Optimal Behavior of Electric Vehicle Parking Lots as Demand Response Aggregation Agents

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***Abstract*—With increasing environmental concerns, the electrification of transportation plays an outstanding role in the sustainable development. In this context, plug-in electric vehicle (PEV) and demand response have indispensable impacts on the future smart grid. Since integration of PEVs into the grid is a key element to achieve sustainable energy systems, this paper presents the optimal behavior of PEV parking lots in the energy and reserve markets. To this end, a model is developed to derive optimal strategies of parking lots, as responsive demands, in both price-based and incentive-based demand response programs (DRPs). The proposed model reflects the impacts of different DRPs on the operational behavior of parking lots and optimizes the participation level of parking lots in each DRP. Uncertainties of PEVs and electricity market are also considered by using a stochastic programming approach. Numerical studies indicate that the PEV parking lots can benefit from the selective participation in DRPs.**

***Index Terms*—Demand response programs, electricity markets, incentive-based programs, parking lot, plug-in electric vehicle, price-based programs, stochastic programming.**

NOMENCLATURE

Superscripts

Act	Activated reserve by ISO.
arv	Arrival.
Cap,Res	Capacity payment for participation in the reserve market.
Cont	Contract.
dep	Departure.
down	Decrease of the stored energy in the parking lot resulted from participating in V2G mode.
Inc	Incentive.
ini	Initial value.
En	Energy.
G2PL	Injection of the grid to the parking lot.
Pen	Penalty.
PEV	Plug-in electric vehicle.
PL	Parking lot.
PL2V	Injection of the parking lot to vehicle.
PL2G	Injection of the parking lot back to the grid.
Res	Reserve.
stay	Staying in the parking lot.
Tariff	Tariff between the parking lot and vehicle.
Sc	Scenario.
up	Increase of the stored energy of the parking lot resulted from charging the PEVs.
V2PL	Vehicle to the parking lot.

Indices (Sets)

i	DRP.
$n(N)$	Parked PEV.
$t(T)$	Time.
$\omega(\Omega)$	Scenarios.

Functions and Operators

Δ	Change in variable amount.
$\mathbb{E}$	Function to obtain the expected value by using the set of scenario Ω.
f_{TG}	Truncated Gaussian distribution.

Parameters and Variables

B	Customer's benefit function.
Cap	Capacity of PEV battery.
Cd	Cost of equipment degradation.
$Cost$	Cost.
d	Demand.
FOR	Forced outage rate of parking lot due to the reliability of distribution network.
Inc	Rate of incentive of reducing the demand.
N	Number of parked PEVs.
P	Power.
Pen	Rate of penalty of not reducing the demand.
$Income$	Income.
soc	State Of the Charge.

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α	Level of participation in each DRP.
η	Charge and discharge efficiency.
λ	Price.
γ	Rate of charge and discharge of PEV.
μ	Contract of a PEV owner for desired SOC.
ς	Incentive function.
ξ	Penalty function.
Γ	Penalty ratio resulted from not delivering the offered energy.

I. Introduction

A. Motivation and Background

DEVELOPING technologies such as Plug-in Electric Vehicle (PEV) provides various opportunities for future systems. In addition to enhancement of system efficiency and operational circumstances, non-renewable fuel consumption and air pollutant emissions will be reduced if PEVs are encouraged in both electrical and transportation systems [1]. Moreover, due to benefits of Demand Response (DR) to attain reliable and efficient electricity markets, Demand Response Programs (DRPs) are also a key element on the sustainable development path [2]. On this basis, the optimal structure of DR aggregation in electricity markets is investigated in [3] and [4]. In this regard, some types of contracts with customers as well as preferences of responsive demand are considered; however, to the best of knowledge the presence of PEVs has not been addressed.

Since high penetration of PEVs can jeopardize the efficiency and reliability of power systems [5], exponential growth of electric vehicles has made the management of the PEVs a crucial issue. In this context, integration of PEVs into the grid is essential. One of the key solutions concerning the integration is effective performance of PEV parking lots. However, managing the required power for charging the PEVs in a parking lot and the potential of the PEVs to inject power back to the grid through different electricity markets is a challenging issue from the parking lot owner viewpoint.

Two main sources of uncertainties including the inherent uncertainties of PEV owners' behavior and the uncertainty of electricity market prices expose the parking lot to a complex problem. In such situation, although participation in tariff-based contracts can decrease the risk of the parking lot, it can limit the profit of this new market player, as a flexible and high-speed storage unit in the demand side. Therefore, the presence of PEVs that participate in DRPs provides the profits of both manageable demands and storage entities for the system operators. On this basis, participation in DRPs can be a profitable option from both power system operators and parking lot owner's points of view. These programs can reduce the risk of participation in the electricity markets for a comparatively small player and increase the profit of this flexible player, as well as improving the reliability and efficiency of power systems.

B. Literature Review

The literature in the field of PEVs can be categorized from different stakeholders points of view. The main stakeholders of PEVs are PEV owners, aggregators, power system operators, specifically Distribution System Operators (DSOs), and parking lots investors.

The PEV owners are interested in minimizing their payments for charging their vehicles, so that their transport requirements are fulfilled. The aggregators are third party entities that have the responsibility of participating in electricity markets on behalf of a large number of PEV owners with the aim of maximizing the profit through market mechanism while satisfying the owners requirements. In addition, DSOs attempt to manage PEVs charging procedure, avoiding system peak increment and even feeder or transformer congestion because of unplanned charge of PEVs [6]. The parking lots investors also follow their own profits as a result of optimal allocation of PEV parking lots.

Different mathematical optimization problems for minimizing the total cost of energy for the PEV owners are presented in [7] and [8]. In [7], the parking pattern is assumed to be fixed, while [8] uses a statistical model to consider the uncertain behavior of PEVs owner without explaining the details.

References [9] and [10] study the problem from a joint PEV owner and aggregator's points of view. The randomness of parking pattern as well as initial SOC is incorporated to the model and a target SOC is also considered in [9]. It is noteworthy that the uncertain behavior of PEV owners is considered through both a realistic trace-based vehicular model for regular PEVs and probabilistic patterns for irregular PEVs in [10]. In [11], an online coordination model is reported for operating PEVs in smart grids to maximize the PEV owners' satisfaction, considering power system constraints.

The problem is investigated from DSO perspective as well in [12] and [13] that include DR management for the future smart grids with a considerable share of PEVs in order to mitigate the increment of peak demand of the system. It should be noted that the randomness of PEVs is modeled in [12] according to real-life practice, whereas in [13] a normal probability distribution function is considered to model the parking pattern and the uncertainty of initial SOC, however the required target level of the SOC is not incorporated to the model.

In [14], the effect of several penetration levels of grid-to-vehicle PEVs on distribution networks has been assessed. In [15], the impact of two states of coordinated and uncoordinated charging of PEV charging stations has been studied on the power quality. In [16], different PEV management approaches including uncontrolled charging, smart charging, V2G and DRPs for day-ahead energy resource scheduling have been compared. In [17], the PEV aggregators have been considered as a type of dispatchable DR and energy storage system with stochastic behavior supplying load or ancillary services. In [18], the real-time operation of PEVs to minimize voltage deviation and network losses has been reported. In [19], in order to optimize the bus voltages and network losses, both vehicle-to-grid and grid-to-vehicle modes of PEVs at diverse penetration levels have been considered. In the mentioned reports, the PEV parking lots have been modeled from the grid's point of view and the profit of PEV parking lot has not been addressed.

