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Evaluating the benefits of coordinated emerging flexible resources in electricity markets

E. Heydarian-Forushani [a], M.E.H. Golshan [a], Pierluigi Siano [b,*]

[a] Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran
[b] Department of Industrial Engineering, University of Salerno, Fisciano (SA) 84084, Italy

HIGHLIGHTS

- Variable renewable energy sources create a flexibility gap in power system operation.
- BESs, PEV PLs and DR are modeled as flexible options.
- DR programs have remarkable impacts in terms of cost and emission reduction.
- PEV PL is not a favorable flexible option by its own due to uncertain behavior of PEV owners.
- Coordinated operation of PEV PLs and BESs under TOU program is the most effective generation mixture.

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ABSTRACT

Increasing share of variable renewable energy sources (VRESs) with the aim of tackling climate changes impose several techno-economic challenges to power system operation. VRESs reduce the available flexibility by displacing existing flexible units due to their priority in dispatch and simultaneously enhance the need for additional flexibility due to their uncertain nature. In this light, the system is faced with a flexibility gap. One way to cover the created flexibility gap is the incorporation of emerging flexible resources into power systems operation. On this basis, this paper proposes a comprehensive flexible generation portfolio including bulk energy storages (BESs), plug-in electric vehicle parking lots (PEV PLs), and demand response (DR) programs. A stochastic market-based model is proposed to coordinate the interactions among these flexibility providers considering different sets of uncertainty, such as wind power generation and PEV owner's behavior. Finally, various generation mixtures are prioritized based on the system operator's economic, technical, and environmental desires to provide a guideline to opt the most effective generation mixture in the context of flexibility promotion.

1. Introduction

1.1. Motivation and related works

Wind power provides new challenges at high penetration levels, since its variable nature increases the need for additional operational flexibility. Operational flexibility aims at securely covering the possible variations at least cost by using enough online flexible resources. Typical solutions to achieve this goal can be separated into two main categories. The first one focuses on designing novel market mechanisms to incentivize flexibility provision in system operations [1–3]. The second one deals with the incorporation of flexible alternatives such as Bulk Energy Storages (BESs), Demand Response (DR), and Plug-in Electric Vehicle Parking Lots (PEV PLs) to the generation mixture. It is noteworthy that there is a huge interest for using these emerging technologies around the world in last few years. In the case of BESs, the pump hydro storage technology is the most widely used BES. However, other BES technologies such as compressed air energy storages as well as advanced batteries gain more attention recently due to the fact that they need no specific geographic location and therefore can be installed across the transmission networks without certain

Abbreviations: ARMA, Autoregressive Moving Average; BES, Bulk Energy Storage; DC, Direct Current; DR, Demand Response; EDRP, Emergency Demand Response Program; G2V, Grid-to-Vehicle; PEV PL, Plug-in Electric Vehicle Parking Lot; RTS, Reliability Test System; SCUC, Security-Constrained Unit Commitment; SO, System Operator; SOC, State of Charge; SOE, State of Energy; TOPSIS, Technique for Order Preference by Similarity to Ideal Solution; TOU, Time of Use; V2G, Vehicle-to-Grid.

* Corresponding author.
E-mail addresses: e.heydarian@ec.iut.ac.ir (E. Heydarian-Forushani), hgolshan@cc.iut.ac.ir (M.E.H. Golshan), psiano@unisa.it (P. Siano).

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Nomenclature

Indices

- b, b' index of system buses $b = 1, \ldots, NB$
- es index of bulk energy storages $es = 1, \ldots, NES$
- i index of conventional units $i = 1, \ldots, NG$
- j index of loads $j = 1, \ldots, NJ$
- k index of segment for linearized incentive payment cost curve $k = 1, \ldots, NK$
- l index of transmission lines $l = 1, \ldots, L$
- m index of segment for linearized fuel cost $m = 1, \ldots, NM$
- n index of PEVs $n = 1, \ldots, N$
- NB number of network buses
- NES number of bulk energy storage units
- NG number of conventional generation units
- NJ number of load points
- NK number of segments for the piecewise linearized incentive payment cost curve
- NM number of segments for the piecewise linearized fuel cost curve of units
- NPL number of PEV parking lots
- NT number of hours under study
- NW number of scenarios
- NWF number of wind farms
- pl index of parking lots $pl = 1, \ldots, NPL$
- PTP index of peak time period hours
- t, t' index of time periods $t = 1, \ldots, NT$
- $t_n^{arv/dep}$ index of arrival/departure time of PEV n
- w index of scenarios $w = 1, \ldots, NW$
- wf index of wind farms $wf = 1, \ldots, NWF$

Parameters and variables

- $C_{es,t}^{ES\_Eng}$ offered energy cost of BESs in discharging mode ($/MW h)
- $C_{es,t}^{ES\_UC/DC}$ offered cost of up/down capacity reserve of BESs ($/MW)
- $C_{es,t}^{ES\_UE/DE}$ offered cost of up/down deployed reserve of BESs ($/MW h)
- $C_{i,t}^{G\_UC/DC}$ offered cost of up/down capacity reserve of conventional generation units ($/MW)
- $C_{i,t}^{G\_UE/DE}$ offered cost of up/down deployed reserve of conventional generation units ($/MW h)
- $C_{i,t,m}^{G\_Eng}$ offered piecewise energy cost of conventional generation units ($/MW h)
- $C_{pl,t}^{PL\_Eng}$ offered energy cost of PLs in PL to grid mode ($/MW h)
- $C_{pl,t}^{PL\_UC/DC}$ offered cost of up/down capacity reserve of PEV PLs ($/MW)
- $C_{pl,t}^{PL\_UE/DE}$ offered cost of up/down deployed reserve of PEV PLs ($/MW h)
- $C_{wf}^{WP\_spill}$ cost of wind spillage ($/MW h)
- $cap_{n,t_n^{arv},t_n^{dep}}^{PEV}$ battery capacity of EV n (kW h)
- $Cap_{pl,t}^{PL,Sc}$ aggregated battery capacity of parking lot (MW h)
- $d_{j,t}^0$ initial electricity demand before DR (MW)
- $DR^{\max}$ maximum DR participation level
- $E_{t,t'}$ price elasticity of demand
- $F_{l,t}^0/F_{l,w,t}$ power flow through line l in the base-case and scenarios (MW)
- $I_{es,t}^{DeES}/I_{es,t}^{ChES}$ binary indicator of discharge/charge status of BESs
- $INC_{j,t,k}$ incentive of segment k in linearized total incentive curve ($/MW h)
- $LRDR_{j,t,k}$ slope of segment k in linearized total incentive curve (MW h)
- $LS_{j,w,t}$ load shedding of load j (MW h)
- MPC_i minimum production cost of conventional generation units ($)
- $N^{PL,\max}$ maximum number of car spaces in the parking lot
- $N_{pl,t}^{PL,Sc}$ aggregated number of PEVs in the parking lot
- $N_{t^{arv},t^{dep}}^{PEV}$ aggregated number of PEVs that arrived to PL at t^{arv} and departed from PL at t^{dep}
- $P_{es}^{ChES,\max}$ maximum charging power of BESs (MW)
- $P_{es}^{DchES,\max}$ maximum discharging power of BESs (MW)
- $P_{es,t}^{ChES}, P_{es,t}^{DchES}$ scheduled charge/discharge power of BESs (MW)
- $P_i^{\min}/P_i^{\max}$ minimum/maximum output of units (MW)
- $P_{i,t,m}^e$ generation of segment m in linearized fuel cost curve (MW h)
- $P_{i,w,t}$ actual power generation of generation units (MW)
- $P_{pl,t}^{En,G2PL}$ injected power of grid to PL (MW)
- $P_{pl,t}^{En,PL2G}$ injected power of PL back to the grid (MW)
- $P_{wf,t}^{WP,\max}$ forecasted wind generation of wind farms (MW h)
- $P_{wf,w,t}^{W}$ actual wind generation of wind farms (MW h)
- $P_{wf,w,t}^{WP\_spill}$ wind power spillage of wind farms (MW h)
- $r_{es,w,t}^{ES\_up/dn}$ deployed up/down spinning reserve of BESs (MW h)
- $r_{i,w,t}^{G\_up/dn}$ deployed up/down spinning reserve of conventional generation units (MW h)
- $r_{pl,w,t}^{PL\_up/dn}$ deployed up/down spinning reserve of PEV PLs (MW h)
- $R_{es,t}^{ES\_UC}, R_{es,t}^{ES\_DC}$ scheduled up/down reserve capacity of BESs (MW)
- $R_{i,t}^{G\_UC}, R_{i,t}^{G\_DC}$ scheduled up/down reserve capacity of conventional generation units (MW)
- $R_{pl,t}^{PL\_UC}, R_{pl,t}^{PL\_DC}$ scheduled up/down reserve capacity of PEV PLs (MW)
- RU_i/RD_i ramp up/down limits of units (MW/h)
- SC_i start-up offer cost of conventional generation units ($)
- $soc_n^{PEV,\min/\max}$ truncation region for the initial SOC of PEV n
- $soc_{n,t_n^{arv},t_n^{dcep}}^{PEV}$ initial SOC of PEV n
- $SOC_{pl}^{\min}/SOC_{pl}^{\max}$ min/max SOC level of parking lot
- $SOE_{pl,t}^{PL,Sc}$ aggregated state of energy of parking lot as a result of arrival/departure of PEVs (MW h)
- $SOE_{pl,w,t}^{PL}$ aggregated state of energy of PL (MW h)
- $SOE_{es}^{ES,\min/\max}$ minimum/maximum energy limit of BESs (MW h)
- $SOE_{es,w,t}^{ES}$ stored energy level of BESs (MW h)
- $SUC_{i,t}$ start-up cost of conventional units ($)
- $U_{i,t}$ binary on/off status indicator of generation units
- $U_{pl,t}^{PL2G}/U_{pl,t}^{G2PL}$ binary status indicator of PL2G/G2PL operation mode of PL
- $Voll_{j,t}$ value of lost load j ($/MW h)
- X_l reactance of line l
- α_{es}^{ini} initial percent charging of BES before scheduling (%)
- $\Gamma^{charge}, \gamma^{discharge}$ charging/discharging rates of pevs (kw/h)
- $\delta_{b,t}^0/\delta_{b,w,t}$ voltage angle of network buses in the base-case and scenarios (rad)
- $\eta_{Ch}^{ES}, \eta_{Dch}^{ES}$ charge/discharge efficiency of BESs
- $\eta_{Ch}^{PL}, \eta_{Dch}^{PL}$ charge/discharge efficiency of parking lot
- $\mu_{soc}, \sigma_{soc}^2$ mean value and variance related to SOC of PEVs
- π_w probability of scenario w
- ρ^{ini} initial electricity price before DR ($/MW h)
- $\rho_j^{LTP/OTP/PTP}$ electricity tariffs of low-load, off-peak and peak time periods in TOU program ($/MW h)
- τ spinning reserve market lead time (h)
- ψ_t^{PL} net electrical charging percentage due to contract of PEV owners for desired SOC

limitations [4]. To sense the applicability of BESs, Department of Energy (DOE) global energy storage database provides comprehensive information about both constructed and under construction BES around the world in details [5].

