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Joint Energy and Reserve Scheduling of a Wind Power Producer in a Peer-to-Peer Mechanism

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***Abstract*—This paper proposes a risk constrained decision making problem for wind power producers (WPPs) in a competitive environment. In this problem, the WPP copts to maximize its likely profit whereas aggregators want to minimize their payments. So, this bi-level problem is converted to a single level one. Then, the WPP offers proper prices to the aggregators to attract them to supply their demand. Also, these aggregators can procure reserve for the WPP to compensate its uncertainties. Therefore, through a peer-to- peer (P2P) trading mechanism, the WPP requests the aggregators to allocate reserve to cover the uncertainties of the wind generation. Also, due to the presence of uncertain resources of the problem, a risk measurement tool is applied to the problem to control the uncertainties. The effectiveness of the model is assessed on realistic data from the Nordpool market and the results show that as the loads become responsive, more loads are allowed to choose their WPP to supply their load. Also, the reserve that is provided by these responsive loads to the WPP increases.**

***Index Terms*—Wind power producer, demand response, scheduling, reserve, peer-to-peer.**

NOMENCLATURE

Sets and indices

$(\cdot)_{t,\omega(\phi)}$	Time t and scenario $\omega(\phi)$.
$t(T)$	Time periods.
$\phi(\Phi)$	Scenarios of rivals' offering prices.
$\omega(\Omega)$	Market prices and loads.
Wpp, Wpp'	Wind power producer (WPP).
N_{Wpp}	Set of WPPs.

Parameters

$E_{t,\omega}^{D}$	Total demand of aggregators (MWh).
$\hat{E}_{t}^{D}$	Expected demand of aggregators (MWh).
$E_{t,\omega}^{NRL}$	Total demand of non-responsive loads (MWh)
$E_{t,\omega}^{wind}$	Wind power (MWh).
$Q_{Wpp,t,\phi}^{Init}$	Initial % of responsive loads supplied by the WPPs.
$P_{t,\omega}^{B^+/B^-}$	Price of Positive (negative) balancing market (€/MWh).
$P_t^{C_{up}} / P_t^{C_{dn}}$	Price of up and down reserve capacity allocated by aggregators (€/MWh).
$P_{t,\omega}^{D,S/B}$	Prices of selling (buying) energy to (from) DA market (€/MWh).
$P_{t,\phi}^{Wpp}$	Offering price by rival WPPs (€/MWh).
$P_{Wpp,Wpp'}^{F}$	The fictitious cost modeling the hesitation of aggregators to shift between WPP and WPP' (€/MWh).
$P_t^{R_{up}} / P_t^{R_{dn}}$	Price of up and down reserve deployed by aggregators (€/MWh).
λ^{R}	Reserve capacity level (%).
$\lambda_{t,\omega}^{del}$	Probability of reserve deployed by aggregators.
$\lambda_{t,\omega}^{FOR}$	Probability of being unable to deploy reserve by aggregators.
$\pi_{\phi} / \pi_{\omega}$	Probability of scenario $\phi(\omega)$.

Variables

$E_{t,\omega}^{B^+/B^-}$	Prices of positive (negative) balancing market (€/MWh).
$E_{t,\omega}^{W}$	Energy supplied by the WPP (MWh).
$E_{t,\omega}^{D,S/B}$	Selling (buying) energy to (from) DA market (MWh).
$R_{t,\omega}^{up/dn}$	Up (down) reserve provided by aggregators (MWh).
$Q_{t,\phi}^{Wpp_0}$	Responsive loads supplied by the WPP (%).
$Q_{t,\phi}^{Wpp}$	Responsive loads supplied by rival WPPs (%).
$Z_{t,\phi}^{Wpp,Wpp'}$	Responsive loads transferred among the WPPs (%).
$P_t^{Wpp_0}$	Offering price by the WPP (€/MWh).
η_{ω} / ξ	Auxiliary variables for CVaR measurement.
β	Risk aversion factor.
α	Confidence level for CVaR calculation.

I. INTRODUCTION

The stochastic nature of wind generation makes substantial challenges to network operation and electricity market management. Wind power needs significant flexibility such as reserve service from other conventional generating units [1]. To this end, in [2], a joint day-ahead (DA) energy and reserve scheduling is investigated in which the producers offer their power strategically and their wind power at generation cost based on a forecast. Moreover, some optimal bidding strategies have been proposed to consider the imbalance penalty prices in the WPP's decision making process [3]. The profit sharing problem for a group of WPPs are studied in [4]. In [5], the opportunities available for WPPs to purchase/schedule reserves is addressed. A stochastic decision making model for WPPs participation is proposed in [6] in which three trading floors including DA, intraday and balancing markets are incorporated. Until recently, the required reserve services have been almost provided by the generation side. However, several types of demand side resources are technically capable of procuring such ancillary services. A joint energy and reserve DA market structure is presented in [7] in which demand side resources participate in the provision of load following reserves. In this regard, a procedure to form the interface between a parking lot and the distribution system operator is provided in [8] and a stochastic framework for a WPP and for a virtual power plant are addressed in [9] and [10]. A decision-making tool based on bi-level complementarity model is investigated in [11], in which the trading floor is considered as joint energy and reserve markets and balancing settlements.

Utilizing different technologies and facilities as supplemental resources to cover the uncertainties of WPPs has been addressed in different works. For example, application of storage devices together with wind power plants has been recommended to decrease imbalance costs [12]. The utilization of demand side resources to provide flexibility reserves alleviates the uncertain nature of wind power generation in [13]. In that study, the WPP purchases reserve from demand response (DR) resources to compensate the uncertainties of wind power. Therefore, the reserve service is supplied from DR resources through peer-to-peer (P2P) trading. The P2P concept is usually implemented within a local distribution system [14]. An integrated demand side management system coordinated with P2P energy trading among the households in the smart grid is provided in [15] and [16] without considering the reaction of customers to the selling prices. A stochastic bi-level decision-making model for an electric vehicle aggregator in a competitive environment is proposed in [17]. Although the reaction of consumers to the offered selling prices by the aggregators in a competitive environment has been studied via a bi-level problem, the participation of customers in providing reserve is neglected. In a competitive environment, various indices are defined to evaluate different aspects of competition such as level of demand [18]. To this end, a comprehensive analysis for the supply share of the under study WPP is made here to assess the contribution of the WPP to attract the loads in the competitive environment. Table I is added to give the contributions of the recent works in view of the existing state of- the-art literature.

