UNIVERSITY OF SOUTHAMPTON

FACULTY OF PHYSICAL SCIENCES AND ENGINEERING

Electronics and Computer Science

Modelling an Agent to Trade on Behalf of V2G Drivers

by

Ibrahem Abdullah Almansour

A thesis submitted in partial fulfilment for the degree of Doctor of Philosophy

December 15, 2018

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF PHYSICAL SCIENCES AND ENGINEERING
Electronics and Computer Science

A thesis submitted in partial fulfilment for the degree of Doctor of Philosophy

MODELLING AN AGENT TO TRADE ON BEHALF OF V2G DRIVERS

by Ibrahem Abdullah Almansour

Due to the limited availability of fuel resources, there is an urgent need for using renewable sources effectively. To achieve this, power consumers should participate actively in the consumption and production of power. Consumers nowadays can produce power and consume a portion of this locally, and they could offer the rest of the power to the grid. This new feature allows for new decisions for the power consumers. Specifically, vehicle-to-grid (V2G), which is one of the most effective sustainable solutions, could provide these opportunities due to its power storage capability. V2G is where an electric vehicle (EV) offers electric power to the grid when parked. Moreover, V2G could use solar and wind power and significantly decrease the amount of primary power that is utilized for transportation. Furthermore, it offers a potential for reducing the consumers' power cost if used effectively.

In this thesis, the specific problems that we discuss can be categorized into three levels of complexity. At the simplest level is the problem of understanding the power market price behavior in the context of V2G, where we have complete information about the vehicle usage behavior and we assume there is one trip a day. At the next level, the problem of uncertainty in power market price is considered, while we keep the same assumption for the vehicle usage behavior. One of the real-life examples of this model is the bus timetable trip, where there is complete information about the trip times and the uncertainty is only on the power market prices side. Lastly, in addition to the problem of the uncertainty in the power market price, the uncertainty in vehicle usage behavior for the drivers is included for possible multiple trips in a day. The real-life example of this model is the normal vehicle drivers, where there is a chance that they will use their vehicle at any time, and so there are two types of uncertainty, in vehicle usage behavior and in the power market prices. For each of these subjects, we proposed a model and also conducted two surveys in order to attain our study aims.

In more detail, initially, we develop an agent to trade on behalf of V2G users in terms of maximising their profits without uncertainty in the power market price. We then run the proposed model in three different scenarios using an optimal algorithm based on backward induction concept and we compare the results for our solution to a simple benchmark. These scenarios have been proposed to model the user behaviour for the duration of a single day where we assume that users drive their cars for a single period per day. Furthermore, these scenarios differ according to when the drivers started using their cars. We show that our solution outperformed the simple strategy in the first scenario by 49%. Moreover, in the second scenario it outperformed the simple strategy by 51%, while in the third scenario our solution outperformed the simple strategy by 10%.

Next, we develop a heuristic algorithm that can trade on behalf of the V2G users in terms of maximising their profits, considering price uncertainty. Our proposed algorithm is combining the concept of consensus algorithms and expected value with a backward induction algorithm. We then run the proposed algorithm with two types of consensus algorithms using Borda, and majority voting, and with expected value algorithm and compare the results for each algorithm. The concept of consensus can be defined as that there are several samples of feasible steps to be considered at each period of time. After solving each sample, the decision that appears most frequently at time t is selected. Simulations show that, expected value algorithm outperform the other two (Borda and majority) under all power market prices scenarios considered.

Finally, we increase the complexity for the problem by considering the uncertainty in the vehicle usage behavior in the context of V2G in addition to the uncertainty in the power market price. Furthermore, we consider the battery degradation cost, which happens because of the charging or discharging actions. To do such, we refine the second model and we use the multinomial logit model to consider the vehicle usage behaviour. We then run the proposed algorithm and the benchmark algorithms and compare the results for each algorithm. Simulation shows that, our proposed algorithm outperforms the naive algorithm for about 15 times in terms to the average profits when we start the experiments with a half amount of battery. Moreover, our proposed algorithm outperforms the naive algorithm for about 5 times in terms to the average profits when we start the experiments with a full amount of battery. On the other hand, our proposed algorithm performs 89% of the complete information algorithm in terms to the average profits when we start the experiments with a half amount of battery. Furthermore, complete information provides almost same results of our proposed algorithm in terms to the average profits when we start the experiments with a full amount of battery. Indeed, this is good result if we consider that, complete information algorithm deals with known information and the proposed algorithm deals with uncertain data.

Declaration of Authorship

I, Almansour. Ibrahem Abdullah, declare that the thesis entitled *Modelling an Agent to Trade on Behalf of V2G Drivers* and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- parts of this work have been published in a number of conference and journal papers (see Section 1.3 for a list).
- parts of this work have been published as:

  Almansour et al. (2017)

  Almansour et al. (2018b)

  Almansour et al. (2018a)

Signed: ....

Date: ....

Acknowledgements

بسم الله الرحمن الرحيم

First and foremost, in the name of Allah, the Most Gracious and the Most Merciful. Alhamdulillah, all praises to Allah for the strengths and His blessing in completing this thesis. Without Him, I could not stay patient and in control in doing this study from the first day until now. Then, praises and Salam always dedicated to my beloved prophet Muhammad, the last prophet and the one who had brought the humanity from the darkness to the brightness.

I realize that I cannot complete this thesis without the aid of others. Lots of people have helped me during my PhD study and it would be impossible to mention all of them. I wish, however, to give my sincerest gratitude and appreciation to all individuals until this thesis can be completely finished.

The first one I should thank after Allah and his prophet Muhammad is the girl who gives the meaning of life, the one who is the happiness in my dictionary. (My hope), you are the best and the most important person in my life and the first reason to complete my PhD study.

Then, thanks to my dearest sister, Sarah who died in real world but still alive in my heart. After that, I want to thank my beloved parents (Mrs. Modhy Alfneekh and Mr. Abdullah Almansour) who always support me emotionally with prayer, love, and patience.

Moreover, I would like to thank my first supervisor Dr Enrico Gerding for the patient guidance, encouragement and advice he has provided through my time as his student. I have been very lucky to have supervisor who cared so much about my work, and who responded to my questions and queries so hastily. Also, I would like to thank my second supervisor Dr Gary Willis for his help and support.

In addition, I would like to extend my appreciation to my brothers and sisters, specially, Zyad, Thamer , Khaled and Fatemah. Furthermore, thank you very much to my aunts Mrs. Lulu, Mrs. Norah, and Mrs. Fatimah Alfneekh, and thank you very much for my second mother Mrs. Modhy Alshaieea. Further, I am grateful to my second father, Mr. Saleh Almiman.

Besides, I would like to extend my gratitude to all of my teachers who teach me during all of my studying period for their efforts in developing my skills and my knowledge (my teachers in Saad ibn Abi Waqqas primary school in Unizah, in Palestine secondary school in Unizah, and in Bin Saadi high school in Unizah).

Moreover, I would like to extend my appreciation to all the participants in this study. I am also grateful to the staff who work in the Saudi Electricity Company for providing information that I used in my study.

Thanks to the best children in my eyes, Rawna, Turki, Fares and the little Sarah. Perhaps they do not know about that, but their pictures and clips were my fuel to complete my PhD trip.

Thanks to all my colleagues and friends in King Abdulaziz City for Science and Technology.

And finally, last but by no means least, I am indebted to all my friends for their help and support, particularly, Abdulelah Alwabel, Fahad Almohemed, Fahad Alquneaier and Raaed Alhulilah.

And the last of my calls is praise to Allah, Lord of the worlds.

Contents

List of Figures

List of Tables

List of Algorithms

Nomenclature

General

A	The set of agent actions
a_t	The chosen action at time t whereas $a_t \in A$
$\overline{a}$	The vector which contains the chosen action for each hour
α	is the different value between selling and buying price
b_{des}	The desired amount of battery level before using time, $b_{des} \in Soc$
b_{init}	The initial value for the battery, $b_{init} \in Soc$
C_b	Battery capital cost
Cd_t	Battery degradation cost at time t
DoD	The depth of discharging in battery
E_s	The total energy storage of the battery
$f^{char}(p_t)$	The function that represent the price charging uncertainty
$f^{dis}(p_t)$	The function that represent the price discharging uncertainty, $p_t^{dis} = p_t^{char} - \alpha$
L_{ET}	Battery lifetime throughput energy in kWh for the particular cycling regime
L_c	Battery lifetime in cycles
p_t	Electricity price at time t
Pr_h	There is a specific probability for each trip to happen
Pr_c	There is a specific probability for each trip to be chosen
Soc	The current state of a battery
T	Number of time steps and can be defined as a T = $\{1, 2, ..., n\}$
$V(x)$	Function represent the battery of charge which left for the driver at the end of day

Chapter 3 & 4

S	Sample scenarios of power market prices
s	One scenario of a sample of power market prices, $s \subset S$
T_a	The available time when the agent can do the actions, $T_a \subset T$
T_{eu}	End time of using, $T_{eu} \in T$
T_{su}	Start of using time $T_{su} \in T$

Chapter 6

A^*	is a set of all possible actions.
j_i	A trip type is a subset of the trip set which contains the whole trip types
$jiBr$	There is a desired amount of battery for each type of trip
S	The scenarios that combine between power market price scenarios and trips scenarios
S_P	The scenarios of the power market prices
S_T	The scenarios of trips
Uji	There is a specific utility function will be received if the trip happen for each trip

Chapter 1

Introduction

The smart grid creates a new decentralised structure in power markets, where renewable sources and storage services have penetrated significantly and been adopted by power consumers (Amin and Wollenberg, 2005). However, smart grid technology faces a number of challenges, such as the increase in petroleum costs. For example, an EU report found that there was a quintupling of petroleum prices between 2002 and 2010 (Tomas, 2013). Yet, this issue differs between the countries. For instance in Saudi Arabia, the electrical power depends on the petroleum in about 40%. Using renewable sources effectively could solve these problems. In order to make this change a reality, the power consumer must actively participate in the consumption and production of the power process. If consumers could produce power and consume a portion of this locally, then they could offer the rest of the power to the grid. Such a new position means that there are new decisions for the power consumers to make. One of the most effective consumer choices is the Vehicle-to-grid (V2G). The V2G could well encourage consumers to change their vehicles from fuel vehicles to electric vehicles (EVs). This is due to its potential for reducing the power cost, if used effectively. The V2G can be defined as a concept whereby an EV offers electric power to the grid when parked (Kempton and Tomić, 2005).

Additionally, according to Kempton and Tomić (2005), as most vehicles are used just 10% of the time, EVs could be used as a large distributed battery and could offer power storage and supplementary services to the smart grid when not being used. Consistent with the above-mentioned results, Almansour et al. (2018b) study found that 90% of the participants used their vehicles for less than 4 hours daily, which meant that the vehicles were not being used about 83% of the time. Thus, V2G could be used to secure extra revenue. For instance, it is expected that, if EV drivers participate in V2G systems, they might receive around 2,500 to 3,000 US dollars annually from trading with the power market (Tomas, 2013). By taking into consideration the arguments of Kempton and Tomić (2005); Almansour et al. (2018b) and Tomas (2013), we can conclude that, until now, V2G technology has not been used effectively.

In the same vein, according to Hota et al. (2014), based on data from interviews with experts in four emerging EV markets, namely the US, France, Norway and Japan, there is an urgent need to conduct more investigations into the applications of EVs, and specifically those related the V2G. Further, Li et al. (2015a) stated that most V2G studies in the literature have considered the power grid systems viewpoint. However, unlike these studies, in the present research, the V2G consumer viewpoint is considered.

As mentioned earlier, there is an opportunity to enjoy certain economic advantages by using V2G. Nevertheless, these advantages have not been capitalised on due to a lack of knowledge on the part of EV drivers. As stated by Mohsenian-Rad and Leon-Garcia (2010), several works have exposed a lack of knowledge among customers regarding how to react to time varying prices in the power market. According to Hopper et al. (2006), a number of studies have shown that many customers cannot participate effectively and respond properly to price differences in power markets. Kahneman (2011) also claimed that people do not usually behave in rational ways, while Dan (2008) put forth the belief they have trouble when it comes to evaluating competing choices in a consistent fashion. In this research our aim is to design an algorithm which trades on behalf of V2G drivers and which can maximise their profit by understanding their vehicle usage. Thus, there are two types of uncertainty which we are dealing with. The first is related to the power market price, while the other pertains to vehicle usage. According to Rigas et al. (2015), there are only a few algorithms that consider the uncertainty in arrival and departure times of using V2G and the load they will execute on the smart grid.

Finally, the V2G technology introduces a new concept, namely vehicle parking lots, since its concern is about keeping the car parked until the pre-determined period has come to an end; indeed, if the drivers take their cars before the specified time, they must pay a penalty for that (Parsons et al., 2014). This new definition of parking lots is in complete contrast with the existing parking lots system, where the drivers have to take their cars before the defined time and if they do not they must pay a penalty for that. There are many parking lots that could be used to apply the V2G concept, such as the parking lots at workplaces, airports and large malls.

In the next section, we will put forth the research challenges of our study.

1.1 Research Challenges

In real life, when an EV drivers need to charge their vehicle, they might be faced with uncertainty regarding how much charge the battery needs, especially if we know that the power market price is changing considerably between each period of time. Indeed, decisions like this will be based on how many trips the driver is likely to make in the period following the charge, as well as the nature of these trips, the expected durations of these trips, and the expected distance of each trip. For instance, the drivers might go to the gym in the following period that is different from if they might going to their work, or if they might go to buy milk for a baby when it finish suddenly. Essentially, this difference stems from the importance of the trip itself, and the probability of it happening. Moreover, this issue is more complex if we consider the V2G concept, whereby the EV drivers have an opportunity to sell (discharge) an amount of their battery electricity when they park their cars. There are numerous factors which might affect matters, such as the battery degradation both when it comes to charging (buying) and discharging (selling). So, if the V2G drivers aim to maximise their profit, they should deal with a very complicated problem which has two types of uncertainties, namely the uncertainty surrounding vehicle usage and the uncertainty surrounding the power market price.

Furthermore, one of the new concepts might be appear as a result of applying V2G concept is the V2G parking lots where the aim of the V2G parking lots owner is predicting accurately how many vehicles might be connected in the following period of time, in order to determine the price of electricity which maximizes its profit when trading in the power market. However, this concept is converse of the existing parking lots since its target is keeping the vehicles parking with a determined period, which defined by the driver when he parks, and he will be pay a penalty if he takes it before this fixed time. On the other hand, if the drivers park their cars for the pre-set duration, then they could make money from it, or at least park for free because of it. In actual fact, V2G parking lots, if designed efficiently, may well be one of the crucial factors which incentivise vehicle drivers to broadly use EVs.

Having discussed the research challenges, in the next section we will provide the research objectives of our thesis.

1.2 Research Objectives

As discussed above, there are many challenges that face V2G owners, and these may affect the degree to which they benefit from using V2G. In order to tackle these challenges, we propose the following four research objectives, which summarise the purpose of this study:

(O_1) To design an algorithm to trade on behalf of V2G drivers that can maximise their profit by understanding power market price behaviour. Here, we consider just one type of uncertainty, that of power market price.

(O_2) To extend the previous algorithm (which trades on behalf of V2G drivers) so that it can maximise their profit by understanding their vehicle usage. Here, we consider two types of uncertainties; these relate to the power market price and vehicle usage behaviour respectively.

(O_3) To collect a dataset of vehicle usage behavior in order to serve our model experiments. Moreover, to investigate the feasibility of using V2G to face the peak demand in the power markets.

(O_4) To provide a better understanding of the factors that are considered by the vehicle drivers when choosing a parking lot. Moreover, this research discusses how they make the decision whether or not to use a V2G parking lot.

Having outlined our research objectives, the next section sets out our contributions in detail.

1.3 Contributions

In this study, we consider the V2G problem in relation to price and vehicle usage uncertainties. To address the uncertainty of price in the context of the V2G, we develop a heuristic algorithm that can trade on behalf of the V2G users to maximise the profit they generate from using V2G as a source of electricity, all the while taking into consideration their behaviour and their incentives. Our proposed algorithm combines two types of consensus voting algorithm (Borda and Majority) and Expected value with a backward induction algorithm. Consensus algorithms are currently commonly used in smart grid settings, and particularly in the context of power allocation for EV charging (Ströhle et al., 2014). Furthermore, Mao et al. (2013) compared four types of voting rules (majority, Borda, Maximin, and Kemeny) and noted that Borda voting is simpler and more accurate than the others. Further, they confirmed that majority voting is one of the most widely-used voting types.

Modelling the time series of power price as a Markov decision process (MDP) and using dynamic programming to deal with it is not new (Shi and Wong, 2011; O'Neill et al., 2010). Furthermore, using consensus algorithms to deal with multiple scenarios is also not new, and has featured in numerous studies such as (Bent and Van Hentenryck, 2004a; Van Hentenryck et al., 2010; Pan et al., 2011). However, the idea of combining these two concepts (dynamic programming and consensus algorithms) and using the resulting combination to design a heuristic V2G algorithm in the context of price uncertainty is novel.

Besides this, to address vehicle usage uncertainty in the context of the V2G, we use the Multinomial Logit Model (MNL) with the consensus algorithm and Expected value with a backward induction algorithm. Since MNL is one of the most widely-used discrete choice models, we apply it in this study because it is highly efficient and easy to apply. Additionally, Yu and Sun (2012) compared four types of typical discrete choice models, namely the Heteroscedastic Extreme Value Model, the Mixed Logit Model, the Multinomial Logit Model, and the Nested Logit Model, by using a travel mode choice case. They found that the MNL model was the first choice if the sample data satisfies the independence from the irrelevant alternatives (IIA) property (this will be explained in detail in Chapter 6).

In this study, we consider the V2G problem in relation to price and vehicle usage uncertainties. We propose a novel heuristic algorithm that maximises the V2G drivers' profit by choosing the best actions for each time period. The contributions of this thesis are as follows:

1. In order to achieve the first objective of this thesis (O_1), we develop an agent to trade on behalf of V2G users to maximise their profit in a day-ahead price market. We then run the proposed model in three different scenarios using an optimal algorithm and compare the results of our solution to a benchmark. We show that our solution outperforms the benchmark strategy in the proposed three scenarios (49%, 51%, and 10%) respectively in terms of profit (Chapter 3). This work has been published as a conference paper (Almansour et al., 2017).

2. Moreover, in order to achieve the first objective (O_1), we model the V2G problem as a Markov decision process (MDP), where the price uncertainty is considered by maximizing the V2G drivers' profits. The decisions are made with consideration of potential profits and drivers' incentives. We then propose a heuristic algorithm that combines backward induction and two types of consensus algorithms which are Borda and majority voting and with Expected value to deal with the price uncertainty. The proposed algorithm can deal with multiple scenarios in terms of price in the power market. Next, we evaluate the proposed algorithm by apply it with two types of consensus algorithms (Borda voting, and Majority voting)

and with Expected value. Simulation results show that apply the proposed algorithm with Expected value outperforms (Borda and Majority) voting algorithm considerably (Chapter 4). This work has been published as a conference paper (Almansour et al., 2018a).

3. Furthermore, to accomplish the third objective (O_3), we investigate the feasibility of using V2G to mitigate the problem of highest electricity peak demand in the summer period in one of the warmest countries of the world (Saudi Arabia). We conduct a survey in order to serve this issue and we use information from the Saudi Arabia electricity authority. The results showed that, V2G is a promising solution to the peak demand challenge in the summer in Saudi Arabia since about 80% of the sample interested in using V2G technology. Moreover, 90% of the participants used their vehicles less than 4 hours daily. Furthermore, in the summer period, most of the participants park their vehicles for the longest time between 13:00 to 18:00, which is the peak demand period. Moreover, we collect a vehicle usage behavior dataset for Saudi drivers in order to run our last model with real data (Chapter 5). This work has been published as a conference paper (Almansour et al., 2018b).

4. Following this, in order to attain the second objective (O_2), we then refine the problem that has been discussed in (Chapter 4) considering the battery degradation issue and the V2G problem in terms to the vehicle usage uncertainty in addition to the power market price uncertainty (Chapter 6).

5. Moreover, in order to achieve the second objective (O_2), the next step involves refining the algorithms proposed in (Chapter 4), which considers price uncertainty in the context of the V2G. Thus, to address price uncertainty in the context of the V2G, we develop a heuristic algorithm that can trade on behalf of the V2G drivers, maximising the profit they make from using the V2G as a source of electricity while taking into consideration their behaviour and their incentives. The proposed algorithm combines two types of consensus algorithms (Borda and Majority voting) and Expected value with a backward induction algorithm, as discussed in Chapter 4. Moreover, to address the vehicle usage uncertainty, we use a Multinomial Logit Model with the consensus algorithms and expected value with a backward induction algorithm. We evaluate the proposed algorithm by comparing it with two benchmark algorithms, which are naive algorithm and a complete information algorithm. The results show that, our proposed algorithm outperforms the naive algorithm by about 15 times in terms to the average profits when we start the experiments with a half amount of battery. Moreover, our proposed algorithm outperforms the naive algorithm for about 5 times in terms of the average profits when we start the experiments with a full amount of battery. On the other hand, our proposed algorithm performs 89% as well as the complete information algorithm in terms to the average profits when we start the experiments with a

half amount of battery. Furthermore, complete information provides almost same results of our proposed algorithm in terms of the average profits when we start the experiments with a full amount of battery. Actually, this is a good result if we consider that, the complete information algorithm deals with known information and the proposed algorithm deals with uncertain data. (Chapter 6)

6. Finally, and to achieve the last objective of this thesis (O_4), as a first stage of designing the V2G parking lots manager agent, we apply a survey of V2G parking lots preferences. Moreover, in terms of the V2G parking lots, which we ask about in a hypothetical manner since they do not yet exist, the survey results show that most of the sample believes that the pricing for early release penalty is more important than the flexibility. Furthermore, most of said participants feel that the payment method is more important than the reservation type when it comes to the payment policy issue. Thus, the payment method and the pricing for early release penalty should be the main issues to be considered during the design of the V2G parking lots manager agent model (Chapter 7).

These contributions are also detailed in the following papers:

- Contributions 1

  Almansour, I. A., Gerding, E. H., and Wills, G. (2017). An agent trading on behalf of v2g drivers in a day-ahead price market. In *Proceedings of the 3rd International Conference on Vehicle Technology and Intelligent Transport Systems - Volume 1: VEHITS,*, pages 135–141. INSTICC, SciTePress

- Contributions 2

  Almansour, I. A., Gerding, E. H., and Wills, G. (2018b). The feasibility of using v2g to face the peak demand in warm countries. In *Proceedings of the 4th International Conference on Vehicle Technology and Intelligent Transport Systems - Volume 1: VEHITS,*, pages 238–242. INSTICC, SciTePress

- Contributions 3

  Almansour, I. A., Gerding, E. H., and Wills, G. (2018a). Automated trading in vehicle-to-grid with price uncertainty using consensus. In *Proceedings of the 2nd International Conference on New Energy Vehicle and Vehicle Engineering (NEVVE 2018)*. NEVVE

Afterward, the following section is describing this thesis structure.

1.4 Thesis Structure

The thesis is structured as follows:

- Chapter 2 describes the background of power markets. Then, it defines the concept of V2G and outlines a number of V2G use implications. After that, it provides an overview of the current state of the art for modelling the EV scheduling problem. Next, this chapter discusses several applications that are related to our work, but they do not discuses the EV scheduling problem specifically. Afterwards, it describes consensus algorithms which is the main concept we use to develop our proposed algorithm.

- Chapter 3 discusses the model proposed to solve the price uncertainty in the V2G context. Firstly, it provides an overview for our model. Then, the problem will be formulated mathematically. Next, it discusses the design of the optimisation module. Afterwards, the experimental evaluation will be considered and the results will be discussed. Finally, the summary will be provided.

- Chapter 4 describes the model proposed to maximize the V2G driver profits with considering of price uncertainty in the power market. Then, in more detail, the problem of price uncertainty in the context of V2G is discussed. After that, our optimization algorithm is considered. Next, it shows the simulation results using the algorithms. Following this, we discuss the results. Finally, we summarize the chapter.

- Chapter 5 discusses the vehicle usage behavior for the vehicles drivers since we need this information to run our model. First, we review a number of related works that discuss this issue and we describe our study briefly. After that, we consider how we collect the data and chose the sample. Next, we discuss and analyze the results. Thereafter, we consider the survey limitations and findings. Afterwards, we describe the power market in Saudi Arabia because we use it as a case study for the power markets. Finally, we summarise this chapter.

- Chapter 6 describes the model proposed to maximize the V2G driver profits with considering of two types of uncertainties which are power market prices and vehicle usage behavior. Then, in more detail, the problem of price uncertainty, and vehicle usage uncertainty in the context of V2G is discussed. After that, our optimization algorithm is considered. Next, it shows the simulation results using the algorithm. Finally, we discuss the results, and then we summarise the chapter.

- Chapter 7 aims to discuss the survey of vehicle parking lots preferences for the current parking lots systems and a new type of parking lots concept. First, we provide an introduction for this survey that includes, its objectives, hypothesis and research questions. Then, we consider how we collect the data and chose the sample. Next, we discuss and analyse the results. Afterward, we consider the survey findings. Finally, we summarise this chapter.

- Chapter 8 provides a detailed summary of the work presented in this research and describes future work in order to achieve the aims listed in the first chapter.

Finally, the Table 1.1 provides a summary of the models and in which chapter that has been discussed in order to draw a road map for this thesis.

Table 1.1: Models road map.

Model	**The problem**	**Chapter**
First	There is not uncertainty in the power market price and we have complete information about the vehicle usage behaviour (one trip a day)	3
Second	There is an uncertainty in the power market price and we have complete information about the vehicle usage behaviour (one trip a day)	4
Third	There is an uncertainty in the power market price and there is another uncertainty in the vehicle usage behaviour where there is a multi trips scenarios. In addition, the battery degradation has been considered	6

Chapter 2

Literature Review

In this chapter we aim to convey a clear picture about the context of our study. First we describe its background, specifically power market types and pricing. Then we define the concept of V2G and outline a number of implications for the use of V2G. After this, we provide an overview of the current state of the art in modelling the EV scheduling problem. We break the problem into two, scheduling a fleet of EVs and scheduling an individual EV. Since our work is focused on an individual EV, we discuss this in more detail. We categorize studies discussing the scheduling of an individual EV based on the methodology into four types, heuristics approaches, learning agents, decision theory, and game theory. Afterward, we discuss the EV battery degradation which is one of the important issues that should be considered when solving the EV scheduling problem. Next, we consider the battery usage uncertainty which is one of our main concerns in this study. Next, this chapter discusses several applications relating to our work, yet not specifically discussing the EV scheduling problem. Finally, the chapter describes consensus algorithms, the main concept behind our development of our proposed algorithm, specifically two types, Borda, and majority voting and the concept of expected value. Then, we provide the summary for this chapter.

2.1 Power Markets

Power markets were established in the early 1990s as a result of international organizational reformation and market liberalization. In each, a member can trade electricity through advance contracts for various delivery periods (Huisman et al., 2007). In the introduction to this chapter we note how it is essential to give a brief definition of the smart grid, since it is one of the main concepts in power market technology and provides the opportunity to trade in the power market. To do so, the smart grid can be defined as a group of emerging electric power information technologies involving household energy management tools and technologies that facilitate communication between customers and electric companies (Keyhani, 2011). We will now briefly describe power market types and pricing as a background to the following section, which discusses the implications of using V2G in these power markets.

2.1.1 Power Markets Types

The electricity market is generally classified into four types, based on control rules. These market types are, baseload power, peak power, spinning reserves, and frequency regulation. They vary in control technique, response time and period of the power dispatch, contract terms and price. Each will be defined briefly, as follows.

2.1.1.1 Baseload Power

Baseload power is a type of power that can be delivered around the clock, typically at a low cost per kWh. It is delivered by natural gas, or coal-fired and large nuclear power plants (Wayne Beaty and Fink, 2006).

2.1.1.2 Peak Power

Peak power is produced and purchased at periods of especially high demand, such as on summer afternoons. It is produced by gas generators that can run for a shorter time, which is about 35 hours (Kamboj et al., 2011). Since peak power is normally required for a maximum of only a hundred hours annually, it is economically viable to use generators that are cheap in terms of capital cost, although each kWh produced is expensive under certain circumstances, using V2G for peak power can be economical (Kempton and Tomić, 2005).

2.1.1.3 Spinning Reserves

Spinning reserves are generators that are available to operate the load on unexpected occasions, such as during generator or transmission line failure. They are used rarely because they only operate in emergencies. The expected usage time of this type of generator is 10 to 60 minutes, between ten and twenty times a year. Consumers need to pay for a spinning reserves service, even if they never use it (Kempton and Tomić, 2005).

2.1.1.4 Frequency Regulation

Frequency regulation is sometimes known as frequency control or automatic generation control, and is used to adjust the frequency and voltage of the electrical grid by matching generation to load demand. This type can be provided with direct real-time control of the electrical grid operator, with the generating component able to receive and respond to signals from and to the smart grid quickly, by increasing or reducing the output of the generator. A number of power markets divide regulation into two types, one for the capability to reduce from a baseline regulation down, and the second to increase power generation from a baseline level regulation up. Further, a generator could contract to offer regulation down, regulation up, or both, on a single contract, because these two are certainly not required at the same time (Kempton and Tomić, 2005).

The next section discusses power market pricing.

2.1.2 Power Market Pricing

In the power market, a member can trade electricity in advance contracts for various delivery periods. These contracts can be classified as short-term or long-term contracts. Short-term contracts can be traded in several types of markets such as day-ahead pricing (DAP) or real-time pricing (RTP). The DAP market includes delivery of electricity the day after and on intra-day markets, including delivery in the quarter-hour or half-hour after the transaction. Further, in the RTP market, prices are computed every five minutes on the basis of real network operating conditions. By contrast, long-term contracts can be traded in advance markets in different delivery periods ranging from a year to a week (Huisman et al., 2007). Mohsenian-Rad and Leon-Garcia (2010) propose different time pricing types to solve the problem of fluctuations in electricity prices from one day to the next: day-ahead pricing (DAP); real-time pricing (RTP); critical-peak pricing (CPP); and time-of-use pricing (TOUP). They claim that this classification considers two matters: first, it permits retail prices to indicate to customers the real fluctuations of wholesale prices, so customers pay the rate at which the electricity is valued at various periods of the day. Secondly, it motivates customers to change their consumption behaviour by using their household appliances during off-peak hours, with benefits for both them and the electricity company.

Here, we focus on DAP, and the RTP pricing. Thus, the next section will briefly discuss DAP and RTP.

2.1.2.1 Day-ahead Price Market

In day-ahead markets, different prices are quoted for delivery in each particular hour of the following day. A number of markets distinguish between daily average peak load and baseload prices; they use the former during peak hours, and the latter for the price over the whole 24 hours. Furthermore, prices are quoted in other markets on the basis of every 30 minutes in countries such as United Kingdom, New Zealand and Australia.

Moreover, in the DAP market quotes for the day-ahead delivery of electricity are offered together for every hour of the following day. The information set to be used for quoting might not be the same for every hour. Huisman et al. (2007) claim that hourly electricity prices do not act as a time series process; in reality, they could be dealt with as a board on which prices of 24 cross-sectional hours differ from one day to other.

2.1.2.2 Real Time Price Market (RTP)

Electricity wholesale prices fluctuate from day to day because storing electricity is expensive. This fluctuation might be as a result of the scale of ordering between high demand mid-afternoon and low demand in the hours of the night. According to Allcott (2011), most retail customers pay an average price that does not reflect the wholesale cost at the time of consumption. Therefore, it can be stated that an effective solution to this problem is a real time pricing (RTP) market. Rigas et al. (2015) define this as a spot market where present prices are calculated every five minutes, depending on real network operating conditions. Moreover, according to Allcott (2011), using a smart grid might increase the flexibility of home prices and reduce the cost of the advanced electricity meters needed to record hourly consumption. In conclusion, it is suggested that using a smart grid in the RTP market might offer an chance for customers to reduce their electricity costs.

2.2 Implications of Using V2G on the Power Market

After discussing the power market types and pricing, the implications of using V2G will be discussed here with the aim of using these power markets efficiently. Before discussing the implications of using V2G in the power market, we need to discuss the concept.

The concept of V2G is where an EV offers electric power to the grid when it is parked. vehicles can be classified as belonging to one of three types: a fuel cell vehicle; a pure battery electric vehicle; or a plug-in hybrid. Fuel cell vehicles can produce power from liquid or gaseous fuel, while pure battery EVs produce power from electricity. These may be charged during low demand periods and discharged when power is required. Finally, plug-in hybrid EVs can work in both fuel cell and pure battery modes. Every EV has three essential components: a control connection to communicate with the electrical grid operator; metering and control devices inside the vehicle board; and a grid connection for electrical power flow. These components might differ, based on the business model of the EV (Kempton and Tomić, 2005).

Figure 2.1 illustrates how electric vehicles connect to the electric power grid, where generators produce electricity and send it to electricity customers across the grid. This electricity might next return to the grid from EVs. The grid operator controls the

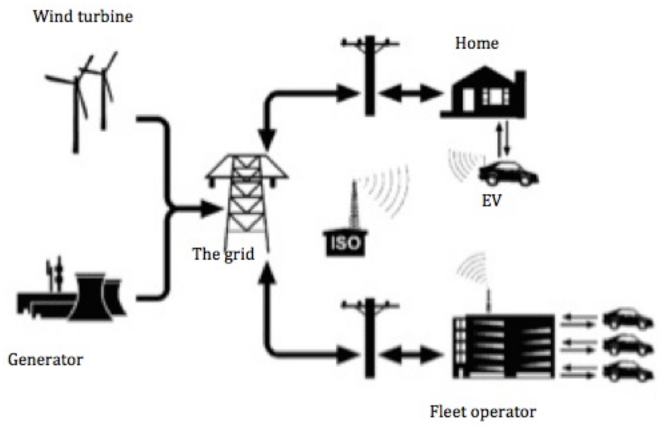

Figure 2.1: Kempton and Tomić (2005) proposal for wireless control communication between electric power grid and vehicles to grid.

communication signals by various methods, such as broadcast radio signals, the cell phone network, an Internet connection or a power line carrier. In any case, the grid operator sends demands for power to a number of vehicles in one of three ways. First, it can be sent to every single vehicle directly. Secondly, it can be sent to the fleet operator control, which, in turn, controls vehicles in individual parking spaces. Finally, it could be sent through a third-party aggregator of the power of dispersed individual vehicles.

After defining the concept of V2G, we now consider the implications of using V2G in the power market.

First, several studies have tried to establish which of the power market types described in section 2.1 is more suited to integration with V2G in terms of maximizing profits for V2G drivers. According to a study by Kempton and Letendre (1997), at peak demand times EVs could be used to decrease peak load by discharging stored electricity from their batteries, or running their on-board generators at these times. They analysed the economic feasibility of discharging EVs battery as a peak power source, as defined in section 2.1.1.2, and as spinning reserves, as described in section 2.1.1.3. They found that in the USA, under the correct settings, this could be economical for both EV drivers and the electric company. Similarly, Kempton and Kubo (2000) applied the Kempton and Letendre approach in the Kanto region of Japan. Their conclusion was that some EV batteries could be used both for peak power and to profit both EV drivers and the electric company, if produced with the special features they propose. Indeed, the desired duration of peaking units could be 35 hours, which for V2G is possible but difficult, due to limited energy storage (Kempton and Tomić, 2005).

EVs could be used to provide spinning reserves, because they can respond rapidly to emergencies when required (they can deliver within two seconds of being alerted and do not have to be run by spinning typical generators). Payment for V2G owners using their cars as spinning reserves would obviously be restricted to the period during which they were available (Kempton and Tomić, 2005; Kamboj et al., 2011). Furthermore, several studies such as by Kempton and Letendre (1997) and Kempton and Kubo (2000) have found that V2G cannot deliver baseload power at a competitive price, as discussed in section 2.1.1.1. This is due to the fact that EVs have some features that do not suit baseload power, such as limited energy storage, a short device lifetime and high energy prices per kWh. Moreover, baseload power does not need EVs' features of quick response time and low standby prices per kWh (Kempton and Tomić, 2005).

Unlike the aforementioned studies that discuss which power market type is highly suited to integration with V2G in terms of maximizing profits for V2G drivers, Tomić and Kempton (2007) studied the economic advantages of using fleets of EVs to deliver electrical power for a frequency regulation market, which is a type of power market discussed in section 2.1.1.4, in four American regional regulation markets. They claim that in terms of energy storage and power electronics, the battery of an EV is better at delivering widely and frequently fluctuating electricity power over short time periods than large generators, because it has been designed to meet the requirements of driving. Thus, these vehicles are appropriate for frequency regulation. The significance of this study is that V2G power from EV fleets is economically feasible. Moreover, EVs could deliver regulation of a higher quality than available sources, because they respond quickly to a signal, can offer minor increments and are distributed. From the electric power sectors perspective, this is a promising source of high quality grid regulation; for EV drivers, it represents an important income stream that might improve the economics of grid-connected EVs and also support their adoption.

In the same context, White and Zhang (2011) studied possible financial gain through using plug-in hybrid EVs as an electrical power source. They report that there is little financial motivation for users when the V2G service is used exclusively for peak reduction, yet major potential when drivers use their V2G for frequency regulation. Moreover, they find that these two uses of V2G technology are not mutually exclusive and propose a dual-use programme that uses V2G for multiple purposes simultaneously. Their suggestion is to use V2G for peak reduction, as there may be a need to design formal storage markets, particularly as demand will escalate with greater penetration by renewable energy technologies. On the other hand, regarding regulation they suggest that the market may be flooded by V2G-based regulation providers at higher contribution rates. White and Zhang state that V2G technology will be used commonly, especially if the need for regulations, reserves and storage rises as they predict. Therefore, to use V2G technology effectively, a V2G driver should have a clear idea about how to use it in terms of maximizing profit.

As we discovered from the literature, the V2G can be economically viable in the peak power market and frequency regulation market. We can summarize the difference between these types of markets in the context of applying V2G technology as follows: the number of times the vehicle's battery is used as a source of power in the frequency regulation market is higher than the number of times it is used in the peak power market. However, usually the price of kWh in the peak power market is higher. Indeed, we believe our work can be used in both markets, namely peak power and frequency regulation.

Dallinger and Wietschel (2012) studied the ability of EVs to balance fluctuations of renewable energy sources (RES) in Germany in 2030. The study had a number of important results. First, EVs can provide a very high power ratio compared to other storage devices. Additionally, the authors report that it is unclear how customers react to price signals. Thus, it is difficult to know the real customer response in the case of applications for load management mechanisms and, until now, the way in which the V2G drivers react to energy prices could not be accurately predicted. This last finding supports our claim that there is a gap here.

Similarly, Saber and Venayagamoorthy (2011) state that V2G could reduce emissions from transportation, and could be used as loads and power storage in a smart grid integrated with RESs. Moreover, they report that the peak load might be very high if a vast number of EVs is coupled randomly to the smart grid. To solve this challenge, Saber and Venayagamoorthy developed a smart grid model that provides the best potential for the maximum utilization of RESs, reducing both the costs and the emissions of electrical power. Moreover, Kavousi-Fard et al. (2015) note that applying the concept of V2G to EVs could decrease the cost of the system by storing energy in an effective way. Saber and Venayagamoorthy (2011) and Kavousi-Fard et al. (2015) support our claim that EVs, when not being used, can be used as a large distributed battery to offer power storage and supplementary services to the smart grid, thus to secure extra revenue.

Battistelli et al. (2012) developed a novel optimization model for energy management within small electric energy systems, including V2G. They used their model to study how V2G contributes to the management of energy resources. Further, they applied robust optimization techniques to deal with the uncertainty of renewable energy sources. Unlike the studies by Tomić and Kempton (2007), Dallinger and Wietschel (2012), Saber and Venayagamoorthy (2011) and White and Zhang (2011), which discuss the ability to use V2G in power markets, Wickert et al. (2010) tried to show the impact of managed EV charging by simulating a model for EVs. The model is divided into three parts: the first represents EV drivers characteristics; the second models the electrical features of EVs; and the final part simulates a decentralized EV energy management. The agent in this simulation framework consists of an EV module and an EV driver module. The EV driver module represents information about user preferences, such as when the driver wishes to start his or her trip and the distance to be driven. Indeed, this simulation has been organized as a set of modules, and that for the driver has been based on statistical data. The study by Wickert et al. is used in our current research to build the proposed agent.

