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Coordination of wind power producers with an energy storage system for the optimal participation in wholesale electricity markets

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A B S T R A C T

The optimal participation of wind-based power resources within electricity markets confronts serious challenges due to the inherent uncertainty of wind speed. Accordingly, these units are forced to make take-or-pay contracts that are typically lower than market-clearing prices. Hence, wind power plants are not able to obtain the maximum possible amount of profit. One of the most promising solutions to deal with this matter is the coordination of wind-based units with flexible resources like energy storage systems. Therefore, this study presents a novel offering strategy of multiple Wind Producers (WPs) coordinated with a Battery Energy Storage System (BESS) in the form of a strategic Virtual Power Plant (VPP). To this end, a bi-level programming framework is proposed in which the VPP's expected profit is maximized at the upper-level (UL) through solving a two-stage stochastic problem. At the first stage, the VPP's optimal offers to the day-ahead (DA) market are determined before the realization of stochastic variables. At the second stage, this participant's real-time (RT) imbalance cost is optimized after determining the true value of uncertain parameters. On the contrary, at the lower-level (LL), the DA market-cleaning process is performed in the presence of conventional power producers. Moreover, this article aims to calculate the amount of net power trading of the VPP's components with the market and with one another. Ultimately, to assess the effectiveness of the provided framework, a sensitivity analysis is conducted by investigating the effect of the BESS presence on the wind-based VPP's optimal operation and expected benefit.

Keywords:
Wind producer
Battery energy storage system
Strategic virtual power plant
Market-clearing process
Bi-level programming problem

1. Introduction

1.1. Motivation

Within a few years, the demand for energy has grown dramatically due to population growth and economic expansion. In this regard, more than fifty percent of the required energy is provided by fossil fuels [1]. Nonetheless, the shortage of these fuel sources, as well as their irreversible environmental impacts, have turned the issue of energy supply into a serious crisis all over the world. As a result, the transition from fossil-based and traditional energy systems to more environmentally friendly and sustainable networks that are equipped with renewable resources is highly vital [2]. Meanwhile, wind-based sources have attracted great attention owing to their high capacity in producing electricity and also the high availability of wind power. Hence, these days, the share of wind-based energy resources in electricity pools has grown rapidly [3]. Nonetheless, the stochastic nature of wind speed and fluctuation in wind power generation lead to serious challenges in the clearing mechanism of electricity markets. Thus, wind power forecast, as well as its accuracy, have become important issues in recent electricity markets and WPs' decision-making procedures. While considerable efforts are taken by WPs to make precise predictions, normally, they contain major errors. These errors prevent WPs from obtaining the maximum possible amount of profit [4]. One of the prevalent solutions to deal with this problem is signing long-term take-or-pay contracts by WPs. Nonetheless, since these contracts are typically lower than market-clearing prices, these producers are still not able to gain a high amount of profit [5]. In this case, one of the best solutions to promote WPs' interest is the coordination of these renewable-based power plants with flexible resources like energy storage systems [6]. Out of the entire types of energy storage units, BESSs have drawn more attention in the last few years. The reason is that, unlike conventional storage resources like compressed air and pumped hydro energy storage, BESSs have no geographical and ecological limitations to be installed at varied locations. Furthermore, owing to their modularity as well as the recent

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Nomenclature

Acronyms

BESS	Battery Energy Storage System
DA	Day-Ahead
KKT	Karush–Kuhn–Tucker
LL	Lower-Level
MPEC	Mathematical Program with Equilibrium Constraints
RT	Real-Time
SDT	Strong Duality Theorem
UL	Upper-Level
VPP	Virtual Power Plant
WEM	Wholesale Electricity Market
WP	Wind Producer

Indices and Sets

$i \in I$	Conventional power producers
$s \in S$	Scenarios
$t \in T$	Times
$w \in W$	WPs
Ξ^{UL}	Set of the UL's decision variables
Ψ^{UL}	Set of the UL's parameters
Ξ^{LL}	Set of the LL's decision variables
Ψ^{LL}	Set of the LL's parameters

Parameters

D	Forecasted electricity demand (MW)
$E^{initial}$	Initial stored energy in the BESS at the beginning of the first hour (MWh)
E^{final}	Final stored energy in the BESS at the end of the last hour (MWh)
E^{max}	Maximum stored energy in the BESS (MWh)
E^{min}	Minimum stored energy in the BESS (MWh)
M	large enough number for non-linear expressions linearization (constant)
P_{ch}^{max}	Maximum BESS charging capacity (MW)
P_{ch}^{min}	Minimum BESS charging capacity (MW)
P_{dch}^{max}	Maximum BESS discharging capacity (MW)
P_{dch}^{min}	Minimum BESS discharging capacity (MW)
P_{g}^{max}	Maximum capacity of the conventional power producer (MW)
P_{g}^{min}	Minimum capacity of the conventional power producer (MW)
P_{WP}	Generated power of WP (MW)
P_{WP}^{max}	Maximum wind power capacity of the WP (MW)
V_{WP}	Wind speed in the installed site of the WP (m/s)
V_{WP}^{ci}	Cut-in speed of the WP (m/s)
V_{WP}^{co}	Cut-out speed of the WP (m/s)
V_{WP}^{Rated}	Rated speed of the WP (m/s)
λ_g	Offer price of the conventional power producer ($/MWh)
λ_{imb}	RT imbalance price ($/MWh)
ρ	Probability of scenarios (constant)
η_{ch}, η_{dch}	BESS charging and discharging efficiency (%)

Variables

E	BESS stored energy at the beginning of each time interval (MWh)
P_{ch}	BESS total charge power (MW)
P_{dch}	BESS total discharge power (MW)
P_g	Output power of the conventional power producer (MW)
$P_{WP,ch}$	Net power trading between the WP and BESS (MW)
$P_{WP,WEM}$	Net power trading between the WP and WEM (MW)
q_{DA}	DA accepted offer of the VPP (MW)
$q_{DA}^{Offer,VPP}$	Quantity offer of the VPP to the DA WEM (MW)
q_{imb}	Imbalance power of the VPP (MW)
λ_{DA}	DA market-clearing price ($/MWh)
μ , σ	Dual variables for the LL's constraints

Binary variables

U_{ch}	BESS charging status (1 if BESS is in the charging mode; otherwise 0)
U_{dch}	BESS discharging status (1 if BESS is in discharging mode; otherwise 0)
X	Binary Variable using for the linearization of non-linear expressions

development of BESS technology, the storage capacity of BESSs can easily be increased at the lowest possible cost of capital [7].

Based on the above explanations, this work proposes a novel offering strategy for the optimal participation of a price-maker VPP consisting of multiple WPs and a large-scale BESS in the DA WEM. Owing to the presence of stochastic variables, i.e., the RT imbalance price as well as wind speeds, a two-stage stochastic programming problem is utilized to model the provided framework. At the first stage, the VPP's optimal offers to DA WEM are determined, while at the second stage, this participant's RT imbalance cost is minimized. On the other hand, to model the offering strategy of the studied VPP, a bi-level programming method is employed, in which the VPP's expected profit is maximized at the UL, whereas the DA WEM is cleared at the LL. In this platform, the market operator minimizes the total operating costs and determines the market-clearing price by receiving offers from various electricity producers.

1.2. Literature review

In the past few years, sundry research studies have been carried out on the optimal involvement of VPPs in electricity markets. Some of the important studies can be highlighted as follows:

A two-stage stochastic model for the optimal thermal/electrical scheduling of a VPP to involve in energy and spinning reserve markets has been suggested in [8]. In the presented framework, the VPP attempts to maximize its profit by aggregating various types of electrical and thermal units such as non-dispatchable and dispatchable resources, demand response programs, storage systems, etc. For modeling the uncertainties that exist in VPP's decision-making process, the Point Estimate Method has been exploited in this study. The results demonstrate that the coordinated performance of flexible resources with stochastic generation units could enhance the VPP's income. A stochastic adaptive robust optimization model has been suggested in [9] for the DA self-scheduling of a VPP taking part in energy and reserve markets. Conventional generation units, energy storage systems, wind power resources, and finally, flexible demands have been aggregated in the VPP platform in order to trade energy with the mentioned markets. In this article, the provided scheme has been formulated as a tri-level problem. A risk-based three-stage stochastic model has been presented in [10] for the optimal involvement of a VPP in a tri-settlement pool market, namely the DA, adjustment, and balancing markets. In this work, a WP cooperates with a group of electric vehicles in the form of a VPP to not only meet vehicles' energy requirements but also offer their excess to the market. The primary objective of this study is to minimize the cost of electric vehicles' demand and maximize the VPP's profit at the same time. A technical–economic dispatch framework has been utilized in [11] for the optimal scheduling of a new-structured VPP that integers two levels of renewable energy, namely a WP with six hydroelectric generators as well as photovoltaic self-consumption systems. The suggested model aims to maximize the VPP's operating profit for each hour of a year. The final results illustrate that the provided management method reduces the system's dependence on the upstream grid and WEM significantly. A coordinated mathematical formulation has been employed in [12] for the bi-objective offering strategy of a wind-photovoltaic-thermal integrated system participating in the deregulated energy and reserve markets. In the suggested framework, not only the expected profit of the integrated system has been maximized but also thermal units' emission cost has been minimized. To evaluate the efficiency of the coordinated platform, the uncoordinated operation of the system's elements, namely wind, photovoltaic, and thermal resources, has been also studied in this article.

For the DA scheduling of VPPs, a stochastic MINLP model has been provided in [13]. The considered VPPs have aggregated several generation units as well as industrial demand response at the distribution and transmission levels to participate in a short-term electricity market. The scheduling problem has been performed from the VPPs' perspective to maximize their expected profit. A decision-making methodology for the short-term scheduling of an industrial VPP in both normal and contingency situations has been raised in ref. [14]. In the considered VPP, various types of generation units, as well as flexible loads, have been integrated. In this regard, the VPP is inclined to maximize its profit from participating in the DA and intra-day electricity markets considering the risk-management aspect. A bi-level multi-objective method has been suggested in ref. [15] for solving the offering strategy of a VPP consisting of dispatchable and non-dispatchable units as well as interruptible loads in energy and regulation markets. The UL of this problem maximizes the VPP's profit, whereas the LL maximizes social welfare by clearing the existing markets. In addition to the profit maximization, another goal of this study is to minimize the VPP's emission using the ε-constraint method. A bi-level optimization model has been used in [16] to decide on the involvement of a multi-carrier VPP that integrates renewable and thermal units in different markets, namely the DA WEM and local heat market. Accordingly, on the one hand, the VPP takes part in the DA WEM and competes with the existing competitors by submitting its bids/offers to this market. On the other hand, the VPP, as a single entity, is able to involve in the local heat market and trade the heat with other thermal producers. Hence, the UL of the problem maximizes the VPP's profit from participating in the aforementioned markets. In contrast, the LL maximizes the WEM social welfare from the market operator's perspective. For the optimal scheduling of a power-to-gas-based VPP, a multi-objective risk aversion optimization approach has been provided in [17]. In order to form this new VPP structure, the power to gas and gas storage systems are integrated with a conventional VPP that includes various types of generation as well as flexible sources. The objective functions of this problem are to maximize the VPP's operating profit and minimize the operation risk. A self-scheduling optimization model has been suggested in [18], in which several WPs and electric vehicles are able to take part in DA energy and reserve markets as a single VPP. Accordingly, the VPP operator schedules the available components to maximize its profit from market participation. In this study, not only the uncertainties of market prices and wind generation but also the entire uncertainties associated with electric vehicles have been considered.

