Automated Trading in Vehicle-to-Grid with Price Uncertainty using Consensus

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ABSTRACT

In recent years, there has been growing interest in computational approaches to using renewable sources more effectively. Specifically, vehicle-to-grid (V2G), which is where an EV offers electric power to the grid when parked, can be used to store 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 consumer's power cost if used effectively. In this work, we develop a novel heuristic algorithm that can trade on behalf of the V2G drivers in terms of maximising their profits in an hour-ahead price (HAP) market, considering price uncertainty. Our proposed algorithm combines the concepts of consensus and expected value with a backward induction approach. We then run the proposed algorithm with two types of consensuses voting rules (Borda and majority voting) and with expected value and compare the results. We run simulations with different scenarios and show that the expected value approach outperforms the other two (Borda and majority) in all these scenarios.

Keywords

V2G, Driving Behaviour, Price Uncertainty, Consensus Algorithms

1. INTRODUCTION

The smart grid creates a new decentralized structure in power markets, in which renewable sources and storage services have seen major penetration and adoption by power consumers [1]. To benefit from this change the power consumer must participate actively 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. One of the ways to do so is though V2G where by an EV offers electric power to the grid when parked [2].

In more detail, as most vehicle are not being used about 83% 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 [3]. Thus, V2G could be used to secure extra revenue [4]. However, until now V2G technology has not been used effectively [2, 4]. Moreover, according to [5], based on data from interviews with experts in four emerging EV markets: the USA, France, Norway and Japan, there is an urgent need to do more investigations in the EVs applications, specifically, related to V2G. Furthermore, most of the V2G researches in the literature are considered from the power grid systems viewpoint [6]. However, different from these studies, here we consider the V2G consumer viewpoint. Additionally, there are number of economics advantages to using V2G which have not been taken up due to the lack of knowledge by EV drivers. Firstly, several researches have exposed a lack of knowledge among customers about how to react to time varying prices in the power market [7]. Besides, a number of studies have shown that many customers cannot participate effectively and respond properly to price differences in power markets [8] and that people usually do not behave in rational ways [9]. In addition, they have trouble in evaluating competing choices in a consistent fashion [10]. Consequently, obtaining the preferences of the customers, so that they may be efficiently represented within the mechanism, is a challenging task [11].

Against this background, in this study our aim is to design an algorithm to trade on behalf of V2G drivers that can maximise their profits by considering power market price uncertainty. To address the uncertainty of price in the context of V2G, we develop a novel heuristic algorithm that can trade on behalf of the V2G users to maximize their profits from using V2G as a source of electricity, taking into consideration their behaviour and their incentives. Our proposed algorithm combines two types of consensus voting rules (Borda and Majority) and expected value with a backward induction approach.

Modeling the time series of power price as a Markov decision process (MDP) and using dynamic programming to deal with it is discussed in [12], [13]. Furthermore, using the consensuses algorithm to deal with multi scenarios can be found in [14], [15], [16]. The novelty of our work is the idea of combining between these two concepts (dynamic programming and consensuses algorithm) and apply it to design a heuristic V2G algorithm under price uncertainty. A consensus algorithm can be defined as that whereby there are several feasible steps to be considered for each period of time. After solving each sample of steps, the decision is selected that appears most frequently of time. Specifically, the contributions of this paper are as follows:

- 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 novel heuristic algorithm that combines between backward induction and two types of consensuses voting rules which are Borda and majority 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 evaluate the proposed algorithm by apply it with two types of consensus voting rules (Borda and Majority) and with expected value. Simulation results show that apply the proposed algorithm with expected value outperforms (Borda and Majority) approaches considerably.

The rest of the paper is organised as follows. Section 2 discusses related work. Then, section 3 describes the proposed model in detail. Next, the design of the optimisation module is discussed in detail in section 4. After that, section 5 discusses the experimental design, shows the simulation results using the algorithm and discusses the results of the experiment. Finally, section 6 concludes our study and provides direction future work.