Finally, Zareen et al. (2015) note that when the V2G drivers charge or discharge their vehicles optimally in the deregulated market, they not only maximize their profit but support the provision of regulation services in emergencies. This claim could be used to highlight the importance of our research.

Based on the reviewed studies discussed here, there are number of useful benefits from using V2G. One of the most important is using it to maximize profits for owners by trading in the power market. To accomplish this, EV scheduling problem should be considered, as the following section discusses.

2.3 EV Scheduling Problem

Several studies have tried to solve the EV scheduling problem in different way, as will be discussed. We divide the studies that discuss the EV scheduling problem into scheduling a fleet of EVs and scheduling an individual EV.

2.3.1 Scheduling a Fleet of EVs

There are several studies that discuss the problem of EV scheduling from an EV fleet operator's perspective, and some of these will be discussed here. First, Wang et al. (2013) propose an optimal V2G aggregator to control the charging and frequency regulation processes of a group of EVs. They discuss a problem where an aggregator has to reduce the total cost of charging the EV fleet in multiple time periods and achieve the required battery level when an EV plugs out. In order to do so, they develop a model with a predictive control-based charging algorithm to find the optimum control sequence for EVs with a specified available state and vehicle information. Li et al. (2015b) discuss the same problem, and consider price uncertainty and battery degradation. Their proposed strategy is dependent on price predictions for housing electricity and market regulation. To do that, they apply stochastic dynamic programming. We differ from (Wang et al., 2013; Li et al., 2015b) in that they consider a fleet of EVs, while our study is of an individual EV, which means we discuss different problem with different conditions and constraints.

Like (Wang et al., 2013; Li et al., 2015b), He et al. (2012); Sundstrom and Binding (2010) discuss the problem of EV scheduling from an EV fleet operator's perspective, yet differ from them in that the aforesaid studies do not consider the constraints of the electricity grid. He et al. (2012) argue that EVs may have an important impact on the power grid due to growth in electricity consumption, therefore it is essential to design intelligent scheduling for their charging and discharging. However, two main difficulties in EV scheduling are that, first, it is difficult to find a globally optimal scheduling solution that can reduce total cost, and second, it is challenging to find a distributed scheduling scheme that can deal with a high number of EVs arriving randomly. To solve these problems, their study proposes a globally optimal scheduling scheme and a locally optimal scheduling scheme for EV charging and discharging. This study first formulated a global scheduling optimization problem in terms of optimizing the charging power, to reduce the cost of the EVs charging and discharging throughout the day. However, this solution is unreasonable as it needs information on the future base loads, and the times of arrival and the charging periods of EVs that will arrive at a future time of day. Thus, to design a sensible scheduling scheme this study formulates a local scheduling optimization problem that proposes to reduce the total cost of the EVs in the current ongoing EV set in the local group.

Likewise, Sundstrom and Binding (2010) propose a novel method for planning the charging of EVs that considers the constraints of the electricity grid. Their solution calculates an individual charging plan for each vehicle to minimize electricity costs, mitigate distribution grid congestion and, moreover, meet the driver's preferences. The planning period for this study is the following day, which is divided into 96 periods of a quarter of an hour. Furthermore, they note that peaks would still occur even if grid constraints were considered in the optimization. Thus, they recommend that future studies should investigate the other objectives and business models of fleet operators to allow the effective integration of EV fleets.

Along the same lines, Shafie-khah et al. (2016) developed a multi-stage stochastic model of an EV aggregation agent to contribute to DAP and intraday electricity markets that considers power market prices and EV drivers' behaviour. Xu et al. (2017) discuss the same problem while considering a worst case scenario. In order to do so, they propose a risk-averse optimal bidding approach for the resource aggregator in DAP markets. Vayá and Andersson (2016) discuss the same issue and consider offering a balancing service to wind power producers. They model the aggregated charging and discharging flexibility of the EV fleet as a probabilistic virtual battery model, allowing for uncertainty in the driving patterns of EVs. Moreover, there is another type of uncertainty in their model, in terms of the balancing requests that are a function of forecasted wind power output. To deal with these uncertainties, they apply a scenario-based robust approach. Caramanis and Foster (2009) likewise propose a decision-support technique for an EV load aggregator that controls battery charging for a group of EVs and considers wind power uncertainty. They show that EV load management can reduce costs by combining effective EV battery charging and using the extra regulation services needed by wind farm expansion.

Furthermore, studies such as those by (Tan and Wang, 2014; Wu et al., 2012) apply a game theory approach to scheduling a fleet of EVs, yet differ in the problems they discuss. Tan and Wang (2014) develop a dynamic MDP to model the charging behaviours in EVs stochastically, building a game theory-based decentralized system for EVs to participate in peak load shaving and frequency regulation. Afterwards, in order to coordinate the EVs fleet in a residential network, they formulate a game theory-based decentralized system. In their study they consider the power quality and economic profits. Similar to Tan and Wang (2014), Wu et al. (2012) use this approach but consider interactions between EVs and aggregators in a V2G market, where EVs participate in offering frequency regulation service to the smart grid. They suggest a mechanism to attain optimal frequency regulation performance in a distributed manner. In their study they used game theory to analyse a V2G market through understanding vehicle-to-aggregator interactions to provide frequency regulation service to power grids. Unlike our study, Wu et al. (2012) do not consider the consumption behaviour of the V2G drivers, to learn and predict the best time to buy and sell electricity. In fact, they only try to include the relationship between EVs and aggregators in a V2G market.

In a similar vein, yet different from the work by Cardoso et al. (2014) on the impact of EV driving schedule uncertainty in the distributed energy resource investment decision for a fleet of EVs, our work considered vehicle usage behaviour for individual V2G drivers in order to maximize their profit. However, Cardoso et al. (2014) serves to highlight the importance of our work.

Finally, V2G could be used to trade in the power market, as discussed earlier. However, Khalid et al. (2013) find that using V2G to trade in the DAP or regulation market is risky, since prices and load demand are uncertain. They designed an optimal day-ahead regulation bidding strategy for a unidirectional V2G algorithm to be used in an EV aggregator. To fix the uncertainties, they applied stochastic programming with a scenario generation technique. Our study differs from Khalid et al. (2013) in that they assume there is an EV aggregator and that it will trade in behalf of V2G drivers, while we assume our agent will trade on behalf of the V2G driver without the aggregator, which means we discuss two different problems. Furthermore, they apply stochastic programming to fix price uncertainty in the power market, thus their solution requires thousands of scenarios to represent every stochastic variable. However, we develop a heuristic algorithm that combines backward induction and consensus algorithms, which do not require this high number of scenarios.

After this discussion of the problem of scheduling of a fleet of EVs, the research investigates that of individual EV scheduling.

2.3.2 Scheduling an Individual EV

We classify the studies that discuss the scheduling of an individual EV into four approaches: heuristics; learning agents; decision theory; and game theory. The following sections discuss each of these types.

2.3.2.1 Heuristics Approaches

Several studies discuss the scheduling of an individual EV using heuristics, such as fuzzy set theory. This is used in works that discuss the scheduling of an individual EV, such as those by (Sedghi and Aliakbar-Golkar, 2013; Ansari et al., 2014; Nasiri and Moghadam, 2014). These use the same methodology but consider different issues. First, Sedghi and Aliakbar-Golkar (2013) propose a scheduling method for the optimal charging of central stationary battery storage units in a medium voltage distribution network, considering the uncertainty impact of EVs. They model it by fuzzy set concepts. Applying a fuzzy model for EVs is appropriate if there is no precise information about the power market. Thus, the solution may be suitable for long-term scheduling based on short-term operation scheduling. Consequently, our study could be integrated with (Sedghi and Aliakbar-Golkar, 2013) work. Likewise, Ansari et al. (2014) use fuzzy set theory to design a new charging strategy that optimizes the EVs charging and the bidding of ancillary service in the power market, considering several market uncertainties. Likewise, Nasiri and Moghadam (2014) discuss the unit commitment problem and take into consideration EVs. Charging and discharging EVs depends on a number of influences such as petroleum prices, electricity prices and driving behaviour. To deal with these uncertainties, they apply fuzzy set theory and probabilistic modelling. They find that EVs drivers behaviour has a major effect on the preparation of producing units at every hour that has significance in terms of raising the operational costs. The research by Nasiri and Moghadam (2014) is one of the studies that we considered when we modelled vehicle usage uncertainty.

Halvgaard et al. (2012) apply another type of heuristics approach, which is an Economic Model Predictive Control (MPC). They use it as a technique to reduce the cost of electricity consumption for a single EV. Furthermore, they find that while it is clear that there should be an incentive for EV drivers to support the balance of power production and charging during off-peak periods, it is unclear whether this should be a centralized or decentralized method. The key difference between Halvgaard et al. (2012) study and our research is that the former tries to reduce the cost of charging a single EV by using MPC based on electricity price predictions and estimated driving patterns, whereas we consider charging and discharging times through discussing V2G.

2.3.2.2 Learning Agents

From a different perspective, several studies apply learning agents to deal with scheduling of individual EVs. First, Valogianni et al. (2014a) use this methodology to discuss the scheduling, taking into consideration household consumption. They develop a learning agent strategy that acts on behalf of EV owners to reduce their electricity bills and the time of peak demand. The study differs from our work in that it discusses the charging of EVs, while we discuss V2G. This makes our problem more complex, since we must consider discharging. In addition, they consider household consumption and we do not.

Using a similar approach, Chis et al. (2013) develop a reinforcement learning algorithm that solves the problem of scheduling the charging of EV batteries. They aim to decrease charging costs for EVs drivers in the long term. Valogianni et al. (2014b) apply this approach to discuss price uncertainty in the power market in the context of EV, yet differ from (Chis et al., 2013) in terms of the period they consider, investigating EV charging over a weekly horizon. Akin to (Chis et al., 2013), we formulate our problem as a MDP. Again, however, our problem is more complicated than that of (Chis et al., 2013; Valogianni et al., 2014b), since we must consider discharging. Furthermore, we differ from them in terms of the period considered.

V2G problems are more complicated if price uncertainty is considered, as the price of electricity is decided each hour, dynamically. Shi and Wong (2011) discuss the real-time V2G control problem, considering price uncertainty. They formulate the problem as a Markov decision process (MDP) and model the price of electricity as a Markov chain with unknown transition probabilities. To solve the problem they develop an online learning algorithm adaptively, using hourly available pricing information. They find that their proposed algorithm varies from algorithms in the literature by modelling price uncertainty considering real-time pricing, and claim the simulation results for their model show that their suggested algorithm is able to increase the benefits for EV drivers considerably. Similar to Shi and Wong (2011), we study price uncertainty in the context of V2G, but our study differs from theirs in the following crucial point, our proposed algorithm is more scalable, so it may be integrated with vehicle usage uncertainty, as we will discuss in section 2.3.4. However, Q-learning does not work well if we consider the uncertainties in vehicle usage since one of the weaknesses of Q-learning is that learning can be very slow (Kochenderfer, 2015), so when we consider the vehicle usage uncertainty the solution space will be too large and Q-learning will be an inefficient technique.

2.3.2.3 Decision Theory

Unlike (Shi and Wong, 2011; Khalid et al., 2013; Sanchez-Martin et al., 2015), who discuss price uncertainty in the context of a V2G driver who uses the car for private use, (Sun et al., 2013; Yang and Yang, 2014; Yang et al., 2014) investigate the optimal charging strategy for a plug-in electric taxi (PET). They aim to maximize operating profit by choosing appropriate charging slots, subject to uncertain electricity prices and time-varying incomes. They claim that this type of vehicle consumes more electricity and that its drivers' charging behaviour differs from that of other EV drivers, so the problem requires special solutions. Thus, they use a backward induction algorithm to find the optimal charging slot. As do (Sun et al., 2013; Yang and Yang, 2014; Yang et al., 2014), we apply backward induction, yet we differ from them in that they use it to tackle the PET problem while we focus on the V2G context, which means we have dissimilar problems and constraints. Moreover, in our heuristic algorithm we combine backward induction and consensus algorithms, and they do not.

2.3.2.4 Game Theory Approaches

There are several studies that use a game theory approach to EV scheduling problem, such as that by Stein et al. (2012). They propose a novel online mechanism that solves this problem by scheduling the allocation of an expiring and continuously produced resource to self-interested agents with private preferences. In their study they focus on pure electric vehicle charging. The average utility of their mechanism was 93% or more of the offline optimal. This study could be improved by considering EVs owners individual preferences. In a similar vein, Ma et al. (2010) propose a novel decentralized charging control strategy for large populations of EVs. They consider conditions where EV agents are rational and weakly connected via their operation costs. They formulate the problem as a class of finite-horizon dynamic games. The approach works by solving a relatively simple local problem, iterating quickly to a global Nash equilibrium. The authors show that their solution does not require significant central computing resources. The main goal of their study is to minimize electricity generation costs by establishing an EV charging schedule that satisfies overnight demand valley. Further, Ma et al. find that by using decentralized control there is a unique Nash equilibrium that almost satisfies social optimality under certain mild conditions. Stein et al. (2012); Ma et al. (2010) focus on pure EV charging while we focus on V2G charging, thus we need to consider discharging. Furthermore, Gerding et al. (2016) studied the setting of a smart vehicle car park, where EVs could be utilized for V2G services while parked. They designed a novel allocation and payment mechanism which truthfully elicits the EV drivers preferences, involving arrival, departure, desired amount of battery, and the costs of discharging. The cost arises due to the batterys loss of efficiency. They stated that solving this problem optimally is intractable, and so they proposed three novel heuristic online scheduling algorithms in order to solve this problem. As noted by Gerding et al. (2016), their study is the first effort to formalize the V2G problem as an online mechanism design problem. In particular, they consider multi agent environment and they maximize the social welfare for the agents. On the other hand, our work maximizes the profit for a single agent. Moreover, in our work we consider the trip type and the probability of each trip type to happen whereas in Gerding et al. (2016), these issues have not been considered. Indeed, the work by Gerding et al. (2016) will be one of our main references in our future work when we consider the multi-agent environment.

In the following section we will discuss the EV battery degradation, which is one of the key issues that should be considered when dealing with the EV scheduling problem.

2.3.3 EV Battery degradation

There exist a number of studies which have discussed the V2G application; indeed, all of these studies considered the cost of battery degradation and concluded that the annual profits resulting from the application of V2G will be approximately EUR 135-151 (Peterson et al., 2010; Schill, 2011). Moreover, Schill (2011); Guille and Gross (2009) concluded that applying V2G crucially depends on the developments of battery technology in the future.

Battery life usually degrades during its time of use, as a result of frequent charging and discharging cycles. This degradation is affected by a number of factors, such as the battery's cycling features (e.g. state of charge, charging, discharging rate), and the battery type (e.g. lithium iron phosphate or lithium nickel cobalt aluminium or any of other types) (Ortega-Vazquez, 2014). These aforementioned factors have different effects on the life of batteries. For example, numerous studies have found that the capacity of nickel cobalt aluminium is sensitive to the depth of discharge of the cycles, and to the total number of cycles. On the other hand, the capacity of lithium iron phosphate batteries is only sensitive to the total number of cycles (Smith et al., 2009). Thus, no single model could be applied for all of the chemistries which are used in the battery industry to model battery degradation (Ortega-Vazquez, 2014). By using the previous statement, we aim to consider a number of general battery degradation features that have an effect on cost. The percentage of the capacity of a battery when the battery expires is one of the crucial factors, and results in the calculated slope of the linear approximation of the battery's life. A number of studies concerning said issue assumed that this percentage is equal to 50% of the battery capacity (Neubauer et al., 2013); other studies, however, assumed that this figure is 80% (Zhou et al., 2011; Millner, 2010).

In the same vein, Wang et al. (2016) developed an approach to quantify the EV battery degradation which is produced by applying V2G services. They used their approach to simulate the EV battery degradation of three vehicles with different daily driving itineraries for approximately 10 years, with and without using V2G. They found that using V2G services reduced the batteries lifetime by 0.48, 0.40, and 0.59 annually, respectively.

Similarly, Gough et al. (2017) discussed the potential for EVs to provide a profit from power supplied to business buildings in the UK; they concluded that the net revenue production was strongly related to the cost of battery degradation. In the same vein, Hoke et al. (2011) proposed a technique to reduce the EV charging cost by considering estimated costs of battery degradation using a simplified lithium-ion battery lifetime model; they focused on lithium-ion (Li-ion) batteries because these represent a main part of vehicle cost (Belt, 2008).

In conclusion, there was more degradation on the battery as a result of applying V2G services, since there were extra charge and discharge cycles on the battery (Zhou et al., 2011). Moreover, Smith et al. (2010) stated that finding the minimum battery size that meets vehicle energy capacity offers an opportunity to decrease vehicle cost considerably. As such, an intelligent charge algorithm could extend battery life, thus maximising the driver's profit.

In addition, Dallinger et al. (2011) discussed the battery degradation issue, but from a different perspective; they developed a new method with which to analyse the economic impacts of V2G regulation reserves by simulating the limitations which stem from unpredictable mobility demands by vehicle drivers. In addition to this, they used the German regulation market as a case study, which used the monthly bids. They concluded that a day ahead price market or hour price market would be the best option. Such a change might be crucial to provide individual regulation, supposing that the cars are mainly used for mobility purposes and cannot deliver the consistent quantity of electricity every hour of the week.

In the next part, we will discuss a number of studies which have considered vehicle usage uncertainty, which is one of the main objectives of this work.

2.3.4 Vehicle usage uncertainty

Before we review a number of studies that have examined vehicle usage behaviour in the EV context, we should clarify that we prefer to use vehicle usage behaviour instead of drivers' behaviour, because the latter is a term usually used to describe the emotions of the drivers, and this is not a point of discussion in our work.

Firstly, among the studies concerning vehicle usage behaviour, a particularly interesting one comes from Goebel and Voß (2012). They developed a time series based technique for forecasting the first daily departure time of commuter vehicles. This task is related to the grid integration of EVs, because it allows for the active management of their power demand through the connection time. A key finding of this study was that, even for commuters, it is very difficult to expect to use historical realisations only. Although their study discussed different angles of vehicle battery usage behaviour, we can use this study to confirm the complexities of the problem.

Furthermore, and as discovered by Wai et al. (2015), vehicle usage behaviour is too complex a model, since the drivers have their own driving patterns, which differ based on their physical circumstances or mood. Thus, we do not consider some of the vehicle usage behaviour factors, such as speed, for the sake of simplicity.

In a similar vein, Kim et al. (2013) developed a method to predict the power requirements of EVs. To do so, their model requires a history of the drivers power consumption, speed, acceleration, and the road information. Likewise, Zhang et al. (2012) designed an estimation technique to compute the remaining driving range by considering numerous factors, such as vehicles current location, remaining battery energy, road map, wind speed, and drivers driving pattern. The crucial difference between our work and that of (Kim et al., 2013; Zhang et al., 2012) is that their model requires high amount of information to work; in contrast, our model can work less amount of information, and thus we can say that our solution is more attractive.

Finally, Ashtari et al. (2012) recorded data on vehicle usage for 76 vehicles over one year in the city of Winnipeg, Canada; they utilised this data to forecast EV charging profiles and electrical range reliability. They found that the appropriate stochastic modelling, such as using an iterative technique with conditional probability density function, might increase the accuracy of the forecasting by 12% compared with current techniques. However, applying the stochastic method requires a huge number of scenarios if it is to work properly.

2.4 Other Related Applications

After reviewing in the previous section a number of studies that discuss the EV scheduling problem, either for a fleet or individual EVs, we now discuss several studies that relate to our work, yet not specifically the EV scheduling problem.

2.4.1 Demand Response

Since EVs have become commonly used, there has been growing interest in using the storage capacity of their batteries to return some energy back to the grid when needed (Han et al., 2010). In this situation, customers would purchase electricity for charging their batteries during low-price periods then sell electricity back to the grid by discharging their batteries when the price is high. Consequently, they not could only assist with balancing supply and demand in the regional electricity market but make money. However, it is difficult for customers to keep watching real-time prices in terms of deciding on the best time to charge or discharge their batteries to secure the highest profit. This study suggests extending the proposal by combining negative loads for discharging. Moreover, it states that price prediction would still be helpful. Indeed, Han et al. (2010) confirms our claim that there is a lack of knowledge among customers about how to react to prices that vary over time in the power market.

To solve the issue raised by Han et al. (2010), that there is price uncertainty in the power market and customers cannot deal with it effectively, O'Neill et al. (2010) investigate real-time pricing in terms of the demand response to answer the problem of whether consumers should use power at the present price or wait and use it in future at an unknown price. In the same vein, Conejo et al. (2010b) develop a real-time demand response algorithm applied to a daily 24-hour horizon and use robust optimization to consider the price uncertainty in their model. Conejo et al. (2010b) and O'Neill et al. (2010) deal with the real-time demand response problem, while Shi and Wong (2011) investigate the issue in the context of V2G control.

2.4.2 Households

As discussed in chapter 1, a smart grid offers an opportunity for customers to use their own storage devices in their homes to maximize their profit. In order to do so, Vytelingum et al. (2010) propose a game theory framework for modelling storage devices in large-scale systems, where each storage device is owned by a self-interested agent that intends to maximize its financial profits. However, in using game theory they have made some implicit assumptions, specifically that agents are rational and have complete information about the market throughout the time period. In reality, the information available to owners of storage devices will not be perfect. We differ from Vytelingum et al. (2010) in number of points. First, we have different experimental settings, since they discuss how individual households could optimize their techniques to save energy, whereas we discuss how V2G drivers could maximize their profit from dealing in the power market. Moreover, Vytelingum et al. (2010) propose having an agent and assume that it has complete information about the market throughout the time period, while we assume it will deal with imperfect information, which is more realistic.

In a related vein, the smart grid can be used to reduce electricity costs for customers, specifically for household heating. A study by Shann and Seuken (2014) discusses the problem of adaptive domestic heating in the smart grid relating to RTP. Specifically, it develops a smart thermostat that automatically heats the household, optimally trading for the customers comfort and cost. They deal with two types of uncertainty, future prices of electricity and the weather forecast. Like this study, we use dynamic programming techniques to compute our optimal policy and deal with DAP market. However, we differ in the experimental settings, since in our problem we consider battery state and time of using the car, and assume we can trade with the power market, while Shann and Seuken (2014) merely buy from it. This makes our problem more complex.

2.4.3 Charging Stations

In contrast to the aforementioned studies, Ghiasnezhad Omran and Filizadeh (2014) and Sanchez-Martin et al. (2015) discuss charging stations, representing one of the applications that we considered in modelling vehicle usage uncertainty. First, Ghiasnezhad Omran and Filizadeh (2014) propose a procedure for location-based prediction of the possible vehicular charging load at charging stations. In order to emulate drivers' charging behaviour they apply fuzzy decision-making systems to three real-life attributes, namely state of charge, parking duration and actual driving distance home. This study does not consider V2G conditions, however we will use the work as a reference when we model vehicle usage behaviour. In a related vein, Sanchez-Martin et al. (2015) argue that applying stochastic behaviour to manage EV charging points is more realistic and develop a stochastic programming model to achieve optimal management, taking into account price variations in day-ahead and intraday electricity markets, together with regulating reserve margins. They divide their model into two phases. In the first, decisions determine DAP purchases and sales. In the second, decisions correspond to intraday markets, and concern reserve requirements and several possible scenarios for vehicle staying pattern. Their model attains power cost reductions of between 1% and 15%, depending on the particular case.

2.4.4 V2G parking lots

Before we discuss the V2G parking lots, we will provide the definition of the parking lots initially. Parking lots can be defined as a site entitled for parking that could either be paved or unpaved (Paidi et al., 2018). There are many parking lots which could be used to apply a V2G concept, such as parking lots at workplaces, airports and large malls. To do so, we study the vehicle drivers' preferences in the parking lots, so as to investigate the feasibility of using V2G parking lots. There exist several studies that have discussed the V2G parking lot issue from different viewpoints, and in this section we will review some of these studies.

Firstly, Hashimoto et al. (2013) developed an auction-based parking reservation system that applies V2G concepts; to evaluate their solution, they simulated a driver's parking duration. This study differs from that of Hashimoto et al. (2013) in numerous ways. Firstly, the latter assumed that all of the parking lots should be reserved for a scheduled time; our assumption, however, is more realistic, since we assume that the drivers may have cancelled or rescheduled their trips. Moreover, they did not consider the tariff types of the V2G parking lots, nor the drivers preferences regarding this issue, which is one of the key objectives of our study.

Additionally, Freeman et al. (2017) discussed the same issue, but from a different perspective, namely a parking lot owners viewpoint. They found that V2G electricity sales could make a profit for them, even when considering the V2G battery degradation cost. Moreover, they studied how the carbon dioxide tax could be used to encourage V2G adoption. Their results showed that the carbon dioxide tax could produce extra opportunities for more profits. However, these profits might be different based on the smart grid generation portfolio.

Furthermore, one of the most relevant works is that by (Parsons et al., 2014). They applied a choice experiment to discuss the potential demand for the V2G drivers. This study differs from their work in many respects. Firstly, they defined the relationship between the vehicle driver and the aggregator (the parking lot agent in our case) as a contract, whereby the drivers have a duty to park their vehicles in the parking lot for a particular number of hours per day or month. However, this is not the case in our work, since we assume that there is no contract between them, and so the drivers can park any time of the day, without any pre-set obligation. Moreover, one of the crucial differences between our work and that of Parsons et al. (2014) is that the latter did not consider the penalty system in the V2G parking lot. Indeed, this study takes into account said system, and treats it as one of the main objectives. However, Parsons et al. (2014) concluded that the contract strategy should be excluded and replaced by a pay-as-you-go strategy, and this is something we consider in our study. Thus, we can use their conclusion to raise the importance of our work. Finally, we must state that there exist numerous other studies in the literature which we choose not to consider. However, here we highlight the studies which are most relevant to our work.

After discussing several applications that we believe relate to our work, we find they did not discuss the EV scheduling problem specifically. Next, we describe consensus algorithms, which are the main concept we use to develop our proposed algorithm. Specifically, these are types of consensus algorithms, namely Borda, majority voting and expected value.

2.5 Consensus Algorithms and Expected Value Concept

The initial studies using online algorithms did not consider any information about the future; they dealt with worst cases, in the form of the competitive ratio (Karlin et al., 1988). Since 2000, studies have started to address online problems, considering information about future uncertainty and how it might improve the algorithms performance (Bent and Van Hentenryck, 2004a). This involves scheduling problems (Chang et al., 2000) and vehicle routing problems (Bent and Van Hentenryck, 2004b). Studying these problems differs in many respects, however the key idea is that having probabilistic information about the future improves the algorithm's performance considerably (Bent and Van Hentenryck, 2004a). Here, we apply a consensus approach, one of the online algorithms that we claim can deal efficiently with the uncertainties of power market prices.

One of the most relevant studies is that by Ströhle et al. (2014). The authors try to maximize social welfare by proposing novel algorithms to solve the problem of allocating uncertain, flexible and multi-unit demand online, given the uncertain supply. They claim their algorithms are extensions of expectation and consensus algorithms from the domain of online scheduling. Specifically, they are applied to the smart grid where uncertain results from renewable generators and conventional requisite supply are combined and are coordinated with flexible, non-preemptive demand. Ströhle et al. (2014) report that their algorithms achieve more than 85% of the efficiency of optimal offline results. This finding supports our claim that the consensus algorithm is one of the online algorithms able to deal efficiently with the uncertainty of power market prices.

We apply the consensus algorithm in a similar fashion to Bent and Van Hentenryck (2004a); Van Hentenryck et al. (2010); Pan et al. (2011). The concept of consensus algorithm is that there are several samples of feasible steps to be considered at each period of time. After solving each sample, the decision that appears most frequently at time t is selected. Pan et al. (2011) state that this could be used to maximize the possibility of attaining an optimal solution in future. We differ from Bent and Van Hentenryck (2004a) Van Hentenryck et al. (2010) in that they make a single decision at each period of time, whereas, as do Pan et al. (2011), we select a group of decisions. To do so, the consensus algorithm considers the whole set of possible combinations of decisions (actions) for each time, t. Unlike Pan et al. (2011), to evaluate each combinations of actions we apply the concept of majority and Borda voting.

In the same vein, Bent and Van Hentenryck (2004b) apply the consensus technique to solve the multiple vehicle routing problem with time windows (VRPTW), considering a dynamic VRPTW with stochastic customers, whereas the aim here is to maximize the serviced customers number. They use a multiple scenario method (MSA) that produces routing plans continuously for scenarios involving known and predictable requests. For every decision, a plan is selected by using a consensus approach. One of the important findings of this study is that, as they state, combining the consensus approach and stochastic information provides a strengths approach that outperforms others.

Two types of consensus algorithms have been used here to deal with power market price uncertainty, namely Borda voting, majority voting and expected value concept. In Borda voting, voters can detail their express preferences. However, to do it efficiently there is a need for a level of numeracy among voters that may not be realistic (Naamani-Dery et al., 2015). This disadvantage might not apply to our case, because our proposed algorithm computes the utility of every action and orders preferences accordingly. In majority voting, the voter selects just one candidate each time, and the winner is the candidate with the highest number of votes. One of the main advantages is that it is easy to apply and compute; even if the number of candidates is high, the computation is easy. On the other hand, a key problem of using majority voting is that it does not consider the whole profile of preferences, since it deals with just the first candidate (Ruta and Gabrys, 2005). The chief difference between Borda and majority voting is that the latter is easier than the first to implement. Further, Borda voting involves more time-consuming computation than majority voting. Finally, the concept of expected value can be defined as a weighted average of all possible results (Ross, 2014). It is used by

(Chang et al., 2000) to develop a novel scheduling strategy. This considers the problem of scheduling an unknown sequence of tasks for a single server, where tasks arrive with the goal of maximizing the total weighted value of the tasks served before a deadline is reached.

2.6 Summary

In this chapter, we started by describing the background of power market, specifically power market types and pricing. Then we defined the concept of V2G and outlined a number of implications for the use of V2G. After this, we provided an overview of the current state of the art in modelling the EV scheduling problem. We divided the problem into two, scheduling a fleet of EVs and scheduling an individual EV. Since our work is focused on an individual EV, we discussed this in more detail. We categorized studies discussing the scheduling of an individual EV based on the methodology into four types, heuristics approaches, learning agents, decision theory, and game theory. Afterward, we discussed the EV battery degradation which is one of the important issues that should be considered when solving the EV scheduling problem. Next, we considered the vehicle usage uncertainty which is one of our main concerns in this study. Next, this chapter discussed several applications relating to our work, yet not specifically discussing the EV scheduling problem. Finally, the chapter described consensus algorithms, the main concept behind our development of our proposed algorithm, specifically two types, Borda, and majority voting and the concept of expected value.

Although existing work considers V2G technology in the power market, they do not totally address the study challenges described in Section 1.1. In the following, we consider why they do not address our study challenges in detail, and briefly provide what we do in this thesis to fix these challenges.

In analysing this literature, as we see in Section 2.2, V2G could be used to regulate electricity frequency and act as an electrical storage device as in Tomić and Kempton (2007), Saber and Venayagamoorthy (2011) and White and Zhang (2011). This provides V2G drivers with the opportunity to earn money and reduce their power costs. To achieve these goals, they should have a clear understanding about how to deal with the power market. However, according to Mohsenian-Rad and Leon-Garcia (2010) and Han et al. (2010) they lack knowledge on how to react to time-varying prices. To solve this issue, O'Neill et al. (2010) and Conejo et al. (2010b) address the problem of price uncertainty in residential demand response, Shi and Wong (2011) discuss the same issue, but in the context of V2G control. Similar to Shi and Wong (2011); Khalid et al. (2013); Sanchez-Martin et al. (2015); Li et al. (2015b), we study price uncertainty in the context of V2G, yet our study differs from theirs in the number of the experimental settings and in its solution.

Moreover, one of the crucial issues which should be considered when discussing the V2G technology is the battery degradation. As we review in Section 2.3.3, there are several studies that discuss this issue from different aspects such as Peterson et al. (2010); Schill (2011); Guille and Gross (2009) which discussed the battery degradation cost. Furthermore, Ortega-Vazquez (2014); Smith et al. (2009); Neubauer et al. (2013); Zhou et al. (2011); Millner (2010) model the battery degradation and discussed the factors that effect on that. Since there is no single model can be applied for all of the chemistries which are used in battery industry in order of modelling the battery degradation as (Ortega-Vazquez, 2014) found, we prefer to consider number of general battery degradation features that effects on the cost. Lastly, Gough et al. (2017) found that the V2G profits is strongly related to the cost of battery degradation.

In addition, in terms of modelling the vehicle usage uncertainty which we consider in Section 2.3.4, we use Goebel and Voß (2012); Wai et al. (2015) to confirm how this problem is very difficult to solve. Furthermore, different from Kim et al. (2013); Zhang et al. (2012); Ashtari et al. (2012), our model does not require a large amount of information to work accurately.

As we discuss in Section 2.5, similar to Bent and Van Hentenryck (2004a); Van Hentenryck et al. (2010); Pan et al. (2011), we apply a consensus algorithm, but in the context of V2G. We differ from Bent and Van Hentenryck (2004a) Van Hentenryck et al. (2010) in that at each period of time they make a single decision while, like Pan et al. (2011), we select several. As do Ströhle et al. (2014), we apply the consensus algorithm to deal with price uncertainty in the power market, yet we differ from them in that we apply it in the V2G context in order to maximize V2G drivers' profits.

In the real world, many problems in decision-making occur because of a lack of perfect information. These problems are common in power markets. In fact, there is uncertainty in most decision-making by power market agents yet, even so, decisions have to be made. According to Conejo et al. (2010a), most decision-making challenges can be formulated as optimization problems. Indeed, the optimal decision for decision-making (optimization problem) may be achieved easily by solving the problem, provided input data are known. However, this is usually not the case; usually, the input data are uncertain so, to deal with this, data can be described through probability functions. One of the applications used in power markets, with several types of uncertainties, is EV. According to Xu and Chung (2014), the main uncertainties that affect EV charging are punctuality, rounding of time, forecast errors of energy consumption, charging component failure and EV absence, aggregator failure and grid realization. They report that the uncertainties they discuss directly affect EVs contribution to system well-being.

Specifically in V2G, as we see in Section 2.3.2, a number of algorithms are proposed to deal with different types of uncertainties in V2G amid uncertainty in the production of renewable power (Pinson et al., 2009) and (Panagopoulos et al., 2012), together with that of EV driving behaviour (Ghiasnezhad Omran and Filizadeh, 2014) and (Shahidinejad et al., 2012). Moreover, several studies discuss uncertainty in power market prices, for instance the work by (Shi and Wong, 2011).

Finally, as a last part of our research, we study the vehicle drivers preferences in the parking lots in order to investigate the feasibility of using V2G parking lots. To do so, in Section 2.4.4, we review number of studies that discussed this issue. Firstly, Hashimoto et al. (2013) design an auction-based parking reservation system that apply V2G concepts and we differ from their study in that, they have not considered the V2G parking lots tariffs types and the drivers preferences in this issue which is one of the key objectives in our study. In the same vein, Parsons et al. (2014) apply a choice experiment to discuss the potential demand for the V2G drivers and one of the main differences between our work and Parsons et al. (2014) is that they have not considered the penalty system in the V2G parking lot but we consider it and deal with it as a one of the main objectives in our study.

Chapter 3

Model with Known Power Market Prices

This chapter discusses the model proposed to solve the price uncertainty in the V2G context. Firstly, it provides an overview for our model. Then, the problem will be formulated mathematically. Next, it discusses the design of the optimisation module. Afterwards, the experimental evaluation will be considered and the results will be discussed. Finally, the summary will be provided.

3.1 Introduction

In order to design our agent, a model has been proposed as Figure 4.1 shows. In this model there are two components that receive input from the V2G driver, vehicle usage behaviour and user incentives. Two factors will be considered to shape vehicle usage behaviour: time, and vehicle usage (habit). In more detail, V2G drivers determine the times when they need to drive their car and when they can park their car. one driving times are given, parking times can be identified, which can be used to sell and buy the electricity. The second factor considered is vehicle usage (habit). In this study, vehicle usage is defined as the daily driving distance.

The data on vehicle usage behaviour and user incentives will be sent to the V2G agent, which is a major component of this model, and it will use this information to trade with the power market. Specifically, this agent will buy and sell electricity from and to the power market, trying to calculate the best time to buy and sell by predicting price behaviour. In doing so, it will maximize the V2G drivers' utility, which is the monetary profit and the level of battery power that is returned to the V2G driver at the end of a day. There is a further important component in this model, namely the power market,

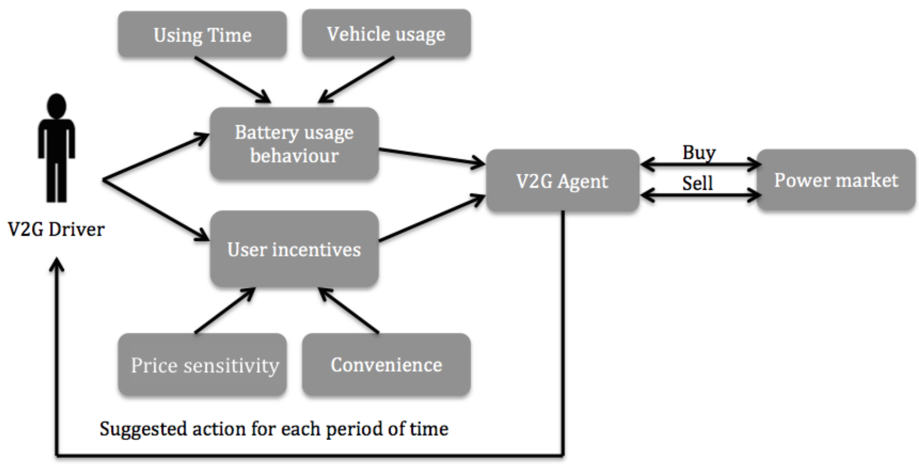

Figure 3.1: Picture showing the first proposed model.

which models the real power market. There are a number of factors that should be considered in designing such a market, such as the real time pricing market.

The model shown in Figure 3.1 is of a simple market, and is used to both understand the problem comprehensively and to design the model precisely. One of the user incentives to be considered is price sensitivity. Furthermore, only a single type of power market has been considered, namely the day-ahead price (DAP) market. In the DAP market, quotes for day-ahead delivery of electricity are offered together for every hour of the following day. The information set to be used for quoting might not be the same for every hour. Here, the V2G agent focuses on the power market side and in the next model (in Chapter 4), the vehicle usage behaviour will be considered.

3.2 Problem Formulation

In more detail, the proposed model will incorporate V2G driver behaviour, which has been defined in this study as usage time. Moreover, it will employ electricity prices for the next day, since we consider only the day ahead price market. By using these two types of information the model will maximize the V2G driver utility function by deciding the the best action for every hour of the day, apart from the usage time allocated to users to drive their cars. The utility has been defined here as the monetary profit and the level of battery power that is returned to the V2G driver at the end of a day. Table 3.1 has been used to explain the notations in details.

Before representing it mathematically, based on the Table 3.1, the notations of our model will be discussed. We will explain using an example. Let us assume a driver wants to use his or her car from time T_{su} until time T_{eu}, that will be considered as saying to the agent that during this period of time it cannot do anything represented in Equation 3.7.