In this study, a risk-constrained stochastic decision making framework for a WPP is addressed. In this model, the WPP competes against the rivals to attract aggregators. Also, the aggregators tend to supply their loads by minimizing their payments. Therefore, a bi-level model is proposed to manage both energy and reserve via a P2P trading floor to cope with the direct interaction and negotiation among WPPs and aggregators. Also, the Supply Share Index (SSI) is defined to evaluate the competition among the WPPs to attract loads. To cope with the uncertainties of the problem, conditional-value-at-risk (CVaR) measure is also used. The main contributions of this work are listed as below:

- Modeling risk-constrained decision making conflict between WPP and aggregators through a bi-level framework by replacing the lower-level problem by its Karush–Kuhn–Tucker (KKT) optimality conditions,
- Investigating the competition among the WPPs to attract aggregators energy supplement and reserve provision through P2P trading floor,
- Introducing the Supply Share Index (SSI) to evaluate the competitive situation among the WPPs and to provide sensitivity analysis to investigate the effect of reserve capacity level on the energy trading, profit and SSI index.

The rest of the paper is arranged as follows: Section II provides the proposed decision-making framework. The stochastic risk-averse bi-level problem is formulated in section III. The case studies together with simulation results are given in Section IV. Finally, Section V gives the conclusions.

II. Framework of Decision making Problem

In this paper, the price taker WPP participates in wholesale market to bid in such market and supply the loads. Also, in retailing layer, the WPP competes against other WPPs to attract the customers. In such competitive market, the WPP should decide to offer proper prices to the customers to attract them. Due to the uncertainties related to wind power, the WPP asks the aggregators to provide reserve for it.

Therefore, through a P2P trading mechanism, the responsive loads can adjust their consumption such that to make reserve. In fact, under a P2P trading floor, the WPP offers energy price based on real time pricing to the aggregators and is able to purchase reserve capacity from them to offset the deviation of its wind generation. The interaction among the WPPs and the aggregators is possible due to the presence of bi-directional communication mechanisms.

The structure of the proposed problem is depicted in Fig. 1. As seen, the WPP should compete against other WPPs to attract loads. In such competitive environment, the WPP should estimate the scenarios of offering prices by rivals. Moreover, the WPP should forecast the required demand of aggregated loads. Here, to model the forecast inaccuracies, rivals' offering prices and the requested demand of loads, normal Probability Distribution Functions (PDF) is considered. Then the PDFs are divided into five discrete intervals as shown in Fig. 2.

The forecasted errors of these mentioned uncertain resources are given by intervals equal to the standard deviation. The generated scenarios are combined to obtain a two-stage

Table I. The contribution of literature in view of existing state of the art.

Reference	Framework	DR and EVs	Provided reserve by	P2P exchanges	Risk aversion	Competition environment	Evaluating the competitive situation	Considered markets	Role of decision maker	From viewpoint of
[4]	Single level		-	-	CVaR	-	-	DA	Price taker	WPP
[6]	Single level	DR	-	-	CVaR	-	-	DA, intraday, balancing	Price maker	WPP
[7]	Single level	DR	Loads	-	CVaR	-	-	DA	Price taker	System operator
[8]	Bi-level	DR	Loads	-	-	-	-	DA, balancing	Price taker	System operator
[9]	Bi-level	DR	-	-	CVaR	✓	-	DA, balancing	Price taker	WPP
[10]	Single level	DR	-	-	CVaR	-	-	DA, balancing	Price taker	Virtual power plant
[17]	Bi-level	EV	-	-	CVaR	✓	-	DA, balancing	Price taker	aggregators
[12]	Bi-level	-	Storage	-	-	✓	-	DA, balancing	Price maker	Storage system
[13]	Bi-level	DR	Loads	✓	CVaR	✓	-	DA, balancing	Price taker	WPP
[16]	-	DR	-	✓	-	-	-	-	-	Microgrid operator
[18]	-	-	-	-	-	✓	✓	-	-	-
This paper	Bi-level	DR/EV	loads	✓	CVaR	✓	✓	DA, balancing	Price taker	WPP

scenario tree as a vector of independent random variables. Due to the large size of this tree, an effective scenario reduction algorithm proposed in [19] is used to reduce the size of the scenarios. The generated scenarios for each variable are reduced by Roulette Wheel Mechanism. To this end, at first, a random number between [0, 1] is generated. According the value of the generated random number, it is fallen in one of the segments of the roulette wheel, which corresponds to a specific load forecast error. The selected forecast error is chosen as the error of the prediction for the specified parameter in this scenario. Each segment of the roulette wheel belongs to each forecast error level based on its corresponding probability. For this purpose, at first, the probabilities of different forecast levels are normalized such that their summation becomes equal to unity. Then the range of [0, 1] is occupied by the normalized probabilities of each forecast error level. After that, random numbers are generated between 0 and 1. Each random number falls in the normalized probability range of a forecast level in the roulette wheel. That forecast level is selected by the roulette wheel mechanism for the respective scenario. The same procedure is utilized by the roulette wheel mechanism to generate all of the scenarios.

The proposed model consists of two levels: one where the WPP is maximizing its likely profit, and another one where the aggregators aim to minimize costs. This profit maximization problem considers that aggregators optimally react to the WPPs' prices. This reaction entails the computation of the demand portion provided by each WPP (the considered WPP and the rivals). Therefore, via a bi-level model, the WPP tends to maximize its expected profit, while, it should also solve the problem from the viewpoint of the aggregators. So, the under study WPP as a decision maker should minimize the costs of the aggregated loads. Also, to compensate the uncertainties of the problem including wind generation unit and the requested demand and the market prices, the WPP requests the aggregated loads to provide reserve for it. In a P2P market, the energy and reserve trading with the aggregated loads occurs. Also, a risk measurement tool such as CVaR is used to control the volatilities of the problem.

Finally, this problem is transformed to a single level one by using KKT optimality conditions. The presented stochastic model is finally formulated as a bi-level problem that the upper level problem represents the maximization of the expected profit of the WPP while the lower level problem states the minimization of energy procurement costs of aggregators. In order to solve the obtained bi-level programming problem by a commercially available optimization solver, it should be converted to an equivalent mixed-integer linear programming (MILP) problem with the following steps:

- Lagrange function of the lower level for a vector of the variable of the upper level is obtained,
- The KKT optimality conditions of the lower level problem is obtained by partial derivatives of the Lagrange function,
- The non-linear complementary slackness conditions are equivalently expressed as a set of linear constraints based on the approach explained in [20],
- The bi-linear products are replaced by the related equivalent linear expressions using duality theory [24].

