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On the plug-in electric vehicles effects investigation in electricity marketing

I. T. Cheon *

Department of Electrical and Electronic Engineering, College of Engineering, Yonsei University, Seoul, South Korea

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ABSTRACT

Plug-in electric vehicles (PEV) have a limited share of the current market. However, it is widely expected that the situation will change in the near future and the penetration of battery-operated vehicles will increase significantly. Indeed, demand response (DR) brings a positive effect on the uncertainties of renewable energy sources, improving market efficiency and enhancing system reliability. The main goal of this paper is to address the economic part, different types of PEV modeling and their management. Vehicle to grid (V2G) and grid-to-vehicle (G2V) concepts are one of the smart grid technologies, which involves the electric vehicles (EV) to improve the power system operation. In the first part of this paper, the V2G and G2V technologies are investigated. In the second part, the electricity markets are studied. In electricity markets section, world applications are investigated and various market categories labeled. Also the application some renewable energy sources such as photovoltaic are discussed.

1. Introduction

Electrification of transportation is a key element to enhance energy security by varying resources of energy, to support economic growth by forming advanced industries and, to conserve the environment by reducing pollutions (Yong et al., 2015). Electric Vehicle Initiative (EVI) and International Energy Agency (IEA) reported that the global Electric Vehicle (EV) stock was more than 180,000 at the end of 2012 (IEA, 2014). The market share of EVs can be significantly increased in most of the countries, since some national targets for EV developments have been considered in the near future. On this basis, several policies have been implemented, such as incentives/subsidies for the purchase cost of EVs and infrastructure requirements (Yong et al., 2015). Moreover, according to the growth of energy sustainability concerns, PEVs are a key element in the sustainable energy systems (Zhang and Xiong, 2015; Jian et al., 2015). Researches on the driving patterns reveal that the overwhelming majority of the EVs can be connected to the grid and trade energy with the electricity markets, while an ample part of the stored energy is eventually remained (Liu et al., 2014; Shafie-Khah et al., 2015) Currently, development of technologies of EVs causes an increase in the market share of these vehicles. Therefore, a massive amount of PEVs jeopardizes the power system's quality and stability (Boynuegri et al., 2014; Wu et al., 2010) and as a result, the management of this new resource have become unavoidable (Sioshansi et al., 2010; Galus et al., 2012). Depending on the level of deregulation of the market, some of the market players (e.g., Demand Response Providers (DRPs) and retailers) can manage the operation of PEVs (Shao et al., 2011).

On this basis, the PEV aggregation agent as a new player in the market is considered to manage the PEVs and control the discharge/charge of their batteries. The assumption is because PEV owners prefer to separate their PEV contracts from the other household consumptions for three reasons. First, the expenses of vehicles have always been separated from households' costs. Second, the PEV may have a major role in current expenditure of the household, since it can increase residential electricity consumption by approximately 50% (Van Haaren, 2011). Third, the PEV has a different nature compared to common electricity end-users due to its ability of charging/discharging, and consequently it can easily participate in different electricity markets (Bessa and Matos, 2013).

The PEV owners' uncertain behavior causes that the PEV aggregation agent should confront numerous challenges in order to contribute in electricity markets. The uncertain feature of this new market player can cause that its primary bids/offers have various deviations from the actual amounts and it consequently poses undesirable costs for the PEV aggregation agent. This is because of the inequity between the scheduled and actual consumption/production. Nevertheless, from the day-ahead session to the balancing one, the PEV aggregation agent is able to gather a number of new data in order to modify its primary bids/offers in an intraday market. Due to the high level of uncertainty of PEV owners' behavior, the PEV aggregation agent requires to take part in short-time session markets, e.g., intraday market. It should be mentioned that, regarding the participation in the intraday markets, there are three major differences between the PEV aggregation agent and other market players (Shafie-Khah et al., 2016a):

1) First, the main source of the thermal and especially renewable energy units to obtain profit is generally the electricity market. Therefore, these market players can directly achieve benefit from participating in the intraday markets because the mentioned markets enable them to cover their uncertainties of electricity generation in the electricity market. On the contrary, the main source of the PEV aggregation agent to obtain profit is the spinning reserve market. On this basis, the PEV aggregation agent can indirectly achieve benefit from the intraday markets. This means that, the aggregation agent should manage the strategic

* *Corresponding Author.*
Email Address: i.t.cheon@gmail.com
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behavior of participating in different markets (Shafie-Khah et al., 2016a).
2) Second, unlike the mentioned above units, the PEV aggregation agent can behave as both consumer and generator. Based on this, the PEV aggregation agent can contribute in the intraday markets as both a seller and a buyer player. In addition to the aggregation agent's own benefit, the intraday markets can achieve benefit from the improvement of the competition level (Shafie-Khah et al., 2016a).
3) Third, in comparison with the other market participants that supply the spinning reserve (e.g., hydro, thermal and energy storage units), the PEV aggregation agent has the highest uncertainty (Shafie-Khah et al., 2016a, 2017b).
The remainder of this paper is organized as follows. In Section 2, the PEV management and V2G capability are presented. Section 3 is dedicated to categorizing the studies from the market viewpoint. In Section 4 the models are examined and finally section 5 concludes the paper.

