Optimal Scheduling of a Virtual Power Plant with Demand Response in Short-Term Electricity Market

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***Abstract*—This paper presents an optimal bidding and offering strategy for a virtual power plant (VPP), which participates in day-ahead (DA) and balancing markets. The VPP comprises distributed energy resources, plug-in electric vehicles (PEVs) and flexible demands. The objective of the problem is maximizing the VPP's profit while demand response (DR) providers who aggregated the loads try to supply the required demand under their jurisdiction with minimum costs. The proposed optimization problem is formulated as a bi-level stochastic scheduling programming to address uncertainties in DA and balancing electricity prices, renewable energy source's (RES) and DR relationship. Simulation results demonstrate the applicability and effectiveness of the proposed model to any real markets. Also, numerical results show that the flexibility of responsive loads and PEVs can improve the VPP operator's energy management and increase its expected profit.**

Keywords*—*Demand response, Electricity market, Mixed-integer linear programming, Virtual power plants, Stochastic scheduling.

NOMENCLATURE

Sets and indices

$(\cdot)_{t,\omega}$	At time t and in scenario ω .
Ch/Dis	Charge/Discharge process.
D	Demand of customers (MW).
t (T)	Time-slot.
ω (Ω)	Index of scenario linked with market prices, loads and charge/discharge of plug-in electric vehicles (PEVs).

Variables

$C_{t,\omega}^{DG_i}$	Generation cost of dispatchable generator (DG) i (€).
E^{D}	Energy of loads supplied by the VPP (MWh).
$E^{Ch/Dis}$	Energy of PEVs supplied by the VPP (MWh).
$E^{B^+} (E^{B^-})$	Energy traded in positive/ negative balancing market (MWh).
$E^{DA_{Buy/Sel}}$	Energy purchased/ sold in DA market (MWh).
$P_{t,\omega}^{DG_i}$	Scheduled power of DG i (MW).
ρ_t^{D}	Price signals provided by the VPP for loads (€/MWh).
$\rho_t^{Ch/Dis}$	Price signals provided by the VPP for charge/discharge process of PEVs (€/MWh).
$\rho_{SU/SD}^{DG_i}$	Start-up/shut down cost of DG unit i (€/MWh).

Parameters

a,b	Cost parameters of DG unit (€/MW).
E^{Cap}	Capacity of PEV battery.
$Elas_{t,t}$, ($Elas_{t,h}$)	Self-elasticity of demand of customers.
E_t^{int}	Initial consumption of customers (MWh).
$E_{t,\omega}^{wind}$	The price associated with wind energy (€/MWh).
π_{ω}	Probability of scenario ω .
$p^{B^+} (p^{B^-})$	Regulation prices (€/MWh).
p^{DA}	DA market price (€/MWh).
$SoC_{t,\omega}$	State-of-charge of PEV.
$\rho_t^{D,\text{int}}$	Average value of DA market prices (€/MWh).
$\eta^{Ch/Dis}$	Charge/discharge efficiency.
$\overline{E}^{wind}$	Maximum energy of wind generation unit (MWh).
$\overline{P}_i / \underline{P}_i$	Upper/lower limit of DG unit active power output (MW).

I. INTRODUCTION

Virtual Power Plant (VPP) allows the incorporation of various generation units such as renewable resources, and energy storage system [1].

Totally, the objective of VPP is to maximize its predictable profit in day-ahead (DA) market and supplying the required energy while minimizing imbalance cost in real-time (RT) balancing market [2].

Based on the VPP concept, the distributed resources are integrated into a single market agent [3]. An attack-robust distributed dispatch was projected in [4].

Although the related nonlinearities of the problem were also treated, the uncertainties of the problem were not considered. A VPP was taken into account in [6] in which a two-stage stochastic MILP model was developed to maximize the VPP expected profit.

A framework for the optimal VPP energy management problem considering correlated demand response was suggested in [7].

A stochastic optimization model was presented in [8], which comprises the distributed generation, storage systems, and electricity consumers aiming the maximization of profit.

High renewables penetration need a large-scale storage facility to accommodate the intermittency of renewable resources [9].

In addition, the VPP should consider the uncertainties of loads when offering energy blocks to the network. In fact, due to a delay between the closure of the DA market and the beginning of the energy delivery period in the real-time periods [10].