2. RELATED WORK

V2G could be used to regulate electricity frequency and act as an electrical storage device as in [17], [18] and [19]. This provides V2G drivers with the opportunity to earn money and reduce their power costs. To achieve these goals, they should have a clear perception about in what way they should deal with the power market. However, according to [7] and [20] they have insufficient awareness on how to respond to time-varying prices. To solve this issue, [13] and [21] address the problem of price uncertainty in residential demand response, [12] consider the similar subject, but from the V2G control perspective.

Similar to [12, 22, 23, 24], we study price uncertainty in the context of V2G, yet our study differs from theirs in several points. specifically, our work differs from [12] in that, our proposed algorithm is more scalable, so it may be integrated with battery usage uncertainty, as we aim to do in future work. However, Q-learning does not work well if we consider the uncertainties in battery usage as we learnt from [25]. Unlike [12, 22, 23], who discuss price uncertainty in the context of a V2G driver who uses the car for private use, [26, 27, 28] investigate the optimal charging strategy for a plug-in electric taxi (PET). They argue 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. As in [26, 27, 28], 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 different problems and constraints. Moreover, in our heuristic algorithm we combine backward induction and consensus algorithms. Further, [24] 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 [29, 24] in that they consider a fleet of EVs, while our study is of an individual EV, which means we have different problem constraints.

Like [14], [15], [16], we apply a consensus algorithm, but in the context of V2G. We differ from [14] [15] in that at each period of time they make a single decision while, like [16], we select several decisions. As in [30], we apply the consensus algorithm to deal with price uncertainty in the power market, yet we differ in that we apply it in the V2G context in order to maximize V2G drivers' profits. In their study, they apply it to discuss the problem of next generation of smart grid, where uncertain output from renewable generators should be integrated to flexible, non-preemptive demand.

Finally, especially in the context of V2G, there are several algorithms that proposed to cope with different kinds of uncertainties such as uncertainty in the production of renewable power [31] [32], with that of vehicle driving behaviour [33] [34]. Also, numbers of research consider uncertainty in power market prices, for example the study by [12]. Moreover, [35] state that when the V2G owners buy (charge) or sell (discharge) in the amount of battery in their vehicles with the power market optimally, they not only increase their income but also support the power market in peak demands periods. After providing the related work, in the next section our proposed model will be discussed.

3. THE MODEL

This section describes the model proposed to maximize the V2G driver profits when considering price uncertainty in the power market. following this, the problem of price uncertainty in the context of V2G is discussed.

3.1 Model Overview

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 preferences. Our proposed algorithm combines two types of consensus algorithms (Borda and Majority voting) and expected value with a backward induction algorithm.

In order to design our proposed algorithm, we use the model of our previous work [36], shown in Figure 1. In this model, there are two modules that receive data from the V2G driver, which are vehicle usage behaviour and user preferences. V2G drivers define the periods when they need to drive their vehicle and when they can park their vehicle, as modelled using time rectangle. If driving periods are stated, parking periods could be defined, which can be utilized to sell and buy the electricity in the battery. The V2G agent will trade with the power market (sell or buy) based on vehicle usage behavior, trying to choose the best period to charge (buy) and discharge (sell) by predicting price behaviour. To do such, the V2G agent will maximize the V2G drivers' utility, which is the monetary profit and the amount of battery power that is returned to the V2G driver at the end of a day.

In this work only a single type of power market has been considered, namely the Hour-Ahead Price (HAP) market. The HAP market is a type of electricity market where the electricity is delivered to the consumer for use in the following hour. Moreover, we assume the V2G drivers' will use

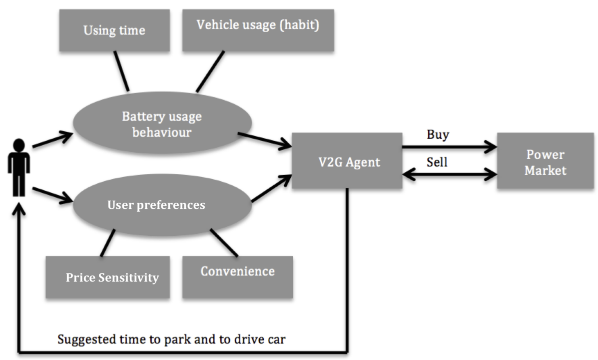

Figure 1: Picture showing our proposed model.

