



# Economic and technical aspects of plug-in electric vehicles in electricity markets



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## ABSTRACT

In this paper, the management of PEVs, uncontrolled or controlled (i.e. aggregated), and their ability to use V2G and G2V technologies are first analysed. The electricity markets are then considered; real world applications are discussed and different market types categorised. The interaction of the PEVs with some renewable energy sources (e.g. solar, wind and biomass) is also examined, and the interaction of the PEVs with demand response programs addressed. Finally, the models of PEVs are categorised and multiple types of modules, the related variables, applied methods and the considered parameters are presented.

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## 1. Introduction

### 1.1. Motivation and aim

Many developments have been made in the last few years regarding plug-in electric vehicles (PEVs) and plug-in hybrid electric vehicles (PHEVs). According to the studies regarding this subject, it is difficult to keep track of all the recent developments. Therefore, using [1,2] helps to simplify the search for further development and investigation.

This paper not only categorises the studies on the aggregator and the markets, but also presents the models that enable understanding of how to manage PEVs and their charging/discharging, battery degradation, etc. The main goal is to address the economic part, different types of PEV modelling and their management.

### 1.2. Background and paper framework

There have been various PEV models and approaches over the last few years. There are deterministic [3], probabilistic [4] and stochastic [5] models, and it has been a challenge to find the best model and the best management. There are several utilised variables in the reported models, but no comprehensive model that considers all components. Here, we examine some relevant reports that could help to develop new appropriate models. The remainder of this paper is organised as follows. In Section 2, the PEV management and V2G capability are presented. For PEV management, it is discussed up to date studies, whether they consider PEVs that are controlled, aggregated/managed or completely uncontrolled. The many perspectives of multiple studies are taken into consideration as for example [6]. Then, it is determined whether current studies discuss the V2G capability of the PEVs and we consider a couple of papers in this context as for example [7].

Section 3 is dedicated to categorising the studies from the market viewpoint. The first topic concerns types of market in which PEVs participate, whether they participate by selling or buying electricity. We present the real life market case of Singapore [8]. It is explained the different markets in which it participates. Some papers also report on the markets that are relevant to the subject, mainly spinning and non-spinning reserve, regulation market (voltage and current) and ancillary services. The second topic concerns the interaction of PEVs with renewable power sources and DR programs. Three different renewable energy sources are explored: photovoltaic, wind and biomass.

In Section 4 the models are examined. There are a large number of features, starting with the type of model regarding uncertainty; the main models are deterministic, probabilistic, and stochastic, as mentioned previously. Following this, the timeline is taken into consideration; the models to study are day-ahead [9] and real time [10] managements. Multiple papers are also reviewed (e.g. [11–13]) in order to highlight which models are the most common and how these models' variables are handled. Furthermore, other features of the models are explored, starting with what kind of parameters are considered in models such as infrastructure cost, V2G-Inverters, battery degradation and fleet management and SOC. It was found different approaches to different papers (e.g.

[14–16]). In addition, the interaction with the electricity network is considered to indicate what has been modelled, whether the distribution or transmission network.

Finally, some features of the power system are investigated. These features include security, reliability, adequacy, quality, stability, loss, frequency and voltage control. There are many reports on the mentioned features such as [17,18]. Some relevant equations in the literature are considered in order to formulate a PEV model.

## 2. Plug-in electric vehicle management

### 2.1. Description

There have been many studies on both aggregated/managed and completely uncontrolled PEVs. The studies are mainly about aggregated/managed PEV due to the disadvantages of the uncontrolled PEV scenario.

In [6], different studies are presented for different charging scenarios, which include uncontrolled domestic charging, uncontrolled off-peak domestic charging, smart domestic charging and uncontrolled public charging throughout the day. The worst case scenario was the uncontrolled domestic charging where all vehicles are charged at the same time. In this case, the charging affects the local distribution in terms of capacity limit. In the second scenario, uncontrolled off-peak domestic charging improves the results because the charging does not occur during off-peak hours. In the third scenario, smart domestic charging, the charging is controlled to optimise according to the needs of filling the load curve, it improves the sales and does not overload the system. The last scenario presented uncontrolled public charging throughout the day, which can be divided into three categories: *industrial*, where people charge while at work, *commercial charging*, and *residential charging* at night. In the latter case, there would be a peak while people are at work. In this scenario, the industrial and commercial loads cannot absorb EV charging load without exceeding the natural peak load if all EVs start charging at the same time.

In [2], the effects of uncontrolled charging on distribution equipment is presented. Uncontrolled charging for a PEV with 50% penetration, the transformer life is reduced by 200–300%. Comparing the scenarios of uncontrolled and smart or controlled charging, the controlled charging increases the life expectancy of the transformers by 100–200%.

In [19], uncontrolled and controlled charging of PEVs is investigated with different penetration levels to show their impacts on the grid. One of the cases is studied on the modified IEEE 23 kV distribution system, where it is observed that high (63%) or low (16%) penetration of the PEVs with the uncontrolled charging results in severe voltage deviations of up to 0.83 p.u., high power losses and higher costs in generation.

