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A robust model for aggregated bidding of energy storages and wind resources in the joint energy and reserve markets

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ABSTRACT

The high reliability and flexibility of Battery Energy Storage (BES) resources in comparison with other renewable technologies promote the development of this technology in smart grids. The fast response of BES to load variations could help the power system operators to maintain the balance of generation and consumption in real-time, and improve the flexibility of the smart grid, effectively. In this work, a new model is presented that determines the aggregated scheduling of BES and Wind Power Resource (WPR) in the joint energy and reserve markets. To evaluate the performance of BES in different markets, the proposed model is divided into day-ahead and real-time planning horizons. According to market prices, ramp rates, marginal costs, and technical constraints of units, the optimal participation levels in different markets are determined. The deployed power in real-time and wind power are considered as the uncertain parameters and the Robust Optimization (RO) framework is proposed to manage the related financial risk based on the worst-case realizations of uncertain parameters. The robust strategy is formulated based on the Mixed Integer Linear Programming (MILP) technique, which can be solved via the branch-and-bound method. Finally, the performance and effectiveness of the model are analyzed via different case studies. Simulation results show that the day-ahead and real-time markets are the best options for buying and selling the energy of BESs, and participation in the reserve market and regulation service increases their profit, significantly. Furthermore, the expected profit greatly depends on the risk preferences of decision-makers, and reducing the variation interval of wind generation by 40 % leads to an increase of 74.65 % in revenues.

1. Introduction

By increasing the penetration level of renewable energy resources in smart distribution grids, market operators face a new challenge that is the balance of consumption and generation in real-time operation. A study by Ref. [1] found that 10 % wind penetration for Scandinavian countries increases reserve requirements by 1.5%–4% of installed wind capacity. Uncertainty of renewable resources such as solar and wind power could disrupt the energy balance and threaten the security of grid. The system operators can utilize flexible resources to neutralize the unpredicted fluctuations of renewable units. Battery Energy Storage (BES) is a promising solution to improve the flexibility of grid. BESs can be used as the backup unit to compensate variations of renewable energy resources such as wind power [2–4]. Despite other renewable units such as wind and solar units that use free energy resources, BESs shall purchase the required electrical energy for charging in low-price periods, and resell it to the grid by discharging electricity in high price periods. Therefore, the profitability of BESs is highly dependent on the structure of the electricity and distribution grid tariffs. Moreover, continues charging and discharging cycles reduce the lifetime of BES that shall be considered in the optimal scheduling [5]. The main advantages of BES in comparison with other renewable technologies are the controllability, fast response, and high ramp rates that could increase its participation level in the reserve and ancillary service markets. Additionally, participation of BES in the joint energy and reserve markets improves the profitability of these units as well as profit margin [6].

The optimal scheduling of BESs and WPRs has been studied in different technical references. Aspects of energy storage economics with respect to arbitrage and regulation are discussed in Ref. [7].

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Nomenclature and abbreviation

Indices and Set

t, T Index and set of hourly time category
$j(\&j', k), N_j$ Index and set of intra-hourly time category
s, N_s Index and set of storages
w, N_w Index and set of wind resources

Constants and Parameters

π^{DA} Day-ahead prices ($/MWh)
π^{RS} Reserve price ($/MWh)
π^{UR}, π^{DR} Up and down regulation prices ($/MWh)
$\rho_s^{CH}, \rho_s^{DCH}$ Marginal cost of BES *sth* in charging and discharging modes ($/MWh)
ρ_w Marginal cost of WPR w*th* ($/MWh)
R_s Ramp-rate of BES *sth* (MW)
R_w Ramp-rate of WPR *wth* (MW)
$P_s^{\min,DCH}, P_s^{\max,DCH}$ Minimum and maximum power of BES s*th* in discharging mode (MW)
$P_s^{\min,CH}, P_s^{\max,CH}$ Minimum and maximum power of BES s*th* in charging mode (MW)
$E_s^{\min}, E_s^{\max}$ Minimum and maximum energy of BES *sth* (MWh)
$P_w^{\min}, P_w^{\max}$ Minimum and maximum capacity of WPR w*th* (MW)
$\overline{P}^{UR}, \overline{P}^{DR}$ Expected deployed power in up and down regulation services (MW)
$\Delta P^{UR}, \Delta P^{DR}$ Variation interval of deployed power in up and down regulation services (MW)
$\overline{P}_w^{RT}$ Expected wind power realization *w*th (MW)
$\Delta\overline{P}_w^{RT}$ Variation interval of wind power realization *w*th (MW)
M Auxiliary constant for linearization
ΔS Duration of intra-hourly interval (h)

Functions

B Income function of owner
C Cost function of owner

Decision variables

$P^{DA,S}, P^{DA,B}$ Selling and buying bids in the day-ahead market (MW)
P^{RS} Reserve bid (MW)
P^{UR}, P^{DR} Deployed power in the up and down regulation services (MW)
$P_s^{DA,CH}, P_s^{DA,DCH}$ Day-ahead scheduling of BES *sth* in charging and discharging modes (MW)
$P_s^{UR,CH}, P_s^{DR,CH}$ Deployed up and down regulation power of BES *sth* in charging mode (MW)
$P_s^{UR,DCH}, P_s^{DR,DCH}$ Deployed up and down regulation power of BES *sth* in discharging mode (MW)
$P_s^{RS,CH}, P_s^{RS,DCH}$ Reserve scheduling of BES s*th* in charging and discharging modes (MW)
P_w^{DA} Day-ahead scheduling of WPR w*th* (MW)
P_w^{UR}, P_w^{DR} Deployed up and down regulation power of WPR w*th* (MW)
P_w^{RS} Reserve scheduling of WPR w*th* (MW)
P_w^{SP} Spilled power of WPR w*th* (MW)
E_s Energy level of BES s*th* (MWh)
P_w^{RT} Realization of wind power in real-time (MW)
A Auxiliary variables for linearization
Γ Auxiliary variable of RO

Binary Variables

α_s, β_s Charging and discharging binary variables of BES *s*th
u_w Commitment status binary variable of WPR w*th*

Abbreviation

BES Battery energy storage
DoD Depth of discharge
DA Day-ahead
MILP Mixed integer linear programming
RO Robust optimization
RT Real time
WPR Wind power resource

Moreover, a deterministic linear model is proposed for scheduling BESs in the day-ahead and real-time markets based on the lifetime constraint and the ancillary market is considered as a source of revenue for the BES. The performance of this model can be improved by considering the technical characteristics of BESs such as ramp-rate. Base on the results of the model, participating in the regulation service market has the potential to generate high revenues. In smart distribution grids, batteries of the electric vehicle can be used to provide the required energy and flexibility of grid [8]. However, the accessibility and location of mobile batteries are still the main challenges of grid operators in utilizing these resources. In Ref. [9], hybrid artificial intelligence technique is proposed for the coordination in the scheduling of mobile BES and photovoltaic panels. In the proposed objective function, different terms such as operation cost of distributed generation units, energy procurement, remunerations of storages, and penalty cost are considered. The uncertainty of renewable resources is an important parameter that has been neglected in this model. Additionally, the proposed model is non-linear and meta-heuristic method is used to solve it. Therefore, the global optimum solution cannot be guaranteed in all circumstances. The proposed stochastic model in Ref. [10] demonstrates that utilizing BES and demand response programs could decrease the operational cost of distribution grids. In this work, a two-stage stochastic model is presented that the optimal scheduling of resources and constraints of grid are evaluated in the upper and lower sub-problems. The available capacity of portable energy storages is considered as an uncertainty. According to the presented results, BES or demand response programs can diminish the negative impact of uncertain parameter. In Refs. [11,12], the uncertainty of mobile BESs' location is modeled in the scheduling problem. It shall be noted that mobile batteries can be charged or discharged in different locations. In Ref. [11], an integer-based stochastic model is proposed to determine the transportation scheme (time and location) of mobile batteries. Therefore, the uncertainty of batteries' location can be considered in the optimal scheduling. Towards minimizing the cost of power imported from the grid, a day-ahead energy management system is proposed for mobile BES in Ref. [12]. Additionally, in the proposed model of [12], the mobile energy storages are used for the voltage control in the distribution network. Purchasing energy in low price period and reselling it within high price period is a solution for gaining profit [13]. A method for generating predictive electricity price signals is presented in Ref. [13] to aid BES operators in making arbitrage decisions. In the proposed stochastic model of [13], the low and high price thresholds are determined for selling and buying energy in the energy market, respectively. In Ref. [14], the scheduling of

BES in the joint energy and regulation markets is formulated as a stochastic bi-level optimization problem that the expected profit of energy storages and social welfare are maximized in the upper and lower sub-problems, respectively. The optimal solution of the proposed model determines the day-ahead scheduling, deployed power in the reserve market, and the balancing market prices. To solve the proposed problem, the lower sub-problem is replaced by the Karush-Kuhn-Tucker (KKT) optimality conditions, and the bi-level problem is converted to a single-level problem. The uncertainty of consumption is evaluated by different scenarios. In other words, the results are sensitive to the initial assumptions, which are considered to generate scenarios. In smart grids, the market-clearing prices are determined by the grid operators, and according to the price signals, participants schedule their self-generating units [15]. The bi-level optimization framework that is presented by Ref. [15] specifies the market-clearing price and scheduling of BESs. The proposed upper minimization sub-problem calculates the clearing price, and the lower maximization sub-problem determines the optimal scheduling of BES. In this work, a possibilistic-stochastic approach is presented to model the data-based and human dependent uncertain parameters such as consumption, generation of photovoltaic panels, wholesale prices and swapping request. One of the main challenges in the aggregated scheduling of BESs and WPRs is variations of uncertain parameters such as energy prices, wind generation [2], deployed power in the regulation market [16]. The proposed methods for modeling the uncertain parameters can be categorized as stochastic and deterministic frameworks [15,17,18]. In the stochastic framework, the behavior of uncertain parameters is approximated by probabilistic distribution functions. Therefore, the achieved results depend on the assumptions and approximations, which are considered to calculate the probabilistic distribution functions. In Ref. [19], the operation of wind and photovoltaic systems with energy storage devices in terms of a two-stage stochastic programming problem is presented. This model has two variables, first-stage variables are the optimal bids and energy flow in the batteries, and second-stage variables are the energy deviations. Additionally, electricity market price, wind, and photovoltaic powers are main sources of uncertainties that is considered in this model. Sometimes due to the lack of data to reliably select a probabilistic model or incomplete understanding of the behavior of uncertain parameters, it is not possible to use stochastic models [20]. In the deterministic or robust framework, a variation interval is considered for the uncertain parameter, and the optimal strategy is determined based on the worst-case realization of uncertain parameters. Therefore, within the variation bound, the optimal strategy guarantees that the expected profit/cost will not be less/more than the calculated value. In other words, the optimal solution is robust against the fluctuations of uncertain parameters within the variation interval.