In the case of PEVs, there are several global targets set by the governments all over the world for using electric vehicles instead of conventional ones. For example in the U.S., it is projected that by 2050 about 62% of the entire vehicle fleet would be hybrid PEVs [6]. It is obvious that this volume of PEVs can play a major role in the electricity market transactions and affect both supply and demand scheduling due to the fact that they are accounted as mobile loads and generators. Regardless of BESs and PEVs, DR is also widely believed to bring multiple benefits to electric power systems as a key resource of flexibility [7]. The pioneer region in the case of DR with more than 80% share of the global market was devoted to North America in 2013 [8]. A comprehensive overview of DR including international experiences, practical evidences, the benefits and enablers as well as the barriers has been thoroughly discussed in [8,9].

Considering such statistics for BESs, PEVs and DR reveal that the changes in system operation and electricity market transactions as a result of incorporation of such emerging technologies need further investigation. It is noticed, each of the mentioned flexible resources has its own specific characteristics and requirements that should be taken into account and this raises the problem complexity. Moreover, incorporation of each flexible resource may affect other market player transactions. Therefore, a comprehensive analysis of these flexibility providers in a market environment becomes crucial for System Operators (SOs) in order to select the most effective generation mixture for promoting the flexibility level in the future power systems.

There are a lot of relevant works that have already addressed the role of BESs [10,11], DR [12,13], and PEVs [14,15] in mitigating the intermittency of wind generation across transmission grids. The authors of [10] have suggested an enhanced Security-Constrained Unit Commitment (SCUC) to represent the role of BESs under normal and contingency operating conditions. An improved stochastic formulation to enhance the flexibility of the commitment schedule for thermal generators, as well as BESs in real-time operation with the limited look-ahead functionality is proposed in [11]. In [12], a DR exchange model has been proposed as an alternative for managing the variability of renewable energy sources. Ref. [13] proposed a two-stage stochastic programming-based joint energy and reserve market clearing model in order to calculate the required reserve as a result of wind power and load variations as well as system component outages, where the day-ahead market is cleared on an hourly basis at the first stage, while the re-dispatch is performed on a minute basis at the second stage.

A comprehensive modeling for PEV PLs participation in energy and reserve markets in wind integrated power grids has been developed in [14] by considering the uncertainty of each individual PEV such as arrival/departure time of PEVs to/from the PL, initial State of Charge (SOC), and battery capacity of PEVs. In [15], a centralized control strategy has been proposed to exploit the PEV batteries for supporting renewable generations considering PEV owners satisfaction. The role of PEVs for providing ancillary services in power grids with significant amount of renewable resources has been investigated in [16]. The authors also assessed the changes in conventional generation dispatch as a result of integration of renewables in the presence and absence of PEVs. The potential impacts of coordinated charging of PEVs on damping the fluctuations of renewable generations considering the empirical driving data for modeling the behavior of PEV owners has been investigated in [17].

However, modeling a comprehensive set of flexible resources and their multilateral interactions in a market environment has been rarely investigated. For instance, a two-stage stochastic SCUC model for the optimal midterm coordination of hydro and natural gas flexibilities for wind energy integration has been presented in [18]. Coupled operation of a BES and a gas thermal unit to mitigate the negative operational impacts of high variable wind generation is investigated in [19]. The obtained results show a reduction in either wind curtailment or required ramp rate by 0.18% and 2.35 MW/min, respectively. The coordinated operation of BESs under different types of DR programs for wind integration has been assessed in [20] with predefined tariff and incentive values. However, previous researches did not consider that DR should be fully compatible with market conditions in renewable based power grids. This is mainly due to the fact that renewable generations have a relatively low operation cost which may result in market clearing price reduction and, accordingly, rebate customer's participation tendency in DR programs.

In addition, the combined operation of ESs and bi-directional EVs under real-time pricing DR in presence of renewable generations has been evaluated for a smart household in [21]. In [22], BESs and hourly DR are integrated into the stochastic day-ahead scheduling of power systems as flexible resources beside thermal units with the aim of managing the variability of renewable generations. The proposed approach considered different sets of uncertainty using Monte Carlo simulation. However, the emerging PEV PLs and the reserve market are not considered in the mentioned study.

It is notable that there are few previous researches that assess the flexibility promotion through improving existing thermal and combined heat and power unit flexibility as it can be seen in [23,24], respectively. The authors of [23] have focused on identifying the importance of specific thermal plant characteristics for addressing two essential challenges including wind ramping and the need to avoid excessive wind curtailment. Moreover, [24] explored opportunities for increasing the flexibility of combined heat and power units for better wind power integration using electrical boilers and heat storage tanks.

Other studies looked at the flexibility concept from distinct point of view. The impact of more accurate forecast of wind generation at different operational time-scales of electricity market has been analyzed in [25]. The paper also quantified both the static and dynamic operational flexibilities considering various generation mixtures. Ref. [26] attempted to determine the relative flexibility of different conventional technologies by proposing a composite flexibility index based on the technical characteristics of conventional units without considering the emerging resources and actual operational status. A combined long-term and hourly simulation approach has been conducted to evaluate the operational flexibility of current and future power plants in [27]. The attained flexibility as a result of coordinated operation of wind generation with hydropower in the market environment has been investigated in [28].

1.2. Aims and contributions

Renewable generations, particularly wind power, affects the generation scheduling due to its uncertainty. On the other hand, incorporation of emerging resources would impact the energy and reserve market transactions. Individual and mutual impacts of these resources have been studied in the literature. However, there is no comprehensive model in the literature, which simultaneously represents the integration of all the given resources. This comprehensive model is vital as it reveals an interpretation of how SOs can utilize the unique characteristics of these resources to manage both energy and reserve markets. As such, this paper contributes to the existing studies by proposing a comprehensive formulation of the given market integrating BESs in the supply-side and DR programs and PEV PLs on the demand-side, while capturing their own specific technological constraints. Moreover, the paper investigates distinctly different generation mixtures as a result of coordinated operation of such emerging resources by defining various case studies. In order to evaluate the effectiveness of each generation mixture, the paper pays attention to not only just one aspect such as other previous studies but also considers economical, technical and environmental aspects to assess the performance of each generation mixture. Lastly, in order to provide a guideline for SOs to opt the most effective generation mixture in the context of flexibility enhancement, various generation mixtures are prioritized according to the SO's economic, technical, and environmental desires.

On this basis, the paper contains several contributions in both presenting new models as well as a novel framework. In short, the main contributions of the paper can be summarized as below:

- Simultaneous modeling of a comprehensive set of flexibility providers including BESs, PEV PLs, and DR programs with the aim of enhancing operational flexibility and highlighting the interactions among them as well as their compensating role in electricity markets;
- Determining the optimal incentive and electricity tariff values in the context of a stochastic market clearing for both incentive-based and price-based DR programs;
- Providing a guideline for SOs to help them in prioritizing various generation mixture based on their economic, technical and environmental desires using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

1.3. Paper organization

Section 2 deals with modeling the flexible generation portfolio including BESs, PEV PLs, and DR programs. The stochastic market clearing formulation is described in Section 3. The results are reported and discussed in Section 4. Some practical implementation aspects of the proposed framework is discussed in Section 5. Finally, some conclusions are drawn in Section 6.

2. Flexible generation portfolio modeling

2.1. Model structure and description

In the proposed framework, the SO has the possibility to employ both the supply-side and demand-side resources to achieve more efficient generation dispatch in energy and reserve markets. Thermal power plants and wind farms are the main generating units at the supply-side, while the not-responsive part of load is the main consumer at the demand-side. Flexible options including BESs, PEV PLs, and responsive loads (i.e., DR) make it possible for the SO to enjoy their flexibility due to the fact that they can either generate or consume power according to the SO's needs and operation condition. On this basis, the BESs and PEV PLs submit their price-quantity offers for participation in energy and reserve markets alongside other conventional units. Also, the responsive loads are modeled based on the price elasticity concept.

In order to reflect the stochastic nature of wind power generation as well as PEV owner's behavior, a two-stage stochastic programming approach is adopted as it can be seen in Fig. 1. The proposed framework is a general model that can be used for handling the variability as a result of various types of stochastic renewable generations under the concept of coordinated operation of flexible resources. So, the model not limited to wind power and it is applicable for other types of variable technologies.

The cost and technical data associated with different market players including generating units, BESs and PEV PLs are the main inputs of the proposed model. For instance, the offered package of conventional generating units not only contains their price-quantity offers for providing energy and up/down reserves but also includes their technical characteristics such as ramp rates, minimum up/down times, minimum/maximum allowable production limits and etc. The same offered packages have been considered for BESs and PEV PLs whilst each generation technology has its own technical parameters. Note that to model the customer's responsiveness, their price elasticity and participation level in DR programs are the main input parameters. In addition, wind generation and PEV owner's scenarios are considered as other inputs.

In the first-stage, the SO determines the optimal hourly schedule of generation units, charge/discharge amounts of BESs, and exchanged power of PEV PLs according to the operating constraints related to each market participant. Moreover, the optimal electricity tariffs and incentive payment are calculated separately for the considered DR programs in order to make it accessible to the consumers in advance. Note that sufficient resources should be dispatched to consider the not-responsive demand in addition to the spinning reserve. According to the fact that uncertain parameters are not realized at the first-stage, all variables of the first-stage are identically used for all occurred scenarios. The variables of the second-stage that vary based on the scenarios are the deployed up/down spinning reserves of conventional units, BESs and PEV PLs from all prepared resources. If the designated reserve capacities in the first-stage are insufficient, this leads to an increase in the expected load shedding or wind power spillage which are costly. This issue generates a signal to the first-stage so that the appropriate amount of reserve capacity will be procured. It is noteworthy that the decisions are made on an hourly basis for the next operating day.