In [5], an uncontrolled PEV load modelling is presented. In this study it is suggested that when users randomly plug-in their vehicles, they must choose the type of charging adequate to their needs and their car. Forecasting tools are used to predict the charging levels. It is also stated that unregulated charging can cause power spikes and safety margins in the power grid. The use

## Nomenclature

### Abbreviations

DoD	Depth of Discharge
DR	Demand Response
EV	Electric Vehicle

G2V	Grid to Vehicle
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PSO	Particle Swarm Optimization
SOC	State-Of-Charge
V2G	Vehicle to Grid
VSM	Voltage Stability Margin

of charging incentives for specific times or locations is suggested in order to regulate the power. An aggregated/managed charging is recommended, which can be uncontrolled by incentivising people to charge in a certain pattern. The customers do not use this charging method if it is inconvenient for them to go to the charging locations, when in an emergency and they need to have enough charge immediately, or they do not need an incentive. Therefore, in such cases it would seem a slight contradiction to call it uncontrolled charging when it is being managed by giving incentives.

Therefore, taking into consideration all the cases presented above, the uncontrolled scenario has many disadvantages in comparison with the PEV charging scenario. In most reports, it is concluded that aggregated/managed charging brings many benefits not only to the user but also to the distributor. Some new strategies are reported to address the issues regarding the coordination of PEVs' charging load in the future smart grid. On this basis, two major charging strategies including multiple tariff policies and centralised controlled charging are investigated in [20], who explores the impacts of these strategies on the distribution network. The charging of the PEV can be controlled by the operator, who can manage it according to needs using smart charge like functions to maximise. Although for the new V2G concept there is a need for aggregation, on the whole, home users cannot negotiate directly with operators and they need an aggregator as a mediator.

In [21], an aggregator based market is presented. It is shown how the market works and the roles of each individual entity, aggregator and user. From the operator point of view, it will be a minimisation of cost problem; to even the load curve, there is a need to turn on power plants or purchase electricity from other countries or entities. By using the V2G concept they reduce the costs of these problems; in this study a minimisation solution from the operator point of view is presented, and monetary rewards are given to the aggregators so that they can negotiate on their behalf. As mentioned before, home users cannot interact with the operator, and they need to enrol on a DR program, which is provided by the aggregator. The aggregator's role is to provide DR services to the operator and to guarantee a reduced electricity bill to the users. It presents a profit maximisation solution for the aggregators. Finally, they consider the problem from the point of view of users, who receive monetary rewards for consuming off-peak and their objective is either a reduced electricity bill or monetary pay. The study presents the equations to maximise the net payoff to the user.

Based on the above discussion, the intention is to present the aggregator scheme and how it all works. There might be some variations in the equations used, but the idea behind it is the same. Taking into consideration both scenarios, the uncontrolled and the aggregated, the differences as well as the advantages and disadvantages of both can be seen. Starting with the aggregated scenario, there is no overload of the system because it is controlled by the operator, the end user has the advantage of monetary rewards and the operator saves on the operational costs of power plants and other power sources. The uncontrolled scenario has

many disadvantages, primarily, the degradation of the PEVs, which is severely increased, the peak problems and a worst efficiency. On this basis, the aggregation/management of the PEVs yields better results than the uncontrolled PEVs.

There has been an increasing tendency for the inclusion of G2V and V2G capability in the models. For example, [7,22–24] include V2G and/or G2V capability consideration in the models. There may be different approaches, markets and battery degradations, all or some of which are included in their algorithms for the subject, but the inclusion of this technology is always present and considered.

For instance, [7] presents a strategy for peak reduction in urban regions in Brazil in a smart grid environment. For this, they develop a model taking into consideration V2G and G2V.

As another example, in [22] an algorithm is developed for integration of the V2G in the current market, which studies its potentialities, grid penetration and introduction into the ancillary service market.

These examples demonstrate that the same concept can be applied to different problems, namely, the peak reduction and the ancillary service.

## 2.2. Model categories

The models of PEV in the literature can be divided into three categories, namely, operator viewpoint, aggregator viewpoint and users/owners viewpoint. An overview of the models is presented below:

### 2.2.1. Operator viewpoint

If the operator could directly control the loads, its objective would be formally expressed as in the following, where daily load profile vector  $y = \{y_t : t \in T\}$ :

$$\max_y \pi W - \sum_{t \in T} c_t(y_t) \quad (1)$$

$$\text{s.t.} \sum_{t \in T} y_t = W \quad (2)$$

where  $W$  denotes watts and  $\pi$  represents the fixed price per watt.

The operator provides monetary rewards  $\lambda = \{\lambda_j \geq 0 : j \in A\}$  to the aggregators, so that they perform DR on its behalf.  $y$  becomes dependent on  $\lambda$ . The operator is willing to dedicate a portion  $\hat{\lambda} = \sum_{j \in A} \lambda_j$  of its DR gain to the aggregators.

The DR gain is the reduction of the power generation cost that results from reward  $\lambda$  and is given by (3):

$$\Delta C(y(\lambda)) = \sum_{t \in T} \Delta c_t(y_t(\lambda)) = \sum_{t \in T} [c_t^0 - c_t(y_t(\lambda))] \quad (3)$$

where  $c_t^0$  is the power generation cost at timeslot  $t$  if no DR is applied.

Operator's problem (min operational cost) with the above considerations would be: (4)

$$\min_{\lambda} \sum_{t \in T} c_t(y_t(\lambda)) + \hat{\lambda} \Delta C(y_t(\lambda)) \quad (4)$$

$$\text{s.t. } 0 \leq \hat{\lambda} \leq 1 \quad (5)$$

$$\lambda_j \geq 0 \quad \forall j \in A. \quad (6)$$

### 2.2.2. Aggregator viewpoint

Since small users (e.g. EV owners) cannot negotiate directly with the operator, they enrol on a DR program provided by an aggregator that aggregates several small residential DR assets into a larger unit, in order to increase their negotiation power. Given that each user is assigned to an aggregator through a contract, we denote with  $D_j$  the set of demands of all the users (i.e. from all individual appliances) under aggregator  $j$ .

