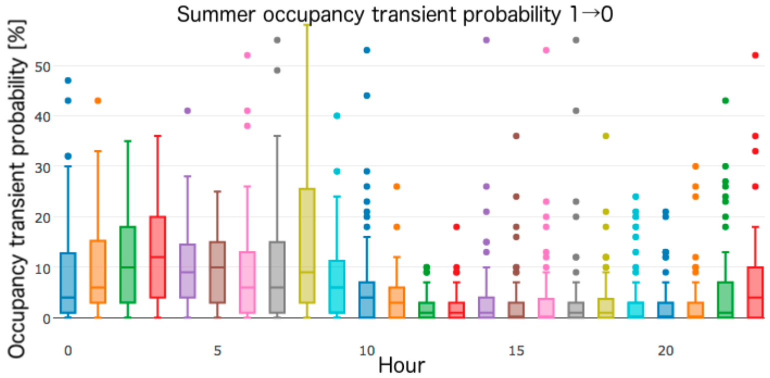
As discussed in the previous section on the occupancy probability, there are differences in the power usage of households from season to season. We are going to take a look at this in depth. Figure 5.13 shows box plots of the occupancy transient probability for the state transition $1 \rightarrow 0$ for the summer and winter periods. One big noticeable difference from this figure is the hour at which people go to bed. The assumption is that during evening hours, people will switch off their devices before going to bed. This switching off of devices will contribute to the state transition of $1 \rightarrow 0$. In the winter periods, the probability of transition $1 \rightarrow 0$ occurring is much higher during the evening hours. However, during the summer months, in which people

[1]Only the transition $1 \rightarrow 0$ is used for the flexibility window

usually have a lot of vacation days, the state transition occurs much later. It occurs during the midnight hours around 2 AM.



(a) Box plot for occupancy transient probability during winter



(b) Box plot for occupancy transient probability during summer

Figure 5.13: Box plots for occupancy transient probabilities for winter/summer for transition of True → False

Evaluation of system model

The biggest challenge in determining the occupancy of a household, was determining the occupancy boundary value. At which value would you deem a household to be present and not present. We have made three assumptions and each assumption would have to be valid in all situations. If there is a situation in which it is not valid, it will not be used. We have seen through testing, that all three assumptions were not always valid. We have decided to determine the occupancy boundary value by looking at the idle energy usage of each household. This idle energy usage is specified as the time period in which people are sleeping from 00:00 to 0:40. From this idle energy usage, the baseline boundary value is extracted. Each household is unique and this method is therefore the best way to determine the occupancy boundary value.

We have determined different temporal metrics and have seen that it is necessary to split up the occupancy and EV charging behavior metrics into weekdays and weekends. Furthermore, it is necessary to also have seasonal metrics, since the occupancy behavior does change form season to season. This is not the case for the EV charging behavior.

5.2 Results of algorithm

In this section we are going to discuss the results of the algorithm and what design decisions have been made to achieve the final configuration of the algorithms. We will first discuss the results of the EV charge scheduling algorithm. Afterwards, the results of V2H/V2G algorithm are going to be discussed.

5.2.1 EV charge scheduling algorithm

The EV scheduling algorithm consists of elements that can be tweaked. Each adjustment in these elements results in a different configuration of the algorithm. The elements that can be tweaked are as follows:

- occupancy boundary value of flexibility window
  This boundary value determines how much the flexibility window can be expanded. The range of this boundary value is [0-1]. If the boundary value is low, the algorithm will become very strict and create the minimum flexibility window that is needed. If the boundary value is high, the algorithm will become less strict and create a bigger flexibility window.

- algorithm objective
  We have defined three types of objectives in the previous chapter. The objectives are cost minimization, comfort maximization and joint objective. The comfort maximization and joint objective have weights that can be changed to prioritize certain preferences.

We have defined two metrics to measure the performance of the algorithm: miss rate and relative savings. These two metrics will be studied to see how each configuration of the EV charge scheduling algorithm performs.

The approach to studying the performance of the algorithm is to first choose a certain objective with specific weights, if necessary. For this chosen objective, the occupancy boundary value for the flexibility window will be varied from 0 to 1 in steps of 0.1 to see how this affects the relative savings and the miss rate.