Table 3.1: Overview of the main notations used.

notation	**Description**
$\overline{a}$	The vector which contains the chosen action for each hour
a_t = *0*	Do nothing
a_t = *1*	Charging
a_t = *-1*	Discharging
Soc	State of charge
b_{des}	Desired amount of battery level before using time
b_{init}	Initial value for the battery
n	Total of hours day
p_t	electricity price at time t
T	Number of time steps
T_{su}	Start of using time
T_{eu}	End time of using
T_a	Available time which the agent can charging or discharging or do nothing
$V(x)$	Function represent the battery of charge which left for the driver at the end of the day

By excluding this usage time, the agent can define the period of time during which it could charge a_t = 1, discharge a_t = -1, or do nothing a_t = 0, as represented in Equation 3.4. Agent will charge (buy) or discharge (sell) from or to the market by considering the hour price p. Moreover, let us assume the driver plans to go to another city and he or she has an initial amount of battery at the start of the day of b_{init}, and needs to have a certain amount of battery b_{des} to achieve this goal without any delay; this issue has been determined by Equation 3.8. At the end of the day the remaining battery state of charge has been represented as a function $V(x)$, where is $x \in Soc$. Furthermore, we define the utility as the monetary profit and the level of battery power that is returned to the V2G driver at the end of a day. Finally, the utility function can be defined as Equation 3.2, if conditions are satisfied, otherwise $U(\overline{a}) = -\infty$. After describing the notations, the problem will be mathematically represented as follows:

$$U^{opt} = \max_{\overline{a} \in \left\{-1,0,1\right\}^T} U(\overline{a}) \tag{3.1}$$

where

$$U(\overline{a}) = -\sum_{t=1}^{T} p_t(a_t) + V\left(b_{init} + \sum_{t=1}^{T} a_t\right) \tag{3.2}$$

Subject to

$$T = \left\{1, 2, 3, ..., n\right\} \tag{3.3}$$

$$a_t \in \{-1, 0, 1\} \tag{3.4}$$

$$T_{eu}, T_{su} \in T \tag{3.5}$$

$$b_{init}, b_{des} \in Soc \tag{3.6}$$

$$a_t = 0 \ \forall \ T_{su} \leq t \leq T_{eu} \tag{3.7}$$

$$b_{init} + \sum_{t=1}^{T_{su}} (a_t) \geq b_{des} \tag{3.8}$$

$$\forall t \in T : Soc = 0 \leq b_{init} + \sum_{t=1}^{T} a_t \leq 100 \tag{3.9}$$

After representing the problem mathematically, the main constraints will be explained. To ensure that the car is available in the using time from T_{su} until time T_{eu} to the driver, we proposed this constraint in Equation 3.7 which says to the agent during this period that it cannot do anything. Moreover, to ensure that the drivers will have their desired amount of battery before their trip, we proposed this constraint in Equation 3.8. Further, to ensure the battery value does not exceed its scope which is between 0 and 100 and to calculates the battery amount after each step we proposed constraint in Equation 3.9.

3.3 The Optimization Module

After formulating the problem in the previous section, the design of this optimization module is discussed in detail in this section.

To build an optimization module to maximize the V2G driver utility function in day-ahead market (DAP), discrete dynamic programming was used, specifically backward induction. This is one of the key approaches in mathematical optimization techniques (Adda and Cooper, 2003). The backward induction concept may be defined as the process of reasoning backwards in time, starting from the end of a problem, selecting a series of optimal actions. Starting with the last time point and deciding on the best action, it continues backwards to the first time point, at every step choosing the best action for each possible situation (Gibbons, 1992).

To apply the backward induction algorithm, the study by Fackler (2004) was used. The authors claim that, at discrete times or discrete states, there is a Markov decision structure. An agent observes the economics of the feasible state, B, in each point of time, t, then chooses an action, a. In the present study, the state space can be used to represent the battery level, B. Moreover, the action, a, has three values: charging, discharging, and doing nothing. The actions to be chosen depend on the battery value. For instance, if it is 0, the agent has just two actions: charging or doing nothing.

This section discusses the optimization module, which is the main goal of this work and the next section outlines the experimental evaluation.

3.4 Experimental Evaluation

The experimental settings will be explained in this section. Next, we will show the simulation results using the benchmark strategy. After that, the experimental scenarios will be discussed. Finally, we will discuss the results.

3.4.1 Experimental settings

The experimental settings were as follows:

- An unlimited budget;

  Indeed, we think it is a realistic assumption since the individuals usually do not consider their entire budget when does a habitual action. For instance, if somebody going to turn a dishwasher, he/she is not going to calculate how much he/she will pay for that and how much he/she has in his/her bank account.

- Only a single agent is considered;

  We start with this now, but in future work we will consider that when we model a multi-agent environment.

- We assume the other individuals do not influence the power market price so assume the price is fixed and the consumer is a price taker.

- We assume different price distributions, depending on time, and these are given by Table 3.2, which represents the buying prices from the power market, and Table 3.3, which represents the selling prices to the power market. These assumptions are used to test the model but it can deal with any price distributions. For each period, the prices are generated as an integer number that ranged between start and the end for each period selected with equal probability.

Table 3.2: Assumptions for prices of electricity, based on time (buying prices from the power market)

Time (hours)	Price (pounds)
1:00 - 8:59	1 - 6
9:00 - 17:59	40 - 60
18:00 - 23:59	7 - 27

Table 3.3: Assumptions for prices of electricity, based on time (selling prices to the power market)

Time (hours)	Price (pounds)
1:00 - 8:59	1 - 4
9:00 - 17:59	20 - 40
18:00 - 23:59	9 - 17

Moreover, to evaluate our model, we ran it in different scenarios with our solution; after that, we ran these scenarios with a benchmark strategy, will be explained in section 3.4.2. Finally, we compared our solution results and those of a benchmark strategy. In more detail, the comparison between these two algorithms was divided into two stages. First, we ran the simulation once per scenario with each algorithm to show what happens at each run. Second, the simulation was run a hundred times to obtain definite results.

3.4.2 Benchmark strategy

Before discussing the results, the benchmark strategy algorithm used to compare the model to evaluate our solution will be explained. It is just applies a forward induction concept. It starts at the first available hour of the day, selects its action by maximizing the utility for each following step. It compares the utility for each choice, and chooses the highest until reaching the final available hour of the day.

3.4.3 Experimental Scenarios

Since our simulation has been assumed to work for a single period per day, three people who drive their cars at different periods of time are used to illustrate scenarios to test this proposed optimization module. All of these scenarios are uniformly distributed.

The first scenario is of people who work normal hours; we assume they start driving their car at any hour of the period from 7:00 to 12:59.

The second scenario is of people who work evenings: we assume that they use their car at any hour of the period from 13:00 to 18:59.

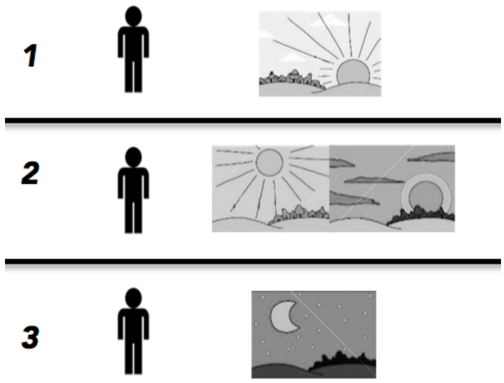

Figure 3.2: Picture showing the proposed usage time for each scenario.

The third scenario is of people who start work early in the morning. We assume they start to drive at any hour of the period from 1:00 to 6:59. Figure 3.2 and Table 3.4 show a summary of each proposed scenario and its vehicle usage time.

Table 3.4: Proposed usage time for each scenario.

Scenario	**Usage Time**
S1	7:00 - 12:59
S2	13:00 - 18:59
S3	1:00 to 6:59

After discussing the experimental evaluation, the next section discusses the results of running the simulation.

3.5 Results

As we mentioned in the previous section, we first ran the simulation once per scenario with each algorithm. We started by running our proposed algorithm.

The first scenario is of person who works normal hours. He drives his car from 9 to 13 and wants his battery level to be 40 or more when he comes to use the vehicle. Depending on the day's price, the utility function will be 99.

The second scenario is of person who works evenings. He uses his car from 18 to 22 and wants his battery level to be 50 or more before he come to use the car. Depending on the day's prices, the utility function will be 29.

The third scenario is of person who work starts early in the morning. He uses his car from 6 to 12 and wants a battery level of 40 or more beforehand. Depending on the day's prices, the utility function will be 131.

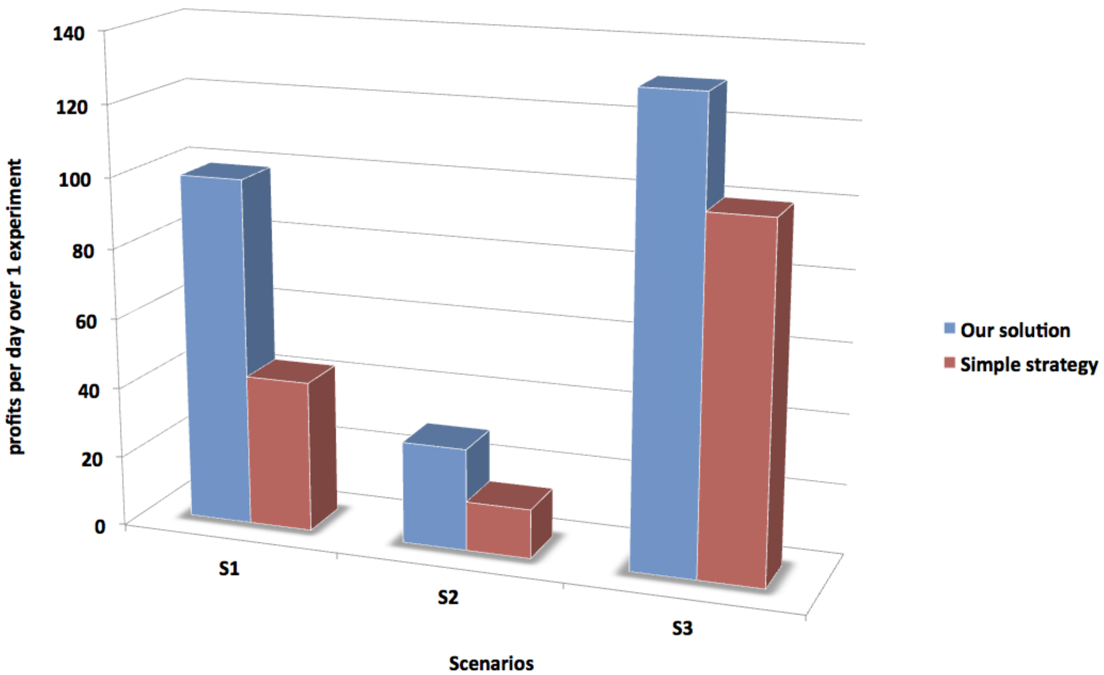

Figure 3.3: Bar chart showing the results after running the simulation one time.

Moreover, to evaluate the performance of our solution, we compared it with that achieved by using a simple strategy algorithm. The crucial difference between our solution and a simple strategy is that the latter has no information about the last point price. Thus, it will trade to maximize the profit for each feasible point, while satisfying model constraints. Table 3.5 and Figure 3.3 provide the results after running the simulation one time with our solution and simple strategy. In the both algorithms, the agent do not do anything in the using time. Moreover, it is charging the battery with the desired amount before the using time. Furthermore, it is charging and discharging (buying and selling) based on the changing on the price.

Table 3.5: The results after running the simulation one time.

Scenario	b_d	**Our solution**	**Simple strategy**
S1	>= 40	99	43
S2	>= 50	29	14
S3	>= 40	131	100

Finally, to build robust results, we ran this simulation a hundred times for each algorithm per scenario, then the average of each scenario was calculated in terms of finding which algorithm is better. The following table provides the average results after running the simulation a hundred times.

Through undertaking this comparison with the first scenario, our solution outperformed simple strategy 49% in terms to the average profits over 100 experiments. Moreover, in the second scenario it outperformed the simple strategy 51%, while in the third scenario

Table 3.6: The average utility results after running the simulation 100 times.

	Our solution	Simple strategy
S1	*97*	*50*
S2	*79*	*39*
S3	*152*	*137*

our solution outperformed the simple strategy 10% in terms to the average profits over 100 experiments. In conclusion, it can be claimed that, this model may serve as a baseline from which to build the model proposed in Figure 3.1, which is one of the aims for this thesis.

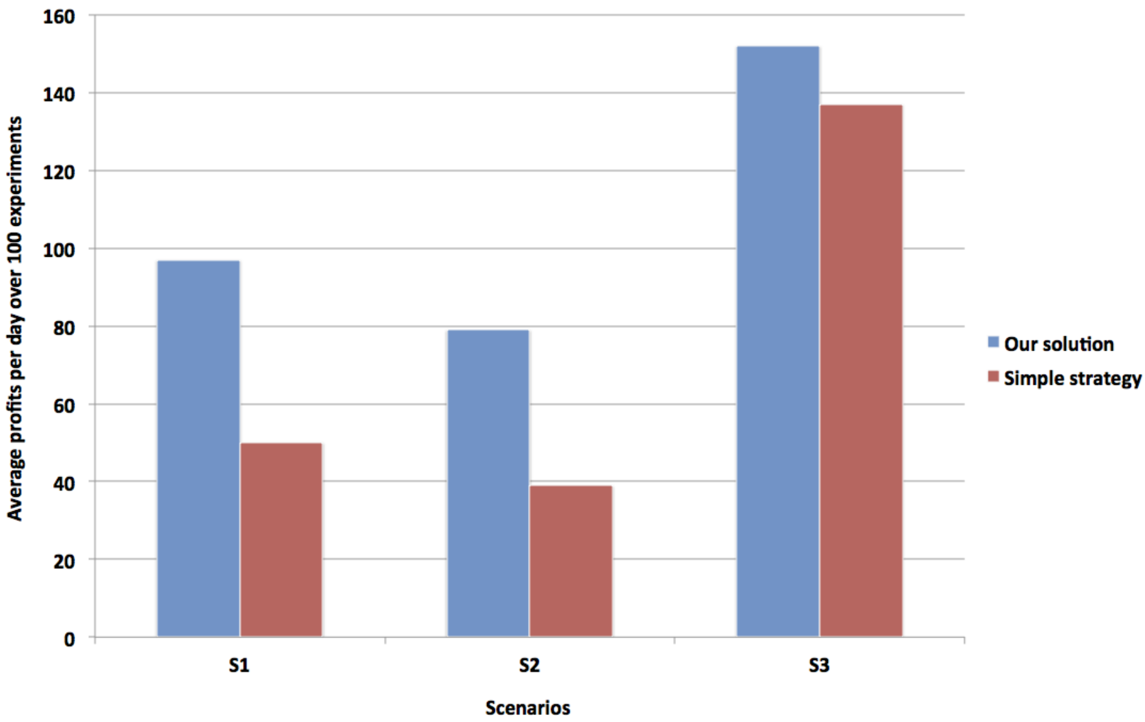

Figure 3.4: Bar chart showing the average utility results after running the simulation 100 times.

3.6 Summary

This chapter discussed the problem of power market price uncertainty in the V2G context. Against this background, this study focused on modelling an initial agent to trade on behalf of V2G drivers in order to maximize their profits, specifically in the DAP market. A backward induction algorithm was used to attain this aim. Three reasonable scenarios were proposed to test this solution, and were run under a benchmark algorithm. The results of the proposed simulation were compared with that of the benchmark algorithm. The results show that our solution was better at maximizing the V2G driver profits in DAP and so it can represent a baseline for future development.

Chapter 4

Model with Price Uncertainty in the Power Market

This chapter describes the model proposed to maximize the V2G driver profits with consideration of price uncertainty in the power market. Then, in more detail, the problem of price uncertainty in the context of V2G will be discussed. After that, our optimization algorithm will be considered. Next, we will show the simulation results using the algorithms. Following, we will discuss the results. Finally, we will summarise the chapter.

4.1 Introduction

In this study our aim is to design an algorithm to trade on behalf of V2G drivers' in order to maximise their profits through understanding their vehicle usage. Thus, there are two types of uncertainty to deal with, prices in the power market, which we will discuss here, and drivers' vehicle usage, which we will consider in Chapter 6.

To address price uncertainty in the context of V2G, we develop a heuristic algorithm that can trade on behalf of the V2G users, maximizing their profits from using V2G as a source of electricity while taking into consideration their behaviour and their incentives. Our proposed algorithm combines two types of consensus algorithm (Borda and majority voting) and expected value with a backward induction algorithm.

In order to design our proposed algorithm, a model has been proposed as shown in Figure 4.1. In this model there are two components that receive data from the V2G driver, vehicle usage behaviour and user incentives. Two factors will be considered to shape vehicle usage behaviour: using time for each trip, and the distance for each trip, which represent the daily trips. V2G drivers determine the times when they need to drive their cars and when they can park their cars for each trip, as modelled using the

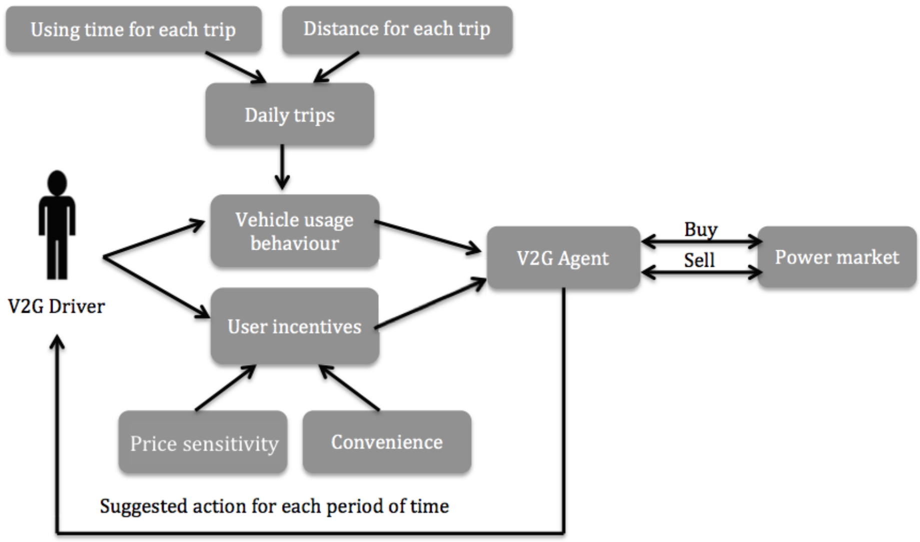

Figure 4.1: Picture showing the second proposed model.

time rectangle. If driving times are defined, parking times can be identified, which can be used to sell and buy the electricity in the battery. The second factor considered is the daily driving distance for each trip.

The data on vehicle usage behaviour and user incentives will be sent to the V2G agent, which is a major component of this model, and it will use this information to trade with the power market. Specifically, this agent will buy and sell electricity from and to the power market, trying to decide the best time to buy and sell by predicting price behaviour. In doing so, it will maximize the V2G drivers' utility, which is the monetary profit and the level of battery power that is returned to the V2G driver at the end of a day. There is a further important component in this model, namely the power market agent, which models the real power market. There are a number of factors that should be considered in designing such a market, such as the real time pricing market.

As the model shown in figure 4.1, there are two types of user incentivises which are price sensitivity and convenience in our model. Here, we consider one of the user incentives which is the price sensitive. Also, the power market agent has been assumed to be an environment for the V2G agent in a similar way to Siegfried et al. (2009) study. The authors show that it is sometimes unclear how to deal with the environment in multi-agent systems, suggesting that, for an environment that needs to be modelled carefully, only essential features should be incorporated in the intended model. They suggest adding auxiliary tasks not connected to the model directly, such as computer conflicting actions, in a simulation environment. Furthermore, only a single type of power market has been considered, namely the Hour-Ahead Price (HAP) market. It can be defined as a type of electricity market where the electricity is delivered to the consumer for use in the following hour. Here, we focus on the V2G driver side and for the future work we will discuss the power market side where we can use a mechanism design to incentive the V2G driver to change their vehicle usage behaviour to reduce the grid peak load. Furthermore, we are aiming to design V2G parking lots where the drivers can park their vehicles and support the grid; as one of the steps to achieve this goal, we collect data about the drivers' preferences in this kind of lots (this has been discussed in details in chapter 7).

As we discussed earlier, there is an opportunity for the V2G drivers' to maximise their profits, if they use the concept of V2G effectively. With the V2G heuristic algorithm proposed and implemented, the V2G agent receives the initial battery state of charge b_{init}, the desired battery state of charge b_{des}, the start of using time T_{su} and the end of using time T_{eu} prior to the beginning of every day, along with n number of power market prices for each following hour. So the uncertainty here comes from the prices and the driving behaviour (vehicle usage) is known here, but in next model which we will discuss in Chapter 6, it will be uncertain. Moreover, the agent can buy or sell for the following hour only, depending on the constraints. Using the aforementioned information, the V2G heuristic algorithm is run for each V2G driver, to find the best available action that can maximise the V2G driver's profit. After computing all the scenarios with the backward induction algorithm, it is possible to find the best action for each hour, depending on the pricing of every specific scenario. Two types of consensus algorithms (Borda voting and majority voting) and the expected value will be applied, and then the chosen action will be implemented.

In summary, in order to model the price in the HAP market, we assume that our agent receives n number of scenarios every hour. We define the scenario as the sample of power market prices for the following hour and we assume that each sample has a different number of prices n. This number of scenarios produces an uncertainty in the price. To deal with this uncertainty, firstly, we model the time series of the power price for each scenario as a Markov decision process (MDP). After that, we propose a novel heuristic algorithm that maximises the V2G drivers' profit by choosing the best actions for each time period.

The assumptions made for this model are as follows:

- In addition to the previous assumptions which we discussed in Chapter 3 assuming there is an unlimited budget. Moreover, only a single agent is considered.
- The battery degradation.

  Battery degradation can be defined in the context of EV as the amount the battery loses from its capacity over time. It differs based on the type of battery. We have not considered this factor, but we believe that the algorithms can be easily adjusted to include it. However, battery degradation has been considered in the next proposed model in Chapter 6, when we consider the vehicle usage uncertainty.

- Some of the essential elements that cost the V2G driver are fixed costs such as the cost of the vehicle, charging points supplied by the consumer, and other elements that have not been considered.

  We have not considered these essential elements because they have a fixed value and we believe that our solution will be the same even if they are considered, since they have a fixed cost. Before discussing the details of the optimisation module, the next section will formulate the problem.

Before discussing the details of the optimization module, the problem will be formulated in the next section.

4.2 Problem Formulation

In this section, the problem will be formulated as a Markov Decision Process (MDP). After that, the problem will be formulated mathematically.

This section describes formulation of the V2G problem under price uncertainty as an MDP. An MDP is described through its state space, action space, and value function. The state space can be used to represent the battery state of charge and it can be represented mathematically as $Soc = \{0, 10, 20, ..., 100\}$ and b_{init} is the initial battery state of charge . We have two types of pricing, charging price that represented mathematically as the function $f^{char}(p_t)$, discharging price that represented mathematically as the function $f^{dis}(p_t)$. The action in our problem can be represented as choosing one action a_t from the action space $A = \{-m, ..., 0, ..., n\}$. We divide the action space for three types of actions, which are, charging actions, discharging actions, and the do nothing action. For instance, we can assume there are three actions that have charging types, fast charging, normal charging, and slow charging. However, since there is number of constraints in our problem, not all the actions can be chosen at a given state. Agent chooses action a_t from a set of actions A by considering the hourly price. We define the vector of chosen actions as $\overline{a} = \langle a_1, ..., a_T \rangle$. At the end of the day the remaining battery state of charge has been represented as a function $V(x)$, where is $x \in Soc$. We define the utility as the monetary profit and the level of battery power that is returned to the V2G driver at the end of a day. The utility function can be defined as:

$$U(b_{init}, \overline{a}) = \sum_{t \in \{1,...,T\}: a_t > 0} -P_t \cdot a_t + \sum_{t \in \{1,...,T\}: a_t < 0} P_t \cdot a_t + V\left(b_{init} + \sum_{t=1}^{T} a_t\right) \quad (4.1)$$

If conditions are satisfied 4.1 applies, otherwise $U(b_{init}, \overline{a}) = -\infty$. In more detail, we now describe the V2G problem under price uncertainty at time t. We assume that

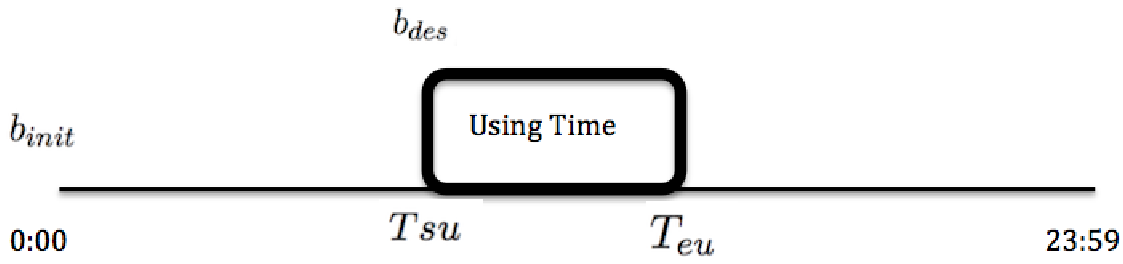

Figure 4.2: Diagram shows some of the notations in our model.

the EV start of using time T_{su} and the end of using time T_{eu} are known. Moreover, we assume that the power market prices for the following hour are unknown data and this uncertainty needs to be modelled. To model the price uncertainty, in our general problem, if we have infinite prices with which to calculate the probability, that will be too complex. For simplicity, if we assume that we have 10 prices with which to calculate the probability, the formula will be 10^{24}. Even with this small number, the problem is unsolvable because it is an exponential problem. Moreover, in the general problem, there is a correlation between the hours' prices, which can be represented as $Pr\,(P_t|P_1...P_{t-1})$. However, for simplicity, we assume that the hours prices in the experiment are independent. However, we claim that our solution is still valid with $Pr(P_t|P_1...P_{t-1})$.

Furthermore, we assume there is n number of power market prices. The V2G agent action should be chosen for time t by the V2G heuristic algorithm after it receives all of the prices from the power market. We proposed that the model should incorporate V2G vehicle usage behaviour, which has been defined in this study as usage time. Moreover, it will employ electricity prices for the next hour, since we consider only the hour ahead price market. By using these two types of information, the model will maximise the expected V2G driver's utility by deciding the best action for every hour of the day, apart from the usage time allocated to users to drive their cars. The expected utility has been defined here as the monetary profit and the level of battery power that is returned to the V2G driver at the end of a day. Here, we deal with the price uncertainty and in Chapter 6, we will consider the uncertainty in the vehicle usage behaviour.

Figure 4.2 illustrates the planning horizon for our model. In detail, it shows the b_{init} which is the initial battery amount at the start of the day. b_{des} is the desired amount of battery at time T_{su}. Between T_{su} and T_{eu} is the usage time, when the agent cannot do anything (do nothing action).

Table 4.1: Notations description

Notation	Description
A	The set of agent actions
a_t	The chosen action at time t
T_{su}	Start of using time
T_{eu}	End time of using
T_a	The available time which the agent can do the actions
Soc	the current state of a battery
b_{init}	The initial value for the battery
b_{des}	The desired amount of battery level before using time
P	Set of prices
V	The value of battery which left for the driver at the end of the day
T	Number of time steps and can be defined as a T = $\{1, ..., n\}$
p_t	Price at time t

Now, the problem will be mathematically represented as follows:

$$EU_t\left(a_t, Soc_t\right) = \begin{cases} \int_{p_t \in P} f^{char}\left(p_t\right) \cdot \left(EU^*_{t+1}\left(Soc_t\right) - p_t\right) dp_t & \text{if } a_t > 0 \\ \\ 0 \qquad \text{if } a_t = 0 \\ \\ \int_{p_t \in P} f^{dis}\left(p_t\right) \cdot \left(EU^*_{t+1}\left(Soc_t\right) + p_t\right) dp_t & \text{if } a_t < 0 \end{cases} \tag{4.2}$$

where

$$EU^*_t\left(Soc_t\right) = argmax_{a_t \in A} EU_t\left(a_t, Soc_t\right) \tag{4.3}$$

$$EU_n\left(a_n, Soc_n\right) = U(b_{init}, \overline{a}) \tag{4.4}$$

Subject to

$$T = \left\{1, 2, 3, ...n\right\} \tag{4.5}$$

$$T_{su}, T_{eu} \in T \tag{4.6}$$

$$b_{init}, b_{des} \in Soc \tag{4.7}$$

$$a_t = 0 \ \forall \ T_{su} \leq t \leq T_{eu} \tag{4.8}$$

$$Soc_t(\overline{a}, b_{init}) = b_{init} + \sum_{t'=1}^{t}(a_{t'}) \tag{4.9}$$

$$Soc_{T_{su}} \geq b_{des} \tag{4.10}$$

$$\forall t \in T : Soc_t = 0 \leq b_{init} + \sum_{t=1}^{T} a_t \leq 100 \tag{4.11}$$

After representing the problem mathematically, the main equations 4.2, 4.3 and the main constraints will be explained. In 4.2, if we charging, the above equation will be conducted whereas the $f({p_t}^{char})$ function that represents the charging price uncertainty. On the other hand if we discharging, the below equation will be conducted whereas the $f({p_t}^{dis})$ function that represents the discharging price uncertainty. In both situations to calculate EU_t, we have to find the EU^*_{t-1}. Thus, we have to do 4.3 first. In 4.3, we calculate the *argmax* for EU^* at t so we have to do 4.2 and 4.3 recursively. Moreover, we propose 4.4 to stop 4.3 and 4.2 at the end of the day n and to return the expected utility. With regard to constraints, we first ensure that the car is available to the driver during the required usage time from T_{su} until time T_{eu}. We proposed this constraint 4.8 which says to the agent during this period that it cannot do anything. Moreover, to ensure that the drivers will have their desired battery state of charge before their trip, we proposed constraint 4.10. Further, to ensure that the battery state of charge does not exceed its scope, which is between 0 and 100, and to calculate the battery amount after each step, we proposed constraint 4.11.

4.3 The Optimization Module

After formulating the problem in the previous section, the design of this optimization module in detail is presented in this section.

4.3.1 Backward Induction

To build an optimisation module to maximise the V2G driver profits in the hour-ahead price (HAP) market, discrete dynamic programming was used, specifically backward induction. This is one of the key approaches in mathematical optimisation techniques (Adda and Cooper, 2003). The backward induction concept may be defined as the process of reasoning backwards in time, starting from the end of a problem, and selecting a series of optimal actions. Starting with the last time point and deciding on the best action, it continues backwards to the first time point, at every step choosing the best action for each possible situation (Gibbons, 1992).

To apply the backward induction algorithm, the study by Fackler (2004) was used. The authors claim that, at discrete times or discrete states, there is a Markov decision structure. An agent observes the economics of the feasible state, Soc_t, in each point of time, t, then chooses an action, a.

A backward induction algorithm will be used to deal with each power market price scenario. So if we have multiple price scenarios we need to improve our idea to deal with this new conditions. To do that, we combine backward induction with two types of consensus algorithms (Borda, majority) voting and with expected value and that what we will discuss in the next section.

4.3.2 Backward Induction with Consensus voting and Expected Value

To deal with the power market price uncertainty, we propose a V2G heuristic algorithm. It combines Borda and majority voting with the expected value algorithm, together with backward induction. The general idea of our algorithm is that, because there are n number of scenarios for the power market price, we apply backward induction with each scenario to find the best action at each hour. Then we apply the concept of a consensus algorithm in order to deal with the n scenarios. Indeed, we apply the consensus algorithm concept because relevant work has been conducted on it already, such as that by (Ströhle et al., 2014), who found it an efficient technique to deal with uncertainty in the power market.

Borda voting is a type of voting where voters select the candidates by ordering them based on their preferences. It determines the winner of the voting by giving each candidate, for every vote, a number of points that reflects its place in the voting. The winner will be the candidate who has the highest points score. It could be described as a consensus-based voting system since it chooses broadly satisfactory candidates, which is not the case in majority voting. There are number of methods to calculate the points for each candidate in Borda voting. We will use one of these methods here, where votes will be counted by giving every candidate a number of points equal to the number of candidates ranked lower than them. Thus, if a candidate is chosen as the first preference it will receive $(n-1)$, if it is chosen as a second preference it will receive $(n-2)$ points, etc., until the candidate that is chosen as the last preference receives zero points. Formally, a candidate will receive $(n-i)$ points if it is ranked in ith place (Zahid and De Swart, 2015). Table 4.2 is an example of a ballot paper of voting in our experiment. On the other hand, in the majority voting rules, in each vote only the winner is considered, so

Table 4.2: Example of a ballot paper of voting in our experiment.

Ranking	Candidate	Formula	Points
First	discharging	$(n-1)$	2
Second	do nothing	$(n-2)$	1
Third	charging	$(n-3)$	0

Algorithm 1: V2G Heuristic algorithm

Input: T_{su}, T_{eu}, b_{init}, b_{des}

Output: It returns the vector *chosenAction*, where each element $chosenAction_t \in A$ is the chosen action at time $t \in T$

$\forall\, t \in T : chosenAction \leftarrow \theta$ // we start with an empty set of chosen action.

$\forall\ \ t \in T : A \leftarrow \{a_1, a_2, ..., a_n\}$ // at every time step there is a set of action A, which is for example can have (charging, discharging, do nothing).

$S \leftarrow GenerateScenarios()$// GenerateScenarios is a function that generates the price scenarios.

foreach $t \in T$ **do**

  $TotalScore \leftarrow Call\ Borda(T_{su}, T_{eu}, b_{init}, b_{des}, S\ )\ |Majority(T_{su}, T_{eu},$

  $b_{init}, b_{des}, S\ )\ |\ Expected\ value(T_{su}, T_{eu}, b_{init}, b_{des}, S\ )$

  $VotingWinner \leftarrow Max(TotalScore)$ // Function that returns the action that provides the highest total score.

  $chosenAction_t \leftarrow VotingWinner$ // Save the voting winner in chosenAction vector.

end foreach

return chosenAction // after compute the whole T, a vector of chosen action will be return.

in every round of voting the winner scores 1 point and the others are ignored (Ruta and Gabrys, 2005). Finally, we combine our offline algorithm (backward induction) with the concept of expected value, as in (Chang et al., 2000).

In the V2G heuristic algorithm (see Algorithm 1) we assume that we have S which is a set of scenarios for the HAP market and the V2G agent can do n number of actions in the discrete time T. For each time step t, which is 1 hour in the experiment, we run the backward induction algorithm (see Algorithm 5) with the all scenarios and votes for the action with each scenario; the rules of voting will differ depending on the type of voting being applied (Borda, see Algorithm 2; majority, see Algorithm 3; or expected value 4). Then, the heuristic algorithm will be run again to compute all of the scenarios for the following hour, aiming to apply the consensus concept. After that, and based on the voting rules, the winner will be chosen as the action for the t period. The new information such as the actions that have been chosen for the previous hours will be considered as known information. After performing the previous steps for the whole time, the result will be a table containing each period of time t and the suggested action for this time period. Our solution satisfies the previous constraints and it considers all the price scenarios with the aim of finding the best action, thus maximising V2G drivers' profits.

We will now describe the algorithms in more detail. In Algorithm 1, the algorithm initially starts with an empty set of chosen actions (line 1), and at every time step there is a set of action A, which, for example, could contain charging, discharging, or do nothing. Following this, the algorithm calls the GenerateScenarios function, which generates the power market price scenarios (line 3). Once this has been achieved, for each time step the algorithm calls the Borda, Majority or Expected value functions and saves the voting winner in the chosenAction vector (lines 4 - 9). Finally, after having computed the whole T, a vector of chosen action will be returned (line 10).

In Algorithm 2, the algorithm firstly assumes that there is a value ActonValua for each action, $a \in A$ (line 2). Following this, between lines 3 and 12, the algorithm computes the best action by applying the Borda voting rule for each scenario, where it calls the V2GBackwardInduction function, which returns the value of each action (lines 4-6). Once this has been achieved, it calls the Sort function, which receives the ActonValuea vector and sorts the actions based on its values and saves them as a vector of indexes (line 7). Following this, the algorithm scores every action based on the Borda voting rule, where I is the total number of actions. For example, if there are three actions, I will be 3 (lines 8-10). Subsequently, for line 11, the summation for each action and its scores after all scenarios will be saved in the TotalScore vector. Finally, the algorithm returns a vector which contains the TotalScore for each action, $a \in A$, with all scenarios, S, by using the Borda voting rule.

In Algorithm 3, the algorithm initially assumes that there is a value ActonValua for each action, $a \in A$ (line 2). Following this, between lines 3 and 11, the algorithm computes the best action by applying the Majority voting rule for each scenario, where it calls the V2GBackwardInduction function, which returns the value for each action (lines 4-6). Subsequently, the algorithm calls the Sort function, which receives the ActonV aluea vector and sorts the actions based on its values and saves them as a vector of indexes (line 7). Once this has been achieved, the algorithm calls the Major- ityVotingScoring function, which assigns one to the first element in the SortedAction vector and zero to the remaining elements (line 8). Following this, the summation for each action and its scores after all scenarios will be saved in the TotalScore vector. Finally, the Majority voting algorithm returns the Score vector, which contains the TotalScore for each action, $a \in A$, with all scenarios, S, by using the Majority voting rule (line 12).

With regard to Algorithm 4, firstly the algorithm assumes that there is a value ActonValua for each action, $a \in A$ (line 2). Following this, between lines 2 and 8, the algorithm computes the best action, applying the expected value concept for each scenario, where it uses V2GBackwardInduction, which is a function that returns the value for each action (lines 3-5). Subsequently, it assigns the value of each action to a score (line 6). Once this has been accomplished, on line 7, the summation for each action and its scores after all scenarios will be saved in the TotalScore vector. Following this, the algorithm calls the AvragingtheTotalScore function to calculate the utility average for each action in the Total score vector and saves them in the ExpectedUtility vector (line 9). Lastly, the algorithm returns the ExpectedUtility vector which contains the average Score for each action, $a \in A$, with all scenarios, S (line 10).

4.4 Experimental Design

We start with a soft constraint whereby the agent has a one-day price scenario in advance and will trade on behalf of V2G drivers with the aim of maximising their profits, with knowledge about when they will use their cars and their desired amount of remaining battery charge before use. Moreover, we assume they will use their cars once a day. To deal with these constraints, we use a backward induction algorithm (Almansour et al., 2017), which has been discussed in detail in Chapter 3. After that, we increase the complexity for this problem by assuming multiple scenario prices in the power market. To deal with this new constraint, we propose an algorithm combining our proposed algorithm from the first experiment with two consensus algorithms (Borda voting and majority voting) and with the expected value, as discussed earlier.

In our proposed algorithm, named the V2G heuristic algorithm (see Algorithm 1) the voters are the decisions of the backward induction algorithm for each scenario at every hour, and the candidates are the set of actions. In this experiment, the V2G agent has three actions, charging, discharging, and doing nothing. Moreover, we assume that we have n number of scenarios for the HAP market. Thus, the number of voters is n and the number of candidates is 3. In detail, first we generate n scenarios for the power market where each hour has a price. Afterwards, for each hour the backward induction computes the utility for each action and ranks it, based on the Borda voting rules, so that the highest profit scores 2 points, the second highest scores 1 point and the last nothing. This step is repeated for all the scenarios and the results recorded. Algorithm 2 shows how Borda voting works. Next, after calculating the number of points for each action, the one that receives the most points is chosen and applied at this hour. The steps are repeated for all the hours and, by the end, we have a table showing the best action to apply at each hour.

In the case of majority voting, the n price scenarios already initiated are used. Then, for each hour, the backward induction computes the utility for each action and ranks it according to the majority voting rules, where just the highest profit is considered, and the action that provides the highest profit scores 1 point and the others are ignored. The prior step will be repeated for all the scenarios and the results saved. Algorithm 3 shows how majority voting works. Afterwards, by calculating the number of points for the actions in all of the scenarios, the one that receives the most points is chosen and applied at this hour. These steps are repeated for all the hours and, by the end, we have a table showing the best action to apply at each hour. Under the expected value algorithm (see Algorithm 4), after each running of the offline algorithm (backward induction), the action that has been chosen will be recorded with its utility after computing all of the scenarios. The average utility function will be calculated and the action that provides the highest utility function will be chosen. Finally, a scenario will be generated, which we assume is a real-world scenario, and the actions produced from each round of voting (Borda, majority and expected value) will be applied, with the aim of finding the one that achieves the most profit.

