Robust Scheduling of Variable Wind Generation by Coordination of Bulk Energy Storages and Demand Response

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Abstract

The intermittent nature of wind generation will lead to greater demands for operational flexibility. Traditionally, reserves came from conventional power plants provide the majority of additional required flexibility leading to higher efficiency losses due to technical restrictions of such units. Recently, demand response programs and emerging utility-scale energy storages gained much attention as other flexible options. Under this perspective, this paper proposes a robust optimization scheduling framework to derive an optimal unit commitment decision in systems with high penetration of wind power incorporating demand response programs as well as bulk energy storages in co-optimized energy and reserve markets. In this regard, an improved demand response model is presented using the economic model of responsive loads based on customer's behavior concept that gives choice right opportunity to customers in order to participate in their desired demand response strategy. Moreover, bulk energy storages are considered to be as active market participants. Computational results demonstrate how coordinated operation of different type of demand response programs and bulk energy storages can help accommodate wind power uncertainty from the economic and technical points of view.

Keywords: Operational flexibility, Demand response programs, Bulk energy storages, Robust optimization, Wind integration.

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1. Introduction

In recent years, wind energy penetration has increased remarkably due to government policies and support schemes to drive more renewable energy into the power market and the prospect for deployment of wind energy continue to

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grow in the future. This high share of variable wind generation may cause to flexibility gap in two ways. On one hand, the stochastic nature of wind generation increase supply side variability and hence increases the need for additional flexibility. On the other hand, wind generation displaces part of flexible conventional units according to their merit order in dispatch and consequently reduces the available flexible capacity of power grid [1]. In the light of the mentioned changes, not only the average operating efficiency decreased but also the system reliability put at risk [2]. Having these impacts in mind, there is an essential need for a greater operational flexibility through new emerging flexible technologies.

The flexibility options are classified into five basic categories including supply side fleet, demand side options, energy storages, network utilization, and improvement of the system operation principles in [1]. Moreover, reference [3] presents the same categorization with the exception that market mechanisms is also considered as an independent option. However, the focus of the current paper is on the potential of Demand Side Management (DSM) and emerging bulk Energy Storages (ESs) as flexible technologies alongside conventional supply side power plants.

Demand Response (DR) is known as a powerful measure that has potential to facilitate grid integration of wind power. In this regard, a comprehensive investigation on the role of DR for handling renewable energy resource intermittency is conducted in [4]. Moreover, a wide range of potential benefits of DR in power system operation, planning, and market efficiency in future smart power grid is presented in [5].

DR can motivate consumers to increase their consumption when there is an extra amount of wind generation and also DR programs can encourage consumers to decrease their load when the wind power output is low. This rationale mechanism reshapes the load profile of the system and result in a flatter net load (load minus wind power) and potentially reduces the need for up and down ramping services. In this regard, Parvania and Fotuhi-Firuzabad [6] propose a load reduction DR program in order to achieve a smoother load profile and decrease the steep ramps of the net load caused by wind generation in a market-based environment. The drawback with this work is that the DR program used in this research only provides load reduction and the effects of load recovery is not studied. Yousefi et al. [7] has gone a step further by considering load reduction as well as load recovery using the self and cross price elasticity concept. However, the mentioned study used a deterministic approach while wind power has a stochastic nature.

The impacts of different types of DR programs on the operation of conventional units in the presence of variable wind generation is explored in [8] using a stochastic programming approach. However, the stochastic optimization approach exhibits some practical drawbacks in the application to large-scale power systems [9]. This is due to the fact that some uncertain parameters are difficult to characterize using distribution functions. Furthermore, obtaining a reliable solution through stochastic programming approach requires a large number of scenario sets, leading to large scale optimization problem that may difficult to solve or computationally intractable [9]. Moreover, the current paper improves the previous DR model considering customer's behavior as described in the next section.