2. Vehicle to grid concept and framework

EV technology has attracted the attentions of government and public due to the growing concerns on the environment and rising cost of fossil fuel. The integration of transportation sector and power grid will lead to many challenging issues to the power system. For instance, a large penetration of EVs will increase the power grid load during the EV charging process. Nevertheless, the projected penetrations of EVs have also opened up the possibility of the V2G implementation. V2G refers to the control and management of EV loads by the power utility or aggregators via the communication between vehicles and power grid.

There are three emerging concepts of grid-connected EV technologies, which are the Vehicle to Home (V2H), Vehicle to Vehicle (V2V) and Vehicle to Grid (V2G) (Shafie-Khah et al., 2016b). V2H refers to the power exchange between the EV battery and home power network. In this case, EV battery can work as energy storage, which provides the backup energy to the home electric appliances and to the home renewable energy sources (Tan et al., 2016). V2V is a local EV community that can charge or discharge EV battery energy among them. V2G utilizes the energy from the local EV community and trades them to the power grid through the control and management of local aggregator (Sortomme and El-Sharkawi, 2010). Generally, V2H, V2V and V2G involve elements such as power sources, power loads, power grid aggregator, power transmission system, communication system, electric vehicles, and vehicle to grid chargers. The framework of a typical V2G system is shown in Fig. 1.

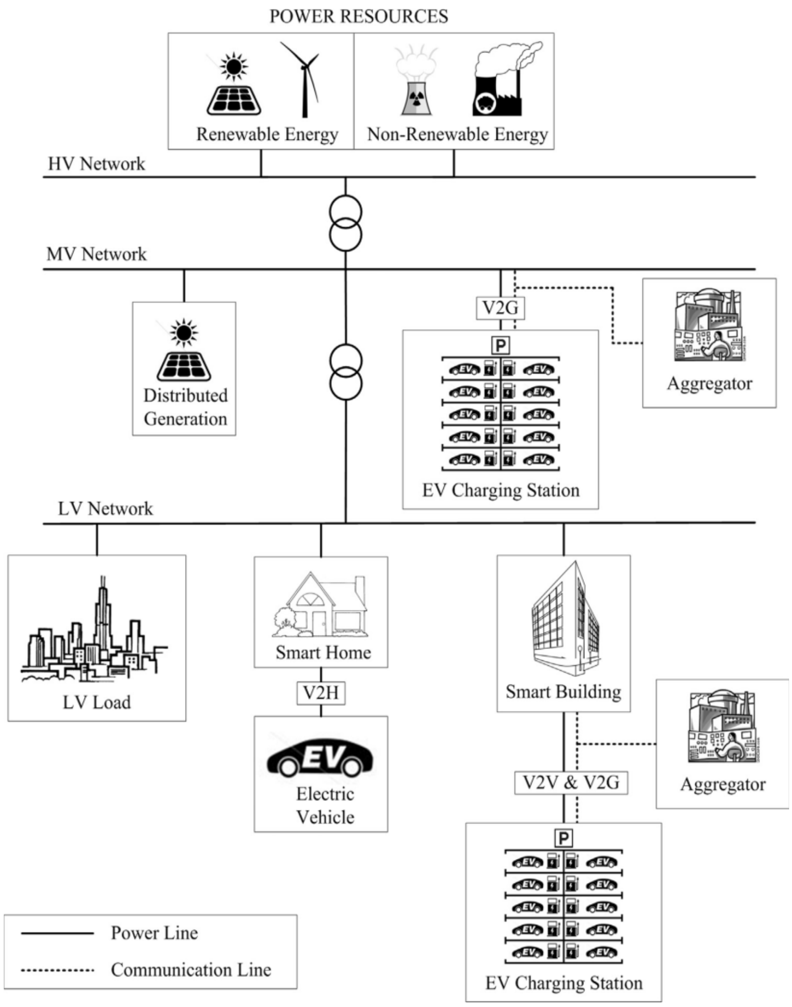

Fig. 1. V2G framework (Tan et al., 2016).

V2G refers to the interaction between electric vehicle and power grid with the assistance of the communication system. Power grid operator utilizes the communication facility to control and manage the power flow between the EV battery and the Power grid in order to achieve desired benefits. In most cases, the objectives of the V2G management are to maximize profit, reduce emissions and improve power quality of the grid.