A three-stage stochastic coordinated model has been raised in [19] to solve the offering strategy of a VPP that consists of WPs, energy storage units, and demand response resources. In this regard, the VPP aims to maximize its income through taking part in the DA, intraday, and balancing markets, sequentially. The provided coordinated model has been compared with an uncoordinated model in which the VPP's components take part in markets individually. The simulation results demonstrate that in the coordinated framework, the VPP's involvement in electricity markets is increased dramatically. In [7], a bi-level model for the offering strategy of price-maker BESS-based VPPs in the DA electricity markets has been employed. Accordingly, at the UL of this problem, different BESS-based VPPs compete with one another to achieve the maximum possible amount of profit by scheduling their owned BESSs. At the LL of this model, the DA market is settled based on the submitted offers from VPPs as well as thermal power plants. In [20], a tri-stage stochastic bi-objective programming model has been exploited to determine the optimal involvement of a wind-storage-thermal integrated system in energy, spinning reserve, and balancing markets. The objectives of the problem are maximizing the benefit of the studied system and reducing the emission costs of thermal power plants. To model the uncertain nature of the existing markets' prices and wind power generation, a scenario-based method has been utilized.

In order to clarify the uniqueness of the presented framework with regards to the previous studies, the taxonomy of the reviewed works is listed according to Table 1.

Table 1
Taxonomy of the reviewed research works.

Reference	Coordination of several decentralized WPs	Price-maker VPP	Modeling the net power trading inside the VPP	Sensitivity analysis of flexible units presence
[8]	×	×	×	×
[9]	×	×	×	×
[10]	×	×	×	×
[11]	×	×	×	×
[12]	×	×	×	×
[13]	✓	×	×	×
[14]	✓	×	×	×
[15]	×	✓	×	×
[16]	×	✓	×	×
[17]	×	×	✓	×
[18]	×	×	×	✓
[19]	✓	×	×	✓
[7]	×	✓	×	✓
[20]	×	×	✓	✓
This Paper	✓	✓	✓	✓

1.3. Contributions

Reviewing the above articles reveals that, typically, self-scheduling models have been developed to determine the VPPs' offering strategy in different markets. Hence, these research studies have not been able to provide a pragmatic platform for investigating the impact of VPPs' offers on clearing prices of the market. On the other hand, in most of the VPPs structure, conventional dispatchable units have been considered as flexible sources to compensate for the intermittency of renewable-based resources. Nonetheless, in recent years, the utilization of these generation units has been restricted owing to the lack of fossil fuels and environmental concerns. Furthermore, by and large, the effect of flexible units' parameters on the optimal operation and expected benefit of VPPs has been analyzed in a limited number of papers. Accordingly, since this study is aimed to cope with the aforementioned gaps, the primary novelty and contributions of the paper could be as follows:

1. Proposing a bi-level stochastic programming framework for the offering strategy of a price-maker wind-based VPP and investigating the effect of its offers on the DA market-clearing prices.
2. Developing a novel mathematical formulation to calculate the amount of net power trading of the VPP's integrated resources with each other and with the WEM.
3. Conducting the sensitivity analysis to scrutinize the effect of the BESS' technical specifications on the optimal operation and profit of the studied VPP.
4. Considering the coordinated and uncoordinated operation between WPs and BESS to evaluate the effectiveness of the suggested VPP structure.

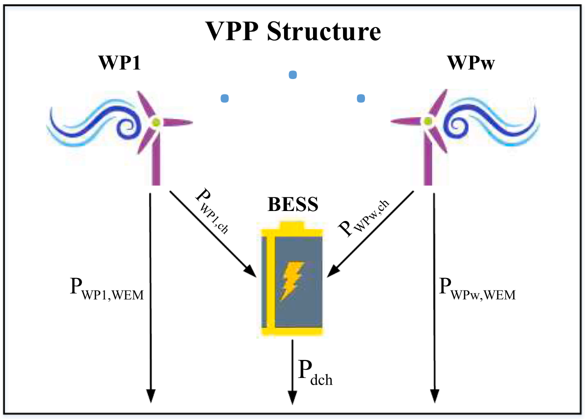

Fig. 1. Structure of the studied VPP.

The remaining of this article is organized as follows: The VPP's structure, the proposed framework, and mathematical formulations are explained in part 2, case studies and sensitivity analysis are conducted in part 3, and ultimately, the conclusion is drawn in part 4.

2. Methods and materials

In this section, initially, the studied VPP's structure, as well as the presented methodology for the optimal participation of this strategic player in DA WEM, are described in detail. Afterward, uncertainty characterization and problem formulations are provided comprehensively.

2.1. *Structure of the Price-maker VPP*

As mentioned earlier, by, the market-clearing prices are affected remarkably by offers of WPs. In other words, in the WEM with a considerable share of wind energy, offers of WPs determine the marginal conventional generators of the market. Nonetheless, WPs are usually incurred a large amount of imbalance cost owing to the inherent variability of wind power generation, as well as the stochastic nature of wind speed [21].

To overcome such a dilemma, this research work aims to provide a cooperative model among various generations as well as flexible units, i.e., WPs and a BESS, for the optimal involvement in the DA WEM. To this end, multiple WPs, which are both technically and economically independent, cooperate with one another in a VPP platform in order to take part in the WEM as a strategic agent and alter the market-clearing prices for their own benefit. On the other hand, these WPs utilize a BESS to compensate for the uncertainty in wind power production and hence minimize their imbalance costs in the RT stage.

Fig. 1 illustrates the collaborative framework between WPs and the BEES clearly. As it is demonstrated, the article tends to model and calculate the net power trading of existing units with one another and with the WEM. This kind of interaction diminishes the difference between the VPP's DA offer and its actual power trading in the RT stage. Consequently, the VPP's RT imbalance cost is reduced to the lowest possible amount.

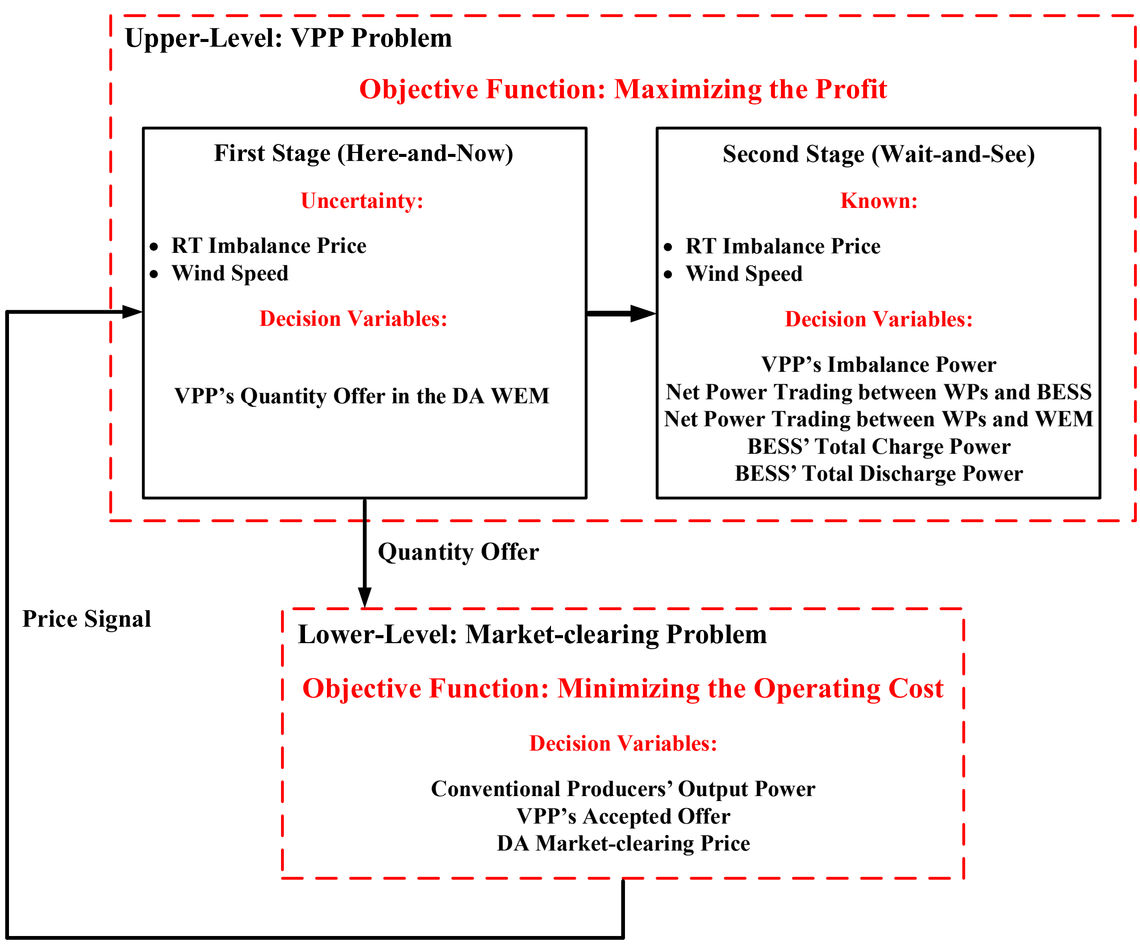

Fig. 2. Scheme of the provided bi-level stochastic model.