The assumptions made for this experiment were as follows:

- We have a different number of price market scenarios which are, $10, 20, 30, ..., 100$ and we propose these numbers to include a sensible range of values in our experiment.
- We run 50 experiments with each scenario.
- This simulation assumes different price distributions, depending on time, as in Table 4.3. This assumption is used to test the model but it can deal with any price distributions. In reality in the HAP market, the overnight prices are the lowest. In the day and the afternoon, the prices are the highest, especially in the summer. In our simulation, because we assume that there is no relation between the hours' prices and in order to simulate the prices we classify them into three types: 1:00 - 8:59, 9:00 - 17:59, and 18:00 - 23:59. We assume that the prices between 1:00 and 8:59 are the lowest, the prices between 9:00 and 17:59 are the highest, and the prices between 18:00 and 23:59 are in the middle between the previous prices.
- For each period, the prices are generated as an integer number that ranged between start and the end for each period selected with equal probability.
- The electricity paid for by domestic consumers can be charges at different rates, commonly called "Economy 7 ", that is it is cheaper at night and more expensive during the day. Similar offer are offers are made to larger industries. So it was not unreasonable to reimburse people for their electricity depending on when they put the electricity back into the Grid. Hence the price structure proposed in the simulation. A limitation of the simulation was that these prices are an estimate and the real prices will be used in future simulations. The simulation is time stepped, so every time step is a discontinuity from the previous step. Each time is a recalculation and not dependent on the previous step. Hence the discontinuity between 23:59 (the previous day) and 00:00 (the start of the next day), is handled as two separate calculation for different days.
- To make the experiment more realistic, we generated different start times and usage times for each running. The distribution of the start of usage numbers lies

Algorithm 2: BordaVoting

Input: T_{su}, T_{eu}, b_{init}, b_{des}, S

Output: It returns a vector which contains the TotalScore for each action $a \in A$ with the all scenarios S by using Borda voting rule

$A \leftarrow \{a_1, a_2, ..., a_n\}$

$\forall\ a \in A : ActonValu_a$ // for each action $a \in A$ there is a value $ActonValu_a$.

foreach $s \in S$ **do**

  foreach $a \in A$ **do**

    $ActonValue_a \leftarrow V2GBackwardInduction(\ T_{su}, T_{eu}, b_{init}, b_{des}, s, a\ )$ // Function that returns the value for each action.

  end foreach

  $a' \leftarrow Sort(ActonValue_a)$// Function that receives $ActonValue_a$ vector and sorts the actions based on its values and save them as a vector of indexes.

  for $i = 1$ *to* I **do**

    $Score_{a'_i} \leftarrow (I - i)$ // Scoring the action based on the Borda voting rule, where is I is the total number of actions. For example, if we have three actions, I will be 3.

  end for

  $TotalScore = TotalScore + Score$ // TotalScore is a vector which contains the summation for each action and its scores after the whole scenarios.

end foreach

return $TotalScore$

in the range 5:00 to 12:00, and the usage time is fixed as 5. Thus, the end of usage time will be the start of using time plus 5. In this experiment, we chose a sample of people who start using their cars at any hour between 5:00 and 12:00, since we assume that many people work in the morning or afternoon period. We generate the start of using time randomly as an integer number ranging between 5:00 and 12:00, selected with equal probability. However, that's will be dynamic in the next model in Chapter 6.

Furthermore, as we mentioned before, since we have not considered the vehicle usage behaviour yet (that will be considered in Chapter 6), the b_{des} and b_{init} are known by the agent before it starts, and they have been fixed for the whole experiment with the values $b_{des} = 40$ and $b_{init} = 60$. We have not yet considered the vehicle usage behaviour so we deal with them as a known and constant value in this experiment. Moreover, since we have also not yet considered the vehicle usage uncertainty, we consider the final state of charge as being zero just for now, but in Chapter 6 we will consider it when we discuss the vehicle usage uncertainty.

Table 4.3: Assumptions for prices of electricity, based on time

Time (hours)	**Price (units)**
1:00 - 8:59	1 - 6
9:00 - 17:59	40 - 60
18:00 - 23:59	7 - 27

After outlining the experimental design, the chapter next discusses the results of running the simulation.

4.5 Results

Table 4.4: Pairs T test results of Borda voting and expected value

S	P value
10	.000
20	.038
30	.046

Table 4.5: Pairs T test results of majority voting and expected value

S	P value
10	.000
20	.003
30	.001
40	.003

In order to evaluate the performance of each algorithm in our solution (Borda, majority and expected value), we ran the simulation with different numbers of scenarios. For each one, we ran the experiment 50 times with a number of scenario cases. The results of these experiments are discussed here. As Figure 4.3 shows, during the entire experiment the performance of the expected value algorithm proves better than the other two (Borda and majority). Throughout, the performance of Borda is better than majority voting, but with very close results. This happens because the backward induction algorithm votes based on the best action, without considering to the variations in the expected utility for each action with Borda and majority voting. However, with the expected value the backward induction algorithm considers the variations in the expected utility for each action, thus expected value results is better than either(Borda and majority) results.

Furthermore, as Figure 4.3 shows, the performance of all the algorithms improves upon increasing the number of scenarios. Additionally, as a result of the difference in the start of usage and end of usage time for each experiment, as discussed in section 6.4.2 and as Figure 4.3 shows, there is a varying amount of increase in profit. This is because sometimes with some of the numbers of scenarios, the experiments that have a start of usage time in the early morning are more than those that start in peak hours. Subsequently, this affects the profits considerably if we compare it with other cases that have experiments with start of usage time in the peak hours more than in the early morning, as Figure 4.4 and Figure 4.5 show. Moreover, by comparing between the results of the three algorithms (Borda voting, majority voting, and expected value) as a pairs using T test, we found that, the results of Borda voting and expected value are significant in

Algorithm 3: Majority Voting

Input: T_{su}, T_{eu}, b_{init}, b_{des}, S

Output: It returns a vector which contains the TotalScore for each action $a \in A$ with the all scenarios S by using Majority Voting rule

$A \leftarrow \{a_1, a_2, ..., a_n\}$
$\forall\ a \in A : ActonValu_a$ // for each action $a \in A$ there is a value $ActonValu_a$.
foreach $s \in S$ **do**
    foreach $a \in A$ **do**
        $ActonValu_a \leftarrow V2GBackwardInduction(\ T_{su}, T_{eu}, b_{init}, b_{des}, s, a\ )$ // Function that returns the value for each action.
        $ActionToSort_a \leftarrow ActonValu_a$// we use ActionToSort as vector that contains the actions which we will sort them.
    end foreach
    $SortedAction \leftarrow Sort(ActionToSort)$// Function that recives $ActionToSort$ vector and sorts the actions based on its values.
    $Score \leftarrow MajorityVotingScoring(SortedAction)$// Function that assigns one to the first element in the vector and zero for the remaining elements.
    $TotalScore = TotalScore + Score$ // TotalScore is a vector which contains the summation for each action and its scores after the whole scenarios.
end foreach
return $Score$

some of the points in S such as 10,20, and 30 as Table 4.4 shows. Further, the results of expected value and majority voting are significant in some of the points in S such as 10,20, 30 and 40 as Table 4.5 shows, since the p values of them are less than .05 (P $\leq$ .05). However, this is not the case for the results of Borda and majority for the points 10,20,30, and 40.

After providing the results of our experiments, in the next section we will summrize this chapter.

4.6 Summary

In this chapter, firstly, we described the model that we proposed to maximize the V2G driver profits with considering of price uncertainty in the power market. Next, we discussed the problem of price uncertainty in the context of V2G. Then, we considered our optimization algorithms. Afterward, we showed the simulation results using the algorithms. Following, we discussed the results.

Next, our survey in vehicle usage behavior will be discussed which has been provided to collect a data that run our last model in chapter 6.

Algorithm 4: Expected Value

Input: T_{su}, T_{eu}, b_{init}, b_{des}, S

Output: It returns a vector which contains the average Score for each action $a \in A$ with the all scenarios S by applying Expected Value concept.

$\forall\ A \leftarrow \{a_1, a_2, ..., a_n\}$
foreach $s \in S$ **do**
  foreach $a \in A$ **do**
    $ActonValu_a \leftarrow V2GBackwardInduction(\ T_{su}, T_{eu}, b_{init}, b_{des}, s, a\ )$ // Function that returns the value for each action.
  end foreach
  $Score \leftarrow ActonValu$// Function that assigns the value of each action to score.
  $TotalScore = TotalScore + Score$ // TotalScore is a vector which contains the summation for each action and its scores after the whole scenarios.
end foreach
$ExpectedUtility \leftarrow AvragingtheTotalScore(TotalScore)$ // AvragingtheTotalScore is a function that calculate the utility function average for each action in the Total score vector and save them in ExpectedUtility vector.
return $ExpectedUtility$

Algorithm 5: V2GBackwardInduction

Input: T_{su}, T_{eu}, b_{init}, b_{des}, s, a

Output: the optimal actions which maximize the V2G driver profits

$\forall\ t \in T : A \leftarrow \{a_1, a_2, ..., a_n\}$
$\forall\ t \in T : Soc \leftarrow \{Soc_1, Soc_2, ..., Soc_n\}$
$t = T$ // start from the last point in the time period.
$Soc \leftarrow b_{init}$
while $t \neq 0$ **do**
  if $(t \geq Teu\ \boldsymbol{or}\ t \leq Tsu)$ **then**
    //to exclude the using time period.
    if $(t = T_{su})\boldsymbol{and}(Soc_t < b_{des})$ **then**
      // to make sure the battery has the desired amount before the using time.
      V2GBackwardInduction(T_{su}, T_{eu}, b_{init}, b_{des}, s)
    else
      $chosenAction = DecisionMaking(Soc_t, t, s)$ // Decision Making Function that returns the action that maximize the utility function.
    $Action = Action + chosenAction$ // Action is a vector which contains the action for each time step.
    $t = t - 1$ // Move backward one time step.
end while
return $Action$

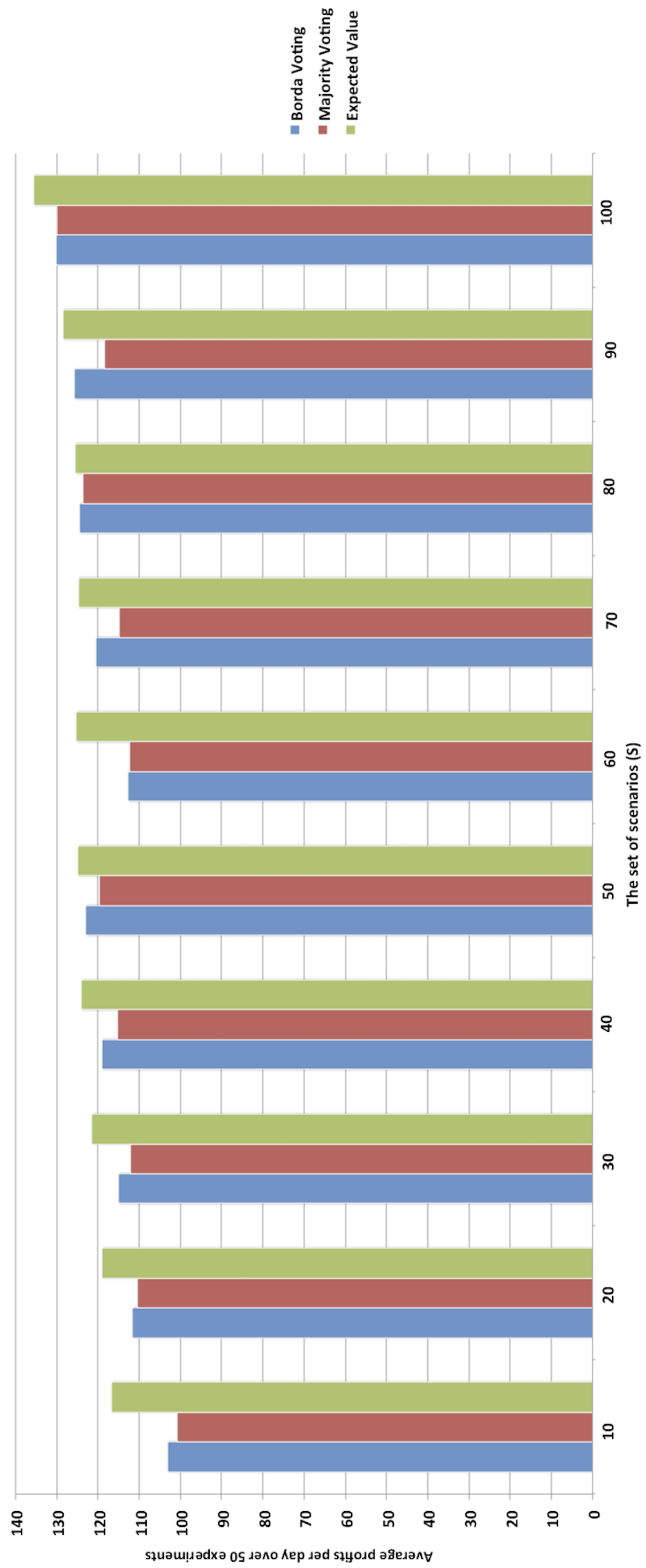

Figure 4.3: Bar chart showing the average profits over 50 experiments with different number of scenarios for Borda, Majority, and Expected value algorithms.

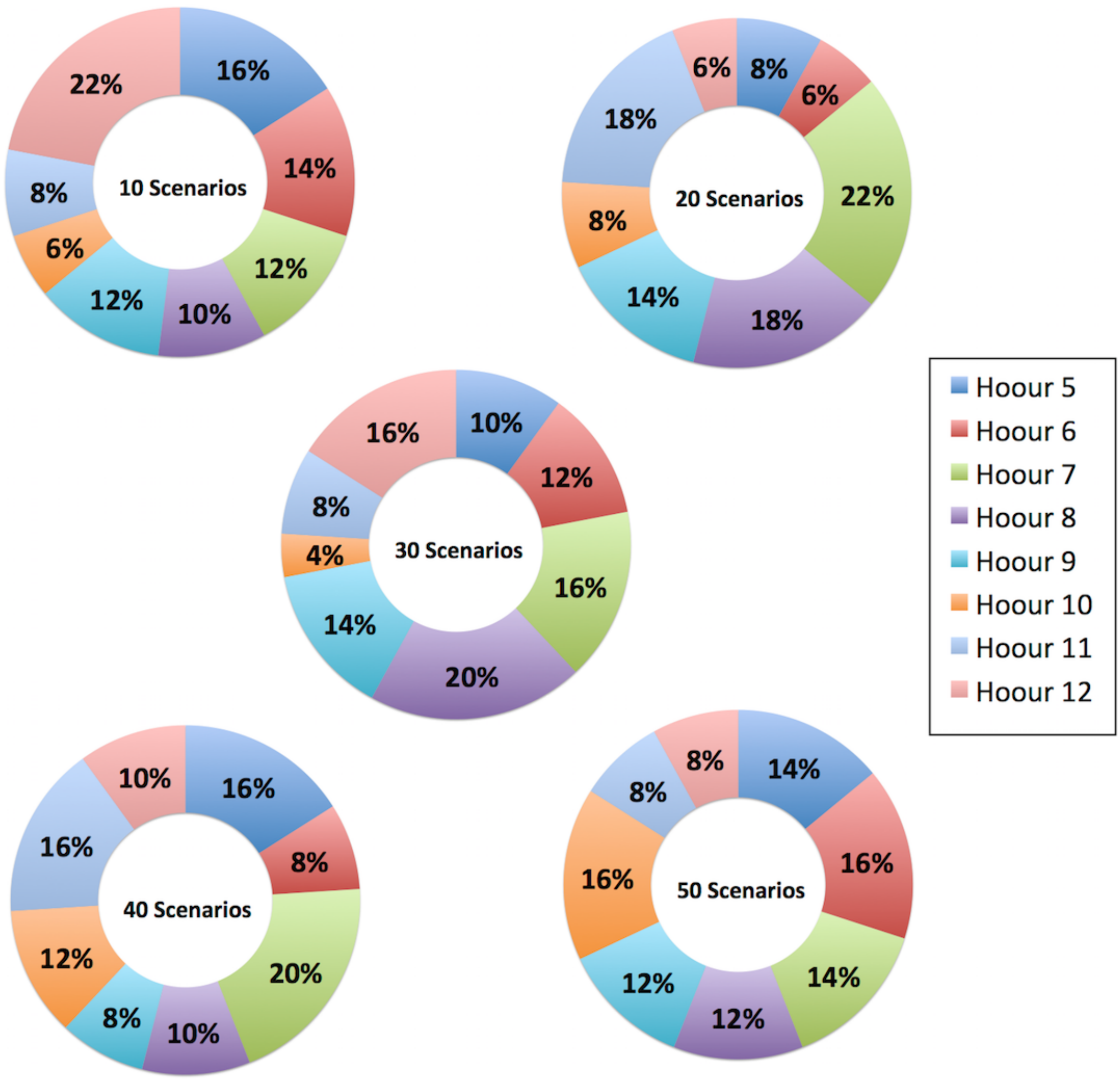

Figure 4.4: Pie charts showing the different start of using time for each experiment that rang between hour 5:00 and hour 12:00 (10 - 50 scenarios).

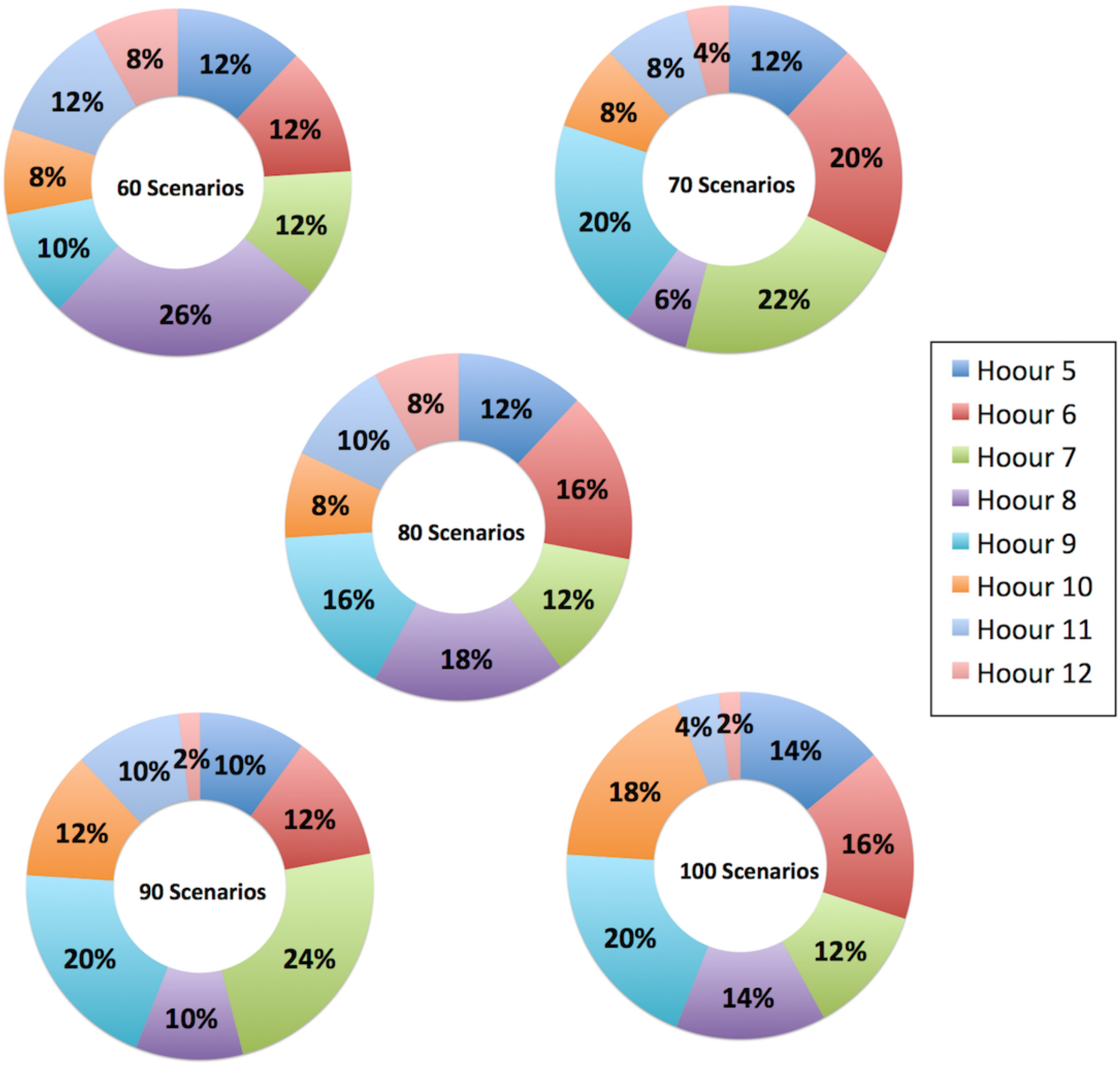

Figure 4.5: Pie charts showing the different start of using time for each experiment that rang between hour 5:00 and hour 12:00 (60 - 100 scenarios).

Chapter 5

Survey of vehicle usage behaviour

This chapter aims to discuss the vehicle usage behavior of the vehicles drivers since we need to this information to run our model. First, we review a number of related works that discuss this issue and then describe our study briefly. Following this, we consider how we collect the data and choose the sample. Next, we discuss and analyse the results. Thereafter, we consider the survey limitations and findings. Afterwards, we describe the power market in Saudi Arabia because we use it as a case study for the power markets. Finally, we summarise this chapter.

5.1 Introduction

In order to make our simulation more realistic, we decide to run it with a vehicle usage behavior dataset for Saudi drivers, which has been collected through a survey. To do so, we have to clarify that, we prefer to use vehicle usage behavior instead of drivers behavior because the later, a terminology usually use to describe the emotional of the drivers and that not what we discussed in our work. Moreover, at present, EVs on the road are rare. Thus, it is difficult to collect the real EV usage behavior so we assume the V2G drivers behave like other vehicle drivers; indeed, this assumption has been used in studies that discuss EV drivers, such as that by (Wu et al., 2010).

There are several studies in the literature that discuss the travel behavior issue. For example, various datasets have been published by the National Household Travel Survey (NHTS, 2016), Danish National Travel Survey (Christiansen and Skougaard, 2015), the Traffic Choices Study dataset collected by the Puget Sound Regional (Council, 2011), and the University of Winnipeg data (Danny Blair, 2011).

To the best of our knowledge, none of the aforementioned studies are suitable for our study purposes because none of them discuss what is the desired amount of battery that drivers require for each trip type. this type of information is the main focus of our

Table 5.1: Trip types in our experiment.

Trip type	**Description**
Unplanned	The kind of trip which happens without any previous planning, such as taking children to hospital for an emergency or going to buy milk for a baby when he/she finishes it suddenly.
Commuting	The type of trip that is usually planned, such as going to work or taking the children to school.
Extra	The kind of trip that has a flexible time so the driver can do it without a specific deadline, such as shopping or going to the gym.

model. Additionally, since we are going to trade with the power market in Saudi Arabia and to make our simulation more consistent, we prefer to collect our dataset from the Saudi drivers.

Specifically, in this survey we aim to capture the following data to run our simulation:

- The probability of each trip type happening.
- The number of trips daily.
- The desired amount of battery for each trip type.
- The distance they drive daily.
- The distance for each trip.
- How the drivers behave if they cannot make their unplanned trips.

Furthermore, for illustration purposes, in this survey, we assume that we have three trip types, namely unplanned, commuting and extra (the definition for each one is in Table 5.1). However, we believe that our model can easily run with any other types of trips.

5.2 Survey Overview

A survey has been designed based on the research objectives in order to capture the real data needed to run our model. In addition, the survey administered to the participants is an online survey named Qualtrics. It offers a usable interface for the participants to answer the survey questions. Furthermore, the extracted data can be simply analysed using statistical tests. In addition, an ethical document named Consent Form is provided to the participants, as is the School Ethics Committee reference number (23726). They are informed of the purposes of the study and of their right to withdraw at any time unconditionally and without reason.

Moreover, the respondents are invited to participate through social networks and emails, and are sent a web link to the survey. Any person with a Saudi driving licence is considered an appropriate participant in this study. A total of 699 participants responded to this survey. Furthermore, there is no relationship between the researcher and the sample. The researcher is an observer of the sample population. However, the researchers friends have been used as survey distributors on social networks, especially twitter and Snapchat. Moreover, the survey has been provided in Arabic and English and the participants chose one of them at the start of the survey. (see appendix A). Following this, we will discuss the results in detail in the following section.

5.3 Results and Analysis

In this section we present a rigorous discussion of the results. To do so, we list the methods that we used to analyze the data. Afterward, we discuss the results in more detail.

Thus, in order to analyse the data, a number of methods are used, as follows:

- **Demonstration, discussion, and analysis of results regarding participants' preferences**.

  This section of the study illustrates the participants' vehicle usage behaviour based on their responses to the survey questions. The results are presented in the form of percentages, tables, and statistical figures.

- **Descriptive statistical methods**.

  A number of descriptive statistical techniques are utilised, such as proportion and means, with the aim of obtaining summary information.

- **Thematic analysis**

  Since we cannot list all the options that can capture participants' preferences, we add open-ended answers to some of the questions in the survey. In order to analyse these answers, thematic analysis (Braun and Clarke, 2006) is applied. We select this technique because the number of answers for these open-ended options stands at approximately 60 in the highest instance; indeed, this means that skimming participants' responses has not consumed a lot of time.

More specifically, we divide the survey into three parts. Firstly, we ask about certain demographic information. Following this, we ask about the respondents' behaviour and preferences in relation to using the vehicle battery (fuel in the conventional vehicles), and this is the core section of the survey. Lastly, we investigate the feasibility of using V2G in Saudi Arabia.

Table 5.2: The participants' age.

Response	Percentage
18 - 25	22.71%
26 - 35	27.37%
36 - 60	46.35%
Over 60	3.58%

As Table 5.2 and Figure 5.1 show, most of the drivers who participate in this survey are between 36 - 60 years old (46.35%). However the minority are over 60 years old (3.58%). Indeed, this is reasonable, since people over 60 are, in comparison to others, less used to dealing with the social networks on which we publish our survey.

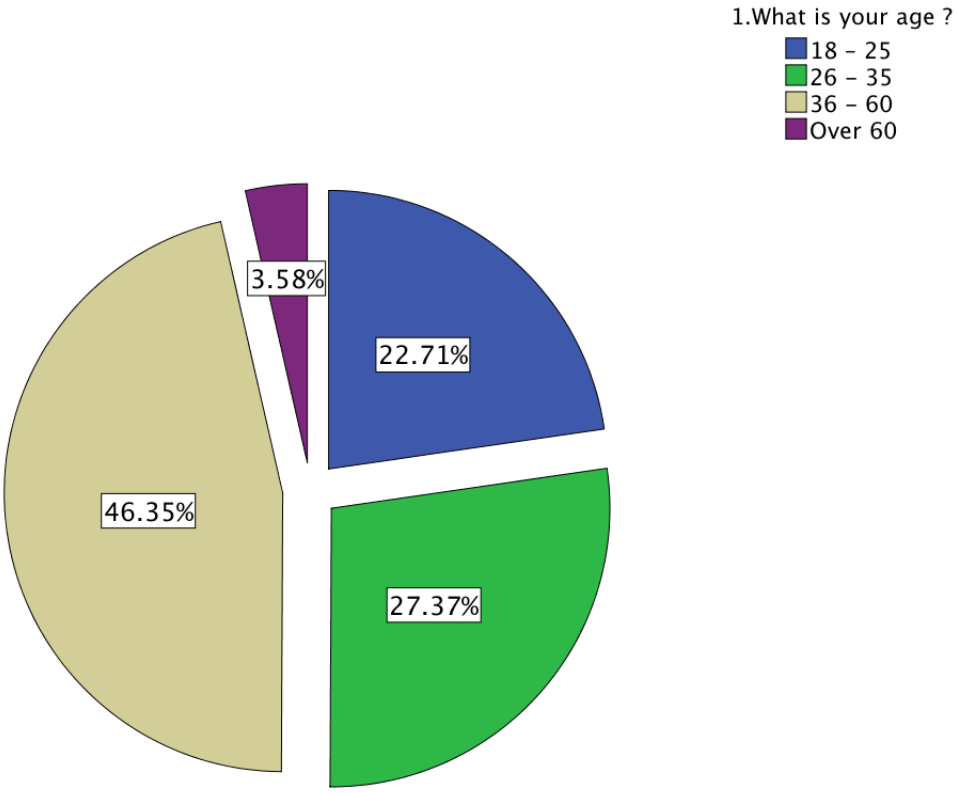

Figure 5.1: Pie chart showing the participants' age.

Table 5.3: The participants' highest educational attainment.

Response	Percentage
Under bachelor	31.73%
Bachelor	59.10%
Master	7%
PhD	2.18%

Furthermore, in the highest educational attainment for the sample we find that the majority of the study participants are people who have a Bachelor degree. This is followed by students currently undertaking a Bachelor degree. After this, and differing

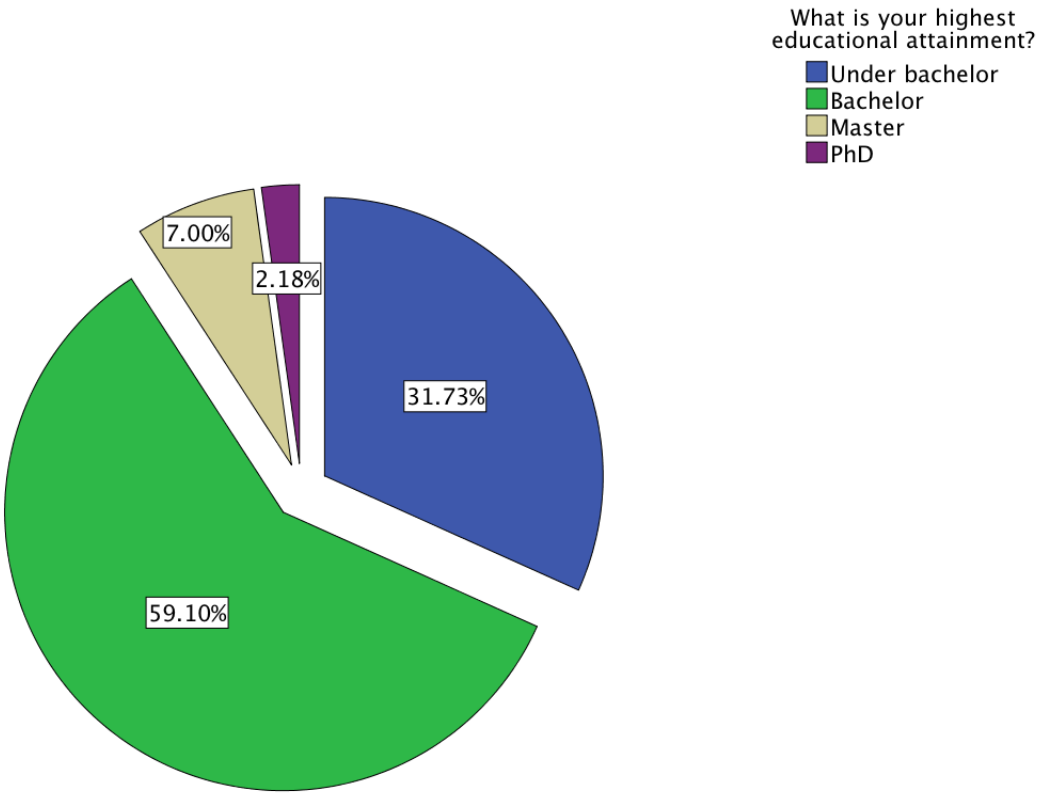

Figure 5.2: Pie chart showing the participants' highest educational attainment.

considerably in number, come those people with a Master degree; indeed, the minority are participants with a PhD, as shown in Table 5.3 and Figure 5.2. In addition, and as seen in Table 5.4 and Figure 5.3, approximately half of the participants work in the public sector, while 20.37% work in the private sector, and the rest do not work.

Table 5.4: Answer to the question: "Do you work in the public or private sector?"

Response	**Percentage**
Public	49.14%
Private	20.37%
Do not work	30.48%

Following this, we ask a number of questions in order to gauge how the participants deal with the vehicle battery uncertainty.

In terms of the number of trips that the drivers make daily, we find the following. The drivers who make 3 - 4 trips daily represent the highest number of participants (approximately 40.07%). Furthermore, the second highest number applies to the people who make 1 - 2 trips (approximately 37.94%). In addition to this, those drivers who make 5 - 6 trips represent only 16% of the participants. By qualifying the fourth option and applying thematic analysis, it can be seen that the most frequent answer is equal to 10 or more times. Thus, we use greater than or equal to 10 times as a fourth option.

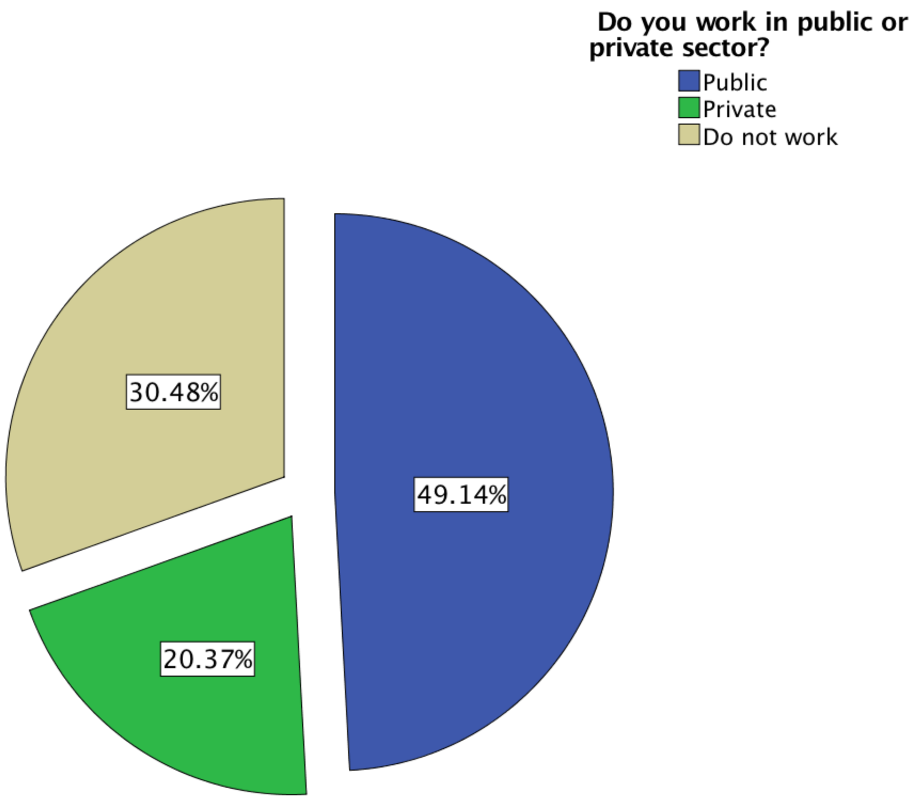

Figure 5.3: Pie chart showing the answer to the question: "Do you work in the public or private sector?"

Table 5.5: The number of cars the participants own.

Response	**Percentage**
1	60.96%
2	20.06%
More than 2	18.97%

Table 5.6: The number of trips the participants make daily.

Response	**Percentage**
1 - 2 trips	37.94%
3 - 4 trips	40.07%
5 - 6 trips	15.96%
None of the above	6.03%

Then, we ask the participants about how many cars do they own and we found that, as Figure 5.4 and Table 5.5 show, 60.96% of the participants have one car. Moreover, 40% of the participants have more than one car (20.06% have two cars and about 18.97% have more than two cars).

After that, we ask the sample about one of the most important items in our survey, which is the probability of each trip type happening daily. The probability of commuting trips to happen during the day is the most type of trips to happen based on the participants,

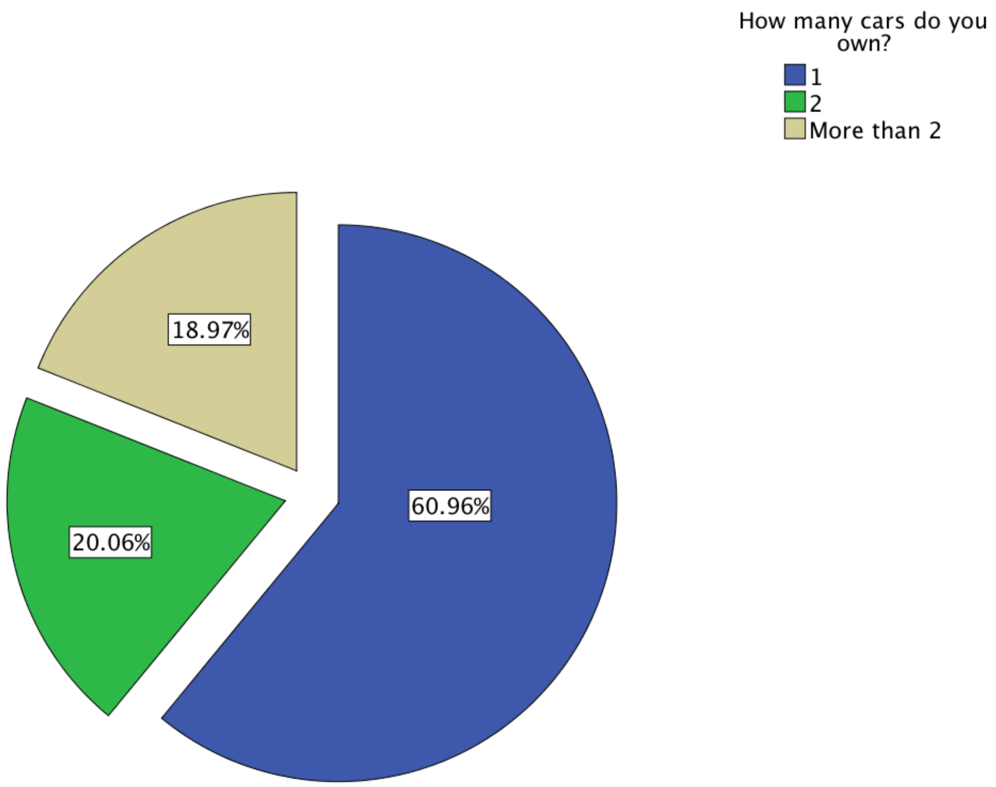

Figure 5.4: Pie chart showing the number of cars the participants own.

Table 5.7: Answer to the question: "What percentage of these (trips) are Unplanned, Commuting, and Extra trips?"

Response	Unplanned	Commuting	Extra
100%	1.58%	12.50%	2.82%
80%	7.39%	30.46%	6.87%
60%	14.08%	32.75%	14.61%
40%	26.58%	14.61%	21.48%
20%	44.01%	8.10%	45.07%
0%	6.34%	1.58%	9.15%

since approximately 30.46% of the participants think that the commuting trip may make up 80% of the trips, and 32.75% of them feel that it might make up 60% of the trips. However, approximatively half of the participants (44% for unplanned trips and 45% for extra trips) think that commuting trips may make up 20% of the total trip number, as Table 5.7 illustrates.

Moreover, as Figure 5.8 shows, approximately half of the participants park their car for the longest time between 00.00 and 06.00. Indeed, this is understandable because people usually sleep during this period. The second highest number is between 07.00 and 12.00, when the participants are at work or at school/university. Finally, there are very close percentages for those who park between 19.00 and 23.00 and those who park in different periods. These have not been defined in the present survey.