2.1. Unidirectional V2G

Unidirectional V2G is a technology that controls the charging rate of EV battery in a single power flow direction between the EV and grid. The realization of the unidirectional V2G is in expensive by adding the simple controller to manage the charge rate. Unidirectional V2G can provide ancillary services to the power grid, such as power grid regulation and spinning reserve. This can enhance the flexibility of the power grid operations. The implementation of unidirectional V2G needs the existence of an attractive energy trading policy between the EV owners and the power utility (Tan et al., 2016). In order to encourage the participation of EV owners, this energy trading policy must guarantee revenues to the EV owners if they charge their EVs during off peak hours and limit the EV charging during on peak periods (Tan et al., 2016). At the same time, the power utility can avoid over loading during on peak hours. In addition, unidirectional V2G can achieve maximization of profit and minimization of emission by using optimization technique (Sortomme and El-Sharkawi, 2010).

2.2. Bidirectional V2G

Bidirectional V2G refers to the dual direction power flow between EV and the power grid to achieve numerous benefits (Tan et al., 2016). A typical bidirectional EV battery charger consists of AC/DC converter and DC/DC converter as depicted in Fig. 2. The AC/DC converter is used to rectify the AC power from the power grid to the DC power during the EV charging mode and inverts the DC power to the AC power before injecting back to power grid in the discharging mode. On the other hand, the DC/DC converter is responsible in controlling the bidirectional power flow by using current control technique. The DC/DC converter acts as a buck or boost converter during charging or discharging mode, respectively.

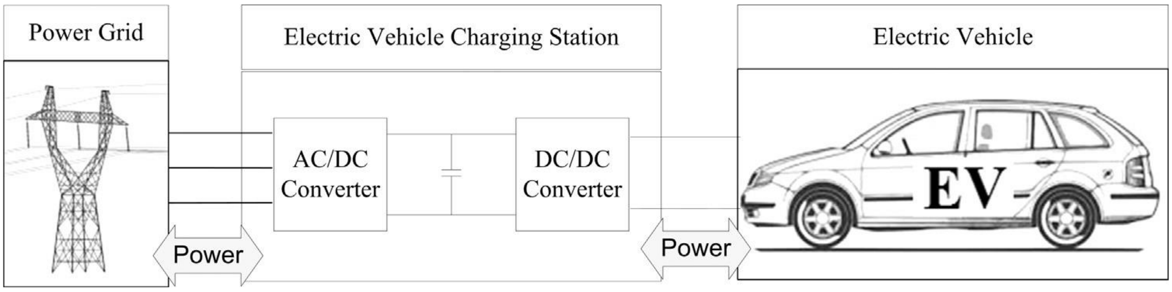

Fig. 2. Power flow diagram for V2G.

3. Electricity markets

3.1. Market types

In Wu et al. (2010); 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 is land operation regulation, (5) system coordination and (6) operational measurement (Romero-Cadaval et al., 2015). 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 Tan et al. (2016) 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 Tan et al. (2016) and Romero-Cadaval et al. (2015); 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.

3.2. Interaction between PEVs and renewable energies

The increase in penetration of renewable energy sources (RES) into the electric power system is quite appealing. The existing power grid suffers from unpredictable and intermittent supply of the electricity from these sources especially wind and PV solar energies (Mwasilu et al., 2014). The electric power production from these RES can be very high (more than the power demand) or very low (less than the power demand) depending on the available energy sources, i.e., wind speed and sun radiation. In short, these RES are variable with time, non-dispatch able with limited control and have low capacity credit especially on the power system planning. Most of the studies revealed that the integration of wind energy conversion systems (WECS) and PV solar systems into the electric power grid is pretty mature and practically viable. However, the promising solution to balance the electricity generation from these RES on the grid can be accomplished by adopting the stationary energy storage systems (ESS) or controllable dispatch loads (Mwasilu et al., 2014). The stationary energy storage systems absorb or supply electricity in the case of excess and low power generation, respectively. As this solution involves high investment cost, it delays the high penetration of the RES into the power system or even increases the overall investment cost.

As pinpointed earlier the electrification of the transportation sector is envisioned by the numerous researchers to populate the sector in a decade to come. Then, the EV batteries can be aggregated and act as the ESS that will pivot the integration of the RES into the power market as dynamic energy storage devices. The EVs can absorb the surplus power generated by the RES through different charging schemes or can deliver power to the grid in the low power generation scenarios and level the grid operations through the V2G schemes (Richardson, 2013). To this end, the EVs will be acting like energy buffer for the grid regulations and ancillary services. Saber and Venayagamoorthy (2010) stated that a possible solution to maintain energy security while reducing GHG emissions can be achieved by integrating the distributed RES (PV solar and wind in this study) and adopting EVs with capability to deliver the V2G services. To simultaneously achieve the GHG emissions and cost reduction, a strategy to optimize maximum utilization of both EVs and RES is required. The authors propose a dynamic optimization approach based on particle swarm optimization. The findings from this study show that for the random charging, the load increases by 10% every year in the power grid but an intelligent scheduling of the EVs (without RES) can solve the problem at the expense of increased cost per day by 1.7% and emissions by 3%. On the other hand, in smart grid mode with both EV-V2G enabled cars and RES, the cost is reduced by 0.9% and emission by 4.3% per day. These results give a glimpse of the perfect match for the interactions between the EVs and RESs in the smart grid infrastructure. The subsequent subchapters assess the integration of the PV solar and wind energies using EVs.