In [11] a bi-level scheduling model for VPPs was developed. A cooperative game model was proposed in [12]. A portfolio of interregional contracts was expressed in [13]. Utilizing demand response (DR) programs besides VPPs as supplemental resources to address the uncertainties has been addressed in recent studies. In [14], a mathematical model for the energy bidding problem of a VPP was presented.

In this paper, in order to show the commercial effects of DR on VPP decision making strategy, the VPP acts as a price taker in DA market to submit energy bidding quantities.

Moreover, the VPP operator can purchase DR services and purchase the excess energy remained in the batteries of PEVs to supply the clients. The overall decision making problem is modeled as a bi-level program, in which in upper level the VPP operator lean towards maximizing its expected profit whereas in lower level, the DR providers try to supply the loads under their jurisdiction by minimizing their costs. To this end, the main contribution of this paper is listed below:

- A stochastic bi-level optimization problem is developed for decision making problem of a VPP in which, in the upper level, the VPP owner takes advantage of the market conditions while in lower level, the DR providers try to provide their loads and PEVs' power by minimizing cost;
- DR potentials are aggregated with renewable resources in a VPP and the commercial effect of DR on the decision making of VPP is investigated such that to address wind uncertainties and exploit wind energy surplus, which slightly increases the expected profit of the VPP operator;
- Purchasing discharge energy remained in the battery of PEVs can bring opportunities for VPP operator to increase its profit compared with only participating in the energy market. Also, this additional energy is used to supply a part of loads instead of committing to the balancing market as a costly market for corrective actions.

The rest of this paper is organized as follows. The proposed framework of the problem is explained in Section II. Then, the formulation of the proposed framework is represented in Section III. Section VI implements the proposed framework on a case study, and the conclusion is provided in Section V.

II. Problem Framework

A VPP, consisting of renewable energy sources (e.g., wind farms), non-renewable energy resources (e.g., thermal generators), and flexible storage facilities (e.g., PEVs) acts as an aggregator. The VPP operator tends to maximize its expected profit by selling energy to short-term electricity markets and to DR providers as retail customers.

The scheduling problem of the VPP can be formulated as a bi-level problem, in which in the upper level, the VPP operator should schedule its resources and decide for optimal bidding strategy such that to maximize its profit. To achieve this objective, VPP dispatches the controllable resources such as distributed generators (DGs) and decides whether to sell energy to the market or purchases electrical energy from it. Moreover, the VPP can compensate for its unexpected shortages in wind generation by implementing DR programs.

In the lower level, the DR provider who aggregates responsive loads and PEVs' demand, lean towards minimizing its imposed costs. The diagram of the proposed problem is shown in Fig. 1. As observed, the VPP operator participates in the DA and the balancing markets and buy and sell energy in order to optimally operate the energy resources.

Due to the extensive infrastructure of advanced metering devices in smart grids, the VPP operator schedules for the resources at the sides of generation and demand such that the required demand of loads is generated by DG units, however, DR programs make scheduling plan flexible.

Moreover, the key aspects of the PEVs are their charging/discharging capabilities with considering their technical constraints. In this infrastructure, the system is served via an energy management system.

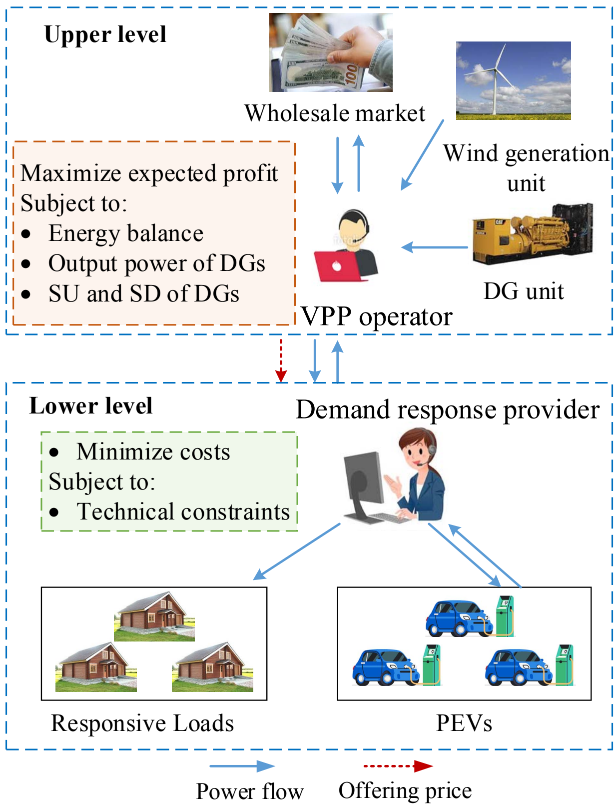

Fig. 1. The structure of the proposed scheme.