In recent years, utility-scale ESs have experienced a very rapid growth and known as an effective alternative to manage renewable energy intermittency by facilitating implementation of corrective actions across the transmission networks. On this basis, different technologies of energy storage can be utilized including batteries, Super capacitors and hybrid energy storage [10]. In [11], three different electrochemical energy storage systems, i.e., batteries, super capacitors, and a dual buffer are compared, and subsequently a framework is presented to optimize the sizing of energy storage and energy management. Plug-in electric vehicles are also a flexible option that can be categorized into both demand side options and energy storages [12]. The mentioned energy storage options can mitigate the wind variability, since they can alleviate the variety between the electricity supply and demand in power systems with high penetration of wind power [13].

The state of the art of the ES's technologies for wind power integration support is discussed in [14] from different aspects. Also, different opportunities and challenges to large-scale adoption of utility-scale ESs that are best suited to reduce the variability associated with stochastic nature of renewable energy sources are addressed in [15]. The state of the art of three different types of ES's technologies namely pump hydro storages, batteries, and fuel cells are reviewed extensively in [16] with application to manage the intermittency of renewable generations. In addition, operation principles and the ability of four kinds of ES's systems to mitigate the uncertainty of wind power including Compressed Air Energy Storage (CAES), superconducting magnetic energy storage, flywheel energy storage system, and hydrogen energy storage system are explained in [17].

Das et al. [18] evaluate the performance and economics of CAES as an active market participant in energy and ancillary co-optimization markets. The paper also considers the cycling costs incurred by conventional power plants as a result of wind power variations. However, it seems that the main drawback with this work is related to deterministic modeling of the objective function where there is not any uncertain parameter in the proposed model.

Pozo et al. [19] propose a stochastic real-time unit commitment to deal with the uncertainty of variable wind generation incorporating generic energy storage units. The paper categorizes the ES benefits in three ways including: reducing the total operation cost, smoothing the power generation profile, and providing sufficient reserve to accommodate large amount of uncertain renewable resources. However, there are certain differences between [19] and the present work, since, in [19], the system load profile is considered to be inelastic, whereas in this paper not only the elastic characteristic of demand has been modeled using different DR strategies, but also robust coordination of bulk ESs and DR programs is investigated. Hence, the paper's main contributions are listed as follow:

- To propose a robust optimization approach that coordinates the optimal operation of bulk ESs and different DR strategies in order to allow system operators to response to wind power variability in a cost effective way.
- To develop an intelligent DR model that gives choice right opportunity to customers in order to participate in different DR strategies based on customer's behavior.
- To assess the technical and economic performance of conventional power plants in energy and reserve markets under various scenarios as a consequence of motion toward a more flexible power grid.

The reminder of the paper is organized as follows. Section 2 deals with the modeling of DR programs, bulk ESs, and uncertain wind power output formulation. A robust optimization model to determine the optimal coordinated scheduling of DR, ESs, and conventional units is presented in section 3. The main results are illustrated in section 4 for the IEEE-RTS test system. Finally, section 5 concludes the paper.

2. Model of DR programs, ESs, and uncertain wind generation

In this section, an improved version of the economic model of responsive loads based on the price elasticity concept and customer's behaviour is presented, firstly. Afterward, a typical bulk ES model and uncertain wind power output formulation are presented respectively in order to integrate into the proposed robust optimization formulation in the next section.

2.1. Improved economic model of responsive loads

In general, DR refers to change in typical consumption pattern of customers in response to change in electricity tariffs or a specified given incentives in order to achieve economic and reliability purposes. According to the given definition, DR programs are categorized in two main groups so-called, Time-Based Rate DR Programs (TBRDRPs) and Incentive-Based DR Programs (IBDRPs). As it has been demonstrated in [20] and due to the fact that customer's reaction in response to TBRDRPs is not similar to his/her reaction in consequence of IBDRPs, the paper proposes an improved intelligent DR model based on the developed concept in [20] that gives choice right opportunity to customers in order to participate in different DR strategies based on customer's behavior.