Fig. 3 illustrates the integration of wind and photovoltaic solar energy sources into the power grid with EVs. The electric vehicles are aggregated at the charging station located at public area or office and can be used to suppress power fluctuations from these RES in the V2G mode. In Fig. 3 we assume all necessary communication and control schemes are available as described in details in the previous section for the V2G and charging scenarios. In Fig. 3 and other subsequent figures Ti stands for the power transformer in the electric grid, where $i = 1,2,\ldots,n$.

3.3. PV solar energy with EVs

Electricity production from PV solar energy has already shown a promising feasibility. The PV solar arrays are usually clustered to cumulatively provide power to the electric grid. With the EVs penetration getting large share, the PV solar power is more likely to be deployed for charging purposes and grid support. A number of analyses have been presented to show that the deployment of the PV solar on the roof of parking lots for charging EVs is quite appealing (Tulpule et al., 2013). Besides, the V2G transactions are also feasible in these PV solar systems (Traube et al., 2012) and an optimal generation scheduling is possible to reduce operating cost and enhance grid operation as reported in Derakhshandeh et al., (2013). Tulpule et al. (2013) performed the energy economics and emission analysis of the workplace charging station based on the PV solar system by comparing optimal charging schemes with uncontrolled ones. A day-time workplace EV charging behavior under this study considers various data including vehicle parking charges and different parking locations to account for the solar insulation variations. Observations from this study reveal that one vehicle would save 0.6 ton of CO_2 emissions per year by using solar charging at the workplace which amounts up to 55% savings in emissions when employing home charging (night charging at home) scheme. And it reduces 0.36 ton of CO_2 emissions when an optimal charging scheme is implemented, which amounts up to 85% savings in emissions if the home charging scheme is adopted. The SMs and communication infrastructure appear to increase cost for the home charging case and make the PV based workplace charging station a better choice. Fig. 4 depicts the configuration of the standalone solar carport charging station at working place or public area.

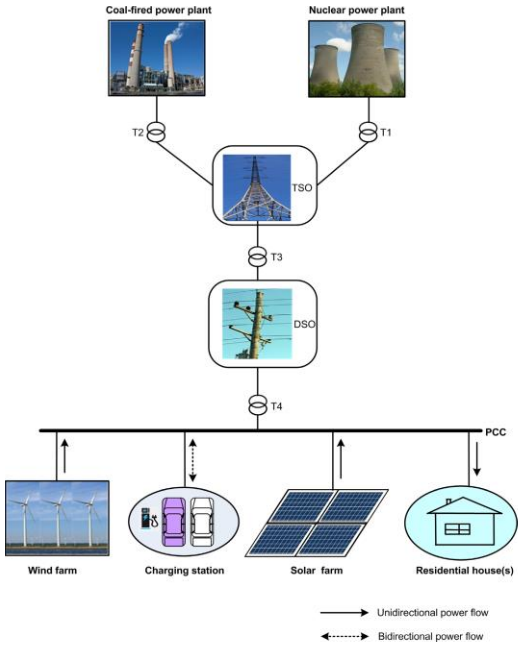

Fig. 3. Wind and PV solar energy sources integration into the electric grid with EVs.

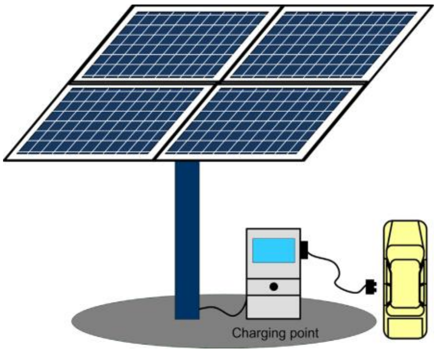

Fig. 4. EV charging station deploying standalone PV solar on rooftop at the parking lot.

3.4. Wind energy with EVs

The concept of using wind energy conversion systems (WECSs) for electricity generation is a prevalent and feasible alternative solution to produce power as discussed previously. The synergy between the WECSs and EVs has been widely investigated by various researchers in different scenarios to deduce their impact and viability onto the electric grid (Lund and Kempton, 2008). The early study by Lund and Kempton (2008) assesses the use of the EVs to provide ancillary services and regulation based on the grid interaction with the WECSs in the US power market. The authors in Lopes et al. (2009) estimated the amount of wind that can securely be integrated into an isolated electric grid with the vicinity of the EVs. In this study the EVs are considered to participate in the primary frequency regulation and their interactions during smart charging mode are also assessed. The EVs through V2G services support the increase of wind penetration from 41% to 59% in the isolated grid. The study assumes that all the available EVs have intermediate charge and are ready for balancing the grid.