B. Description of Peer-to-Peer Trading Floor

Under P2P electricity trading mechanism, the responsive loads can schedule their consumption to adjust it. Then, in the competition environment, the WPP competes against other rival WPPs to attract the customers. Then, the group of aggregated loads submit their energy requirement to the under study WPP. The WPP supplies the required demand through its wind generation or it may participate in DA market. These aggregated loads with demand side management system can also provide reserve to the system. Therefore, through a P2P trading mechanism, the WPP requests the aggregators to allocate reserve to cover the uncertainties of the wind generation unit. In this case, the loads under the jurisdiction of the load aggregators can reduce their consumption to provide upward reserve while they can increase their consumption to procure downward reserve.

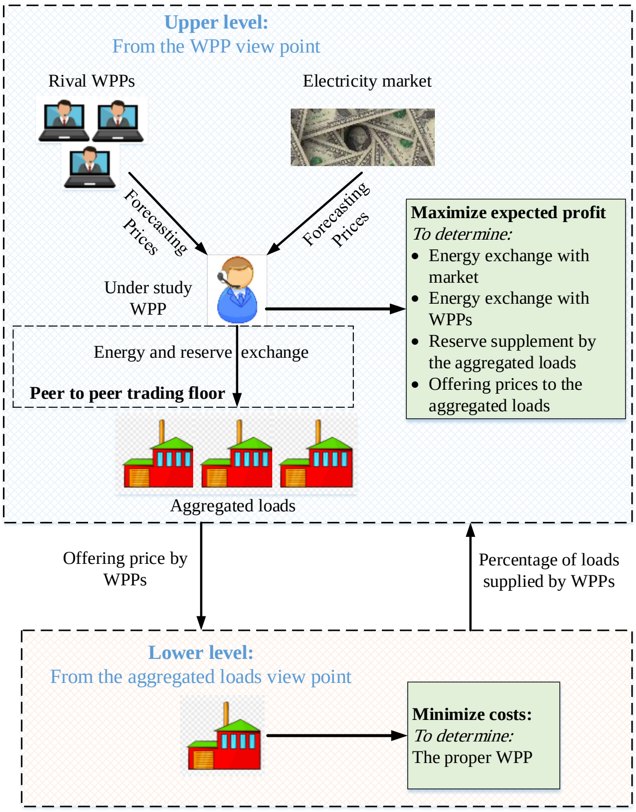


Fig. 1. The structure of the problem.

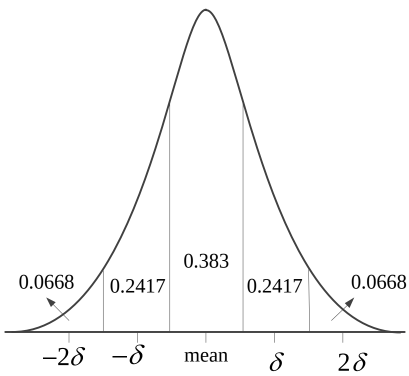


Fig. 2. Five segment approximation of normal distribution.

III. Mathematical Model of the Proposed Bi-Level Problem

A. Bi-level formulation of the problem

Here, the bi-level problem from the viewpoint of the WPP is formulated. In this bi-level problem, the WPP decides from the upper level and aims to maximize its expected profit as bellow:

$$Max\sum_{\omega\in\Omega}\pi_{\omega}\sum_{t\in T}\begin{bmatrix} E_{t,\omega}^{D,S}P_{t,\omega}^{D,S}-E_{t,\omega}^{D,B}P_{t,\omega}^{D,B} \\ +E_{t,\omega}^{B^+}P_{t,\omega}^{B^+}-E_{t,\omega}^{B^-}P_{t,\omega}^{B^-} \\ +E_{t,\omega}^{W}P_{t}^{Wpp_0} \\ -(R_{t,\omega}^{up}P_t^{C_{up}}+R_{t,\omega}^{dn}P_t^{C_{dn}}) \\ +(-R_{t,\omega}^{up}P_{t,\omega}^{R_{up}}+R_{t,\omega}^{dn}P_{t,\omega}^{R_{dn}})\lambda_{t,\omega}^{del} \\ +(R_{t,\omega}^{up}P_{t,\omega}^{R_{up}}+R_{t,\omega}^{dn}P_{t,\omega}^{R_{dn}})\lambda_{t,\omega}^{del}\lambda_{t,\omega}^{FOR} \end{bmatrix} \tag{1}$$
$$+\beta(\xi-\frac{1}{1-\alpha}\sum_{\omega=1}^{\Omega}\pi_{\omega}\eta_{\omega})$$

where, the line term of the objective function stands costs from trading energy with the DA market, the second line explains the penalty of participating in balancing market. The third line represents the revenue from selling energy to the aggregators. The fourth line expresses the costs supplying reserve capacity allocated by aggregators. The costs related to the real deployment of reserves are specified in the fifth line, while the sixth line represents income earned from those aggregators that could not provide reserve.

The risk measurement cost is given in the last line to hedge against volatilities. In the lower-level problem, the aggregators tend to minimize their payments through supplying the loads under their jurisdiction with the following objective:

$$Min\begin{bmatrix} \hat{E}_t^{D}[P_t^{Wpp_0}Q_{t,\phi}^{Wpp_0}] \\ +\hat{E}_t^{D}[\sum_{\substack{Wpp\in N_{Wpp}\\ Wpp\neq Wpp_0}}P_{t,\phi}^{Wpp}Q_{t,\phi}^{Wpp}] \\ +\sum_{Wpp\in N_{Wpp}}\sum_{\substack{Wpp'\in N_{Wpp}\\ Wpp\neq Wpp'}}\hat{E}_t^{D}P_{Wpp,Wpp'}^{F}Z_{t,\phi}^{Wpp,Wpp'} \\ -(R_{t,\omega}^{up}P_t^{C_{up}}+R_{t,\omega}^{dn}P_t^{C_{dn}}) \\ +(-R_{t,\omega}^{up}P_{t,\omega}^{R_{up}}+R_{t,\omega}^{dn}P_{t,\omega}^{R_{dn}})\lambda_{t,\omega}^{del} \\ +(R_{t,\omega}^{up}P_{t,\omega}^{R_{up}}+R_{t,\omega}^{dn}P_{t,\omega}^{R_{dn}})\lambda_{t,\omega}^{del}\lambda_{t,\omega}^{FOR} \end{bmatrix} \tag{2}$$