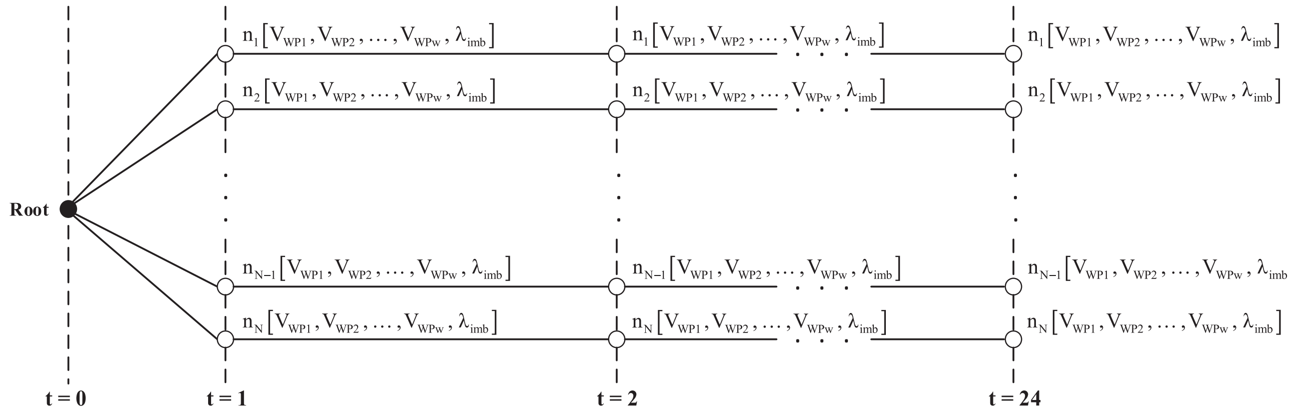

Fig. 3. Representation of scenario tree.

2.2. Proposed methodology

The primary aim of this research work is to propose a proper framework for the optimal participation of a wind-based VPP in the DA WEM as a strategic player. For modeling the decision-making mechanism of the price-maker VPP in the studied problem, considering the DA market-clearing process as well as optimizing the objective function of the market operator in the presence of the VPP's conventional rivals are required. To this end, a bi-level stochastic model is suggested in this article. The reason is that, the bi-level optimization method has the capability to solve specific problems in which one optimization problem is nested within another [22].

The outline of the proposed framework is illustrated in Fig. 2. As it is clear in this figure, the outer optimization layer of this problem maximizes the VPP's expected profit in two DA and RT stages. Accordingly, the VPP submits the quantity of its offer to the DA WEM by examining the situation of the existing WPs. These offers enter into the DA WEM problem as input parameters. Based on these values and other conventional power producers' offers, the market operator solves the inner optimization layer to minimize its DA operating costs and determine the market-clearing points. By considering the market prices and accepted offers that are returned from the inner to the outer layer as well as by the realization of stochastic variables, including the RT imbalance price and wind speeds, the VPP attempts to reduce its RT imbalance cost through dispatching the available flexible unit, i.e., the BESS. In the end, to better clarify the suggested bi-level stochastic model, linking and non-linking decision variables of the UL and LL are depicted in Fig. 2 as well.

2.3. Uncertainty modeling

As previously mentioned, aggregated WPs inside the considered VPP are both technically and economically independent that are located in varied sites. Hence, wind speed profiles are different for the existing decentralized WPs. Accordingly, in the raised model, there are two types of stochastic parameters, namely wind speeds in installed areas as well as RT imbalance price. For the realization of these uncertain variables, a large enough number of scenarios must be created in such a way to indicate the probabilistic character of them. For this purpose, the Monte Carlo Simulation technique is exploited in this article. As a first step, by using historical data, the Normal PDF for each parameter's error is generated. In the next step, based on the created PDFs, the value of the forecasting parameters, as well as expression $Z(t,s) = Z^{Forecast}(t) + Z^{Error}(t,s)$, the required number of scenarios is established [23]. As it is clear in the provided equation, in order to obtain scenario $Z(t,s)$ for each uncertain variable, its predicted value, $Z^{Forecast}(t)$, and a negative or positive error, $Z^{Error}(t,s)$, are added. In this case, $Z^{Error}(t,s)$ is achieved from the PDF of errors utilizing random numbers.

In this study, to convert the discrete outcome of stochastic variables to the integrated set of scenarios, the concept of the scenario tree is implemented. By and large, a scenario tree includes two elements, nodes and stages, where nodes represent the state of uncertain parameters at a certain time period, while stages illustrate the time step of the problem. In the constructed tree, links between nodes are considered as desired scenarios [24].

The constructed tree for the suggested scenario-based stochastic model is displayed in Fig. 3. It is notable that in this figure, n_N refers to the N^{th} node of the scenario tree.

In this study, it is assumed that three decentralized WPs aggregated inside the VPP. Hence, in the decision-making process of this entity, there are four stochastic parameters, namely three wind speed profiles and RT imbalance prices. For each of these parameters, 20 discrete scenarios are generated at each hour. By the combination of these discrete scenarios through the scenario tree concept, 160,000 scenarios at each stage and 3,840,000 scenarios in total are obtained. Since solving the raised optimization problem in the presence of all generated scenarios results in computational complexity, the established scenarios must be decreased to a sufficient number by executing an appropriate reduction algorithm. In the paper, the mix of the fast forward/backward method in the SCENRED2-GAMS [25] is exploited to reduce the total scenarios to 10, which represent the value of four uncertain parameters at 24 h. This algorithm uses the Kantorovich distance concept to preserve possible scenarios by minimizing the distance between original and reduced scenarios [26]. Table 2 reports the probability of each reduced scenario.

2.4. Problem formulation

In this section, both layers' objective function and their associated constraints are mathematically formulated.

2.4.1. Objective function and constraints of the UL: VPP problem

The objective function of this level is to maximize the expected profit of the strategic VPP utilizing the two-stage stochastic programming

Table 2
probabilities of each reduced scenario.

# S	1	2	3	4	5	6	7	8	9	10
$\rho(s)$	0.083	0.094	0.101	0.113	0.159	0.111	0.123	0.075	0.071	0.070

method. The objective function is stated as the difference between the VPP's income from taking part in the DA WEM and its imbalance cost in the RT stage. The imbalance cost of the VPP determines a penalty cost that the entity should pay to the market operator owing to the increase or decrease in its RT power production compared to the DA offers.

$$OF_{UL} = \mathrm{Max} \sum_{t=1}^{T} \left\{ \lambda_{DA}(t) \cdot q_{DA}(t) - \sum_{s=1}^{S} \rho(s) \cdot [\lambda_{imb}(t,s) \cdot q_{imb}(t,s)] \right\} \tag{1}$$

where, imbalance power of the VPP at each time and each scenario is computed by expression (2).

$$q_{imb}(t,s) = q_{DA}(t) - \sum_{w=1}^{W} P_{WP}(w,t,s) + P_{ch}(t,s) - P_{dch}(t,s), \ \forall t,s \tag{2}$$

As it is observed in the above equation, $q_{imb}(t,s)$ is calculated as the difference between the VPP's accepted offer in the DA market and its actual power trading in the RT stage. Clearly, the presented modeling is implemented in such a way that the VPP is motivated to offer most of its power to the DA WEM. In other words, in both cases where the VPP's RT power generation is higher or lower than its DA accepted offer, $q_{imb}(t,s)$ enters as a positive term into the objective function. Consequently, inasmuch as the existence of the imbalance power always leads to a reduction in the studied VPP's expected benefit, this player tends to submit a significant percentage of its generation capacity in the DA stage.

Subject to:

1. Constraint of the VPP's Offer to the DA WEM:

The quantity offer of the VPP is a nonnegative decision variable that is restricted to the total installed wind capacities of the existing WPs, as stated in inequality (3).

$$0 \leqslant q_{DA}^{Offer,VPP}(t) \leqslant \sum_{w=1}^{W} P_{WP}^{max}(w), \ \forall t \tag{3}$$

2. Constraints of WPs:

Based on the generated scenarios for the wind speed of each WP aggregated inside the VPP, the output power of these producers is calculated as follows [27]:

$$P_{WP}(w,t,s) = \begin{cases} 0 & , V_{WP}(w,t,s) < V_{WP}^{ci}(w) \\ P_{WP}^{max}(w) \cdot \dfrac{V_{WP}(w,t,s) - V_{WP}^{ci}(w)}{V_{WP}^{Rated}(w) - V_{WP}^{ci}(w)}, & V_{WP}^{ci}(w) \leqslant V_{WP}(w,t,s) \leqslant V_{WP}^{Rated}(w) \\ P_{WP}^{max}(w) & , V_{WP}^{Rated}(w) \leqslant V_{WP}(w,t,s) \leqslant V_{WP}^{co}(w) \\ 0 & , V_{WP}(w,t,s) > V_{WP}^{co}(w) \end{cases} \tag{4}$$

As demonstrated in the structure of the studied wind-based VPP in Fig. 1, WPs are able to sell their wind production to the WEM or store it in the BESS. Hence, the output power of each WP is equal to the sum of the injected power production into the WEM and injected wind generation into the BESS during the charging mode. Eq. (5) is provided to formulate the power production of WPs at t^{th} time and s^{th} scenario.

$$P_{WP}(w,t,s) = P_{WP,WEM}(w,t,s) + P_{WP,ch}(w,t,s), \ \forall w,t,s \tag{5}$$

3. Constraints of the BESS:

The mathematical and technical model of the existing flexible unit, i.e., BESS, is presented in expressions (6)–(13). Accordingly, the share of each WP in charging the BESS is modeled in Eq. (6).

$$P_{ch}(t,s) = \sum_{w=1}^{W} P_{WP,ch}(w,t,s), \ \forall t,s \tag{6}$$

The consumption and generation power of the BESS are restricted by Eqs. (7) and (8), respectively. Moreover, inequality (9) is utilized to prevent the BESS from charging and discharging at the same time [28].

$$P_{ch}^{min}.U_{ch}(t,s) \leqslant P_{ch}(t,s) \leqslant P_{ch}^{max}.U_{ch}(t,s), \ \forall t,s \tag{7}$$

$$P_{dch}^{min}.U_{dch}(t,s) \leqslant P_{dch}(t,s) \leqslant P_{dch}^{max}.U_{dch}(t,s), \ \forall t,s \tag{8}$$

$$U_{ch}(t,s) + U_{dch}(t,s) \leqslant 1, \ \forall t,s \tag{9}$$

The stored energy in the BESS and its associated constraints are stated in expressions (10)–(13):

$$E(t,s) = E^{initial}, \ \forall t = 1,s \tag{10}$$

$$\begin{aligned} E(t+1,s) &= E(t,s) + P_{ch}(t,s) \cdot \eta_{ch} \\ &\quad - P_{dch}(t,s)/\eta_{dch}, \ \forall t < 24,s \end{aligned} \tag{11}$$

$$\begin{aligned} E^{final} &= E(t,s) + P_{ch}(t,s) \cdot \eta_{ch} \\ &\quad - P_{dch}(t,s)/\eta_{dch}, \ \forall t = 24,s \end{aligned} \tag{12}$$

$$E^{min} \leqslant E(t,s) \leqslant E^{max}, \ \forall t,s \tag{13}$$

In this regard, the initial and final amount of energy stored in the BESS at the beginning of the first hour and at the end of the last hour are formulated by Eqs. (10) and (12), respectively. Furthermore, the alteration of energy stored at each time period as well as its upper and lower limitations are expressed in Eqs. (11) and (13), respectively.