4. Modeling of plug-in electric vehicles

PEVs are additions to existing load. They are distinctly different from other electrical loads due to their nature in high mobility and unpredictability. There are mainly three key factors which may influence the effect of PEVs on distribution networks, namely the charging characteristics of the electric vehicles, PEVs user profile and PEVs battery charger.

Since not all FEVs start charging simultaneously, it is assumed in this paper that, the time of switching on an individual charger is a random variable, with a probability density function (PDF) f(t), which is determined by the electricity tariff, the pattern of vehicle traffic and the charging characteristics. The initial state of charge (SOC) of the PEV battery before recharging (i.e., residual capacity since last charge) is also assumed to be a random function of the total distance it travels since it was last charged. The initial SOC, E_i can be assumed therefore as a probability density function of h(E), where E is the SOC, which varies from zero to the full capacity of the battery.

In order to determine the variation of FEVs battery charging power demand with time during a recharge cycle, a statistical distribution of the initial state-of-charge before recharging is needed. This is because the FEVs charging curve depends on the initial state-of-charge before recharging.

According to the general information available on personal automobile travel (Shafie-Khah et al., 2016b), for private cars, the daily travel distance subjects to a normal distribution with a mean of 22.3 miles and a standard deviation of 12.2 miles.

Given the average daily travel distance, the SOC at the beginning of a recharge cycle (residual battery capacity) can be estimated using Eq. 1, assuming that the SOC of a PEV drops linearly with the distance of travel.

$$E_i = \left(1 - \frac{\alpha \times d}{d_R}\right) \times 100\% \qquad (1)$$

where E_i represents the initial SOC of an FEV battery, d is the daily distance travelled by a car, which is a random variable, α is the number of days the FEV has travelled since last charge, d_R is the maximum range of the FEV. A typical value for d_R is 100 miles (Bessa and Matos, 2013). Assuming all private FEVs are recharged once every two days and that recharge is carried to completion. The probability density function h for the initial battery SOC is given by Eq. 2, which is derived from Eq. 1 and the distribution of daily travel distance obtained from (Shafie-Khah et al., 2016b).

$$h(E; \mu, \sigma) = \frac{1}{\frac{d_R}{\alpha}(1-E)\sqrt{2\pi\sigma^2}} e^{\frac{\left[\ln(1-E) - \left(\mu - \ln\left(\frac{d_R}{\alpha}\right)\right)\right]^2}{2\alpha^2}}, 0 < E < 1 \qquad (2)$$

where h is the probability density function of a log-normal distribution, μ and σ are respectively, the mean and standard deviation. This model has taken into account the effect of the interval in number of days between recharge of a PEV battery on the initial SOC. The initial SOC has a mean 44% after two days' travel for private PEVs. Start time of battery recharging: The start time of battery charging, determined by the purpose of the use of the PEVs and by the electricity tariff rate structure, has an element of randomness.

It is assumed in this paper that private PEVs are mainly for commuting purpose and the distribution of FEVs trips (shown in percentage of daily traffic versus time of day) complies with Fig. 5. It can be observed that there are two peaks for weekdays, the morning peak (8.00–09.00 am) and the evening peak (5.00–6.00 pm), while there is one peak (12.00 am–1 pm) for weekends (Shafie-Khah et al., 2016b).

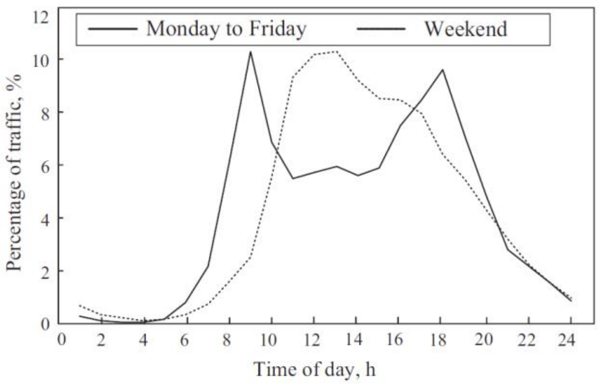

Fig. 5. Trips in progress by time of day and day of week.

The PEV load demand can be dictated to some extent by the electricity tariff structure. In this paper, three types of typical electricity tariff structures are given consideration: fixed electricity rate, time-of-use electricity rate, and real-time electricity rate. The fixed electricity rate refers to the tariff in which energy charge per kW h remains constant regardless of the time of use. Time-of use electricity price divides the tariff into two main blocks: Off peak and on-peak price (Shafie-Khah et al., 2016b). The real-time price, i.e., the electricity rate per kW h varies by time of day and month of year, as shown in Fig. 6, is based on the wholesale price in the Shafie-Khah et al. (2016b) These ignore any capital recovery or standing charge element to the tariff structure. Figs. 5 and 6 will be used to determine the percentage of PEVs to be charged at each time instant.