In [21], a two-stage robust model is presented for coordination between BESs and demand response programs to promote the profit of electricity supplier. An analysis of the profitability strategy has also been conducted based on the energy storage system's capacity. In Ref. [22], a robust model is proposed for the scheduling of BES according to the uncertainties of solar power and energy prices. In the proposed model, BES is used as the backup resource to compensate variations of produced power by solar panels. The production of solar panels and electricity price are two sources of uncertainty, which are considered in Ref. [22]. These uncertain parameters are characterized by a controllable polyhedral uncertainty. In Ref. [16], a robust model is proposed for simultaneous offering of BES in day-ahead energy, spinning reserve, and regulation markets. In this work, market prices as well as energy deployment in spinning reserve and regulation markets are considered as the uncertain parameters. This model is linearized by strong duality theorem that reduces the computational complexities. In Ref. [23], the coordinated operational dispatch scheme for WPR and BES is evaluated. The main advantage of the proposed dispatch scheme is that it can reduce the impact of wind power forecast errors while extending the lifetime of BES. The model is suitable for planning problems, but not for operations. To reduce the impact of wind power fluctuations by using BES, a new coordination control method is presented in Ref. [24] that determines optimal set power point of BES based on the variations of wind generation. However, this model can be used to control the coordinated generation of BES and WPR without considering economic optimization. The proposed risk-based model [25] for the coordinated operation of WPR and BES, minimizes the power deviation penalty for the real-time operation while simultaneously maximizing profit for the real-time bidding. Additionally, the wind uncertainty is modeled by the stochastic approach. The battery degradation model developed in Ref. [26] can accurately predict battery degradation and related costs during battery operation and cycling.

Literature review demonstrates that less attention has been paid to the aggregated bidding strategy of BESs and WPRs in the multiple markets based on the technical constraints of resources and uncertainties of the market. As shown in Fig. 1, based on the technical constraints of generating units and forecasts, owners of BESs and WPRs can submit aggregated energy and reserve bids in the day-ahead market. The power system operator deploys reserve power based on the accepted bids, in order to maintain a balance between generation and consumption. It shall be noted that the deployed power in the regulation service is an uncertain parameter that is determined based on the imbalance power of the system in the real-time. Furthermore, wind power is very volatile, and if the owners cannot provide the deployed power that is determined by the power system operator, they will be penalized. BESs can be used as a backup resource to compensate the uncertainty of wind power. The aggregated bidding strategy gives the owner of resources an opportunity to compensate for variation in wind power through proper scheduling of BESs. In this work, a robust model is proposed for the aggregated bidding strategy of BESs and WPRs in the joint energy and reserve markets. In the presented model, the renewable resources' owners can sell the generating power to day-ahead,

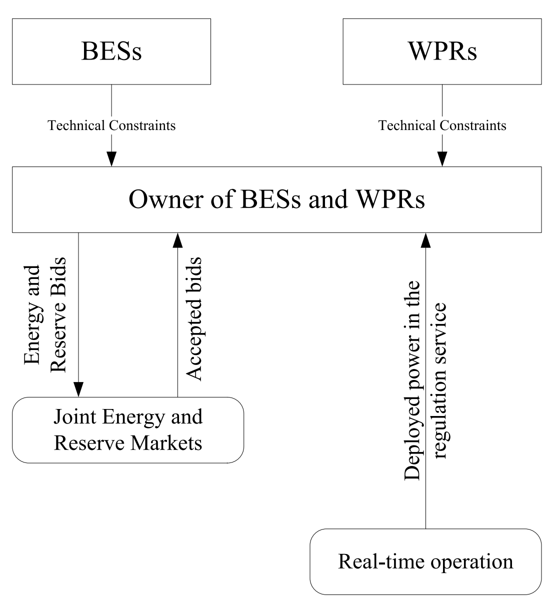

Fig. 1. BES and WPR participation in multiple markets.

reserve markets. Moreover, the required energy for BES charging can be supplied from the day-ahead market. To cover the fluctuations of WPRs, BES is used as the backup resource. Therefore, the proposed model could demonstrate the value of BES's flexibility to compensate the uncertainty of WPR in the aggregated bidding strategy.

To show the effectiveness of BESs, the optimization problem is decomposed in the day-ahead and real-time planning horizons. The wind power generation and the deployed power in the real-time regulation service are considered as uncertainty resources, and the RO method is proposed to manage the related financial risk. In the RO methodology, the uncertain parameters are characterized by a variation bound, and the optimal scheduling in joint energy and ancillary service markets is determined based on the worst-case realizations of prices and wind power. To improve the accuracy of results, the model is linearized by the big M theory, and it is formulated based on the MILP method [26]. Finally, the branch-and-bound algorithm is addressed to solve the proposed MILP-based optimization problem. The research gaps, which are covered in this work are:

- Modeling of technical aspects of BESs and WPRs for aggregated bidding strategy in the joint energy and reserve markets,
- Evaluating the impacts of uncertainties associated with deployed power in the regulation service and wind power generation.

The main contributions of this work can be summarized as follows:

- In this work, a new aggregated bidding strategy is proposed for coordinated operation of BESs and WPRs instead of using the storage as the backup unit of the wind resources. Therefore, the decision makers are able to reschedule their resource after acceptance of bids in the joint energy and reserve markets.
- Based on the uncertainties of wind generation and the deployed power in the regulation service market, a robust model is presented for the aggregated bidding strategy of BESs and WPRs in the joint energy and reserve markets. Using the aggregated bidding model, owners can reduce the financial risk associated with uncertain parameters in the optimal strategy.
- Based on technical constraints and flexibility of generating units, this model can determine the optimal participation level of resources in multiple markets. The proposed model can show the value of BESs' flexibility in reserve and regulation markets. To improve the accuracy of the results, the risk-based model is linearized, which increases the model's running speed in real-time simulations.

Fig. 2 summarizes the procedure of proposed scheduling model.

The rest of the paper is organized as follows: In section 2, the deterministic linear model for aggregated bidding strategy of BES and WPR in the multiple markets is presented. In section 3, the uncertain parameters and the related financial risk are modeled by RO methodology. To evaluate the performance and effectiveness of the model, the simulation results are given in section 4. Finally, conclusions are presented in section 5.

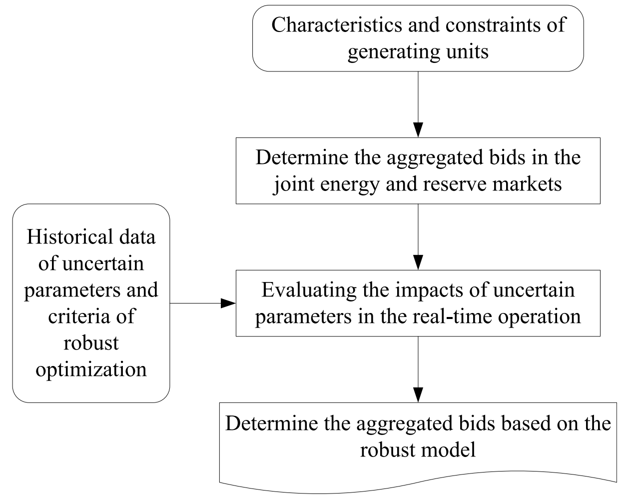

Fig. 2. Procedure of the proposed scheduling model.

2. Deterministic model for aggregated scheduling of BESs and WPRs

The profit maximization is the main objective of renewable resources' owner, as a private investor that is shown in Eq. (1):

$$Max \sum_{t=1}^{T} B_t - C_t \tag{1}$$

where:

B is the income function of owner,
$C$is the cost function of owner,
t and T are index and set of hourly time category.

As mentioned before, the generating power of BESs and WPRs can be sold in the day-ahead energy and reserve markets. Moreover, the required power for the charging BES can be purchased from the day-ahead market. Within the real-time horizon, the reserve bids are deployed in the up or down-regulation services. Therefore, the income function can be formulated by Eq. (2):

$$\begin{aligned} B_t = &\left(\pi_t^{DA}.P_t^{DA,S} - \pi_t^{DA}.P_t^{DA,B} + \pi_t^{RS}.P_t^{RS}\right) \\ &+ \left(\sum_{j=1}^{N_j} \Delta S_j.\left(\pi_{t,j}^{UR}.P_{t,j}^{UR} + \pi_{t,j}^{DR}.\mathrm{P}_{t,j}^{DR}\right)\right) \end{aligned} \tag{2}$$

where ΔS is the duration of interval hourly interval that is 5 min for the regulation service. In (2), the first and second terms represent the day-ahead and real-time incomes, respectively. The day-ahead income is calculated based on the net value of trading power in the energy market and reserve markets. The real-time income is specified based on the deployed power in the regulation ancillary service.