In fact, despite of the mentioned study in [20] that investigated the effects of customer's behavior for IBDRPs and TBRDRPs separately, this paper evaluates the impacts of both IBDRPs and TBRDRPs simultaneously and consequently gives an opportunity to customers to response to their favorite DR program. Furthermore, it should be noted that authors in [20] just assess the applicability of Time of Use (TOU) program as a TBRDRP; whereas the current paper investigates the effects of the whole TBRDRPs including TOU, Real-Time Pricing (RTP), and Critical Peak Pricing (CPP). In this study, TBRDRPs are interpreted as mandatory programs which are usually implemented obligatory by system operators while IBDRPs are named as voluntary programs that are motivated customers using an incentive payment.

In order to avoid restatement of general model of economic loads based on price elasticity of demand, the consumer's consumption after DR implementation has been derive directly from the model developed by Aalami et al. [21] as it can be seen in Eq. (1). It is noteworthy that the model is based on the customer's benefit function and the formulation procedure is explained step by step in [21].

$$d_t = d_t^0 \left\{ 1 + \sum_{t'=1}^{NT} Elas_{tt'} . \frac{[\rho_{t'} - \rho_{t'}^0 + A_{t'}]}{\rho_{t'}^0} \right\} \tag{1}$$

Eq. (1) represents the customer's modified consumption as a consequence of TBRDRPs as well as IBDRPs as a linear function. It is notable that in the above equation, $A_{t'}$ is a positive value in peak periods and zero in other periods. This model is extended by Teimourzadeh Baboli et al. [20] as it can be seen in Eq. (2) considering human behavioral aspects.

$$d_t = d_t^0 \left\{ 1 + \sum_{t'=1}^{NT} Elas_{tt'} . \frac{[\rho_{t'} - \rho_{t'}^0 + \eta_A A_{t'}]}{\rho_{t'}^0} \right\} \tag{2}$$

In Eq. (2), η_A is a weighting coefficient that represents the customer's tendency to participate in one of the IBDRPs or TBRDRPs. In other word, the more value for the coefficient indicates that customers make more response to IBDRPs in compare with TBRDRPs. Although such a model considers customer's behavior in response to incentives, but the fact that has not been addressed is that customer's response to IBDRPs affect the customers participation in other TBRDRPs and vice versa. Therefore, the model is improved as given in Eq. (3) which considers the movements of customer's interest from participation in obligatory TBRDRPs to voluntarily IBDRPs.

$$d_t = d_t^0 \left\{ 1 + \sum_{t'=1}^{NT} Elas_{tt'} . \frac{[(1-\eta_A)(\rho_{t'} - \rho_{t'}^0) + \eta_A A_{t'}]}{\rho_{t'}^0} \right\} \tag{3}$$

2.2. Typical bulk ES model

It is well known that bulk ES technologies can bring significant benefits such as arbitrage, load following, spinning reserve, stability improvements, and enhancing dispatchability of renewable resources from the system operator's point of view according to their operation moods [22]. Reviewing the previous works reveals that the most widely used bulk ES technology is pump hydro storage. However, the recent studies are concentrated on emerging bulk ESs such as CAESs and advanced batteries. In order to find an appropriate sense about bulk ES technologies, rating power of various ESs are compared as it can be seen in Table 1 [14].

"See Table 1 at the end of the manuscript".

It is noteworthy that the global energy storage database of U.S. Department of Energy has given comprehensive information about the realization of different operational and under construction ES sites in real world, in details [23].