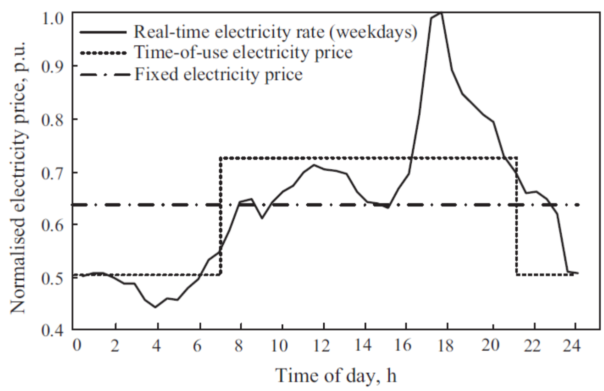

Fig. 6. Electricity tariff structure.

5. Results

5.1. 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 Dallinger et al. (2014) 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 in to consideration to predict the battery's degradation. Other parameters are grid power and grid management. Another model is presented in Das et al. (2013) which also begins by modeling 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 modeling, 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 that based on research on the battery (Guenther et al., 2013). It is also considered the SOC and driving cycles and charging strategies are used in order to simulate PEVs. In Napierala et al. (2014); 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 analyze the charging curve of a day of charging. In Iversen, et al. (2014); it is presented a Markov model in order to optimize 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.

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.

5.1.1. Modeling a PEV aggregator

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

Driving behavior

Driving behavior is modeled 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:

$$t_{drive,m}(k) = 0.7211k_m + 5 \tag{3}$$

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

$$SOC_{n,t+tdrive} = SOC_{n,t} - \frac{k_m.\eta_{k_m}}{E_{bat}} \tag{4}$$

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

To calculate the period of optimization, 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:

$$\Delta t(m) = (t_{start,m+1} - t_{start,m}) - t_{drive,m} \tag{5}$$

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

$$SOC_{n,\Delta t} = \frac{k_{m+1}.\eta_{k_m}}{E_{bat}} \tag{6}$$

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

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:

$$N_{cycle} = a.DOD^b \tag{7}$$

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 life time 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 through put, 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}.

$$\pi(0, DOD) = \frac{C_{bat}}{N_{cycle}(DOD)} \tag{8}$$

The costs for one processed kilowatt-hour are given by:

$$\pi_{energy}(0, DOD) = \frac{C_{bat} DOD E_{bat}}{N_{cycle}(DOD)} \tag{9}$$

The general degradation costs are:

$$\pi_{energy}(0, DOD, DOD_{end}) = \pi(0, DOD_{end}) - \pi(0, DOD_{start}), \text{for } DOD_{end} < DOD_{start} \tag{10}$$

The cost per discharge unit π unit as a function of the DOD before the discharge is:

$$\pi_{unit} = \pi(DOD, DOD + 1\%) == \pi(0, DOD + 1\%) - \pi(0, DOD) = \frac{C_{bat}}{N_{cycle}(DOD+1\%)} - \frac{C_{bat}}{N_{cycle}(DOD)} \tag{11}$$

5.2. Modeling the grid

In the literature, the main focus of PEVs has been its distribution role in the electricity network that was found in Shafie-Khah et al. (2016b). 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.

5.3. 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 (Shafie-Khah et al., 2016b) and discusses security network, while other PEV studies considers imply 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 (Ostadrahimi and Radan, 2014) 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 (Bessa and Matos, 2012).

The per unit optimal power loss reduction, $\Delta P_{LS_{V2G_{opt}}}$, for a single vehicle is defined as:

$$\Delta P_{LS_{V2G_{opt}}} = 3c\alpha X_1[(2 - X_1) + \lambda X_1 - c] \quad (12)$$

The parameters of $\Delta P_{LS_{V2G_{opt}}}$ are obtained online for real-time computation of the power loss (Table 1).

Table 1
Types of renewable sources interacted with PEVs.

Studies	Renewable sources interaction		
	Wind	Solar	Biomass
Bessa and Matos (2012)	-	×	-
Dextreit and Kolmanovsky (2013)	×	×	×
Drude et al. (2014)	×	×	-
Alizadeh et al. (2013)	×	-	-
Pelzer et al. (2014)	-	-	×

6. Conclusion

This paper addressed the topic of PEV management and V2G cap ability. 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 modeling. To deal with the uncertain variables there are stochastic techniques that can be used, such as deterministic methods, probabilistic distributions, and others.