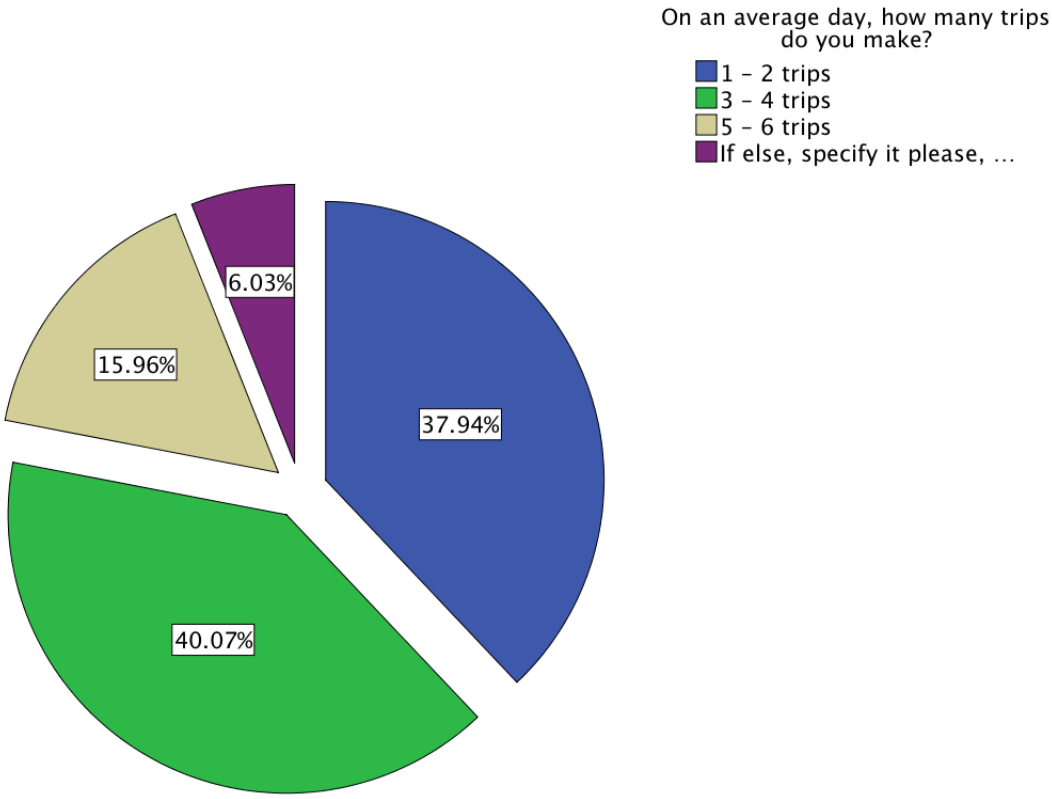

Figure 5.5: Pie chart showing the number of trips the participants make daily.

Table 5.8: The longest period through the day the participants park their cars.

Response	**Percentage**
Between 00:00 and 6:00	44.05%
Between 07:00 and 12:00	20.24%
Between 13:00 and 18:00	16.07%
Between 19:00 and 23:00	10.71%
None of the above	8.93%

Table 5.9: Answer to the question: "How many hours do you drive your car daily?"

Response	**Percentage**
1 - 2 hours	46.23%
3 - 4 hours	42.06%
5 - 6 hours	8.93%
None of the above	2.78%

In terms of the amount of fuel which drivers desire in their vehicle, this depends on the trip types, with our findings revealing the following. As Table 5.10 shows, for all trip types, most of the participants prefer 60% as the level of fuel they want, and on the other hand, the lowest number prefer their vehicle to be at 20%. Furthermore, we find that the participants' fuel amount preferences for their vehicles are the same for both

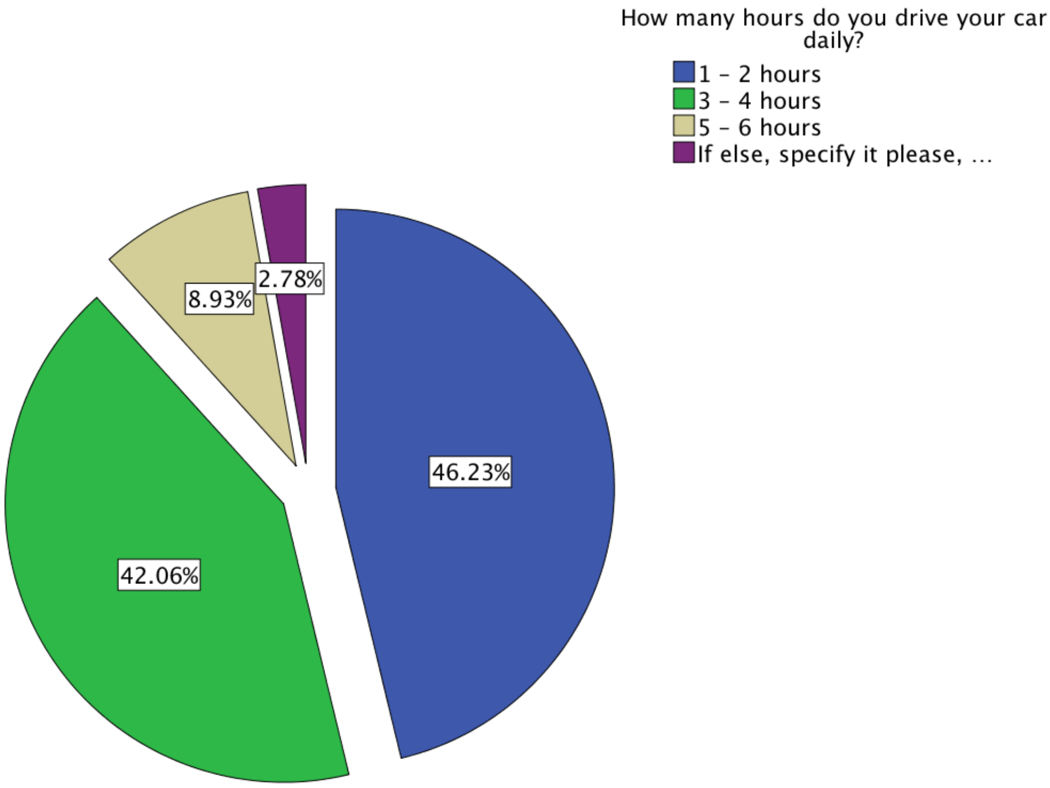

Figure 5.6: Pie chart showing the numbers of hours the participants drive daily.

commuting and extra trips.

Table 5.10: Answer to the question: "When there is a possibility that you will use your car for an unplanned, commuting, or extra trip, what is the minimum amount of fuel you want in your car?"

Response	**Unplanned**	**Commuting**	**Extra**
100%	25%	20.04%	23.44%
80%	16.87%	22.62%	22.82%
60%	28.77%	34.72%	28.37%
40%	20.63%	16.87%	18.45%
20%	8.73%	5.75%	6.94 %

Additionally, based on the participants expectations, the trip types are mostly the same in aim of the distances they expect to drive as Figure 5.9 illustrates. Most of the participants' expect to drive between 11 - 20 KM, while the minority of the participants feel that they drive less than 5 KM; indeed, roughly the same percentage can be applied to those who think they drive more than 50 KM. We think that this is reasonable, since we do not see any relation between type of trip and distance. In order to model this issue, for each trip type, the distances are generated as an integer number that ranges between the options with equal probability.

Furthermore, to model how the drivers behave if they cannot make the unplanned trip, we ask the participants what they are going to do if they have an unplanned trip and the

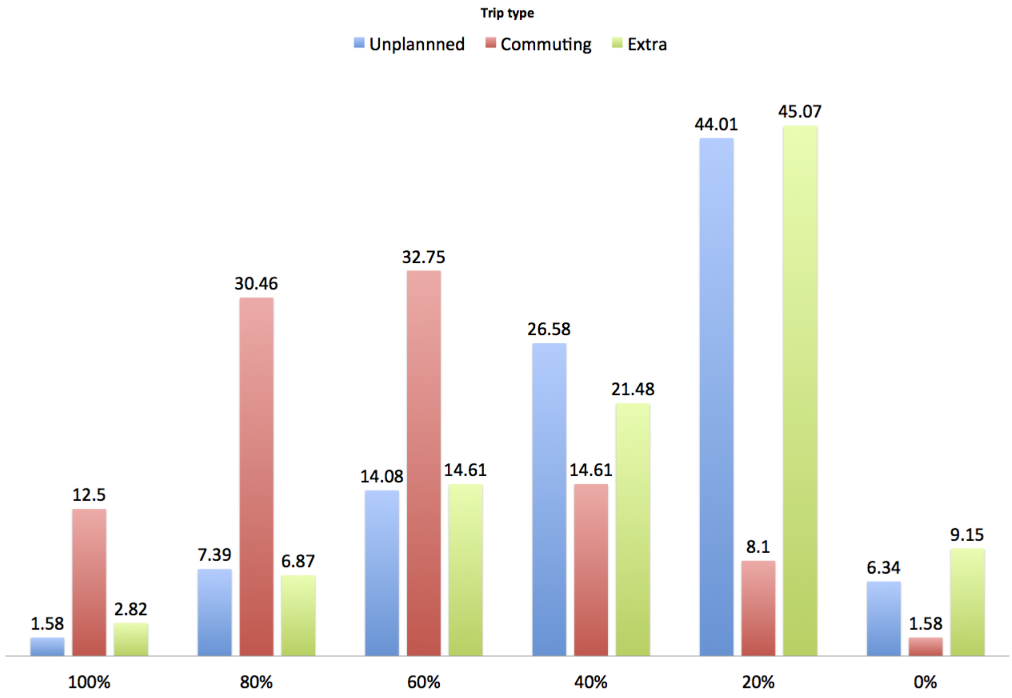

Figure 5.7: Bar chart showing the trip types with probability.

Table 5.11: Answer to the question: "When you want to use your car for an unplanned trip and your car is unavailable, what are you going to do:"

Response	**Percentage**
Take taxi	24.21%
Call your friend or one of your family to take you	60.91%
Walk	5.75%
If else, specify it please,	9.13%

car is unavailable. Most of the sample prefer to call their friend or one of their family members to take them (60.91%). The second highest choice is to take a taxi (24.21%). Following this, open answer is selected as the third highest. There are many responses provided by the participants which we have not listed in our options, such as the use of a spare car for those with more than one car, the borrowing of a car, and the renting of a car. However, the most repeated answer is rent a car, and thus we will consider this and ignore the others, as the latter are repeated only two or three times, which is a small number when dealing with 699 total responses. Finally, the minority select walk, which is understandable because of the difficult weather in Saudi Arabia.

Finally, to investigate the feasibility of using the V2G in Saudi Arabia, we provide two questions at the end of the survey, as follows:

Q1 : Are you interested in using the EV instead of the fuel vehicles if you receive some economic and environmental benefits?

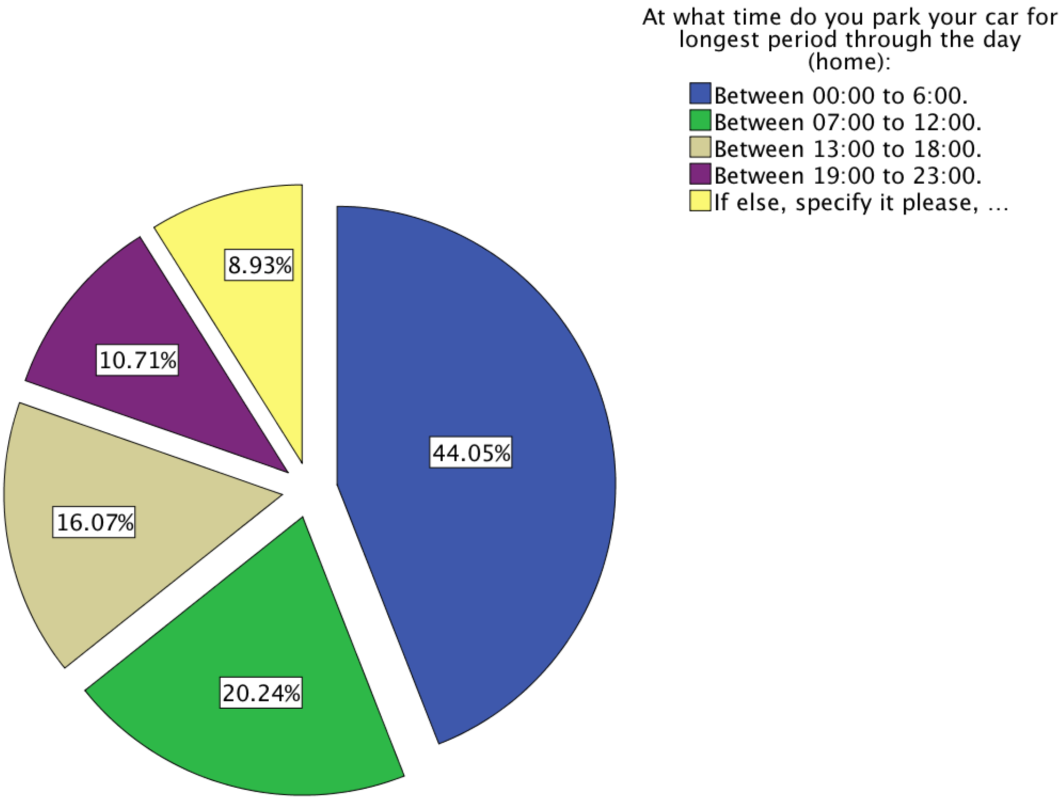

Figure 5.8: Pie chart showing the longest period through the day the participants park their cars.

Q2 : If you receive more economical benefits from using V2G, are you interested in using the V2G?

Initially, it is essential to clarify that we explained the concept of V2G to the participants before we asked these two questions. In more detail, for the first question, the majority of the sample prefer to use EV (approximately 85%), as shown in Figure 5.12; this is a good indication. For the rest, by applying the thematic analysis method, we can establish that these answers are the most frequent answers in terms of why the participants prefer to not use the EV. The first reason is that, because the EV is less than the fuel vehicle in terms of the performance. Moreover, a great deal of time is needed to charge the EV. Furthermore, according to the participants, the EV until now has been too expensive if we compare it with the fuel vehicle. Lastly, the current infrastructures in Saudi Arabia does not support this type of vehicle.

Before we discuss the study findings, we will briefly analyse the power data that confirms there is a peak demand problem in the summer in Saudi Arabia. We got Figure 5.13 from the Saudi Electricity company which shows a typical daily load curve during summer, and it is clear that the peak demand on Friday is more than the other days. This is because Friday is the social day in Saudi Arabia, and in other Muslim countries; indeed, more people gather on this day than on any other day. On a weekday, at 1:00 the curve is decreasing steadily until 7:00, following which the curve is rising gradually with some fluctuations until 18:00. Then, the peak curve is reducing until the end of the day. From this figure, we can conclude that the peak demand period at the summer in Saudi Arabia is between 7:00 and 18:00. In additional, we have obtained Figure 5.14 from the Saudi Electricity company which is an updated version of the current peak demand. This chart covers 4 days in August 2017. As the figure shows, the numbers are almost the same as those in Figure 5.13, which pertains to the year 2015. In the following section we will discuss the study findings.

5.4 Survey Findings

- Approximately 40% of the sample have more than one vehicle, which gives them a chance to use the spare vehicle to trade in the power market with more relaxed conditions. Accordingly, we expect that the V2G technology might play a crucial rule in the Saudi power market.
- Most of the participants (approximately 90%) use their vehicles for less than 4 hours (1 - 2 or 3 - 4), thus meaning that the vehicles are not being used approximately 83% of the time. As such, we can use this time to trade with the power

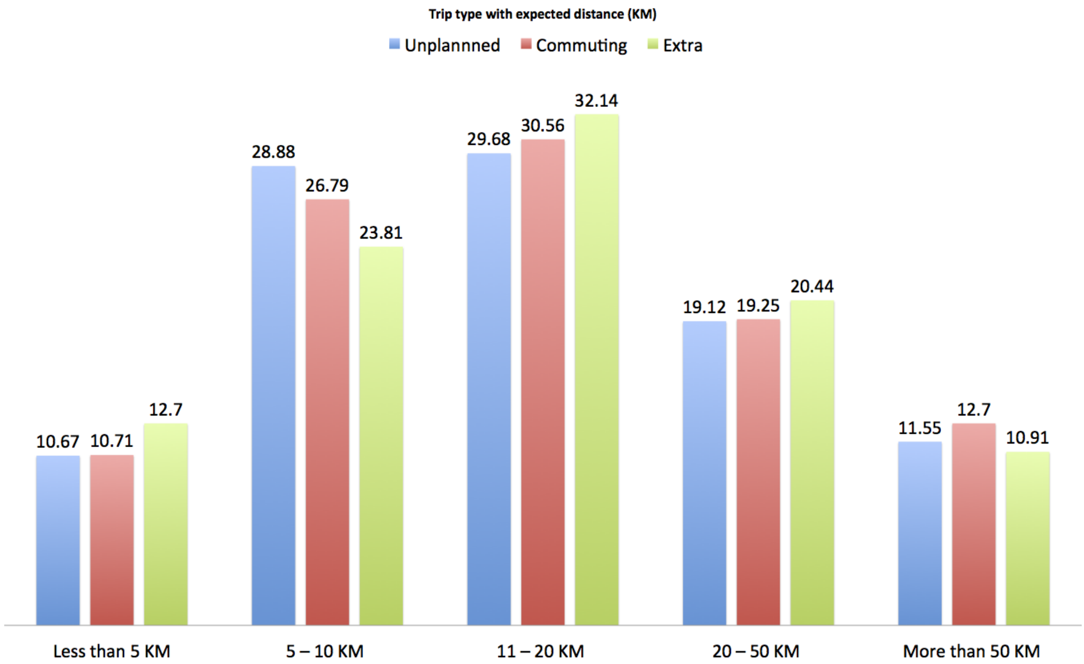

Figure 5.9: Bar chart showing the tripe types with expected distances.

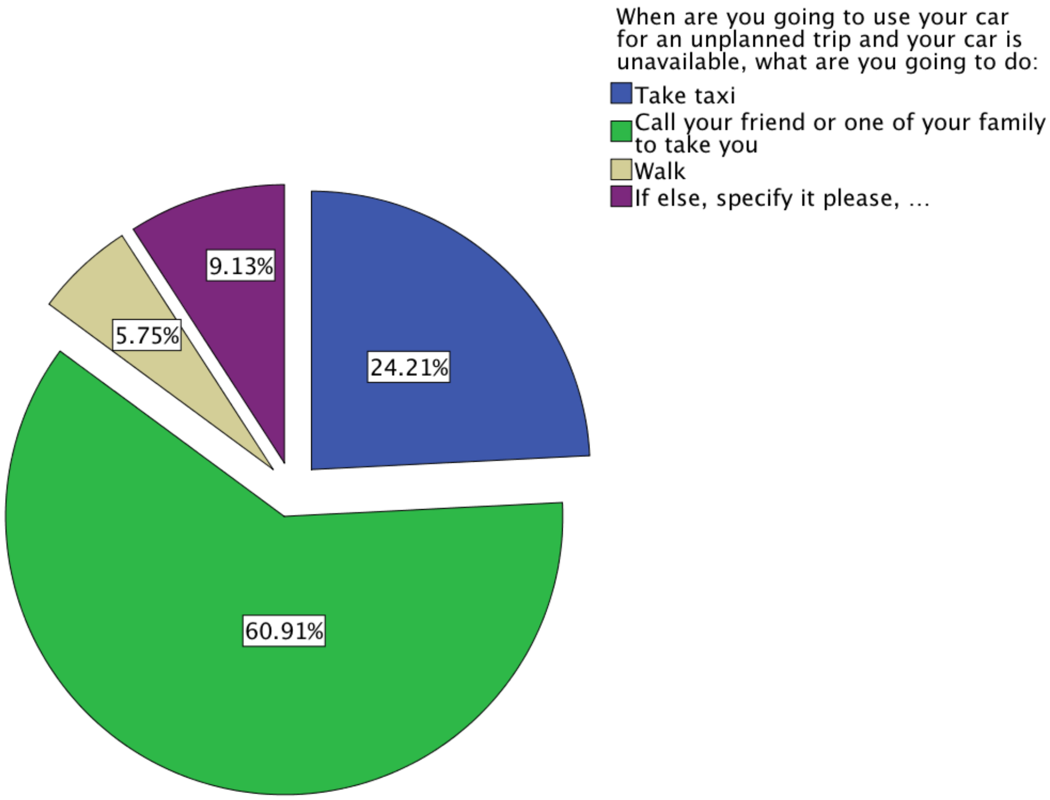

Figure 5.10: Pie chart showing the answer to the question: "When you are going to use your car for an unplanned trip and your car is unavailable, what do you do?"

market if we apply the V2G concept without disturbing the drivers and if we use this time in a clever way.

- Around 85% of the participants are interested in using EV generally and V2G technology specifically; indeed, this is a promising result if we consider that society has no awareness of these technologies. Consequently, based on these results, we believe that if we encourage people and educate them on such technologies, these numbers might increase.

- The findings reveal that drivers park for the longest period between 00:00 and 06:00 on normal days, which is understandable because this is usually the time during which people sleep. However, in the summer season this changes, with people parking for the longest period between 13.00 and 18.00. As stated in the Electricity & Cogeneration Regulatory Authority (ECRA) report, the electricity peak demand in Saudi Arabia is very high during the summer period and it is predicted that this will increase rapidly over the following decade (ECRA, 2011). By combining the last two sentences we can claim that using V2G in Saudi Arabia could support the grid in facing the predicted peak demand during the summer period in the next decade.

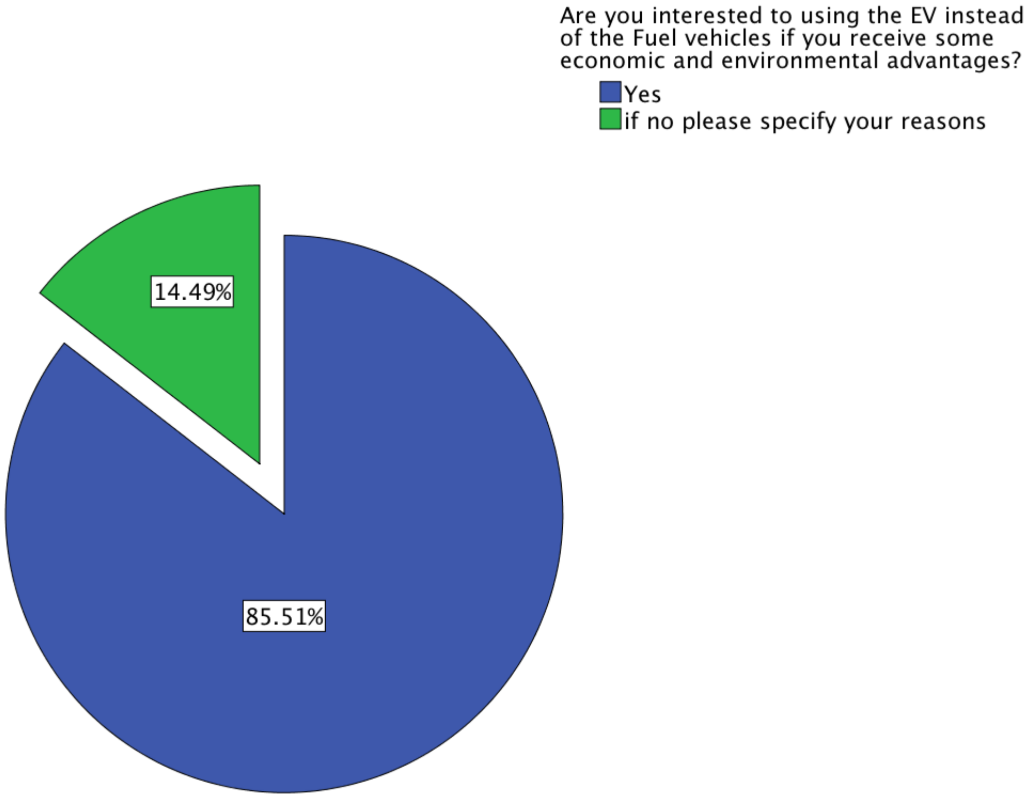

Figure 5.11: Pie chart showing the choosing between EV or conventional vehicles.

- As stated by the participants, the trip types are the same in terms of the distances they expect to drive. Thus, there is not relation between the type of trip and the expected driving distance.

Having discussed the survey findings, we now examine the limitations of this study in the next section.

5.5 Survey Limitations

This study attempts to gauge drivers' vehicle usage behaviour. It has a number of strengths although at the same time it has a number of weaknesses. The first limitation is that, the participants are just the males and this because we focus on the people they have a driver license in Saudi Arabia and until now just the meals can drive legally in the Saudi Arabia. However, that has been changed and the women start driving in Saudi Arabia since 23 June 2018. Moreover, we cannot capture the whole population because this survey is an online survey, and thus we may miss some types of people, such as old men who do not use the Internet.

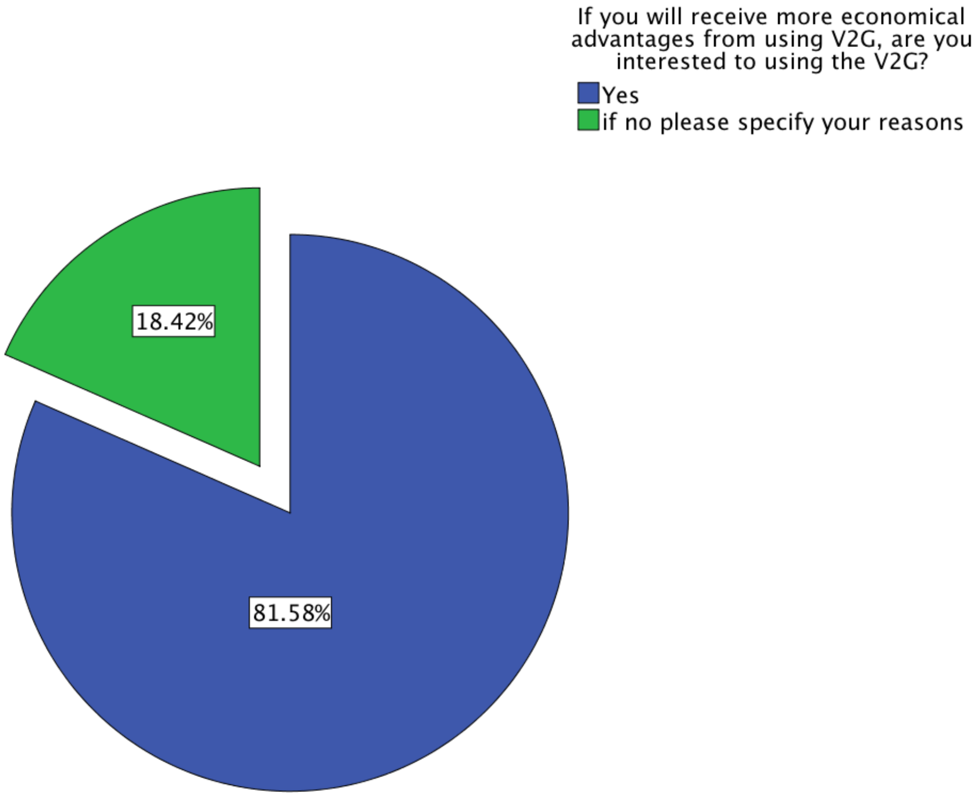

Figure 5.12: Pie chart showing the answer to the question: "If you will receive more economical advantages from using V2G, are you interested in using the V2G?"

The third limitation in this study is that, we just focus on the following data (the probability of each trip type happening, the number of trips daily, the desired amount of battery for each trip type, the distance they drive daily, the distance for each trip, and how the drivers behave if they cannot make their unplanned trips); indeed, such occurrences might affect the drivers' vehicle usage behaviour, which is what we use to run our simulation model. However, we believe that if we collect more information, then we can improve the strength of this study.

In the following part, the power market in Saudi Arabia will be described, since we use this as a case study for the power markets in our model.

5.6 Power Market in Saudi Arabia

Flat rate pricing is a popular global retail market, where consumers are charged the same rate for power through the day and the night. The problem with this type of power pricing is that the consumers are overcharged for some power, usually during non-peak periods, and are undercharged for some power, usually during peak times.

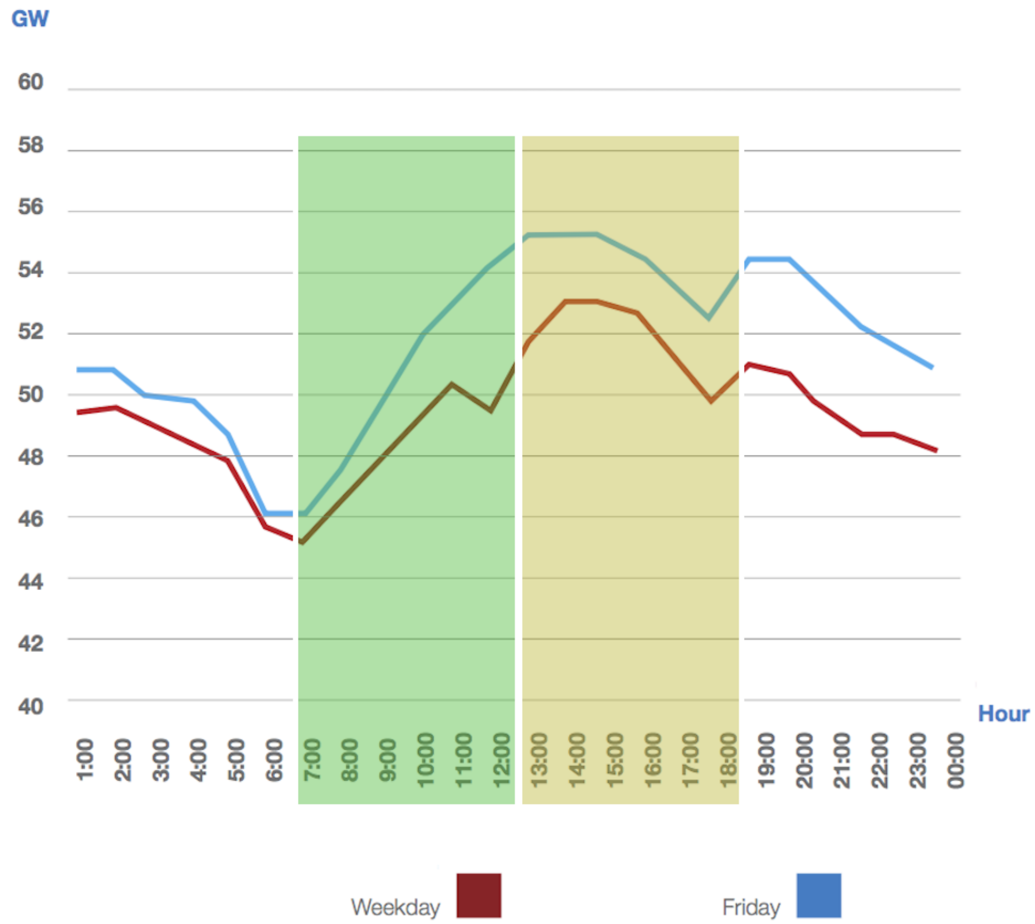

Figure 5.13: Typical daily load curve during the summer.

Thus, this pricing type does not encourage consumers to change demand to different times.

The second type is real-time pricing, where the consumer is charged based on the real prices of generation, transmission and distribution. A third choice for retail consumers is Time-of-use (TOU) pricing, which is between flat rate pricing and RTP. It has the benefit of being able to generally predict power prices on a daily and seasonal basis. Moreover, it decreases the risk for consumers by offering some certainty about the price.

ECRA chose to apply TOU tariffs as a pricing model in Saudi Arabia, since they give more certainty to the consumers, and the multi-tariffs are already approved and applied in the industrial sector (ECRA, 2013). In order to apply this change, the Saudi electricity company should develop its infrastructure and create a smart grid while also offering smart meters for consumers; indeed, this is something which is currently being worked on, although it may take a long time due to the size of Saudi Arabia itself.

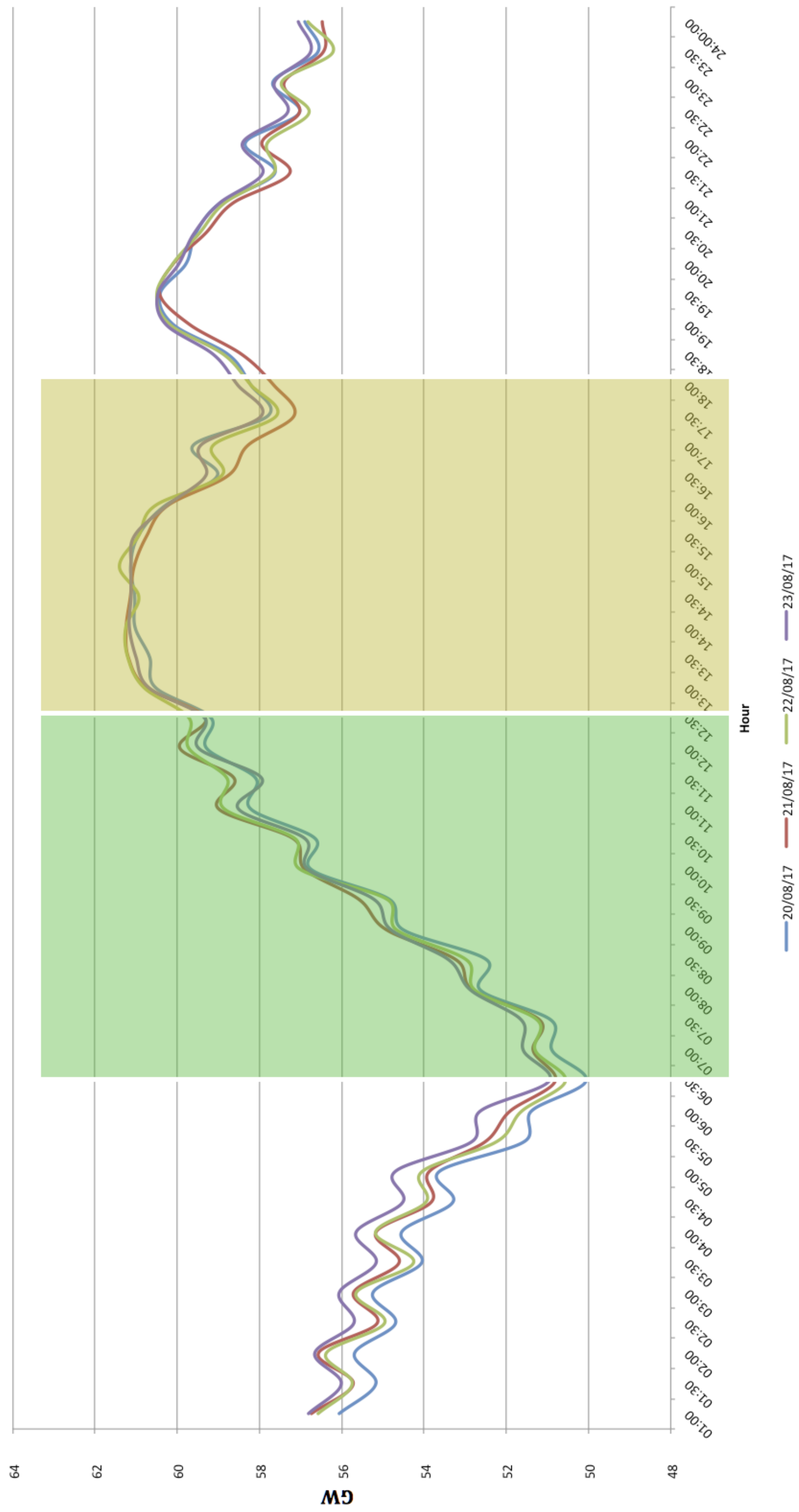

Figure 5.14: Peak demands for 4 days in August 2017.

The existing pricing policy in Saudi Arabia is a flat rate policy, and as stated by ECRA in their report, they are planning to apply Time-of-Use tariffs in the future. However, we believe that the RTP market represents a more efficient way of pricing, where the price depends on the real prices of generation; indeed, since we believe that this kind of market fits our study, we choose to apply RTP market pricing. Thus, in order to simulate this issue, we take the existing pricing for power from the Saudi electricity company and the demand for each hour for one month in Saudi Arabia.

Furthermore, it is very important to consider that these prices are considerably lower than their equivalent in many countries around the world (approximately 80 - 90% lower), since the Saudis apply substantial discounts to oil, which is thought to represent approximately 66% of the world's power generation (ECRA, 2011).

Finally, we use the data from Saudi Arabia's power market and the consumption patterns and preferences of its citizens as an example to run our simulation. However, we also believe that our work can be applied to any other countries. Thereafter, the summary of this chapter will be provided.

5.7 Summary

This chapter has presented real data regarding how vehicle drivers deal with battery uncertainty (fuel in the conventional vehicles). Firstly, several studies concerning this topic are reviewed. Following this, discussion switches to how we collect the data and choose the sample. Afterwards, the results are discussed and analysed. Subsequently, the survey limitations and findings are considered. Finally, the power market in Saudi Arabia is described.

Chapter 6

Model with Vehicle Usage and Price Uncertainty

This chapter describes the model proposed to maximize the V2G driver profits with considering to two types of uncertainties which are power market prices and vehicle usage behavior. Then, in more detail, the problem of price uncertainty, and vehicle usage uncertainty in the context of V2G will be discussed. After that, our optimization algorithm will be considered. Next, we will show the simulation results using our solution and the benchmark algorithms. Finally, we will discuss the results, and then we will summarise the chapter.

6.1 Introduction

In this study our aim is to design an algorithm to trade on behalf of V2G drivers in order to maximise their profits through understanding their vehicle usage. During this process, there are two types of uncertainty to deal with, namely prices in the power market, which we discussed in Chapter 4, and drivers vehicle usage, which we will discuss in the final sections.

To address price uncertainty in the context of V2G, we developed a heuristic algorithm that can trade on behalf of the V2G users, maximising their profits from using V2G as a source of electricity while taking into consideration their behaviour and their incentives. Our proposed algorithm combines two types of consensus algorithm (Borda and majority voting) and expected value with a backward induction algorithm, as discussed in Chapter 4. Moreover, to address the vehicle usage uncertainty we used the multinomial logit model with the consensus algorithms and expected value with a backward induction algorithm.

As discussed earlier, there is an opportunity for the V2G drivers to maximise their profits if they use the concept of V2G effectively. With the V2G heuristic algorithm proposed and implemented, the V2G agent receives the initial battery state of charge, the desired battery state of charge for each trip type, the start of using time and the end of using time for each trip; the agent also receives the probability of each trip happening prior to the beginning of every day, along with the number of power market prices for each following hour and the number of daily trips. Thus, the uncertainty here comes from the prices and the vehicle usage behaviour. Moreover, the agent can buy or sell for the following hour only, depending on the constraints. Using the aforementioned information, the V2G heuristic algorithm is run for each V2G driver in order to find the best available action that can maximise the V2G drivers profit based on the feasible trips that can be made. After computing all the scenarios with a backward induction algorithm, and multinomial logit model, it is possible to find the best action for each hour, depending on the pricing of every specific scenario, and the probability of each feasible trip happening and being chosen. Two types of consensus algorithms (Borda voting and majority voting) and the expected value will be applied, following which the chosen action will be implemented.

On the other hand, to model the vehicle usage behaviour, we assume that our agent receives number of trips scenarios every hour. We define the scenario as the combination of a sample of power market prices for the following hour and a sample of trips. This number of scenarios produces two types of uncertainties, one is related to the price while the other is related to the vehicle usage behaviour. To deal with the price uncertainty, we firstly model the time series of the power price for each scenario as a Markov decision process (MDP). Besides this, to deal with the vehicle usage uncertainty we use a multinomial logit model to model how the drivers chose their trips. Following this, we propose a novel heuristic algorithm that maximises the V2G drivers profit by choosing the best actions for each time period based on the feasible trips.

Before we formulate the problem in the next section, we will discuss the model assumptions that we used in our work. In addition to the previous assumptions which we discussed in Chapter 3 and Chapter 4 assuming the budget is unlimited. Moreover, we assume that the other people do not influence the power market price and thus we also assume that the price is fixed and the consumer is a price taker. However, while we start with this now, in future work we will consider it when we model a multi-agent environment. Furthermore, we assume that the drivers are going to choose the trips that maximise their utilities. Indeed, we apply this assumption because we think it is reasonable and in order to simplify the complexity of the problem. Additionally, some of the essential elements that cost the V2G driver are fixed costs, such as the cost of the vehicle, charging points supplied by the consumer, and other elements that have not been considered. We have not considered these essential elements because they have a fixed value and we believe that our solution will be the same even if they are considered, since they have a fixed cost. Finally, because our work has not focused specifically on battery degradation, we prefer to choose the Kempton and Tomić (2005) model and apply it in our work; this is because it is a simple model to apply and has been used broadly in a number of studies concerning battery degradation (Zhou et al., 2011; Wang et al., 2016; Dallinger et al., 2011). However, we believe that our model can be easily adjusted to include any other battery degradation model. Before discussing the details of the optimisation module, in the next section we will formulate the problem.