For instance, when the market prices are high, the energy management system decides to supply the demands through the wind power plant and the discharge energy of PEVs and even, to sell energy in the markets.

Therefore, the advanced measurement and communication infrastructure are required that the controllable loads are expected to control their demand flexibly in response to the prices. Therefore, the reaction of consumers is explicitly modeled via demand elasticity. In such circumstances, the economic relation between the VPP operator and DRPs is modeled as a bi-level programming problem to model the responses.

III. MATHEMATICAL FORMULATION

In this section, the proposed stochastic bi-level problem is formulated. In the upper-level of the problem, the VPP operator as decision maker and in the lower level, the DR providers as mediators are modeled.

A. Upper-Level Problem

The objective from the VPP viewpoint is as follow:

$$Maximize \quad \sum_{\omega=1}^{\Omega} \pi_{\omega}.profit_{\omega} \tag{1}$$

where, $profit_{\omega}$ represents profit of the VPP in scenario ω is and defined as:

$$\begin{aligned} profit_{\omega} = \sum_{t\in T} [& (E_{t,\omega}^{DA_{Sel}} \rho_{t,\omega}^{DA_{Sel}} + E_{t,\omega}^{D}\rho_t^{D} + E_{t,\omega}^{Ch}\rho_t^{Ch} + E_{t,\omega}^{+}\rho_{t,\omega}^{+}) \\ & -(E_{t,\omega}^{DA_{Buy}} \rho_{t,\omega}^{DA_{Buy}} + E_{t,\omega}^{-}\rho_{t,\omega}^{-} + E_{t,\omega}^{Dis} \rho_{s_0,t}^{Dis} \\ & + \rho_{SU}^{DG_i} + \rho_{SD}^{DG_i} + C_{t,\omega}^{DG_i})] \end{aligned} \tag{2}$$

Equation (2) consists of the energy sold to DA market, loads and PEV owners, minus the energy purchased from DA, the discharge of PEVs and from the DG units. Also, the energy deviations are compensated in balancing market. Moreover, the fuel cost of DG units can be formulated as a linear function as below:

$$C_{t,\omega}^{DG_i} = a + bP_{t,\omega}^{DG_i} \tag{3}$$

The objective function of the upper level is restricted with the following constraints. The constraint (4) represents that energy bought from the DA market and the power generated from both DG and wind units and discharge energy of PEVs should supply the charge of PEVs, customers of DR providers and as well as the energy that the VPP sell to the DA market.

$$\begin{aligned} & E_{t,\omega}^{DA_{Sel}} + E_{t,\omega}^{D} + E_{t,\omega}^{Ch} - E_{t,\omega}^{Dis} = \\ & E_{t,\omega}^{DA_{Buy}} + E_{t,\omega}^{wind} + E_{t,\omega}^{DG_1} + E_{t,\omega}^{DG_2} - E_{t,\omega}^{B^+} + E_{t,\omega}^{B^-} \end{aligned} \tag{4}$$

The energy generated by DG and wind units are limited by constraints (5) and (6), respectively.

$$\underline{P} \le E_{t,\omega}^{DG_{1/2}} \le \overline{P} \tag{5}$$

$$E_{t,\omega}^{wind} \le \overline{E}_t^{wind} \tag{6}$$

B. Lower-Level Problem

In the lower level, the objective of the DR providers consists of the minimization of the payments to supply loads and EVs charge minus the revenue of discharge process.

$$Minimize \left[\hat{E}_t^{D}\rho_t^{D} + \hat{E}_t^{Ch}\rho_t^{Ch} - \hat{E}_t^{Dis}\rho_t^{Dis} \right] \tag{7}$$

The lower level problem is restricted with the following constraints. The constraints (8)-(11) impose technical limits on PEVs batteries that should be considered in the problem at each time period.