This paper models a generic bulk ES as an active market player that can not only independently offer in day-ahead energy market, but also provide up/down spinning reserve and even more non-spinning reserve through both its charging and discharging operations. On this basis, a generic bulk ES is modeled by Eqs. (4)-(12).

$$0 \le P_{jt}^{ChES} + P_{jt}^{dsr} \le P_j^{ChES,\max} I_{jt}^{ChES} \tag{4}$$

$$0 \le P_{jt}^{DeES} + P_{jt}^{usr} \le P_j^{DeES,\max} I_{jt}^{DeES} \tag{5}$$

$$0 \le P_{jt}^{DeES} + P_{jt}^{usr} + P_{jt}^{nsr} \le P_j^{DeES,\max} \tag{6}$$

$$I_{jt}^{DeES} + I_{jt}^{ChES} \le 1 \tag{7}$$

$$0 \le sr_{jt\omega}^{ESU} \le P_{jt}^{usr} \tag{8}$$

$$0 \le sr_{jt\omega}^{ESD} \le P_{jt}^{dsr} \tag{9}$$

$$E_{jt}^{ES} = E_{j(t-1)}^{ES} + \eta_{Ch}\left(P_{jt}^{ChES} + P_{jt}^{dsr}\right) - \eta_{DeCh}\left(P_{jt}^{DeES} + P_{jt}^{usr} + P_{jt}^{nsr}\right) \tag{10}$$

$$E_j^{ES,\min} \le E_{jt}^{ES} \le E_j^{ES,\max} \tag{11}$$

$$E_{j,initial}^{ES} = \alpha_j E_j^{ES,\max} \tag{12}$$

The limits on the capacity of ES while getting charged and discharged are considered in Eqs. (4) and (5), respectively. Note that Eqs. (4) and (5) have two terms including day-ahead energy and up/down spinning reserve capacity markets and also Eq. (6) deals with the non-spinning reserve capacity provided by bulk ES. Moreover, Eq. (7) prevents simultaneous charge and discharge operation of ES at a same hour. Eqs. (8) and (9) restrict the actual deployed real-time reserves for corrective actions in the worst case according to the scheduled reserve capacity in day-ahead market. The amount of stored energy within reservoir of bulk ES *j* at hour *t* as a function of energy stored until hour *t-1*, participation in energy and up/down spinning reserve markets is represented by Eq. (10). The maximum and minimum levels of storages in hour *t* are also considered through Eq. (11). Finally, Eq. (12) shows the initial stored energy level of bulk ES as a function of its maximum reservoir capacity.

2.3. Uncertain wind power output formulation

Higher penetration of variable renewable energy resources such as wind power have posed new challenges on system operator's performance and motivated them to look for an effective approach that produces robust unit commitment and ensures the system reliability in real-time operation. Recently, robust optimization has gained a significant attention due to its computationally efficient and preserving simplicity of the model.

In order to model uncertain wind power output, as shown in [24]-[25], it is assumed that the wind power output is within an interval $\left[W_{bt}^{*}-W_{bt}^{-},W_{bt}^{*}+W_{bt}^{+}\right]$ where the forecasted value of wind power at bus *b* in hour *t* is W_{bt}^{*}. Also, the lower and upper range of deviations from W_{bt}^{*} is represented by W_{bt}^{-} and W_{bt}^{+}, respectively. It should be noted that the mentioned interval can be determined based on historical data or an interval forecast for the wind power output. However, without loss of generality, we can use quantiles for generated the interval considering the interval range is equal to the 0.95- and .05-quantiles of the random wind power output, respectively as in [24]-[25]. On this basis, the actual wind power output, $w_{bt\omega}$, can be any value in the given interval. In order to adjust the conservatism of the robust optimization problem, the paper employs the uncertainty budget parameter, Γ_b that is an integer parameter between 0 and *T* which restrict the number of hours in which the wind power output is far away from its forecasted value at bus *b*. Therefore, it is obvious that $\Gamma_b=0$ is related to the deterministic case. It is notable that the worst case actual wind power output scenario happens when wind power output gets its upper limit, lower limit, or forecasted value so that the total number of hours in which wind power output is not as its forecasted value should be equal or less than the uncertainty budget. As it is stated in [24], the robust optimal scheduling solution will be feasible for any other wind power scenario with probability nearly higher than 95% when $\Gamma_b \geq 8$. On this basis, in this study the value of uncertainty budget is set to 8. Meanwhile, system operators can consider further values for Γ_b to guarantee the obtained solutions more and more. Accordingly, the wind power uncertainty set can be expressed as Eq. (13).

