An Agent Trading on Behalf of V2G Drivers in a Day-ahead Price Market

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Abstract: Due to the limited availability of fuel resources, there is an urgent need for converting to use renewable sources efficiently. To achieve this, power consumers should participate actively in power production and consumption. Consumers nowadays can produce power and consume a portion of it locally, and then could offer the rest of the power to the grid. Vehicle-to-grid (V2G) which is one of the most effective sustainable solutions, could provide these opportunities. V2G can be defined as a situation where electric vehicles (EVs) offer electric power to the grid when parked. We developed an agent to trade on behalf of V2G users to maximize their profits in a day-ahead price market. We then ran the proposed model in three different scenarios using an optimal algorithm and compared 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.

1 INTRODUCTION

One of the most effective sustainable solutions is that of electric vehicles (EVs), because of their power storage capability. They could use solar and wind power and significantly decrease the amount of power that are utilized for transportation because they are more effective than internal combustion vehicles. Moreover, EV batteries could offset the volatility of wind and solar production when they are plugged into the grid. Vehicle-to-grid (V2G) has the potential to further encourage consumers to change their vehicles from fuel vehicles to EVs. This is due to its ability to reduce the power cost, if used effectively. V2G can be defined as an approach whereby an EV offers electric power to the grid when parked. (Kempton and Tomić, 2005) found that, most cars are not used 90% of the time, so EVs can be used to provide power storage and supplementary services to the smart grid during this period when they not being used. Therefore, V2G could be used to provide extra money. For example, it is expected that, if an EV owners contribute in V2G systems, they could take around (2500 to 3000) U.S. dollars yearly (Tomas, 2013). Moreover, (Li et al., 2015) found that the majority of V2G studies are discussed from the perspective of the power grid. In contrast, here we take the consumer's perspective.

In this research there are a large number of diverse actors with individual behaviours and incentives that need to be considered such as the different power markets and V2G drivers' behaviours. Thus, according to Siegfried et al. (2009), an agent-based model might be the first choice to model the problem. Therefore, our research models an agent to trade on behalf of V2G in terms of maximising their profit of using V2G as a source of electricity with consideration to their behaviours and their incentives.

The rest of the paper is organised as follows. The related work will be discussed in Section 2. Afterward, the proposed model will be described in Section 3. Then, Section 4 discusses the design of the optimisation module. Next, the experimental evaluation will be considered in section 5. Finally, the conclusion of our study will be discussed in section 6.

2 RELATED WORK

V2G could be used to support the smart grid (Tomić and Kempton, 2007), (Saber and Venayagamoorthy, 2011) and (White and Zhang, 2011). This offers V2G drivers an opportunity to cut their power costs and receive money. To do so, they should have a clear understanding about how to deal with the power market. However, there is a lack of knowledge among consumers about how to deal with time varying prices in

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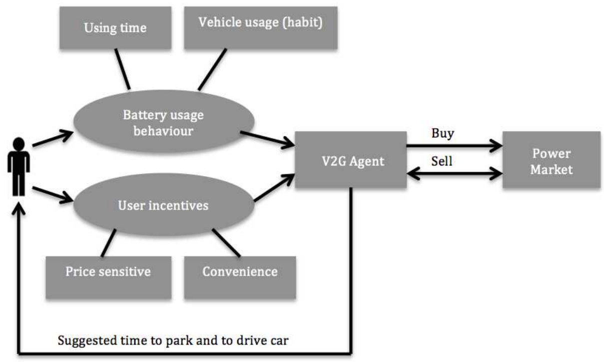

Figure 1: Picture showing our proposed model.

the power market (Mohsenian-Rad and Leon-Garcia, 2010) and (Han et al., 2010). To fix that, (O'Neill et al., 2010) study the price uncertainty problem used reinforcement learning in the residential demand response algorithm. In the same vein, (Conejo et al., 2010) developed a real-time demand response algorithm applied to a daily 24-hour horizon and used robust optimization to consider the price uncertainty in their model (Conejo et al., 2010) and (O'Neill et al., 2010) dealt with the real-time demand response problem. However, (Shi and Wong, 2011) discuss the same issue in the context of V2G control.