The problem is restricted with the following constraints. The balancing constraint is given as below:

$$\begin{aligned} &E_{t,\omega}^{wind}-E_{t,\omega}^{D,S}+E_{t,\omega}^{D,B}-E_{t,\omega}^{B^+}+E_{t,\omega}^{B^-}+R_{t,\omega}^{up}-R_{t,\omega}^{dn} \\ &=E_{t,\omega}^{W}+E_{t,\omega}^{NRL}\ /\ N_{Wpp} \end{aligned} \tag{3}$$

The constraints related to CVaR are described as bellow [21]:

$$\sum_{\omega\in\Omega}\pi_{\omega}\sum_{t\in T}\begin{bmatrix} E_{t,\omega}^{D,S}P_{t,\omega}^{D,S}-E_{t,\omega}^{D,B}P_{t,\omega}^{D,B} \\ +E_{t,\omega}^{B^+}P_{t,\omega}^{B^+}-E_{t,\omega}^{B^-}P_{t,\omega}^{B^-} \\ +E_{t,\omega}^{W}P_{t}^{Wpp_0} \\ -(R_{t,\omega}^{up}P_t^{C_{up}}+R_{t,\omega}^{dn}P_t^{C_{dn}}) \\ +(-R_{t,\omega}^{up}P_{t}^{R_{up}}+R_{t,\omega}^{dn}P_{t}^{R_{dn}})\lambda_{t,\omega}^{del} \\ +(R_{t,\omega}^{up}P_{t}^{R_{up}}+R_{t,\omega}^{dn}P_{t}^{R_{dn}})\lambda_{t,\omega}^{del}\lambda_{t,\omega}^{FOR} \end{bmatrix} \tag{4}$$
$$+\eta_{\omega}-\xi\geq 0$$

$$\eta_{\omega}\geq 0 \tag{5}$$

The WPP forecasts its share to supply the demand in the competitive market as in (6) [22]:

$$E_{t,\omega}^{W}=E_{t,\omega}^{D}\sum_{\phi\in\Phi}\pi_{\phi}X_{t,\phi}^{Wpp_0} \tag{6}$$

The constraints related to model the competition is given in (7) and (8). Equation (7) shows the demand shifting among the rival WPPs and the under study WPP. Based on this relation, it is seen that the loads may come to a WPP (positive sign) or they might leave it and go to the other rivals (minus sign). So, the initial percentage of loads changes. Relation (8) denotes that all of the load should be supplied by all of the WPPs. So, total 100 percent of loads are connected to the WPPs to be supplied. Also, each load can be connected to only one WPP.

$$\begin{aligned} &Q_{t,\phi}^{Wpp}=Q_{Wpp,t,\phi}^{Init}+ \\ &\sum_{\substack{Wpp\in N_{Wpp}\\ Wpp\neq Wpp'}}Z_{t,\phi}^{Wpp,Wpp'}-\sum_{\substack{Wpp'\in N_{Wpp}\\ Wpp'\neq Wpp}}Z_{t,\phi}^{Wpp',Wpp} \end{aligned} \tag{7}$$

$$Q_{t,\phi}^{Wpp_0}+\sum_{\substack{Wpp\in N_{Wpp}\\ Wpp\neq Wpp_0}}Q_{t,\phi}^{Wpp}=100\% \tag{8}$$

The two level problems are replaced with their equivalent using KKT optimality conditions. Also, by using duality theory, bilinear products are converted to linear expressions [23].

A. Supply Share Index (SSI)

In order to measure the value of competition among the WPPs, the Supply Share Index (SSI) is defined. Based on the definition of this index, the competition power of the under study WPP equals with the ratio of total supply capacity of rival WPPs to the total demand of loads. As a competition measurement, the SSI can be calculated for any agent of the market as bellow:

$$SSI=\frac{Total\quad Supply\quad Capacity\quad of\quad rival\quad WPPs}{Total\quad Demand} \tag{9}$$

Based on (9), *SSI* for the WPP measures the percentage of the supply capacity that is supplied by the rivals. Then, the under study WPP can supply the rest of load. The maximum amount of *SSI* is 1, meaning that the total load is supplied by the rival WPPs. If the *SSI* is lower than 1, it is concluded that the rival WPPs could not attract the loads and the role of the WPP is prominent to meet the loads.

IV. Case Study and Numerical Results

Realistic data are extracted from Nordic market [25] to assess the efficiency of the proposed bi-level model. In this regard, three WPPs are considered that the understudy one and its rivals are identified as WPP_0 and WPP_1, WPP_2 and WPP_3, respectively. The average price of DA market and the forecasted energy of wind energy is shown in Fig. 3 and Fig. 4, respectively. Also, the required energy of total load is depicted in Fig. 4. The negative and positive balancing prices are 1.1 and 0.9 of DA price, respectively. The results are given for the main case with DR=40%.

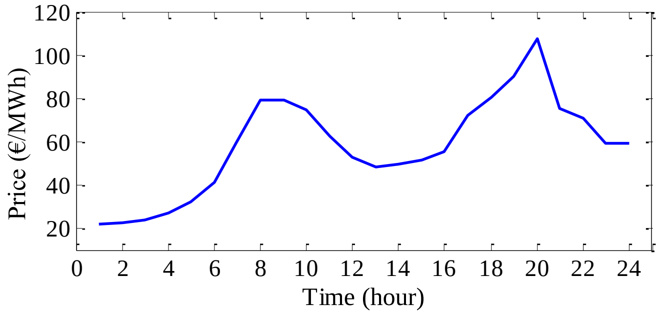


Fig. 3. The mean DA market price.