We will first look at the objective of cost minimization. In Figure 5.14, we can see the graph for the relative savings of the EV bill and miss rate for different occupancy boundary values. We see that for low values of boundary value, the relative savings is around 12% and the miss rate is close to 0%. As the boundary value increases, the relative savings and miss rate increase too. At a certain point, both the values of relative savings and the miss rate start to saturate. The value for which the relative savings saturate is 27.6% and that of miss rate is 11.1%.

Definition of attributes

There are various configurations for the EV scheduling algorithm that can be tested. Studying all the graphs for each configuration can be cumbersome. To aid this, we will extract two attributes for each metric from the graph. The first one is the **saturation value**. The horizontal line at which the value of the metric does not increase anymore will be called the saturation value. The second attribute is the **saturation point**. The point on the x axis where the value of the metric is 90% of its saturation value is defined as the saturation point. The saturation point is basically the boundary value at which the metric starts to saturate.

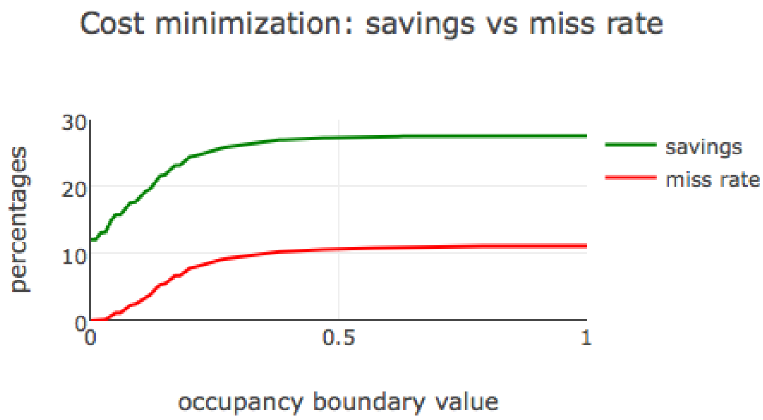


Figure 5.14: Graph showing the relative savings and miss rate for different boundary values

Different configurations

Now that we have defined the two attributes, it becomes easier to compare the different configurations of the EV scheduling algorithm. All the various configurations can be seen in Table 5.4. The configurations in which the objective is comfort maximization and joint objective have a comfort level function with 4 weights. The weights that were attributed can also be seen in this table. The saturation point and the saturation value of relative savings and miss rate are also included in this table.

When we study Table 5.4 in depth, we see that for the cost minimization objective the relative savings that can be achieved is the highest (27.6%), but the miss rate is also the highest (11.2%). The metric, relative savings, does saturate much earlier than the miss rate. Relative savings saturate at a boundary value of 0.29 and the miss rate at 0.36. If you would choose an occupancy boundary value at which you can have maximum relative savings, it would be for the boundary value 0.29. The miss rate at that boundary value is 9.4%. It would be 2% lower than the maximum miss rate.

Let's take a look at the results for the comfort maximizing objective. When we start with the equal weights, we see that the max relative savings is 11.2% and max miss rate is 5.9%. When we prioritize user's preferences by giving w_{occup} and/or w_{charge} higher weights, the savings actually go down by around 2%. We would expect the miss rate to go down also, since we are prioritizing user's preferences. But the max miss rate for all comfort maximizing objective hover around 6%. It is only when we prioritize the price (w_{price}) and midnight charging ($w_{midnight}$) that the relative savings go up, while the max miss rate stays at 6%.

The last objective that we have to look at is the joint objective. The joint objective prioritizes different things depending on the price boundary. What gets prioritized is as follows:

$$\text{prioritize} \begin{cases} \text{prices, if price\_comfort} \leq 0.8 \\ \text{user's preferences, otherwise} \end{cases} \tag{5.5}$$

We have set the price comfort boundary to 0.8. This corresponds to 32 cents/kWh. In Table 5.4, we can see what the weights are for when user's preferences are prioritized. In all cases when the prices are prioritized, w_{price} gets a weights of 2 and the rest of the weights get a weight of 1. We see that the relative savings that can be achieved with joint objective is between 7% and 9%.