According to Eq. (3), the generation cost is calculated based on the marginal costs of BES and WPR:

$$C_t = \Delta S_j . \sum_{j=1}^{N_j} \left(\begin{array}{l} \sum_{s=1}^{N_s} \left(\begin{array}{l} \rho_s^{DCH} . P_{t,j,s}^{DA,DCH} \\ + \rho_s^{CH} . P_{t,j,s}^{DA,CH} \end{array} \right) \\ + \sum_{w=1}^{N_w} \rho_w . P_{t,j,w}^{DA} \end{array} \right) + \Delta S_j . \sum_{j=1}^{N_j} \left(\begin{array}{l} \sum_{s=1}^{N_s} \left(\begin{array}{l} \rho_s^{DCH} . \left(P_{t,j,s}^{UR,DCH} - P_{t,j,s}^{DR,DCH} \right) \\ + \rho_s^{CH} . \left(P_{t,j,s}^{DR,CH} - P_{t,j,s}^{UR,CH} \right) \end{array} \right) + \\ \sum_{w=1}^{N_w} \rho_w . \left(P_{t,j,w}^{UR} - P_{t,j,w}^{DR} \right) \end{array} \right); \quad \forall t \in T \tag{3}$$

where, $\rho_s^{CH} \rho_s^{DCH}$, and ρ_w are marginal costs of BES in charging and discharging modes, and wind resources, respectively. The first and second terms of Eq. (3) show the day-ahead and real-time costs. BES can participate in the up-regulation service by increasing/decreasing discharging/charging power. Similarly, in the down-regulation service, the discharging/charging power of BES shall be decreased/increased. Therefore, participation in the down/up-regulation service in discharging/charging mode decreases the generation cost of BESs and vice versa.

Equality constraints (4)–(6) shows that the day-ahead bids are fixed within intra-hourly periods.

$$P_{t,j,s}^{DA,DCH} = P_{t,j',s}^{DA,DCH}; \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, N_s, \forall j, j' = 1, \ldots, N_j \tag{4}$$

$$P_{t,j,s}^{DA,CH} = P_{t,j',s}^{DA,CH}; \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, N_s, \forall j, j' = 1, \ldots, N_j \tag{5}$$

$$P_{t,j,w}^{DA} = P_{t,j',w}^{DA}; \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, N_s, \forall j, j' = 1, \ldots, N_j \tag{6}$$

The day-ahead energy and reserve bids, and the real-time deployed power in the up and down regulation services can be represented by Eqs. (7)–(11), respectively.

$$P_t^{DA,S} = \sum_{s=1}^{N_s} P_{t,j,s}^{DA,DCH} + \sum_{w=1}^{N_w} P_{t,j,w}^{DA}; \quad \forall t \in T \tag{7}$$

$$P_t^{DA,B} = \sum_{s=1}^{N_s} P_{t,j,s}^{DA,CH}; \quad \forall t \in T \tag{8}$$

$$P_t^{RS} = \sum_{s=1}^{N_s} P_{t,j,s}^{RS,CH} + P_{t,j,s}^{RS,DCH} + \sum_{w=1}^{N_w} P_{t,j,w}^{RS}; \quad \forall t \in T \tag{9}$$

$$\mathrm{P}_{t,j}^{UR} = \sum_{s=1}^{N_s} P_{t,j,s}^{UR,DCH} + P_{t,j,s}^{UR,CH} + \sum_{w=1}^{N_w} P_{t,j,w}^{UR}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j \tag{10}$$

$$\mathrm{P}_{t,j}^{DR} = \sum_{s=1}^{N_s} P_{t,j,s}^{DR,DCH} + P_{t,j,s}^{DR,CH} + \sum_{w=1}^{N_w} P_{t,j,w}^{DR}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j \tag{11}$$

According to Eq. (12)–(14), the reserve bids are fixed within the intra-hourly period.

$$P_{t,j,s}^{RS,CH} = P_{t,j',s}^{RS,CH}; \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, N_s, \forall j, j' = 1, \ldots, N_j \tag{12}$$

$$P_{t,j,s}^{RS,DCH} = P_{t,j',s}^{RS,DCH}; \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, N_s, \forall j, j' = 1, \ldots, N_j \tag{13}$$

$$P_{t,j,w}^{RS} = P_{t,j',w}^{RS}; \quad \forall t = 1, \ldots, T, \forall w = 1, \ldots, N_w, \forall j, j' = 1, \ldots, N_j \tag{14}$$

In the day-ahead planning interval, P^{RS} is a variable and it is added as a constraint to the real-time optimization problem. Moreover, $\mathrm{P}_{t,j}^{UR}$ and $\mathrm{P}_{t,j}^{DR}$ are uncertain parameters, which are specified by the power system operator. The procedure of modeling these uncertain parameters will be presented in the next section. As shown in Eq. (15) and (16), the deployed power in the up and down-regulation services shall be less than the offered reserve capacity:

$$\mathrm{P}_{t,j}^{UR} \le P_t^{RS}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j \tag{15}$$

$$\mathrm{P}_{t,j}^{DR} \le P_t^{RS}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j \tag{16}$$

One of the main parameters that limits the operation of BES is the energy capacity. Eq. (17) provides the hourly and intra-hourly stored energy of BES.

$$E_{t,k,s} = E_{t,k-1,s} + \sum_{j=1}^{k} \Delta S_j . \left(P_{t,j,s}^{DA,CH} - P_{t,j,s}^{DA,DCH} + P_{t,j,s}^{DR,CH} - P_{t,j,s}^{UR,DCH} \right); \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, N_s, \forall k = 1, \ldots, N_j \tag{17}$$

As seen in Eq. (17), the stored energy depends on the energy level within the previous intra-hourly interval. Moreover, the index j is started from 1. To calculate $E_{t,1}$, the energy level at the previous period or $E_{t,0}$ is needed. According to Eq. (18), $E_{t,0}$ is equal to E_{t-1,N_j}. Equality constraint Eq. (19) shows that within the operation period, the net value of charged and discharged power is zero.

$$E_{t,0,s} = E_{t-1,N_j,s}; \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, N_s \tag{18}$$

$$E_{ini,s} = E_{T,N_j,s}; \quad \forall s = 1, \ldots, N_s \tag{19}$$

The main technical limitations of BESs and WPRs are capacity and ramp-rate constraints, which are represented as follows:

Capacity constraint: The capacity constraint contains the power capacity of BES in day-ahead planning (Eq. (20)–(25)), the deployed power of BES in regulation service (Eq. (26)–(31)), the energy capacity in the real-time (Eq. (32)), the capacity of WPR in the day-ahead planning (Eq. (33)–(36)), the deployed power of WPR in the regulation service (Eq. (37) and (38)). As mentioned before, that the wind generation capacity (P^{RT}) is an uncertain parameter. Therefore, in the day-ahead horizon, it is considered as a parameter that is specified in real-time planning.

$$P_s^{\min,CH} . \alpha_{t,j,s} \le P_{t,j,s}^{DA,CH} \le P_s^{\max,CH} . \alpha_{t,j,s}; \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, N_s, \forall j = 1, \ldots, N_j \tag{20}$$

$$0 \le P_{t,j,s}^{RS,CH} \le P_s^{\max,CH}.\alpha_{t,j,s} - P_{t,j,s}^{DA,CH}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{21}$$

$$P_{t,j,s}^{DA,CH} + P_{t,j,s}^{RS,CH} \le P_s^{\max,CH}.\alpha_{t,j,s}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{22}$$

$$P_s^{\min,CH}.\alpha_{t,j,s} \le P_{t,j,s}^{DA,CH} - P_{t,j,s}^{RS,CH}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{23}$$

$$P_s^{\min,DCH}.\beta_{t,j,s} \le P_{t,j,s}^{DA,DCH} \le P_s^{\max,DCH}.\beta_{t,j,s}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{24}$$

$$0 \le P_{t,j,s}^{RS,DCH} \le P_s^{\max,DCH}.\beta_{t,j,s} - P_{t,j,s}^{DA,DCH}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{25}$$

$$0 \le P_{t,j,s}^{UR,CH} \le P_{t,j,s}^{RS,CH}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{26}$$

$$0 \le P_{t,j,s}^{DR,CH} \le P_{t,j,s}^{RS,CH}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{27}$$

$$0 \le P_{t,j,s}^{UR,DCH} \le P_{t,j,s}^{RS,DCH}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{28}$$

$$0 \le P_{t,j,s}^{DR,DCH} \le P_{t,j,s}^{RS,DCH}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{29}$$

$$P_{t,j,s}^{DA,DCH} + P_{t,j,s}^{RS,DCH} \le P_s^{\max,DCH}.\beta_{t,j,s}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{30}$$

$$P_s^{\min,DCH}.\beta_{t,j,s} \le P_{t,j,s}^{DA,DCH} - P_{t,j,s}^{RS,DCH}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{31}$$

$$E_s^{\min}.(\alpha_{t,j,s} + \beta_{t,j,s}) \le E_{t,j,s} \le E_s^{\max}.(\alpha_{t,j,s} + \beta_{t,j,s}); \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{32}$$

$$0 \le P_{t,j,w}^{DA} \le \mathrm{P}_{t,j,w}^{RT}.u_{t,j,w}; \quad \forall t = 1,\dots,T, \forall w = 1,\dots,N_w, \forall j = 1,\dots,N_j \tag{33}$$

$$0 \le P_{t,j,w}^{RS} \le \mathrm{P}_{t,j,w}^{RT}.u_{t,j,w} - P_{t,j,w}^{DA}; \quad \forall t = 1,\dots,T, \forall w = 1,\dots,N_w, \forall j = 1,\dots,N_j \tag{34}$$

$$P_{t,j,w}^{DA} + P_{t,j,w}^{RS} \le \mathrm{P}_{t,j,w}^{RT}.u_{t,j,w}; \quad \forall t = 1,\dots,T, \forall w = 1,\dots,N_w, \forall j = 1,\dots,N_j \tag{35}$$

$$0 \le P_{t,j,w}^{DA} - P_{t,j,w}^{RS}; \quad \forall t = 1,\dots,T, \forall w = 1,\dots,N_w, \forall j = 1,\dots,N_j \tag{36}$$

$$0 \le P_{t,j,w}^{UR} \le P_{t,j,w}^{RS}; \quad \forall t = 1,\dots,T, \forall w = 1,\dots,N_w, \forall j = 1,\dots,N_j \tag{37}$$

$$0 \le P_{t,j,w}^{DR} \le P_{t,j,w}^{RS}; \quad \forall t = 1,\dots,T, \forall w = 1,\dots,N_w, \forall j = 1,\dots,N_j \tag{38}$$