$$D := \left\{ w \in \Re^{|B|\times|T|} :\ w_{bt\omega} = W^{*}_{bt} + Z^{+}_{bt\omega} W^{+}_{bt} - Z^{-}_{bt\omega} W^{-}_{bt},\ \sum_{t=1}^{T} \left(Z^{+}_{bt\omega} + Z^{-}_{bt\omega} \right) \leq \Gamma_b \right\} \quad (13)$$

In the above equation $Z^{+}_{bt\omega}$ and $Z^{-}_{bt\omega}$ are binary variables that determined the realization of wind power output. For instance, if $Z^{+}_{bt\omega} = 1$, the wind power output reaches its upper bound while if $Z^{-}_{bt\omega} = 1$, the wind power output reaches its lower bound. Also, if both of them are 0, forecasted value is attained. The conservatism of the model is also considered through the uncertainty budget as given in the above equation. The robust optimization formulation that incorporates wind power uncertainty using the predefined uncertainty set is presented in the following section.

3. Robust scheduling formulation

3.1. Objective function

The objective function is related to determination of the day-ahead energy and reserve dispatch in power systems under high penetration of wind power considering the cooperative scheduling of emerging bulk ESs and different type of DR strategies. Such an optimization problem is a two-stage decision making problem including day-ahead energy and reserve dispatch (here-and-now decisions) as well as the redispatch at the balancing stage (wait-and-see decisions) due to the realization of the wind power. The conceptual representation of the proposed robust scheduling problem can be sketched as show in Fig. (1).

"*See Fig. 1 at the end of the manuscript*".

The Independent System Operator (ISO) purpose is to minimize both of the day-ahead dispatch costs as well as worst case balancing costs, simultaneously. The day-ahead dispatch costs include: energy dispatch cost and spinning and non-spinning reserve capacity costs that are provided through conventional generation units and bulk ESs in market environment. Wind power producers are also offers their price-quantity packages to ISO according to their forecasted power generation with the exception that unlike other market players, ISO integrates the total amount of offered wind generation in the energy generation dispatch due to their merit order. As described former, mandatory TBRDRPs and voluntary IBDRPs are also considered as DR strategies that implement by ISO. Therefore, the cost as a result of incentive payment in peak hours to customers is incorporated to the day-ahead dispatch costs.

The worst case corrective actions are performed by adjusting up/down deployed reserve through conventional generation units and bulk ESs. Moreover, ISO has the possibility of curtailing a partial of the wind power generation or shedding customers load in emergency circumstances. The objective function can be mathematically formulated as it can be seen in Eq. (14).