6.2 Problem Formulation

This section describes formulation of the V2G problem under price and vehicle usage uncertainty. Firstly, we describe the V2G problem under price uncertainty as an MDP, some of the information has been provided in the model in chapter 4. However, we refine it here because we have not considered the battery degradation in the previous model and because we need it here to draw the whole picture of this new model.

In order to model the battery degradation we refine the utility function that we discussed in Chapter 4. To do so, in either charging or discharging actions there is a cost should be considered which we represent as a battery degradation function $Cd(a_t, Soc_t(\overline{a}, b_{init}))$. So the utility function will be defined as:

$$
\begin{aligned}
U(b_{init}, \overline{a}) = & \sum_{t \in \{1,\ldots,T\}: a_t > 0} (-P_t \cdot a_t) - Cd(a_t, Soc_t(\overline{a}, b_{init})) \\
+ & \sum_{t \in \{1,\ldots,T\}: a_t < 0} (P_t \cdot a_t) - Cd(a_t, Soc_t(\overline{a}, b_{init})) + V\left(b_{init} + \sum_{t=1}^{T} a_t\right)
\end{aligned} \tag{6.1}
$$

If conditions are satisfied 6.1 applies, otherwise $U(b_{init}, a) = -\infty$. Additionally, we assume that, for each trip j, the EV start of using time j_{su} and the end of using time j_{eu} are unknown, we defined that as a vehicle usage uncertainty and it will be discussed in the following paragraphs.

Furthermore, we assume there is n number of power market prices. The V2G agent action should be chosen for time t by the V2G heuristic algorithm after it receives all of the prices from the power market. We proposed that the model should incorporate V2G vehicle usage behaviour, which will be discussed in Section 6.3.2. Moreover, it will employ electricity prices for the next hour, since we consider the hour ahead price market. By using these two types of information, the model will maximise the expected V2G drivers utility by deciding the best action for every hour of the day, apart from the usage time allocated to users to drive their cars. The expected utility has been defined here as the monetary profit and the level of battery power that is returned to the V2G driver at the end of a day.

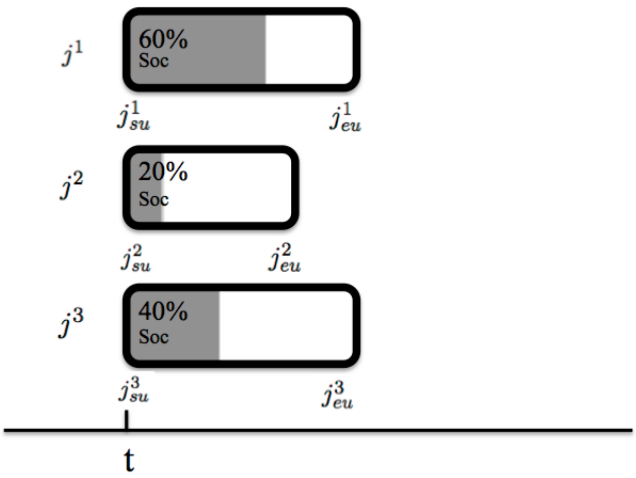

Figure 6.1: Diagram shows an example for the planning horizon for three trips in our model.

In terms of the V2G problem under vehicle usage uncertainty, we assume that the vehicle driver has a number of trips daily, which we set as m. We define a trip terminology as the task to be accomplished by a vehicle. Each trip in our model can be defined by the following factors: the departure time, the duration, the flexibility of the trip, the trip type, the difference in the state of charge, the utility of the trip if it is made at the desired time, the probability of the trip happening, and the desired amount of battery that has been required to make the trip. Furthermore, in our model we deal with two types of probabilities. The first is the probability of each trip happening while the second is the probability of the trip being chosen by the V2G drivers if the favourite trip cannot be made. The expected utility in terms of the vehicle usage has been defined here as the monetary profit that will be received if the chosen trip can be made without delay.

Figure 6.1 illustrates the planning horizon for if we have three trips j^1, j^2, and j^3 at time t. In detail, j^i_{su}, and j^i_{eu} are the periods time for each trip, and the gray color is the desired amount of battery for each trip. Certainly, considering each trip at every time step, and the variations between the trips in terms of difference of state of charge and desired amount of battery before the trip and the consequences of that make this problem too complex.

Now, the problem will be mathematically represented as follows:

$$\begin{aligned} EU^*_t\,(a_1,...,a_{t-1},j_1,...,j_{t-1}) = argmax_{a_t \in A^*} EU_t(a_1,...,a_{t-1},a_t,j_1,..,j_{t-1}) \\ + \sum_{i=1}^{t} BU(a_i, Soc_i(a_i,...,a_i,j_i,...,j_{i'})) \end{aligned} \tag{6.2}$$

where

$$EU_t(a_1,...,a_{t-1},a_t,j_1,...,j_{t-1}) = \sum_{j_t \in J} Pr_h(j_t|j_1,...j_{t-1}) \cdot (CU(j_i, Soc_t(a_1,...,a_t,j_1,...,j_{t'}))$$
$$+(EU^*_{t+duration}(a_1,...,a_t,j_1,...,j_t)) \tag{6.3}$$

$$Soc_t(a_1,...,a_t,j_1,...,j_{t'}) = b_{init} + \sum_{i=1}^{t} a_i - \sum_{i=1}^{t'} consumption(j_i) \tag{6.4}$$

$$CU(j_i, Soc_t(a_1,...,a_t,j_1,...,j_{t'})) = \begin{cases} U_{j^i} & \text{if } Soc_t \geq j^i_{Br} \\ 0 & \text{otherwise} \end{cases} \tag{6.5}$$

$$BU_t\left(a_1,...,a_t,j_1,...,j_{t'}\right) = \begin{cases} \int_{p_t \in P} f^{char}\left(p_t\right) \cdot \left(-p_t\right) dp_t - Cd_t\left(a_t, Soc_t(a_1,...,a_t,j_1,...,j_{t'})\right) \\ \text{if } a_t > 0 \\ 0 \quad \text{if } a_t = 0 \\ \int_{p_t \in P} f^{dis}\left(p_t\right) \cdot \left(p_t\right) dp_t - Cd_t\left(a_t, Soc_t(a_1,...,a_t,j_1,...,j_{t'})\right) \\ \text{if } a_t < 0 \end{cases} \tag{6.6}$$

$$EU_{m+1}\left(a_1,...,a_{t-1},a_t,j_1,...,j_{t-1}\right) = V\left(Soc_i(a_i,...,a_i,j_i,...,j_{i'})\right) \tag{6.7}$$

Subject to

$$a_t = 0 \ \forall \ j^i_{su} \leq t \leq j^i_{eu} \tag{6.8}$$

$$\forall t \in T : 0 \leq Soc_t \leq 100 \tag{6.9}$$

$$Cd_t\left(a_t, Soc_t\right) = \frac{C_b}{L_{ET}} \cdot a_t \cdot Soc_t \tag{6.10}$$

$$L_{ET} = L_c \cdot E_s \cdot DoD \tag{6.11}$$

Table 6.1: Overview of the main notations used.

Notation	**Description**
A^*	is a set of all possible actions.
T	number of time steps and can be defined as a T $= \{1, 2, ..., n\}$.
$j^i \subset J$	j_i a trip type is a subset of the trip set which containes the whole trip types.
$\forall\ t \in T : J_t = \{j_1, j_2, ..., j_n\}$	at every time step, there is a set of trips can be done.
$b_{init}, j^i_{Br} \in Soc$	the initial amount of battery and the desired amount of battery for each trip type are element of state of charge set.
$\forall j^i \in J : Pr_h\left(j^i_t\right)$	there is a specific probability for each trip to happen Pr_h.
$\forall j^i \in J : j^i_{Br}$	there is a desired amount of battery for each type of trip.
$\forall j^i \in J : U_{j^i}$	there is a specific utility function will be received if the trip happen for each trip.

After representing the problem mathematically, the key equations 6.2, 6.3, 6.5, 6.6 and the main constraints will be explained. In 6.2 , we calculate the argmax for EU^* so we have to do 6.3 ,6.5, and 6.6 recursively. However, we have to clarify that we start the day by $EU^*_1(b_{init}, \emptyset, \emptyset)$ where we do not chose the first action and we do not know what is the first trip. In 6.3, the expected utility $EU_t(a_1, ..., a_{t-1}, a_t, j_1, ..., j_{t-1})$ will be calculated based on the probability of the trip to happen $Pr_h\left(j^i_t\right)$ and the utility $CU(j_i, Soc_t(a_1, ..., a_t, j_1, ..., j_{t'}))$ which receives if the trip happens, as that calculated in 6.5. $CU(j_i, Soc_t(a_1, ..., a_t, j_1, ..., j_{t'}))$ receives U_{j^i}, if the trip can be done ($Soc_t \geq j^i_{Br}$) and 0 if it cannot be done. Moreover, in this equation we propose $EU^*_{t+duration}$ to consider the expected utility for the following trip, and to do so, we compute it at time step $t + duration$ whereas the duration is the using time of the trips at time t. Additionally, we propose 6.7 to stop 6.3 and to compute the utility of the trips that have been done at the end of the day. In addition, we propose $V\left(Soc_i(a_i, ..., a_i, j_i, ..., j_{i'})\right)$, which is a function that converts the level of battery power that is returned to the V2G driver at the end of the day to monetary value. Also, to calculate the battery amount after each step, we propose 6.4. Here, $consumption(j_i)$ is a function to compute the consumption of doing each trip. Besides, in 6.6, if we charging, the above equation will be conducted whereas the $f^{char}(p_t)$ function that represents the charging price uncertainty. On the other hand if we discharging, the below equation will be conducted whereas the $f^{dis}(p_t)$ function that represents the discharging price uncertainty. Either in charging or discharging situation we subtract the cost of the battery degradation $Cd_t\left(a_t, Soc_t\right)$. Here, we model the battery degradation $Cd_t\left(a_t, Soc_t\right)$ as (Kempton and Tomić, 2005) as 6.10, where C_b is battery capital cost, and L_{ET} is battery lifetime throughput energy in kWh for the particular cycling regime. To do so, we have to do

6.11 first, where L_c is lifetime in cycles, E_s the total energy storage of the battery, and DoD is the depth-of-discharge for which L_c was determined.

With regard to constraints, we first ensure that the car is available to the driver during the required usage time from j_{su}^i until time j_{eu}^i. We proposed this constraint 6.8 which says to the agent during this period that it cannot do anything. Further, to ensure that the battery state of charge does not exceed its scope, which is between 0 and 100 we proposed 6.9. Finally, the main notations used are provided in Table 6.1.

6.3 The Optimization Module

After formulating the problem in the previous section, the design of this optimisation module is discussed in detail in the present section.

In order to solve our problem, we divided our simulation into two modules. The first module is our proposed heuristic algorithm, which will be discussed in detail in the following section. The second module is the user behaviour module where we apply the MNL, which will be discussed in the second section.

6.3.1 Proposed heuristic algorithm

We start with a soft constraint whereby the agent has a one-day price scenario in advance and will trade on behalf of V2G drivers with the aim of maximising their profits; the agent will also have knowledge about when they will use their cars and their desired amount of remaining battery charge before use. Moreover, we assume that they will use their cars once a day. To deal with these constraints, we use a backward induction algorithm (Almansour et al., 2017) - something which has been discussed in detail in Chapter 3. Following this, we increase the complexity of said problem by assuming multiple scenario prices in the hour ahead price market (Almansour et al., 2018a); indeed, this has been discussed in detail in Chapter 4.

Here, in addition to the former constraints, we consider the uncertainty in the drivers vehicle usage where we have multiple daily trips scenarios. To deal with this new constraint, we propose an algorithm which combines our proposed algorithm from the previous model in Chapter 4 with two consensus algorithms (Borda voting and majority voting) and with the expected value; we also apply the multinomial logit model to deal with the daily trips issue, as discussed earlier.

In our proposed algorithm, termed the V2G heuristic V.2 algorithm (see Algorithm 6), the voters are those who make the decisions related to the backward induction algorithm for each scenario at every hour, and the candidates constitute the set of actions. In this experiment, the V2G agent has three actions, namely charging, discharging, and doing nothing. Moreover, we assume that we have n number of scenarios for the power market prices and m number of scenarios for the trips for each t. Thus, the number of voters is n, while the number of candidates is 3. More specifically, we firstly generate n scenarios for the power market, where each hour has a price. Following this, we generate m scenarios for trips.

For each trip in each scenario if the state of charge Soc is grater than or equal the desired amount of battery of the trip j^i_{Br}, the utility will be U_{j^i} which is defined based on the trip type. However if it does not, the utility will be 0. After commuting the all trips, the expected utility of applying these trips will be computed based on the probability for each trip to happen and the utility of doing this trip. Then, the trip will be chosen by applying MNL method, which will be discussed in details in next section.

Afterwards, for each hour the backward induction computes the utility for each action and ranks it, based on the Borda voting rules, so that the highest profit scores 2 points, the second highest scores 1 point and the last nothing. This step is repeated for all the scenarios and the results recorded. (Algorithm 2 in Chapter 4) shows how Borda voting works. Next, after calculating the number of points for each action, the one that receives the most points is chosen and applied at this hour. The steps are repeated for all the hours and, by the end, we have a table showing the best action to apply at each hour.

In the case of majority voting, the n price scenarios already initiated are used. Then, for each hour, the backward induction computes the utility for each action and ranks it according to the majority voting rules, where just the highest profit is considered, and the action that provides the highest profit scores 1 point and the others are ignored. The prior step will be repeated for all the scenarios and the results saved. (Algorithm 3 in Chapter 4) shows how majority voting works. Afterwards, by calculating the number of points for the actions in all of the scenarios, the one that receives the most points is chosen and applied at this hour. These steps are repeated for all the hours and, by the end, we have a table showing the best action to apply at each hour. Under the expected value algorithm (see Algorithm 4 in Chapter 4), after each running of the offline algorithm (backward induction), the action that has been chosen will be recorded with its utility function after computing all of the scenarios. The average utility function will be calculated and the action that provides the highest utility function will be chosen.

After computing the expected utility of the vehicle usage behavior (EUD) and expected utility of the power market price (EU) for each scenario, the U_s will be the summation of them. Then, the algorithm applies the consensus rules (Borda, majority and expected value) and it choses the trip and the action that maximise U_s. Next, the chosen trip will be applied and the Soc is computing based on that.

Finally, a scenario which combines the price and the trips will be generated; we assume that this is a real-world scenario, and the actions produced by each round of voting

(Borda, majority and expected value) will be applied, the aim being to find the one that achieves the most profit.

We will now describe Algorithm 6 in more detail. Initially, the algorithm starts with an empty set of chosen actions (line 1) and an empty set of chosen trips (line 2). Moreover, it assumes at every time step that there is a set of action A, which, for example, can contain charging, discharging, or do nothing) (line 3). In addition, at every time step there is a set of trips, J, which can contain commuting trip, extra trip, or do nothing (line 4). Furthermore, on line 5, the algorithm assigns the initial amount of battery to be the state of charge. Further, it calls the GenerateScenarios function to sample the price scenarios (line 6) and the GenerateTripScenarios function to sample the trips might come u scenarios (line 7). Following this, the algorithm matches $STrip$ and SP and saves that in S as a subset of the scenarios combinations (line 8). Subsequently, between lines 9 and 28 the algorithm computes the best available action for each time step as follows. Between lines 10 and 19, the algorithm deals with each scenario as follows. It computes the utility for each trip (lines 11 - 19). It uses a conditional statement to compute the utility of the trip. If the state of charge is larger or equal to the desired amount of the battery for the trip, then the utility will be U_{ji}, else the utility will be zero. Following this, on line 20, the algorithm computes the expected utility for each trip and saves them in the EUD vector. Subsequently, between lines 22 and 24, the algorithm computes the EU for each action and saves them in the EU vector. The algorithm then calculates the utility of the scenario by doing the summation to EUD and EU and saving the result in Us (line 25). Subsequently, the algorithm adds U_s to U, the latter of which is a vector which contains the summation for each scenario utility (line 26). Once this has been achieved, the algorithm calls one of the three voting algorithms, namely Borda, Majority or Expected value, and saves the result in the TotalScore vector (line 27). The algorithm then chooses the action and the trips that maximise TotalScore, where $A\&J$ is a vector which contains the chosen action and trips (line 29). Next, on line 31, the algorithm calls the UserBehaviour function, which represents how the users choose their trips. It then saves the results for the former step in $A\&J$, which is a vector that contains the chosen action and the expected trip for each time step (line 33). Following this, the algorithm computes the Soc after doing the chosen action and trip (line 34). Finally, after computing the whole T, a vector of chosen action will be returned.

6.3.2 User behaviour module

To model how the drivers might choose their trips we propose User behavior Algorithm 7. In this algorithm we apply Multinomial logit model technique. In this section we will discuss the Multinomial logit model in details.

Discrete choice models used to describe how the decision makers select among several options. The decision makers could be persons, organizations, or any other decision-making unit, and the options might be goods, actions, or any other choices or items over which choice must be made. To apply discrete choice framework, the set of alternatives called the choice set should attained three features. Firstly, the options should be mutually exclusive from the decision makers viewpoint. Secondly, the choice set should be exhaustive which means that all potential options should be considered. Finally, the number of choices should be finite (Train, 2009). In fact, we cannot consider the all factors that effect each choice decision as their determinants are observed partly or cannot be measured. Consequently, discrete choice models apply stochastic assumptions to consider the unobserved factors correlated to choice alternatives, taste variation, and heterogeneous choice sets (Baltas and Doyle, 2001).

We apply Multinomial logit model (MNL) because it is one of the most widely used discrete choice model since its formula for the choice probabilities takes a closed form and is readily interpretable. Originally, Luce (2005) derived the logit model formula from independence from irrelevant alternatives (IIA) property, which are assumptions about the features of choice probabilities. Luc was inspired by the work of McFadden et al. (1973) and Ben-Akiva and Lerman (1985) which are the most important studies discuss the discrete choice model. Furthermore, Yu and Sun (2012) compared between four types of typical discrete choice models which are Heteroscedastic Extreme Value, Mixed logit model, Multinomial logit model, and Nested logit model by using a travel mode choice case. They conclude that MNL model is the first choice if sample data satisfied with IIA property.

For the purposes of this research, discrete choice modelling methods, and specifically the Multinomial Logit model has been applied to model how the drivers choose their trips. In discrete choice model, the probability of an individual choosing a given choice from a finite set of options is a function of the context variables and the relative attraction of the option under consideration. The MNL probability can be expressed as

$$P_{ij} = \frac{\exp\left(V_{ij}\right)}{\sum_{k=1}^{J} \exp\left(V_{ik}\right)}, k \in C_t \tag{6.12}$$

Where i is the decision maker, j is choice item and V_{ij} is the observable utility for ith decision maker on the jth choice and C is the available choice set.

The logit probabilities offer several desirable features. First, P_{ij} should be between one and zero like any other probability. Furthermore, The relation of the logit probability to representative utility is sigmoid, or S-shaped. This feature has implications for the influence of variations in explanatory variables. If the utility of an alternative is very small compared with other choices, a small increase in the utility of the alternative has tiny effect on the chosen probability and the other choices are still sufficiently better that this tiny increase. Also, if one choice is far superior to the other alternatives, the growth of its representative utility has tiny effect on the choice probability. Actually, the sigmoid shape of logit model is a common feature of the discrete choice models and has significant inferences for the decision makers (Train, 2009).

In more details, in our model we deal with two types of probabilities. The first one is the probability for each trip to happen and the second is the probability for the trip to be chosen by the V2G drivers. In details, one of the important issues that we have to consider in our model is that, how the drivers choosing their favorite trip. In order of answering this question our model trying to deal with this issue by applying the multinomial logit model. Indeed, if we consider each trip duration that makes the problem more complex and unsolvable, so the MNL approach seems to be a reasonable method to sample the solution.

To do that, we have to compute the expected utility for doing each available trip by applying 6.3. After that, we model how the V2G drivers choosing their trips by using multinomial logit model. Here we assume V_{ij} is $CU\,(j_i, Soc_t)$ and we compute it from 6.5. Moreover, we compute the probability for each trip by applying 6.12. Where is C_t is the is the set of the available trips at t. Finally, the trip that has the highest probability will be chosen.

As we mentioned earlier the choice should be mutually exclusive. Thus, in our model if we have two trips j_1 and j_2, and there is a probability to one of them to happen alone or there is a probability for both of them to happen together. We are applying the mutually exclusive rule by assuming the options are a trip j_1 might be happened only, or trip j_2 only, or j_1 and j_2.

After discussing the optimization module, the next part considers the experimental settings and benchmark algorithms.

6.4 Benchmark Algorithms and Experimental Settings

In this section, the benchmark algorithms that we applied will be considered. After that, the experimental settings which we used in our experiments will be discussed.

6.4.1 Benchmark Algorithms

Before discussing the results, it is important to explain the benchmark algorithms used to compare the model and to evaluate our solution. Here, we proposed two benchmark algorithms, which are complete information and naive algorithm. We use complete information algorithm as an upper bound benchmark and naive algorithm as a lower bound benchmark. The definition of each one will be provided in the following sections.

6.4.1.1 Complete Information Algorithm

This algorithm starts at the last available hour of the day chooses its action by maximizing the utility for each next step, compares the utility for each choice, and selects the highest until reaching the first available hour of the day. The Complete Information algorithm here is different form the proposed algorithm in that, it has full information about the day trips.

6.4.1.2 Naive Algorithm

It starts at the first available hour of the day, charge the battery until reach the maximum rate of charging. Actually, it just applies a forward induction technique and it is goal is keeping the battery full most of the time.

6.4.2 Experimental Settings

Before we provide the assumptions made for these experiments, we must clarify that all of these assumptions have been used to illustrate purposes but the model is generic and can be used with any data. Now, the assumptions made for this experiment are as follows:

- We start the day with the full amount of battery ($b_{in} = 100$) since we assume that people fully charge their batteries at night. Moreover, we start the day with a half amount of battery ($b_{in} = 50$) in another experiments in order to run the simulation under different circumstances.
- We assume there are three types of trips in our experiment (j^1, j^2, j^3), which are commuting trips j^1, extra trips j^2, and unplanned trips j^3.
- The initial values of the probability of each trip type happening $Pr_h\left(j_t^i\right)$, the number of trips daily, the desired amount of battery for each trip type j_{Br}^i, the distance drivers drive daily, and the distance for each trip, have been used from the data extracted from the survey (which has been discussed in chapter 5).
- We apply the price of the Saudi Arabia power market for one month, which is August 2017.
- We assume the utility that is receiving if commuting trip done is 100 ($U_{j^1} = 100$), if extra trip done is 20 ($U_{j^2} = 20$), and if unplanned trip done is 3 ($U_{j^3} = 3$).
- the desired amount of battery for commuting trip is 60% of the battery ($j_{Br}^1 =$ 60%), the desired amount of battery for extra trip is 40% of the battery ($j_{Br}^2 =$

40%) and the desired amount of battery for unplanned trip is 30% of the battery (j^3_{Br} = 30%).

- It is necessary to model the sale price in the power market, and this information has not existed until now in the Saudi power markets, which is our case study in this simulation. In order to achieve said goal, we use this assumption to produce the sale price. Sale price for each hour = buying price $-\alpha$. Where α is a random number that we generated for each hour by using Excel; this number is between 25 and 90 halalah (it is like cents).

- To compute the battery degradation cost Cd in the experiments, we set ($C_d = .08$ US dollar , which is equal to .30 halalah / kWh, we convert it to Saudi riyal in aim of the constancy for the other study factors.). This is based on the (CALB 100 Ah CA Series Lithium Iron Phosphate Battery), see West (2018). However, we belief our model can work with any type of batteries.

- The number of trips daily is generated as an integer number within these options (1 - 2, 3 - 4 and 5 - 6) trips with equal probability at the start of each trips scenario.

- We generate the trips scenarios randomly. Following this, we use the MatchMaking function to allocate the power market price scenarios to the trips scenarios randomly.

- To model the consumption of each trip in our simulation we have to consider the trip distance. To do so, we use the date that we collected in the survey which has been discussed in Chapter 5. As the survey, most of the participants' expect to drive between 11 - 20 KM, while the minority of the participants feel that they drive less than 5 KM; indeed, roughly the same percentage can be applied to those who think they drive more than 50 KM. We think that this is reasonable, since we do not see any relation between type of trip and distance. In order to model this issue, for each trip type, the distances are generated as an integer number that ranges between the options (< 5 KM, 6 - 10 KM, 11 - 20 KM, 21 - 50 KM, and > 50 KM) with equal probability.

- To model each trip duration, we generate the duration time randomly as an integer number ranging between 1 and 5 hours, selected with equal probability. Then, the j^i_{su} will be generated randomly and the j^i_{eu} will be equal to the summation of the duration time and the j^i_{su}.

- To test our solution, we run our heuristic algorithm and the benchmark algorithm with what we call real trips. To generate the real trip, we use the Roulette Wheel Selection algorithm (Holland and Goldberg, 1989). We apply this algorithm to generate a trip randomly between a set of trips; indeed, for each trip there is a different probability of it happening. In more details, by using the data extracted from the survey in chapter 5, the probability of commuting trip to happen is 60%

($Pr_h\left(j^1\right) = 60\%$), the probability of extra trips to happen is 25% ($Pr_h\left(j^2\right) = 25\%$), and the probability of unplanned trip to happen is 15% ($Pr_h\left(j^3\right) = 15\%$). However, we have to clarify that, in the survey most of the participants think that the probability of unplanned and extra trips is 20% but we change them slightly in order to make some variance in the experiment.

- To convert the remaining amount of battery charge at the end of the day to monetary value, we generate an offering price randomly and assume that we will sell it at this price.

With this section having outlined the benchmark algorithms and experimental settings, the following section discusses the results of running the simulation.

6.5 Results

In order to discuss the results we must explain the differences between our proposed algorithm and the benchmark algorithms. To achieve this, it is vital to point out the crucial difference between our solution and the complete information algorithm, namely that the latter has full information about the day trips scenario. Moreover, in our solution, if the chosen trip cannot be made, an alternative trip will be made after applying the MNL, and will receive the utility of doing the trips. On the other hand, in the complete information algorithm, if the chosen trip cannot be made, it will receive nothing. Additionally, we have to clarify that, we chose the results of our proposed algorithm with expected value in order to do the comparison with the benchmark algorithms. Actually, we chose it because it outperforms the borda and majority voting at all of the experiments.

After running the experiments 600 times with different number of scenarios and under different circumstances in terms to compare between the naive algorithm and complete information algorithm with our proposed algorithm we found the following.

In terms to the comparison with the naive algorithm we found that, our proposed algorithm outperforms the naive algorithm in terms to the average profits when we start the experiments with a half amount of battery ($b_{in} = 50$), as the following results, in the case of 10 scenarios our proposed algorithm outperforms the naive algorithm 12.55 times, in the case of 50 scenarios our proposed algorithm outperforms the naive algorithm 15.13 times, and in the case of 100 scenarios our proposed algorithm outperforms the naive algorithm 16.39 times, as figure 6.2 shows. Moreover, our proposed algorithm outperforms the naive algorithm in terms to the average profits when we start the experiments with a full amount of battery ($b_{in} = 100$), as the following results, in the case of 10 scenarios our proposed algorithm outperforms the naive algorithm 4.94 times, in the case of 50 scenarios our proposed algorithm outperforms the naive algorithm 5.15

times, and in the case of 100 scenarios our proposed algorithm outperforms the naive algorithm 5.33 times, as figure 6.3 illustrates. The error bars in Figure 6.2 and Figure 6.3 show the 95% confidence interval of each algorithm results. Since these error bars do not overlap and the sample sizes are equal we can conclude that, the difference between our proposed algorithm and the naive algorithm results is statistically significant with a P value ≤ 0.05 (Payton et al., 2003).

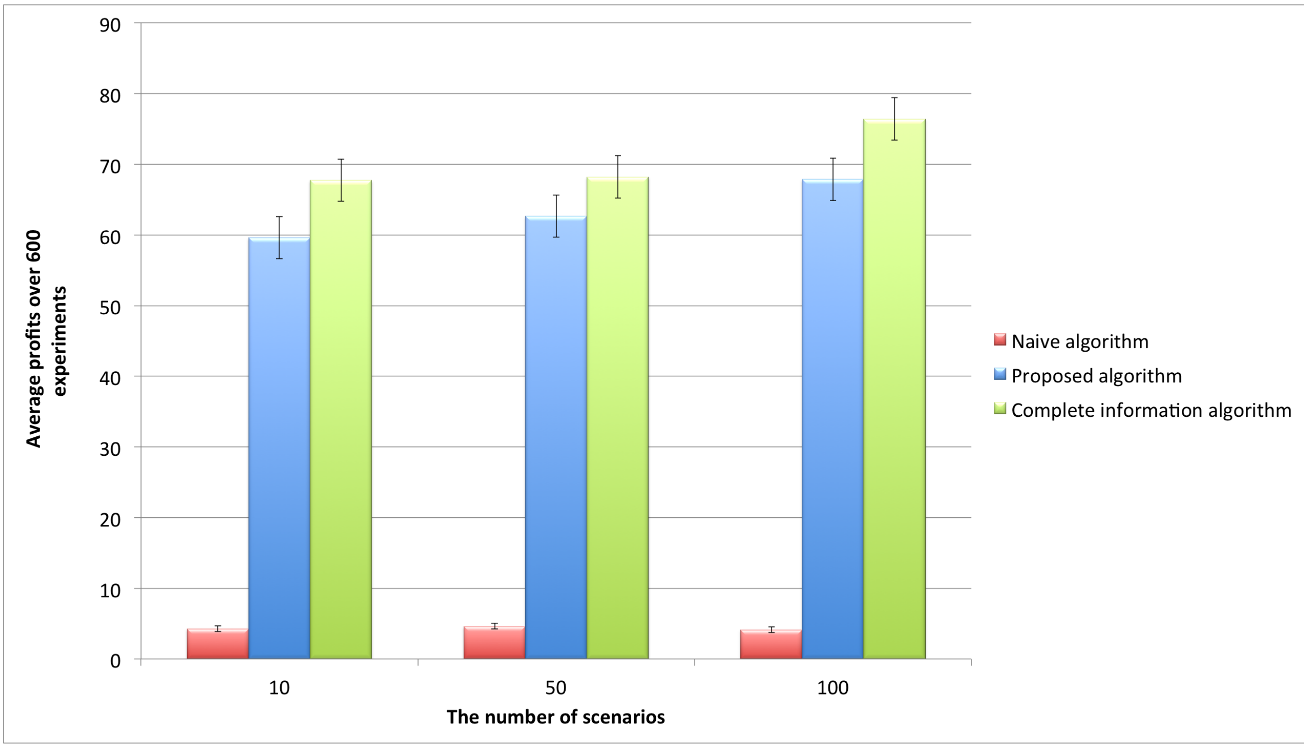

Figure 6.2: Bar chart showing the average profits over 600 experiments with different number of scenarios for our proposed algorithm with naive algorithm and complete information algorithm when we start the day with a half amount of battery ($b_{in} = 50$) with the error bars.

On the other hand, in terms to the comparison with the complete information algorithm the results show that, our proposed algorithm provides close performance of the complete information algorithm in terms to the average profits when we start the experiments with a half amount of battery ($b_{in} = 50$), as the following results, in the case of 10 scenarios our proposed algorithm performs 88% of the complete information algorithm, in the case of 50 scenarios our proposed algorithm performs 91% of the complete information algorithm, and in the case of 100 scenarios our proposed algorithm performs 88% of the complete information algorithm, as figure 6.2 shows. Furthermore, the complete information algorithm almost same our proposed algorithm in terms to the average profits when we start the experiments with a full amount of battery ($b_{in} = 100$) as figure 6.3 shows. The error bars in Figure 6.2 shows the 95% confidence interval of each algorithm results when we start the experiments with a half amount of battery ($b_{in} = 50$). Since these error bars do not overlap and the sample sizes are equal we can conclude that,

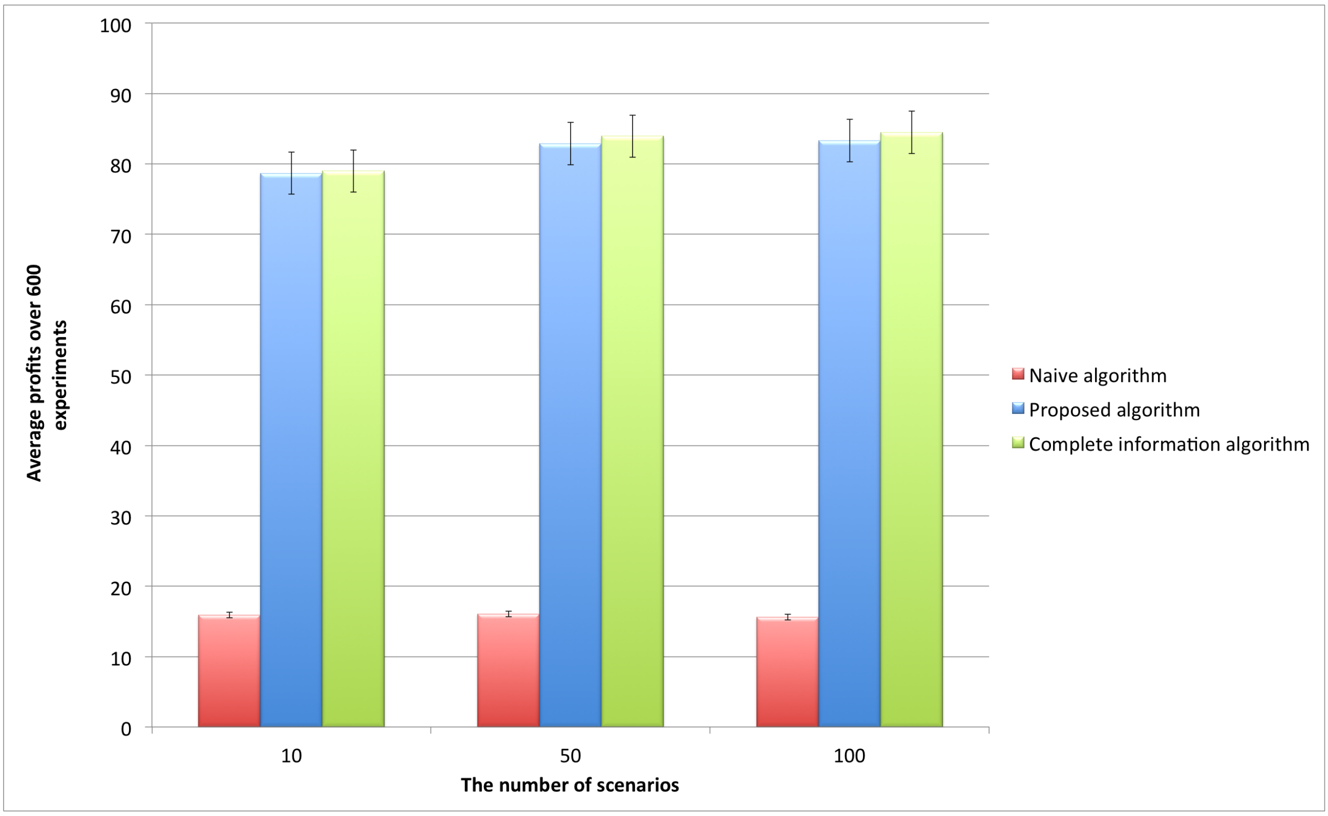

Figure 6.3: Bar chart showing the average profits over 600 experiments with different number of scenarios for our proposed algorithm with naive algorithm and complete information algorithm when we start the day with a full amount of battery ($b_{in} = 100$) with the error bars.

the difference between our proposed algorithm and the complete information algorithm results is statistically significant with a P value ≤ 0.05 (Payton et al., 2003). However, the error bars in Figure 6.3 shows there is an overlap between the error bars so the difference between our proposed algorithm and the complete information algorithm results is not statistically significant, when we start the experiments with a full amount of battery ($b_{in} = 100$). This is might be each algorithm starts the experiment with a full amount of battery so it can work with relaxed conditions. This is a promising result if we consider that the the complete information algorithm deals with full information data and our solution deals with uncertain data. In conclusion, the results show that our solution provides promising results and can therefore represent a baseline for future development.

Having now provided the results of our experiments, in the next part we will provide the summary of this chapter.

6.6 Summary

This chapter described the model that proposed to maximize the V2G driver profits with considering of two types of uncertainties which are power market prices and vehicle usage behavior. Afterward, in more detail, the problem of price uncertainty in the context of V2G is discussed. Next, our optimization algorithm is considered. Then, the simulation results using the algorithm are shown and the results are discussed.

We have discussed how to design an algorithm to trade on behalf of V2G drivers that can maximise their profit by understanding power market price behaviour and their vehicle usage. With this having been achieved, we next present a survey of V2G parking lots preferences, as a first stage in designing the V2G parking lots manager agent.

Algorithm 6: V2G Heuristic algorithm V.2

Input: $j^i_{Br} \forall j^i \in J$, b_{init}, $U_{j^i} \forall j^i \in J$, $Prh_{j^i} \forall j^i \in J$

Output: It returns the vector *chosenAction*, where each element $chosenAction_t \in A$ is the chosen action at time $t \in T$

$\forall\ t \in T : chosenAction \leftarrow \theta$ // we start with an empty set of chosen action.

$\forall\ t \in T : SelctedTrip \leftarrow \theta$ // we start with an empty set of chosen trip.

$\forall\ A \leftarrow \{a_1, a_2, ..., a_n\}$ // at every time step there is a set of action A, which is for example can have (charging, discharging, do nothing).

$\forall\ t \in T : J \leftarrow \{j_1, j_2, ..., j_n\}$ // at every time step there is a set of trips J, which is for example can have (commuting trip, extra trip, do nothing).

$Soc \leftarrow b_{init}$

$S_P \leftarrow GenerateScenarios()$// GenerateScenarios is a function that sample the price scenarios

$S_{Trip} \leftarrow GenerateTripScenarios()$// GenerateTripScenarios is a function that sample the trips might come up scenarios.

$S \leftarrow MatchMaking(S_{Trip}, S_P)$ //match S_{Trip} and S_P and save that in S to be a subset of the scenarios combinations.

foreach $t \in T$ **do**

    foreach $s \in S$ **do**

        foreach $j \in J$ **do**

            // Conditional statement to compute the utility of the trip. If the state of charge is larger or equal to the desired amount of the battery of the trip, then the utility will be U_{j^i}, else the utility will be zero.

            if $(Soc_t \geq j^i_{Br}\ )$ **then**

                $CU_{j^i} = U_{j^i}$

                $CU_J = CU_J + CU_{j^i}$

                else

                $CU_{j^i} = 0$

                $CU_J = CU_J + CU_{j^i}$

        end foreach

        $EUD \leftarrow computeEUD(Prh_{j^i} \forall j^i \in J, CU_J)$ // Function computes the expected utility for each trip and save them in EUD vector.

        $J_s \leftarrow max(EUD)$ // max is a function that returns the highest trip value.

        foreach $a \in A$ **do**

            $EU_a = V2GBackwardInduction(j_{su} \forall\ j \in J, Soc_t, j^i_{Br} \forall j^i \in J, s)$ // EU is a vector which contains the EU for each action.

        end foreach

        $U_s = EUD + EU$ // The utility of the scenario is the summation of EUD and EU.

        $U = U_s + U$ // U is a vector which contains the summation for each scenario utility.

        $TotalScore \leftarrow Call\ Borda(U)\ |Majority(U)\ |\ Expected\ value(U)$

    end foreach

    $A\&J_t \leftarrow max(TotalScore)$ // chose the action and the trips that maximise TotalScore where A& J is a vector which contains chosen action and trips.

    receive the real trip.

    $J_t \leftarrow$ Call User Behaviour $(Prh_j \forall\ j \in J$, Soc, $j^i_{Br} \forall\ j \in J$, $EUD)$

    // UserBehaviour is function to represent how the users choose their trips.