After the determination of the optimal generation dispatch in the energy and reserve markets, the proposed method adopts a multi attributes decision-making method to provide a guideline for the SO to opt for the most effective generation mixture in the context of flexibility promotion. For this purpose, various generation mixtures are prioritized using TOPSIS technique based on the SO economic, technical and environmental desires. The conceptual schematic of proposed framework is illustrated in Fig. 1.

2.2. BESs operational model

Based on the aforementioned structure, two sets of constraints are presented here in order to model the BESs participation in energy and up/down reserve markets. First-stage constraints including limitations on charging/discharging power in energy and up/down reserve capacity markets are modeled in (1)–(3). The constraints on the capacity of BESs while getting charged and discharged are formulated through Eqs. (1) and (2), respectively. It is noticed that Eqs. (1) and (2) have two terms including day-ahead energy and up/down spinning reserve capacity markets. Moreover, Eq. (3) avoids simultaneous operation of BESs in charging and discharging modes [20].

$$0 \leqslant P_{es,t}^{ChES} + R_{es,t}^{ES\_DC} \leqslant P_{es}^{ChES,\max} I_{es,t}^{ChES} \tag{1}$$

$$0 \leqslant P_{es,t}^{DchES} + R_{es,t}^{ES\_UC} \leqslant P_{es}^{DchES,\max} I_{es,t}^{DeES} \tag{2}$$

$$I_{es,t}^{DeES} + I_{es,t}^{ChES} \leqslant 1 \tag{3}$$

Other constraints pertaining to the second-stage variables are given through (4)–(8). Inequalities (4), (5) ensure that the deployed real-time reserve for corrective actions be lower than the amount of procured capacity reserve at the first-stage. It is noteworthy that

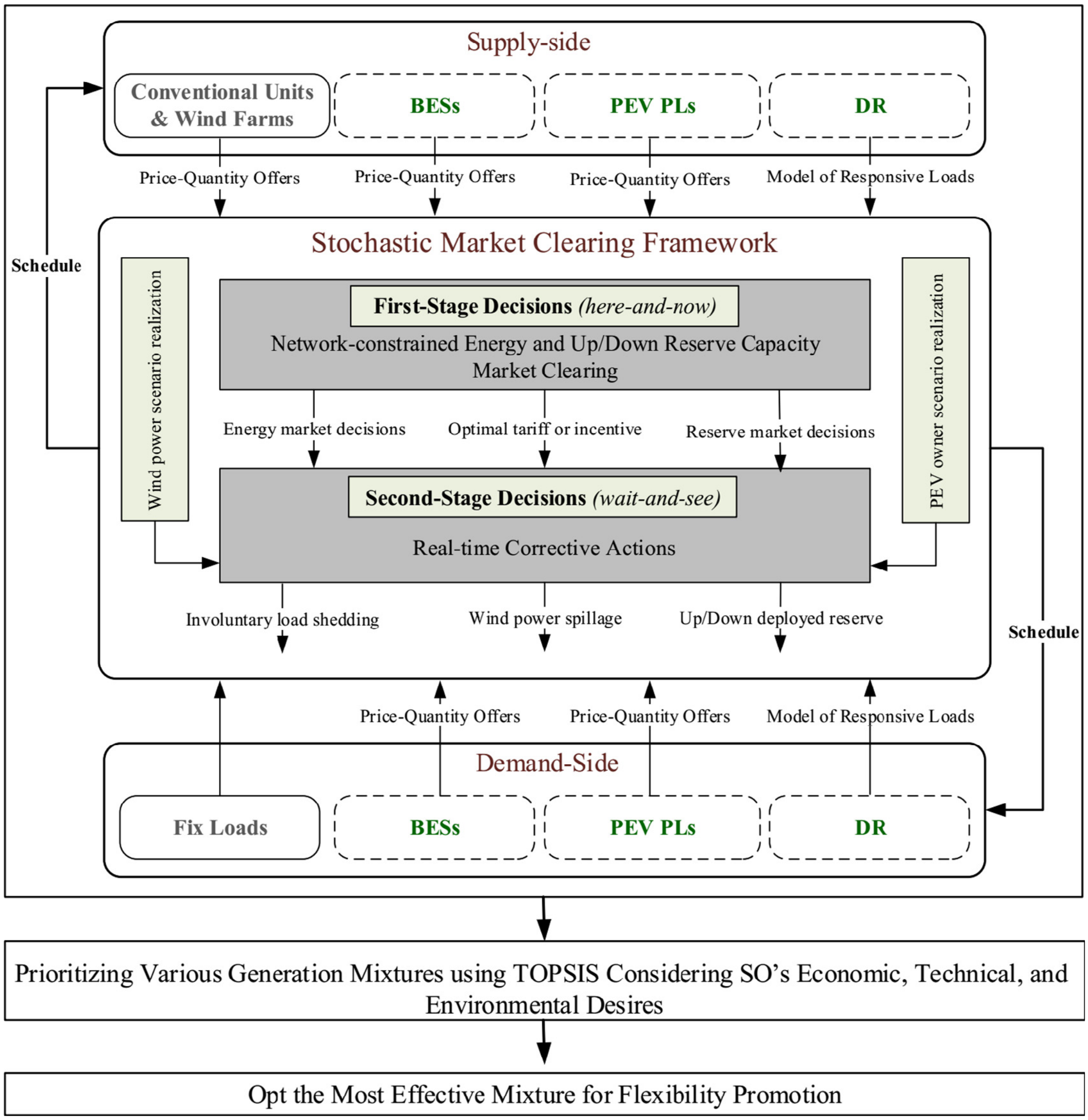

Fig. 1. Conceptual schematic of the proposed model.

reserve capacity mechanism has been employed here since the electricity market clears stochastically. Hence, it can ensure the availability of reserve in the real-time operation. This is a well-known mechanism which currently implemented in actual markets such as Danish area of the Nordpool [29]. Also, there are several previously published papers that considered the same market mechanism and constraints for capacity and deployed reserve as it can be seen in [30–34]. The amount of stored energy within reservoir of each BES at hour t as a function of energy stored until hour $t-1$ and charging/discharging in energy and up/down spinning reserve markets is represented by Eq. (6). The State of Energy (SOE) limits of BESs based on the manufacturer suggestions is also modeled in (7). Finally, Eq. (8) shows the initial SOE value of BESs as a function of their maximum reservoir capacity [20].

$$0 \leqslant r_{es,w,t}^{ES\_up} \leqslant R_{es,t}^{ES\_UC} \tag{4}$$

$$0 \leqslant r_{es,w,t}^{ES\_dn} \leqslant R_{es,t}^{ES\_DC} \tag{5}$$

$$SOE_{es,w,t}^{ES} = SOE_{es,w,t-1}^{ES} + \eta_{Ch}^{ES}(P_{es,t}^{ChES} + r_{es,w,t}^{ES\_dn}) - (P_{es,t}^{DchES} + r_{es,w,t}^{ES\_up})/\eta_{Dch}^{ES} \tag{6}$$

$$SOE_{es}^{ES,\min} \leqslant SOE_{es,w,t}^{ES} \leqslant SOE_{es}^{ES,\max} \tag{7}$$

$$SOE_{es,w,initial}^{ES} = \alpha_{es}^{ini} SOE_{es}^{ES,\max} \tag{8}$$

2.3. PEV PLs operational model

The PEV PL is an intermediary entity that can participate in the energy and reserve markets on behalf of PEV owners. The capability of PEVs to operate in both Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) modes allow SOs enjoying the benefits of flexible supply/demand. However, as the primary task of PEVs is for transportation, the provision of flexibility from PEVs is subject to many constraints related to the randomness of each PEV owner's behavior. A detailed model for PEV PLs is considered including arrival/departure time of PEVs to/from the PL, the initial SOC, and battery capacity of the PEVs.

The randomness of arrival/departure time of each PEV is modeled as given in (9), (10) employing Truncated Gaussian distribution considering the fact that $t_n^{arv} \leqslant t_n^{dep}$ as in [14,35]. The arrival time of each PEV is modeled with the mean value μ_{arv}, the standard deviation σ_{arv}, the lower bound equals the minimum arrival time $t_n^{arv,\min}$ and the upper bound equals the maximum arrival time $t_n^{arv,\max}$. The truncation region to produce the scenarios of departure time is considered as presented in (10) according to the fact that the lower bound of the departure time of each PEV is $Max(t_n^{dep,\min}, t_n^{arv})$.