The strategy of aggregator  $j$  is composed of the compensation vector  $p_j = \{p_{jt} : t \in T\}$ . Let  $d_j = \{d_{jt} : t \in T\}$  denote the cumulative load of aggregator  $j$  at time slot  $t$ , over all the demands in  $D_j$ , which results from compensation  $p_j$ .

From the side of aggregator  $j$ , the DR gain  $\Delta c$  of (1.3) depends on its own compensation strategy  $p_j$ , but also on the compensation strategy of aggregators other than  $j$  denoted by  $P_{-j} = (p_1, \dots, p_{j-1}, p_{j+1}, \dots, p_I)$ . The same holds for the actual reward received by aggregator  $j$ , since power generation cost at time slot  $t$  is a function of the corresponding total load,  $y_t = \sum_{j \in A} d_{jt}$ .

The objective of aggregator  $j$  is to maximise its net profit by solving the following optimisation problem:

Aggregator's  $j$  problem (max net profit):

$$\max_{p_j} \lambda_j \Delta c(p_j, P_{-j}) - \sum_{t \in T} p_{jt} d_{jt}(p_j) \quad (7)$$

$$\text{s.t. } p_{jt} \geq 0 \quad \forall t \in T \quad (8)$$

The first term corresponds to the reward received from the operator, while the second term is the compensation provided to the users.

### 2.2.3. Users/owners viewpoint

At home, under the current model of flat pricing, users tend to use their appliances at the most convenient time throughout the day, driven by their personal preference. For example, most people activate the cooling system during the hottest part of the day, thus creating demand peaks. We define  $x_i^0 = \{x_{it}^0 : t \in T\}$  as the reference consumption profile of appliance  $i$  that reflects its preferable power consumption profile in the absence of any DR incentives.

The users issue a set of demands  $D$  for the following day – total daily electricity requirement of  $W_i$  Watts. We assume  $W_i$  to be fixed and independent of the provided rewards. The operator charges a flat price  $\pi$  for each Watt of consumption, which incurs a fixed daily cost of  $\pi W_i$  for demand  $i$ .

User problem (max net payoff):

$$\max_{x_i} \sum_{t \in T} x_{it} p_{jt} - V_{it}(x_{it}) \quad (9)$$

$$\text{s.t. } x_{it} \geq 0, \quad \forall t \in T \quad (10)$$

$$\sum_{t \in T} x_{it} = W_i \quad (11)$$

where the disutility function  $V_{it}$  captures the dissatisfaction caused due to deviation from the reference consumption. Function  $V_{it}$  may be taken to be convex, since the differential dissatisfaction of a user increases as the amount of deviation from the reference power consumption increases. An indicative example of such a function used throughout this paper is

$$V_{it}(x_{it}) = v_i (x_{it} - x_{it}^0)^2 \quad (12)$$

They call  $v_i \geq 0$  the inelasticity parameter of demand  $i$ .

## 3. Electricity markets

### 3.1. Market types

In [8] a price-responsive strategy for a market using the V2G concept is presented. The market considered in the study is Singapore. They begin by describing the base, central and peak load of the market. It is stated that 96% of the electricity generation is provided by gas and oil power plants, and that with flexibility the previously stated three types of loads can be covered. As a result, there is only one entity to regulate the market. As these sources are highly reliable with low fluctuations, and the electricity market is easy to predict, it is an efficient method to use. Because of their efficiency and low cost, it is not a viable market for the use of V2G concept.

Another kind of service provided is the ancillary service, which can be divided into six main categories: (1) active power control reserve, (2) voltage support, (3) compensation of active power losses, (4) black start and island operation regulation, (5) system coordination and (6) operational measurement [25]. The active power control reserve compensates the fluctuations and it consists of primary, secondary and tertiary controls, depending on the durations of time that they are providing the ancillary service. In a normal market, compensation would be given to providers of these kinds of services, or if there is too much power for holding the power generation which is good for cars with V2G and G2V implementation. The Singapore market is different because these kinds of compensations do not exist.

In [26] it is stated that with the development of smart grids and V2G technology, it is easy for people who own PEVs to inject power into the grid and to receive power at all times. Power can be injected at peak times to obtain maximum revenue and charge at off-peak times when the price is at a minimum. V2G networks are an important part of smart grids because they can provide better ancillary services than traditional approaches. The biggest challenge of the V2G in the power system is giving ability to control it.

In [27] the author examines PEVs with V2G implementation. This cannot be considered a power source; the V2G is a form of storing and then releasing energy. That said, PEVs cannot produce new electricity for the system; the only applicable function of PEVs is for storing energy, off peak, unwanted renewable energy and base-load energy. Then, after storing the electricity, they can resupply using the V2G whenever necessary. The authors suggest supplying the system at peak periods so it would not be necessary to peak fossil fuel plants.

Taking into consideration the discussed papers, the PEVs are good for ancillary services, with V2G and G2V technology, because of their fast charging and discharging, ability to store power and provide power when needed. Additionally, selling at peak power is where maximum profits can accrue; obviously, they would not provide the entire peak, just a part of it, with the base load power, but this can only happen in markets where compensation is given for selling and buying power, which does not happen in Singapore. There are also further studies regarding other countries including Germany in [28]. The base load because of their low prices of production would obviously be kept as it is provided by power plants.