$$\begin{aligned}
\underset{\Xi_D}{Min}\ & \sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(SUC_{it}+MPC_iU_{it}+\sum_{m=1}^{NM}(P_{itm}^{e}\cdot C_{itm}^{e})\right)+\sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(C_{it}^{UC}P_{it}^{usr}+C_{it}^{DC}P_{it}^{dsr}+C_{it}^{NSR}P_{it}^{nsr}\right)\\
+\ & \sum_{t=1}^{NT}\sum_{j=1}^{NES}\left(C_{jt}^{ES,Energy}P_{jt}^{DeES}+C_{jt}^{ES,U}P_{jt}^{usr}+C_{jt}^{ES,D}P_{jt}^{dsr}+C_{jt}^{ES,NSR}P_{jt}^{nsr}\right)\\
+\ & \sum_{t=1}^{NT}\sum_{b=1}^{NB}C_b^{wind}W_{bt}^{*}+\sum_{t\in Tpeak}\eta_A A_t\left(d_t^{TBRDRP}-d_t\right)\\
+\ & \max_{w\in D}\min_{\Xi_B}\left[\begin{array}{c}\sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(C_{it}^{UE}sr_{it\omega}^{U}-C_{it}^{DE}sr_{it\omega}^{D}\right)+\sum_{t=1}^{NT}\sum_{j=1}^{NES}\left(C_{jt}^{UE}sr_{jt\omega}^{ES,U}-C_{jt}^{DE}sr_{jt\omega}^{ES,D}\right)\\
+\sum_{t=1}^{NT}\sum_{b=1}^{NB}\left(VOLL_{bt}LS_{bt\omega}\right)+\sum_{t=1}^{NT}\sum_{b=1}^{NB}\left(C^{spillage}WS_{bt\omega}\right)+\sum_{t=1}^{NT}\sum_{b=1}^{NB}\left(C_b^{wind}\left(w_{bt\omega}-W_{bt}^{*}\right)\right)\end{array}\right]
\end{aligned}\tag{14}$$

In the formulation above, Ξ_D and Ξ_B indicate the set of day-ahead and balancing stage decision variables, respectively. Notice that in the model above, we can introduce an auxiliary variable β representing the worst case recourse cost in a similar manner as [26], which is the optimal objective function value of the inner max-min problem in Eq. (14). As stated in [26], the objective function could then solve as a single minimization problem after enforcing the following constraints:

$$\beta\geq\left[\begin{array}{c}\sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(C_{it}^{UE}sr_{it\omega}^{U}-C_{it}^{DE}sr_{it\omega}^{D}\right)+\sum_{t=1}^{NT}\sum_{j=1}^{NES}\left(C_{jt}^{UE}sr_{jt\omega}^{ES,U}-C_{jt}^{DE}sr_{jt\omega}^{ES,D}\right)\\
+\sum_{t=1}^{NT}\sum_{b=1}^{NB}\left(VOLL_{bt}LS_{bt\omega}\right)+\sum_{t=1}^{NT}\sum_{b=1}^{NB}\left(C^{spillage}WS_{bt\omega}\right)+\sum_{t=1}^{NT}\sum_{b=1}^{NB}\left(C^{wind}\left(w_{bt\omega}-W_{bt}^{*}\right)\right)\end{array}\right]\tag{15}$$

As a consequence the constraint above, the objective function is converted to a typical minimization problem as represented in Eq. (16).

$$\begin{aligned}
\underset{\Xi_D}{Min}\ & \sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(SUC_{it}+MPC_iU_{it}+\sum_{m=1}^{NM}(P_{itm}^{e}\cdot C_{itm}^{e})\right)+\sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(C_{it}^{UC}P_{it}^{usr}+C_{it}^{DC}P_{it}^{dsr}+C_{it}^{NSR}P_{it}^{nsr}\right)\\
+\ & \sum_{t=1}^{NT}\sum_{j=1}^{NES}\left(C_{jt}^{ES,Energy}P_{jt}^{DeES}+C_{jt}^{ES,U}P_{jt}^{usr}+C_{jt}^{ES,D}P_{jt}^{dsr}+C_{jt}^{ES,NSR}P_{jt}^{nsr}\right)\\
+\ & \sum_{t=1}^{NT}\sum_{b=1}^{NB}C^{wind}W_{bt}^{*}+\sum_{t\in Tpeak}\eta_A A_t\left(d_t^{0}-d_t\right)\\
+\ & \beta
\end{aligned}\tag{16}$$

The objective function should be minimized considering constraints given in Eqs. (3)-(13), Eq. (15) and the following constraints. It is notable that the remaining constraints can be separated explicitly into day-ahead and balancing stage constraints.