Another observation can be made concerning the miss rate saturation level. If the objective is either comfort maximization or joint objective, regardless of the weights, the saturation value of miss rate for all the configurations is all around 6%. The saturation point for miss rate is also the same for all these configurations. Regardless of higher weights for w_{occup} and/or w_{charge}, the miss rate does not go down.

Evaluation of the different configurations

The three objectives of cost minimization, comfort maximization and joint objective are defined to prioritize which hours the EV should be charged.

					savings saturation		miss rate saturation	
objective	w_{price}	w_{occup}	w_{charge}	$w_{midnight}$	**sat point**	**value [%]**	**sat point**	**value [%]**
cost min	0	0	0	0	0.29	27.6	0.36	11.2
comfort max	1	1	1	1	0.24	11.2	0.19	5.9
comfort max	1	2	1	1	0.19	9.1	0.19	6.1
comfort max	1	1	2	1	0.21	8.6	0.19	5.9
comfort max	1	2	2	1	0.19	7.1	0.19	6.1
comfort max	1	1	1	2	0.26	12.1	0.19	5.9
comfort max	2	1	1	1	0.22	12.3	0.19	5.9
comfort max	2	1	1	2	0.25	13	0.19	5.9
joint	1	1	2	1	0.22	8	0.19	5.9
joint	1	2	1	1	0.2	9	0.19	6.1
joint	1	2	2	1	0.2	6.9	0.19	6.1

Table 5.4: Different configurations for EV charge scheduling algorithm

We see that if the objective is cost minimization, we can achieve maximum relative savings, but the miss rate is higher.

We initially thought that a good trade-off would be to use comfort maximization in which occupancy and charge probability can be prioritized. The assumption is that prioritizing these two properties would reduce the saturation value of the miss rate, but we see that regardless of what configuration of comfort maximization is chosen, the saturation level of miss rate for all them is around 6%. The same pattern can be seen for the joint objective.

The flexibility window is used in all three objectives. But the objectives do not dictate how wide the window should be. The occupancy boundary value dictates how wide the window should be. Since the occupancy boundary determines the length of the window, the users' preferences [2] are already taken into account. In all three objectives, the flexibility window takes the occupancy boundary into account to determine the likelihood of someone to be at home. After the flexibility window is created, we have various time slots in the flexibility window. Each time slot has relatively high chances of occupancy, depending on the strictness of the occupancy boundary value. This is the reason why in the case of the comfort maximizing and joint objective, the miss rate is the same for all the different configurations. The saturation point at which the miss rate starts to saturate, is also the same for all the configurations.

Because of the design in which the flexibility window already takes user's preferences into account, it defeats the purpose for having a comfort maximizing and joint objective. It will have negligible effect on the end result to reduce the miss rate.

The proposed solution is to only use the cost minimization objective. One way in which user's preferences can be taken into account is playing with the occupancy boundary value used for the flexibility window. If the user wants to prioritize their preferences, thus minimizing the miss rate, a

[2] Only the probability to leave the home is taken into account. The charge probability is not taken into account.

lower occupancy boundary value will be chosen. If the user wants to have a higher relative savings, they can choose a higher occupancy boundary value to achieve that. Achieving higher relative savings is also accompanied by a higher miss rate. A good trade-off between relative savings and miss rate is to choose the boundary value of 0.1. In this instance, the relative savings is 18.5% and the miss rate is 3%.

An observation of Figure 5.14 for the cost minimization objective is that the savings do not start at 0% for boundary value of 0. The savings start at 12%. The reasons for this is because the flexibility window is allowed to be expanded to the fullest during midnight resulting in more savings. Another reason for this is because choosing to charge more during 1 hour instead of spreading the charging over 2 hours can have an effect on the savings.

5.2.2 V2H/V2G scheduling algorithm

The V2H/V2G scheduling algorithm also has various elements that can be tweaked. One thing that will not be tweaked, is the objective when EV charge scheduling is executed in this algorithm. The objective will always be cost minimization since this is the best objective as determined in the previous section. The elements that can be tweaked for V2H/V2G algorithm are as follows:

- occupancy boundary value of flexibility window

- SoC threshold
  The SoC threshold is the minimum SoC that is required for the (H)EV. The SoC may not drop below the SoC threshold.