There have been several studies regarding different types of markets that do not apply to real life markets. However, only as an overall study, there are many markets to which this kind of idea can be applied. For example, regarding spinning and non-spinning reserves, there are some reports, such as [19,29–31], which take these kinds of markets into consideration. Regulation markets are presented in [27,32]. Ancillary services, voltage and frequency regulations are presented in [2,22,24,31,33].



### 3.2. Interaction between PEVs and renewable energies

There are two studies that connect other resources to PEVs, while others examine its interactions with mainly renewable energy sources; some examples regarding this matter can be found in [3,7,10,34–37].

In particular, two renewable energy resources, photovoltaic and wind, have been discussed. As regards photovoltaic, [3] studies the interaction of the photovoltaic panel in the rooftop of a house with a PEV. The study proposes a Markov chain model in order to simulate the charge and discharge processes that occur in energy storage, which enables estimating the charge level of energy storage system at the end of any day, using the photovoltaic and the PEV. Also, there are studies regarding the storage and utilisation of photovoltaic energy such as [31,38].

In terms of wind energy, this subject is more specifically discussed in reports like [35,36]. Due to the high wind fluctuation, this leads to a high variation in the power generation, which must be balanced by other sources. The battery storage-based Plug-In Electric Vehicles may be a possible solution to balance the wind power variations in the power systems with high wind power penetrations. In [36], the integration of plug-in electric vehicles in the power systems with high wind power penetrations is studied.

There are also studies regarding other areas, for example, [34,39,40]. It is shown other types of renewable energy interaction, which is biomass energy. The studies indicate that bioelectricity in a vehicle is a more effective use of biomass than conversion to biofuels.

In relation to DR programs, there have been studies regarding this subject, such as [21,26,41,42]. The concept of demand and response takes into consideration a smart grid; that is, all smart appliances and multi-agent systems will be operated by settings on a smart meter. The customer turns smart appliances on and off and charges the plug-in electrical vehicle based on the priorities that have been set. The customer can turn on the maximum number of smart appliances and charge a plug-in electrical vehicle at minimal cost of electricity, maximising its profit or savings. In [43], a multi-layer framework based on multi-agent systems is reported to model the interaction between electricity market players in a market consisting of PEV and DR aggregators, as well as renewable energy producers. The wholesale market players such as PEV aggregator, DR aggregator and generation companies are placed in the first layer, while in the second layer, customers including PEV owners and responsive demands are modelled.

## 4. Modelling of plug-in electric vehicles

### 4.1. Deterministic/stochastic models

There are many models with different approaches to the problem, and those mainly used are probabilistic, deterministic and stochastic. Taking these into consideration, in terms of probabilistic, there are reports like [4,44,45], although [45] considers some variables deterministically.

It is explained in [44] the advantage of using probabilistic instead of deterministic; namely, a single charging station cannot know which charging station has the shortest queue unless some information is exchanged among stations. Using the probabilistic approach does not require any direct exchange of information and thus has good scalability properties.

As for the deterministic approach, in [3], for example, it is exactly opposite to the above; it has a central manager who controls all the stations, and the objective of that control is to manage deterministically the charging station in order to maximise the

profit. In [1], this review paper presents different probabilistic and also deterministic models from the literature.

The many uncertain variables associated with PEVs' behaviour, using stochastic programming, has been widely addressed in the literature. These uncertainties are related to the number of PEVs in an aggregated form (e.g. charging stations and parking lots) and arrival SOC of each PEV, which depends on the travel pattern of EV owner. The battery capacity is another uncertainty of the PEVs that is related to the EV battery class [46]. The total aggregated capacity and SOC for EVs plugged-in at the PL are derived from the model.

For stochastic models, there are many different approaches and models. For example, in [5] a stochastic model based on queuing theory for EV charging demand is used. In [47] a bi-level type of charging is taken into consideration, while in [48] the problem of V2G services is formulated as a mixed-integer stochastic linear program. In [49], the uncertainties of PEVs are modelled by using the information gap decision theory as the risk management tool. In addition, Markov model has been broadly utilised to simulate the uncertainties of PEVs [50]. Due to the feature of EV motion, a discrete-state and discrete-time Markov chain can be used for EV movement models. On this basis, drive cycle trajectories can be appropriately modelled through a Markov chain, based on the assumption that the trip duration and the Markov model are independent. It should be noted that the Markov chain driven cycle models could be employed in conjunction with real-world daily travel distance data to generate the stochastic models of daily driven cycles [51]. Therefore, simulation of closed-loop PEV models takes place across stochastic distributions of drive cycles, in order to obtain the probability distributions.

Most models found are deterministic or probabilistic models. Although some of the variables used in the problem can be considered stochastic, the models use data that have been collected from real-time management to make them probabilistic or deterministic.

### 4.2. Time horizon

The main focus found in current models being developed is on short-term markets. In studies such as [52], they simulate using short-term real-time. Long-term is not applied in models but in studies to determine whether it compensates the investment according to the payoff and because of battery degradation whether it compensates the investment. However, for markets, economical modulation, tariff and others, it is being used for short-term modelling.

As regards the short-term, for example, in [9,31,53,54], the day-ahead market is used. In the market the distribution system operator predicts congestion for the coming day and publishes prior to the beginning of the day the market conditions, the prices and the places where it may be cheaper.

Another short-term method which can be explored is the real-time method, for example, in [10,23,55–57]. The algorithm operates in real-time and does not require any prior knowledge of the statistical information of the system.