Other works such as [20] and [21] look at the problem from the parking lot investor's point of view. In [20], a heuristic method has been employed to optimize the parking lot allocation as a multi-objective problem. In [21], a two-stage model has been presented to find the optimal place and sizing of parking lots considering the network constraints.

C. Contributions

Although many works in the literature have studied the PEVs, the operational behavior of these new electricity market players has been rarely addressed. Furthermore, participation of these players in DRPs as responsive demands has not been investigated.

This paper models the operational behavior of PEV parking lots and their participation in both incentive-based and price-based DRPs. To this end, a stochastic programming approach is employed and impacts of several DRPs such as Real Time Pricing (RTP), Time of Use (TOU), Emergency Demand Response Program (EDRP), Critical Peak Pricing (CPP) and Interruptible/Curtailabe (I/C) services on operational behavior of the parking lot are investigated. In addition, the participation level of PEV parking lot in each DRP is optimized in order to find the best combination of the DRPs. According to the mentioned expression, the contributions of this paper can be summarized as below:

- Modeling the PEV parking lots as demand response aggregation agents, participating in both incentive-based and price-based DRPs
- Optimizing the participation level of PEV parking lots in each DRP

D. Paper Organization

Section II describes the stochastic model of the PEV parking lot that participates in different DRPs. Section III is designated to uncertainty characterization. Section IV devotes the numerical results. Section V concludes the paper.

II. Modeling the PEV Parking Lot Participation in Demand Response Programs

A. Modeling the Demand Response Programs

DRPs aim to make consumers more sensitive to variations of electricity prices in different hours. DRPs encourage electricity consumers to change their electricity use in response to fluctuations of price over the time, or to offer incentives, or to charge penalties that are considered to provide lower use during high electricity prices or when the power system reliability is threatened. DRPs can be categorized into two major groups, namely, price-based programs, and incentive-based programs. Each mentioned group can also be categorized into some subsets as illustrated in Fig. 1. Details of the DRPs have been discussed in [22].

Assuming that the customer's electricity demand at hour t is changed from d_t^{ini}, initial amount of demand, to d_t, due to price changes or an incentive payment or a penalty consideration, the impacts of DRPs on a customer's consumption can be formulated as below:

$$\Delta d_t = d_t^{\text{ini}} - d_t \tag{1}$$

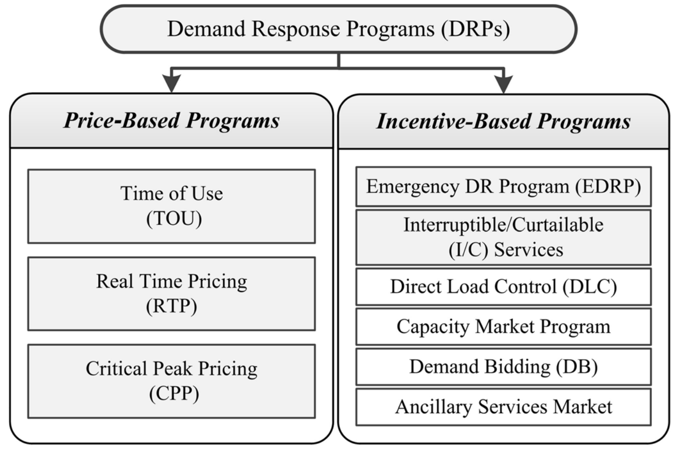


Fig. 1. Classification of demand response programs.

The amount of incentive, ς_t, is expressed as:

$$\varsigma_t = Inc_t \, \Delta d_t \tag{2}$$

Similarly, the amount of penalty, ξ_t, can be formulated as:

$$\xi_t = Pen_t \left(d_t^{\text{Cont}} - \Delta d_t \right) \tag{3}$$

where d_t^{Cont} denotes the contract level for hour t.

The customer's benefit, B, at hour t can be as follows [23]:

$$B_t = Income_t - d_t \, \lambda_t + Inc_t \, \Delta d_t - Pen_t \left(d_t^{\text{Cont}} - \Delta d_t \right) \tag{4}$$

where, $Income_t$ is the customer's utility from the use of d kWh of electrical energy during t-th hour. In other words, this term represents the value of electricity for the consumers. It should be noted that the mentioned utility can reflect the production income, if the customer is an industrial demand and can be the productivity, if it is a commercial demand. The second term of (4) is related to the cost of consumed electrical energy of the customer at hour t. Moreover, the last two terms are associated with the incentive and penalty payment of customer at hour t, respectively. On this basis, the total benefit of the responsive demand during time interval, T, can be formulated as bellow:

$$B_{tot} = \sum_{t=1}^{T} \Big(Income_t - d_t \, \lambda_t + Inc_t \, \Delta d_t - Pen_t \left(d_t^{\text{Cont}} - \Delta d_t \right) \Big) \tag{5}$$

Eq. (5) represents a general model to calculate the decision variable of the responsive demand's benefit for both price-based and incentive-based DRPs containing both single- and multi-period responses. The total benefit, B_{tot}, expresses the main variable of a responsive demand to decide how to respond to price and incentive/penalty changes. In this paper, the PEV parking lot is considered as a responsive demand who participates in different DRPs. Accordingly, in Section II-B, the mentioned general model is particularly applied to the PEV parking lot as a specific responsive demand.

B. Modeling the PEV Parking Lot

In the future sustainable systems, the installation of parking lots with appropriate connection necessities of PEVs is unavoidable. In such systems, introduction of some new agents such as parking lot owners/operators is required. These new agents should manage the charging/discharging of PEVs considering several uncertainties.

In this paper, the behavior of PEVs and the electricity market signals for reserve activation are considered to be uncertain. The uncertain characteristics are modeled by generating several scenarios. To this end, a stochastic model is utilized to provide the scenarios of the number, SOC, and battery capacity of the PEVs as well as the activated amount of reserve. The details of the uncertainty characterization are expressed in Section IV.

In order to model the behavior of parking lot owners/operators, the amounts of power and reserve traded between the parking lot and the grid are calculated based on the scenarios of uncertainty characterization. In other words, according to patterns of arrival/departure of electric vehicles to/from parking lot and electricity market scenarios, the sold power to the parking lot and the sold power back to the grid are calculated in both the reserve and energy markets. The parking lot operator aims to maximize the profit through the market interaction and DRPs besides the income resulted from contracts with its customers. To this end, the parking lot participates in both energy and reserve markets and various DRPs whereas representing the optimal behavior for interaction with PEVs.

Although the PEVs parked in the parking lot can be operated as battery energy storages, the parking lot is required to charge them up to the minimum required SOC. Since the parking lots are limited energy resources, in this paper a time interval is considered. This enables the parking lot to decide what time to charge the PEVs and what time to sell energy back to the grid. This is the major difference between parking lots and other distributed generations.