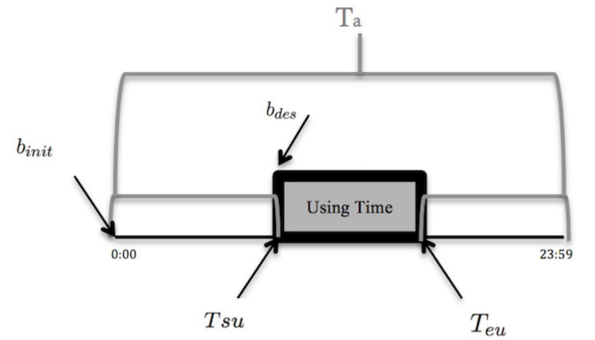

Figure 2: Diagram shows the planning horizon for our model.

their cars once a day.

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, the desired battery state of charge, the start of using time and the end of using time prior to the beginning of every day, along with s number of power market prices for each following hour. So the uncertainty here comes from the prices and the driving behaviour (battery usage). Before discussing the details of the optimisation module, the next section will formulate the problem.

3.2 Problem Formulation

This section describes formulation of the V2G problem under price uncertainty as markov decision process (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_{in} is the initial battery state of charge . We have two types of pricing, charging price P that represented mathematically as the vector $\overline{p}^{ch} = \langle p_1^{ch}, ..., p_T^{ch} \rangle$, discharging price that represented mathematically as the vector $\overline{p}^{di} = \langle p_1^{di}, ..., p_T^{di} \rangle$, where $\overline{p}^{ch}$ and $\overline{p}^{di} \subset P$ .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 is three actions that have charging types, fast charging, normal charging, and slow charging. However, since there are a number of constrains in our problem, and so not all the actions can be chosen at a given state. An agent choses action a_t from a set of action A by considering the hourly power market price and we define the vector of chosen action 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:

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

If conditions in Equations [5-12], which we will discussed in this section later, are satisfied, Equation 1 applies, otherwise $U(b_{in}, a) = -\infty$. We now describe the V2G problem under price uncertainty at time t. We assume that the EV has a start of using time T_{su} and the end of using time T_{eu} which are known in advance. Moreover, we assume that the power market prices for the following hour are unknown and this uncertainty needs to be modelled. To model the price uncertainty, in the general problem, there is a correlation between the hours prices, which can be represented as $P(P_t|P_1...P_{t-1})$. However, for simplicity, we assume that the hours' prices in the experiment are independent. However, we claim that our solution is still valid with $P(P_t|P_1...P_{t-1})$.

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 battery usage behaviour, which has been defined in this study as usage time. 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 future work we will consider the uncertainty in the battery usage behaviour.

Figure 2 illustrates the planning horizon for our model. In detail, it shows the b_{in} 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). T_a is the available time when the agent can chose any action, while considering the constraints, and we defined this as $T_a \subset T$.

Now, the problem will be mathematically represented as follows:

$$EU_t\left(a_t, Soc_t\right) = \begin{cases} \int_{p_t \in P^{ch}} f\left({p_t}^{ch}\right) \cdot \left(EU^*_{t-1}\left(Soc_t\right) - {p_t}^{ch}\right) \\ \quad dp_t^{ch} \\ \quad if\ a_t > 0 \\ \\ \int_{p_t \in P^{di}} f\left({p_t}^{di}\right) \cdot \left(EU^*_{t-1}\left(Soc_t\right) + {p_t}^{di}\right) \\ \quad dp_t^{di} \\ \quad if a_t < 0 \end{cases} \tag{2}$$