Comparing both the short-term methods, it is easy to note the differences between the day-ahead and real-time. Overall real-time can lead to more infrastructure costs.

### 4.3. Uncertain variables

There are very different models that use different variables; in papers such as [4,10–12,21,22,55] are different models, all with different approaches. However, they all have constant and similar variables. For example, comparing most of their models we can find common stochastic variables like the number of cars or batteries (referred to as batteries and not car in one paper), the price

of the electricity, the SOC of the cars and the maximum SOC of the cars. Diving behaviour is also considered in one of the models, and also the state of the battery.

In [10] is presented a given problem and all the considerations and uncertain variables. The objective of the paper is to develop a modelling system for a parking lot of a university campus, which contains around 1500 parking spaces. The uncertain variables are the percentage of cars parking daily and the size of the cars – whether they are small cars, mid-size SUVs or full-size SUVs or picks-ups – because of their energy consumption. Other uncertain variables are the arrival and departure of the vehicles and their initial state of charge (SOC) when arriving at the park.

In [41] a model of charging and discharging is presented. Many different variables are considered some of which are stochastic. The variables that are present in this work consist of driving patterns, the state of the battery – degradation is the main concern because it can be influenced by a number of different random factors – the electricity price, the current state of charge and the maximum SOC. They do not consider the number of vehicles.

In general, there might be some variations between models. As in the previous case, the model is for a particular unit so they do not consider the number of vehicles. For other cases they might consider the number of vehicles but not the driving pattern, as in one of the papers. However, most of them use the stochastic variables mentioned above in their models.

In [13], a different approach is used for state-of-energy instead of state-of-charge (SOC), because of the easy derivation of power and energy quantities in the model. SOC is a more accurate variable for describing battery state, as it includes cell voltage variations. However, at the aggregator level, where the charging power of thousands of EV is estimated, the SOE variable includes battery characteristic, which they present is more simplistic for that scale.

#### 4.4. Stochastic techniques

There are two different methods applied to uncertain variables. As in [10], for the uncertain variables it was developed a statistical probability distribution in order to simplify it.

In [31] the uncertain variables are the uncertain energy prices, balancing prices, stochastic energy availability and demand, so deterministic method is applied in order to simply the uncertainties and problem.

There are two different methods as regards how variables are treated; [5,11,45,58,59] are some examples of different methods or studies.

Particularly, in [5] a stochastic model is used based on queuing theory. They have many stochastic variables, customers randomly arriving, EVs being randomly plugged in and others. In the study, it is considered the differences between the three methods of supplying the DR, day-ahead and real-time. These unknown variables are treated by adopting a statistical method, through estimating and forecasting using historical data.

#### 4.5. Modelling the PEV stations

##### 4.5.1. Modelling PHEV exchange station

A deterministic integer programming model is developed that considers scheduling multiple PHEV exchange station operations. It is assumed that there exists a central manager who maximises profit over all locations and the finite time horizon of the problem. The objective function maximises the total profit [11].

The model is expressed as below:

$$\sum_{t=1}^T \sum_{j=1}^n p_e (x_{pjt} + \alpha x_{sjt}) - p_e (r_{jt} - (x_{pjt} + x_{sjt})) - \pi \sigma_j (x_{cjt}^+ + x_{cjt}^-) \quad (13)$$

subject to:

$$x_{cjt}^+ \leq b_j - x_{fjt} \text{ For } j = 1, \dots, n, \text{ for } t = 1, \dots, T \quad (14)$$

$$(x_{pjt} + x_{sjt}) + x_{cjt}^- \leq x_{fjt} \text{ For } j = 1, \dots, n, \text{ for } t = 1, \dots, T \quad (15)$$

$$x_{fjt+1} = x_{fjt} - (x_{pjt} + x_{sjt}) + x_{cjt}^+ - x_{cjt}^- \text{ for } j = 1, \dots, n, \text{ for } t = 1, \dots, T \quad (16)$$

$$x_{cjt}^+, x_{cjt}^- \leq k_j \text{ For } j = 1, \dots, n, \text{ for } t = 1, \dots, T \quad (17)$$

$$x_{pjt} \leq r_{jt} \text{ For } j = 1, \dots, n, \text{ for } t = 1, \dots, T \quad (18)$$

$$\sum_{j \in \Phi} x_{sjt} \leq \sum_{j \in \Phi} (r_{jt} - x_{pjt}) \quad \forall \Phi \in \Phi, \text{ for } t = 1, \dots, T \quad (19)$$

$$x_{pjt} \geq \beta_p r_{jt} \text{ For } j = 1, \dots, n, \text{ for } t = 1, \dots, T \quad (20)$$

$$\sum_{j \in \Phi} x_{sjt} \geq \beta_s \left( \sum_{j \in \Phi} (r_{jt} - x_{pjt}) \right) \quad \forall \Phi \in \Phi, \text{ for } t = 1, \dots, T \quad (21)$$

$$\sum_{j=1}^n x_{cjt}^+ \leq c_{tout} \text{ for } t = 1, \dots, T \quad (22)$$

$$\sum_{j=1}^n x_{cjt}^- \leq c_{tin} \text{ for } t = 1, \dots, T \quad (23)$$

$$0 \leq x_{fjt} \leq b_j \text{ For } j = 1, \dots, n, \text{ for } t = 1, \dots, T \quad (24)$$