V2G problems are more complicated if price uncertainty is considered, as the price of electricity is decided each hour, dynamically. (Shi and Wong, 2011) discussed the real- time V2G control problem considering price uncertainty. Similar to (Shi and Wong, 2011), we study price uncertainty in the context of V2G, but our study differs from theirs in that, Our algorithm is more scalable, thus it could be used when we consider the battery usage behavior as we plan for our future work. Though, they applied Q-learning, which does not work effectively when considering the battery usage behavior as we concluded from (Guo et al., 2004)

In contrast to the aforementioned studies, (Ghiasnezhad Omran and Filizadeh, 2014), (Sanchez-Martin et al., 2015),(Valogianni et al., 2014), (Gonzalez Vaya and Andersson, 2013), and (Halvgaard et al., 2012) studies will be used as references of our model when we are going to model the driving behaviour in our future work. In details, (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. 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 price markets. Along the same line, (Halvgaard et al., 2012) use Economic Model Predictive Control as a technique to reduce the cost of electricity consumption for a single EV. Likewise, (Valogianni et al., 2014) propose an algorithm termed Adaptive Management of EV Storage, which is applied by a learning agent that acts on behalf of individual EV users and schedules EV charging over a weekly horizon. They used reinforcement learning to learn user consumption behaviour and schedule charging with the objectives of maximizing user benefit. The key difference between our work and the aforementioned studies is that they have not considered the V2G issue but we have.

Specifically in V2G, 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) (Panagopoulos et al., 2012), together with that of EV driving behaviour (Ghiasnezhad Omran and Filizadeh, 2014) (Shahidinejad et al., 2012). Moreover, several studies discuss uncertainty in power market prices, for instance the work by (Shi and Wong, 2011). 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.

3 THE MODEL

This section describes the model proposed to solve the research problem. After that, the problem of price uncertainty in the context of V2G is discussed.

3.1 Model Overview

In order to design our agent, a model has been proposed as shown in Figure 1. In this model there are two components that receive input from the V2G driver, battery usage behaviour and user incentives. Two factors will be considered to shape battery 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 and the average speed.

The data on battery 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, 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 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 sensitive. Furthermore, only a single type of power market has been considered, namely the day-ahead price (DAP) market. We chose the DAP market because it is more practical to the people to plan for the following day power market price. 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 future work, the driving behaviour and the user incentives 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 1 has been used to explain the notations in details.

Table 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
B	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 and can be defined as a T = $\{1, 2, ..., n\}$
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

Before representing it mathematically, based on the Table 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 7. 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 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 8. At the end of the day the remaining battery state of charge has been represented as a function $V(x)$, where is $x \in B$. 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 2, if conditions are satisfied, otherwise $U(\overline{a}) = -\infty$. After describing the notations, the problem will be mathematically represented as follows:

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

where

$$U(\overline{a}) = -\sum_{t=1}^{T} p_t(a_t) + V\left(b_{init} + \sum_{t=1}^{T} a_t\right) \tag{2}$$

Subject to

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

$$a \in \{-1, 0, 1\} \tag{4}$$

$$T_{eu}, T_{su} \in T \tag{5}$$

$$b_{init}, b_{des} \in B \tag{6}$$

$$a = 0 \; \forall \; T_{su} \leq t \leq T_{eu} \tag{7}$$

$$b_{init} + \sum_{t=1}^{T_{su}} (a_t) \geq b_{des} \tag{8}$$

$$T_a = (T - (T_{eu} - T_{su})) \tag{9}$$

$$\forall t \in T : B = 0 \leq b_{init} + \sum_{t=1}^{T} a_t \leq 100 \tag{10}$$

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 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 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 10.

4 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 Markova 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. It can be represented mathematically as

$$B = \{0, 10, 20, ..., 100\} \tag{11}$$

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.

5 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.

5.1 Experimental Settings

The experimental settings are as follows:

- An unlimited budget;
- The price depends on the available supply;
- Only a single agent is considered;
- The pricing strategy is a fixed price;
- We assume different price distributions, depending on time, and these are given by Table 2. This assumption is 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.