- price boundary
  The price boundary is what is needed for V2G. V2G will only be executed when the current price for electricity is higher than the price boundary. If this is the case, it signals that the supply of the electricity is struggling and executing V2G is needed.

By varying the values of these elements, we can see how this affects the relative savings and miss rate of the algorithm. The relative savings in this V2H/V2G section concerns the relative savings that can be achieved on the whole electricity bill including EV charging.

V2H configuration

We first start by solely looking at V2H execution. We vary the SoC threshold from 0% to 100% and for each SoC threshold we check the miss rate and the relative savings for different boundary values. For each SoC threshold, we extract the saturation value of miss rate and relative savings. The result of this can be seen in Figure 5.15. As the SoC boundary is increased, the saturation value of relative savings decreases and that of miss rate increases.

A good trade-off that can be achieved between relative savings and miss rate is by choosing a SoC boundary of 60%. The saturation value of relative savings is 9.9% and that of miss rate is 6.4%. However, as the miss rate saturates much later than relative savings, choosing the occupancy boundary value wisely can result in a lower miss rate. By choosing the saturation point of relative savings as occupancy boundary value, we will achieve a miss rate of 5.2% while keeping relative savings at 9.9%.

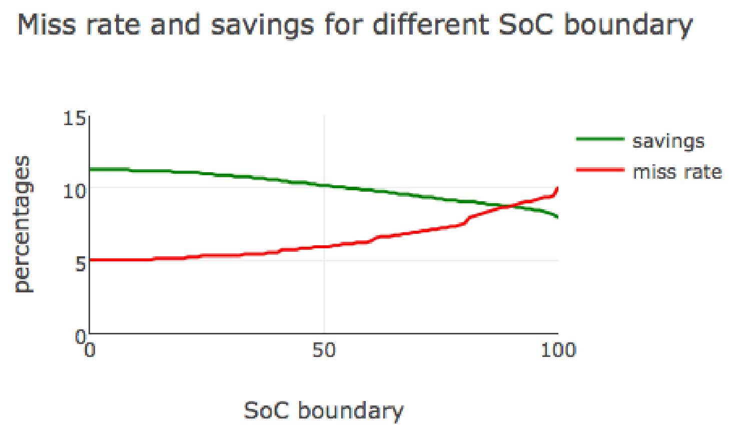


Figure 5.15: V2H: Saturation values of miss rate and relative savings for different SoC boundaries

V2H/V2G configuration

For the V2G configuration, we can vary the SoC boundary, occupancy boundary value and price boundary. We decided to choose a SoC boundary where a good trade-off can be achieved between relative savings and miss rate. This happens at a SoC boundary of 60%. This results in a saturation values for relative savings of 9.9% and miss rate of 6.4%. This trade-off is chosen for V2H/V2G configuration in order to simplify the analysis and see whether this trade-off can be improved further by varying the price boundary.

In Figure 5.16, the saturation values of miss rate and relative savings can be seen for different values of price boundary. The price boundary is varied between 5 c/kWh to 50 c/kWh. We see that the relative savings is the highest when price boundary is equal to 5. The relative savings at that point is 10.8%. For higher values of the price boundary, the relative savings saturate at 10%. The relative savings ranges between 10% and 10.8% for different values of price boundary. The miss rate hardly changes and stays stable at around 6%.

Figure 5.16: V2H/V2G: Saturation values of miss rate and relative savings for different price boundaries

Evaluation of V2H and V2H/V2G

We will first evaluate the configuration of only V2H. By increasing the SoC boundary, less capacity of the EV battery can be used for V2H execution. As a result, the relative savings decrease. On the other hand, the miss rate will increase, as repetitive charging and discharging of the battery will occur more often at higher SoC boundaries. The increased frequency of the repetitive charge and discharge of the battery, will cause a higher miss rate.

Studying Figure 5.15 of the V2H configuration in depth, we see that relative savings range between 8% and 11.3%. There is not a big variability in this range. The reason for this is because around 90% of the (H)EVs have a battery of either 17.1 or 24 kWh. If the dataset contained (H)EVs with a bigger battery capacity, the relative savings that could be achieved would have a bigger range for different SoC boundaries.