$$x_{fj0} = b_j \text{ For } j = 1, \dots, n \quad (25)$$

$$x_{fjt}, x_{pjt}, x_{sjt}, x_{cjt}^+, x_{cjt}^- \in \{\mathbb{Z}^+ \cup 0\} \text{ For } j = 1, \dots, n, \text{ for } t = 1, \dots, T \quad (26)$$

where  $T$  denotes the Time horizon.  $N$  is the number of exchange locations.  $\Phi$  represents the set of all clusters.  $P_e$  is the price to exchange a battery.  $\alpha$  denotes the discount rate if an exchange request is satisfied at a secondary location.  $R_{jt}$  states the number of exchange requests at location  $j$  at time  $t$ .  $\pi$  represents the power price (earnings) to charge (discharge) one battery at time  $t$ .  $\sigma_j$  denotes the normalised energy received (for charging) or given (for discharging) when charging one battery at location  $j$ .  $b_j$  is the number of batteries at location  $j$ .  $k_j$  represents the number of plug-ins available for charging/discharging at location  $j$ .  $B_p$  and  $B_s$  denote the customer service level for primary and secondary customers, respectively.  $C_{tout}$  is the capacity of the power grid eligible for charging batteries (grid to exchange locations) at time  $t$ .  $C_{tin}$  is the capacity of the power grid eligible for discharging batteries (exchange locations to grid) at time  $t$ .  $x_{pjt}$  and  $x_{sjt}$  represent the variables of the number of primary and secondary batteries exchanged at location  $j$  at time  $t$ , respectively.  $x_{cjt}^-$  and  $x_{cjt}^+$  are variables of the number of batteries charging and discharging at location  $j$  at time  $t$ , respectively.  $x_{fjt}$  denotes the variable of the number of full batteries at location  $j$  at time  $t$ .

##### 4.5.2. Modelling the V2G parking lot

The V2G units are either charging or dis-charging their batteries. For  $n$ -VPL comprising of V2G units supplying power to the grid, and vehicles charging their batteries, and the net power,  $P_{net}$ , to the grid is

$$P_{net} = \sum_{i=1}^{n_0} P_{EVoI} \left( 1 - e^{-\frac{\beta_i t_{ci}}{t_{max}}} \right) - P_{max} \left( n_d - \sum_{i=1}^{n_d} e^{-\frac{\alpha_i t_{ci}}{t_{max}}} \right) \quad (27)$$

where  $\alpha_i$  and  $\beta_i$  are, respectively, the battery charging and discharging constants for an  $i$ -th V2G unit, requiring charging time  $t_{ci}$ , and discharging time  $t_{si}$ . The parameters  $P_{max}$  and  $P_{EVoI}$ , respectively, represent the maximum battery capacity and initial power in the V2G battery [10].

#### 4.6. Terms of costs and constraints

There are many parameters considered in different papers. Here, some models and the parameters that they consider will be presented.

For example, in the model in [41], two different parameters are considered. One of the main focuses is on the battery degradation; it is explained the theory behind it and the factors that influence the battery degradation, which concerns temperature, number of cycles, SOC swing, charging rate and waiting period between charges and SOC in swinging periods. As a consequence, the SOC is taken into consideration to predict the battery's degradation. Other parameters are grid power and grid management.

Another model is presented in [54], which also begins by modelling the battery degradation. Various parameters are considered, namely, open circuit voltage, internal resistances and the capacitance. In this way, they can obtain the terminal voltage to model the battery. For the battery modelling, it is also considered the SOC, from three perspectives – the current SOC, minimum SOC and maximum SOC – in order to determine the state of the battery, and to model the capacity loss of the battery. Monetary parameters, time parameters and energy parameters are used to carry out an economic analysis of the system.

Some papers that develop models with different parameters, for example, [14], are also based on research on the battery. It is also considered the SOC and driving cycles and charging strategies are used in order to simulate PEVs. In [15], a study of an EV fleet is performed which is one of the parameters, and the vehicles that drive multiple distances and charge are studied in order to analyse the charging curve of a day of charging. In [16], it is presented a Markov model in order to optimise fleet management; other parameters considered are maximum/minimum rate of charge, maximum and minimum storage of the battery, time varying electricity price, charging and discharging battery efficiency, battery capacity and diving patterns.

Another approach that has been used in terms of battery management (for example, in [60]) concerns the battery swapping station, which is a parameter present in the model. The battery station determines optimal charging/discharging schedules for batteries, and identifies the batteries that should be replaced to match the battery demand.

There are two other parameters, namely, V2G inverters and infrastructure costs. However, these parameters are not considered in many models. Indeed, they have been introduced in a long-term scale economic analysis, but they have not been considered for management and short-term models.

##### 4.6.1. Modelling a PEV aggregator

Below is an example of the implementation of multiple variables mentioned previously. In this model, the PEV has been optimised taking into consideration the driving patterns and battery degradation. The details of the model are presented.

**4.6.1.1. Driving behaviour.** Driving behaviour is modelled using the probabilities introduced in different mobility surveys.

The driving time of the trip  $m$ ,  $t_{drive,m}$  is calculated according to the linear function:

$$t_{drive,m}(k) = 0.7211k_m + 5 \quad (28)$$

In order to calculate the operation schedule of the PEV agent, the following mobility parameters are necessary.

$$SOC_{n,t+drive} = SOC_{n,t} - \frac{k_m \cdot \eta_{km}}{E_{bat}} \quad (29)$$

The SOC after the new trip will be the initial SOC subtracted from the distance multiplied by the conversion efficiency of the electricity into mechanical energy, divided by the usable energy of the battery.