The objective function is to maximize the parking lot's profit. By applying the general model of responsive demands (i.e., (5)) to the PEV parking lot's characteristics, the objective function is formulated via a bi-level stochastic programming as presented in (6).

$$\begin{aligned}
&\underset{P^{\mathrm{En,PL2G}}_{\omega,t,i},P^{\mathrm{En,G2PL}}_{\omega,t,i},P^{\mathrm{Res}}_{\omega,t,i},soc^{\mathrm{up}}_{\omega,t,i},soc^{\mathrm{down}}_{\omega,t,i},\alpha_i}{\text{Maximize}} \quad \left\{profit^{\mathrm{PL}}\right\} \\
&= \sum_{t=1}^{T}\left[\begin{array}{l}
\mathbb{E}_{\Omega_1}\displaystyle\sum_{i\in \mathrm{DRPs}} \alpha_i\Big\{Income^{\mathrm{En,PL2G}}_{\omega,t,i} + Income^{\mathrm{Cap,Res}}_{\omega,t,i} \\
\qquad + Income^{\mathrm{En,Tariff}}_{\omega,t,i} - Cost^{\mathrm{En,Tariff}}_{\omega,t,i} \\
\qquad - Cost^{\mathrm{En,G2PL}}_{\omega,t,i} - Cost^{\mathrm{Deg,En}}_{\omega,t,i} \\
\qquad + Income^{\mathrm{stay}}_{\omega,t,i} + Income^{\mathrm{Inc}}_{\omega,t,i} \\
\qquad - Cost^{\mathrm{Pen}}_{\omega,t,i}\Big\} \\
+\ \mathbb{E}_{\Omega_2|\Omega_1}\left[\begin{array}{l}\alpha_i\Big\{Income^{\mathrm{Res,Act}}_{\omega,t,i} - Cost^{\mathrm{Deg,Res}}_{\omega,t,i} \\
- Cost^{\mathrm{Unavailable}}_{\omega,t,i} - Cost^{\mathrm{Res,Tariff}}_{\omega,t,i}\Big\}\end{array}\right]
\end{array}\right]
\end{aligned} \tag{6a}$$

The first level of the problem (i.e., *here-and-now*) consists of nine cost/income terms. The first term, $Income^{\mathrm{En,PL2G}}_{\omega,t,i}$, denotes the parking lot's income obtained from selling energy back to the grid as presented in (6b).

$$Income^{\mathrm{En,PL2G}}_{\omega,t,i} = P^{\mathrm{En,PL2G}}_{\omega,t,i}\,\lambda^{\mathrm{En}}_{t,i} \tag{6b}$$

where $\lambda^{\mathrm{En}}_{t,i}$ is the energy price associated with the type of DRP. $P^{\mathrm{En,PL2G}}_{\omega,t,i}$ is the perking lot's offer to the energy market that is obtained from discharging the PEVs' battery.

Since, it is assumed that the parking lot can have an income from offering its possible capacity to the reserve market, the second term of (6a), $Income^{\mathrm{Cap,Res}}_{\omega,t,i}$, denotes the mentioned capacity payment income as presented in (6c).

$$Income^{\mathrm{Cap,Res}}_{\omega,t,i} = P^{\mathrm{Res}}_{\omega,t,i}\,\lambda^{\mathrm{Cap,Res}}_{t} \tag{6c}$$

The next term of (6a), $Income^{\mathrm{En,Tariff}}_{\omega,t,i}$, denotes the income received from PEVs' owners to charge their batteries as formulated in (6d).

$$Income^{\mathrm{En,Tariff}}_{\omega,t,i} = soc^{\mathrm{up}}_{\omega,t,i}\,\lambda^{\mathrm{Tariff,PL2V}}_{t} \tag{6d}$$

where $soc^{\mathrm{up}}_{\omega,t,i}$ represents how much stored energy in the parking lot is increased because of charging the PEVs. It should be noted that the increase in the parking lot's stored energy can be also resulted from arrival of new PEVs to the parking lot, however, this is not reflected in the amount of $soc^{\mathrm{up}}_{\omega,t,i}$ as presented in corresponding formulation in the reminder of this paper.

The next term of (6a), $Income^{\mathrm{En,Tariff}}_{\omega,t,i}$, is the cost related to the value that is paid to PEV owners because of delivering energy from their batteries back to the energy market.

$$Cost^{\mathrm{En,Tariff}}_{\omega,t,i} = soc^{\mathrm{down}}_{\omega,t,i}\,\lambda^{\mathrm{Tariff,V2PL}}_{t} \tag{6e}$$

where $soc^{\mathrm{down}}_{\omega,t,i}$ shows the reduction of parking lot's stored energy due to discharging the PEVs' battery. The reduction of parking lot's stored energy because of PEVs' departure is not reflected the amount of $soc^{\mathrm{down}}_{\omega,t,i}$ as presented in corresponding formulation in the rest of this paper.

The fifth term of (6a), $Cost^{\mathrm{En,G2PL}}_{\omega,t,i}$, represents the cost of purchasing energy from the grid as presented in (6f).

$$Cost^{\mathrm{En,G2PL}}_{\omega,t,i} = P^{\mathrm{En,G2PL}}_{\omega,t,i}\,\lambda^{\mathrm{En}}_{t,i} \tag{6f}$$

Eq. (6g) indicates the battery degradation costs resulted from operation in the V2G mode in energy market.

$$Cost^{\mathrm{Deg,En}}_{\omega,t,i} = P^{\mathrm{En,PL2G}}_{\omega,t,i}\,Cd \tag{6g}$$

The income received from the parking usage tariff in each hour, $Income^{\mathrm{stay}}_{\omega,t,i}$, can be calculated by the number of parked PEVs in that hour multiplied by the tariff of staying in the parking lot as presented in (6h).

$$Income^{\mathrm{stay}}_{\omega,t,i} = N^{\mathrm{PEV}}_{\omega,t,i}\,\lambda^{\mathrm{Tariff,stay}} \tag{6h}$$

As described in Section II-A, the PEV parking lot as a participant in incentive-based DRPs can have an income/cost because of incentive/penalty of the programs. On this basis, the last two terms of *here-and-now* level, i.e., $Income^{\mathrm{Inc}}_{\omega,t,i}$ and $Cost^{\mathrm{Pen}}_{\omega,t,i}$, are respectively related to the incentive income and penalty cost because of participating in the incentive-based DRPs.

$$Income_{\omega,t,i}^{\mathrm{Inc}} = Inc_{t,i}\,\Delta P_{\omega,t,i}^{\mathrm{En,G2PL}} \tag{6i}$$

$$Cost_{\omega,t,i}^{\mathrm{Pen}} = Pen_{t,i}\left(P_{t,i}^{\mathrm{Cont}} - \Delta P_{\omega,t,i}^{\mathrm{En,G2PL}}\right) \tag{6j}$$

where $\Delta P_{\omega,t,i}^{\mathrm{En,G2PL}}$ is defined as the initial power that the parking lot receives from the grid (i.e., in a fixed-rate tariff) minus the received power in an incentive-based DRP. $P_{t,i}^{\mathrm{Cont}}$ is the contract level of the parking lot in program i.