In the end, the set of decision variables as well as the set of parameters for the UL problem are as follows:

$$\Xi^{UL} = \{ q_{DA}^{Offer,VPP}(t), P_{WP,WEM}(w,t,s), P_{WP,ch}(w,t,s) \\ P_{ch}(t,s), P_{dch}(t,s), U_{ch}(t,s), U_{dch}(t,s), E(t,s) \}$$

$$\Psi^{UL} = \{ \rho(s), \lambda_{imb}(t,s), P_{WP}(w,t,s), P_{WP}^{max}(w), P_{ch}^{max} \\ P_{ch}^{min}, P_{dch}^{max}, P_{dch}^{min}, E^{initial}, E^{final}, E^{max}, E^{min}, \eta_{ch}, \eta_{dch} \}$$

2.4.2. *Objective function and constraints of the LL: Market-clearing problem*

As noted, in the LL of this problem, the DA market-clearing procedure is performed. To this end, the entire producers of the market submit their offers to the DA WEM. Then, the system operator settles the DA market according to its forecasted electricity demand. Accordingly, the objective function is minimizing the expected operating cost of the system, including conventional power producers' generation costs in the DA stage.

$$OF_{LL} = \text{Min} \sum_{t=1}^{T} \sum_{i=1}^{I} \{\lambda_g(i) \cdot P_g(i,t)\} \tag{14}$$

For the sake of simplicity, it is assumed that the price of each conventional producers' offers to the DA WEM is fixed between its minimum and maximum power production. Accordingly, based on Eq. (14), the operating cost of the market is calculated by multiplying the accepted amount of offers by its price.

Subject to:

1. Constraint of the VPP's Accepted Offer in the DA WEM:

In the market-clearing procedure, the accepted offer of the strategic VPP, which is a non-negative variable, has to be limited to its quantity offer to the DA WEM, as expressed in Eq. (15).

$$0 \le q_{DA}(t) \le q_{DA}^{Offer,VPP}(t), \ \forall t \quad \underline{\mu}(t), \overline{\mu}(t) \tag{15}$$

2. Constraint of Conventional Power Producers:

According to Eq. (16), conventional power producers' submitted offers to the DA WEM are confined to their minimum and maximum generation capacities [29].

$$P_g^{min}(i) \le P_g(i,t) \le P_g^{max}(i), \ \forall i,t \quad \underline{\sigma}(t), \overline{\sigma}(t) \tag{16}$$

3. Constraint of the DA Power Balance:

In general, accepted offers of the market participants, namely the VPP and conventional power producers should satisfy the forecasted demand of the system.

$$\sum_{i=1}^{I} P_g(i,t) + q_{DA}(t) = D(t), \ \forall t \quad \lambda_{DA}(t) \tag{17}$$

Note that base on Eqs. (14) and (17), the offers are accepted from the lowest price until the demand of the market is satisfied. The amount and price of these offers are depicted in this article with P_g and λ_g, respectively.

It is noteworthy that dual variables associated with the LL's constraints are indicated after a colon. Additionally, the dual variable associated with the power balance constraint, $\lambda_{DA}(t)$, represents the DA market-clearing price.

Ultimately, the set of primal and dual decision variables as well as the set of parameters for the LL problem is as follows:

$$\Xi^{LL} = \{q_{DA}(t), \lambda_{DA}(t), P_g(t), \underline{\mu}(t), \ \overline{\mu}(t), \underline{\sigma}(t), \overline{\sigma}(t)\}$$

$$\Psi^{LL} = \left\{\lambda_g(i), P_g^{max}(i), P_g^{min}(i), D(t)\right\}$$

Table 3
Specifications of wind turbines.

# WP	$V_{WP}^{ci}(m/s)$	$V_{WP}^{Rated}(m/s)$	$V_{WP}^{co}(m/s)$	$P_{WP}^{max}(MW)$
WP_1	3	11.5	25	25 × 3.0
WP_2	3	13.0	25	20 × 3.6
WP_3	4	12.5	25	20 × 5.0

2.4.3. Reformulation of the presented bi-level framework to a single-level model

As it is clear, the inner layer of the problem is linear, continuous, and hence convex. This matter allows the bi-level model to be reformulated to a single-level MPEC by substituting the LL problem with its KKT conditions [30]. The generic mathematical formulation of the bi-level problems, as well as their transformation into MPECs utilizing the KKT conditions, have been investigated in greater detail in [21,31]. By developing the Lagrangian function of the LL and applying its KKT conditions, the final single-level model of the considered bi-level problem is formulated in the following:

$$\begin{aligned} OF_{\Xi^{UL},\Xi^{LL}}^{Single-Level} &= \text{Max} \sum_{t=1}^{T} \{\lambda_{DA}(t) \cdot q_{DA}(t) \\ &- \sum_{s=1}^{S} \rho(s) \cdot \left[\lambda_{imb}(t,s) \cdot \left\{ q_{DA}(t) - \sum_{w=1}^{W} P_{WP}(w,t,s) + P_{ch}(t,s) - P_{dch}(t,s) \right\}\right]\} \end{aligned} \tag{18}$$

Subject to:

$$\text{Equations } (3)-(13), \text{ and } (17) \tag{19}$$

$$-\underline{\mu}(t) + \overline{\mu}(t) - \lambda_{DA}(t) = 0, \ \forall t \tag{20}$$

$$\lambda_g(i) - \underline{\sigma}(i,t) + \overline{\sigma}(i,t) - \lambda_{DA}(t) = 0, \ \forall i,t \tag{21}$$

$$0 \le q_{DA}(t) \perp \underline{\mu}(t) \ge 0, \ \forall t \tag{22}$$

$$0 \leqslant q_{DA}^{Offer,VPP}(t) - q_{DA}(t) \ \perp \ \overline{\mu}(t) \geqslant 0, \ \forall t \tag{23}$$

$$0 \le P_g(i,t) - P_g^{min}(i) \perp \underline{\sigma}(i,t) \ge 0, \ \forall i,t \tag{24}$$

$$0 \le P_g^{max}(i) - P_g(i,t) \perp \overline{\underline{\sigma}}(i,t) \ge 0, \ \forall i,t \tag{25}$$

2.4.4. Linearization of non-linear terms

Notable that the final MPEC of the studied problem is non-linear owing to the existence of two non-linearity sources, the product of $\lambda_{DA}(t) \cdot q_{DA}(t)$ in Eq. (1), and the KKT complementary constraints in expressions (22)–(25).

To linearize the non-linear term inside the UL's objective function, the Strong Duality Theorem (SDT) and the presented KKT conditions are exploited [32,33]. The SDT declares that if a problem is convex, its primal and dual objective functions have the same value at the optimal point. In this regard, the dual of the LL problem is written as Eq. (26) in below:

$$\begin{aligned} \sum_{t=1}^{T} \sum_{i=1}^{I} \{\lambda_g(i) \cdot P_g(i,t)\} = \sum_{t=1}^{T} \{ &-\overline{\mu}(t) \cdot q_{DA}^{Offer,VPP}(t) + D(t) \cdot \lambda_{DA}(t) \\ &+ \sum_{i=1}^{I} \left(\underline{\sigma}(i,t) \cdot P_g^{min}(i) - \overline{\sigma}(i,t) \cdot P_g^{max}(i)\right)\} \end{aligned} \tag{26}$$

From Eqs. (20) and (23):

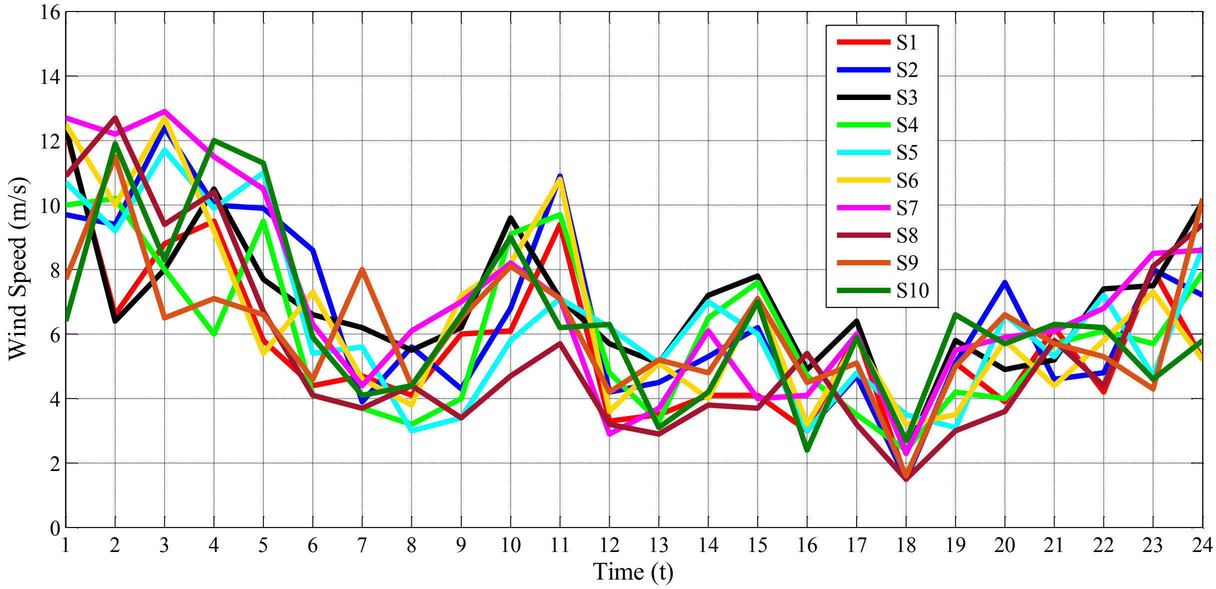

Fig. 4. Wind speed of the second WP for reduced scenarios.

Table 4
Input data of the battery energy storage system.

E^{min} (MWh)	E^{max}(MWh)	$P_{ch}^{min}/P_{dch}^{min}$(MW)	$P_{ch}^{max}/P_{dch}^{max}$(MW)	η_{ch}(%)	η_{dch}(%)
10	100	0	20	90	90

$$\overline{\mu}(t) = \mu_{-}(t) + \lambda_{DA}(t) \tag{27}$$

$$\overline{\mu}(t)\cdot q_{DA}^{Offer,VPP}(t) = \overline{\mu}(t)\cdot q_{DA}(t) \tag{28}$$

By replacing Eq. (27) in Eq. (28) and using Eq. (22):

$$\overline{\mu}(t)\cdot q_{DA}^{Offer,VPP}(t) = [\mu_{-}(t) + \lambda_{DA}(t)]\cdot q_{DA}(t) = \lambda_{DA}(t)\cdot q_{DA}(t) \tag{29}$$

Ultimately, considering expressions (26) and (29), the non-linear term can be converted to a linear one, according to Eq. (30).