Therefore, the number of available PEVs in the PL is an uncertain parameter depending on the arrival/departure time of PEVs as modeled in (11)–(13). The available number of PEVs in the PL at hour t, $N_{pl,t}^{PL,Sc}$, number of arrived PEVs to the PL, $N_{pl,t}^{arv}$ and the number of departed PEVs from the PL, $N_{pl,t}^{dep}$, are given by (11)–(13), respectively [14]. Furthermore, (14) guarantees that the number of parked PEVs not to be greater than the number of car spaces in the PL [14,35].

$$t_n^{arv} = f_{TG}(x; \mu_{arv}, \sigma_{arv}^2, (t_n^{arv,\min}, t_n^{arv,\max})) \tag{9}$$

$$t_n^{dep} = f_{TG}(x; \mu_{dep}, \sigma_{dep}^2, (Max(t_n^{dep,\min}, t_n^{arv}), t_n^{dep,\max})) \tag{10}$$

$$N_{pl,t}^{PL,Sc} = N_{pl,t-1}^{PL,Sc} + N_{pl,t}^{arv} - N_{pl,t}^{dep} \tag{11}$$

$$N_{pl,t}^{arv} = \sum_{t \in t_n^{dep}} N_{t_n^{arv}, t_n^{dep}}^{PEV} \tag{12}$$

$$N_{pl,t}^{dep} = \sum_{t \in t_n^{arv}} N_{t_n^{arv}, t_n^{dep}}^{PEV} \tag{13}$$

$$N_{pl,t}^{PL,Sc} \leqslant N^{PL,\max} \tag{14}$$

It is noticed that the aggregated number of PEVs that arrived to the PL at t^{arv} and departed from the PL at t^{dep} can be formulated according to each PEV arrival and departure time as expressed in (15).

$$N_{t^{arv}, t^{dep}}^{PEV} = \sum_n PEV_{n, t_n^{arv}, t_n^{dep}} \quad t_n^{arv} \leqslant t \leqslant t_n^{dep} \tag{15}$$

The uncertainty related to the initial SOC of each individual PEV at the arrival time is also modeled using the Truncated Gaussian distribution in (16) [14,35]. The aggregated accessible energy amount of the PL depends on the available amount of energy from the previous hour in addition to the energy level of newly arrived/departed PEVs to/from the PL as represented by (17). The total SOE of new arrived/departed PEVs to/from the PL are calculated through (18) and (19), respectively. It is noteworthy that the SOC determines the percentage of total battery capacity contains energy which is expressed in percent and varied between 0 and 100%. Zero is for an empty battery while 100% is for a full charged one. Instead, the SOE represents the actual state of energy of the battery in MW h.

$$soc_{n, t_n^{arv}, t_n^{dep}}^{PEV} = f_{TG}(x; \mu_{soc}, \sigma_{soc}^2, (soc_n^{PEV,\min}, soc_n^{PEV,\max})) \tag{16}$$

$$SOE_{pl,t}^{PL,Sc} = SOE_{pl,t-1}^{PL,Sc} + SOE_{pl,t}^{arv} - SOE_{pl,t}^{dep} \tag{17}$$

$$SOE_{pl,t}^{arv} = \sum_n \sum_{t \in t_n^{dep}} soc_{n, t_n^{arv}, t_n^{dep}}^{PEV} cap_{n, t_n^{arv}, t_n^{dep}}^{PEV} \tag{18}$$

$$SOE_{pl,t}^{dep} = \sum_n \sum_{t \in t_n^{arv}} soc_{n, t_n^{arv}, t_n^{dep}}^{PEV} \ cap_{n, t_n^{arv}, t_n^{dep}}^{PEV} \tag{19}$$

Since the capacity of each PEV depends on its battery class, twenty-four classes of PEV batteries are considered with their related occurrence probability as described in [14,35]. Consequently, the aggregated capacity of the PL at each time interval can be calculated as in (20)–(22). As it can be seen in (20), the total capacity of PL depends on the remaining capacity of PL from the previous hour in addition to the aggregated capacity of new arrived PEVs minus the aggregated capacity of departed PEVs from the PL at each time step. The aggregated capacity of new arrived and departed PEVs can be obtained through (21) and (22), respectively.

$$Cap_{pl,t}^{PL,Sc} = Cap_{pl,t-1}^{PL,Sc} + Cap_{pl,t}^{arv} - Cap_{pl,t}^{dep} \tag{20}$$

$$Cap_{pl,t}^{arv} = \sum_n \sum_{t \in t_n^{dep}} cap_{n, t_n^{arv}, t_n^{dep}}^{PEV} \tag{21}$$

$$Cap_{pl,t}^{dep} = \sum_n \sum_{t \in t_n^{arv}} cap_{n, t_n^{arv}, t_n^{dep}}^{PEV} \tag{22}$$

The PEV PL constraints associated with the market clearing stage is given in (23)–(25) [35]. The maximum amounts of tradable power between the PL and the grid as the energy and capacity reserve services are formulated in (23) and (24). The amounts of PEV PL participation in energy and reserve markets is limited by the number of available PEVs and charging/discharging rates related to the PL infrastructures. Moreover, the flow of power should be only in one direction (i.e., PL to grid or vice versa) at each hour as considered in (25).

$$P_{pl,t}^{En,PL2G} + R_{pl,t}^{PL\_UC} \leqslant \gamma^{discharge} N_{pl,t}^{PL,Sc} U_{pl,t}^{PL2G} \tag{23}$$

$$P_{pl,t}^{En,G2PL} + R_{pl,t}^{PL\_DC} \leqslant \gamma^{charge} N_{pl,t}^{PL,Sc} U_{pl,t}^{G2PL} \tag{24}$$

$$U_{pl,t}^{G2PL} + U_{pl,t}^{PL2G} \leqslant 1 \tag{25}$$

The second-stage constraints are related to the actual system operation depending on scenario realizations as presented in (26)–(32) [14,35].

$$0 \leqslant r_{pl,w,t}^{PL\_up} \leqslant R_{pl,t}^{PL\_UC} \tag{26}$$

$$0 \leqslant r_{pl,w,t}^{PL\_dn} \leqslant R_{pl,t}^{PL\_DC} \tag{27}$$

$$P_{pl,t}^{En,PL2G} + r_{pl,w,t}^{PL\_up} \leqslant \gamma^{discharge} N_{pl,w,t}^{PL,Sc} \tag{28}$$

$$P_{pl,t}^{En,G2PL} + r_{pl,w,t}^{PL\_dn} \leqslant \gamma^{charge} N_{pl,w,t}^{PL,Sc} \tag{29}$$

$$\begin{aligned} SOE_{pl,w,t}^{PL} = {} & SOE_{pl,w,t-1}^{PL} + SOE_{pl,w,t}^{arv} - SOE_{pl,w,t}^{dep} + \eta_{Ch}^{PL}(P_{pl,t}^{En,G2PL} + r_{pl,w,t}^{PL\_dn}) \\ & - (P_{pl,t}^{En,PL2G} + r_{pl,w,t}^{PL\_up})/\eta_{Dch}^{PL} \end{aligned} \tag{30}$$

$$P_{pl,t}^{En,PL2G} + r_{pl,w,t}^{PL\_up} \leqslant \psi_t^{PL} SOE_{pl,w,t}^{PL} \tag{31}$$

$$SOC_{pl}^{\min} Cap_{pl,w,t}^{PL,Sc} \leqslant SOE_{pl,w,t}^{PL} \leqslant SOC_{pl}^{\max} Cap_{pl,w,t}^{PL,Sc} \tag{32}$$

The linkage between the first and second-stage variables is made by (26), (27). In fact, the constraints in (26) and (27) demonstrate the relationship between the procured spinning reserve in the first-stage and the deployed spinning reserve in the second-stage.

Inequalities (28), (29) are similar to (23), (24) due to the fact that the total exchanged power between the grid and the PL depends on the available number of PEVs in the PL which is subjected to the input scenarios. The aggregated SOE of the PL at each time interval depends on the remaining energy from previous time interval, the SOE of arrived/departed PEVs, amounts of exchanged power with the grid in energy and reserve markets as demonstrated in (30) [35]. Constraint (31) limits the maximum injected power of PL to the grid due to its contract with PEV owners related to the desired SOC at the departure time. In other words, the PL must aggregate the required SOC assigned in the PEV contracts for each hour and then schedule the injection back to the grid in both energy and up reserve markets as formulated in (31). In order to assure the battery lifetime of PEVs in the PL, maximum and minimum limits of each PEV's SOC should be considered which affect the aggregated SOE of the PL as expressed in (32).

2.4. Economic model of responsive loads

In this paper, two most popular DR programs namely, Time of Use (TOU) and Emergency Demand Response Program (EDRP) are considered to model the consumer's reactions to changes in electricity tariffs and incentive payment, respectively. The TOU program motivates the customers to decrease or shift some parts of their initial consumption by changing the electricity tariffs. Typically, TOU rates establish two or more daily periods so-called low-load, off-peak and peak for predetermined tariffs for each period so that the higher rates belong to the peak period. Here, a modified version of a TOU rate is considered in which the optimum TOU tariffs of each load bus are determined as decision variables in order to achieve the rates with higher consistency to the actual system operation [36].

The mathematical formulation of the proposed dynamic TOU program based on the price elasticity of demand concept is given in (33)–(37) [36,37]. The modified demand considering TOU program is represented in (33). As observed in (33), different electricity tariffs in various periods are the main driver for changing the customer's demand. The reasonable relations between the calculated tariffs in different periods are considered through (34)–(36). These constraints are due to the fact that the electricity tariff during the off-peak period should be lower than the tariff during the peak-time. Moreover, the obtained tariff during the low-load must be lower than the tariff during the off-peak period. Also, constraint (37) restricts the change in load as a result of DR at each time interval since just a portion of the total load is responsive.

$$d_{j,t} = d^0_{j,t}\left\{1 + \sum_{t'\in LTP} E_{t,t'}\frac{[\rho^{LTP}_j - \rho^{ini}]}{\rho^{ini}} + \sum_{t'\in OTP} E_{t,t'}\frac{[\rho^{OTP}_j - \rho^{ini}]}{\rho^{ini}} + \sum_{t'\in PTP} E_{t,t'}\frac{[\rho^{PTP}_j - \rho^{ini}]}{\rho^{ini}}\right\} \tag{33}$$

$$\rho^{LTP}_j \leqslant \rho^{ini} \tag{34}$$

$$\rho^{LTP}_j \leqslant \rho^{OTP}_j \leqslant \rho^{PTP}_j \tag{35}$$

$$\rho^{PTP}_j \geqslant \rho^{ini} \tag{36}$$

$$-DR^{\max} \times d^0_{j,t} \leqslant \Delta d_{j,t} \leqslant DR^{\max} \times d^0_{j,t} \tag{37}$$

The EDRP is also considered in order to model the consumer's behavior in response to an incentive payment. It is noteworthy that, EDRP is a voluntary DR program in which the customers may reduce their typical consumption during the peak load period in exchange for an incentive payment. The modified demand considering EDRP implementation and its associated cost is formulated in (38) and (39), respectively [37]. It is notable that the cost of EDRP is calculated by multiplying the incentive value and the consumption change as a result of EDRP implementation.

$$d_{j,t} = d^0_{j,t}\left[1 + \sum_{t'=1}^{NT} E_{t,t'}\frac{inc_{j,t'}}{\rho^{ini}}\right] \tag{38}$$

$$C^{EDRP} = \sum_{t\in PTP}\sum_{j=1}^{NJ} d^0_{j,t}\left[\sum_{t'=1}^{NT} E_{t,t'}\frac{inc^2_{j,t'}}{\rho^{ini}}\right] \tag{39}$$

Note that, equation (39) is replaced with its approximated piecewise linear form in order to preserve the model linearity. Constraint (37) should be also considered according to customer participation level.