The second level of the stochastic programing (i.e., *wait-and-see*) consists of four cost/income terms related to the activated amount of reserve by ISO. The first term, $Income_{\omega,t,i}^{\mathrm{Res,Act}}$, represents the income resulted from delivering the quantity of reserve as formulated in (6k). It should be mentioned that, in order to model the capacity payment and delivering the activated quantity of reserve in a general form, two different tariffs are considered.

$$Income_{\omega,t,i}^{\mathrm{Res,Act}} = P_{\omega,t,i}^{\mathrm{Res,Act}}\,\lambda_t^{\mathrm{Res}} \tag{6k}$$

where $P_{\omega,t,i}^{\mathrm{Res,Act}}$ is the activated quantity of reserve that is not greater than the offered capacity to the reserve market ($P_{\omega,t,i}^{\mathrm{Res,Act}} \le P_{\omega,t,i}^{\mathrm{Res}}$).

The second term of *wait-and-see* level, $Cost_{\omega,t,i}^{\mathrm{Deg,Res}}$, represents the battery degradation costs resulted from operation in V2G mode in the reserve market.

$$Cost_{\omega,t,i}^{\mathrm{Deg,Res}} = P_{\omega,t,i}^{\mathrm{Res,Act}}\,Cd \tag{6l}$$

The third term of *wait-and-see* level, $Cost_{\omega,t,i}^{\mathrm{Unavailable}}$, denotes the penalty cost arisen from not being available to deliver the offered reserve while it is activated by the ISO. FOR^{PL} shows the inability of the parking lot to inject power back to the grid and it can be arisen from a network failure or from the parking lot itself. As presented in (6m), if the parking lot cannot provide the requested quantity of reserve, it has to pay a penalty based on Γ^{Res} that can be determined by the regulatory body.

$$Cost_{\omega,t,i}^{\mathrm{Unavailable}} = P_{\omega,t,i}^{\mathrm{Res,Act}}\,\lambda_t^{\mathrm{Res}}\,\Gamma^{\mathrm{Res}}\,FOR_t^{\mathrm{PL}} \tag{6m}$$

Finally, the last term of (6a) denotes the cost related to the value that is paid to PEV owners because of delivering energy in the reserve market.

$$Cost_{\omega,t,i}^{\mathrm{Res,Tariff}} = P_{\omega,t,i}^{\mathrm{Res,Act}}\,\lambda_t^{\mathrm{Tariff,V2PL}} \tag{6n}$$

In (6), α_i represents the participation level of PEV parking lot in each DRP. In other words, this variable determines how much the PEV parking lot should participate in different DRPs. On this basis we have:

$$0 \le \alpha_i \le 1 \quad \forall i \in \mathrm{DRPs} \tag{7}$$

$$\sum_{i \in \mathrm{DRP}} \alpha_i = 1 \tag{8}$$

In (6), degradation cost of PEVs' battery, Cd, is considered for extra cycling of the battery due to operation in V2G mode. The amount of Cd can be calculated from (9) [24].

$$Cd = \frac{C^{Battery}}{L_{ET}} \tag{9}$$

where $C^{Battery}$ is the capital cost of PEV battery and L_{ET} is the battery lifetime.

Giving the charge/discharge rate of PEV batteries, the maximum amounts of tradable power between the parking lot and the grid are formulated in (10) and (11).

$$P_{\omega,t}^{\mathrm{En,G2PL}} \le N_{\omega,t}^{\mathrm{PEV}}\,\gamma^{\mathrm{charge}} \quad \forall\omega, \forall t \tag{10}$$

$$P_{\omega,t}^{\mathrm{En,PL2G}} + P_{\omega,t}^{\mathrm{Res,Act}} \le N_{\omega,t}^{\mathrm{PEV}}\,\gamma^{\mathrm{discharge}} \quad \forall\omega, \forall t \tag{11}$$

The total SOC of the parking lot in each hour can be achieved from its stored energy in previous hour, the power traded with the grid, and the SOC of arrived or departed vehicles as formulated in (12).

$$\begin{aligned} soc_{\omega,t} = {} & soc_{\omega,t-1} + soc_{\omega,t}^{\mathrm{arv}} - soc_{\omega,t}^{\mathrm{dep}} \\ & + P_{\omega,t}^{\mathrm{En,G2PL}}\,\eta^{\mathrm{charge}} \\ & - \left(P_{\omega,t}^{\mathrm{En,PL2G}} + P_{\omega,t}^{\mathrm{Res,Act}}\right)\Big/\eta^{\mathrm{discharge}} \quad \forall\omega, \forall t \end{aligned} \tag{12}$$

The SOC of arrived PEVs can be calculated by the supposed scenario for parking lot's SOC as expressed in (13), whereas, the SOC of departed PEVs is related to the supposed scenarios as well as the behavior of parking lot in charging or discharging of PEVs.

$$soc_{\omega,t}^{\mathrm{arv}} = \sum_{n=1}^{N_{\omega,t}} Cap_{n,\omega,t}^{\mathrm{PEV}}\,soc_{n,\omega,t}^{\mathrm{PEV,ini}} \quad \forall\omega, \forall t \tag{13}$$

where $soc_{\omega,t}^{\mathrm{arv}}$ is the aggregated amount of stored energy that is added to the parking lot only because of new PEVs arrival.

In order to calculate the surplus SOC that remains in PEVs while their departure, (14) and (15) can be respectively utilized [21]. $soc_{\omega,t}^{\mathrm{up}}$ represents how much electrical energy is injected to the PEVs. On the contrary, $soc_{\omega,t}^{\mathrm{down}}$ denotes the amount of electrical energy that is taken out of the PEVs. These two variables are used to calculate $Income_{\omega,t,i}^{\mathrm{En,Tariff}}$ and $Cost_{\omega,t,i}^{\mathrm{En,Tariff}}$ as presented in (6d) and (6e).

$$soc_{\omega,t}^{\mathrm{up}} = \begin{cases} 0 & soc_{\omega,t}^{\mathrm{dep}} \le \left(soc_{\omega,t-1}^{\mathrm{Sc}} - soc_{\omega,t}^{\mathrm{Sc}}\right) \\ soc_{\omega,t}^{\mathrm{dep}} - \left(soc_{\omega,t-1}^{\mathrm{Sc}} - soc_{\omega,t}^{\mathrm{Sc}}\right) & \text{Otherwise} \end{cases} \tag{14}$$

$$soc_{\omega,t}^{\mathrm{down}} = \begin{cases} 0 & \left(soc_{\omega,t-1}^{\mathrm{Sc}} - soc_{\omega,t}^{\mathrm{Sc}}\right) \le soc_{\omega,t}^{\mathrm{dep}} \\ \left(soc_{\omega,t-1}^{\mathrm{Sc}} - soc_{\omega,t}^{\mathrm{Sc}}\right) - soc_{\omega,t}^{\mathrm{dep}} & \text{Otherwise} \end{cases} \tag{15}$$

where $soc_{\omega,t}^{\mathrm{Sc}}$ denotes the stored energy in the parking lot obtained from the input scenarios. In other words $soc_{\omega,t}^{\mathrm{Sc}}$ shows the stored energy in the parking lot in each hour, if there is no energy trading between the parking lot and the grid and can be calculated by (16).

$$soc_{\omega,t}^{\mathrm{Sc}} = \sum_{n=1}^{N_{\omega,t}} Cap_{n,\omega,t}^{\mathrm{PEV}}\,soc_{n,\omega,t}^{\mathrm{PEV,Sc}} \quad \forall\omega, \forall t \tag{16}$$

where $soc_{n,\omega,t}^{\mathrm{PEV,Sc}}$ denotes the PEV's SOC by assuming that the parking lot does not trade energy with the grid. Accordingly, the value of $soc_{n,\omega,t}^{\mathrm{PEV,Sc}}$ is only related to the input scenarios as presented in Section III.