    $A\&J = A\&J + A\&J_t$ // $A\&J$ is a vector which contains the chosen action and the expected trip for each time step.

    Soc_t = consumption (Soc, J_t, a_t) // function compute the Soc after doing the chosen action and trip.

end foreach

return chosenAction $\forall t \in T$ // after compute the whole T, a vector of chosen action will be return.

Algorithm 7: User Behaviour

Input: $Prh_j \forall\ j \in J$, Soc, $j^i_{Br} \forall\ j \in J$, EUD

Output: the selected trip j_s

$\forall\ t \in T : J \leftarrow \{j_1, j_2, ..., j_n\}$

Compute the expected utility for each trip.

$j_s =$ the chosen trip after applying MNL

return j_s

Chapter 7

Survey of V2G Parking lots Preferences

This chapter aims to discuss the survey of vehicle parking lots preferences for the current parking lots systems and a new type of parking lots concept. First, we provide an introduction for this survey that includes it is objectives, hypothesis and research questions. Then, we consider how we collect the data and choose the sample. Next, we discuss and analyse the results. Afterward, we consider the survey findings. Finally, we summarise this chapter.

7.1 Introduction

There are many parking lots could be used to apply a V2G concept such as the parking lots at the workplaces, airports and the big malls. To do so, we study the vehicle drivers' preferences in the parking lots in order to investigate the feasibility of using V2G parking lots. In details, the aim of this study is to provide a comprehensive understanding of how V2G drivers satisfy about a parking lot and how they make a decision whether or not use the V2G parking lot. Moreover, it discusses the factors that considered by the vehicle drivers when choosing the parking lot. Furthermore, it investigates which payment policy type and early release penalty systems they prefer.

Indeed, we use this survey as a first phase of our future work where we are going to model a multi agents environment, and we assume the V2G lots agent is one of the most important players which may effect in the power market. The objectives of this survey can be summarised as the following:

- The factors that considered by the vehicle drivers when choosing the parking lot will be discussed.

- What is the better type of payment policy could be used in the V2G parking lots.
- What is the better type of early release penalty policy could be used in the V2G parking lots.

Moreover, the hypothesis for this survey is that, the types of payment policy and early release penalty system influence the decision of vehicle driver of choosing the parking lot. This comprehensive hypothesis could be divided into the following sub-hypotheses.

- H1: The type of payment policy of the parking lots will have a significant impact on the vehicle drivers decision for parking their vehicles.
- H2: The early release penalty system of the parking lots will have a significant impact on the vehicle drivers decision for parking their vehicles.
- H3: Most of the vehicle drivers pay more than what they need in the parking lots.

Furthermore, before providing an overview about the survey in the next section, we are listing the survey research questions here.

- To what extent does the type of payment policy of the parking lots influence the vehicle drivers' choice to park their vehicles?
- Would an early penalty system of the parking lots influence the vehicle drivers choice to leave before 30 minutes to the hour from the parking lot?
- How accurate are the drivers in predicting how long the period of parking and how they deal with that?

7.2 Study Overview

A survey has been designed based on the research purposes in order to capture the V2G parking lots preferences. The appropriate use of data collection methods is necessary for this study in terms of ensuring that accurate and reliable data are obtained.

Furthermore, the survey administered to the participants is an online survey named Qualtrics. It provides a usable interface for the participants to response the survey questions. Moreover, the extracted data can be simply analysed using statistical tests. Additionally, an ethical document named Consent Form is provided to the participants, as is the School Ethics Committee reference number (31362). They are informed of the purposes of the study and of their right to withdraw at any time unconditionally and without reason.

Besides, the respondents are invited to participate through social networks and email, and are sent a web link to the survey. Any person with a driving license and has experience with parking lots concept is considered an appropriate participant in this study. A total of 81 participants responded to this survey. Also, there is no relationship between the researcher and the sample. The researcher is an observer of the sample population. Furthermore, the participants are from the University of Southampton student society (see appendix B). Following this, we will discuss the results in detail in the following section.

7.3 Results and Analysis

In this part we provide a deep discussion of the results. To do so, we list the methods that we applied to analyse the data. Afterward, we discuss the results in more detail. Therefore, in order to analyse the data, a number of methods are used, as follows:

- **Demonstration, discussion, and analysis of results regarding participants' preferences**.

  This section of the study illustrates the participants parking lots preferences' based on their responses to the survey questions. The results are presented in the form of percentages, tables, and statistical figures.

- **Descriptive statistical methods**.

  A number of descriptive statistical techniques are utilised, such as proportion and means, with the aim of obtaining summary information.

More specifically, we divide the survey into three sections. Firstly, we ask about certain demographic information. After that, we ask about the respondents behaviour and preferences in relation to using the existing vehicle parking lots. Specially, the accuracy of the expectations of the drivers in the parking period at two types of existing vehicle parking lots systems, which are pay on foot parking and pay and display parking. Finally, we ask the participants about their preferences for hypothetical vehicle parking lots which represent our conception about the V2G parking lots.

Additionally, a Likert scale questionnaire was used to collect information about how the views of the study participants vary regarding certain questions. As said by Matell and Jacoby (1971), there is not optimum number of Likert scale items. Indeed, this choice is based on the question types that the study is discussed. Here, we use a 5-point Likert scale questionnaire to reflect how the participants realize the questions. The scale ranged from 5, which is strongly agree, to 1, which is strongly disagree.

Table 7.1: The participants' age.

Response	Percentage
18 - 28	14.81%
29 - 39	72.22%
40 - 50	9.26%
51 - 60	3.70%

Before we discuss the results we have to clarify that, we exclude the all responses for the participants who seems to be answer randomly where we ask the question and ask it again conversely, that technique has been used to increase the credibility of this study. 27 responses have been excluded from 81 as a total so the remaining sample is 54 participants.

As Figure 7.1 and Table 7.1 show, most of the drivers who participate in this survey are between 29 - 39 years old (72.22%). Then, the second majority is the drivers who are between 18 - 28 years old (14.81%) However the minority are between 51 - 60 years old. Indeed, this is reasonable, since people in this period are, in comparison to others, less used to dealing with the social networks on which we publish our survey.

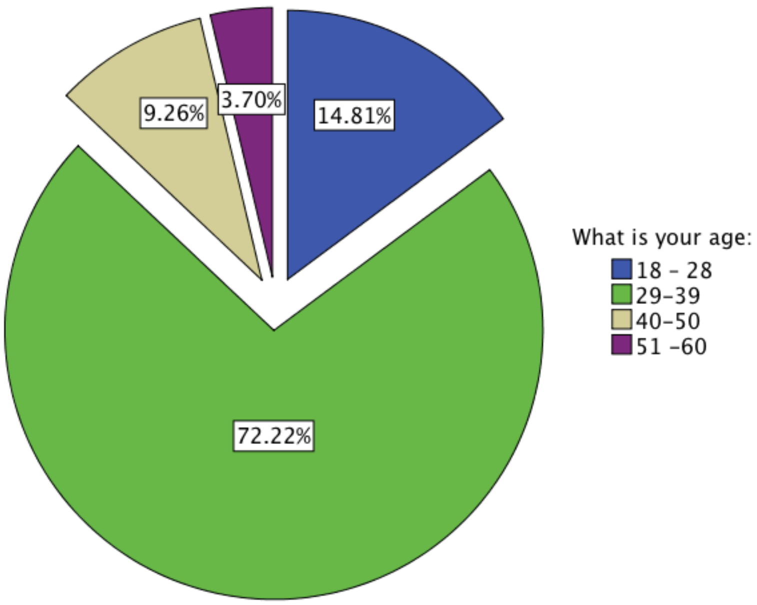

Figure 7.1: Pie chart showing the participants' age.

Moreover, as the Figure 7.2 and Table 7.2 illustrate, in the highest educational attainment for the participants we find that the majority of the study sample is people who have a Master degree. This is followed by students currently undertaking a Bachelor degree. After that, the participants who have a PhD in a very close percentage with the previous group. After this, and differing considerably in number, come those people with a Diploma and under bachelor degree. Actually, we feel that this is understandable because we apply this survey in a university society.

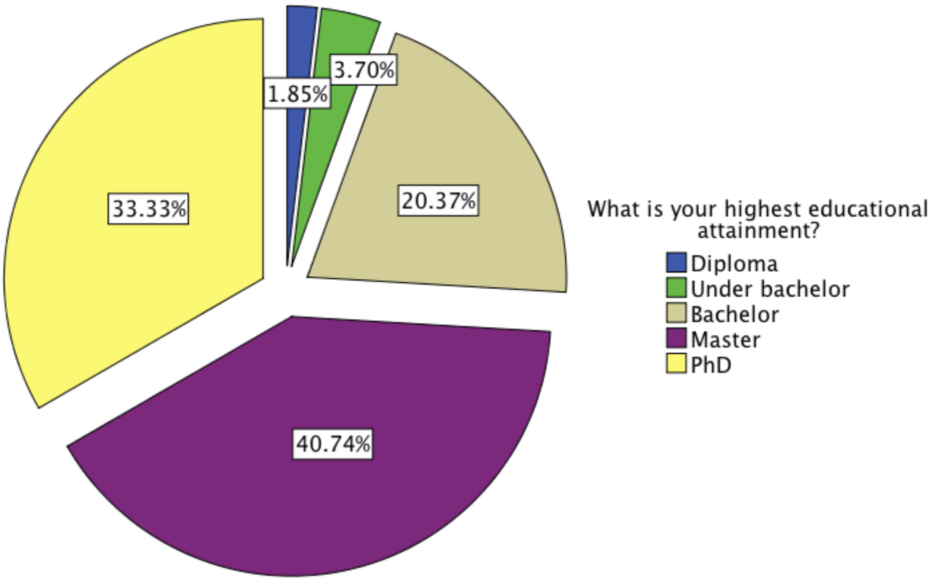

Figure 7.2: Pie chart showing the participants' highest educational attainment.

Table 7.2: The participants' highest educational attainment.

Response	**Percentage**
Diploma	1.85%
Under bachelor	3.70%
Bachelor	20.37%
Master	40.74%
PhD	33.33%

Afterwards, in order investigate the drivers' accuracy in expecting the parking period when they park their cars, we divided the parking lots into two types, which are pay on foot parking and pay and display parking.

In more details, pay on foot parking can be defined as where the drivers can park and pay at a payment machine before returning to their cars (for example, the West quay car parking). On the other hand, pay and display parking can be defined as where the drivers can park their cars, and then pay the machine based on the period of time they choose to issue a ticket to be displayed (for example, the university of Southampton car parking).

In terms of the pay on foot parking type we receive the following results. For the question, on average, when parking your car, how often do you know how long will you be parking. (Within 30 minutes leeway). As the Figure 7.3 and Table 7.3 show the majority of the participants choose often (44.4%) and sometimes (40.7%). Then, with a considerable different of percentage the participants who choose always(7.4%) and rarely (5.6%). However, the minority of the participants are those who choose not at all (1.9%).

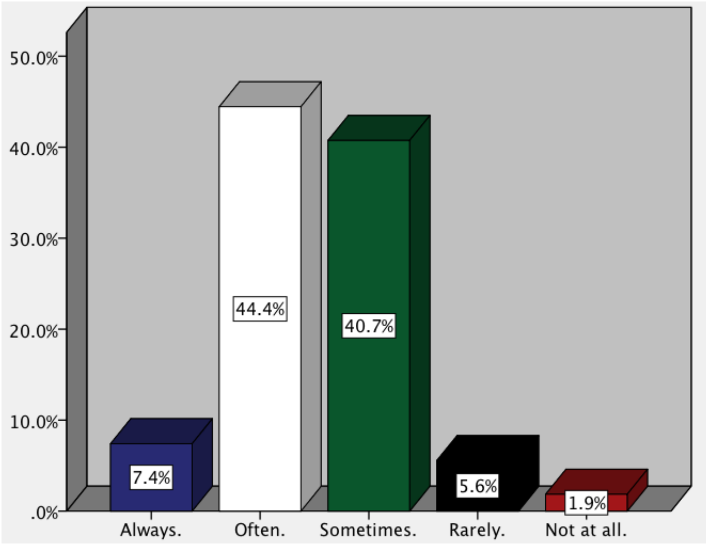

Figure 7.3: Bar chart showing the answer to the question: "On average, when parking your car, how often do you know how long will you be parked. (Within 30 minutes leeway)."

Table 7.3: Answer to the question: "On average, when parking your car, how often do you know how long will you be parking. (Within 30 minutes leeway)."

Response	Percentage
Always	7.4%
Often	44.4%
Sometimes	40.7%
Rarely	5.6%
Not at all	1.9%

Table 7.4: Answer to the question: "On average, when parking your car, what is the difference between the expected time of parking and the actual period you spend?"

Response	Percentage
There is no difference	7.4%
Less than one hour	64.8%
1 - 2 hours	20.4%
2 - 3 hours	7.4%

Moreover, as the Figure 7.4 and Table 7.4 display, most of the participants think that the difference between the expected time of parking and the actual period they spend is less than one hour (64.8%). Furthermore, (20.4%) of the participants state this difference is between 1 and 2 hours and (7.4%) of the sample claim there is no difference between their expectations time of parking and the actual period they spend and with the same percentage those who think this difference is between 2 and 3 hours.

Thereafter, we ask about the pay and display parking. The first question about this type of parking is that, on average, when you are parking your car for a specific time, how

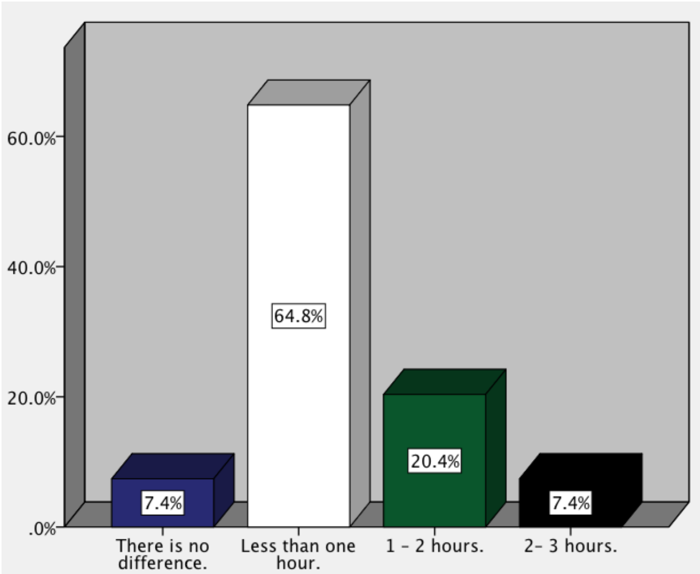

Figure 7.4: Bar chart showing the answer to the question: "On average, when parking your car, what is the difference between the expected time of parking and the actual period you spend?"

often do you take your car before the time is finished up? (within 30 minutes leeway), and the responses are as the following. About the half of the participants say they often do that (44.4%). Following, more than a quarter of the sample are chosen sometimes (31.5%). In contrast, the minority of the participants are rarely or not at all do that, as Figure 7.5 and Table 7.5 show.

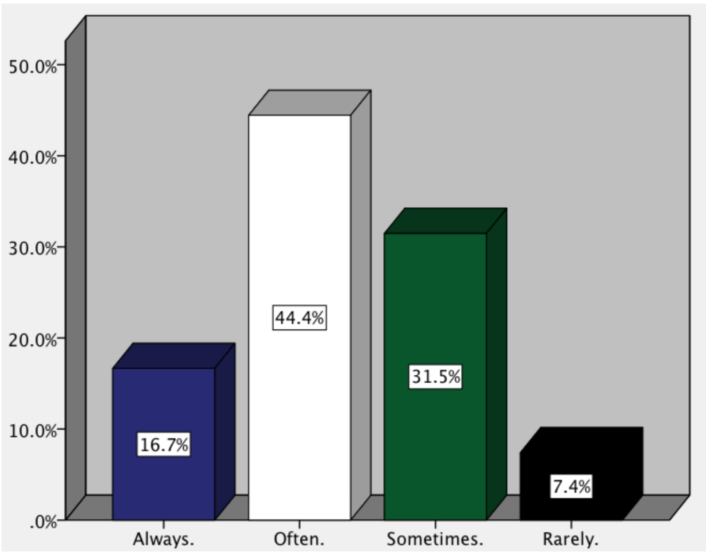

Figure 7.5: Bar chart showing the answer to the question: "On average, when you are parking your car for a specific time, how often do you take your car before the time is finished up? (Within 30 minutes leeway)."

In addition, as Figure 7.6 and Table 7.6 illustrate, the majority of the sample is come back to the machine to issue a new ticket once time on average (44.4%), and (29.6%)

Table 7.5: Answer to the question: "On average, when you are parking your car for a specific time, how often do you take your car before the time is finished up? (Within 30 minutes leeway)."

Response	Percentage
Always	16.7%
Often	44.4%
Sometimes	31.5%
Rarely	7.4%

Table 7.6: Answer to the question: "On average, when you are parking your car for a specific time, how many times do you come back to the machine to issue a new ticket?"

Response	Percentage
Never	29.6%
Once	44.4%
2 - 3 times	24.1%
4 times	1.9%

of them is never doing that. Then, with a very close number for the never option, is the people who come back to the machine to issue a new ticket 2 or 3 times on average (24.1%). However, just (1.9%) state they do that 4 times.

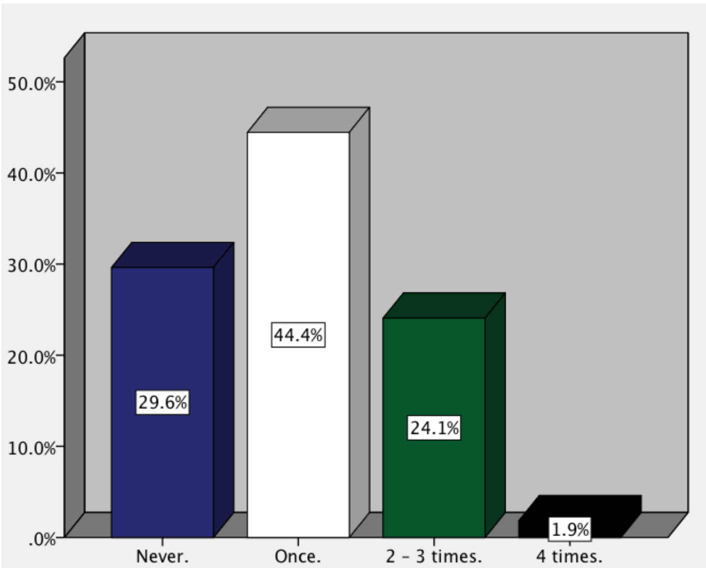

Figure 7.6: Bar chart showing the answer to the question: "On average, when you are parking your car for a specific time, how many times do you come back to the machine to issue a new ticket?"

Lastly, to conclude this part we ask the participants about that, when parking your car, which one of the following sentences best describes your expectation. As Figure 7.7 shows, the majority of the sample state, it is fairly easy for them to determine the parking period time, (44.4%). After that, as the second majority are the people claim that, it is neither easy nor difficult for them to determine the parking period time, (20.4%) and the people who state, it is difficult for them to determine the parking period time (22.3%). However, the people who think, it is easy for them to determine the parking period time is (13.0%) of the sample.

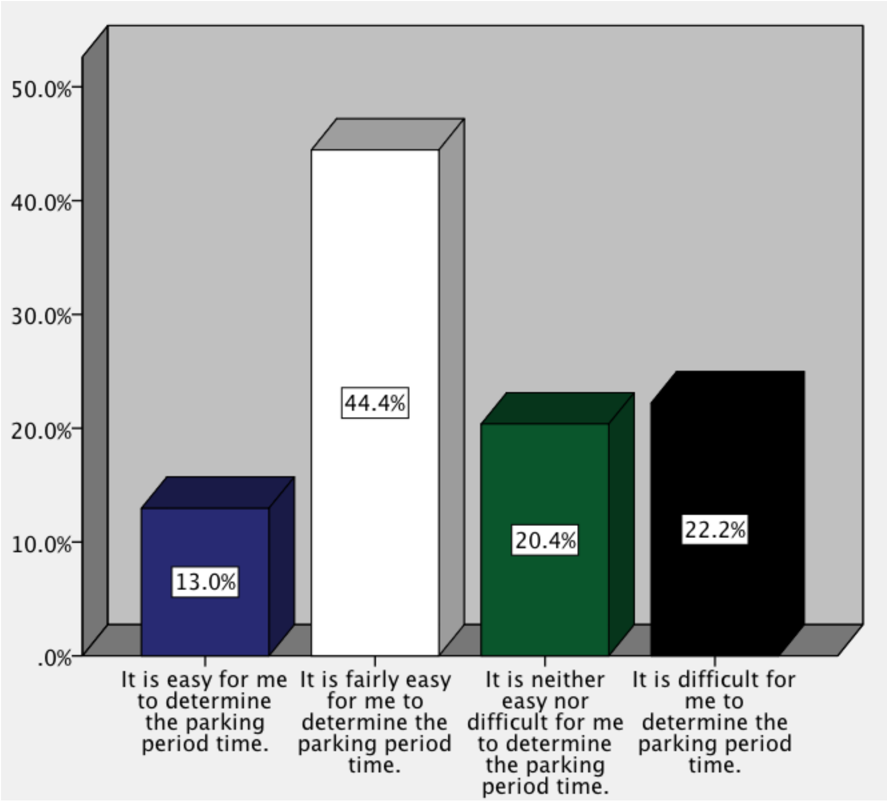

Figure 7.7: Bar chart showing the answer to the question: "When parking your car, which one of the following sentences best describes your expectation:"

Then, we ask the participants in the third part of this survey about their preferences about hypothetical vehicle lots which do not exist yet. Specifically, we are aiming to investigate how the participants behave about the payment policy and early release penalty policy in this new concept.

In this part, we start with this introduction for the participants, we would like you to imagine that, sometime in the future, you are parking in a new type of parking lot which we named it as Unizah parking (for the same purpose as the parking lots today). There are two payment policy options. Each option will be described in terms of the payment method and reservation type. As the Figure 7.8, illustrates, the majority of the sample prefer the option of pay as you go based on variable hourly prices and there is no reservation (76.27%). In contrast, the rest of the sample choose Pay in advance and reserve in advance as a preferred option (23.73%).

After that, to understand why the people prefer the first or the second option we ask the following question. After selecting your choice, which sentence best describes your decision?

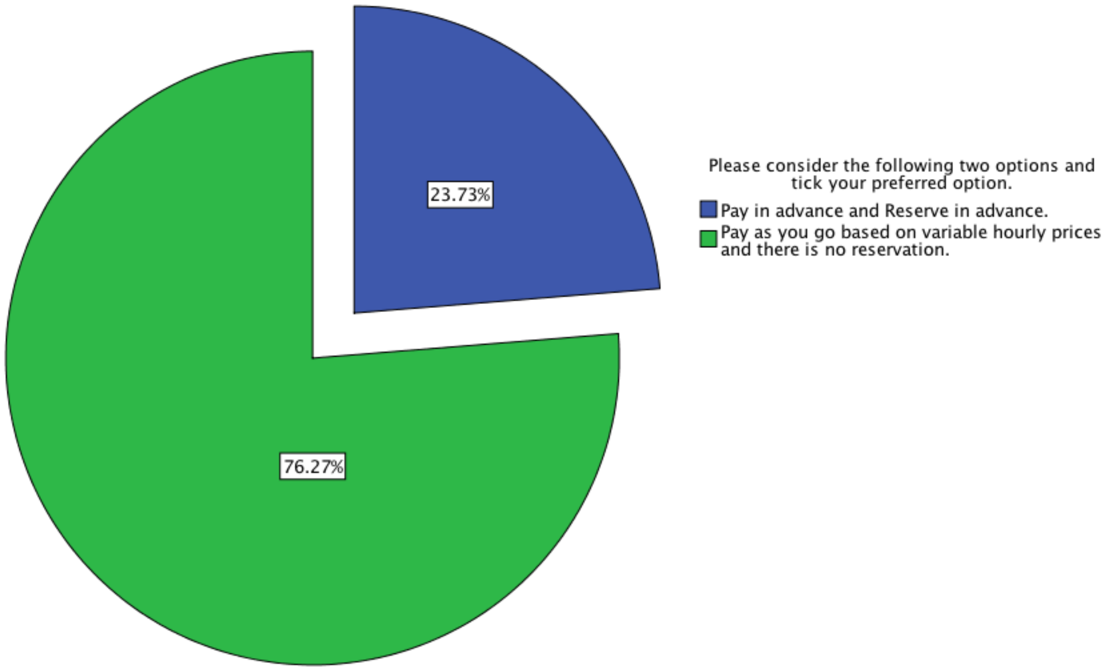

Figure 7.8: Pie chart showing the choosing between two hypothetical parking lots in terms to payment method and reservation type.

I think that payment method is more important than the reservation type when I choose my option. As the Figure 7.9 shows, the majority of the sample state they agree with this statement, agree (44.4%), and strongly agree (20.4%). However, less than 10% of the sample disagree with that (disagree 5.6% , and strongly disagree 3.7%).

To test the credibility of the previous question, we ask it conversely and we found that, most of the participants disagree with this statement, I think that reservation type is more important than the payment method when I choose my option (33.3% disagree and 13.0% strongly disagree). However, the minority agree with this statement, 14.8% strongly agree and 3.7% agree.

Moreover, in terms of investigate the sample preferences about the early release penalty policy, which is a new concept of the vehicle lots, which we defined it to them as, where if the drivers leave before the time they specified they need to pay a penalty. This will be defined in terms of two factors, which are pricing and flexibility. As Figure 7.11 shows, approximately two third of the sample prefer to pay extra money at the time they park to have the flexibility of leaving any time, (57.41%). Further, about quarter of the sample prefer to accept to pay a penalty more than choice A (which will be discussed later as a lowest preferred option) if they take their car before the period they defined. But they will receive a discount if they take it at the defined period. However, There is

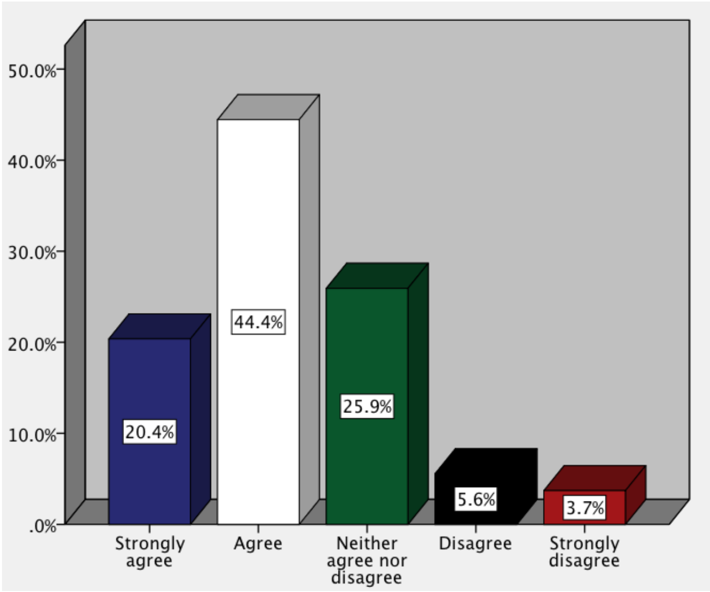

Figure 7.9: Bar chart showing the answer to the question: " I think that payment method is more important than the reservation type when I choose my option".

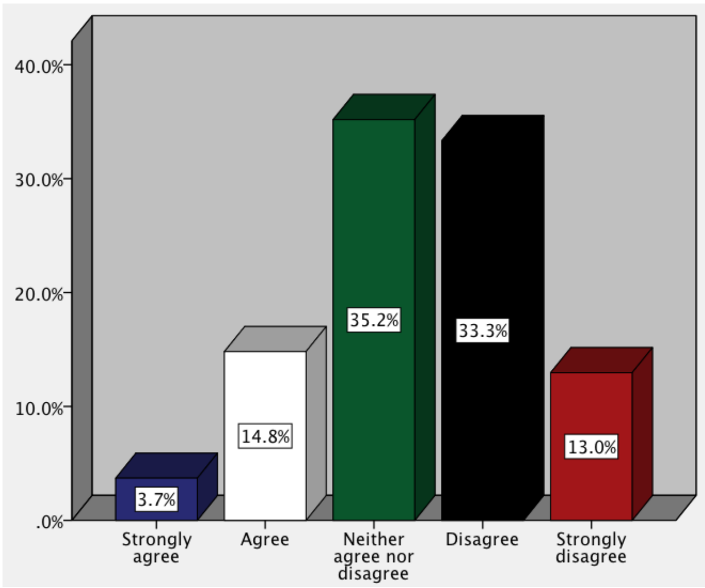

Figure 7.10: Bar chart showing the answer to the question: "I think that reservation type is more important than the payment method when I choose my option".

not any flexibility in this option, (27.78%). Then, as a lowest preferred option, accept to pay a penalty if they take their cars before the defined period is finished. However, there is not any flexibility in this option, (14.81%).

To understand how the people are choosing their preferences in the previous question, we provide the following statement, I think that pricing for early release penalty is more important than the flexibility when I choose my option, and we ask them about their opinion of this statement. About 40% of the sample agrees with that (5.6% strongly

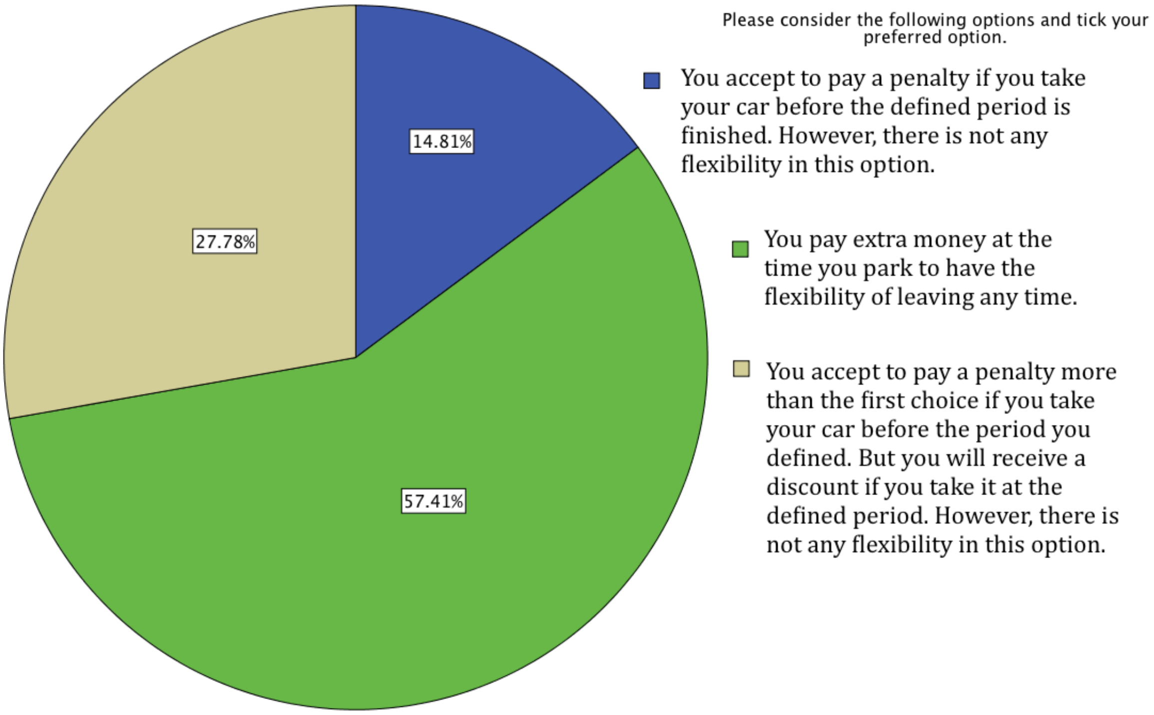

Figure 7.11: Pie chart showing the choosing between three hypothetical parking lots systems which differ in early release penalty policy.

agree and 35.2% agree). In contrast, 25.9% disagree with it and only 11.1% strongly disagree, as Figure 7.12 illiterates.

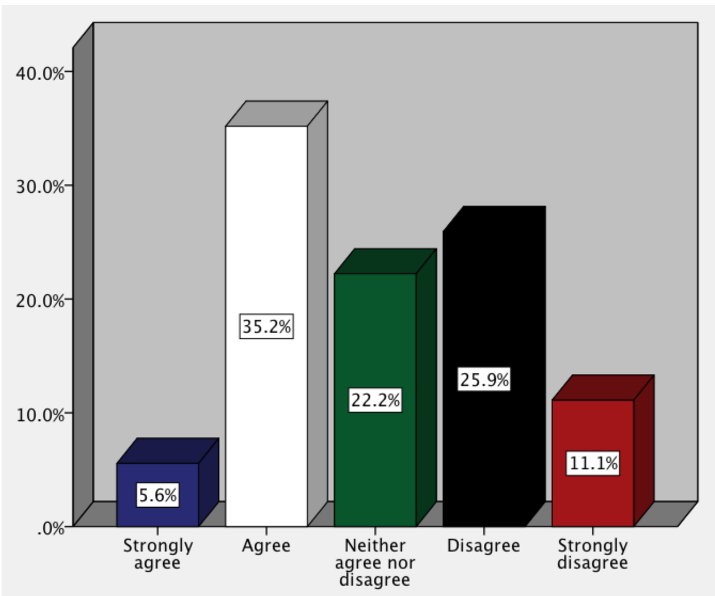

Figure 7.12: Bar chart showing the answer to the question: "I think that pricing for early release penalty is more important than the flexibility when I choose my option".

After that, to test the credibility of the previous question, we ask it conversely and we found that, most of the sample agrees with that, the flexibility is more important than the pricing for early release penalty when they choose their options (37.0%). On the other hand, there is about (22.2%) disagreeing with that.

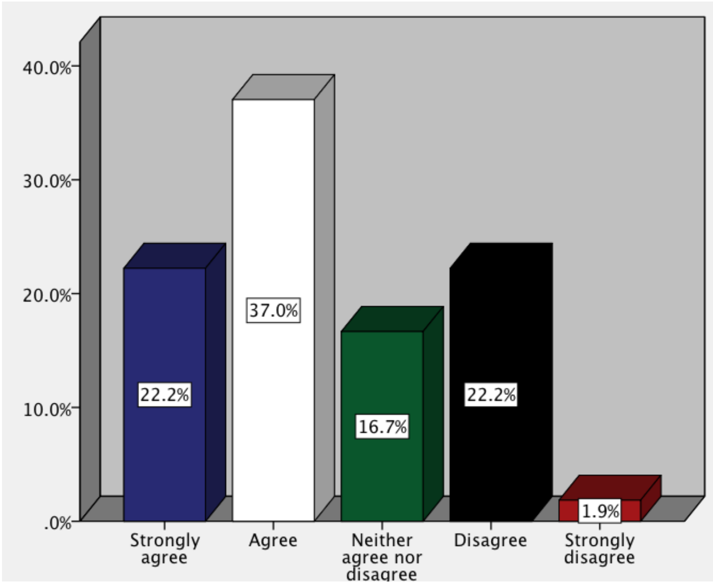

Figure 7.13: Bar chart showing the answer to the question: "I think that flexibility is more important than the pricing for early release penalty when I choose my option".

Next, as a last part of this survey we ask the participants which one is more important factor when they select the parking lots, and the results are as the following. As Figure 7.14 shows, half of the sample (51.9%) agrees with that the payment policy is more important than the early release penalty . Furthermore, (20.4%) of the participants strongly agree with that. On the other hand, when we converse the statement to test the credibility we found that, the majority of the sample disagree with, early release penalty policy is more important than the payment policy when they select the parking lots (48.1%) and (11.1%) strongly disagree with that as the Figure 7.15 shows.

Finally, before we discuss the findings in the section we will provide the results of applying one sample T-test for number of the questions in our survey. As Table 7.7 shows , the P values of questions (1,4,6,10,12, and 14) are less than .05 ($P \leq .05$) which means they are statistically significant. However, the questions (3,5, and 7) are not statistically significant because the p values of them are greater than .05 ($P \geq .05$). Indeed, this will give this study more credibility because there are some tests that have not succeeded.

7.4 Survey Findings

- In terms to the pay on foot parking type, about the half of the sample (51.8%) they parking their cars and know how long will be parking most of the time (often and always). Moreover, in this type of parking lots, most of the participants think

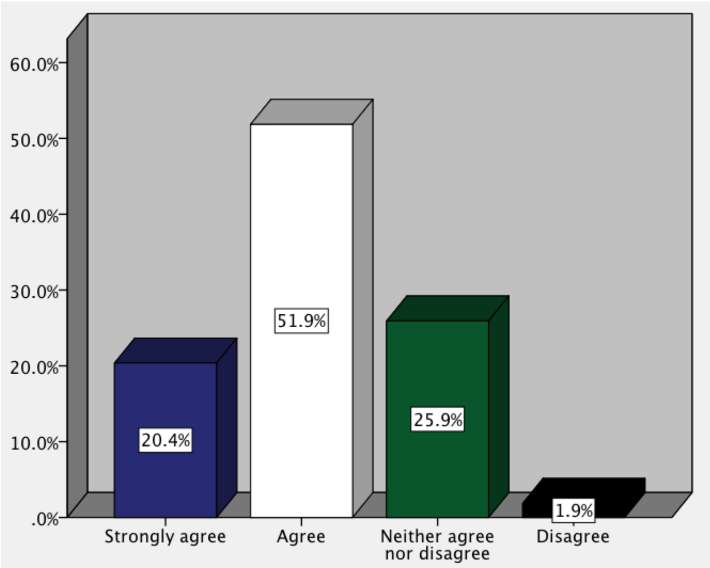

Figure 7.14: Bar chart showing the answer to the question: "I think that the payment policy is more important than the early release penalty policy when I select the parking lots".

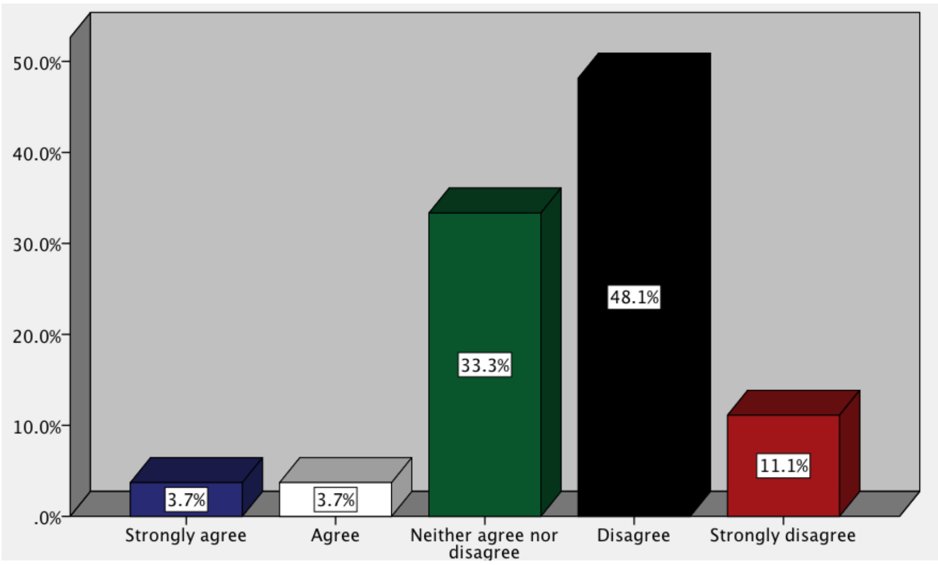

Figure 7.15: Bar chart showing the answer to the question: "I think that the early release penalty policy is more important than the payment policy when I select the parking lots".

that the difference between the expected time of parking and the actual period they spend is less than one hour (72.2%).

- About the half of the participants say they often take their cars before the period they determined is finished up (44.4%) in the pay and display parking type. In addition, about one third of the sample is never come back to the machine to issue a new ticket.

Table 7.7: The results of applying T-test.

Question	**Mean**	**Standard deviation**
1	2.02	.629
3	2.50	.795
4	2.28	.712
5	2.30	.838
6	1.98	.789
7	2.52	.986
10	3.37	1.015
12	3.02	1.14
14	2.09	.734

- By combining between the aforementioned points and that, (57.4%) of the participants think it is easy to determine the parking period, we can conclude that, the V2G parking lots concept could be used broadly since most of the people can determine the parking period correctly.