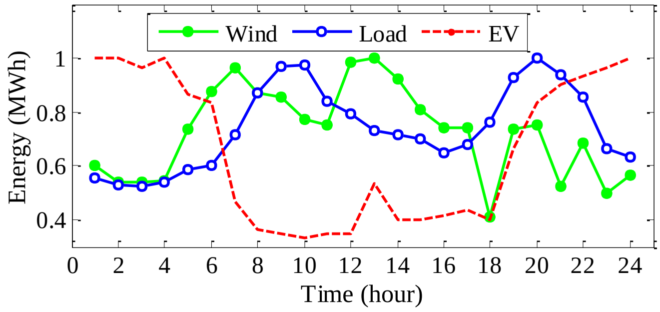


Fig. 4. Total required demand of loads, EVs and predicted wind energy.

Simulations are run using CPLEX 12.6.0.0 under GAMS 24.2.2 on a Dell Precision laptop with an Intel Core™ i7 @ 2.6 GHz processor and 16 GB of RAM [26].

The energy bought/sold from/to DA market is illustrated in Fig. 5. With comparing this figure with Fig. 4, it is seen that when the load is low and the wind generation is high, the WPP sells the produced energy (i.e., hours 12:00-16:00). While, when the load is high and the wind generation is low, the WPP should purchase energy to supply its demand. For example, at hour 18:00, although the electricity price is high, the WPP purchases energy from DA market to supply its load.

Fig. 6 shows the surplus and deficit energy that is compensated in the balancing market. Since the WPP has wind power units, it usually sells its excess energy. Also, when the wind generation is low, the WPP buys its energy deficit to supply its load. It is seen that since the balancing market is an expensive trading floor, the WPP decides to participate in such market less than the other markets. It is seen that during peak hours, the WPP participates in negative balancing market to purchase energy to supply its load. But, during off-peak hours, the WPP takes part in positive balancing market to sell its excess energy (i.e., hour 12:00-16:00).

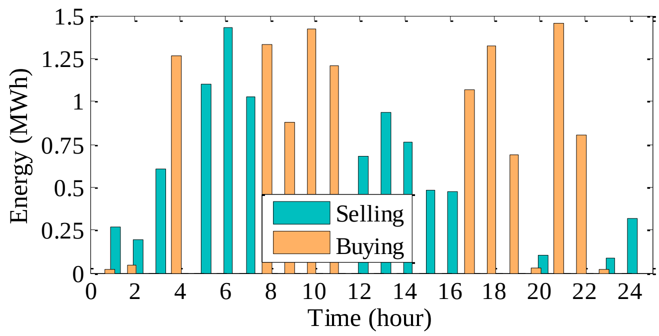


Fig. 5. The buying/selling energy from/to DA market.

The up and down reserve that is allocated by the loads for the WPP is illustrated in Fig. 7 and Fig. 8, respectively. As shown, up reserve occurs most of the times because, the WPP may be confronted with under production, so the loads can participate in up reserve and decrease their consumption. On the other hand, the WPP may have overproduction that the loads consume it. Also, it can be seen that the overproduction occurs simultaneously at the time of peak hours. So, the WPP obtains revenue from the customers. The average price offered by all WPPs is illustrated in Fig. 9.

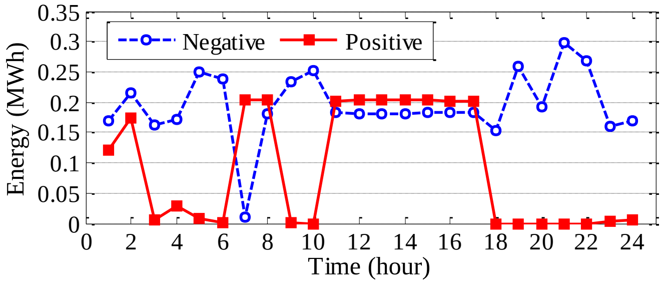


Fig. 6. The surplus and deficit energy compensated in balancing market.

Moreover, the percentage of loads that is supplied by the WPPs is given in Fig. 10. From Fig. 9, it is interpreted that the prices are often near each other at each hour. Because, the WPPs tend to offer competitive prices to attract the aggregators to supply their demand from them. Also, the aggregators supply their loads from the cheapest WPP to save money.

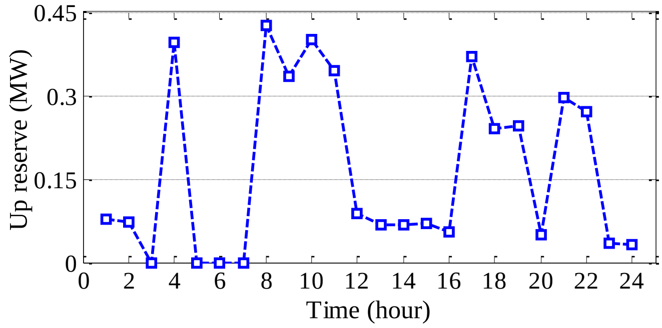


Fig. 7. Up reserve in β=0.01 and DR=20%

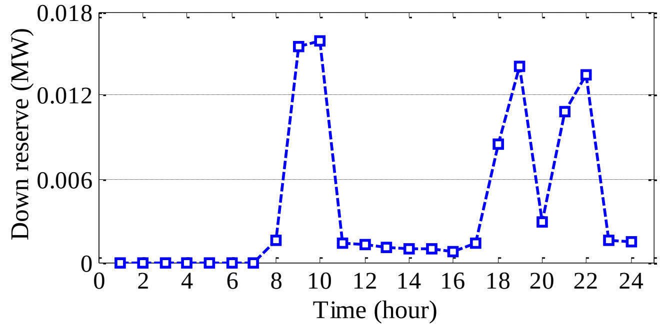


Fig. 8. Down reserve in β=0.01 and DR=20%

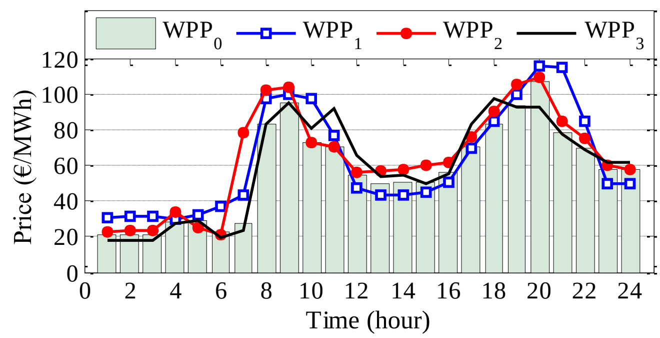


Fig. 9. Prices offered by rival WPPs.