In order to maintain the battery lifetime, maximum and minimum limits of each PEV's SOC should be respected by the parking lot as presented in (17).

$$soc_n^{\text{PEV,min}} \leq soc_{n,\omega,t}^{\text{PEV}} \leq soc_n^{\text{PEV,max}} \quad \forall n, \forall \omega, \forall t \qquad (17)$$

Based on (17), PEV parking lot ensures that each PEV battery not to be discharged less than its minimum SOC, $soc_n^{\text{PEV,min}}$, and not to be charged more than its maximum SOC, $soc_n^{\text{PEV,max}}$.

As a consequence of (17), the parking lot's SOC is limited between the aggregated amount of minimum and maximum PEVs' SOCs that can be expressed as (18).

$$\sum_{n=1}^{N_{\omega,t}} soc_n^{\text{PEV,min}} \leq soc_{\omega,t} \leq \sum_{n=1}^{N_{\omega,t}} soc_n^{\text{PEV,max}} \quad \forall \omega, \forall t \qquad (18)$$

PEV owners may usually have some expectations about the usage pattern of their PEV's battery while taking part in the V2G mode. These expectations can be declared as desired SOC at the departure time [25]. In order to meet the PEV owners' expectations, the parking lot should predict their stay duration to reduce uncertainty. In this paper, it is assumed that a contract is signed between the parking lot and PEV owners in order to allow the parking lot to operate the PEV in the V2G mode. Then, the parking lot should aggregate the desired SOC assigned in the contracts for each hour to limit the maximum power exchange with the grid. The term μ denotes this aggregated percentage. The calculation of μ can be carried out by using various probabilistic methods that are used for discrete probability problems. Therefore, the parking lot aggregates the desired SOC for each hour and considers a constraint for the injection back to the grid as formulated in (19) [21].

$$P_{\omega,t}^{\text{En,PL2G}} + P_{\omega,t}^{\text{Res,Act}} \leq \mu_t \, soc_{\omega,t} \quad \forall \omega, \forall t \qquad (19)$$

In this paper, a constant term is considered for μ. In other words, it is assumed that the parking lot signs the same contract with all PEVs in terms of desired SOC at the departure time. According to (19), the total injection of parking lot back to the grid is less than the required SOC of the parking lot due to its contracts with the PEV owners.

III. Uncertainty Characterization

A. Modeling the Uncertainties of PEVs' Behavior

In order to model the uncertainties of PEVs' behavior, truncated Gaussian distribution is widely employed for arrival and departure times and the SOC at arrival [26], [27]. The details of PEV's probability distributions are expressed in Table I.

In order to generate the scenarios of PEVs, behavior of each PEV is modeled by using (20)-(23). Eq. (20) is employed to generate scenarios for the SOC of each PEV when arriving to the parking lot.

$$\begin{aligned} soc_n^{\text{PEV,ini}} &= f(x) \\ &= f_{TG}\left(x; \mu_{soc}, \sigma_{soc}^2, \left(soc_n^{\text{PEV,min}}, soc_n^{\text{PEV,max}}\right)\right) \; \forall n \end{aligned} \qquad (20)$$

TABLE I
PEVs' Probability Distribution

	Mean	Standard deviation	Min	Max
Initial PEV SOC (%)	50	25	30	90
Arrival time (h)	8	3	5	17
Departure time (h)	16	3	11	24

where f_{TG} denotes the truncated Gaussian distribution. μ and σ^2 are mean value and variance of the random variable, respectively. $(soc_n^{\text{PEV,min}}, soc_n^{\text{PEV,max}})$ represents the truncation region. Eq. (21) is used to generate the scenarios of arrival time of each PEV.

$$t_n^{\text{arv}} = f(x) = f_{TG}\left(x; \mu_{arv}, \sigma_{arv}^2, \left(t_n^{\text{arv,min}}, t_n^{\text{arv,max}}\right)\right) \quad \forall n \qquad (21)$$

Eq. (22) should be considered to guarantee that the generated scenarios are logic.

$$t_n^{\text{arv}} < t_n^{\text{dep}} \quad \forall n \qquad (22)$$

On this basis, truncation region to generate the scenarios of departure time is considered as presented in (23).

$$\begin{aligned} t_n^{\text{dep}} &= f(x) \\ &= f_{TG}\left(x; \mu_{dep}, \sigma_{dep}^2, \left(\text{Max}\left\{t_n^{\text{dep,min}}, t_n^{\text{arv}}\right\}, t_n^{\text{dep,max}}\right)\right) \quad \forall n \end{aligned} \qquad (23)$$

The stored energy of each PEV in each hour without considering the energy trading between the parking lot and the grid can be formulated as (24).

$$soc_{n,t}^{\text{PEV,Sc}} = \begin{cases} soc_n^{\text{PEV,ini}} & t_n^{\text{arv}} \leq t < t_n^{\text{dep}} \\ 0 & \text{Otherwise} \end{cases} \qquad (24)$$

The capacity of each PEV depends on the PEV battery class. Reference [28] has reported twenty four classes of PEV batteries. In order to model the uncertainties of different types of PEVs in the parking lot, the probability distribution of the battery capacities is employed as presented in Fig. 2.

The number of parked PEVs in the parking lot, N_t^{PEV}, can be formulated as (25).

$$N_t^{\text{PEV}} = N_t^{\text{PEV,arv}} - N_t^{\text{PEV,dep}} + N_{t-1}^{\text{PEV}} \quad \forall t \qquad (25)$$

where $N_t^{\text{PEV,arv}}$ and $N_t^{\text{PEV,dep}}$ denote the number of arrived PEVs to and departed from parking lot at time t, respectively.

Eq. (26) ensures that the number of parked PEVs not to be greater than the number of car spaces in the parking lot.

$$N_t^{\text{PEV}} \leq N^{\text{PEV,max}} \quad \forall t \qquad (26)$$

B. Modeling the Uncertainties of Activated Amount of Reserve

Market players require reasonable methods to predict the probability that the spinning reserve is called and generated in day-ahead competitive electricity markets in order to integrate such incomes to their objective functions in an appropriate way. In [29] and [30], it is assumed that the probability of calling and generating spinning reserve through the

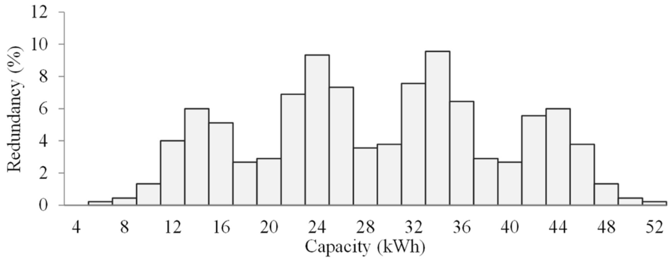


Fig. 2. Distribution of PEV battery classes.