where

$$EU^*_t\left(Soc_t\right) = argmax_{a_t \in A} EU_t\left(a_t, Soc_t\right) \tag{3}$$

$$EU_n\left(a_n, Soc_n\right) = U(b_{in}, \overline{a}) \tag{4}$$

Subject to

$$T = \{1, 2, 3, ...n\} \tag{5}$$

$$T_{su}, T_{eu} \in T \tag{6}$$

$$b_{in}, b_{des} \in Soc \tag{7}$$

$$a_t = 0\ \forall\ T_{su} \le t \le T_{eu} \tag{8}$$

$$Soc_t = b_{in} + \sum_{t'=1}^{t}(a_{t'}) \tag{9}$$

$$Soc_{T_{su}} \ge b_{des} \tag{10}$$

$$\forall t \in T : Soc_t = 0 \le b_{in} + \sum_{t=1}^{T} a_t \le 100 \tag{11}$$

$$0 \le Soc_t \le 100 \tag{12}$$

After representing the problem mathematically, the main equations 2, 3 and the main constraints will be explained. In 2, if we charging, the above equation will be conducted whereas the $f({p_t}^{ch})$ function that represents the charging price uncertainty. On the other hand if we discharging, the below equation will be conducted whereas the $f({p_t}^{di})$ 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 3 first. In 3, we calculate the *argmax* for EU^* at t so we have to do 2 and 3 recursively. Moreover, we propose 4 to stop 3 and 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 constraint 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 10. Further, to ensure that the battery state of charge does not exceed its scope, which is between 0 and 100 we proposed 12, and to calculate the battery amount after each step, we proposed constraint 11.

4. THE OPTIMIZATION MODULE

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

4.1 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

Algorithm 1: V2G Heuristic algorithm

Input: T_{su}, T_{eu}, b_{in}, 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.

$\forall\ A \leftarrow \{a_1, a_2, ..., a_n\}$// 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**

- $TotalScore \leftarrow Call\ Borda(T_{su}, T_{eu}, b_{in}, b_{des}, S\ ) \ |Majority(T_{su}, T_{eu}, b_{in}, b_{des}, S\ )\ |\ Expected\ value(T_{su}, T_{eu}, b_{in}, b_{des}, S\ )$
- $VotingWinner \leftarrow Max(TotalScore)$ // Function that returns the action that provides the highest total score.
- $chosenAction_t \leftarrow VotingWinner$

end foreach

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

optimisation techniques [37]. 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 [38].

To apply the backward induction algorithm, the study by [39] 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, Soc_t, in each point of time, t, then chooses an action, a.

Backward induction algorithm will be used to deal with each power market price scenario. In aim of 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.

4.2 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 s number of scenarios for the power market price, we apply backward induction (offline algorithm) with each scenario to find the best action at each hour. Actually, [36] apply that and find it is an efficient technique to deal with this issue. Then we apply the concept of a consensus algorithm (online algorithm) in order to deal with the s scenarios. Indeed, we apply the consensus algorithm concept because relevant work has been conducted on it already, such as that by [30], who found it an efficient technique to deal with uncertainty in the power market. Moreover, we apply Borda and majority because [40] compare four types of voting rules (majority, Borda, maximin, and Kemeny) and note that Borda voting is simpler and more accurate than the others. Furthermore, they confirm that majority voting is one of the most widely used voting types.

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 [41]. Table 1 is an example of voting in our experiment. On the other hand, in the majority voting rules, in each vote only the winner is considered, so in every round of voting the winner scores 1 point and the others are ignored [42]. Finally, we combine our offline algorithm (backward induction) with the concept of expected value, as in[43].

Table 1: Example of voting in our experiment.

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

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, see Algorithm 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.

In summary, in order to model the price in the HAP market, we assume that our agent receives s 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 s. 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 MDP. Then, we propose a novel heuristic algorithm that maximises the V2G drivers' profit by choosing the best actions for each time period.

5. EXPERIMENTAL EVALUATION

In this section, the experimental settings will be explained. After that, we will show the simulation results using the algorithm. Finally, we will discuss the results.