Error! Not a valid bookmark self-reference. shows the expected profit versus CVaR in three β and in all DR values. As expected, with increasing risk aversion parameter, the expected profit decreases while CVaR value increases. The reason is that when the WPP becomes more risk averse, it purchases more energy from stable resources which are usually expensive. Therefore, the profit scenarios that are far from the mean value would be omitted from both sides. So, the WPP should pay more to supply its load and as the result, its profit decreases. It shows that with increasing DR, the expected profit increases. Because, when more loads become responsive, they are allowed to choose their WPP to supply their load. So, the under study WPP can offer more appropriate prices to attract customers.

TABLE I. EXPECTED PROFIT VERSUS CVAR IN DIFFERENT DR VALUES AND RISK AVERSION PARAMETER

DR	*β=0.01*		*β=5*		*β=10*	
	CVaR	profit	CVaR	profit	CVaR	profit
10	-111.38	-322.10	-111.1	-877.0	-110.9	-1432.2
20	-81.36	81.90	-81.36	-324.10	-81.36	-730.92
30	-55.68	485.71	-55.68	207.82	-55.68	-70.613
40	-30.01	889.52	-30.01	739.75	-30.01	589.69
50	-6.73	1293.29	-5.05	1267.72	-5.05	1242.43
60	13.87	1696.78	14.37	1768.09	14.37	1839.97
70	18.34	2099.28	18.35	2190.84	18.35	2282.60
80	22.12	2498.70	22.13	2609.15	22.13	2719.84
90	25.91	2890.75	25.92	3020.09	25.92	3149.7
100	29.69	3277.69	29.70	3425.91	29.70	3574.44

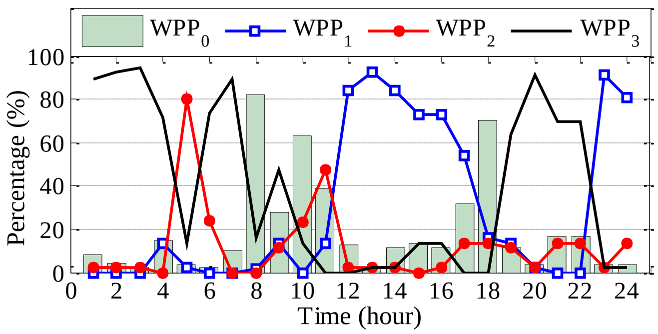


Fig. 10. Percentage of loads supplied by all WPPs.

For example, at 8:00, the under study WPP suggests the lowest price. So, it has the highest supplying percentage of loads. Moreover, at 14:00, WPP_1 offers the lowest price, so most of the loads are supplied by this WPP.

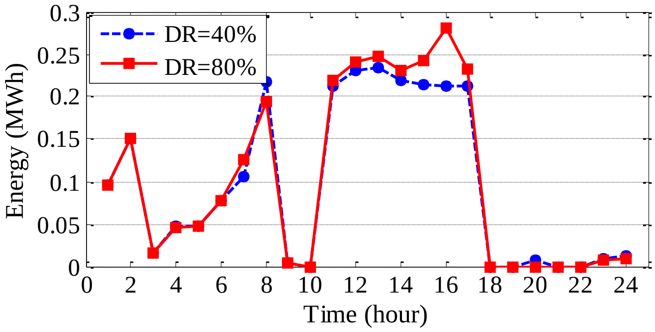
Table II provides the energy trading of the WPP with the network and the reserve provided by the loads. It is seen that as the loads become more responsive and with increasing demand response percentage, the loads can make more reserve for the WPP. Therefore, the WPP can sell more energy to DA market. Since the loads may require more energy at some hours such as off-peak hours, the WPP purchases the required energy from the DA market. Also, to compensate the energy deviation of wind generation, the WPP enters the balancing market. By increasing the DR participants, the energy compensation from the balancing market remains approximately constant. In fact, by participating more loads in DR programs, the uncertainties that result in revenue losses to the WPP due to the penalties in imbalance settlements did not increase. Therefore, the WPP has the opportunities to purchase or schedule some reserves in a P2P trading floor to offset part of its deviation rather than being fully penalized in the real time market. Moreover, this table shows that the WPP decides to trade energy and reserve in different risk aversion factors. When the WPP decides to behave less risk aversely, the WPP purchases more energy from DA market in lower DR percentages. But, when the WPP becomes more risk averse, in higher DR participants, the WPP purchases less energy from DA market. Because, when the loads become more responsive, they can adjust their demand and even curtail or shift their consumption. Therefore, the WPP buys less energy from DA market as it becomes more risk averse. Also, with increasing β, the WPP sells less energy to DA market. That is because, as

TABLE II. DIFFERENT POINTS AND VALUES IN ALL DR PERCENTAGE AND RISK AVERSION PARAMETER

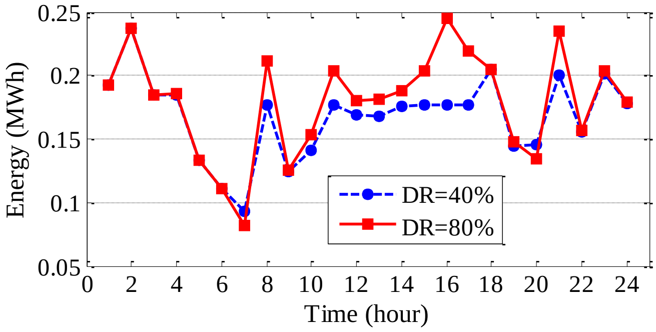
β=0.01										
Values	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
DA buy	10.00	10.63	11.37	12.28	13.467	14.66	15.42	15.90	15.99	16.31
DA sell	3.002	4.542	6.218	8.088	10.271	12.50	14.73	16.90	18.73	20.50
Positive	2.27	2.281	2.311	2.325	2.322	2.308	2.527	2.46	2.355	2.406
Negative	4.04	4.036	4.029	4.028	4.033	4.059	4.379	4.29	4.031	3.969
Up reserve	1.15	2.353	3.540	4.724	5.907	7.089	8.177	9.17	10.10	11.09
Down reserve	0.139	0.195	0.221	0.235	0.243	0.245	0.246	0.248	0.267	0.289
β=5										
Values	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
DA buy	10.02	10.67	11.41	12.28	13.32	14.40	15.420	15.90	15.99	16.31
DA sell	3.002	4.542	6.218	8.08	10.27	12.27	14.49	16.657	18.49	20.26
Positive	2.27	2.293	2.315	2.32	2.32	2.43	2.612	2.600	2.486	2.53
Negative	4.03	4.016	4.00	4.02	3.96	3.94	4.22	4.191	3.922	3.85
Up reserve	1.15	2.3503	3.534	4.72	5.85	7.021	8.177	9.17	10.10	11.09
Down reserve	0.139	0.198	0.221	0.235	0.248	0.246	0.247	0.249	0.269	0.290
β=10										
Values	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
DA buy	10.02	10.72	11.53	12.28	13.31	14.40	15.44	15.90	15.99	16.31
DA sell	3.002	4.542	6.218	8.088	10.271	12.23	14.44	16.58	18.41	20.18
Positive	2.27	2.308	2.352	2.325	2.322	2.458	2.667	2.65	2.52	2.578
Negative	4.03	3.978	3.951	4.028	3.967	3.93	4.21	4.17	3.90	3.83
Up reserve	1.15	2.352	3.524	4.724	5.850	7.021	8.176	9.17	10.10	11.09
Down reserve	0.139	0.198	0.231	0.235	0.248	0.248	0.254	0.257	0.276	0.297