References

Alizadeh M, Scaglione A, Davies J, and Kurani KS (2013). A scalable stochastic model for the electricity demand of electric and plug-in hybrid vehicles. IEEE Transactions on Smart Grid, 5(2): 848-860. https://doi.org/10.1109/TSG.2013.2275988

Bessa RJ and Matos MA (2012). Economic and technical management of an aggregation agent for electric vehicles: A literature survey. European Transactions on Electrical Power, 22(3): 334-350. https://doi.org/10.1002/etep.565

Bessa RJ and Matos MA (2013). Optimization models for EV aggregator participation in a manual reserve market. IEEE Transactions on Power Systems, 28(3): 3085-3095. https://doi.org/10.1109/TPWRS.2012.2233222

Boynuegri AR, Uzunoglu M, Erdinç O, and Gokalp E (2014). A new perspective in grid connection of electric vehicles: Different operating modes for elimination of energy quality problems. Applied Energy, 132: 435-451. https://doi.org/10.1016/j.apenergy.2014.07.050

Dallinger D, Link J, and Büttner M (2014). Smart grid agent: Plug-in electric vehicle. IEEE Transactions on Sustainable Energy, 5(3): 710-717. https://doi.org/10.1109/TSTE.2014.2298887

Das R, Thirugnanam K, Kumar P, Lavudiya R, and Singh M (2013). Mathematical modeling for economic evaluation of electric vehicle to smart grid interaction. IEEE Transactions on Smart Grid, 5(2): 712-721. https://doi.org/10.1109/TSG.2013.2275979

Derakhshandeh SY, Masoum AS, Deilami S, Masoum MA, and Golshan MH (2013). Coordination of generation scheduling with PEVs charging in industrial microgrids. IEEE Transactions on Power Systems, 28(3): 3451-3461. https://doi.org/10.1109/TPWRS.2013.2257184

Dextreit C and Kolmanovsky IV (2013). Game theory controller for hybrid electric vehicles. IEEE Transactions on Control Systems Technology, 22(2): 652-663. https://doi.org/10.1109/TCST.2013.2254597

Drude L, Junior LCP, and Rüther R (2014). Photovoltaics (PV) and electric vehicle-to-grid (V2G) strategies for peak demand reduction in urban regions in Brazil in a smart grid environment. Renewable Energy, 68: 443-451. https://doi.org/10.1016/j.renene.2014.01.049

Galus MD, Waraich RA, Noembrini F, Steurs K, Georges G, Boulouchos K, and Andersson G (2012). Integrating power systems, transport systems and vehicle technology for electric mobility impact assessment and efficient control. IEEE Transactions on Smart Grid, 3(2): 934-949. https://doi.org/10.1109/TSG.2012.2190628

Guenther C, Schott B, Hennings W, Waldowski P, and Danzer MA (2013). Model-based investigation of electric vehicle battery aging by means of vehicle-to-grid scenario simulations. Journal of Power Sources, 239: 604-610. https://doi.org/10.1016/j.jpowsour.2013.02.041

IEA (2014). Global EV outlook: factsheet. International Energy Agency. Paris, France.

Iversen EB, Morales JM, and Madsen H (2014). Optimal charging of an electric vehicle using a Markov decision process. Applied Energy, 123: 1-12. https://doi.org/10.1016/j.apenergy.2014.02.003

Jian L, Zheng Y, Xiao X, and Chan CC (2015). Optimal scheduling for vehicle-to-grid operation with stochastic connection of plug-in electric vehicles to smart grid. Applied Energy, 146: 150-161. https://doi.org/10.1016/j.apenergy.2015.02.030

Liu Z, Wang D, Jia H, and Djilali N (2014). Power system operation risk analysis considering charging load self-management of plug-in hybrid electric vehicles. Applied Energy, 136: 662-670. https://doi.org/10.1016/j.apenergy.2014.09.069

Lopes JP, Almeida PR, and Soares FJ (2009). Using vehicle-to-grid to maximize the integration of intermittent renewable energy resources in islanded electric grids. In the International Conference on Clean Electrical Power, IEEE, Capri, Italy: 290-295. https://doi.org/10.1109/ICCEP.2009.5212041

Lund H and Kempton W (2008). Integration of renewable energy into the transport and electricity sectors through V2G. Energy Policy, 36(9): 3578-3587. https://doi.org/10.1016/j.enpol.2008.06.007

Mwasilu F, Justo JJ, Kim EK, Do TD, and Jung JW (2014). Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration. Renewable and Sustainable Energy Reviews, 34: 501-516. https://doi.org/10.1016/j.rser.2014.03.031

Napierala A, Blasius E, Nickusch M, Schönrath HJ, Reich J, Krüger D, and Binnenbruck R (2014). Investigation of electric vehicle grid support capability. Energy Procedia, 46: 220-226. https://doi.org/10.1016/j.egypro.2014.01.176