Decision variables $u_{t,j,w}, \alpha_{t,j,s}, \beta_{t,j,s}$ are day-ahead planning binary variables that demonstrate the commitment status of WPRs, and BESs in the charging and discharging modes, respectively. Within the intra-hourly intervals, the commitment status of BESs and WPRs cannot be changed that is shown by Eq. (39)–(41). Additionally, Eq. (42) prevents simultaneous charging and discharging in BESs.

$$u_{t,j,w} = u_{t,j',w}; \quad \forall t = 1,\dots,T, \forall w = 1,\dots,N_w, \forall j,j' = 1,\dots,N_j \tag{39}$$

$$\alpha_{t,j,s} = \alpha_{t,j',s}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j,j' = 1,\dots,N_j \tag{40}$$

$$\beta_{t,j,s} = \beta_{t,j',s}; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j,j' = 1,\dots,N_j \tag{41}$$

$$0 \le \alpha_{t,j,s} + \beta_{t,j,s} \le 1; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{42}$$

Ramp-rate constraint: For the safe operation of BESs and WPRs, the rate of changing power shall be within the permissible intervals. According to Eq. (26)–(29) and Eq. (37) and (38), the deployed power in the real-time horizon is less than the offered capacities. In other words, the satisfaction of ramp-rate constraint in the day-ahead horizon guarantees the safe operation of resources in the real-time horizon. The ramp-rate constraints of BESs and WPRs in the day-ahead planning can be represented by Eq. (43)–(48) and Eq. (49)–(51), respectively.

$$-R_s \le P_{t,j,s}^{DA,CH} - P_{t,j-1,s}^{DA,CH} \le R_s; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{43}$$

$$-R_s \le P_{t,j,s}^{DA,DCH} - P_{t,j-1,s}^{DA,DCH} \le R_s; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{44}$$

$$P_{t,j,s}^{RS,CH} + P_{t,j-1,s}^{RS,CH} \le R_s; \quad \forall t = 1,\dots,T, \forall s = 1,\dots,N_s, \forall j = 1,\dots,N_j \tag{45}$$

$$P_{t,j,s}^{RS,DCH}+P_{t,j-1,s}^{RS,DCH}\le R_s;\quad \forall t=1,\ldots,T,\ \forall s=1,\ldots,N_s,\ \forall j=1,\ldots,N_j \tag{46}$$

$$-R_s\le\left(P_{t,j,s}^{DA,CH}-P_{t,j-1,s}^{DA,CH}\right)+\left(P_{t,j,s}^{RS,CH}+P_{t,j-1,s}^{RS,CH}\right)\le R_s;\quad \forall t=1,\ldots,T,\ \forall s=1,\ldots,N_s,\ \forall j=1,\ldots,N_j \tag{47}$$

$$-R_s\le\left(P_{t,j,s}^{DA,DCH}-P_{t,j-1,s}^{DA,DCH}\right)+\left(P_{t,j,s}^{RS,DCH}+P_{t,j-1,s}^{RS,DCH}\right)\le R_s;\quad \forall t=1,\ldots,T,\ \forall s=1,\ldots,N_s,\ \forall j=1,\ldots,N_j \tag{48}$$

$$-R_w\le P_{t,j,w}^{DA}-P_{t,j-1,w}^{DA}\le R_w;\quad \forall t=1,\ldots,T,\ \forall w=1,\ldots,N_w,\ \forall j=1,\ldots,N_j \tag{49}$$

$$P_{t,j,w}^{RS}+P_{t,j-1,w}^{RS}\le R_w;\quad \forall t=1,\ldots,T,\ \forall w=1,\ldots,N_w,\ \forall j=1,\ldots,N_j \tag{50}$$

$$-R_w\le\left(P_{t,j,w}^{DA}-P_{t,j-1,w}^{DA}\right)+\left(P_{t,j,w}^{RS}+P_{t,j-1,w}^{RS}\right)\le R_w;\quad \forall t=1,\ldots,T,\ \forall w=1,\ldots,N_w,\ \forall j=1,\ldots,N_j \tag{51}$$

Similar to the energy level of BES Eq. (17), the ramping constraint depends on the output power of generating unit within the previous intra-hourly interval. To calculate $P_{t,0}$, the equality constraints Eq. (52)–(57) are added to the problem:

$$P_{t,0,s}^{DA,DCH}=P_{t-1,N_j,s}^{DA,DCH};\quad \forall t=1,\ldots,T,\ \forall s=1,\ldots,N_s \tag{52}$$

$$P_{t,0,s}^{DA,CH}=P_{t-1,N_j,s}^{DA,CH};\quad \forall t=1,\ldots,T,\ \forall s=1,\ldots,N_s \tag{53}$$

$$P_{t,0,w}^{DA}=P_{t-1,N_j,w}^{DA};\quad \forall t=1,\ldots,T,\ \forall w=1,\ldots,N_w \tag{54}$$

$$P_{t,0,s}^{RS,CH}=P_{t-1,N_j,s}^{RS,CH};\quad \forall t=1,\ldots,T,\ \forall s=1,\ldots,N_s \tag{55}$$

$$P_{t,0,s}^{RS,DCH}=P_{t-1,N_j,s}^{RS,DCH};\quad \forall t=1,\ldots,T,\ \forall s=1,\ldots,N_s \tag{56}$$

$$P_{t,0,w}^{RS}=P_{t,N_j,w}^{RS};\quad \forall t=1,\ldots,T,\ \forall w=1,\ldots,N_w \tag{57}$$

Spillage power: In real-time planning, to prevent the injection of extra power by WPRs to the grid, and for the safe operation of these resources, the spilled power is considered that is formulated by Eq. (58). According to Eq. (59) the spilled power shall be less than the real-time realization of wind power.

$$P_{t,j,w}^{SP}=\mathrm{P}_{t,j,w}^{RT}-\left(P_{t,j,w}^{DA}+P_{t,j,w}^{UR}-P_{t,j,w}^{DR}\right);\quad \forall t=1,\ldots,T,\ \forall j=1,\ldots,N_j,\ \forall w=1,\ldots,N_w \tag{58}$$

$$0\le P_{t,j,w}^{SP}\le \mathrm{P}_{t,j,w}^{RT}.u_{t,j,w};\quad \forall t=1,\ldots,T,\ \forall j=1,\ldots,N_j,\ \forall w=1,\ldots,N_w \tag{59}$$

The spilled power of WPR is the difference between the realization of wind power and the scheduled power of WPR, and its maximum value is limited to P^{RT} that is an uncertain parameter. The procedure of linearization is provided in Appendix A.

Accordingly, the objective function can be formulated as Eq. (60), that the first and second terms represent the maximum day-ahead and real-time profits.

$$\underset{\substack{DA:\ P_{t,j,s}^{DA,DCH},P_{t,j,s}^{DA,CH},P_{t,j,s}^{RS,CH},P_{t,j,s}^{RS,DCH},\\ P_{t,j,w}^{RS},u_{t,j,w},\alpha_{t,j,s},\beta_{t,j,s}\\ RT:\ P_{t,j,s}^{UR,DCH},P_{t,j,s}^{UR,CH},P_{t,j,w}^{UR},P_{t,j,s}^{DR,DCH},\\ P_{t,j,s}^{DR,CH},P_{t,j,w}^{DR,DCH},P_{t,j,w}^{SP},\mathrm{P}_{t,j}^{UR},\mathrm{P}_{t,j}^{DR}\mathrm{P}_{t,j,w}^{RT}\\ ;\quad \forall t,\forall j,\forall s,\forall w}}{Max}\ \sum_{t=1}^{T}\left(\begin{array}{l}\left(\begin{array}{l}\pi_t^{DA}.\left(\sum_{s=1}^{N_s}P_{t,j,s}^{DA,DCH}-P_{t,j,s}^{DA,CH}+\sum_{w=1}^{N_w}P_{t,j,w}^{DA}\right)\\ +\pi_t^{RS}.\left(\sum_{s=1}^{N_s}P_{t,j,s}^{RS,CH}+P_{t,j,s}^{RS,DCH}+\sum_{w=1}^{N_w}P_{t,j,w}^{RS}\right)\\ -\sum_{s=1}^{N_s}\rho_s^{DCH}.P_{t,j,s}^{DA,DCH}+\rho_s^{CH}.P_{t,j,s}^{DA,CH}-\sum_{w=1}^{N_w}\rho_w.P_{t,j,w}^{DA}\end{array}\right)+\\ \sum_{j=1}^{N_j}\Delta S_j.\left(\begin{array}{l}\pi_{t,j}^{UR}.\left(\sum_{s=1}^{N_s}P_{t,j,s}^{UR,DCH}+P_{t,j,s}^{UR,CH}+\sum_{w=1}^{N_w}P_{t,j,w}^{UR}\right)\\ +\pi_{t,j}^{DR}.\left(\sum_{s=1}^{N_s}P_{t,j,s}^{DR,DCH}+P_{t,j,s}^{DR,CH}+\sum_{w=1}^{N_w}P_{t,j,w}^{DR}\right)\\ -\sum_{s=1}^{N_s}\rho_s^{DCH}.P_{t,j,s}^{UR,DCH}+\rho_s^{CH}.P_{t,j,s}^{DR,CH}+\sum_{w=1}^{N_w}\rho_w.P_{t,j,w}^{UR}\end{array}\right)\end{array}\right) \tag{60}$$

$$s.t.:\ \text{DA Constraints}:\text{Eq.}(4)-(6),(12)-(13),(20)-(25),(33)-(36),(39)-(57).$$

$$\text{RT Constraints}:\text{Eq.}(15)-(16),(18)-(19),(26)-(32),(37)-(38),(58)-(59)$$

As mentioned before, in this work the deployed power in the regulation services and available wind power are considered as uncertain resources. The procedure of modeling these parameters is presented in section 3.