the WPP decides to behave more conservatively, it trades less energy with volatile sources. With increasing β, in lower DR participants, the WPP participates the same in all β values. But, with increasing DR, as the WPP behaves more risk aversely, it participates in positive balancing market as a more stable trading floor, although it is more expensive. While, with increasing β, the WPP trades more energy in negative balancing market, because, it might require energy to purchase to support its loads. Also, from Table II, it can be seen that when the WPP behaves less risky, it trades less up reserve. Because, as the WPP becomes more risk averse, it tries to trade less reserve via a P2P floor. Because, the WPP tends to trade with a more stable source. However, it trades more down reserve in such P2P trading floor with the customers. The reason is that the loads may consume more energy. Therefore, they may participate in providing down reserve to procure energy for their consumption. Then, although the WPP becomes more risk averse, it allows the aggregated loads to provide down reserve due to their consumption.

Fig. 11 illustrates the expected energy trading in both positive and negative balancing market in DR=40% and DR=80%. It is seen that as more loads participate in DR programs, the WPP has the opportunity to attract more customers. As the result, the WPP should participate in balancing market to cover more energy deviation compared with the case with lower DR participants.



(a)



(b)

Fig. 11. Energy trading in (a) positive, (b) Negative balancing market in DR=40% and DR=80%.

Although, in some hours such as 7:00, the opposite occurs, the WPP's participation in balancing market often increases with increasing DR participants. Moreover, it is seen that during off-peak hours (11:00-17:00), usually the WPP tends to cover the energy deviations. That is because, during this period, the demand is low, while the wind generation is high. So, the WPP should sell the extra energy in positive balancing market. Also, in some scenarios, the WPP may confront with opposite conditions to purchase the energy deficit. So, it participates during this period in negative balancing market.

In the competitive environment, due to the presence of EVs, the owners may participate in discharge process. The WPPs offer discharge prices to the EV owners in order to attract them not only for charge, but also to purchase the stored energy in the batteries of their EVs. In order to evaluate the contribution of the under study WPP to supply required demand of loads and charge of EVs, SSI is illustrated in Fig. 12 in the conditions with and without considering discharge process. In such competitive environment, the WPP offers discharging prices to the EV owners to attract them. In this regard, when SSI tends to 100%, it means that the rivals are capable to supply demand. While SSI is low, it means that the share of rivals to supply loads is low. Therefore, the WPP contributes highly to meet loads. Based on this index, when EVs participate in discharge process, the share of rivals reduces and consequently, the WPP has more opportunity to supply loads.

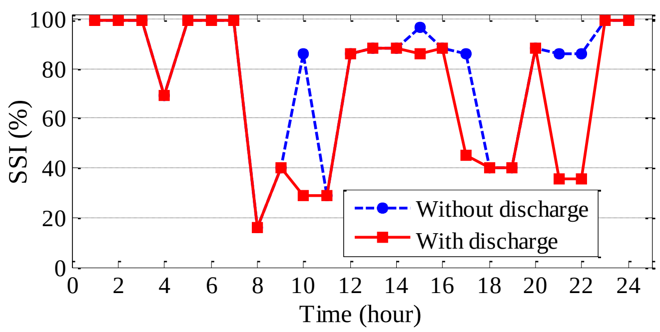


Fig. 12. Supply Share index (SSI)

Table IV provides the values of expected profit variation and the SSI in different DR participants and risk aversion factor. As seen, with increasing DR participants, the percentage of expected profit increase as it is expected. While, as the WPP behaves more risk aversely, it loses more profit. In order to quantitatively characterize the extent share exercised by the under study WPP, SSI is employed. In this table, the SSI index for different DR flexibility values is given. As seen from the table, with increasing DR participants, the share of rival WPPs increases, although ΔEP augments which yields the increment of the expected profit of the WPP. In fact, with increasing DR level, the loads drive flexibility due to load shifting and shedding, although their daily consumption remains the same. Also, by developing communication mechanism between responsive loads and WPPs, more loads will be more free to choose their WPP to supply their required demand. So, with increasing DR level, the WPPs may lose the loads, however their expected profit augments. From this table, as the WPP behaves more risk aversely, the SSI reduces significantly. In fact, the conservative WPP mitigates its profit volatility by decreasing the amount of supplied client demand.

TABLE IV. PROFIT DEVIATION AND SSI VERSUS DR LEVELS AND RISK AVERSION FACTORS.