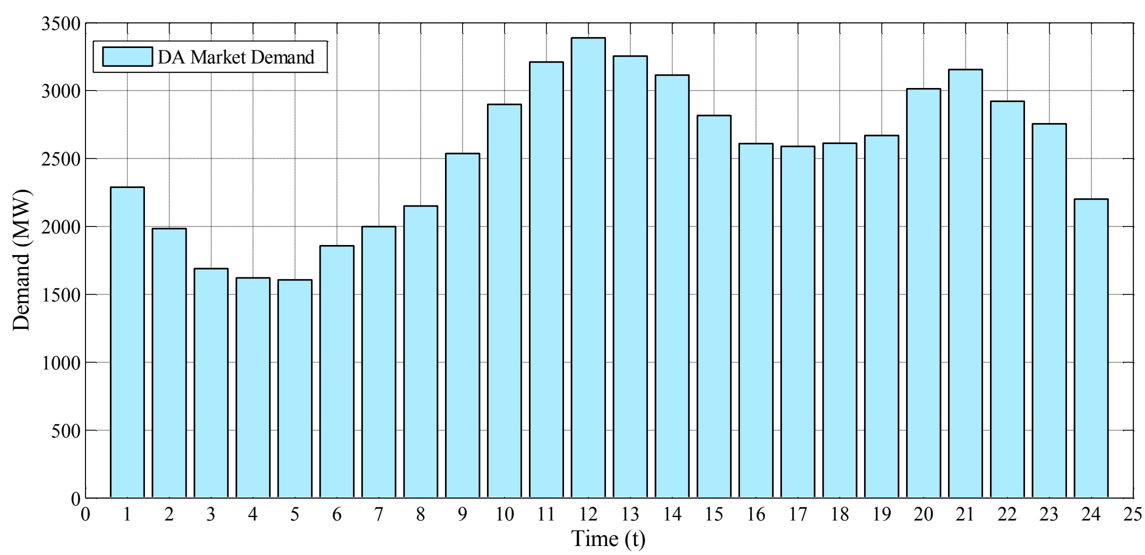

Fig. 5. Predicted load profile of the system.

Table 5
Technical characteristics of conventional power producers.

# i	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10	i11	i12	i13
P_g^{min}(MW)	80	50	50	20	10	30	0	10	0	10	0	10	20
P_g^{max}(MW)	800	800	500	280	180	110	65	110	50	90	130	100	200
λ_g($/MWh)	28.6	20.5	30.1	45.2	62.7	68.2	75.14	81.4	88.4	90.4	101.7	111.4	122.3

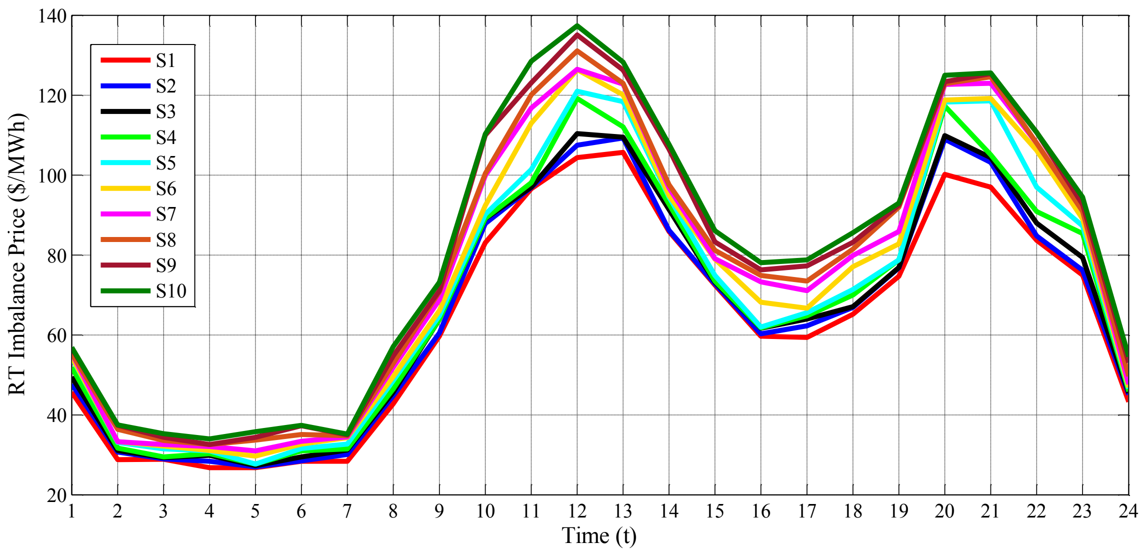

Fig. 6. RT imbalance price for reduced scenarios.

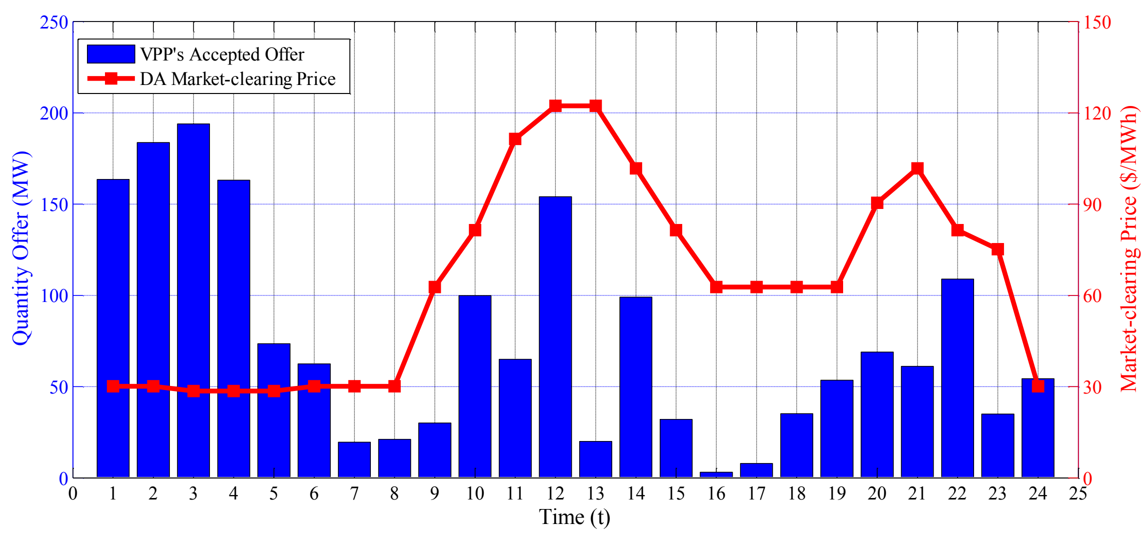

Fig. 7. VPP's accepted offer and the DA market-clearing price in the absence of the BESS.

$$\sum_{t=1}^{T}\{\lambda_{DA}(t)\cdot q_{DA}(t)\} = \sum_{t=1}^{T}\{D(t)\cdot\lambda_{DA}(t)\}+ \sum_{t=1}^{T}\sum_{i=1}^{I}\left\{\sigma_{-}(i,t)\cdot P_g^{min}(i) - \overline{\sigma}(i,t)\cdot P_g^{max}(i) - \lambda_g(i)\cdot P_g(i,t)\right\} \tag{30}$$

For the linearization of complementary constraints, the Big-M method is deployed in this study [34]. To this end, non-linear expressions are replaced by the following set of equations, in which M is a very large number and X is an auxiliary binary variable.

$$\begin{gathered} 0\leqslant f \perp g \geqslant 0 \\ \Rightarrow f\geqslant 0\ ,\ g\geqslant 0 \ \Rightarrow \begin{cases} f\leqslant M\cdot X \\ g\leqslant M\cdot(1-X) \end{cases} \end{gathered} \tag{31}$$

3. Case study

In this part of the article, the presented methodology for the DA offering strategy of the price-maker VPP is investigated in two different case studies. Afterwards, the sensitivity analysis is conducted to evaluate the effect of the BESS' technical specifications on the optimal operation of the considered VPP.

3.1. Input data

Before analyzing the simulation results, the considered system and its related input data are introduced in this section. Accordingly, the studied VPP comprises of three decentralized WPs. Wind turbine specifications of each WP are reported in Table 3 [35].

By considering the normal PDF of errors as well as the forecasted values, ten reduced scenarios are utilized to model the uncertainty of wind speeds in installed sites. The wind speed of the second WP is depicted in Fig. 4 as an example.

Furthermore, the characteristics of the studied flexible unit, namely the BESS, are provided in Table 4 [36].

Concerning the DA WEM, which is cleared by the ISO, it is notable that the amount of electricity demand is considered deterministic. The system's forecasted demand is displayed in Fig. 5 [32].

Additionally, thirteen conventional power producers are considered as rivals of the VPP in the DA WEM. These units' technical characteristics, as well as their offers to the market, are given in Table 5 [37,38].

Similar to wind speeds, to model the uncertainty of the RT imbalance prices, ten reduced scenarios are deployed according to the aforementioned approach in Section 2.3. Fig. 6 demonstrates these prices.

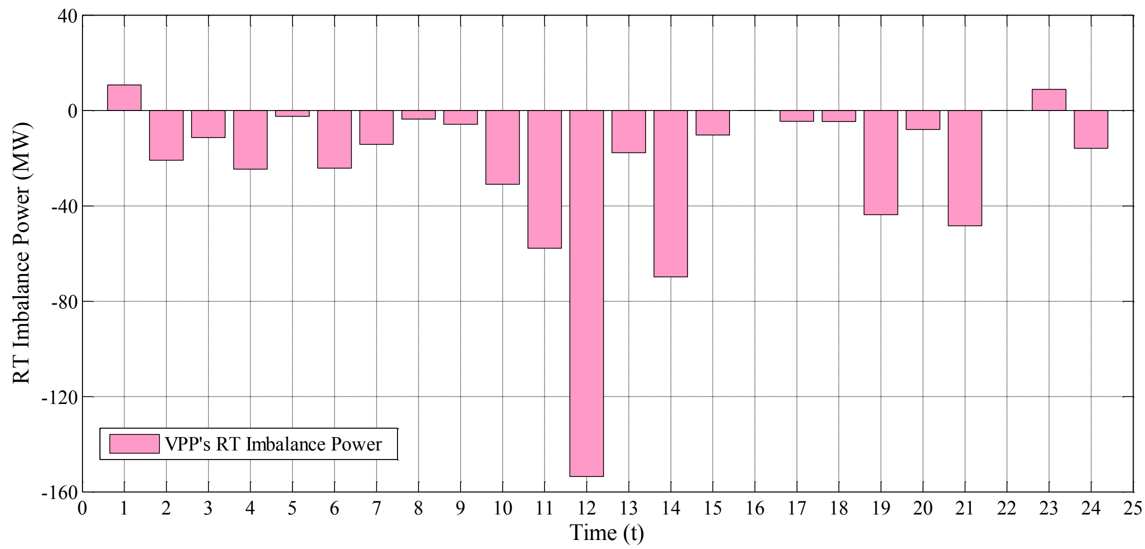

Fig. 8. VPP's RT imbalance power in scenario 7 and in the absence of the BESS.