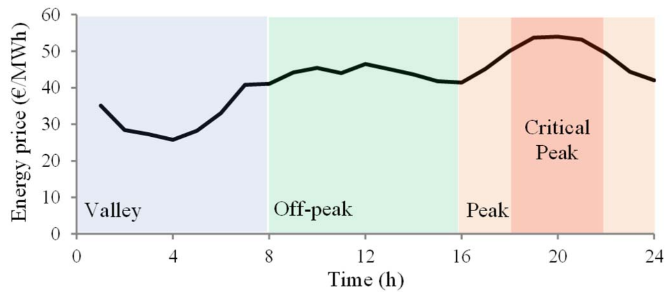


Fig. 3. Hourly prices of the energy market.

day is constant in the day-ahead markets which have conflict with competitive market principles. The uncertainty in calling and generating spinning reserve is considered in [31] using artificial neural networks. In this paper, the uncertain amount of the activated reserve, $P_{\omega,t}^{\text{Res,Act}}$, is also considered uniformly distributed between zero and PEV parking lot's offered quantity. This source of uncertainty is characterized as a *wait-and-see* stochastic variable in the second level of the stochastic programing. The probability distribution function of the amount of the activated reserve is expressed as:

$$f(x) = \begin{cases} 1/P_{\omega,t}^{\text{Res}}, & 0 \leq x \leq P_{\omega,t}^{\text{Res}} \\ 0, & \text{Otherwise} \end{cases} \tag{27}$$

IV. Numerical Results

The proposed model is tested on a PEV parking lot signifying one thousand parking stations that participates in the Spanish electricity market [32]. According to [32], the hourly prices of energy market in November 2013 used in both V2G and G2V modes are illustrated in Fig. 3. The hours between 1 and 8 are considered as valley period. The hours 9 to 16 are off-peak period. The hours between 17 and 24 are peak period, while the hours 18 to 22 denote critical peak period. The prices of reserve market are also utilized from the mentioned market. According to [33], it is assumed that each charging station of the parking lot is operated at a charging rate of 3.3 kW per hour. The tariffs of energy and reserve between the parking lot and the PEV owners are extracted from [24]. The problem is modeled as a Mixed Integer Linear Programming (MILP) and solved by CPLEX12 [34].

In order to study the operational behavior of the parking lot, various price-based and incentive-based DRPs are considered, as respectively presented in Tables II and III.

TABLE II
CONSIDERED CASES FOR THE PRICE-BASED DEMAND RESPONSE PROGRAMS

	Electricity price (€/MWh)			
Case	**Valley**	**Off-peak**	**Peak**	**Critical peak**
Base case (fixed-rate tariff)	41.8	41.8	41.8	41.8
TOU	20.9	41.8	62.7	62.7
CPP	41.8	41.8	41.8	100
RTP	as indicated in Fig. 3			

TABLE III
CONSIDERED CASES FOR THE INCENTIVE-BASED DEMAND RESPONSE PROGRAMS

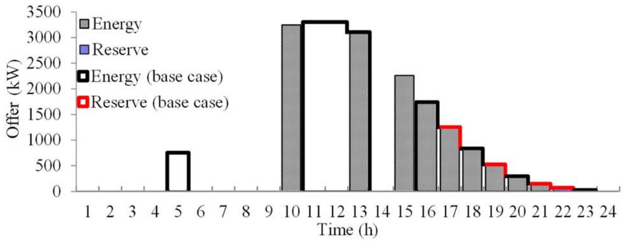
Case	Valley	Off-peak	Peak	Critical peak
EDRP	-	-	-	4.18 €/MWh incentive for demand reduction
I/C services	-	5 % load curtailment for one hour	10 % load curtailment for one hour	

TABLE IV
OBTAINED PARTICIPATION LEVEL IN THE PROPOSED METHOD

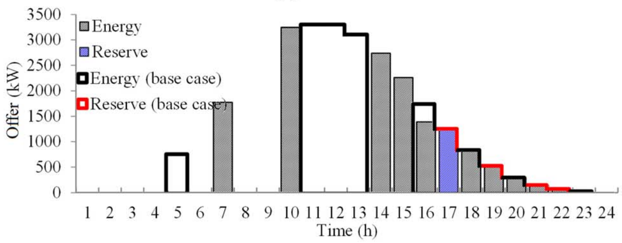
DRP	TOU	CPP	RTP	EDRP	I/C services
α_i	0.59	0.26	0.0	0.15	0.0

As it can be seen in Table II, in the base case, a fixed rate tariff is considered equal to the average of hourly prices that presents the behavior of the parking lot without participation in any DRPs. A type of TOU is taken into account in which the considered tariff in valley period is half the off-peak tariff, and the peak tariff is 50 percent higher than the off-peak tariff. The off-peak tariff is considered equal to the average of hourly prices (i.e., equal to the fixed rate tariff). In CPP program, a large amount of price, 100 /MWh, is set for the critical peak period. In Table III, two incentive-based DRPs are presented. In EDRP case, an incentive equal to 10 % of the average price, i.e., 4.18/MWh, is considered for the load reduction. On this basis, if the responsive customer decreases its demand during the critical peak period, it receives the mentioned amount of incentive. In the I/C services, it is assumed that a signal sends to the PEV parking lot to reduce the demand for one hour. It is assumed that the amount of the load curtailment in the peak hours is twice of the one in the off-peak hours.

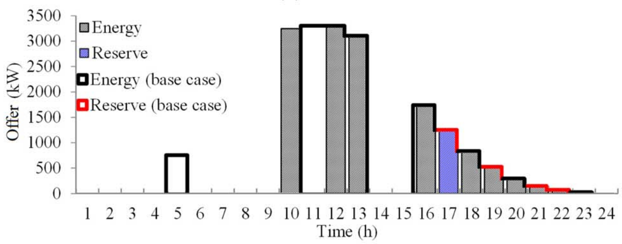
The PEV parking lot can participate in the mentioned DRPs to supply a part of its demand. The objective is to compare the programs and investigate the parking lot's behavior to select between the DRPs. By using the variable of level of participation in each DRP, α_i, the parking lot can optimize how much of its demand to be dedicated to each DRP. In order to analyze the impact of different DRPs on the behavior of parking lot different cases are studied. To this end, by setting the variable α_i equals to 1, participation of parking lot is modeled in a specific DRP. Meanwhile, by considering α_i as a variable, the proposed DRP share is obtained as presented in Table IV.