3. Stochastic market clearing formulation

3.1. Objective function

The objective function is the total operation cost as expressed in (40). The generation costs of thermal units including start-up cost, minimum production cost and up/down capacity reserve costs are shown in the first line of (40). Also, the second line pertains to piecewise linear fuel cost of thermal units. The costs related to BES and PEV PL entities for providing energy and capacity reserve services are expressed in the third and fourth lines in (40), respectively. The cost related to the EDRP is modeled in the fifth line. The second part of costs in the objective function are devoted to the corrective actions embedded in scenarios. The some major measures that can be used by the SO during the real-time stage in order to accommodate the uncertainty in wind generation after scenarios realization are up/down reserves of conventional units, BESs, and PEV PLs, load shedding and wind spillage as it can be seen in the last part of (40).

Minimize

$$\begin{aligned}
&\sum_{t=1}^{NT}\left[\sum_{i=1}^{NG}(SUC_{i,t} + MPC_i U_{i,t} + C^{G_UC}_{i,t}R^{G_UC}_{i,t} + C^{G_DC}_{i,t}R^{G_DC}_{i,t})\right.\\
&\quad + \sum_{i=1}^{NG}\sum_{m=1}^{NM} P^e_{i,t,m}\,C^{G_Eng}_{i,t,m} + \sum_{es=1}^{NES}(C^{ES_Eng}_{es,t}P^{DchES}_{es,t} + C^{ES_UC}_{es,t}R^{ES_UC}_{es,t} + C^{PL_DC}_{es,t}R^{ES_DC}_{es,t})\\
&\quad \left.+ \sum_{pl=1}^{NPL}(C^{PL_Eng}_{pl,t}P^{En,PL2G}_{pl,t} + C^{PL_UC}_{pl,t}R^{PL_UC}_{pl,t} + C^{PL_DC}_{pl,t}R^{PL_DC}_{pl,t}) + \sum_{j=1}^{NJ}\sum_{k=1}^{NK} LRDR_{j,t,k}\,INC_{j,t,k}\right]\\
&\quad + \sum_{t=1}^{NT}\sum_{w=1}^{NW}\pi_w\left(\sum_{i=1}^{NG} C^{G_UE}_{i,t}r^{G_up}_{i,t,w} - C^{G_DE}_{i,t}r^{G_dn}_{i,t,w} + \sum_{es=1}^{NES} C^{ES_UE}_{es,t}r^{ES_up}_{es,w,t} - C^{ES_DE}_{es,t}r^{ES_dn}_{es,w,t}\right.\\
&\quad \left.+ \sum_{pl=1}^{NPL} C^{PL_UE}_{pl,t}r^{PL_up}_{pl,t,w} - C^{PL_DE}_{pl,t}r^{PL_dn}_{pl,t,w} + \sum_{j=1}^{NJ} Voll_{j,t}LS_{j,w,t} + \sum_{wf=1}^{NWF} C^{WP_spill}_{wf}P^{WP_spill}_{wf,w,t}\right)
\end{aligned} \tag{40}$$

3.2. First-stage constraints

The first-stage constraints are associated with the base-case. In order to model the network, the energy balance between the generation and demand at each bus is modeled considering the DC power flow constraint and transmission line limits as expressed in (41)–(43). The DC power flow has been used here due to two main reasons. Firstly, the paper focuses just on active power and reserve scheduling. Secondly, the DC power flow maintains the linearity of optimization problem which has significant superiorities in comparison with non-linear one. Different terms in left hand side of (41) are associated with the generated power from conventional units, charging/discharging power of BESs, injected power from PL to grid and vice versa, scheduled power of wind farms and the residual demand after DR implementation. It is noticed that in (41), G_b, ES_b, PL_b, WF_b, J_b, L_b represent a set of generating units, energy storages, parking lots, wind farms, loads and transmission lines which are connected to Bus b, respectively. The transmission thermal flow limits are considered in (43). The generation unit constraints are listed in (44)–(49). Block energy output of conventional units as a result of linearization of fuel cost and their limit are represented in (44). Feasible operating ranges of thermal units are defined in (45), (46). Constraints (45) and (46) limit the output power of a generating unit, taking also into account the hourly scheduled up and down reserve margins, respectively.

Up and down reserve capacity restrictions due to ramp rates and spinning reserve market lead-time are given in (47) and (48), respectively. Note that τ is the time during which the reserves should be fully deployed. The start-up cost of generation units is formulated in (49). Typically the wind power generation scheduled in the day-ahead market is considered equal to its forecasted value. However, in this study it is considered that the SO schedules the optimal amount of wind at each period according to the techno-economic optimization within the limits imposed by (50).

$$\sum_{i\in G_b} P_{i,t} + \sum_{es\in ES_b}(P^{DchES}_{es,t} - P^{ChES}_{es,t}) + \sum_{pl\in PL_b}(P^{En,PL2G}_{pl,t} - P^{En,G2PL}_{pl,t}) + \sum_{wf\in WF_b} P^{WP,S}_{wf,t} - \sum_{j\in J_b} d_{j,t} = \sum_{l\in L_b} F^0_{l,t} \tag{41}$$

$$F^0_{l,t} = (\delta^0_{b,t} - \delta^0_{b',t})/X_l \tag{42}$$

$$-F^{\max}_l \leqslant F^0_{l,t} \leqslant F^{\max}_l \tag{43}$$

$$P_{i,t} = \sum_{m=1}^{NM} P^e_{i,t,m},\ 0 \leqslant P^e_{i,t,m} \leqslant P^{\max}_{i,m} \tag{44}$$

$$P_{i,t} + R^{G\_UC}_{i,t} \leqslant P^{\max}_i\ U_{i,t} \tag{45}$$

$$P_{i,t} - R^{G\_DC}_{i,t} \geqslant P^{\min}_i\ U_{i,t} \tag{46}$$

$$0 \leqslant R^{G\_UC}_{i,t} \leqslant RU_i\ \tau \tag{47}$$

$$0 \leqslant R^{G\_DC}_{i,t} \leqslant RD_i\ \tau \tag{48}$$

$$SUC_{i,t} \geqslant SC_i(U_{i,t} - U_{i,t-1}) \tag{49}$$

$$0 \leqslant P^{WP,S}_{wf,t} \leqslant P^{WP,\max}_{wf,t} \tag{50}$$

3.3. Second-stage constraints

The second-stage constraints should be satisfied for each scenario realization. The power balance is guaranteed as formulated in (51). The auxiliary tools for managing the variations as a result of wind generation in real-time stage includes the up/down deployed reserve by conventional units, BESs and PEV PLs alongside the load shedding as well as wind power spillage as illustrated in (51). The deployed up and down spinning reserves in each scenario cannot exceed the previously scheduled reserve capacities established by the market clearing (52), (53). Constraint (54) defines an auxiliary variable equal to the scheduled generation output augmented by the deployment of up spinning reserve minus the deployment of down spinning reserve. The related limits on the net power output of generating units are considered in (55). A portion of available wind production may be spilled if it is necessary to facilitate the operation of the power system. This is enforced by (56). Moreover, the SO can decide to shed a part of the modified demand in order to maintain the consistency of the system as formulated in (57).

$$\sum_{i\in G_b}(r^{G\_up}_{i,w,t} - r^{G\_dn}_{i,w,t}) + \sum_{wf\in WF_b}(P^W_{wf,w,t} - P^{WP,S}_{wf,t} - P^{WP\_spill}_{wf,w,t}) + \sum_{es\in ES_b}(r^{ES\_up}_{es,w,t} - r^{ES\_dn}_{es,w,t}) + \sum_{pl\in PL_b}(r^{PL\_up}_{pl,w,t} - r^{PL\_dn}_{pl,w,t}) + \sum_{j\in J_b} LS_{j,w,t} = \sum_{l\in L_b} F_{l,w,t} - F^0_{l,t} \tag{51}$$

$$0 \leqslant r^{G\_up}_{i,w,t} \leqslant R^{G\_UC}_{i,t} \tag{52}$$

$$0 \leqslant r^{G\_dn}_{i,w,t} \leqslant R^{G\_DC}_{i,t} \tag{53}$$

$$P_{i,w,t} = P_{i,t} + r^{G\_up}_{i,w,t} - r^{G\_dn}_{i,w,t} \tag{54}$$

$$P^{\min}_i\ U_{i,t} \leqslant P_{i,w,t} \leqslant P^{\max}_i\ U_{i,t} \tag{55}$$

$$0 \leqslant P^{WP\_spill}_{wf,w,t} \leqslant P^W_{wf,w,t} \tag{56}$$

$$0 \leqslant LS_{j,w,t} \leqslant d_{j,t} \tag{57}$$

Ramping constraints, minimum up/down time of generating units, and network constraints in the second-stage have been also considered even if, for the sake of conciseness, their mathematical formulation is omitted.

4. Numerical results

4.1. Input data and assumptions

Numerical case studies are conducted on the modified IEEE Reliability Test System (RTS 24-bus) which is a well-known test system and its data is available in [38]. The IEEE RTS has 26 generation units including generation technologies such as oil/steam, oil/combustion turbine, coal/steam and nuclear without considering 6 hydro units. The offered cost for energy, reserve capacity and the deployed reserve of generation units are extracted from [14] as given in Table 1. Furthermore, two most popular pollutants are considered to conduct the emission calculation. The emission function slopes and the start-up emission of conventional units are the same as those for corresponding unit fuel cost curves, all multiplied by conversion factors of 0.2 and 0.5 for SO_2 and NO_x emission, respectively [39]. The peak of the day is assumed to be 2850 MW and the value of lost load and the cost of wind spillage are presumed to be 200 and 40 $/MW h, respectively.

The wind generation capacity in the IEEE RTS system is 900 MW which is provided by six 150 MW wind farms located at buses 1, 4, 6, 18, 21 and 22. An Autoregressive Moving Average (ARMA) model is used to generate wind speed scenarios based on South East and North of South Australia wind speed data. The wind speed scenarios are reduced to ten scenarios for each wind farm using K-means clustering technique [40] and then transformed into power scenarios considering the Vestas 3 MW turbine model. Also, two PEV PLs with 13,500 car stations each are located at nodes 8 and 24. The aggregated number of PEVs in the PL, SOE of the PL, and the capacity of available PEVs in the PL are modeled using three scenarios for each PL based on the randomness of PEV owner's behavior. The rest assumptions for the PL parameters are represented in Table 2.