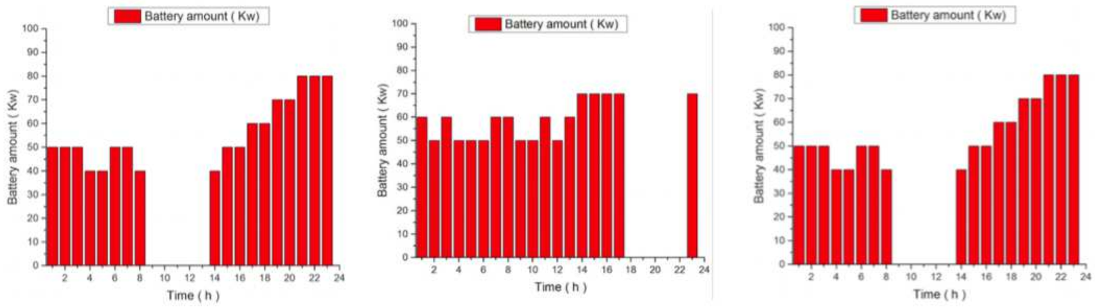

Figure 2: Bar charts of proposed scenarios with our solution.

Table 2: Assumptions for prices of electricity, based on time.

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

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 5.1.1. 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.

5.1.1 Benchmark Strategy

Before discussing the results, the benchmark strategy algorithm used to compare the model to evaluate our solution will be explained. It starts at the first 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 last available hour of the day.

5.1.2 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.

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.

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

5.2 Results

We first ran the simulation once per scenario with each algorithm. We started by running our proposed algorithm. Table 3 and Figure 2 show the results of simulation runs.

Table 3: Summary table of proposed scenarios with our solution.

Scenario	T_{su}	T_{eu}	b_d	utility
First	9	13	>= 40	***104***
Second	18	22	>= 50	***43***
Third	6	12	>= 40	***116***

Moreover, to evaluate the performance of our solution, we compared it with that achieved by using a benchmark strategy algorithm. The crucial difference between our solution and the benchmark strategy, which explained in 5.1.1, 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 4 and Figure 3 provide the results of proposed scenarios after applying a benchmark strategy.

Table 4: Summary table of proposed scenarios with benchmark strategy.

Scenario	T_{su}	T_{eu}	b_d	utility
First	9	13	>= 40	***31***
Second	18	22	>= 50	***22***
Third	6	12	>= 40	***89***

As shown in the results, the agent does 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

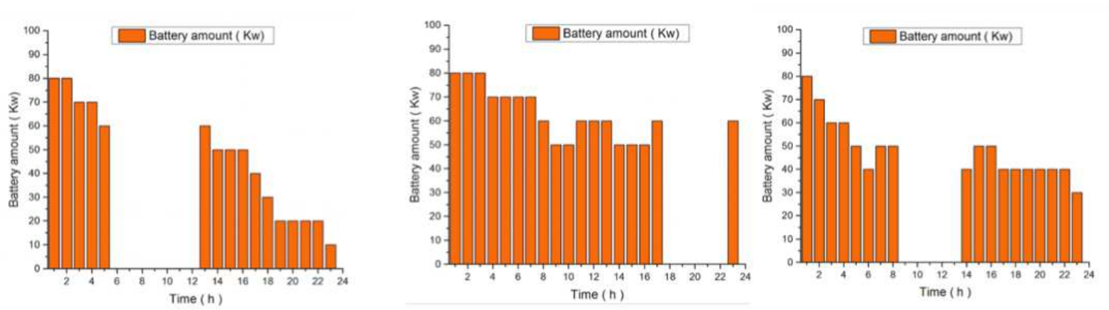

Figure 3: Bar charts of proposed scenarios with benchmark strategy.

and selling) based on the changing on the price. 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. Table 5 provides the average results after running the simulation a hundred times.

Table 5: The average utility results after running the simulation 100 times.

Scenario	**Our solution**	**Benchmark strategy**
First	*97*	*50*
Second	*79*	*39*
Third	*152*	*137*

Through undertaking this comparison with the first scenario, our solution outperformed benchmark strategy in 49%. Moreover, in the second scenario it outperformed the benchmark strategy in 51%, while in the third scenario our solution outperformed the benchmark strategy in 10%.

6 CONCLUSIONS AND FUTURE WORK

This study discussed the problem of the lack of knowledge among customers about how to react to prices varying in time in the power market, specifically the V2G driver. 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.

For future work, driving behaviour will be modelled in order to improve the proposed model through using real data. Furthermore, the battery degradation will be considered. Moreover, to make the proposed model more realistic, a dynamic price market will be considered. This task will be divided into two subtasks. First, the real price market will be modelled to behave as a market by means of using real data from one of the European power markets. Second, the optimization module that has been modelled in the current research will be refined to deal with dynamic prices.

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