3. Robust scheduling model

To model uncertain parameters, the variation intervals of deployed power in the up and down-regulation services, and real-time realization of wind power are represented by Eq. (61)–(63), respectively.

$$-\Delta P_{t,j}^{UR} \leq P_{t,j}^{UR} - \overline{P}_{t,j}^{UR} \leq \Delta P_{t,j}^{UR}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j \tag{61}$$

$$-\Delta P_{t,j}^{DR} \leq P_{t,j}^{DR} - \overline{P}_{t,j}^{DR} \leq \Delta P_{t,j}^{DR}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j \tag{62}$$

$$-\Delta P_{t,j,w}^{RT} \leq P_{t,j,w}^{RT} - \overline{P}_{t,j,w}^{RT} \leq \Delta P_{t,j,w}^{RT}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j \tag{63}$$

In the RO framework, the optimal strategy is determined based on the worst-case realizations of uncertain parameters. According to Eq. (64), the worst-case of a maximization objective function can be rewritten as a Max-Min optimization problem.

$$Max$$

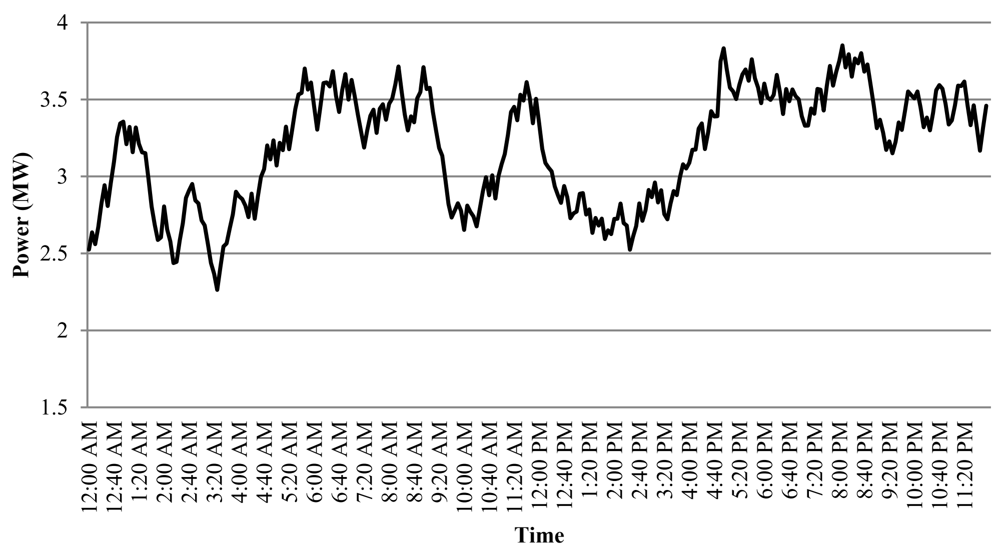

Fig. 3. Expected values of extracted wind power.

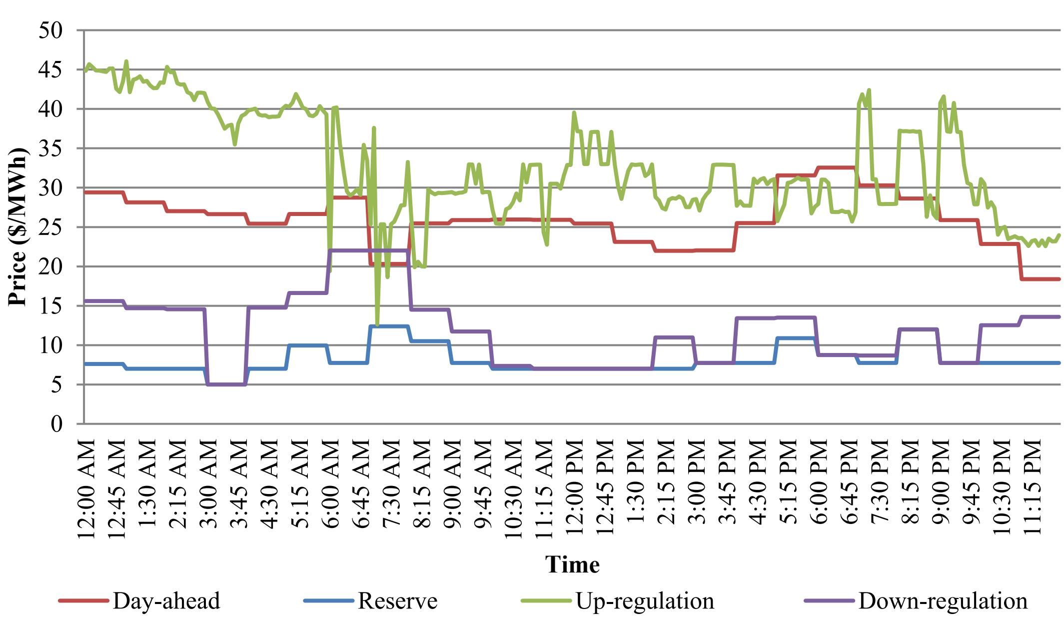

Fig. 4. Price data of January 24, 2016 of New York electricity market-west region.

$$P_{t,j,s}^{UR,DCH}, P_{t,j,s}^{UR,CH}, P_{t,j,w}^{UR}, P_{t,j,s}^{DR,DCH}, P_{t,j,s}^{DR,CH}, P_{t,j,w}^{DR,DCH}, P_{t,j,w}^{SP} \underset{\mathrm{P}_{t,j}^{UR}, \mathrm{P}_{t,j}^{DR}, \mathrm{P}_{t,j,w}^{RT}}{Min} \sum_{t=1}^{T} \times \sum_{j=1}^{N_j} \Delta S_j . \left(\begin{array}{l} \pi_{t,j}^{UR} . \left(\sum_{s=1}^{N_s} P_{t,j,s}^{UR,DCH} + P_{t,j,s}^{UR,CH} + \sum_{w=1}^{N_w} P_{t,j,w}^{UR} \right) \\ + \pi_{t,j}^{DR} . \left(\sum_{s=1}^{N_s} P_{t,j,s}^{DR,DCH} + P_{t,j,s}^{DR,CH} + \sum_{w=1}^{N_w} P_{t,j,w}^{DR} \right) \\ - \sum_{s=1}^{N_s} \rho_s^{DCH} . P_{t,j,s}^{UR,DCH} + \rho_s^{CH} . P_{t,j,s}^{DR,CH} + \sum_{w=1}^{N_w} \rho_w . P_{t,j,w}^{UR} \end{array} \right) \tag{64}$$

In Eq. (64), the inner optimization problem specifies the worst-case realization of uncertain parameters, and the outer optimization problem determines the variables of the real-time scheduling problem in a way that maximizes the worst-case. Eq. (65) shows that the minimization problem can be replaced by the auxiliary variable Γ [27]:

$$\underset{\substack{DA:\, P_{t,j,s}^{DA,DCH}, P_{t,j,s}^{DA,CH}, P_{t,j,s}^{RS,CH}, P_{t,j,s}^{RS,DCH}, \\ P_{t,j,w}^{RS}, u_{t,j,w}, \alpha_{t,j,s}, \beta_{t,j,s} \\ RT:\, P_{t,j,s}^{UR,DCH}, P_{t,j,s}^{UR,CH}, P_{t,j,w}^{UR}, P_{t,j,s}^{DR,DCH}, \\ P_{t,j,s}^{DR,CH}, P_{t,j,w}^{DR,DCH}, P_{t,j,w}^{SP}, \mathrm{P}_{t,j}^{UR}, \mathrm{P}_{t,j}^{DR}, \mathrm{P}_{t,j,w}^{RT}, \Gamma \\ ; \quad \forall t, \forall j, \forall s, \forall w}}{Max} \sum_{t=1}^{T} \left(\begin{array}{l} \pi_t^{DA} . \left(\sum_{s=1}^{N_s} P_{t,j,s}^{DA,DCH} - P_{t,j,s}^{DA,CH} + \sum_{w=1}^{N_w} P_{t,j,w}^{DA} \right) \\ + \pi_t^{RS} . \left(\sum_{s=1}^{N_s} P_{t,j,s}^{RS,CH} + P_{t,j,s}^{RS,DCH} + \sum_{w=1}^{N_w} P_{t,j,w}^{RS} \right) \\ - \sum_{s=1}^{N_s} \rho_s^{DCH} . P_{t,j,s}^{DA,DCH} + \rho_s^{CH} . P_{t,j,s}^{DA,CH} - \sum_{w=1}^{N_w} \rho_w . P_{t,j,w}^{DA} \end{array} \right) + \Gamma$$

$$s.t.:$$

$$\Gamma \leq \sum_{j=1}^{N_j} \Delta S_j . \left(\begin{array}{l} \pi_{t,j}^{UR} . \left(\sum_{s=1}^{N_s} P_{t,j,s}^{UR,DCH} + P_{t,j,s}^{UR,CH} + \sum_{w=1}^{N_w} P_{t,j,w}^{UR} \right) \\ + \pi_{t,j}^{DR} . \left(\sum_{s=1}^{N_s} P_{t,j,s}^{DR,DCH} + P_{t,j,s}^{DR,CH} + \sum_{w=1}^{N_w} P_{t,j,w}^{DR} \right) \\ - \sum_{s=1}^{N_s} \rho_s^{DCH} . P_{t,j,s}^{UR,DCH} + \rho_s^{CH} . P_{t,j,s}^{DR,CH} + \sum_{w=1}^{N_w} \rho_w . P_{t,j,w}^{UR} \end{array} \right) \tag{65}$$

$$\text{DA Constraints} : \text{Eq.}(4)-(6), (12)-(13), (20)-(25), (33)-(36), (39)-(57).$$

$$\text{RT Constraints} : \text{Eq.}(15)-(16), (18)-(19), (26)-(32), (37)-(38), (58)-(59), (61)-(63)$$

In Eq. (65), the maximum value of the continuous auxiliary variable Γ represents the lower bound of the real-time problem. The presented optimization problem is a MILP-based problem, which is solved by the branch and bound method.