$$SoC_{t,\omega} = SoC_{t-1,\omega} + \eta^{Ch} E_{t,\omega}^{Ch} - \frac{1}{\eta^{Dis}} E_{t,\omega}^{Dis} \tag{8}$$

$$\underline{SoC} \times E^{Cap} \le SoC_{t,\omega} \le \overline{SoC} \times E^{Cap} \tag{9}$$

$$0 \le \eta^{Ch} \times E_{t,\omega}^{Ch} \le (\overline{SoC} \times E^{Cap}) - SoC_{t-1} \tag{10}$$

$$0 \le \frac{1}{\eta^{Dis}} E_{t,\omega}^{Dis} \le SoC_{t-1,\omega} \tag{11}$$

Moreover, the energy consumption of customers at time t is obtained as follows [16]:

$$E_t = E_t^{\text{int}} \exp \sum_{h\in T} Elas_{t,t} \ln[\frac{\rho_t^{D}}{\rho_t^{D,\text{int}}} + \frac{1}{1 + Elas_{t,t}^{-1}}] \tag{12}$$

IV. CASE STUDY

A. Input Data

A modified case study is considered which includes 2 wind farms and 2 conventional thermal units [13]. The data of conventional thermal units are extracted from [17]. Wind, electricity prices, load and EVs scenarios are generated based on [16].

The electricity market data are taken from Nordpool [18] and shown in Fig. 2. Demand of loads and PEVs, together with the average of forecasted wind energy are illustrated in Fig. 3.

A number of 1000 initial scenarios are produced by means of Monte Carlo simulation. The optimization is performed on CPLEX using GAMS software [19].

B. Results and Discussion

Operating optimally, the VPP tends to satisfy both loads and PEVs at maximum profit. The VPP not only considers its own energy sources (such as wind energy unit and DGs), but also the electricity market. The amount of energy transactions in the DA market are shown in Fig. 4.

As illustrated from this figure, the VPP operator arbitrage on the price differences such that to minimize its energy procurement costs. For example, it sells large amount of energy during high price periods (e.g., 10:00–16:00) to obtain more profit.

But, it purchases some energy blocks during high demand loads (e.g., 17:00–20:00), since most of the PEV owners charge their vehicles for the next day transportation. Also, it is seen that the VPP operator usually tries to sell the energy to the network to attain more benefit.

For example, from 12:00-14:00 that the loads are in off-peak period (see Fig. 3), the operator sells high energy blocks to the network. But, during peak hours (8:00-10:00), the operator prefers to supply its loads and then sell the extra energy to the upstream. Therefore, at this period, the VPP sells less energy to the market. The energy imbalances are compensated in regulation market as in Fig. 5. The VPP bids the energy surplus and the energy deficit in positive and negative balancing markets, respectively.

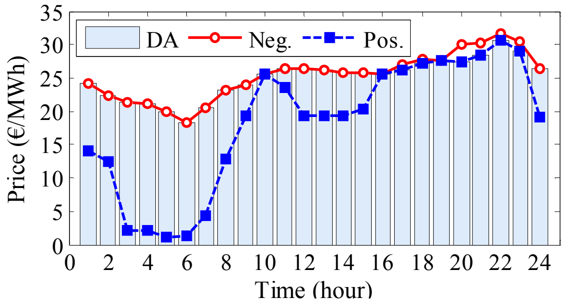

Fig. 2. The average of DA and balancing electricity prices.

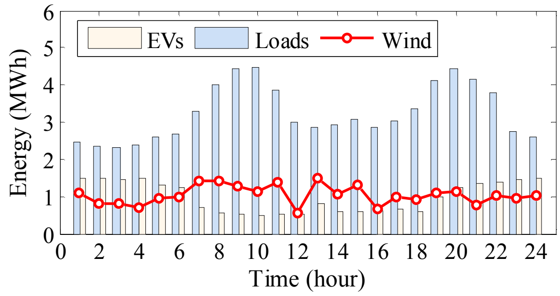

Fig. 3. Demand of loads and PEVs, together with the average of forecasted wind energy.

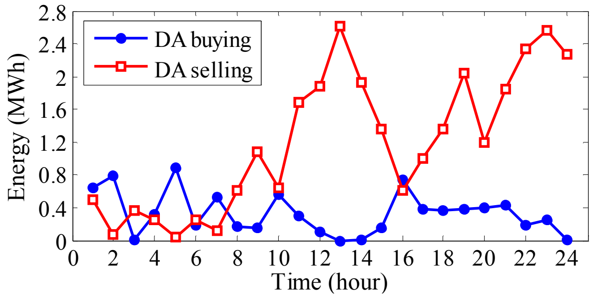

Fig. 4. Energy exchange of VPP with DA market.