Case	beta	DR Capacity level					
		0	20	40	60	80	100
ΔEP (%)	0.01	0	7.61	11.58	15.52	19.39	22.59
	1	0	7.61	11.58	15.52	19.39	22.59
	5	0	7.56	11.56	15.60	19.40	22.60
	10	0	7.52	11.52	15.59	19.41	22.61
SSI (%)	0.01	48.12	66.87	66.91	66.91	48.12	66.87
	1	86.50	86.50	86.72	86.66	86.5	86.5
	5	86.54	86.35	86.64	86.77	86.54	86.35
	10	86.66	86.66	87.66	87.66	86.66	86.66

The daily up and down reserve provision by the responsive loads are shown in Fig. 13 and Fig. 14, respectively. It is seen, different portions of total load capacity including 25%, 50%, 75% and 100% make contract with the WPPs. At each portion, the trend of up and down reserve allocating by the loads is illustrated in both figures. It is seen that up reserve provision is performed during most hours of the operating day. In fact, the loads favor up reserve because it allows them to obtain both capacity and allocating revenues. Therefore, by increasing the portions of total load capacity, more up reserve is allocated by the loads. In contrast, down reserve provision is high specifically during peak hours. That is because the customers turn on their loads especially during night time hours that can provide down reserve services. Major reason for lower values of down reserve is that the loads only receive the capacity revenue while they should pay for the reserve allocating. While, in up reserve, loads receive revenue due to both contracting and allocating.

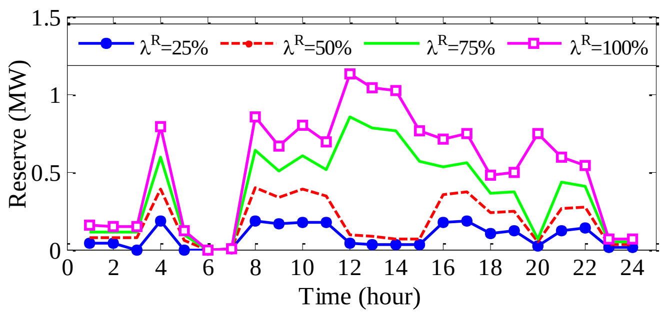


Fig. 13. Up spinning reserve in different reserve capacities.

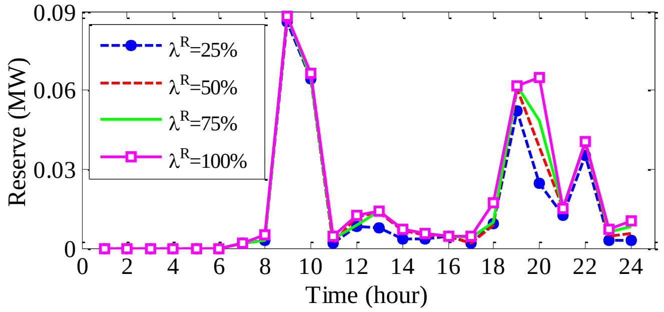


Fig. 14. Down spinning reserve in different reserve capacities.

As seen, with increasing reserve capacity level (λ^R), the expected profit of the WPP increases in both cases without and with discharge process. With increasing the portion of capacity of load level participating in reserve markets, the expected profit of the WPP augments. Also, when the WPP makes contract with the loads, the SSI reduces that leads to more participation of the under study WPP to attract the responsive loads in the competitive market to provide more reserve. Therefore, the more participation of loads in the reserve, the higher the profit of the WPP. On the other hand, by increasing the participation of loads to provide reserve services, the WPP sells less energy to DA market that may be instead offered to the reserve market. While the WPP purchases more volume of energy from the DA to supply the loads. Such a tradeoff materializes because the potential revenue obtained with this trend is satisfying to the WPP. With increasing capacity reserve level, the purchases from the positive balancing market augments marginally that is because the customers may fail to deploy their contract. In contrast, the supplement from negative balancing market reduces that denotes the WPP could fulfill the energy requirements from the customers who participates in reserve services.

When the customers participate in discharge process, the WPP obtains more profit. Also, based on the SSI, it can be observed that the WPP receives more opportunity in the competitive market to attract the customers. The DA selling augments while the DA buying reduces that both may be due to the discharge of the aggregated EVs.

When EVs participate in discharge process, the WPP may sell the extra energy to the positive balancing market, however, it may confront with lower lack of energy to be supplied from the negative balancing market. Moreover, with comparing the cases without and with discharge process, it is seen that the up and down reserve services change marginally.

TABLE V. DIFFERENT POINTS IN VARIOUS RESERVE CAPACITY LEVELS

λ^R	No P2P	25%	50%	75%	100%
Without discharge					
profit	3128.7	3240.3	3284.7	3304.5	3336.71
SSI	34.26	33.52	32.18	28.69	27.22
DA sell	4.21	6.00	5.30	3.47	3.59
DA buy	21.19	21.11	20.78	26.44	25.91
Positive	2.25	2.18	2.23	2.24	2.29
Negative	4.24	4.21	4.21	4.17	4.11
Up reserve	-	1.99	4.30	9.06	12.75
Down reserve	-	0.32	0.37	0.39	0.43
With discharge					
profit	3198.6	3308.4	3350.5	3369.4	3389.9
SSI	33.49	34.01	32.7	30.52	20.04
DA sell	5.08	7.58	6.72	4.80	4.39
DA buy	20.34	18.66	19.13	22.46	22.51
Positive	2.25	2.21	2.26	2.28	2.30
Negative	4.22	4.20	4.16	4.10	4.08
Up reserve	-	1.90	4.35	8.60	12.75
Down reserve	-	0.32	0.37	0.41	0.44

V. CONCLUSION

In this paper, a risk constraint joint energy and reserve problem has been proposed. In this problem, the under study WPP competes against other WPPs to attract customers. Also, the customers can allocate reserve for the WPP such that the uncertainties of wind generation are compensated. To this end, due to the competitive environment, a bi-level problem has been proposed. Then, this problem, is converted to a single level problem. Moreover, to hedge against the uncertainties of stochastic resources, the WPP applies a CVaR approach. The results shown that, when the WPP becomes more risk averse, it should pay more to trade energy with more stable resources. Also, the profits far from the mean profit would be eliminated. The WPP sells its over generation in the balancing market and purchases its energy deficit to compensate the volatilities. Also, by participating with more loads in DR programs, the uncertainties that result in revenue losses to the WPP due to the penalties in the balancing market did not increase. So, the WPP has the opportunity to purchase or schedule some reserves via a P2P trading floor to offset part of its deviation rather than being fully penalized in the real time market.

In addition, SSI index is defined based on which the competition among the WPPs is analyzed under the conditions of participating EV owners in discharging process. From this index, it can be concluded that when EV owners participate in discharge process, the share of rivals reduces and consequently, the WPP has more opportunity to meet loads. Moreover, results show that the WPP benefits from the provided reserve by the loads due to the additional revenue. Also, with increasing the reserve load capacity, lower SSI obtains which yields that the under study WPP stay in the game.

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