For V2H/V2G operation, we used a SoC boundary of 60%. We saw that only for very low price boundaries does the relative savings increase. In fact, the relative savings only range between 10% and 10.8%. There are hardly any extra savings that can be gained from V2G. The pricing dataset that was used for this thesis, had relatively stable electricity prices with hardly any pricing spikes. If there were more pricing spikes, the relative savings could have been higher. However, the electricity company would not want the user to earn too much money from V2G execution, since V2G execution happens at a monetary loss for the electricity company.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

In this thesis we considered the charging of EVs. Once the EVs become prevalent, they will indeed put huge stress on the power plants or generation and supply systems. The proposed a way to handle this by considering the cost of the energy and comfort level together to make a sustainable system. The idea is to use the periods of low energy usage to charge EVs. Furthermore, the EVs could also be used as power sources, to benefit from them during high demand of energy. This way the power plants would see almost a constant demand and usage, in the long run, making them more efficient.

We can conclude that shifting EV charging is beneficial for the user. The algorithm for scheduling EV charging can achieve relative savings of up to 27%. However, the miss rate will be 11.1%. By choosing the occupancy boundary value wisely, we can achieve a relative savings up to 18.5% and reduce the miss rate to 3%. It is up to the user to choose the value of the occupancy boundary. If a lower boundary value is chosen, a lower miss rate will be prioritized. If a higher boundary value is chosen, the relative savings will be prioritized. This will empower the user based on his/her requirement.

If we compared the result of this algorithm with the research done by Brush, et al., [18], we see that they achieved a relative savings of 12.5% by shifting EV charging completely to midnight without considering the discomfort caused to the users. Our algorithm is able to achieve higher relative savings while taking user's preferences into account. Even when the EV charge algorithm of presented in this thesis is with strict constraint of 0% miss rate, it can achieve a relative savings of 11%.

We have designed three different objectives to aid the decision making for choosing which hours to schedule the EVs. However, we saw that the comfort maximization objective and joint objective hardly had any effect on the miss rate. We deemed these two objectives that takes user's preferences into account ineffective. The reason for this is because, during the creation of the flexibility window, the user's preferences will be taken into account. The occupancy boundary value determines the length of the flexibility window. These two objectives would be useful if there were no flexibility windows in the design or if all flexibility windows had a fixed length.

The V2H implementation only used the cost minimization objective. We see that the maximum relative savings of 11% can be achieved when the SoC boundary is 0%. However, this means that the EV cannot be used at all for driving and decreases the lifespan of the battery. A trade-off is to choose a SoC boundary of 60%. At this boundary value, the maximum relative savings are 9.9% and the miss rate is 6.4%.

We also considered V2G. The V2G implementation was integrated with V2H. To simplify the many configurations that were possible with V2H/V2G, we decided to choose a SoC boundary at which a good trade-off can be achieved between relative savings and miss rate. This happens at a SoC boundary of 60%. V2G was only executed when the current electricity price exceeds the price boundary. The only element that is variable here is the price boundary. We tested V2H/V2G implementation for different price boundaries to see what the maximum value of relative savings and miss rate would be. We saw that the relative savings and miss rate hardly change at all. This happens because the pricing dataset which was used has relatively stable electricity prices. There were hardly any price surges. More price surges would have benefited the user cost wise.

A non-intrusive method was introduced to create a model of the household's electricity usage and EV charging behavior. This model looks at energy data collected by smart meters and does not require bluetooth beacons or GPS trackers. The V2H/V2G algorithm combined with EV charge scheduling takes user preferences into account to perform well on either relative savings or miss rate. The user has the final decision whether a high relative savings or low miss rate should be achieved.

6.2 Future Work

We still need to find a better way to integrate more of the preferences of the users during creating the flexibility window. Exploring the V2H/V2G implementation without a flexibility window for EV charge scheduling can also be a good approach. In this case, the comfort maximization and joint objectives will play a big role in a windowless scheduling policy.

Another point of improvement is to integrate concepts of game theory concerning the cooperative and non-cooperative interaction between the three actors in this thesis: household, grid and EV. The EV battery is the single resource that has to be shared among all three of them.

The needs from the standpoint of the electricity companies could also be explored more in depth. As more RES are integrated into the grid, the intermittent nature of RES will have to be taken into account. More elaborate schemes could be designed for shaving off the peak power demand on the grid and improving the constrained power supply.

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