Ostadrahimi A and Radan A (2014). Utilization of interleaved converter to improve battery performance in electric and electrical hybrid vehicles. In The 5th Annual International Power Electronics, Drive Systems and Technologies Conference, IEEE, Tehran, Iran: 624-628. https://doi.org/10.1109/PEDSTC.2014.6799449

Pelzer D, Ciechanowicz D, Aydt H, and Knoll A (2014). A price-responsive dispatching strategy for Vehicle-to-Grid: An economic evaluation applied to the case of Singapore. Journal of Power Sources, 256: 345-353. https://doi.org/10.1016/j.jpowsour.2014.01.076

Richardson DB (2013). Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration. Renewable and Sustainable Energy Reviews, 19: 247-254. https://doi.org/10.1016/j.rser.2012.11.042

Romero-Cadaval E, Barrero-González F, González-Romera E, and Milanés-Montero MI (2015). Using plug-in electric vehicles to implement ancillary services in smart distribution grids. In: Rajakaruna S, Shahnia F, and Ghosh A (Eds.), Plug in Electric Vehicles in Smart Grids: 309-349. Springer, Singapore. https://doi.org/10.1007/978-981-287-299-9_11

Saber AY and Venayagamoorthy GK (2010). Plug-in vehicles and renewable energy sources for cost and emission reductions. IEEE Transactions on Industrial Electronics, 58(4): 1229-1238. https://doi.org/10.1109/TIE.2010.2047828

Shafie-Khah M, Heydarian-Forushani E, Golshan MEH, Siano P, Moghaddam MP, Sheikh-El-Eslami MK, and Catalão JPS (2016a). Optimal trading of plug-in electric vehicle aggregation agents in a market environment for sustainability. Applied Energy, 162: 601-612. https://doi.org/10.1016/j.apenergy.2015.10.134

Shafie-Khah M, Moghaddam MP, Sheikh-El-Eslami MK, and Catalão JPS (2015). Optimised performance of a plug-in electric vehicle aggregator in energy and reserve markets. Energy Conversion and Management, 97: 393-408. https://doi.org/10.1016/j.enconman.2015.03.074

Shafie-Khah M, Neyestani N, Damavandi MY, Gil FAS, and Catalão JPS (2016b). Economic and technical aspects of plug-in electric vehicles in electricity markets. Renewable and Sustainable Energy Reviews, 53: 1168-1177. https://doi.org/10.1016/j.rser.2015.09.079

Shao S, Pipattanasomporn M, and Rahman S (2011). Demand response as a load shaping tool in an intelligent grid with electric vehicles. IEEE Transactions on Smart Grid, 2(4): 624-631. https://doi.org/10.1109/TSG.2011.2164583

Sioshansi R, Fagiani R, and Marano V (2010). Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system. Energy Policy, 38(11): 6703-6712. https://doi.org/10.1016/j.enpol.2010.06.040

Sortomme E and El-Sharkawi MA (2010). Optimal charging strategies for unidirectional vehicle-to-grid. IEEE Transactions on Smart Grid, 2(1): 131-138. https://doi.org/10.1109/TSG.2010.2090910

Tan KM, Ramachandaramurthy VK, and Yong JY (2016). Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques. Renewable and Sustainable Energy Reviews, 53: 720-732. https://doi.org/10.1016/j.rser.2015.09.012

Traube J, Lu F, and Maksimovic D (2012). Photovoltaic power system with integrated electric vehicle DC charger and enhanced grid support. In the 15th International Power Electronics and Motion Control Conference, IEEE, Novi Sad, Serbia. https://doi.org/10.1109/EPEPEMC.2012.6397399

Tulpule PJ, Marano V, Yurkovich S, and Rizzoni G (2013). Economic and environmental impacts of a PV powered workplace parking garage charging station. Applied Energy, 108: 323-332. https://doi.org/10.1016/j.apenergy.2013.02.068

Van Haaren R (2011). Assessment of electric cars' range requirements and usage patterns based on driving behavior recorded in the National Household Travel Survey of 2009. Fu Foundation School of Engineering and Applied Science, New York, USA.

Wu D, Aliprantis DC, and Gkritza K (2010). Electric energy and power consumption by light-duty plug-in electric vehicles. IEEE Transactions on Power Systems, 26(2): 738-746. https://doi.org/10.1109/TPWRS.2010.2052375

Yong JY, Ramachandaramurthy VK, Tan KM, and Mithulananthan N (2015). A review on the state-of-the-art technologies of electric vehicle, its impacts and prospects. Renewable and Sustainable Energy Reviews, 49: 365-385. https://doi.org/10.1016/j.rser.2015.04.130

Zhang S and Xiong R (2015). Adaptive energy management of a plug-in hybrid electric vehicle based on driving pattern recognition and dynamic programming. Applied Energy, 155: 68-78. https://doi.org/10.1016/j.apenergy.2015.06.003