5.1 Experimental settings

The experimental settings are as follows. We have a different number of price market scenarios which are,$|S| = \{10, 20, 30, ..., 100\}$ and we propose these numbers since we believe when we have large number that will more accurate but will consume more computational time. Thus, we propose them to include a sensible range of values in our experiment. Moreover, this simulation has different price distributions, depending on time, as in Table 2. This 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. 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.

A limitation of the simulation was that 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.

Table 2: Electricity prices, based on time in our experiments.

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

In addition, 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 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.

Furthermore, as we mentioned before, since we have not considered the battery usage behaviour yet (that will be done in future work), the b_{des} and b_{in} are known by the agent before it starts, and they have been fixed for the whole experiment with the values $b_{des} = 40$ and $b_{in} = 60$. Moreover, since we have also not yet considered the battery usage uncertainty, we consider the final state of charge as being zero just for now, but in the future we will consider it when we discuss the battery usage uncertainty.

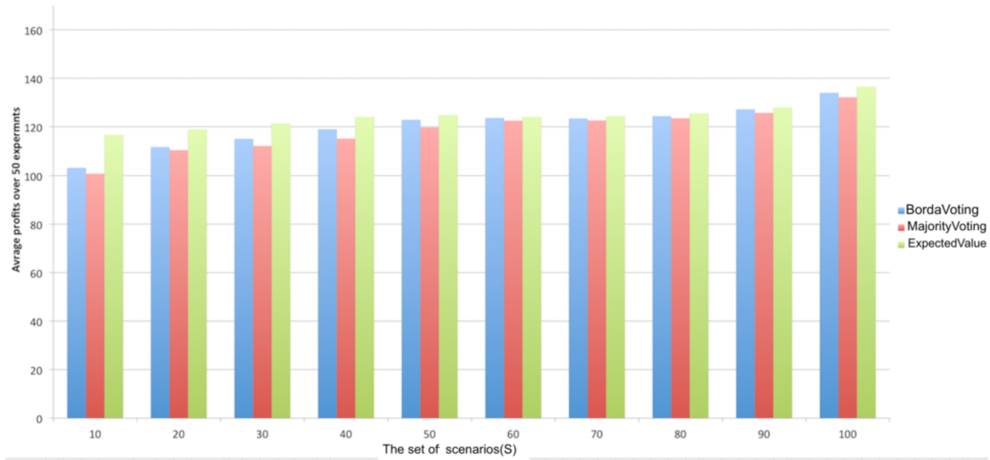

Figure 3: Bar chart showing the average profits over 50 experiments with different number of scenarios for Borda, Majority, and expected value algorithms.

Algorithm 2: BordaVoting

Input: T_{su}, T_{eu}, b_{in}, 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**
    $ActonValue_a \leftarrow V2GBackwardInduction(\ T_{su}, T_{eu}, b_{in}, b_{des}, s, a\ )$// 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 .
  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 $TotalScore$

5.2 Results

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 shown in Figure 3, 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. We can justify this issue by that, using Borda and Majority voting algorithms with backward induction whereas backward induction is the voter in our experiment. It votes based on the best action, without considering to the variations in the expected utility for each action. Unlike Borda and Majority voting, the Expected value considers variations in the expected utility for each action, thus is better than either.

Furthermore, as Figure 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 5.1 , there is a varying amount of increase in profit. This is because, 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. Moreover, by comparing between the results of the three algorithms (Borda voting, majority voting, and expected value) by using a paired T-test, we found that, the results of Borda voting and expected value are significant in some of the points such as 10, 20, 30, and 40. Further, the results of expected value and majority voting are significant in the same points. However, this is not the case for the results of Borda and majority for the points 10, 20, 30, and 40.