4. Simulation results

In this section, the proposed model is tested on a system with one 3 MW WPR and 2 × 30 MW BESs. The initial energy, the minimum and maximum capacities of BESs are 15, 0, and 30 MWh, respectively [16]. The expected extractable wind power is represented in Fig. 3. Moreover, the price data of January 24, 2016 of New York electricity market-west region is used in this section [16]. The day-ahead, real-time, reserve and regulation prices are presented in Fig. 4.

To evaluate the performance of the proposed model, different case studies and scenarios are proposed in this section, which are represented in Table 1.

4.1. Base case study for validating

Case I: In this case, only the day-ahead energy market is considered for energy trading, and the reserve market and uncertain parameters are neglected. Moreover, the ramp rates of BESs in charging and discharging modes are 5 MW/h (BES#1) and 3 MW/h (BES#2) [28], and the ramp rate of WPR is 3 MW/h [29]. Fig. 5 shows the optimal generation and energy level of BESs and WPR. The charging and discharging powers of BESs are demonstrated by the negative and positive values of power, respectively. Evidently, BES has to purchase energy to charge batteries within the low-price periods and resell it in discharging mode within the high-price periods. Therefore, the profit of BESs depends on the difference between energy prices in peak and off-peak periods. The marginal costs of BESs and WPR are 1 and 3 $/MW, respectively. Moreover, identical marginal costs are considered for charging and discharging. The profits of BES#1, BES#2, WPR are 206.10, 123.66, and 1690.20 $, respectively. By comparing BES#1 and BES#2, it is evident that an increase in ramp rate increases profits for the resource owner. Moreover, comparing the presented results with [16] shows that the profit of BES is highly dependent on the ramp-rate constraint and considering this limitation reduces the profit of BES from 1622 $ to 206.10 $.

Table 1
Case studies and scenarios.

Case study	Scenario	Energy market	Reserve market	Uncertain parameters	Description
I		✓	✗	✗	
II	A	✓	✓	✗	Reserve bids are deployed in the down-regulation.
	B	✓	✓	✗	Reserve bids are deployed in the up-regulation.
	C	✓	✓	✗	Charging and discharging bids are deployed in the down and up-regulation services, respectively.
III	A	✓	✓	✓	The variation intervals of wind power and deployed power are 10 %.
	B	✓	✓	✓	The variation intervals of wind power and deployed power are 50 %.

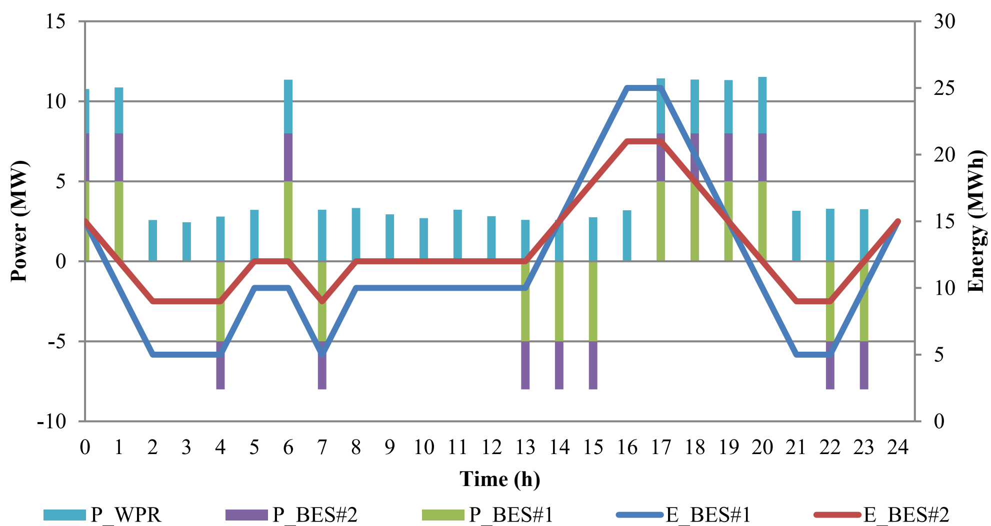

Fig. 5. State of charge and power of resources in Case I.

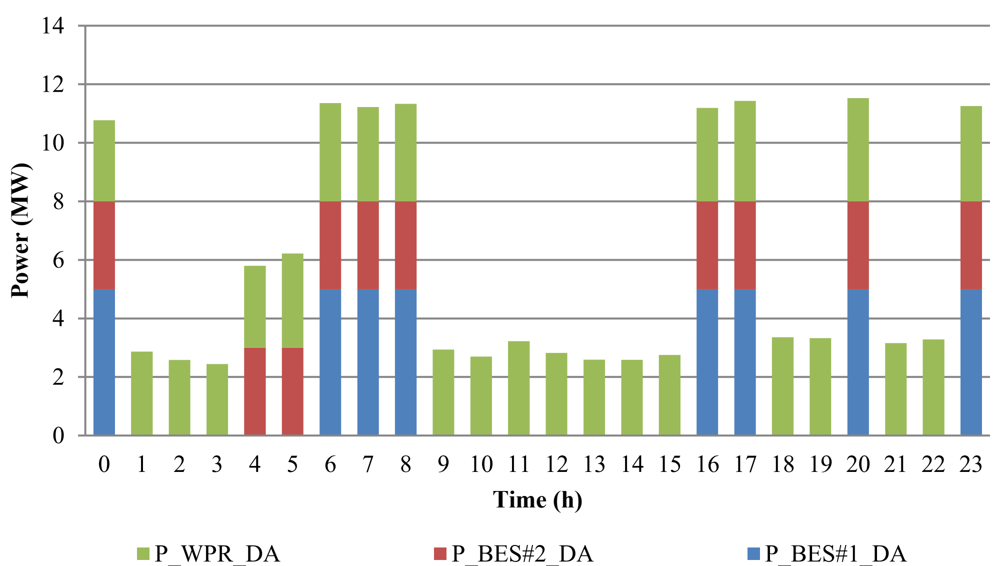

Fig. 6. Day-ahead bids in Case II-Scenario A.

4.2. Case studies for evaluating the impact of uncertainty parameters

Case II: In the second case study, the day-ahead and reserve markets are considered as available marketplaces for the trading of energy. Additionally, the impacts of uncertain parameters are neglected in this case study. For the regulation service, three scenarios are considered, which are:

- Scenario A: All the reserve bids are deployed in the down-regulation service.

- Scenario B: All the reserve bids are deployed in the up-regulation service.
- Scenario C: Charging and discharging bids are deployed in the down and up-regulation services, respectively.

Figs. 6 and 7 show the day-ahead and reserve bids in Case II-Scenario A, respectively. In this case, BESs prefer to purchase the required power for charging from the reserve case study and resell it in the day-ahead market. In the down-regulation service, BES shall reduce the discharged power. In other words, BESs purchase energy from the reserve market but they cannot inject it into the grid in the discharging mode that leads to full charging of storages and reduces their participation levels in the reserve market. Therefore, BESs prefer to sell their energy in the day-ahead market. Additionally, WPRs shall spill their generating power to be able to participate in the down-regulation service. Therefore, they just receive the capacity price that is less than the day-ahead price. Therefore, the WPRs prefer to sell energy in the day-ahead market.

As mentioned before, BESs can participate in the up-regulation service by increasing/decreasing the discharging/charging power. Therefore, participation of BESs in the up-regulation service in the discharging mode could decrease the available energy that can be sold to the energy market. In this scenario, the required energy for charging of storages is purchased from the day-ahead market and BESs resell the stored energy to the reserve market in the discharging mode. The day-ahead and reserve bids in Case II-Scenario B are presented in Figs. 8 and 9, respectively.

Figs. 10 and 11 show day-ahead and reserve bids in Case II-Scenario C. Evidently, considering both up and down-regulation service improves BESs' role in the reserve market. Simulation results show that the profit of WPRs in case of participation in the day-ahead, down and up-regulation services are 1690, 1530, and 2812.64 $, respectively. However, there is no guarantee that all bids of WPRs are deployed in the up-regulation service. Therefore, WPRs prefer to submit their bids in the day-ahead market that is more reliable.

The profits of different scenarios in the day-ahead and real-time planning horizon are tabulated in Table 2. According to the presented results and in Scenario B, BESs have to purchase power from the day-ahead market. Therefore, the net profit of Scenario B in the day-ahead planning is negative. Moreover, the total profit shows that considering the reserve market and both up and down-regulation services, increase the profit of BESs, significantly.