As mentioned above, there are two different sets of uncertainties in the proposed model. The first uncertainty set includes ten scenarios related to wind power generation represented by w_{wind}. Moreover, the second uncertainty set has three scenarios associated with PEV owner's behavior denoted by w_{PEV}. Hence, the total number of scenarios composing the scenario tree is 30 which is calculated from $w_{wind} \times w_{PEV}$ and represented by w throughout the paper.

Four equal BES units with 60 MW h capacity each, located at nodes 6, 7, 19 and 23 are considered. The maximum charging/discharging power of BESs is 60 MW and their initial energy level is set to 50% of their capacities. The state of charge of BESs is assumed to be between 10% and 90% according to the suggestion of manufacturers. The offered costs of all BESs for providing energy and reserve are the same as for PEV PLs. Note that the cost of PEV PLs and BESs for energy production (i.e., 13.5 $/MW h) is considered equal to the average market clearing price of the 24-h scheduling horizon. Also, the cost of providing up/down capacity reserves are assumed to be 40% of the energy production cost as considered for conventional units. The system load curve is divided into three

Table 1
Generation units cost parameters [14].

	Generation unit no.							
	i1-i5	i6-i9	i10-i13	i14-i16	i17-i20	i21-i23	i24	i25-i26
SC_i ($)	87.4	15	715.2	575	312	1018.9	2298	0
MPC_i ($)	5.25	5	7.5	8.5	6.25	15	20	0
$C_{i,t,1}^{G\_Eng}$ ($/MW h)	23.41	29.58	11.46	18.6	9.92	19.2	10.08	5.31
$C_{i,t,2}^{G\_Eng}$ ($/MW h)	23.78	30.42	11.96	20.03	10.25	20.32	10.66	5.38
$C_{i,t,3}^{G\_Eng}$ ($/MW h)	26.84	42.82	13.89	21.97	10.68	21.22	11.09	5.53
$C_{i,t,4}^{G\_Eng}$ ($/MW h)	30.4	43.28	15.97	22.72	11.26	22.13	11.72	5.66
$C_{i,t}^{G\_UC}$ ($/MW)	10.44	14.61	5.33	8.33	4.21	8.29	4.35	2.19
$C_{i,t}^{G\_DC}$ ($/MW)	10.44	14.61	5.33	8.33	4.21	8.29	4.35	2.19
$C_{i,t}^{G\_UE}$ ($/MW h)	26.11	36.53	13.32	20.76	10.53	20.72	10.89	5.47
$C_{i,t}^{G\_DE}$ ($/MW h)	26.11	36.53	13.32	20.76	10.53	20.72	10.89	5.47

Table 2
The input data for the PEV PLs.

γ^{charge} (kW/h)	$\gamma^{discharge}$ (kW/h)	$\eta_{Ch/Dch}^{PL}$ (%)	ψ_t^{PL} (%)	$C_{pl,t}^{PL\_Eng}$ ($/MW h)	$C_{pl,t}^{PL\_UC/DC}$ ($/MW h)	$SOC_{pl}^{\min}$ (%)	$SOC_{pl}^{\max}$ (%)
22	22	90	40	13.5	5.4	30	90

periods: low-load (1:00–8:00), off-peak (9:00–16:00), and peak period (17:00–24:00). The potential of DR implementation is considered to be 10% of the total load. Furthermore, the price elasticity values are extracted from [37].

4.2. Simulation results

The proposed model was solved using CPLEX 12.5.0 under GAMS software. The considered case studies are given in Table 3.

Operational flexibility enhancements should be justified simultaneously considering different aspects. From an economic viewpoint, additional flexibility provision results in extra costs that should be minimized while from a technical perspective the flexibility describes the system's ability to ramp resources in order to assure the supply and demand balance. From an environmental point of view, the lack of enough flexibility may lead to significant wind curtailment, and consequent increase of emissions. On this basis, the total operation cost, pollutant emission, and ramping of conventional units are introduced as flexibility metrics to explore the most effective generation mixture as represented in Fig. 2. Comparing C2, C3, C5 and C9 reveals that the implementation of DR programs (C5 and C9), particularly TOU, has a higher impact on decreasing either the operation cost and pollutant emission.

For instance, the system operation cost as a result of implementing TOU (C5) and EDRP (C9) are reduced by 10.14% and 5%, respectively. It should be noted that the optimal value of incentive for EDRP at all load points is 1.69 $/MW h, while the obtained electricity tariffs of TOU are 13.5, 15.42 and 15.42 $/MW h for low-load, off-peak, and peak time period, respectively. Also as it can be clearly observed a cost and emission reduction as a result of incorporating BESs or PEV PLs (C2 or C3) is insignificant.

Technically, the implementation of TOU (C5) and EDRP (C9) decreases the daily need for ramp from 4577 MW to 4290 and 4570 MW, respectively. However, optimal operation of BESs (C3) can reduce the daily need for ramp to 4213 MW, although the PEV PLs have vice versa impact due to the fact that the PEV PLs are not fully dispatchable due to unpredictability in PEV owner's behavior. The reduction in operation cost, emission and daily need for ramp in the coordinated cases is much lower than that in the cases without coordination according to the compensation role of the flexible resources for each other. In this respect, the share of either BESs or PEV PLs in term of providing down spinning reserve is shown in Fig. 3 for case C4.

It is observed that BESs provide much more down spinning reserve when there is not the possibility for PEV PLs due to restrictions related to the availability of PEVs. For instance, at hour 4:00 BESs provide all the down reserve by charging the excess of wind generation, whereas the PL's share is zero due to the fact that there is no PEV in the PLs. Similarly, in hours between 17:00 and 24:00 the role of BESs is dominant due to a lower number of parked PEVs. On the other hand, the scheduled amount of down spinning reserve provided by PLs is much higher than the BESs in hours 6:00–16:00, when the capacity of PLs is higher, due to the higher number of parked PEVs.

The aggregated SOE of BESs in coordination with PL (C4) and TOU (C7) are compared in Fig. 4. In general, in the early morning, particularly from hour 4:00, BESs start to charge through energy and down spinning reserve markets due to the high volume of wind generation. The energy level remains with minor changes until hour 17:00. Afterward, BESs' energy level sharply drops due to the low volume of wind generation in this period which results in discharging BESs much more through the up reserve market.

Implementing TOU increases the energy level of BESs during the peak period due to the fact that TOU motivates the consumers to decrease their consumption during peak period when there is a deficit of wind generation. This also happens with more intensity

Table 3
A summary of case studies.

Case No.	Conventional units	DR	BESs	PLs
C1	Yes	No	No	No
C2	Yes	No	No	Yes
C3	Yes	No	Yes	No
C4	Yes	No	Yes	Yes
C5	Yes	TOU	No	No
C6	Yes	TOU	No	Yes
C7	Yes	TOU	Yes	No
C8	Yes	TOU	Yes	Yes
C9	Yes	EDRP	No	No
C10	Yes	EDRP	No	Yes
C11	Yes	EDRP	Yes	No
C12	Yes	EDRP	Yes	Yes

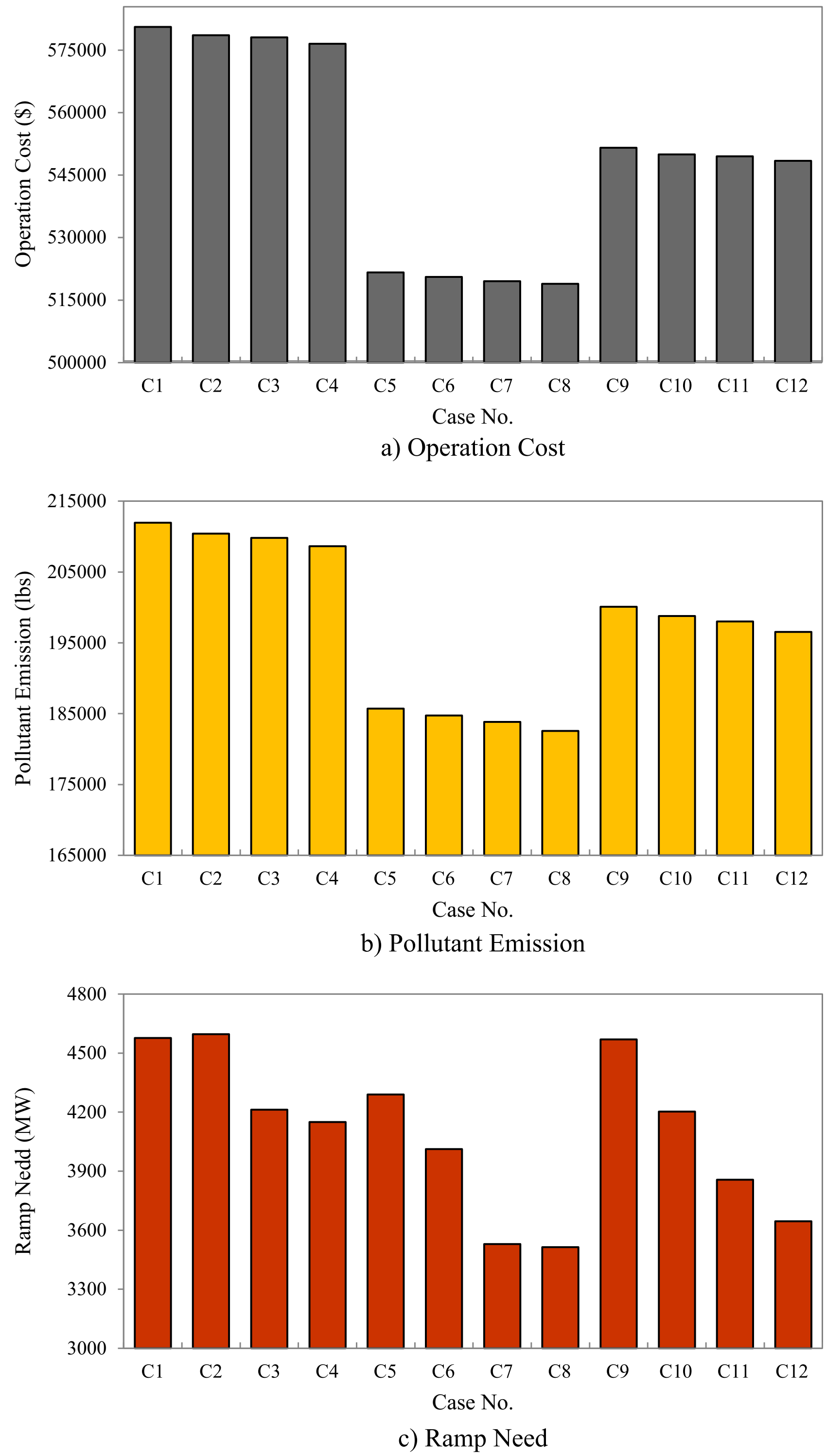

Fig. 2. Comparison of Flexibility metrics for 24-h scheduling horizon.

in the case of coordinated operation of BESs with PEV PLs (C4). In this case, the deficit of wind generation during the peak period (i.e., hours 17–24) is mainly compensated by PLs rather than BESs. In this regard, the two PEV PLs inject 118.97 MW h of energy to the grid in both reserve up and energy markets, while draw 3.26 MW h from the grid at the same time. Therefore in both C4 and C7, PLs and DR are partially replaced with BESs which causes the BESs energy level to drop less.