To calculate the period of optimisation, we need to have the grid management time, which is calculated using the current time and the next trip time and the driving time given by  $t_{start,m}$ ,  $t_{start,m+1}$  and  $t_{drive,m}$  respectively. Then management time is then given by:

$$\Delta t(m) = (t_{start,m+1} - t_{start,m}) - t_{drive,m} \quad (30)$$

Finally, the necessary energy for the next trip is calculated by

$$SOC_{n,\Delta t} = \frac{k_{m+1}\eta_{km}}{E_{bat}} \quad (31)$$

As an alternative, they suggest a 100% SOC can be used.

**4.6.1.2. Battery degradation.** Three models of control have been suggested for the battery. The first consists of a model based on the depth of charge, and, accordingly, the battery degradation is influenced by the depth of charge. The life cycle depends on the DoD by the function:

$$N_{cycle} = a \cdot DoD^b \quad (32)$$

The parameters  $a$  and  $b$  vary with each battery; for example, they suggested that for li-ion batteries  $a=1331$  and  $b=-1.825$ . The discussed model indicates the highest lifetime for a fully charged battery without cycling. However, when considering calendar life, a SOC of 100% is the most demanding condition. This contradiction indicates a weakness of the model.

The second model, which is based on energy throughput, there are no formulas. They state that for some batteries the DoD is not the most important factor but the capacity fade is. Then, they use as an example the A123 systems and their website for consultation. The last model is Discharge Costs. When the battery is discharged, the degradation costs are a function  $\pi(DoD_{start}, DoD_{end})$ . Additional parameters are the cost for the battery  $C_{bat}$ , and the usable energy of the battery  $E_{bat}$ .

$$\pi(0, DoD) = \frac{C_{bat}}{N_{cycle}(DoD)} \quad (33)$$

The costs for one processed kilowatt-hour are given by

$$\pi_{energy}(0, DoD) = \frac{C_{bat} DoD E_{bat}}{N_{cycle}(DoD)} \quad (34)$$

The general degradation costs are

$$\pi(DoD_{start}, DoD_{end}) = \pi(0, DoD_{end}) - \pi(0, DoD_{start}) \text{ for } DoD_{end} < DoD_{start} \quad (35)$$

The cost per discharge unit  $\pi$  unit as a function of the DoD before the discharge is

$$\pi_{unit} = \pi(DoD, DoD+1\%) = \pi(0, DoD+1\%) - \pi(0, DoD) = \frac{C_{bat}}{N_{cycle}(DoD+1\%)} - \frac{C_{bat}}{N_{cycle}(DoD)} \quad (36)$$

#### 4.7. Modelling the grid

In the literature, the main focus of PEVs has been its distribution role in the electricity network. This can be found in [2,30,61]. The burden of electric mobility will be mainly on the distribution system that, particularly during the peak hours, will be exposed to critical operation conditions by a large number of high density simultaneous loads. V2G technology, by adding control capabilities to the charge and discharge of cars' batteries, can increase the benefits from their whole energy storage capacity. Distributors can then be helped in the active management of the network by the services. As for transmission, no models were found that suggested such tendency.

#### 4.8. Features of the power system

Security is one of the features that should be researched because the security of the home user is very important. The smart interaction between users and operators, whereby they have access to the user patterns, is of slight concern because not only through PEVs but also by using domestic appliances can patterns of home usage be made, which presents a high security risk to the user.

This is not really the focus of only PEV studies but also smart grid studies on V2G and PEVs; [17] discusses security network, while other PEV studies consider simply the security of supply and power.

There are studies that present their method to solve some features that they consider to be a problem. For example, considering the reliability of the system [18] presents a solution for better reliability and suggestion for the use of a converter. As regards losses, two studies consider these kinds of system features [1,62]. The latter is more focused on the losses and presents a way to minimise it, and how it influences the system and tools for system optimisation.

In [63] the focus of the study is on power quality improvement in a smart grid involving EVs. It evaluates scenarios in order to determine the consequences of the PEVs on large scales. In [64], a harmonic simulation based on a multiphase model investigates the power quality impact of PEVs. The results indicate that the current technologies of PEVs have no significant harmonic impact on the power system. However, reported results in [65] show that PEVs cause a higher level of overload to the distribution transformers compared with plug-in HEVs. [66] indicates the possibility of PEVs compensating the voltage drops caused by motor start-up or inductive loads by using the local reactive power injection. In addition, PEVs can help in low voltage ride-through of photovoltaic systems. In [66], it is also reported that the active power injection of PEVs during photovoltaic transients could retain the system stability.

In [67], it is stated that V2G control has the potential to provide frequency regulation service for a power system operation from electric vehicles. A decentralised V2G control method is proposed for EVs to participate in primary frequency control. In addition, there are some studies that approach all the subjects in a generalised way; for example, [2] discusses briefly all the subjects previously mentioned – voltage and frequency control, stability, reliability and efficiency.

A PEV can be considered as a small portable power plant to improve the security and reliability of a power system [68]. On this basis, an intelligent unit commitment with PEVs that operate in V2G mode is reported for power system cost and emission minimisation. Since the number of PEVs is high, the unit commitment problem is more complex than conventional problems that are solved for only thermal power plants. In order to tackle this complexity, Particle Swarm Optimisation (PSO) is adopted in the literature [69]. PSO can solve these types of complex constrained optimisation problems. Therefore, it is widely employed in energy resource scheduling for smart grids with a large number of PEVs [70].