Table 6
VPP's revenue, imbalance cost, traded energy, and imbalance energy during the day in the absence of the BESS.

	DA Stage		RT Stage		Hourly Profit ($)
	Traded Energy (MWh)	Revenue ($)	Imbalance Energy (MWh)	Imbalance Cost ($)	
T1	163.4	4922.8	−47.6	2696.1	2226.7
T2	183.7	5532.2	−28.2	895.9	4636.2
T3	193.9	5537.1	−42.5	1328.5	4208.6
T4	163.0	4656.4	−53.1	1630.9	3025.5
T5	73.5	2100.3	−14.5	430.6	1669.7
T6	62.5	1881.8	−33.8	1092.1	789.7
T7	19.5	587.2	−13.9	450.2	137.0
T8	21.1	636.0	−5.4	355.2	280.8
T9	30.0	1881.3	−14.5	938.5	942.8
T10	99.8	8123.8	−42.2	3942.6	4181.3
T11	65.0	7241.0	−49.0	5340.7	1900.3
T12	154.0	18834.2	−150.1	18210.1	624.1
T13	20.0	2446.0	−13.1	1525.5	920.5
T14	99.0	10068.3	−76.1	7215.9	2852.4
T15	32.0	2604.8	−17.1	1313.0	1291.8
T16	3.1	192.8	−1.9	123.0	69.8
T17	7.8	490.1	−3.0	203.0	287.1
T18	35.1	2203.6	−17.9	1297.1	906.5
T19	53.5	3354.2	−27.3	2273.8	1080.4
T20	68.9	6232.8	−27.2	3278.4	2954.3
T21	61.1	6212.6	−33.4	3863.0	2349.6
T22	108.9	8868.0	−35.8	3726.7	5141.4
T23	35.0	2629.9	−12.5	1260.4	1369.5
T24	54.3	1635.4	−18.2	888.8	746.6
Total	1808.3	108872.7	−778.3	64280.0	44592.7

3.2. *Results and discussion*

The presented model in expressions (18)–(31) is a MILP problem that is solved in the GAMS software by the CPLEX solver. A computer with 8 GB RAM and Intel Core i7-4510U CPU (2.60-GHz) has been utilized for the simulation.

3.2.1. *Case study 1: Strategic VPP in the absence of the BESS*

In the first case, the offering strategy of the price-maker VPP is investigated without considering the flexible unit, i.e., the BESS. In this condition, the considered VPP is not able to adjust its shortage or surplus energy in the RT stage. As a result, the VPP is forced to pay the penalty for the existing difference between its DA accepted offer and its RT wind power productions. It is necessary to illustrate that this penalty is calculated according to the price of energy in the balancing market, as displayed in Eq. (1).

The accepted offer of the VPP in the DA WEM is depicted in Fig. 7. Moreover, in this figure, the DA market-clearing prices are represented as well.

Nonetheless, since the RT wind power productions of the VPP is directly related to wind speeds and their scenarios, there will be a difference between this entity's RT generations and its DA accepted offers. This difference for a typical scenario, scenario 7, is demonstrated in Fig. 8.

As shown in this figure, merely in two hours of the day, namely hours 1 and 23, the VPP has produced more power in the RT stage in comparison to the DA offers. Therefore, in the remaining hours, the VPP has encountered an energy shortage, and it has to pay the penalty for this imbalance to the market operator.

To better evaluate the total revenue, imbalance cost, and profit of the VPP during the studied day, the cost and revenue distribution of the entity in two DA and RT stages, as well as its traded and imbalance energy, are provided in more detail in Table 6. It should be pointed out that in this table, for calculating the imbalance cost and energy of the VPP in the RT stage, scenarios and their probability have also been taken into account. The last column of this table expresses the hourly profit of the studied VPP that has been achieved by subtracting the DA income from RT imbalance cost. Moreover, in the last row of the mentioned table, the VPP's total exchanged as well as imbalance energy in both stages has been calculated.

According to the obtained results, the daily revenue of the VPP from taking part in the DA WEM is equal to 108872.7 $. On the other hand, since the VPP does not have any flexible unit for adjusting its power in the RT stage, this strategic player has lost 64280.0 $ of its income. Hence, the VPP's final amount of profit has decreased to 44592.7 $.

3.2.2. *Case study 2: Strategic VPP in the presence of the BESS*

In the second case, the offering strategy of the studied VPP in the DA WEM is studied by considering the BESS, which is introduced in Table 4. In this case, the VPP can adjust its surplus or shortage energy in the RT stage via the storage capacity of the BESS.

Similar to case study 1, the accepted offer of the VPP in the DA WEM and the clearing price of the DA market at each hour of the studied day, are depicted in Fig. 9.

The significant point as to Fig. 9 is that in several hours of the day, the DA market-clearing prices have increased in comparison to the first

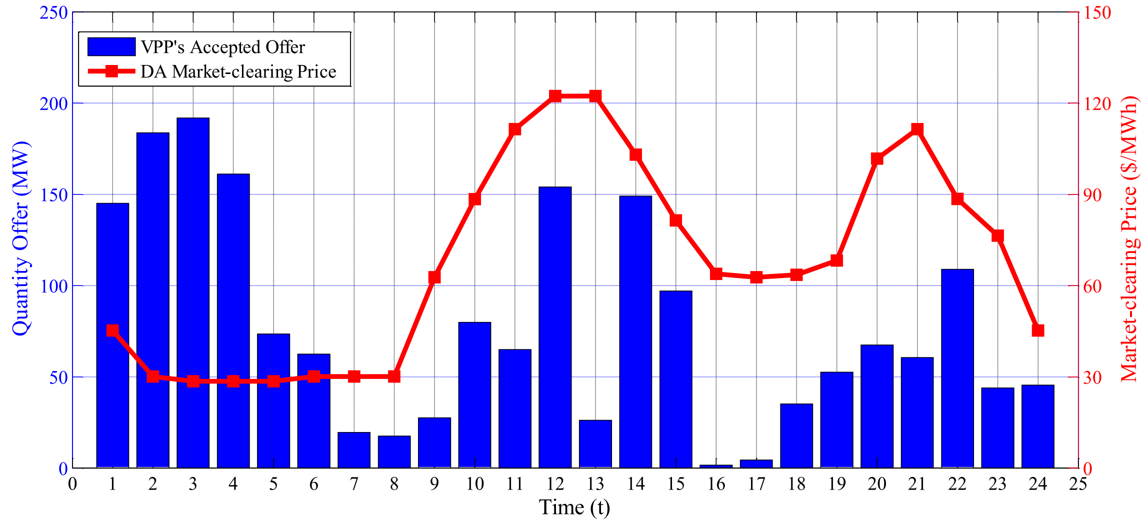

Fig. 9. VPP's accepted offer and the DA market-clearing price in the presence of the BESS.

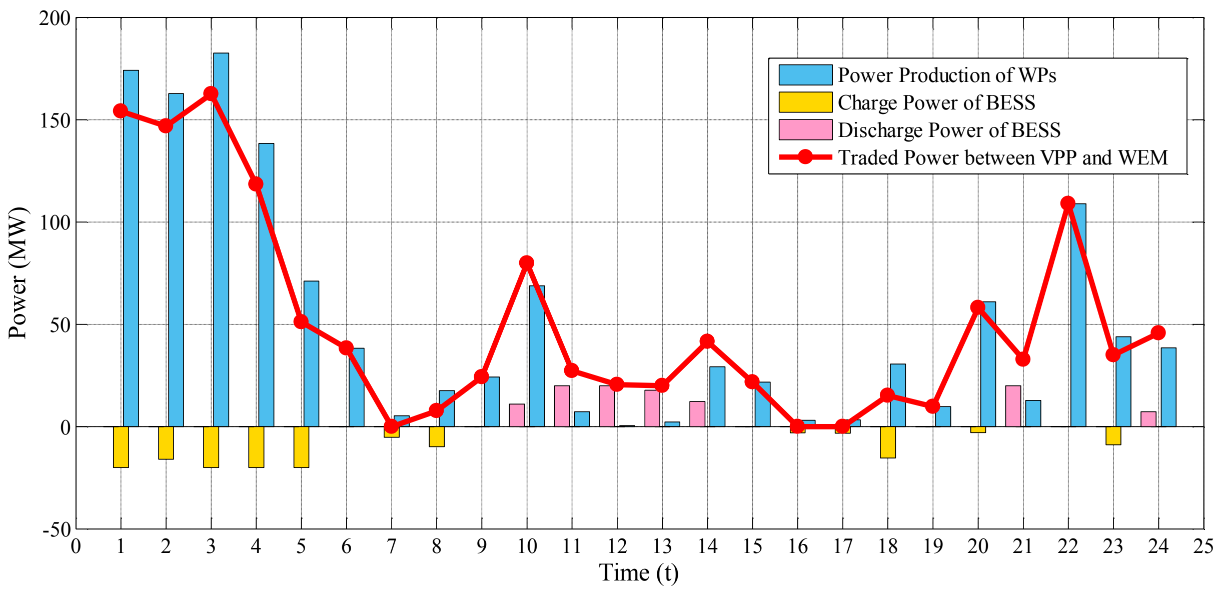

Fig. 10. VPP's traded power with the WEM in scenario 7 and in the presence of the BESS.

case. The reason is that in the presence of the flexible unit, the VPP's offers to the DA WEM have decreased. For instance, at hour 10, by reducing the offer of the price-maker VPP to the DA WEM up to 20 MW, the price of energy at this hour has increased up to 7 $ compared to case 1.

In order to investigate the role of the BESS in the RT operation of the VPP, the impact of the BESS' charged and discharged power on the traded energy between the VPP and WEM is illustrated for a sample scenario, namely scenario 7, in Fig. 10.

As shown in this figure, the VPP has adjusted its wind power generations by charging and discharging the BESS. In other words, the VPP has stored part of its produced power in the BESS during off-peak hours; hence its delivered power to the WEM is less than the output power of the available WPs. On the contrary, in peak hours, the VPP's delivered power to the WEM is more than the power production of WPs. That is because, in these hours, the BESS has discharged its power to the network. Indeed, the BESS' storage capacity has been exploited by the VPP in other to not only maximize its profit in the DA stage but also minimize its imbalance cost in the RT stage.