Case III: In this case, the impacts of uncertain parameters (deployed power in the regulation service and available wind power) are evaluated by two scenarios:

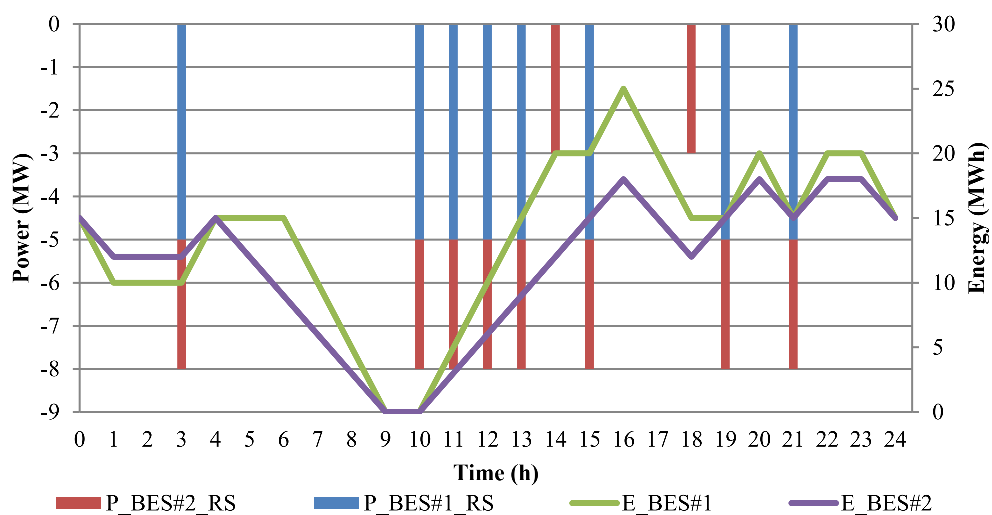

Fig. 7. State of charge and reserve bids in Case II-Scenario A.

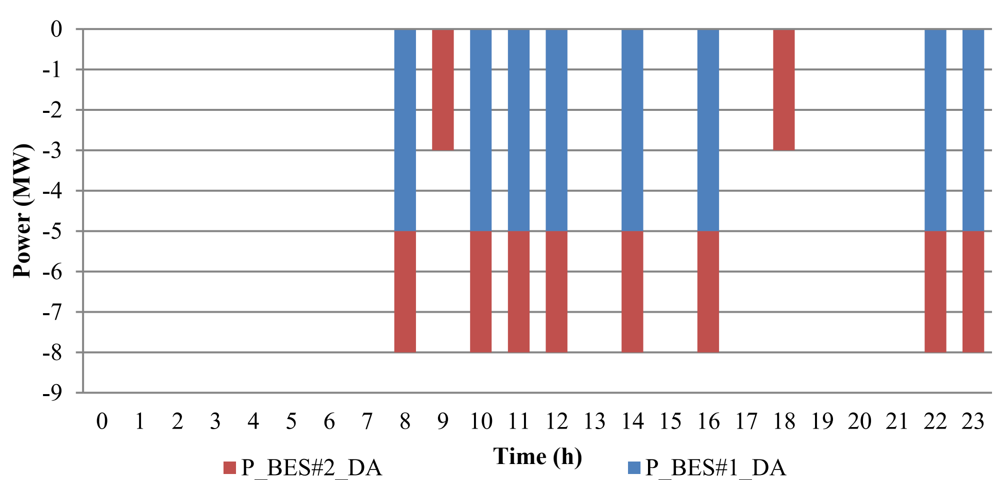

Fig. 8. Day-ahead bids in Case II-Scenario B.

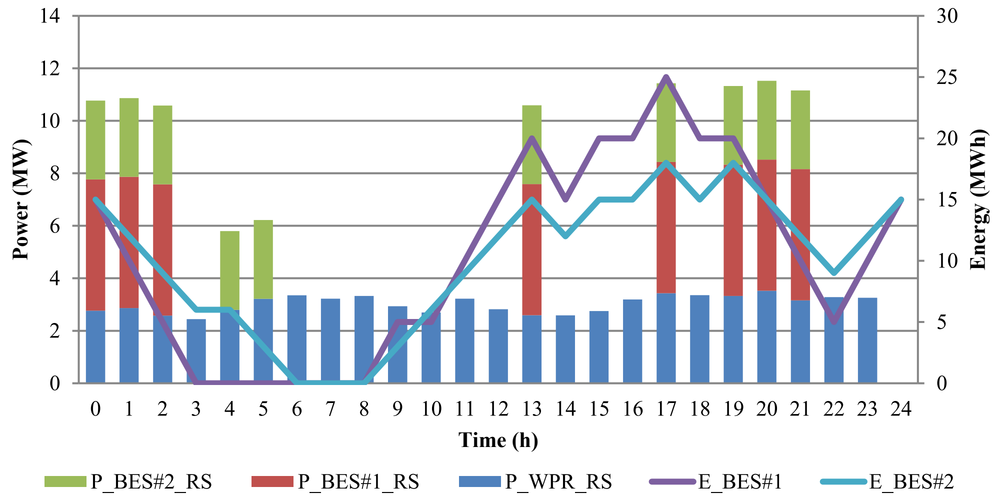

Fig. 9. State of charge and reserve bids in Case II-Scenario B.

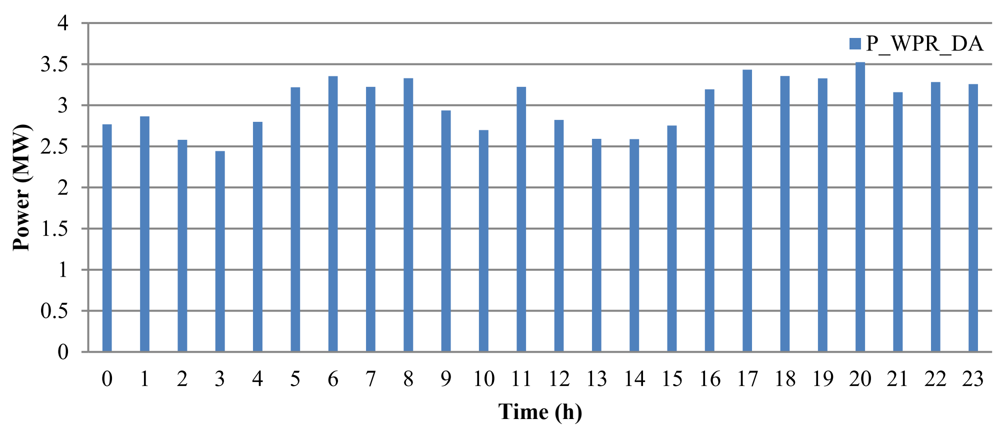

Fig. 10. Day-ahead bids in Case II-Scenario C.

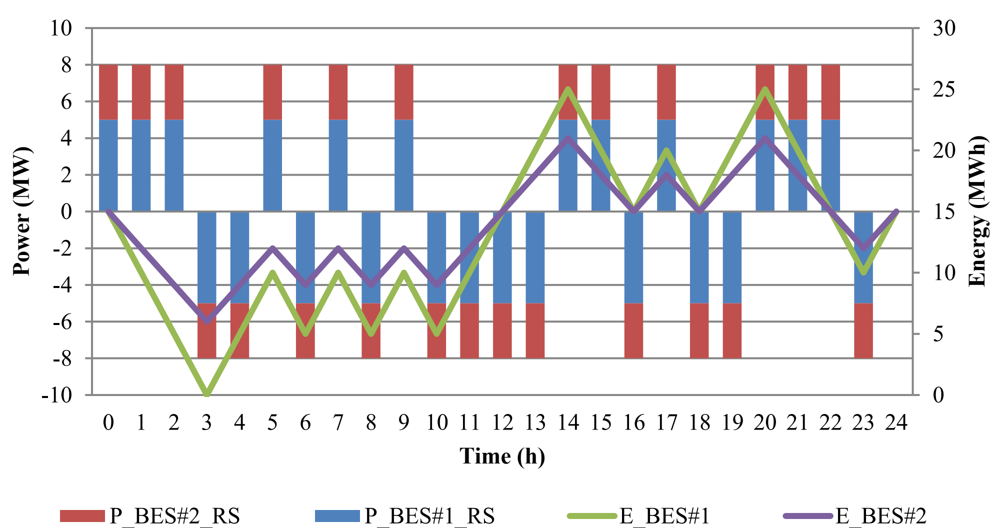

Fig. 11. State of charge and reserve bids in Case II-Scenario C.

- Scenario A: The variation intervals of wind power and deployed power are 10 %.
- Scenario B: The variation intervals of wind power and deployed power are 50 %.

Table 2
Profit of different scenarios of Case II ($).

	Day-ahead			Real-time			Total
	BES#1	BES#2	WPR	BES#1	BES#2	WPR	
Scenario A	1281.25	966.24	1690.20	247.75	201.81	0	4387.25
Scenario B	−662.55	−527.97	631.73	1427.47	1089.30	2180.92	4138.90
Scenario C	975.30	585.21	1690.23	2578.39	1547.03	0	7376.21

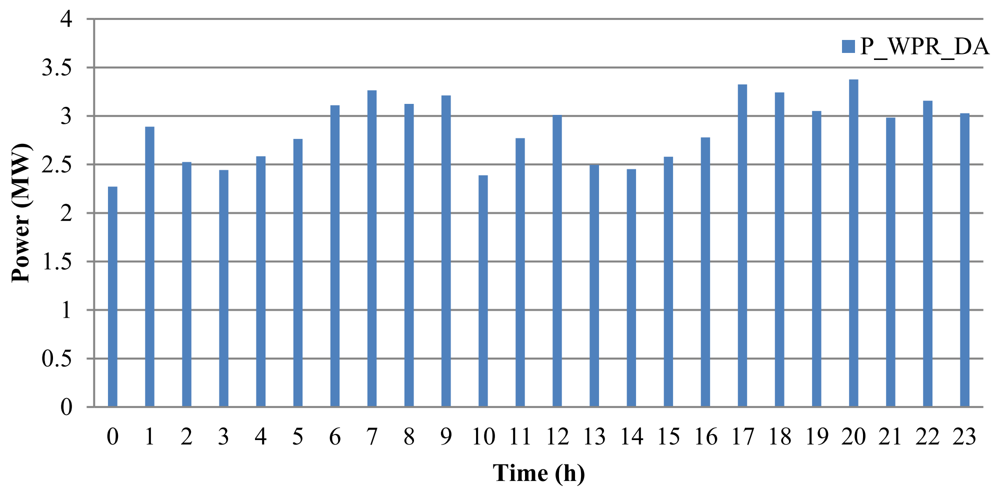

Fig. 12. Day-ahead bids in Case III-Scenario A.