6. CONCLUSIONS AND FUTURE WORK

This study discusses price uncertainty in the power market in the context of V2G. Specifically, we introduce a novel heuristic algorithm to trade on behalf of V2G drivers in order to maximize their profits, specifically in the HAP market. To deal with the price uncertainty, our proposed algorithm combines backward induction and two types of consensus algorithms, namely Borda and Majority voting, and the expected value algorithm. The results of the proposed simulation were compared with two consensus voting rules and expected value approach, running under our proposed algorithm. The results show that the performance of our heuristic algorithm with expected value outperformed Borda and Majority voting under all the various power market prices scenarios in order to maximize V2G driver profits in HAP through considering price uncertainty. In conclusion, in this work we achieve our first objective, to design an algorithm to trade on behalf of V2G drivers and to maximize profit while considering uncertainty in power market prices.

Algorithm 3: Majority Voting

Input: T_{su}, T_{eu}, b_{in}, 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

$\forall\ A(s) \leftarrow \{a_1, a_2, ..., a_n\}$
foreach $s \in S$ **do**
  foreach $a \in A$ **do**
    $ActonValu_a \leftarrow V2GBackwardInduction(\ T_{su}, T_{eu}, b_{in}, b_{des}, s, a\ )$ // 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 $Score$

For future work, the model for vehicle usage uncertainty will be designed. Next, to make the proposed model more realistic, real driving behaviour data will be considered. Moreover, the battery degradation issue will be considered. Furthermore, the optimization module will be refined to deal with these two types of uncertainties (prices and vehicle usage) in the context of V2G.

REFERENCES

[1] Amin SM, Wollenberg BF. Toward a smart grid: power delivery for the 21st century. Power and Energy Magazine, IEEE. 2005;3(5):34–41.

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

Algorithm 4: Expected Value

Input: T_{su}, T_{eu}, b_{in}, 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_{in}, b_{des}, s, a $ActonValu_a)$ // Function that returns the value for each action.
  end foreach
  $Score \leftarrow ActonValu$// Function that assigns .
  $TotalScore = TotalScore + Score$// 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_{in}, b_{des}, s
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.
$Soc \leftarrow b_{in}$
while $t \neq 0$ **do**
  if $(t \geq Teu$ ***or*** $t \leq Tsu)$ **then**
    //to exclude the using time period.
    if $(t = T_{su})$ ***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_{in}, b_{des}, s)
    else
      $chosenAction = DecisionMaking(Soc_t, t, s)$ // Decision Making Function that returns the action that maximize the utility function .
    $Action = Action + chosenAction$
    $t = t - 1$
end while
return $Action$

[3] Almansour IA, Gerding EH, Wills G. 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,. INSTICC. SciTePress; 2018. p. 238–242.

[4] Tomas M. European Union energy policy integration: A case of European Commission policy entrepreneurship and increasing supranationalism. Energy policy. 2013;55:435–444.

[5] Hota AR, Juvvanapudi M, Bajpai P. Issues and solution approaches in PHEV integration to smart grid. Renewable and Sustainable Energy Reviews. 2014;30:217–229.

[6] Li Z, Chowdhury M, Bhavsar P, He Y. Optimizing the performance of vehicle-to-grid (V2G) enabled battery electric vehicles through a smart charge scheduling model. International Journal of Automotive Technology. 2015;16(5):827–837.

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

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

[9] Kahneman D. Thinking, fast and slow. Macmillan; 2011.

[10] Dan A. Predictably irrational: the hidden forces that shape our decisions. HarperCollins New York:; 2008.

[11] Rogers A, Ramchurn S, Jennings N. Delivering the Smart Grid : Challenges for Autonomous Agents and Multi-Agent Systems Research. AAAI. 2012;.

[12] Shi W, Wong VW. Real-time vehicle-to-grid control algorithm under price uncertainty. In: Smart Grid Communications (SmartGridComm), 2011 IEEE International Conference on. IEEE; 2011. p. 261–266.

[13] O'Neill D, Levorato M, Goldsmith A, Mitra U. Residential demand response using reinforcement learning. In: Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on. IEEE; 2010. p. 409–414.