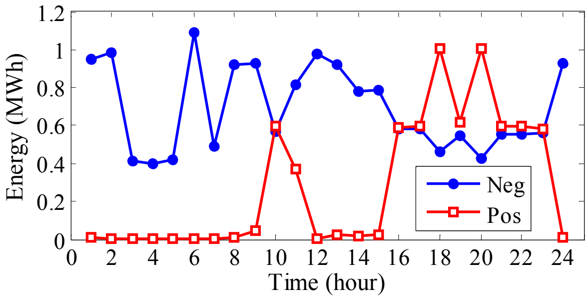

Fig. 5. Negative and positive energy imbalance.

The unit commitment of DG units is shown in Fig. 6. By comparing Figure 6 and Figure 2, it can be comprehended that the behavior of both DG units is driven by the DA market price. Output power of both DG units increase based on their unit fuel cost and startup cost.

Fig. 7 provides the DA bidding amounts of VPP in diverse levels of DR participation.

It is seen that without DR services, the VPP operator can submit more energy blocks to DA market to obtain more revenue from selling energy.

While, with increasing DR participants, there are more flexible electricity customers that require to supply their load.

Therefore, the VPP operator should purchase more energy from DA market instead of selling energy. Moreover, in high DR participants, the VPP should bid for energy in DA wholesale market.

Fig. 8 shows the probable profit of the VPP operator in all DR participants. As seen, when DR participant increases, the VPP can efficiently address wind uncertainties. Responsive loads can enable a VPP to purchase DR services. In this regard, the DRPs can adjust their loads in such a way not only to minimize their own payments, but also to supply their required demand.

The offering price of the VPP to the customers and PEV owners in different discharge percentage is shown in Fig. 9. From Fig. 9, only three discharge percentage are selected in order to prevent crowding data in the figures.

As seen, with increasing discharge process, the VPP offered lower prices to supply loads and charge process of PEVs.

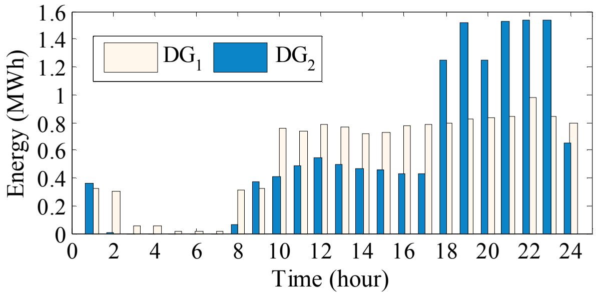

Fig. 6. Unit commitment result of DG units.

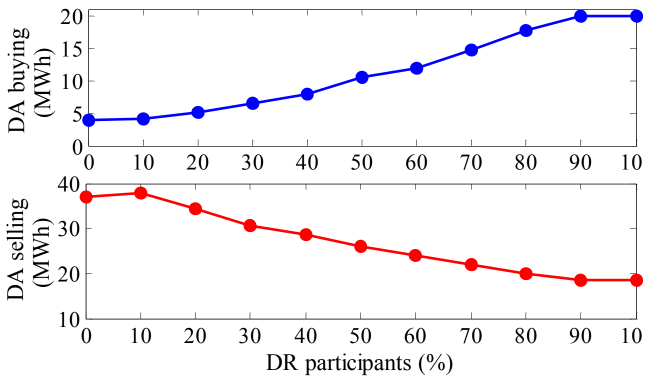

Fig. 7. The energy trading of VPP in DA market in different DR participants.

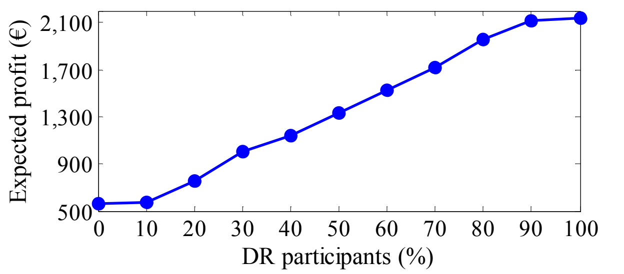

Fig. 8. Expected profit of VPP operator in different DR participants.

Because, with reducing the price of supplying energy, the VPP operator can offer fair prices in order to attract more PEV owners to charge their vehicles and discharge it whenever they are called.