3.1. Day-ahead dispatch constraints

- DC power flow equation

$$\sum_{i\in G_b} P_{it} + \sum_{j\in ES_b}\left(P_{jt}^{DeES} - P_{jt}^{ChES}\right) + W_{bt}^{*} - \left(LD_b\, d_t\right) = \sum_{l\in L_b} F_{lt}^{0} \qquad \forall b,\forall t \tag{17}$$

$$F_{lt}^{0} = \left(\delta_{bt}^{0} - \delta_{b't}^{0}\right)\big/ X_l \qquad \forall l,\forall t \tag{18}$$

- Transmission line flow limits

$$-F_l^{\max} \le F_{lt}^{0} \le F_l^{\max} \qquad \forall l,\forall t \tag{19}$$

- Generation units start-up cost constraint

$$SUC_{it} = SC_i\,(U_{it} - U_{i(t-1)}) \qquad \forall i,\forall t \tag{20}$$

- Power generation constraints

$$P_{it} = \sum_{m=1}^{NM} P_{itm}^{e} \qquad \forall i,\forall t \tag{21}$$

$$0 \le P_{itm}^{e} \le P_{im}^{\max} \qquad \forall i,\forall t,\forall m \tag{22}$$

$$P_i^{\min} U_{it} \le P_{it} \le P_i^{\max} U_{it} \qquad \forall i,\forall t \tag{23}$$

$$P_{it} + P_{it}^{usr} + P_{it}^{nsr} \le P_i^{\max} \qquad \forall i,\forall t \tag{24}$$

$$P_{it} + P_{it}^{usr} \le P_i^{\max} U_{it} \qquad \forall i,\forall t \tag{25}$$

$$P_{it} - P_{it}^{dsr} \ge P_i^{\min} U_{it} \qquad \forall i,\forall t \tag{26}$$

- Up- and down-spinning and non-spinning reserve limits

$$0 \le P_{it}^{usr} + P_{it}^{nsr} \le RU_i\,\tau \qquad \forall i,\forall t \tag{27}$$

$$0 \le P_{it}^{dsr} \le RD_i\,\tau \qquad \forall i,\forall t \tag{28}$$

$$0 \le P_{it}^{nsr} \le \left(1 - U_{it}\right) RU_i\,\tau \qquad \forall i,\forall t \tag{29}$$

- Minimum up and down time constraints

$$\sum_{t'=t+2}^{t+MUT_i} \left(1-U_{it'}\right)+MUT_i \left(U_{it}-U_{i,t-1}\right) \le MUT_i \qquad \forall i,\forall t \tag{30}$$

$$\sum_{t'=t+2}^{t+MDT_i} U_{it'}+MDT_i \left(U_{i,t-1}-U_{it}\right) \le MDT_i \qquad \forall i,\forall t \tag{31}$$

- Ramp up and ramp down rate limits

$$P_{it}-P_{i,t-1} \le RU_i\, U_{it}+P_i^{\min}\left(1-U_{i,t-1}\right) \qquad \forall i,\forall t \tag{32}$$

$$P_{i,t-1}-P_{it} \le RD_i\, U_{i,t-1}+P_i^{\min}\left(1-U_{it}\right) \qquad \forall i,\forall t \tag{33}$$

3.2. Balancing stage constraints

- DC power flow equation in worst case

$$\sum_{i\in G_b}\left(sr_{it\omega}^{GU}-sr_{it\omega}^{GD}\right)+\sum_{j\in ES_b}\left(sr_{jt\omega}^{ESU}-sr_{jt\omega}^{ESD}\right)+LS_{bt\omega}+\left(w_{bt\omega}-W_{bt}^{*}-WS_{bt\omega}\right)=\sum_{l\in L_b}F_{lt\omega}-F_{lt}^{0} \qquad \forall b,\forall t,\omega \tag{34}$$

$$F_{lt\omega}=\left(\delta_{bt\omega}-\delta_{b't\omega}\right)/X_l \qquad \forall l,\forall t,\omega \tag{35}$$