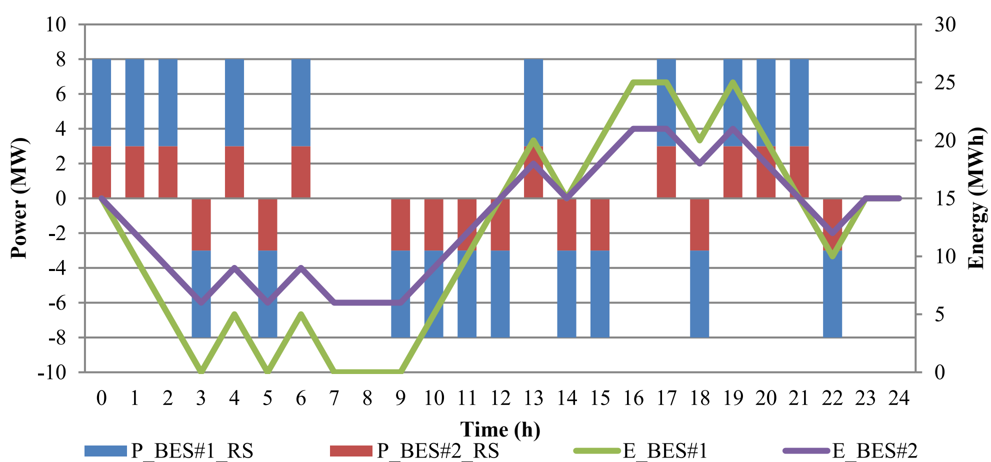

Fig. 13. State of charge and reserve bids in Case III-Scenario A.

Considering the uncertainty of deployed power in the regulation service reduces the participation level of BESs in the reserve market. As mentioned before, in RO methodology the optimal strategy is specified based on the worst-case realization of uncertain parameters within the variation interval. Therefore, the generating power of WPR in the day-ahead market is specified based on the minimum generating power. It shall be noted that in this procedure, the determined strategy is the optimal solution of worst-case realization of uncertain parameters and for other realizations, it is a feasible solution. Figs. 12 and 13 show day-ahead and reserve bids in Case III- Scenario A, respectively. The length of the variation interval is specified based on the risk preferences of decision-makers. Moreover, increasing the length of the variation interval covers more realizations of uncertain parameters.

The impact of increasing the variation interval of uncertain parameters is evaluated in Scenario B. The day-ahead and reserve bids in Case III- Scenario B are shown in Figs. 14 and 15, respectively. Comparing Figs. 12 and 14 shows that increasing the variation interval of deployed power in the regulation service, increases the traded power of BESs in the day-ahead market. Moreover, in this scenario, BESs prefer to buy energy from the day-ahead market and resell it in the reserve market.

The optimal profits in Scenarios A and B of Case III are provided in Table 3. The length of variation interval depends on the risk preferences of decision-makers. Risk-averse decision-makers choose the greater variation interval to hedge the financial risk. On the contrary, risk-taker decision-makers choose the smaller variation interval in the hope that obtain the higher profit.

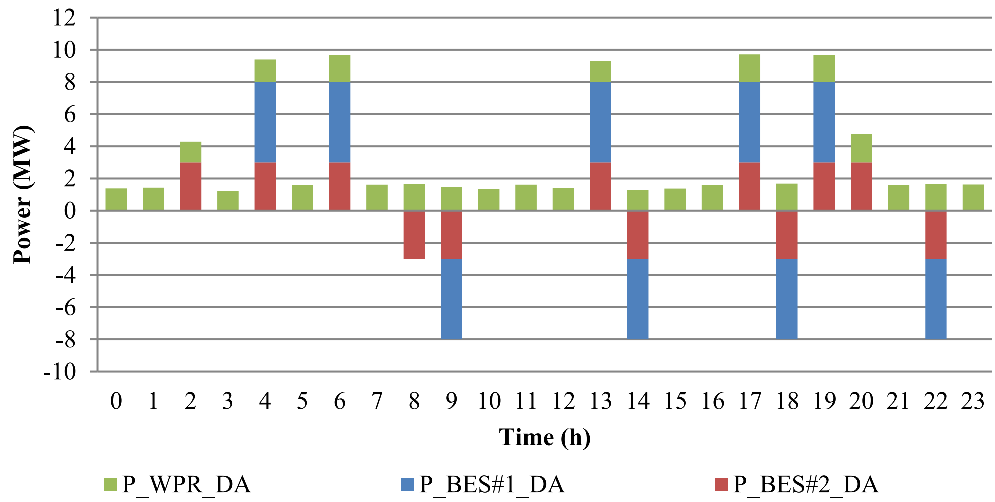

Fig. 14. Day-ahead bids in Case III-Scenario B.

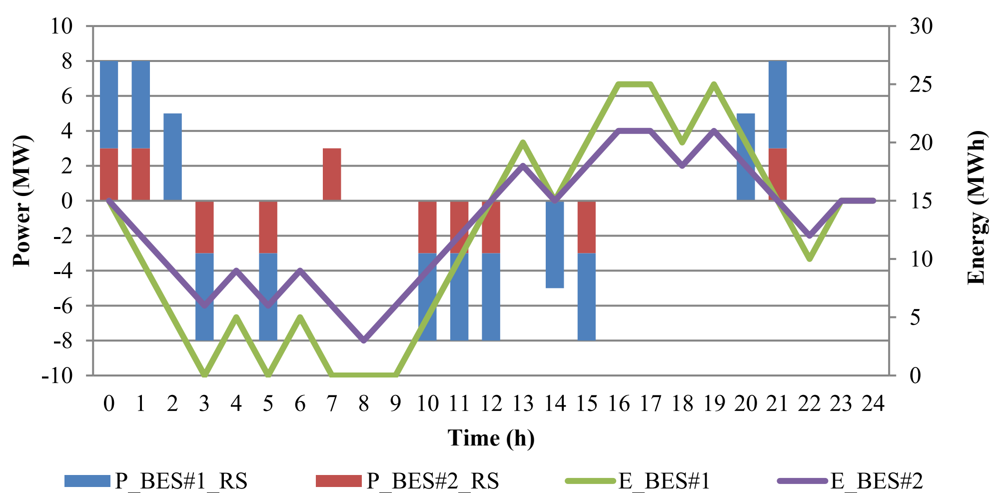

Fig. 15. State of charge and reserve bids in Case III-Scenario B.

Table 3
Profit of difference scenarios of Case III ($).

	Day-ahead			Real-time			Total
	BES#1	BES#2	WPR	BES#1	BES#2	WPR	
Scenario A	783.40	470.04	1521.21	2198.22	1318.93	0	6291.80
Scenario B	594.65	397.53	845.11	1195.91	569.21	0	3602.41

According to the presented results, increasing the uncertainty interval reduces the optimal profit and vice versa. Therefore, the optimal profit of risk-taker owners is higher than the risk-averse ones.

5. Conclusions

In this paper, a robust model is proposed for the aggregated bidding strategy of WPRs and BESs in the joint energy and reserve markets. In the proposed model, the real-time realization of wind power and the deployed power in the regulation services are considered as uncertain parameters. The model is formulated as a MILP optimization problem and the branch-and-cut method is addressed to solve it. Simulation results show that participation of BES in the reserve and regulation service can increase the expected profit, significantly. According to our case studies, participating in the joint energy and reserve markets increases owners' profit from 1622 $ to 4138.90 $ (in the worst case)/7376.21 $ (in the best case). Comparing the presented results with [16] shows that the profit of BES is highly dependent on the ramp-rate constraint. Moreover, increasing the ramp rate leads to a higher profit for the owner of resources. According to the presented results, participation of BESs in the up-regulation service in the discharging mode could decrease the available energy that can be sold to the energy market. For BESs, the best situation is that discharging and charging reserves are deployed in the up and down regulation services, respectively. However, the risk of deployed power is a challenge for decision-makers. Therefore, the deployed power in the regulation service and the wind generation are modeled by the RO methodology. Considering the uncertainty of deployed power in the regulation service reduces the participation level of BESs in the reserve market. In the RO framework, the optimal solution is determined based on the worst-case realization of uncertainty parameters. Therefore, the most reliable market for the participation of WPR is the day-ahead market. By increasing the uncertainty of these parameters, the owners prefer to purchase the required energy for charging storage from the day-ahead market and resell it in the regulation service. The length of the variation interval is specified based on the risk preferences of decision-makers. Simulation results demonstrate that increasing the variation interval of wind generation from 10 % to 50 % decreases the expected profit from 6291.80 $ to 3602.41 $.

As future work, the authors are going to model the impact of BESs' lifetime in the aggregated bidding strategy of renewable resources.

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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Appendix A

Eq. (59) can be replaced by Eq. (A.1), as follow:

$$0 \le P^{SP}_{t,j,w} \le A_{t,j,w}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j, \forall w = 1, \ldots, N_w \tag{A.1}$$

The linearization auxiliary variable or A is modeled as follows:

$$A_{t,j,w} \ge 0; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j, \forall w = 1, \ldots, N_w \tag{A.2}$$

$$A_{t,j,w} \le M.u_{t,j,w}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j, \forall w = 1, \ldots, N_w \tag{A.3}$$

$$A_{t,j,w} \le P^{RT}_{t,j,w}; \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j, \forall w = 1, \ldots, N_w \tag{A.4}$$

$$A_{t,j,w} \ge P^{RT}_{t,j,w} - M.(1 - u_{t,j,w}); \quad \forall t = 1, \ldots, T, \forall j = 1, \ldots, N_j, \forall w = 1, \ldots, N_w \tag{A.5}$$

where, M is the auxiliary big value.

Contributions

Meysam Khojasteh: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Pedro Faria**: Conceptualization, Methodology, Validation, Writing – review & editing. **Zita Vale**: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

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