On the other hand, based on Fig. 1, each integrated unit inside the VPP is responsible for providing part of the exchanged power between the VPP and WEM in the RT stage. To evaluate the share of the existing resources, the total amount of produced energy by these units for scenario 7 has been depicted in Fig. 11. As it is clear, the highest share in the delivered energy to the WEM is related to the third WP, and the lowest share is related to the BESS. Furthermore, this figure displays the VPP's total traded energy with the WEM in the RT stage, as well as its DA accepted offer during the whole day. The difference between these two aforementioned parameters leads the VPP to lose some part of its obtained DA profit in the RT stage.

In addition, for scenario 7, the share of each WP in charging the BESS is shown in Fig. 12. Obviously, the entire WPs have stored part of their generations in the BESS, and the largest share belongs to the first WP. Note that the difference between the BESS' charged energy and its discharged energy to the WEM is due to the energy loss in the charging/discharging procedures, as well as the remaining energy in the battery at the end of the day.

As clear in the above figures, the problem formulation of this research work is conducted in such a way that the net power exchanges between components of the VPP are calculated precisely. Thus, by

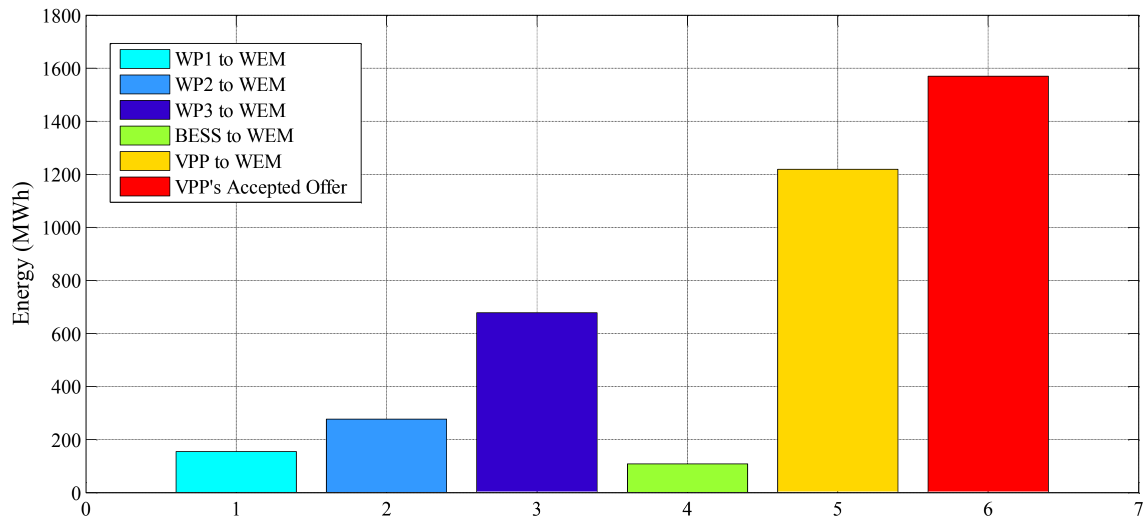

Fig. 11. Share of each unit in the RT traded power between the VPP and WEM in scenario 7.

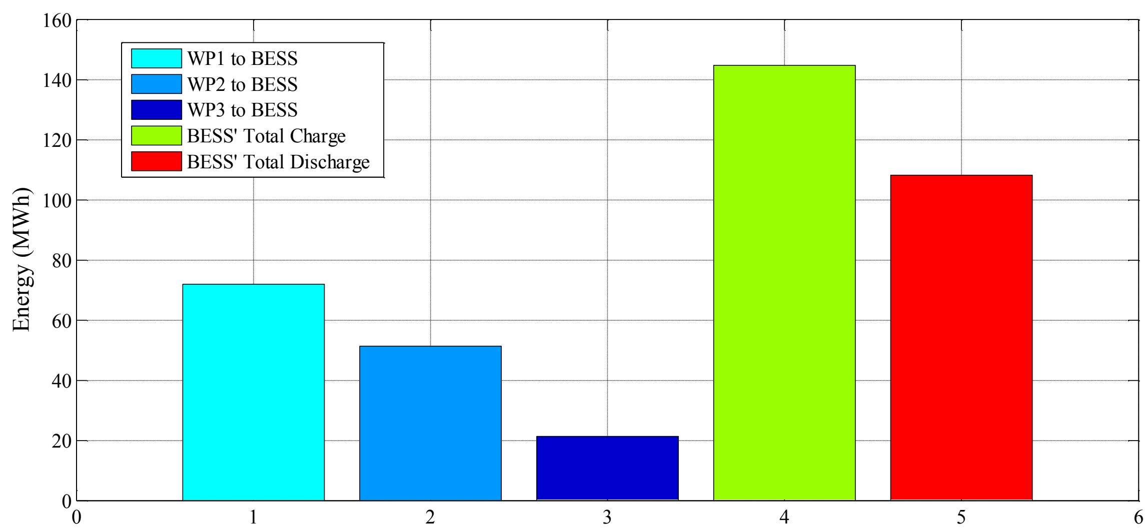

Fig. 12. Share of each WP in charging the BESS in scenario 7.

Table 7
WPs traded energy with the WEM and BESS in different scenarios.

	WP1		WP2		WP3	
	to WEM (MWh)	to BESS (MWh)	to WEM (MWh)	to BESS (MWh)	to WEM (MWh)	to BESS (MWh)
S1	158.6	91.8	117.0	18.4	497.8	8.1
S2	231.8	96.8	226.5	2.5	520.7	24.5
S3	159.7	71.7	171.0	33.3	537.7	46.0
S4	79.8	76.0	124.6	20.4	468.4	74.7
S5	132.8	110.3	170.4	29.7	541.3	22.0
S5	161.9	94.2	232.9	10.3	488.5	45.1
S7	154.6	72.0	277.4	51.4	678.7	21.4
S8	177.7	83.2	175.9	10.4	582.8	41.6
S9	300.1	111.3	121.2	9.4	439.8	30.6
S10	131.7	107.9	200.1	1.9	534.3	62.0
Total	162.1	91.1	185.2	21.2	533.6	36.8

utilizing this method, several privately owned resources are able to involve in different electricity markets in the form of a coalition, i.e. VPP, and settle financial transactions with respect to their traded energy with one another. This issue is highly important since the amount of exchanged power among the VPP's components has not been determined in previous studies. Indeed, the proposed method of this study provides a structure for the cooperative collaboration of several WPs with the BESS.

Table 7 compares the performance of WPs in different scenarios. In this table, the amount of WPs' traded energy with the WEM and BESS are reported separately. In the last row of the table, based on the occurrence probability of each scenario, the total energy during the studied day is calculated. As shown, WP1 has the most transferred energy to the BESS, and WP3 has the most delivered energy to the WEM. Moreover, WP1 has the highest wind power generation in scenario 3, while WP2 and WP3 have the highest wind power production in scenario 7. This issue arises from the different wind speeds in the WPs' installed sites.

In this case study, the strategic VPP's profit, revenue, imbalance cost, traded energy, and finally, imbalance energy in each hour of the day in both DA and RT stages are also investigated, as stated in Table 8. Similar to Table 6, in order to determine the imbalance energy and cost of the VPP in the RT stage, scenarios and their probability of occurrence have been considered. Accordingly, the VPP has obtained 98919.3 $ income from participation in the DA WEM. On the contrary, the VPP's imbalance cost in the RT stage is equal to 46316.8 $ owing to the existence of the imbalance energy. Therefore, according to the last column of the

Table 8
VPP's revenue, imbalance cost, traded energy, and imbalance energy during the day in the presence of the BESS.

	DA Stage		RT Stage		Hourly Profit ($)
	Traded Energy (MWh)	Revenue ($)	Imbalance Energy (MWh)	Imbalance Cost ($)	
T1	143.4	4320.4	−41.7	2381.8	1938.6
T2	163.7	4929.8	−21.7	691.8	4238.0
T3	173.9	4965.9	−41.3	1291.0	3674.8
T4	143.0	4085.2	−53.1	1630.9	2454.3
T5	53.5	1529.1	−14.3	422.8	1106.3
T6	42.5	1279.4	−24.6	782.0	497.4
T7	0.0	0.0	0.0	0.0	0.0
T8	7.6	230.0	−0.1	33.7	1960.3
T9	30.0	1881.3	−12.4	802.2	1079.1
T10	79.8	6495.8	−22.1	2000.3	4495.5
T11	65.0	7241.0	−29.0	3185.0	4056.0
T12	154.0	18834.2	−130.1	15784.8	3049.4
T13	20.0	2446.0	0.0	0.0	2446.0
T14	99.0	10068.3	−64.0	6063.5	4004.8
T15	32.0	2604.8	−24.1	1838.3	766.5
T16	0.1	5.6	−0.1	5.0	0.6
T17	4.7	296.9	−4.3	289.1	7.7
T18	15.1	949.6	−8.6	608.1	341.5
T19	30.0	2046.0	−8.8	935.6	1110.4
T20	58.0	5246.5	−6.7	774.1	4472.4
T21	64.9	6595.8	−19.8	2303.6	4292.3
T22	108.9	8861.3	−31.0	3007.4	5853.9
T23	35.0	2629.9	−12.1	1027.5	1602.4
T24	45.7	1376.5	−9.7	458.2	918.2
Total	1569.9	98919.3	−579.8	46316.8	52602.4

Table 9
Comparison between two case studies.

	DA Stage		RT Stage		Profit ($)
	Traded Energy (MWh)	Revenue ($)	Imbalance Energy (MWh)	Imbalance Cost ($)	
Case 1	1808.3	108872.7	778.3	64280.0	44592.7
Case 2	1569.9	98919.3	579.8	46316.8	52602.4
Difference	−238.4	−9953.4	−198.5	17963.1	8009.7
Difference (%)	−13.2	−9.1	−25.5	−27.9	18.0

table, the final profit of the strategic VPP is equal to 52602.4 $, which has a significant increase in comparison to case 1.

In the end, the optimal performance of the considered VPP in both cases is compared in Table 9. Accordingly, the offered energy by the VPP to the DA WEM in case 2 has decreased up to 238.4 MWh in comparison to case 1. As a result, the DA income of the VPP, in this case, has decreased up to 9953.4 $, namely 9.1%. On the other hand, in the RT stage, this entity's imbalance energy in case 2 has diminished up to 198.5 MWh as opposed to case 1. This matter has led to a decrease in the imbalance cost of the VPP up to 17963.1 $, namely 27.9%. To sum up, the VPP's ultimate amount of profit in case 2 has increased up to 8009.7 $, or 18%, compared to case1.