[14] Bent R, Van Hentenryck P. The Value of Consensus in Online Stochastic Scheduling. In: ICAPS. vol. 4; 2004. p. 219–226.

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

[16] Pan F, Bent R, Berscheid A. Online dynamic scheduling for charging PHEVs in V2G. Los Alamos National Laboratory (LANL); 2011.

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

[18] Saber AY, Venayagamoorthy GK. Plug-in vehicles and renewable energy sources for cost and emission reductions. Industrial Electronics, IEEE Transactions on. 2011;58(4):1229–1238.

[19] White CD, Zhang KM. Using vehicle-to-grid technology for frequency regulation and peak-load reduction. Journal of Power Sources. 2011;196(8):3972–3980.

[20] Han S, Han SH, Sezaki K. Design of an optimal aggregator for vehicle-to-grid regulation service. In: Innovative Smart Grid Technologies (ISGT), 2010. IEEE; 2010. p. 1–8.

[21] Conejo AJ, Morales JM, Baringo L. Real-time demand response model. Smart Grid, IEEE Transactions on. 2010;1(3):236–242.

[22] Khalid MW, Al-Awami AT, Sortomme E. Stochastic-programming-based bidding strategy for V2G services. In: Innovative Smart Grid Technologies Europe (ISGT EUROPE), 2013 4th IEEE/PES. IEEE; 2013. p. 1–5.

[23] Sanchez-Martin P, Lumbreras S, Alberdi-Alen A. Stochastic Programming Applied to EV Charging Points for Energy and Reserve Service Markets. Power Systems, IEEE Transactions on. 2015;p. 198 – 205.

[24] Li Z, Jiang Y, Zhang X, Tian W. Market-Based Optimal Control of Plug-In Hybrid Electric Vehicle Fleets and Economic Analysis. Journal of Energy Engineering. 2015;p. 04015025.

[25] Guo M, Liu Y, Malec J. A new Q-learning algorithm based on the metropolis criterion. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics). 2004;34(5):2140–2143.

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

[27] Yang J, Yang Z. Pricing scheme for aggregate load scheduling of plug-in electric taxi fleet. In: Control Conference (CCC), 2014 33rd Chinese. IEEE; 2014. p. 7589–7594.

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

[29] Wang R, Li Y, Wang P, Niyato D. Design of a V2G aggregator to optimize PHEV charging and frequency regulation control. In: Smart Grid Communications (SmartGridComm), 2013 IEEE International Conference on. IEEE; 2013. p. 127–132.

[30] Ströhle P, Gerding EH, de Weerdt MM, Stein S, Robu V. 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. International Foundation for Autonomous Agents and Multiagent Systems; 2014. p. 437–444.

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

[32] Panagopoulos AA, Chalkiadakis G, Koutroulis E. Predicting the power output of distributed renewable energy resources within a broad geographical region. 2012;.

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

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

[35] Zareen N, Mustafa M, AbuJarad SY, Moradi M. Optimal Strategies Modeling in Electricity Market for Electric Vehicles Integration in Presence of Intermittent Resources. Arabian Journal for Science and Engineering. 2015;40(6):1607–1621.

[36] Almansour IA, Gerding EH, Wills G. 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,. INSTICC. SciTePress; 2017. p. 135–141.

[37] Adda J, Cooper RW. Dynamic economics: quantitative methods and applications. MIT press; 2003.

[38] Gibbons R. Game theory for applied economists. Princeton University Press; 1992.

[39] Fackler PL. Applied computational economics and finance. MIT press; 2004.

[40] Mao A, Procaccia AD, Chen Y. Better Human Computation Through Principled Voting. In: AAAI. Citeseer; 2013. .

[41] Zahid MA, De Swart H. The Borda majority count. Information Sciences. 2015;295:429–440.

[42] Ruta D, Gabrys B. Classifier selection for majority voting. Information fusion. 2005;6(1):63–81.

[43] Chang HS, Givan R, Chong EK. On-line Scheduling via Sampling. In: AIPS; 2000. p. 62–71.