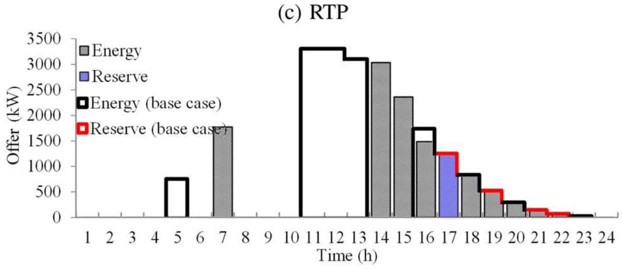
(a) TOU



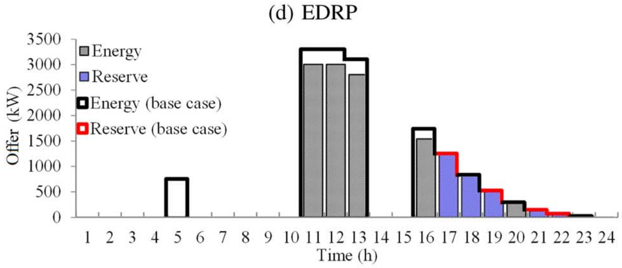
(b) CPP



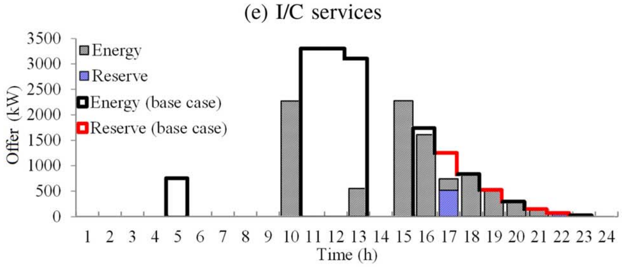
(c) RTP



(d) EDRP



(e) I/C services



(f) Proposed

Fig. 4. Parking lots offer to the energy and reserve markets (V2G mode).

The parking lot offers to participate in the energy and reserve markets in different cases are indicated in Fig. 4. As it can be seen, different DRPs change the optimal offering strategy of parking lot for both the energy and reserve markets. Contrary to the base case, participating in all DRPs causes the parking lot not to inject power to the grid at hour 5, when the energy price is low and no incentive is suggested. Moreover, due to the high energy tariffs in peak period through the TOU program, the parking lot has the lowest motivation to participate in the reserve market. On the contrary, participation in the I/C services causes that the parking lot switches to participate in the reserve market during the peak period, in order not to discharge the PEVs in the hours when 10 percent of its demand can be curtailed and the parking lot cannot charge some parts of its PEVs. Furthermore, it can be observed that, by participating in CPP and EDRP that both are characterized by the critical peak period, parking lot injects power back to the grid in hours 14-16.

In the base case, the PEV parking lot participates in the reserve market in hours 17, 19, 21 and 22. The highest amounts of offer to the reserve market happen in hours 17 and 19 when the capacity of PEV parking lot is higher, due to the higher number of parked PEVs. However, implementation of different DRPs changes the behavior of parking lot for participating in the spinning reserve market. On this basis, when TOU is implemented, in the mentioned hours, the parking lot prefers to offer to the energy market rather than the spinning reserve market, because the energy tariff is significantly high in the peak hours. Therefore, in this case, the power system cannot benefit from the presence of PEV parking lots for supplying the spinning reserve. By implementation of CPP and RTP, since the tariff of energy is extremely high in the critical peak period, hour 17 is the only hour that the PEV parking lot participates in the reserve market. Similarly, by implementation of EDRP, because of incentive payments in the critical peak period, the parking lot participate in the energy market in the mentioned period and the hour 17 is the only hour for offering to the reserve market. From the power systems point of view, I/C services have the highest impact on motivating the parking lot to supply spinning reserve; however, its participation in the energy market is similar to the base case. In the proposed case, the PEV parking lot tends to participate more in the energy market than in the spinning reserve market. In this case, the behavior of parking lot is a mixture of its behavior in implementation of TOU, CPP and EDRP, because its demand is dedicated to these three DRPs.

The initial and obtained stored energies in the parking lot are compared in different cases in Fig. 5. This figure shows that the pattern of charging and discharging of the PEVs is changed depending on the energy tariffs and incentives/penalties. By comparing the TOU with base case, it can be observed that the PEV parking lot stores more energy in the TOU case, especially in the valley and off-peak periods. In CPP and EDRP cases, the parking lot charges the PEVs that are parked in critical peak period in closer time to the period in order to avoid extra costs. Consequently, the stored energy in the parking lot in hour 13 is increased, in spite of decreasing the number of parked PEVs in the parking lot. The operational pattern of PEV parking lot in the RTP case is similar to the base case. However, the amount of stored energy in almost all hours is

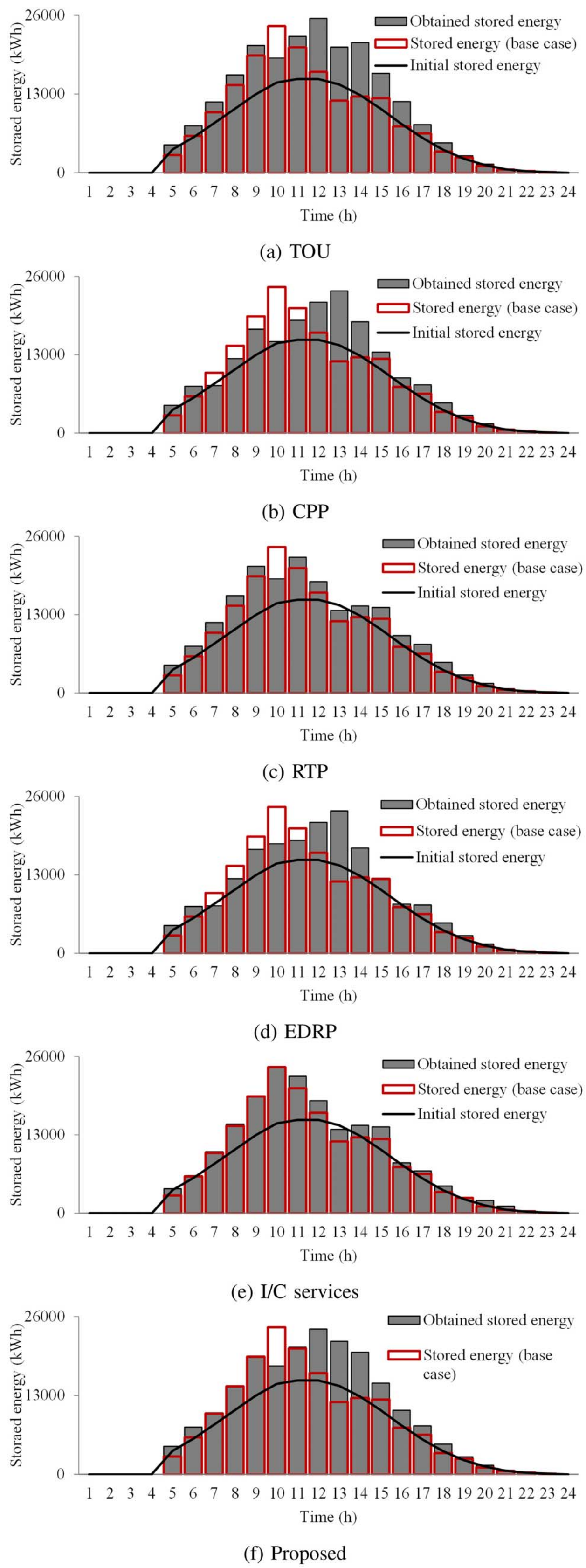


Fig. 5. Stored energy of the parking lot.