- In pay on foot parking type, 61.1 % of the sample took their cars before the time they determined they will be finished up most of the time (always or often). Furthermore, in pay and display parking type, the majority of the sample (70%) came back to the machine to issue a new ticket (between 1 to 4 times) and usually the pricing will be cheaper if the driver issues one ticket for the whole parking period. For example, if the driver going to park for 4 hours and he specified the period issuing a ticket for that, he will pay less amount than another driver who issues a ticket for one hour 4 times. By considering the former statements we can conclude that most of the vehicle drivers pay more than what they need in the parking lots.

- In terms to the V2G parking lots, which we ask about it as hypothetical situations because it does not exists yet; we found that most of the participants think payment method is more important than the reservation type in the payment policy issue. Furthermore, (40%) believe that pricing for early release penalty is more important than the flexibility. Thus, payment method and pricing for early release penalty should be the main factors to be considered in the V2G parking lots manager agent model designing.

7.5 Summary

This chapter has presented real data regarding vehicle parking lots preferences for the current parking lots systems and a new type of parking lots concept. Firstly, an introduction for the survey that includes, it is objectives, hypothesis and research questions have been provided. Next, the results are discussed and analysed. Afterward, the survey findings are considered.

In the following chapter, the conclusions of this thesis and the future work will be provided.

Chapter 8

Conclusions and Future Work

In this chapter, we provide an overview of the contributions of this thesis towards modelling an agent to trade on behalf of V2G drivers. To achieve this, we firstly summarise the research conducted within each particular topic addressed. Moreover, we explain how we attained each of the research objectives which were specified at the outset of the present thesis. Following this, we outline a number of general ideas regarding future work that could follow our study and put forth numerous promising research plans.

8.1 Conclusions

The work in this thesis can be divided into four parts. We first designed an algorithm to trade on behalf of V2G drivers and which is able to maximise said drivers' profits by understanding the power market price behaviour. Following this, we extended the previous algorithm so that it traded on behalf of V2G drivers and was also able to maximise their profits by taking into account their vehicle usage. In light of the above, there are two types of uncertainties which should be considered; these uncertainties are related to the power market price and vehicle usage behaviour. Furthermore, we collected a dataset of vehicle usage behaviour in order to serve our model experiments and to investigate the feasibility of using V2G to tackle the peak demand in warm countries. Finally, the last part was focused on providing a better understanding of V2G drivers level of satisfaction with a parking lot and how they make the decision whether or not to use the V2G parking lot. Moreover, this research discussed the factors which are considered by the vehicle drivers when choosing a parking lot. Furthermore, it investigated which payment policy type and early release penalty systems they prefer.

More precisely, we firstly considered the problem without any uncertainty in the power market price side. To achieve this, our first model focused on modelling an initial agent to trade on behalf of V2G drivers in order to maximise their profits. A backward induction algorithm was used to attain this aim. Following this, we ran the proposed model in three different scenarios using an optimal algorithm and compared the results of our solution to a benchmark. Simulation results showed that our solution outperformed the benchmark strategy in the proposed three scenarios by 49%, 51%, and 10% respectively in terms of profits (Chapter 3).

We then increased the complexity of the problem by considering the price uncertainty in the power market where the price changes every hour. In order to achieve this, we modelled the V2G problem as a Markov decision process (MDP), where the price uncertainty is considered by maximising the V2G drivers profits. The decisions were made in consideration of potential profits and drivers incentives. Following this, we developed a heuristic algorithm that combined backward induction with two types of consensus algorithms, namely Borda and majority voting, and with expected value to deal with the price uncertainty. The proposed algorithm can deal with multiple scenarios in terms of price in the power market. We evaluated the proposed algorithm by applying it with two types of consensus algorithms (Borda voting and majority voting) and with expected value. The results showed that when our proposed algorithm was applied with expected value it outperformed the voting algorithms (Borda and Majority) considerably (Chapter 4).

Additionally, as a part of this thesis and in order to run our simulation for the last model in (Chapter 6), we conducted a survey of vehicle usage behaviour. Furthermore, to the best of our knowledge, none of the studies in the literature were suitable for our study purposes because none of them discussed the desired amount of battery that drivers require for each trip type. This type of information was the main focus of our model. To obtain said information, we conducted a survey of vehicle usage behaviour aimed at drivers in Saudi Arabia and also used information from the Saudi Arabia electricity authority. Indeed, since we planned to trade with the power market in Saudi Arabia and to make our simulation more consistent, we preferred to collect our dataset from Saudi drivers. Moreover, we investigated the feasibility of using V2G to mitigate the problem of highest electricity peak demand in the summer period in one of the warmest countries of the world (Saudi Arabia). Indeed, with 80% of the sample interested in using V2G technology, we concluded that V2G is a promising solution when it comes to the problem of peak demand in the summer in Saudi Arabia. Besides this, 90% of the participants used their vehicles for less than four hours a day. Additionally, in the summer period, most of the participants stated that they park their vehicles for the longest time between 13:00 and 18:00, which is the peak demand period (Chapter 5).

Likewise, we increased the complexity for the problem by considering the uncertainty in the vehicle usage behaviour in the context of V2G, as well as the uncertainty in the power market price. Further, we considered the battery degradation cost, which arises because of the charging or discharging actions. To achieve this, we refined the second model and used the multinomial logit model with the consensus algorithms and expected value, along with a backward induction algorithm. The result of the simulation showed that our proposed algorithm outperforms the naive algorithm for about 15 times in terms of the average profits when we started the experiments with half the amount of battery. Moreover, our proposed algorithm outperforms the naive algorithm for about 5 times in terms of the average profits when we started the experiments with the full amount of battery. On the other hand, our proposed algorithm performs 89% of the complete information algorithm in terms of the average profits when we started the experiments with half the amount of battery. Furthermore, our proposed algorithm provides almost same results of complete information in terms of the average profits when we started the experiments with the full amount of battery (Chapter 6).

Finally, in order to achieve the last goal of this thesis, we conducted a survey of the vehicle drivers preferences in the parking lots so as to investigate the feasibility of using V2G parking lots. We found that, in the pay on foot type of parking lot, 51% of the participants were parking their cars and knew, most of the time, how long they would be parking for (often and always). Additionally, 72.2% of the participants believed that the difference between the expected time of parking and the actual period they spent was less than one hour. On the other hand, in the pay and display parking type, 44.4% of the sample stated that they often took their vehicles before the period they determined had ended. Furthermore, one third of the participants stated that they never returned to the machine to purchase a new ticket. By combining the aforementioned points we were able to conclude that the V2G parking lots concept could be used broadly because most people could correctly determine the parking period. Furthermore, with regard to the V2G parking lots, all of the situations put to the respondents were hypothetical, since the concept does not yet exist. We found that most of the sample believed that the pricing for early release penalty is more important than flexibility. In addition, most of them felt that the payment method is more important than the reservation type in relation to the payment policy issue. It was therefore concluded that payment method and pricing for early release penalty should be the main factors to be considered when designing the V2G parking lots manager agent model (Chapter 7).

In conclusion, the specific problems that we faced can be categorised into three levels of complexity. The first of these is the problem of the power market price without uncertainty in the context of V2G, which is not too complex a problem. Following this there is the problem of the uncertainty power market side, which is a complex problem. Lastly comes the problem of the uncertainty in the power market with consideration given to the uncertainty in vehicle usage behaviour for the drivers for multiple trip scenarios in a day; indeed, this is too complex a problem. For each of these topics, we proposed three models and conducted two surveys which satisfied our study objectives.

With the thesis conclusions now having been discussed, the following section will provide some ideas that could be used to extend our work.

8.2 Future Work

Notwithstanding these accomplishments, there still exist number of issues should be considered to extend our work. To do so, the future work of this research can be summarised to threefold directions:

- The first direction is that, after considering the V2G drivers side here, we are planning to discuss the power market side where we can use a mechanism design (it can be defined as a domain in economics where applying an engineering method to design economic incentives in orders to attain desired goals, where players behave rationally. In other words, it can be defined as reverse game theory) to incentive the V2G drivers to change their vehicle usage behavior to reduce the grid peak load, when we model a multi-agent environment. Currently, we assume the other drivers do not influence the power market price so assume the price is fixed and the consumer is a price taker. However, in the future work we will change the previous assumption, when we discuss the multi-agent environment.
- The second direction is that, we are aiming to design V2G parking lots manager agent as a one of the most important players that may effect in the power market at a multi agents environment. Indeed, this is will be a second phase of our previous work in (Chapter 7) where we collected data about the drivers preferences in this kind of lots.
- Finally, after considered the feasibility of using the V2G to face the electricity peak demand in the summer season in the warmest countries in (Chapter 5) and in our published paper (Almansour et al., 2018b). In order of improve this study, we are planning to quantify the benefits of using V2G to support the grid at the peak demand in the summer in Saudi Arabia as a second phase of the study.

Appendix A

Survey in vehicle usage behaviour

Table A.1: Trips types definitions.

Trip type	**Description**
Unplanned	The kind of trip which happens without any plan before like take children for hospital for emergency or going to buy a milk for a baby when it finish suddenly.
Commuting	The type of trip that happens usually with a plan such as going to the work or taking the children to school.
Extra	The kind of trip that has a flexible time so the driver can do it without specific deadline such as shopping or go to the gym.

Please answer the following questions:

1. What is your age:
   - 18 - 25
   - 26 - 35
   - 36 - 60
   - Over 60
2. What is your highest educational attainment?
   - Under bachelor
   - Bachelor
   - Master
   - PhD

3. Do you work in public or private sector?
   - Public
   - Private
   - Do not work
4. How many cars do you own?
   - 1
   - 2
   - More than 2
5. Usually, what is the purpose for your first trip at the start of the day?
   - Unplanned trip
   - Commuting trip
   - Extra trip
6. On an average day, how many trips do you make?
   - 1 - 2 trips
   - 3 - 4 trips
   - 5 - 6 trips
   - If else, specify it please, ?

   a. What the percentage of these (trips) are unplanned trips?
   - 100%
   - 80%
   - 60%
   - 40%
   - 20%
   - 0%

   b. What the percentage of these (trips) are commuting trips?
   - 100%
   - 80%
   - 60%
   - 40%
   - 20%
   - 0%

c. What the percentage of these (trips) are extra trips?

- 100%
- 80%
- 60%
- 40%
- 20%
- 0%

7. At what time do you park your car for longest period through the day (home):

   - Between 00:00 to 6:00.
   - Between 07:00 to 12:00.
   - Between 13:00 to 18:00.
   - Between 19:00 to 23:00.
   - If else, specify it please, ?

8. How many hours do you drive your car daily?

   - 1 - 2 hours
   - 3 - 4 hours
   - 5 - 6 hours
   - If else, specify it please, ?

   Note: Unplanned trip: The kind of trip which happens without any plan before like take children for hospital for emergency or going to buy a milk for a baby when it finish suddenly.

9. When there is a probability to use your car for an unplanned trip what is the minimum amount of fuel you want in your car:

   - 100%
   - 80%
   - 60%
   - 40%
   - 20%

10. How many kilometers you drive if you make unplanned trip:
    - Less than 5 KM
    - 5 - 10 KM
    - 11 - 20 KM
    - 21 - 50 KM
    - More than 50 KM

    Note: Commuting trip: The type of trip that happens usually with a plan such as going to the work or taking the children to school.

11. When there is a probability to use your car for a commuting trip what is the minimum amount of fuel you want in your car:
    - 100%
    - 80%
    - 60%
    - 40%
    - 20%

12. How many kilometers you drive if you make commuting trip:
    - Less than 5 KM
    - 5 - 10 KM
    - 11 - 20 KM
    - 21 - 50 KM
    - More than 50 KM

    Note: Extra trip: The kind of trip that has a flexible time so the driver can do it without specific deadline such as shopping or go to the gym.

13. When there is a probability to use your car for an extra trip what is the minimum amount of fuel you want in your car:
    - 100%
    - 80%
    - 60%
    - 40%
    - 20%

14. How many kilometers you drive if you make extra trip:

    - Less than 5 KM
    - 5 - 10 KM
    - 11 - 20 KM
    - 21 - 50 KM
    - More than 50 KM

    Note: Unplanned trip: The kind of trip which happens without any plan before like take children for hospital for emergency or going to buy a milk for a baby when it finish suddenly.

15. When are you going to use your car for an unplanned trip and your car is unavailable, what are you going to do:

    - Take taxi
    - Call your friend or one of your family tov take you
    - Walk
    - If else, specify it please, ?

    Note: The concept of vehicle to grid (V2G) is where an EV offers electric power to the grid when parked.

16. Are you interested to using the EV instead of the Fuel vehicles if you receive some economic and environmental advantages?

    - Yes
    - No

17. If you will receive more economical advantages from using V2G, are you interested to using the V2G?

    - Yes
    - No

18. In the summer, at what time do you park your car for longest period through the day:

    - Between 00:00 to 6:00.
    - Between 07:00 to 12:00.
    - Between 13:00 to 18:00.
    - Between 19:00 to 23:00.
    - If else, specify it please, ?

Appendix B

Survey in V2G Parking lots Preferences

Please answer the following questions:

1. What is your age:
   - 18 - 28
   - 29 - 39
   - 40 - 50
   - 51 - 60
   - Over 60
2. What is your highest educational attainment?
   - Diploma
   - Under bachelor
   - Bachelor
   - Master
   - PhD

When you are using pay on foot parking, where you can park and pay at a payment machine before returning to your car (For example, the West quay car parking).

3. On average, when parking your car, how often do you know how long will you be parking. (Within 30 minutes leeway). (Please tick one box only)
   - Always.
   - Often.
   - Sometimes.
   - Rarely.
   - Not at all.
4. On average, when parking your car, what is the difference between the expected time of parking and the actual period you spend? (Please tick one box only)
   - There is no difference.
   - Less than one hour.
   - 1 - 2 hours.
   - 2 - 3 hours.
   - More than 3 hours.

When using pay and display parking, where you can park your car, and then pay the machine based on the period of time you choose to issue a ticket to be displayed (For example, the university of Southampton car parking).

5. On average, when you are parking your car for a specific time, how often do you take your car before the time is finished up? (Within 30 minutes leeway). (Please tick one box only)

    - Always.
    - Often.
    - Sometimes.
    - Rarely.
    - Not at all.

6. On average, when you are parking your car for a specific time, how many times do you come back to the machine to issue a new ticket? (Please tick one box only)

    - Never.
    - Once.
    - 2 - 3 times
    - 4 times.
    - More than 4 times.

7. When parking your car, which one of the following sentences best describes your expectation:

    - It is easy for me to determine the parking period time.
    - It is fairly easy for me to determine the parking period time.
    - It is neither easy nor difficult for me to determine the parking period time.
    - It is difficult for me to determine the parking period time.
    - It is extremely difficult for me to determine the parking period time.

We would like you to imagine that, sometime in the future, you are parking in a new type of parking lot which we named it as Unizah parking (for the same purpose as the parking lots today).

There are two payment policy options. Each option will be described in terms of the:

- Payment method;
- Reservation type;

In the following questions, please look at the two available options and state which one you would prefer to be adopted.

8. Please consider the following two options and tick your preferred option.
    - Pay in advance and reserve in advance.
    - Pay as you go based on variable hourly prices and there is no reservation.
9. After selecting your choice, which sentence best describes your decision?

    I think that payment method is more important than the reservation type when I choose my option:
    - Strongly agree
    - Agree
    - Neither
    - Disagree
    - Disagree Strongly
10. I think that reservation type is more important than the payment method when I choose my option:
    - Strongly agree
    - Agree
    - Neither
    - Disagree
    - Disagree Strongly

We would like you to imagine that, we are going to add new policy for Unizah parking, that is an early release penalty policy, where if you leave before the time you specified you need to pay a penalty. This will be defined in terms of two factors:

- Pricing;
- Flexibility;

In the following questions, please look at the three available options and state which one you would prefer to be adopted.

11. Please consider the following options and tick your preferred option.
    - You accept to pay a penalty if you take your car before the defined period is finished. However, there is not any flexibility in this option.
    - You pay extra money at the time you park to have the flexibility of leaving any time.
    - You accept to pay a penalty more than choice A if you take your car before the period you defined. But you will receive a discount if you take it at the defined period. However, There is not any flexibility in this option.
12. I think that pricing for early release penalty is more important than the flexibility when I choose my option:
    - Strongly agree
    - Agree
    - Neither
    - Disagree
    - Disagree Strongly
13. I think that flexibility is more important than the pricing for early release penalty when I choose my option. (Please tick one box only)
    - Strongly agree
    - Agree
    - Neither
    - Disagree
    - Disagree Strongly

14. I think that the payment policy is more important than the early release penalty policy when I select the parking lots. (Please tick one box only)

    - Strongly agree
    - Agree
    - Neither
    - Disagree
    - Disagree Strongly

15. I think that the early release penalty policy is more important than the payment policy when I select the parking lots. (Please tick one box only)

    - Strongly agree
    - Agree
    - Neither
    - Disagree
    - Disagree Strongly

References

Adda, J. and Cooper, R. W. (2003). *Dynamic economics: quantitative methods and applications*. MIT press.

Allcott, H. (2011). Rethinking real-time electricity pricing. *Resource and Energy Economics*, 33(4):820–842.

Almansour, I. A., Gerding, E. H., and Wills, G. (2017). An agent trading on behalf of v2g drivers in a day-ahead price market. In *Proceedings of the 3rd International Conference on Vehicle Technology and Intelligent Transport Systems - Volume 1: VEHITS,*, pages 135–141. INSTICC, SciTePress.

Almansour, I. A., Gerding, E. H., and Wills, G. (2018a). Automated trading in vehicle-to-grid with price uncertainty using consensus. In *Proceedings of the 2nd International Conference on New Energy Vehicle and Vehicle Engineering (NEVVE 2018)*. NEVVE.

Almansour, I. A., Gerding, E. H., and Wills, G. (2018b). The feasibility of using v2g to face the peak demand in warm countries. In *Proceedings of the 4th International Conference on Vehicle Technology and Intelligent Transport Systems - Volume 1: VEHITS,*, pages 238–242. INSTICC, SciTePress.

Amin, S. M. and Wollenberg, B. F. (2005). Toward a smart grid: power delivery for the 21st century. *Power and Energy Magazine, IEEE*, 3(5):34–41.

Ansari, M., Al-Awami, A. T., Abido, M., and Sortomme, E. (2014). Optimal charging strategies for unidirectional vehicle-to-grid using fuzzy uncertainties. In *T&D Conference and Exposition, 2014 IEEE PES*, pages 1–5. IEEE.

Ashtari, A., Bibeau, E., Shahidinejad, S., and Molinski, T. (2012). Pev charging profile prediction and analysis based on vehicle usage data. *IEEE Transactions on Smart Grid*, 3(1):341–350.

Baltas, G. and Doyle, P. (2001). Random utility models in marketing research: a survey. *Journal of Business Research*, 51(2):115–125.

Battistelli, C., Baringo, L., and Conejo, A. (2012). Optimal energy management of small electric energy systems including v2g facilities and renewable energy sources. *Electric Power Systems Research*, 92:50–59.

Belt, J. (2008). Long term combined cycle and calendar life testing. In *214th Electrochemical Society Meeting*.

Ben-Akiva, M. E. and Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand*, volume 9. MIT press.

Bent, R. and Van Hentenryck, P. (2004a). The value of consensus in online stochastic scheduling. In *ICAPS*, volume 4, pages 219–226.

Bent, R. W. and Van Hentenryck, P. (2004b). Scenario-based planning for partially dynamic vehicle routing with stochastic customers. *Operations Research*, 52(6):977–987.

Braun, V. and Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, 3(2):77–101.

Caramanis, M. and Foster, J. M. (2009). Management of electric vehicle charging to mitigate renewable generation intermittency and distribution network congestion. In *Decision and Control, 2009 held jointly with the 2009 28th Chinese Control Conference. CDC/CCC 2009. Proceedings of the 48th IEEE Conference on*, pages 4717–4722. Ieee.

Cardoso, G., Stadler, M., Bozchalui, M. C., Sharma, R., Marnay, C., Barbosa-Póvoa, A., and Ferrão, P. (2014). Optimal investment and scheduling of distributed energy resources with uncertainty in electric vehicle driving schedules. *Energy*, 64:17–30.

Chang, H. S., Givan, R., and Chong, E. K. (2000). On-line scheduling via sampling. In *AIPS*, pages 62–71.

Chis, A., Lundén, J., and Koivunen, V. (2013). Scheduling of plug-in electric vehicle battery charging with price prediction. In *Innovative Smart Grid Technologies Europe (ISGT EUROPE), 2013 4th IEEE/PES*, pages 1–5. IEEE.

Christiansen, H. and Skougaard, B. Z. (2015). Documentation of the danish national travel survey (2015 version).

Conejo, A. J., Carrión, M., and Morales, J. M. (2010a). *Decision making under uncertainty in electricity markets*, volume 1. Springer.

Conejo, A. J., Morales, J. M., and Baringo, L. (2010b). Real-time demand response model. *Smart Grid, IEEE Transactions on*, 1(3):236–242.

Council, P. S. R. (2011). Traffic choices study.

Dallinger, D., Krampe, D., and Wietschel, M. (2011). Vehicle-to-grid regulation reserves based on a dynamic simulation of mobility behavior. *IEEE Transactions on Smart Grid*, 2(2):302–313.

Dallinger, D. and Wietschel, M. (2012). Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles. *Renewable and Sustainable Energy Reviews*, 16(5):3370–3382.

Dan, A. (2008). Predictably irrational: the hidden forces that shape our decisions.

Danny Blair, Caleigh Christie, M. M. B. M. (2011). Auto21 research data. Technical report, University of Winnipeg.

ECRA (2011). Bringing demand-side management to the kingdom of saudi arabia. Technical report, Electricity & Cogeneration Regulatory Authority (ECRA).

ECRA (2013). Smart metering and smart grids strategy for the kingdom of saudi arabia. Technical report, ECRA.

Fackler, P. L. (2004). *Applied computational economics and finance.* MIT press.

Freeman, G. M., Drennen, T. E., and White, A. D. (2017). Can parked cars and carbon taxes create a profit? the economics of vehicle-to-grid energy storage for peak reduction. *Energy Policy*, 106:183–190.

Gerding, E., Stein, S., Ceppi, S., and Robu, V. (2016). Online mechanism design for vehicle-to-grid car parks.

Ghiasnezhad Omran, N. and Filizadeh, S. (2014). Location-based forecasting of vehicular charging load on the distribution system. *Smart Grid, IEEE Transactions on*, 5(2):632–641.

Gibbons, R. (1992). *Game theory for applied economists.* Princeton University Press.

Goebel, C. and Voß, M. (2012). Forecasting driving behavior to enable efficient grid integration of plug-in electric vehicles. In *Online Conference on Green Communications (GreenCom), 2012 IEEE*, pages 74–79. IEEE.

Gough, R., Dickerson, C., Rowley, P., and Walsh, C. (2017). Vehicle-to-grid feasibility: A techno-economic analysis of ev-based energy storage. *Applied Energy*, 192:12–23.

Guille, C. and Gross, G. (2009). A conceptual framework for the vehicle-to-grid (v2g) implementation. *Energy Policy*, 37(11):4379–4390.

Halvgaard, R., Poulsen, N. K., Madsen, H., Jorgensen, J., Marra, F., and Bondy, D. E. M. (2012). Electric vehicle charge planning using economic model predictive control. In *Electric Vehicle Conference (IEVC), 2012 IEEE International*, pages 1–6. IEEE.

Han, S., Han, S. H., and Sezaki, K. (2010). Design of an optimal aggregator for vehicle-to-grid regulation service. In *Innovative Smart Grid Technologies (ISGT), 2010*, pages 1–8. IEEE.

Hashimoto, S., Kanamori, R., and Ito, T. (2013). Auction-based parking reservation system with electricity trading. In *Business Informatics (CBI), 2013 IEEE 15th Conference on*, pages 33–40. IEEE.

He, Y., Venkatesh, B., Member, S., and Guan, L. (2012). Optimal Scheduling for Charging and Discharging of Electric Vehicles. *IEEE transactions on smart grid*, 3(3):1095–1105.

Hoke, A., Brissette, A., Maksimović, D., Pratt, A., and Smith, K. (2011). Electric vehicle charge optimization including effects of lithium-ion battery degradation. In *Vehicle Power and Propulsion Conference (VPPC), 2011 IEEE*, pages 1–8. IEEE.

Holland, J. and Goldberg, D. (1989). Genetic algorithms in search, optimization and machine learning. *Massachusetts: Addison-Wesley.*

Hopper, N., Goldman, C., Bharvirkar, R., and Neenan, B. (2006). Customer response to day-ahead market hourly pricing: Choices and performance. *Utilities Policy*, 14(2):126–134.

Hota, A. R., Juvvanapudi, M., and Bajpai, P. (2014). Issues and solution approaches in phev integration to smart grid. *Renewable and Sustainable Energy Reviews*, 30:217–229.

Huisman, R., Huurman, C., and Mahieu, R. (2007). Hourly electricity prices in day-ahead markets. *Energy Economics*, 29(2):240–248.

Kahneman, D. (2011). *Thinking, fast and slow.* Macmillan.

Kamboj, S., Kempton, W., and Decker, K. S. (2011). Deploying power grid-integrated electric vehicles as a multi-agent system. In *The 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*, pages 13–20. International Foundation for Autonomous Agents and Multiagent Systems.

Karlin, A. R., Manasse, M. S., Rudolph, L., and Sleator, D. D. (1988). Competitive snoopy caching. *Algorithmica*, 3(1-4):79–119.

Kavousi-Fard, A., Niknam, T., and Fotuhi-Firuzabad, M. (2015). Stochastic reconfiguration and optimal coordination of v2g plug-in electric vehicles considering correlated wind power generation. *IEEE Transactions on Sustainable Energy*, pages 822 – 830.

Kempton, W. and Kubo, T. (2000). Electric-drive vehicles for peak power in Japan. *Energy Policy*, 28(1):9–18.

Kempton, W. and Letendre, S. E. (1997). Electric vehicles as a new power source for electric utilities. *Transportation Research Part D: Transport and Environment*, 2(3):157–175.

Kempton, W. and Tomić, J. (2005). Vehicle-to-grid power fundamentals: calculating capacity and net revenue. *Journal of power sources*, 144(1):268–279.

Keyhani, A. (2011). *Design of smart power grid renewable energy systems.* John Wiley & Sons.

Khalid, M. W., Al-Awami, A. T., and Sortomme, E. (2013). Stochastic-programming-based bidding strategy for v2g services. In *Innovative Smart Grid Technologies Europe (ISGT EUROPE), 2013 4th IEEE/PES*, pages 1–5. IEEE.

Kim, E., Lee, J., and Shin, K. G. (2013). Real-time prediction of battery power requirements for electric vehicles. In *Proceedings of the ACM/IEEE 4th International Conference on Cyber-Physical Systems*, pages 11–20. ACM.

Kochenderfer, M. J. (2015). *Decision making under uncertainty: theory and application.* MIT press.

Li, Z., Chowdhury, M., Bhavsar, P., and He, Y. (2015a). Optimizing the performance of vehicle-to-grid (v2g) enabled battery electric vehicles through a smart charge scheduling model. *International Journal of Automotive Technology*, 16(5):827–837.

Li, Z., Jiang, Y., Zhang, X., and Tian, W. (2015b). Market-based optimal control of plug-in hybrid electric vehicle fleets and economic analysis. *Journal of Energy Engineering*, page 04015025.

Luce, R. D. (2005). *Individual choice behavior: A theoretical analysis.* Courier Corporation.

Ma, Z., Callaway, D., and Hiskens, I. (2010). Decentralized charging control for large populations of plug-in electric vehicles. In *Decision and Control (CDC), 2010 49th IEEE Conference on*, pages 206–212. IEEE.

Mao, A., Procaccia, A. D., and Chen, Y. (2013). Better human computation through principled voting. In *AAAI*. Citeseer.

Matell, M. S. and Jacoby, J. (1971). Is there an optimal number of alternatives for likert scale items? study i: Reliability and validity. *Educational and psychological measurement*, 31(3):657–674.

McFadden, D. et al. (1973). *Conditional logit analysis of qualitative choice behavior.* Institute of Urban and Regional Development, University of California.

Millner, A. (2010). Modeling lithium ion battery degradation in electric vehicles. In *Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES), 2010 IEEE Conference on*, pages 349–356. IEEE.

Mohsenian-Rad, A.-H. and Leon-Garcia, A. (2010). Optimal residential load control with price prediction in real-time electricity pricing environments. *Smart Grid, IEEE Transactions on*, 1(2):120–133.

Naamani-Dery, L., Golan, I., Kalech, M., and Rokach, L. (2015). Preference elicitation for group decisions using the borda voting rule. *Group Decision and Negotiation*, pages 1–19.

Nasiri, S. and Moghadam, M. P. (2014). Probabilistic and fuzzy modeling of charging and discharging of electric vehicles in presence of uncertainties applied to unit commitment problem. *Majlesi Journal of Mechatronic Systems*, 3(4).

Neubauer, J., Brooker, A., and Wood, E. (2013). Sensitivity of plug-in hybrid electric vehicle economics to drive patterns, electric range, energy management, and charge strategies. *Journal of Power Sources*, 236:357–364.

NHTS (2016). National household travel survey.

O'Neill, D., Levorato, M., Goldsmith, A., and Mitra, U. (2010). Residential demand response using reinforcement learning. In *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*, pages 409–414. IEEE.

Ortega-Vazquez, M. A. (2014). Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty. *IET Generation, Transmission & Distribution*, 8(6):1007–1016.

Paidi, V., Fleyeh, H., Håkansson, J., and Nyberg, R. G. (2018). Smart parking tools suitability for open parking lots: A review. In - *RESIST*,. INSTICC, SciTePress.

Pan, F., Bent, R., and Berscheid, A. (2011). Online dynamic scheduling for charging phevs in v2g. Technical report, Los Alamos National Laboratory (LANL).

Panagopoulos, A. A., Chalkiadakis, G., and Koutroulis, E. (2012). Predicting the power output of distributed renewable energy resources within a broad geographical region. In *Proceedings of the 20th European Conference on Artificial Intelligence*.

Parsons, G. R., Hidrue, M. K., Kempton, W., and Gardner, M. P. (2014). Willingness to pay for vehicle-to-grid (v2g) electric vehicles and their contract terms. *Energy Economics*, 42:313–324.

Payton, M. E., Greenstone, M. H., and Schenker, N. (2003). Overlapping confidence intervals or standard error intervals: what do they mean in terms of statistical significance? *Journal of Insect Science*, 3(1):34.

Peterson, S. B., Whitacre, J., and Apt, J. (2010). The economics of using plug-in hybrid electric vehicle battery packs for grid storage. *Journal of Power Sources*, 195(8):2377–2384.

Pinson, P., Papaefthymiou, G., Klockl, B., Nielsen, H. A., and Madsen, H. (2009). From probabilistic forecasts to statistical scenarios of short-term wind power production. *Wind energy*, 12(1):51–62.

Rigas, E. S., Ramchurn, S. D., and Bassiliades, N. (2015). Managing electric vehicles in the smart grid using artificial intelligence: A survey. *IEEE Transactions on Intelligent Transportation Systems*.

Ross, S. M. (2014). *Introduction to probability models*. Academic press.

Ruta, D. and Gabrys, B. (2005). Classifier selection for majority voting. *Information fusion*, 6(1):63–81.

Saber, A. Y. and Venayagamoorthy, G. K. (2011). Plug-in vehicles and renewable energy sources for cost and emission reductions. *Industrial Electronics, IEEE Transactions on*, 58(4):1229–1238.

Sanchez-Martin, P., Lumbreras, S., and Alberdi-Alen, A. (2015). Stochastic programming applied to ev charging points for energy and reserve service markets. *Power Systems, IEEE Transactions on*, pages 198 – 205.

Schill, W.-P. (2011). Electric vehicles in imperfect electricity markets: The case of germany. *Energy Policy*, 39(10):6178–6189.

Sedghi, M. and Aliakbar-Golkar, M. (2013). Optimal storage scheduling in distribution network considering fuzzy model of pevs. In *Electrical Power Distribution Networks (EPDC), 2013 18th Conference on*, pages 1–6. IEEE.

Shafie-khah, M., Heydarian-Forushani, E., Golshan, M., Siano, P., Moghaddam, M., Sheikh-El-Eslami, M., and Catalão, J. (2016). Optimal trading of plug-in electric vehicle aggregation agents in a market environment for sustainability. *Applied Energy*, 162:601–612.

Shahidinejad, S., Filizadeh, S., and Bibeau, E. (2012). Profile of charging load on the grid due to plug-in vehicles. *Smart Grid, IEEE Transactions on*, 3(1):135–141.

Shann, M. and Seuken, S. (2014). Adaptive home heating under weather and price uncertainty using gps and mdps. In *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*, pages 821–828. International Foundation for Autonomous Agents and Multiagent Systems.

Shi, W. and Wong, V. W. (2011). Real-time vehicle-to-grid control algorithm under price uncertainty. In *Smart Grid Communications (SmartGridComm), 2011 IEEE International Conference on*, pages 261–266. IEEE.

Siegfried, R., Lehmann, A., El Abdouni Khayari, R., and Kiesling, T. (2009). A reference model for agent-based modeling and simulation. In *Proceedings of the 2009 Spring Simulation Multiconference*, page 23. Society for Computer Simulation International.

Smith, K., Markel, T., Kim, G.-H., and Pesaran, A. (2010). Design of electric drive vehicle batteries for long life and low cost. In *Accelerated Stress Testing and Reliability (ASTR), IEE Workshop on*, pages 6–8.

Smith, K., Markel, T., and Pesaran, A. (2009). Phev battery trade-off study and standby thermal control. In *26th Int. Battery Seminar & Exhibit, Fort Lauderdale, FL.*

Stein, S., Gerding, E., Robu, V., and Jennings, N. R. (2012). A Model-Based Online Mechanism with Pre-Commitment and its Application to Electric Vehicle Charging. In *Proceedings of the 11th International Conference on Autonomous Agents and Multi-agent Systems*, volume 2, pages 4–8. International Foundation for Autonomous Agents and Multiagent Systems.

Ströhle, P., Gerding, E. H., de Weerdt, M. M., Stein, S., and Robu, V. (2014). Online mechanism design for scheduling non-preemptive jobs under uncertain supply and demand. In *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*, pages 437–444. International Foundation for Autonomous Agents and Multiagent Systems.

Sun, L., Yang, J., and Yang, Z. (2013). Optimal charging strategy of plug-in electric taxi. In *Control and Automation (ICCA), 2013 10th IEEE International Conference on*, pages 1532–1537. IEEE.

Sundstrom, O. and Binding, C. (2010). Planning electric-drive vehicle charging under constrained grid conditions. In *Power System Technology (POWERCON), 2010 International Conference on*, pages 1–6. IEEE.

Tan, J. and Wang, L. (2014). Real-time coordinated management of phevs at residential level via mdps and game theory. In *PES General Meeting— Conference & Exposition, 2014 IEEE*, pages 1–5. IEEE.

Tomas, M. (2013). European union energy policy integration: A case of european commission policy entrepreneurship and increasing supranationalism. *Energy policy*, 55:435–444.

Tomić, J. and Kempton, W. (2007). Using fleets of electric-drive vehicles for grid support. *Journal of Power Sources*, 168(2):459–468.

Train, K. E. (2009). *Discrete choice methods with simulation.* Cambridge university press.

Valogianni, K., Ketter, W., and Collins, J. (2014a). Learning to schedule electric vehicle charging given individual customer preferences. In *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*, pages 1591–1592. International Foundation for Autonomous Agents and Multiagent Systems.

Valogianni, K., Ketter, W., Collins, J., and Zhdanov, D. (2014b). Effective Management of Electric Vehicle Storage using Smart Charging. *AAAI*.

Van Hentenryck, P., Bent, R., and Upfal, E. (2010). Online stochastic optimization under time constraints. *Annals of Operations Research*, 177(1):151–183.

Vayá, M. G. and Andersson, G. (2016). Self scheduling of plug-in electric vehicle aggregator to provide balancing services for wind power. *IEEE Transactions on Sustainable Energy*, 7(2):886–899.

Vytelingum, P., Voice, T. D., Ramchurn, S. D., Rogers, A., and Jennings, N. R. (2010). Agent-based micro-storage management for the smart grid. In *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: volume 1-Volume 1*, pages 39–46. International Foundation for Autonomous Agents and Multiagent Systems.

Wai, C. K., Rong, Y. Y., and Morris, S. (2015). Simulation of a distance estimator for battery electric vehicle. *Alexandria Engineering Journal*, 54(3):359–371.

Wang, D., Coignard, J., Zeng, T., Zhang, C., and Saxena, S. (2016). Quantifying electric vehicle battery degradation from driving vs. vehicle-to-grid services. *Journal of Power Sources*, 332:193–203.

Wang, R., Li, Y., Wang, P., and Niyato, D. (2013). Design of a v2g aggregator to optimize phev charging and frequency regulation control. In *Smart Grid Communications (SmartGridComm), 2013 IEEE International Conference on*, pages 127–132. IEEE.

Wayne Beaty, H. and Fink, D. (2006). *Standard handbook for electrical engineers*. The McGraw-Hill Companies.

West, E. (2018). Calb 100 ah ca series lithium iron phosphate battery.

White, C. D. and Zhang, K. M. (2011). Using vehicle-to-grid technology for frequency regulation and peak-load reduction. *Journal of Power Sources*, 196(8):3972–3980.

Wickert, M., Baier, A., Lichtner, P., and Prior, J. (2010). Benefit of a simulation model of a decentralized energy management system for electric vehicle charging. *2010 Emobility - Electrical Power Train*, pages 1–7.

Wu, C., Member, S., and Mohsenian-rad, H. (2012). Vehicle-to-Aggregator Interaction Game. *IEEE Transactions on Smart Grid*, 3(1):434–442.

Wu, Q., Nielsen, A. H., Ostergaard, J., Cha, S. T., Marra, F., Chen, Y., and Træholt, C. (2010). Driving pattern analysis for electric vehicle (ev) grid integration study. In *Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES*, pages 1–6. IEEE.

Xu, N. and Chung, C. (2014). Uncertainties of ev charging and effects on well-being analysis of generating systems. *Power Systems, IEEE Transactions on*, pages 2547 – 2557.

Xu, Z., Hu, Z., Song, Y., and Wang, J. (2017). Risk-averse optimal bidding strategy for demand-side resource aggregators in day-ahead electricity markets under uncertainty. *IEEE Transactions on Smart Grid*, 8(1):96–105.

Yang, J. and Yang, Z. (2014). Pricing scheme for aggregate load scheduling of plug-in electric taxi fleet. In *Control Conference (CCC), 2014 33rd Chinese*, pages 7589–7594. IEEE.

Yang, Z., Sun, L., Chen, J., Yang, Q., Chen, X., and Xing, K. (2014). Profit maximization for plug-in electric taxi with uncertain future electricity prices. *Power Systems, IEEE Transactions on*, 29(6):3058–3068.

Yu, L. and Sun, B. (2012). Four types of typical discrete choice models: Which are you using? In *Service Operations and Logistics, and Informatics (SOLI), 2012 IEEE International Conference on*, pages 298–301. IEEE.

Zahid, M. A. and De Swart, H. (2015). The borda majority count. *Information Sciences*, 295:429–440.

Zareen, N., Mustafa, M., AbuJarad, S. Y., and Moradi, M. (2015). Optimal strategies modeling in electricity market for electric vehicles integration in presence of intermittent resources. *Arabian Journal for Science and Engineering*, 40(6):1607–1621.

Zhang, Y., Wang, W., Kobayashi, Y., and Shirai, K. (2012). Remaining driving range estimation of electric vehicle. In *Electric Vehicle Conference (IEVC), 2012 IEEE International*, pages 1–7. IEEE.

Zhou, C., Qian, K., Allan, M., and Zhou, W. (2011). Modeling of the cost of ev battery wear due to v2g application in power systems. *IEEE Transactions on Energy Conversion*, 26(4):1041–1050.