The aggregated initial and obtained stored energies in the PLs are compared for cases C2 and C6 in Fig. 5. According to Fig. 5, the initial energy level of PLs begins to increase from hour 5:00, while gradually falling from hour 13:00 due to the arrived/departed PEVs to/from the PLs. By comparing the case C2 with C6, it can be seen that the PEV PLs store less energy when scheduling in coordination with TOU program, particularly in the low-load and off-peak periods. In case C2, the PEV PLs inject 51.91 MW h to

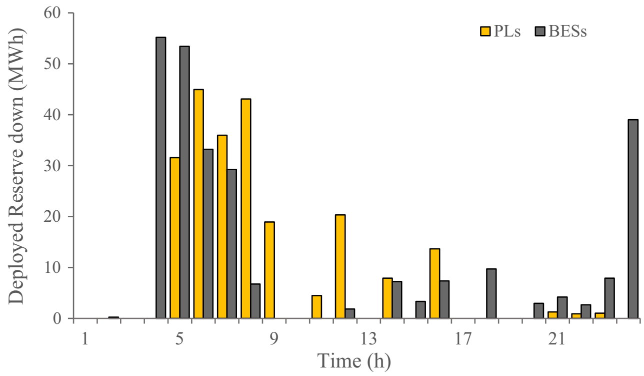

Fig. 3. Share of BESs and PEV PLs in provision of down reserve in case C4.

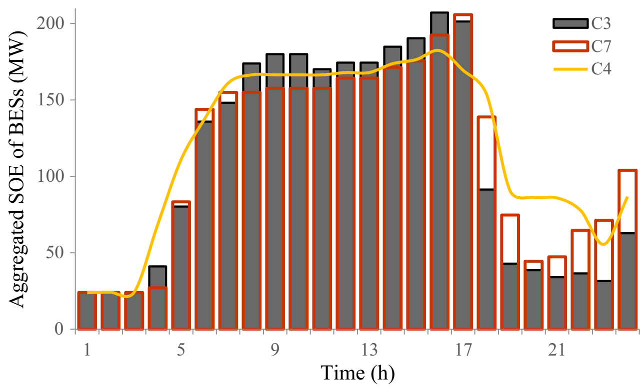

Fig. 4. Aggregated SOE of BESs in the given cases.

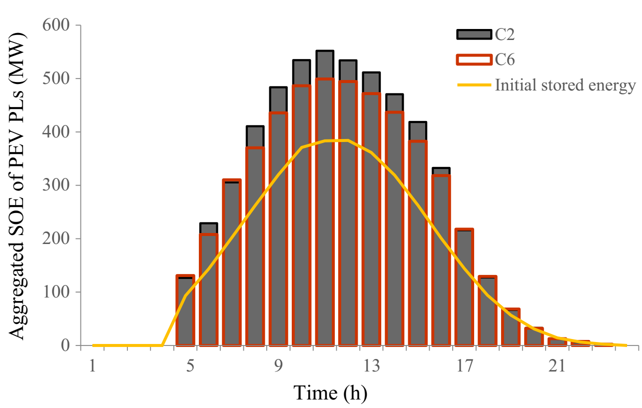

Fig. 5. Aggregated SOE of PEV PLs with and without TOU implementation.

the grid in both energy and up reserve markets, while absorb 210.09 MW h through down reserve market. However, in case C6, when TOU is implemented, the amounts of injected and absorbed power to/from the grid decline to 6.85 MW h and 138.75 MW h, respectively. So, the aggregated SOE of the PLs decrease by implementing TOU.

The impacts of DR on market transactions of either BESs or PEV PLs have been analyzed. As listed in Table 4, implementing TOU decreases the market transactions of PEV PLs by 33.33%, whereas the total exchanged power of BESs negligibly increase. The main reason is that PEV PLs are not quite dispatchable resources since their scheduling deals with several uncertain parameters related to the PEV owner's behavior. So, the SO prefers to schedule more manageable resources such as BESs and DR in comparison with PLs.

Table 4
Market transactions of BESs and PEV PLs under different DR programs.

Case No.	Energy Market (MW h)	Up/Down Reserve (MW h)	Change in market Transactions (%)		
			Total	Energy	Reserve
C2	133.17	251.59	–	–	–
C3	209.52	301.07	–	–	–
C6	84.35	172.18	−33.33	−36.66	−31.56
C7	199.27	319.50	+1.60	−4.89	+6.12
C10	162.61	246.05	+6.21	+22.11	−2.20
C11	226.63	343.26	+11.61	+8.17	+14.01

The wind spillage amounts for the given cases are shown in Fig. 6. In case C8, the wind spillage volume decreases by 13.34% in comparison with case C1. Also, it can be noted that implementing EDRP (C9) is not an appropriate option for improving wind integration. On this basis, SO have been forced to use more capacity of BESs and PLs in order to avoid wind generation waste as it can be seen in Table 4. For instance, an increase of 11.61% in the exchanged power of BESs in the market in case C11, reduces wind power spillage by 8.11% in comparison with the case when EDRP is exclusively implemented. However, it can be observed that implementing dynamic TOU with optimal tariffs is an effective option for facilitating wind integration. This goal is achieved mainly through load shifting from the peak periods, where the wind generation is low to low-load periods where the amounts of wind generation is relatively high. The obtained results demonstrated that different generation mixtures have distinct and partly conflicting impacts. In order to compare the effectiveness of various generation mixtures, the considered cases (C1-C12) are prioritized by means of TOPSIS. The obtained weights for operation cost, pollutant emission, and daily required ramp are 0.14, 0.22, and 0.64, respectively applying the entropy method. More details of TOPSIS and entropy methods can be found in [41].

The priorities have been calculated using the TOPSIS method as shown in Fig. 7 where C8 has the highest priority and C7 is in the second priority with a negligible difference. Individual implementation of DR programs (C5 and C9) cannot be an effective strategy for the SO. In fact, although DR has remarkable impacts in terms of cost and emission reduction, it could not play a positive role in decreasing the ramp need.

In addition, the pair comparison of the same scenarios under TOU and EDRP (C8 vs. C12 or C6 vs. C10) represents that the implementation of TOU is more favorable than EDRP to meet the flexibility requirement. Another important point is that PEV PL cannot be considered as a flexible tool by its own due to its uncertain features. Having this in mind, the coordinated operation of PEV PLs with TOU, BESs, and EDRP is more effective as shown in Fig. 7.

5. Practical implementation aspects

To sum up, it is clear that coordinated scheduling of emerging flexible resources in energy and ancillary services beget significant benefits for the SOs. However, a number of barriers still outstanding for practical implementation of the proposed framework, mainly in demand-side, which need further research effort. For instance, in the case of PEVs the main deficit from PEV owner's point of view is devoted to degradation of PEV batteries as a result of multiple charging and discharging which may reduce the battery lifetime and impose some costs and troublesome to the PEV owners. Also, full incorporation of PEVs into the electricity market requires several communication, control and power measurement infrastructures.

Although the wide applicability of DR has been addressed in various sectors such as residential [42] and industrial [43], there are

Table 5
Optimization statistics for two given cases.

Case No.	No. of single constraints	No. of single variables	No. of discrete variables	No. of iterations	Solution times (s)
C1	79,862	37,586	1872	45,916	7.1
C8	318,409	174,512	2160	226,523	769.8

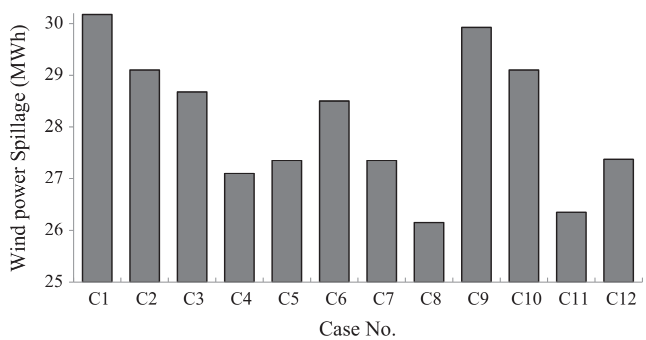

Fig. 6. Wind spillage in the given cases.

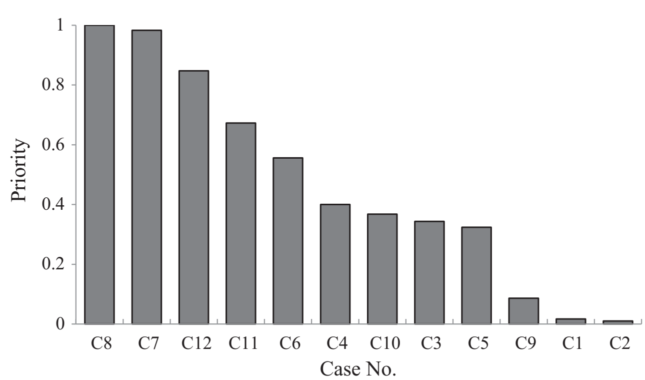

Fig. 7. The priority of various generation mixtures.

also some fundamental barriers for full DR implementation that hope to be solved in near future to access the huge potential of DR. The authors in [9] categorized the DR barriers into fundamental and secondary barriers. Economic, social and technological barriers reflecting both power system as well as information and communication technology aspects has been introduced as fundamental barriers. The economic barriers are market failures and market barriers. Social barriers also divided to organizational and behavioral barriers. The technological barriers were classified as sensing, computing, communication, technology standardization and technological skills. Moreover, the secondary barriers includes political/regulatory, market structures, physical and understanding barriers. More details of the aforementioned deficits can be found in [9].