In this regard, Fig. 10 illustrates the discharging prices offered by the VPP to the PEV owners. It is observed that with increasing discharge percentage and injection the stored energy of PEVs to the grid, the VPP offers lower discharge prices. The reason is that the applicants who like to discharge their vehicles increase and as the result, the operator can purchase their injected energy with lower prices. Table I provides energy exchange of VPP in DA and balancing market and the expected profit of the VPP operator in different discharge percentages.

From Table 1, the trend of buying energy from DA market increases. The reason is that with increasing discharge percentage, the VPP operator offers lower prices to the customers and for charge mode for PEVs as seen in Fig. 9.

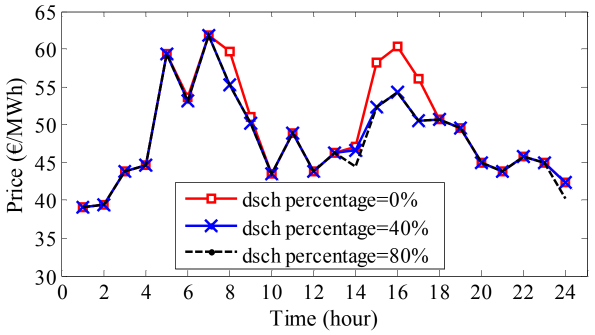

Fig. 9. Price signal offered by the VPP to the customers and PEV owners.

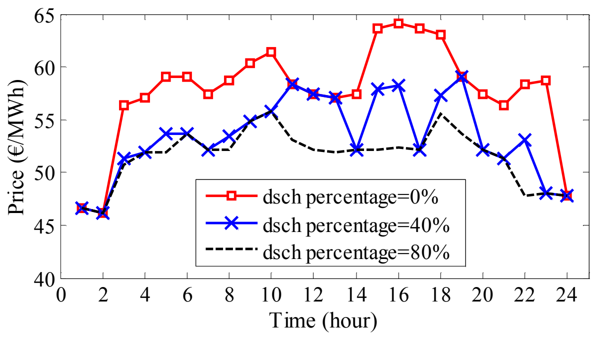

Fig. 10. Discharge price offered by the VPP to the PEV owners.

TABLE I. COMPARING RESULTS FOR DIFFERENT DISCHARGE PERCENTAGE

Discharge (%)	DA energy buying	DA energy selling	Positive power exchange	Negative power exchange	Expected profit
0	7.473	29.319	6.721	15.957	1097.38
20	7.383	29.131	6.721	17.909	1148.67
40	8.416	27.605	6.721	16.512	1170.30
60	8.650	27.350	6.721	16.580	1176.47
80	8.746	27.051	6.721	16.620	1186.06
100	8.890	27.030	6.721	16.780	1190.02

Therefore, more clients are encouraged to supply their demand and the VPP operator should purchase more energy from DA market. Also, it is seen from Table I, the energy sold in DA market decreases. That is also due to the increment of the value of loads supplied by the VPP operator.

Moreover, it is deduced from Table I that in different discharge percentage, the VPP operator tries not to change its energy exchange in the balancing market, because it is a costly trading floor that may incur extra costs to the VPP operator. Also, as expected, it is inferred from the table that the discharge process contributes to more expected profit for the VPP operator.

V. CONCLUSION

A bi-level stochastic optimization structure for a VPP is formulated. In the proposed problem, in the upper level, the VPP operator takes advantage of the market conditions while in the lower level, the DRPs who act as a load-serving entity, try to supply the loads and PEVs under their jurisdiction while minimizing their costs. Since the manipulation of responsive loads and PEVs can significantly change the decision making of the VPP operator, their effects on the decisions made by the operator are investigated. Considering the results obtained from this study, several influential conclusions can be deduced which are listed below:

- The commercial effect of DR on the decision making of the VPP is investigated which show the increment of the probable profit of the VPP operator due to integration of DR with wind generation unit;
- The PEVs as flexible loads are considered as a proper resource of energy that their behavior can significantly change the process of the system operator. In this regard, the results suggest that purchasing discharge energy remained in the battery of PEVs can bring opportunities for VPP operator to increase its profit compared with only participating in the energy market;
- The discharge process is used to supply a part of loads and even increase the probable profit of the VPP operator, instead of fully committing to the balancing market as a costly market for corrective actions.

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