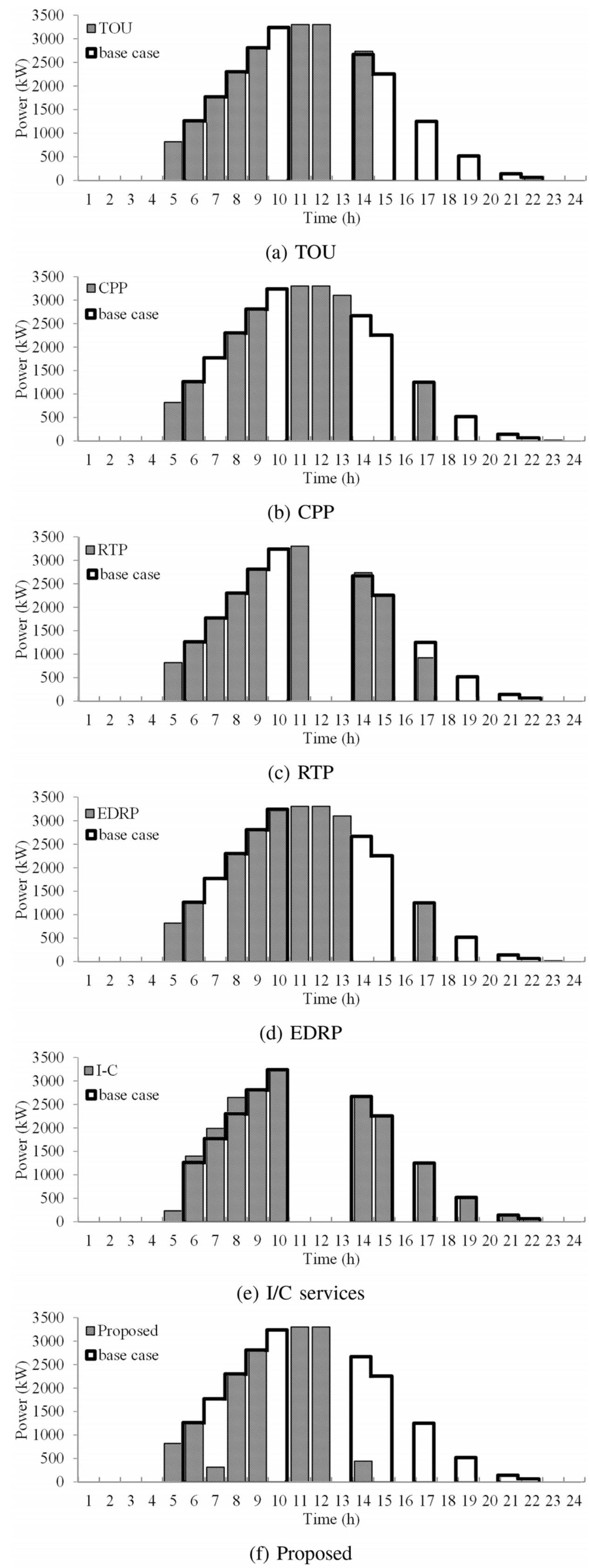


Fig. 6. Injected power from the grid to the parking lot.

more than the one in base case; because, in RTP case, the parking lot prefers to participate in the energy market (V2G mode) rather than to supply spinning reserve.

According to Fig. 5, it should be noted that the amount of stored energy is dependent on the hourly price. Thus, the stored energy in hour 10 is lower than the one in

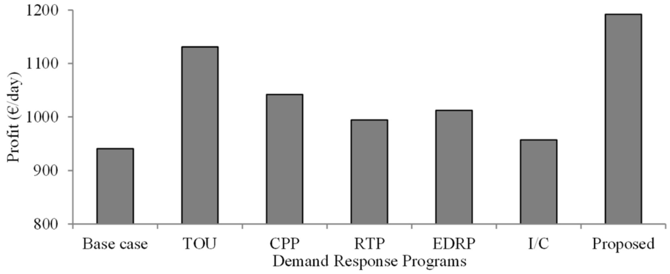


Fig. 7. Comparison of the parking lot's expected profit.

hours 9 and 11. I/C services do not have a significant impact on the pattern of energy storing. However, in this case, the parking lot stores larger amount of energy in off-peak period compared to the base case. This means that, the parking lot stores energy in its PEVs before the peak period when it broadly participates in the reserve market. In the proposed case, the parking lot stores energy before hour 12 to have enough energy in the PEVs battery after that hour. This helps the parking lot to lessen the purchased power from the grid in the peak period.

The injected power from the grid to the parking lot in different cases is indicated in Fig. 6. As it can be observed, in base case, the parking lot does not charge the PEVs battery at hour 5 since there is no car departed at hour 6. However, implementation of DRPs causes the parking lot to charge the PEVs at hour 5 due to the higher tariffs of energy in other periods. It can be seen that, in TOU, CPP, RTP and EDRP cases, the parking lot has low consumption in the peak and critical peak periods in order to decrease the charging cost.

By comparing base case and TOU case, it can be concluded that the injected power from the grid to the parking lot is almost the same and only the time of the injection is different due to different energy prices in each period. As a result, in TOU case, the parking lot receives no power from the grid in the peak period. It should be noted that, the injected power to the parking lot has the highest amount in almost all DRPs in hours 11 and 12 when the maximum number of cars are parked and the energy tariff is not high. According to I/C services, in hours 5 to 8, the parking lot charges the PEVs battery in order to use their stored energy in the off-peak and peak periods when its demand can be irrupted/curtailed. By implementation of the proposed method, the parking lot does not receive power from the grid during the peak period that can significantly reduce the charging cost.

The comparison of the parking lot's profit in different cases is shown in Fig. 7. As it can be seen, all DRPs can increase the parking lot's profit. Among different DRPs, TOU has more effect on the profit, although the number of PEVs in the parking lot in the valley period is generally low and this market player cannot use a main part of the period to charge its PEVs. Following the TOU, participating in CPP and EDRP has the highest profit for the parking lot. Combination of these three DRPs in the proposed method can increase the parking lots profit more than 26% compared to the base case.

V. CONCLUSION

In this paper, a new model was proposed to reflect the impacts of several demand response programs on operational behavior of a PEV parking lot by using a stochastic programing approach. Accordingly, both price-based and incentive-based programs were studied and participation of the parking lot in the demand response programs was investigated considering the uncertainties of PEVs' behavior and activated amount of reserve by the ISO. Moreover, optimal participation level of PEV parking lot in each DRP was modeled that determined how much the PEV parking lot should have participated in different DRPs. The results indicated that a parking lot, because of its nature in place of a charging station, behaved similar to a large demand in the system and consequently participation in different demand response programs significantly affected its operational behavior. Therefore, the pattern of charging and discharging of PEVs, the traded energy with the grid and participation in the reserve market were meaningfully influenced by the type of these demand response programs. It was observed that some type of DRPs such as TOU could increase the parking lot's profit, however these programs could decrease the benefit of power system from supplying the spinning reserve by the parking lot. The results showed that the participation of PEV parking lots in the selected combination of the DRPs could significantly increase its profit.

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