In order to indicate the application of the proposed model, the computation time and other optimization statistics of the model are reported in Table 5. To this end, the optimization statistics for two cases including C1 and C8 are compared. Case C1 is associated with the base-case where there is no emerging flexible option while C8 is devoted to the most effective generation mixture. A 64-bit Intel core i5 laptop is employed as the platform with 4 GB DDR3 of RAM and 2.3 GHz processors to accomplish aforementioned cases.

6. Conclusion

This paper proposed a stochastic network-constrained market clearing model incorporating emerging flexible resources such as BESs, PEV PLs, and DR programs to precisely evaluate the individual and combined operation mode of a set of flexible resources to support large-scale wind generation in joint energy and reserve markets. The key findings of several conducted analyses are summarized as below:

- DR programs have a remarkable impacts in terms of cost and emission reduction, but they could not decrease the ramp need significantly. Note that the costs of the infrastructure for DR implementation have been ignored here. If these costs are accounted for DR implementation, this may affect the cost effectiveness of DR.
- PEV PL is not a favorable flexible resource by its own due to its uncertain characteristics related to PEV owners behavior, whereas the combined operation of TOU and BESs beside PEV PL can improve its dispatchability.
- TOU program is more effective than EDRP in facilitating wind integration.
- Coordinated operation of PEV PLs and BESs under TOU program is the most effective generation mixture that results in a reduction of operation cost, emission, and ramp need by 10.6%, 13.9%, and 23.2%, respectively. Also, the wind power curtailment decreases by 13.3%. This implies that proportional investment and development of different flexibility options (not only just one technology) may bring more advantages from both short-term and long-term perspectives.

References

[1] Ela E, O'Malley M. Scheduling and pricing for expected ramp capability in real-time power markets. IEEE Trans Power Syst 2016;31(3):1681–91.
[2] Ela E, Milligan M, Bloom A, Botterud A, Townsend A, Levin T, et al. Wholesale electricity market design with increasing levels of renewable generation: incentivizing flexibility in system operations. The Electr J 2016;29(4):51–60.
[3] Ramos A, De Jonghe C, Gómez V, Belmans R. Realizing the smart grid's potential: defining local markets for flexibility. Utilities Policy 2016;40:26–35.
[4] Das T, Krishnan V, McCalley JD. Assessing the benefits and economics of bulk energy storage technologies in the power grid. Appl Energy 2015;139:104–18.
[5] http://www.energystorageexchange.org/.
[6] Duvall M, Knipping E, Alexander M, Tonachel L, Clark C. Environmental assessment of plug-in hybrid electric vehicles. Volume 1: nationwide greenhouse gas emissions, vol. 1015325. Palo Alto, CA: Electric Power Research Institute; 2007.
[7] Siano P. Demand response and smart grids—a survey. Renew Sustain Energy Rev 2014;30:461–78.
[8] Paterakis NG, Erdinç O, Catalão JP. An overview of demand response: key-elements and international experience. Renew Sustain Energy Rev 2017;69:871–91.
[9] Good N, Ellis KA, Mancarella P. Review and classification of barriers and enablers of demand response in the smart grid. Renew Sustain Energy Rev 2017;72:57–72.
[10] Wen Y, Guo C, Pandžić H, Kirschen DS. Enhanced security-constrained unit commitment with emerging utility-scale energy storage. IEEE Trans Power Syst 2016;31(1):652–62.
[11] Li N, Uçkun C, Constantinescu EM, Birge JR, Hedman KW, Botterud A. Flexible operation of batteries in power system scheduling with renewable energy. IEEE Trans Sustain Energy 2016;7(2):685–96.
[12] Wu H, Shahidehpour M, Alabdulwahab A, Abusorrah A. Demand response exchange in the stochastic day-ahead scheduling with variable renewable generation. IEEE Trans Sustain Energy 2015;6(2):516–25.
[13] Paterakis NG, Erdin O, Bakirtzis AG, Catalo JP. Qualification and quantification of reserves in power systems under high wind generation penetration considering demand response. IEEE Trans Sustain Energy 2015;6(1):88–103.
[14] Heydarian-Forushani E, Golshan MEH, Shafie-khah M. Flexible interaction of plug-in electric vehicle parking lots for efficient wind integration. Appl Energy 2016;179:338–49.

[15] Nguyen HN, Zhang C, Mahmud MA. Optimal coordination of G2V and V2G to support power grids with high penetration of renewable energy. IEEE Trans Transp Electrification 2015;1(2):188–95.
[16] Pavić I, Capuder T, Kuzle I. Low carbon technologies as providers of operational flexibility in future power systems. Appl Energy 2016;168:724–38.
[17] Schuller A, Flath CM, Gottwalt S. Quantifying load flexibility of electric vehicles for renewable energy integration. Appl Energy 2015;151:335–44.
[18] Kamalinia S, Wu L, Shahidehpour M. Stochastic midterm coordination of hydro and natural gas flexibilities for wind energy integration. IEEE Trans Sustain Energy 2014;5(4):1070–9.
[19] Devlin J, Li K, Higgins P, Foley A. System flexibility provision using short term grid scale storage. IET Gener Transm Distrib 2016;10(3):697–703.
[20] Heydarian-Forushani E, Golshan MEH, Moghaddam MP, Shafie-khah M, Catalão JPS. Robust scheduling of variable wind generation by coordination of bulk energy storages and demand response. Energy Convers Manage 2015;106:941–50.
[21] Erdinc O, Paterakis NG, Mendes TD, Bakirtzis AG, Catalão JP. Smart household operation considering bi-directional EV and ESS utilization by real-time pricing-based DR. IEEE Trans Smart Grid 2015;6(3):1281–91.
[22] Wu H, Shahidehpour M, Alabdulwahab A, Abusorrah A. Thermal generation flexibility with ramping costs and hourly demand response in stochastic security-constrained scheduling of variable energy sources. IEEE Trans Power Syst 2015;30(6):2955–64.
[23] Kubik ML, Coker PJ, Barlow JF. Increasing thermal plant flexibility in a high renewables power system. Appl Energy 2015;154:102–11.
[24] Chen X, Kang C, O'Malley M, Xia Q, Bai J, Liu C, et al. Increasing the flexibility of combined heat and power for wind power integration in China: modeling and Implications. IEEE Trans Power Syst 2015;30(4):1848–57.
[25] Wang Q, Wu H, Florita AR, Martinez-Anido CB, Hodge BM. The value of improved wind power forecasting: grid flexibility quantification, ramp capability analysis, and impacts of electricity market operation timescales. Appl Energy 2016;184:696–713.
[26] Oree V, Hassen SZS. A composite metric for assessing flexibility available in conventional generators of power systems. Appl Energy 2016;177:683–91.
[27] Brouwer AS, van den Broek M, Seebregts A, Faaij A. Operational flexibility and economics of power plants in future low-carbon power systems. Appl Energy 2015;156:107–28.
[28] Hirth L. The benefits of flexibility: the value of wind energy with hydropower. Appl Energy 2016;181:210–23.
[29] Energinet.dk, Regulation A: principles for the Electricity Market; Dec. 2007. <http://www.energinet.dk>.
[30] Morales JM, Conejo AJ, Ruiz JP. Economic valuation of reserves in power systems with high penetration of wind power. IEEE Trans Power Syst 2009;24(2):900–10.
[31] Bouffard F, Galiana FD, Conejo AJ. Market-clearing with stochastic security—Part I: formulation. IEEE Trans Power Syst 2005;20(4):1818–26.
[32] Parvania M, Fotuhi-Firuzabad M. Demand response scheduling by stochastic SCUC. IEEE Trans Smart Grid 2010;1(1):89–98.
[33] Sahin C, Shahidehpour M, Erkmen I. Allocation of hourly reserve versus demand response for security-constrained scheduling of stochastic wind energy. IEEE Trans Sustain Energy 2013;4(1):219–28.
[34] Wu H, Shahidehpour M, Al-Abdulwahab A. Hourly demand response in day-ahead scheduling for managing the variability of renewable energy. IET Gener Transm Distrib 2013;7(3):226–34.
[35] Shafie-khah M, Heydarian-Forushani E, Osorio GJ, Gil FA, Aghaei J, Barani M, et al. Optimal behavior of electric vehicle parking lots as demand response aggregation agents. IEEE Trans Smart Grid 2016;7(6):2654–65.
[36] Heydarian-Forushani E, Golshan MEH, Shafie-khah M. Flexible security-constrained scheduling of wind power enabling time of use pricing scheme. Energy 2015;90:1887–900.
[37] Aalami HA, Moghaddam MP, Yousefi GR. Demand response modeling considering interruptible/curtailable loads and capacity market programs. Appl Energy 2010;87:243–50.
[38] Reliability test system task force. The IEEE reliability test system – 1996. IEEE Trans Power Syst 1999;14(3):1010–20.
[39] Parvania M, Fotuhi-Firuzabad M, Shahidehpour M. Assessing impact of demand response in emission-constrained environments. In: Power and energy society general meeting; 2011. IEEE. p. 1–6.
[40] Ippolito L, Loia V, Siano P. Extended fuzzy C-means and genetic algorithms to optimize power flow management in hybrid electric vehicles. Fuzzy Optim Decis Making 2003;2(4):359–74.
[41] Aalami HA, Moghaddam MP, Yousefi GR. Modeling and prioritizing demand response programs in power markets. Electr Power Syst Res 2010;80(4):426–35.
[42] Siano P, Sarno D. Assessing the benefits of residential demand response in a real time distribution energy market. Appl Energy 2016;161:533–51.
[43] Shoreh MH, Siano P, Shafie-khah M, Loia V, Catalão JP. A survey of industrial applications of demand response. Electr Power Syst Res 2016;141:31–49.