**Table 1**

Types of renewable sources interacted with PEVs.

Studies	Renewable sources interaction		
	Wind	Solar	Biomass
[1–3,10]		X	
[4,34]	X	X	X
[7,46]	X	X	
[5,6, 35–37]	X		
[8,9,39,40]			X

**Table 2**

Types of uncertainty models.

Studies	Type of models		
	Deterministic	Stochastic	Probabilistic
[1,3,5,8,26,33,43,46,50,51,56,68]		X	
[2,4,5,24,27,28]			X
[6,35]	X		
[7,48]	X		X

**Table 3**

Types of time horizon studied.

Studies	Time horizon	
	Day-ahead	Real-time
[1,4,5,9,31,48,57]	X	
[2,3,6–8,10,23,52,55,56]		X
[43,68]	X	X

**Table 4**

Types of variables presented.

Studies	Variables					
	N° vehicles	SOC	Time	Driving patt.	Price	SOE
[1,4]		X	X	X		
[2,4,10,12,33,43,46,68]	X	X	X	X	X	
[3,6,11,21]	X		X		X	
[5,13]	X		X		X	X
[7,22]	X	X	X		X	
[8,41]		X	X	X	X	
[9,55]			X		X	

##### 4.8.1. Modelling the features of power system

**4.8.1.1. Power loss formulation.** The per unit optimal power loss reduction,  $\Delta P_{LS\_V2G\_opt}$ , for a single vehicle is defined as

$$\Delta P_{LS\_V2G\_opt} = 3c\alpha X_1[(2 - X_1) + \lambda X_1 - c] \quad (37)$$

where the quantity  $x_i$  represents the position of the  $i$ -th V2G parking lot and  $c$  is the sizing, while the load pattern  $\lambda$  defines the loading characteristic of the line segment ( $\lambda=0$  represents uniformly distributed load, while  $\lambda=1$  represents lumped loads). Hence, the range,  $0 < \lambda < 1$ , defines the bounds of possible load pattern. The following parameters are defined

$$c = I_c(I_1)^{-1} \quad (38)$$

$$\lambda = I_2(I_1)^{-1} \quad (39)$$

$$\alpha = (1 + \lambda + \lambda^2)^{-1} \quad (40)$$



The quantities  $I_G$ ,  $I_1$  and  $I_2$  are, respectively, the injected reactive current, and the reactive current at the beginning and at the end of the feeder line segment. The parameters of  $\Delta P_{LS\_V2G\_opt}$  are obtained online for real-time computation of the power loss (Tables 1–4).

**4.8.1.2. Energy loss formulation.** The per unit optimal energy loss reduction,  $\Delta EL_{opt\_V2G}$ , in a three-phase distribution line segment is defined as (for  $n=1$ )

$$\Delta EL_{opt\_V2G} = \frac{3\alpha c}{1-\lambda} \left[ F_{LD} - c + \frac{c^2}{4F_{LD}} \right] T \quad (41)$$

$$F_{LD} = \frac{Q}{S}, \quad (42)$$

where  $T$  is the total period of supply.

**4.8.1.3. Voltage stability formulation.** The computational equation can be formulated as below:

$$VSI_m = \left( 2 \frac{V_m}{V_k} \cos(\delta_k - \delta_m) - 1 \right)^2 \quad (43)$$

where  $VSI_m$  is the voltage stability for node  $m$ .  $V_m$  and  $V_k$  are node voltage at  $m$  and  $k$ , respectively.  $\delta_m$  and  $\delta_k$  represent the voltage angle at node  $m$  and  $k$ , respectively.

The voltage stability margin (VSM) of such a feeder depicted in the figure presented in the paper is given by

$$VSM_{k,m} = \prod_{i \in \Omega} VSI \quad (44)$$

where  $VSI$  is the voltage stability complex and  $\Omega$  is a set of branches constituting the entire length of the feeder. A feeder with the lowest value of VSM is considered the weakest feeder. This can be defined as

$$VSM_{sys} = \min(VSM_1, VSM_2, \dots, VSM_j) \quad (45)$$

where  $j$  is the number of feeders in the system. The system  $VSM_{sys}$  is an indicator of the nearness of the system to voltage collapse.

## 5. Conclusion

This paper addressed the topic of PEV management and V2G capability. An example of a PEV management model was presented, showing the multiple perspectives of this management. The electricity markets were also explored, starting with a brief analysis. It can be noted that in the base market the PEV does not play a role, while other markets (for example, spinning reserves and ancillary services) will be the main focus of this kind of service. Renewable energy sources were then considered, namely, wind and photovoltaic energy, deterministic and stochastic models and also time horizon (long-term and short-term). Almost every study uses short-term, followed by a separation of day-ahead and real-time modelling. The uncertain variables present in the models are those where the models differ the most; it is common to consider SOC, number of vehicles, price and time, and less common to consider SOE and driving patterns. To deal with these uncertain variables there are stochastic techniques that can be used, such as deterministic methods, probabilistic distributions and others. As regards costs and constraints, there are some differences regarding, for example, infrastructure costs, V2G inverters, battery, charging and discharging rates, maximum and minimum storage. In terms of the grid, some studies take this into consideration due to concerns regarding overloading the grid at peak hours, but only a few do so. Finally, the features of the power system are normally taken into consideration; these are stability, reliability, efficiency, voltage and frequency control. The multiple studies were analysed in the present paper to provide important knowledge for further developments in this area.

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