3.2.3. *Sensitivity analysis*

As illustrated in the first and second case studies, the VPP's optimal operation in the DA WEM, as well as its final profit, are affected by various factors, some of which are wind speed, RT imbalance price, storage capacity of the BESS, and finally, charging/discharging capacity of the BESS. In the following, to better investigate the impact of the BESS' storage and charging/discharging capacities as well as RT imbalance prices on the VPP's obtained profit, sensitivity analysis is conducted in three different parts. To this end, by keeping all parameters but one constant, the effect of the studied parameter on the strategic VPP's daily benefit is assessed.

3.2.3.1. Sensitivity analysis of the BESS' storage capacity. The expected profit of the VPP is closely related to the storage capacity of the BESS. In other words, the VPP's benefit can be enhanced considerably by reducing its RT imbalance cost in the presence of more storage capacity. To prove this matter, by altering the storage capacity of the BESS from zero to 170 MWh, the amount of the VPP's profit is calculated. The variation of the VPP's benefit with regard to the variation of the BESS' storage capacity is depicted in Fig. 13.

Based on the above figure, initially, the derivative of VPP's profit with regard to the BESS' storage capacity is reasonable. Nonetheless, gradually, by an increase in the storage capacity of the BESS, the derivative of the profit reduces and finally reaches the saturation zone. Ultimately, in capacities greater than 160 MWh, by an increase in the capacity, the profit of the VPP remains constant. Additionally, as it is clear in the above figure, the VPP's profit in the capacity of 10 MWh is lower than its profit in the capacity of 0 MWh. The reason is that, the cost of the lost energy during the charging and discharging procedure is

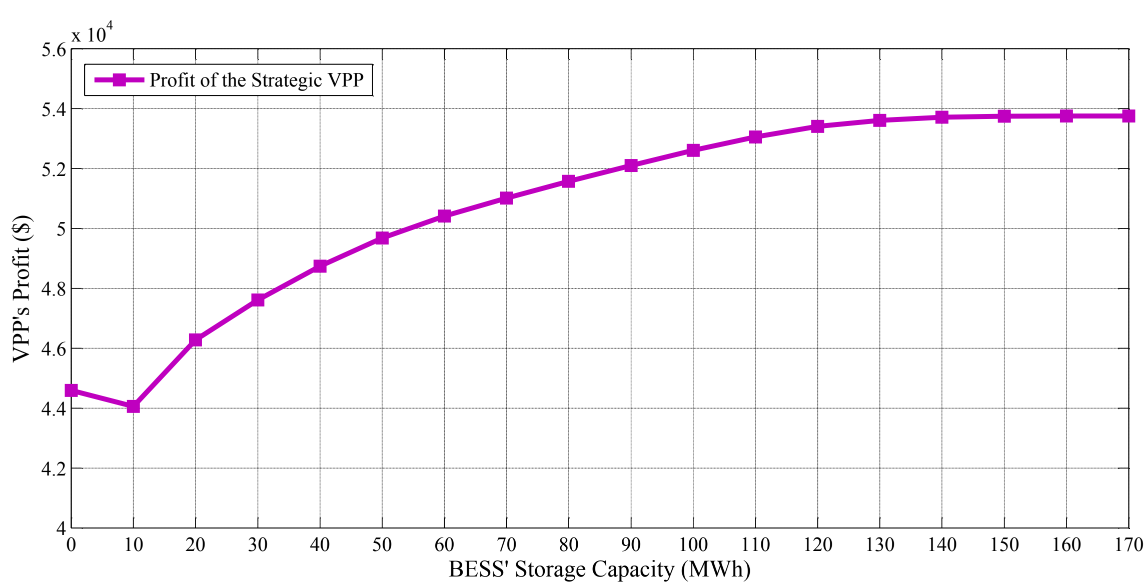

Fig. 13. Sensitivity analysis of the BESS' storage capacity.

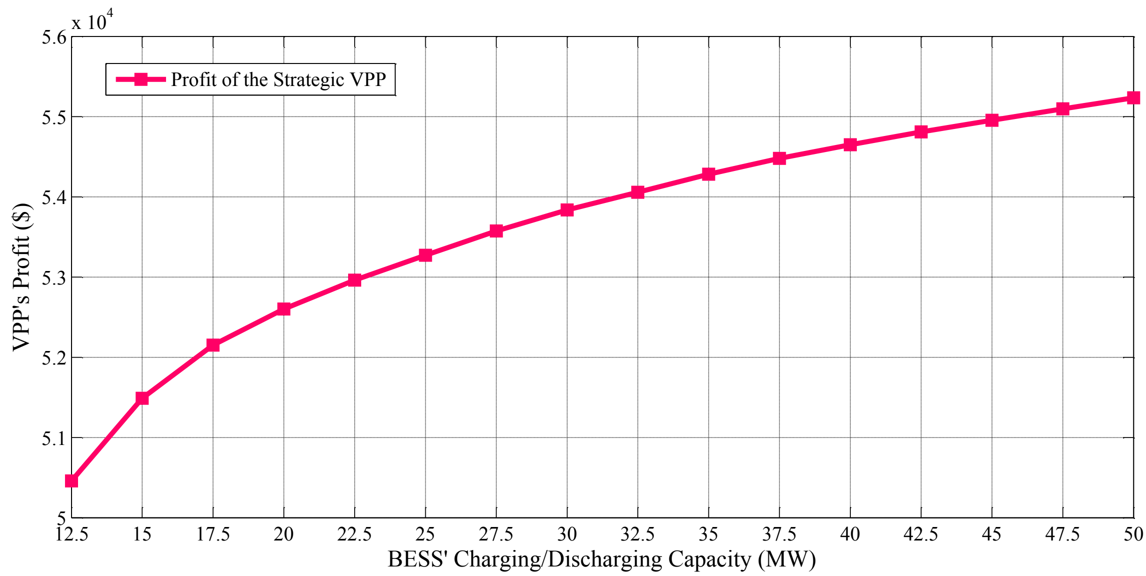

Fig. 14. Sensitivity analysis of the BESS' charging/discharging capacity.

Table 10
Sensitivity analysis of the RT imbalance price.

Studied Cases	RT Imbalance Price ($/MWh)	DA Revenue ($)	RT Imbalance Cost ($)	Daily Profit ($)
Case 1	70% Base RT Price	248509.6	−154568.9	93940.7
Case 2	80% Base RT Price	203043.9	−129458.2	73585.7
Case 3	90% Base RT Price	156560.2	−97112.5	59447.8
Base Case	Base RT Price	98919.3	−46316.8	52602.4
Case 4	110% Base RT Price	69497.9	−19650.3	49847.7
Case 5	120% Base RT Price	64696.3	−16356.3	48340.0
Case 6	130% Base RT Price	62510.4	−15421.8	47088.5

greater than the reduction in the VPP's RT imbalance cost. As a result, in the low storage capacities, the profit of the considered VPP is reduced.

3.2.3.2. Sensitivity analysis of the BESS' charge/discharge capacity. In this case, the effect of changes in the charge/discharge capacity of the BESS on the VPP's daily benefit is analyzed. For this purpose, the BESS' charging/discharging capacity is increased from 12.5 MW to 50 MW with steps 2.5 MW. The variation of the VPP's profit with regard to the variation of the BESS' charge/discharge capacity is demonstrated in Fig. 14.

As could be expected, by increasing the capacity of charge/discharge, the amount of profit has enhanced as well. Similar to the previous sensitivity analysis, firstly, the profit has enhanced remarkably. However, gradually, this increase in the amount of benefit has diminished. For instance, by increasing the charging/discharging capacity from 12.5 MW to 15 MW, the strategic VPP's profit has increased up to 1030 $. Nevertheless, by enhancing the capacity from 47.5 MW to 50 MW, the expected profit has only increased nearly about 139 $.

Therefore, WPs are able to estimate their optimal investment in energy storage sectors by conducting similar sensitivity analysis in order to maximize their daily profit from participation in varied electricity markets.

3.2.3.3. Sensitivity analysis of the RT imbalance price. By keeping the technical specifications of the considered BESS constant, the alteration of the benefit of the VPP with regard to the alteration of the RT imbalance price is scrutinized in this section. For this goal, six different cases are investigated in which the RT imbalance prices are changed by 30%, 20%, and 10% compared to the base case.

Accordingly, in cases 1, 2, and 3, the RT imbalance price has been decreased up to 30%, 20%, and 10%, respectively, compared to the base RT imbalance price, which is displayed in Fig. 6. On the contrary, in cases 4, 5, and 6, the RT imbalance price has been increased up to 10%, 20%, and 30%, respectively, compared to the base RT imbalance price. In Table 10, the DA revenue, RT imbalance cost, and profit of the VPP in these cases are compared with each other.

As clear in the above table, in the first case, which has the lowest RT imbalance price, the VPP's highest possible amount of profit has been achieved. By increasing the RT imbalance price in case 2, the expected profit has diminished considerably. Nonetheless, gradually, by increasing the RT imbalance price, the rate of profit reduction has decreased. For example, in the first step, the daily benefit of the VPP has decreased up to 20,355 $, while in the last step, this profit has diminished nearly about 1251 $.

4. Conclusion

The participation of WPs in the WEM is one of the most serious challenges of power networks with high wind penetration owing to the stochastic nature of their energy productions. One of the efficient approaches for the WPs' optimal participation in electricity markets that promote their net profits is aggregating them in the form of a VPP. This study presented an offering strategy for a wind-based VPP as a price-maker participant in the DA WEM. To this end, a bi-level scheme was proposed, in which at the UL of the problem, the VPP optimizes its profit, and at the L, the DA energy price is extracted by modeling the DA WEM. Consequently, in the presented formulation, the VPP was able to determine the market-clearing price by adjusting its offers to the WEM. Moreover, in this study, for reducing the VPP's imbalance cost in the RT stage, the coordination of WPs with a large-scale BESS was suggested. Accordingly, the VPP has the capability to decrease its RT imbalance cost by utilizing the storage capacity of the flexible unit.

Finally, two case studies, with and without the presence of the BESS, were performed to investigate the flexible unit's impact on the optimal performance of the strategic VPP. The obtained results demonstrated that the BESS has a significant role in reducing the RT imbalance cost and leads to an increase in the VPP's profit up to 18%. On the other hand, the sensitivity of the VPP's total profit to different factors like the storage capacity of the BESS, charge/discharge capacity of the BESS, and

RT imbalance price was also analyzed in this article.

CRediT authorship contribution statement

Mojtaba Dadashi: Conceptualization, Methodology, Writing – original draft. **Kazem Zare:** Supervision, Project administration, Writing – review & editing. **Heresh Seyedi:** Validation, Formal analysis. **Miadreza Shafie-khah:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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