- Transmission line flow limits in worst case

$$-F_l^{\max} \le F_{lt\omega} \le F_l^{\max} \qquad \forall l,\forall t,\omega \tag{36}$$

- Deployed up- and down-spinning reserve limits

$$0 \le sr_{it\omega}^{GU} \le P_{it}^{usr} \qquad \forall i,\forall t,\omega \tag{37}$$

$$0 \le sr_{it\omega}^{GD} \le P_{it}^{dsr} \qquad \forall i,\forall t,\omega \tag{38}$$

- Involuntary load shedding limit

$$0 \le LS_{bt\omega} \le LD_b\, d_t \qquad \forall b,\forall t,\omega \tag{39}$$

- Wind spillage limit

$$0 \le WS_{bt\omega} \le w_{bt\omega} \qquad \forall b,\forall t,\omega \tag{40}$$

4. Numerical studies

4.1. Input data characterization and assumption

The modified IEEE 24-bus RTS is used to evaluate potential benefits of the proposed coordinated dispatch model including bulk ESs and DR programs in co-optimized energy and reserve markets. In this respect, it is assumed that the six hydro units, which were on bus 22, are excluded. Also, two 500 MW wind farms (nearly 25% of total install generation capacity) and two 20MW bulk ES units are integrated in buses 21 and 22, respectively. The required data of the mentioned test system including generation units and network parameters are taken from [27]. The hourly load corresponds to a weekend day in winter as given in [27] while the peak of the day is assumed 2670 MW. The generation units offer energy is based on four linear segments between their minimum and maximum generation limits as stated in [19]. Moreover, it is presumed that generation units offer capacity cost for up spinning, down spinning, and non-spinning reserves are at the rates of 40%, 40%, and 20% of their highest incremental cost of producing energy, respectively. Moreover, the cost of deployed reserves at the redispatch stage is considered to be at the rate of highest incremental cost of producing energy as well. The spinning reserve market lead time is assumed to be 10 minutes. In order to have a realistic generation pattern for wind power, average of one-year historical data related to Sotavento wind farm is considered and scaled as forecasted wind power generation so that the total daily wind forecast is 6108 MWh while the total daily load is 53160 MWh (i.e. 11.5%). The initial electricity price is obtained by calculating the average of market clearing price before DR implementation which is approximately equal to 15 $/MWh. It is noteworthy that the load curve is divided into three periods: low-load period (1:00-8:00), off-peak period (9:00-16:00), and peak period (17:00-24:00).

It is noticed that the current paper investigates the effects of various DR strategies including TBRDRPs as well as IBDRPs. Under this perspective, TOU, RTP, and CPP programs are considered as obligatory DR programs while Emergency DR Program (EDRP) is applied as an IBDRP. The TOU tariffs at the low-load and peak period is 7.5 $/MWh and 30 $/MWh, respectively, otherwise it is assumed to be 15 $/MWh. Moreover, the electricity tariffs for the RTP program are considered as the obtained market clearing prices at each hour. In order to investigate the effects of CPP program, two hours with highest demand (i.e. 18 and 19) are considered as critical hours in which the rates of electricity set to be 60 $/MWh otherwise it is assumed to be 15 $/MWh. Moreover, the value of incentive payment at peak period is 15 $/MWh.

The values of self and cross price elasticity of demand are extracted directly from [21]. The ES is assumed to have 1:1 charge to discharge ratio and 4:1 reservoir energy capacity to discharge ratio with charging/discharging efficiency of 80%. Moreover, the bulk ES energy and up- and down spinning reserve offers are considered to be 10 $/MWh, 6 $/MWh, and 6 $/MWh, respectively. Also, the offered cost of ES for providing non-spinning reserve is assumed to be 2 $/MWh. The state of charge of ESs is assumed to be between 10% and 90% according to the suggestion of some manufacturers and the initial state of the charge of both ESs is considered to be 50%. The value of incentive for wind power integration that ISO should pay to wind power producer and penalty for wind power curtailment which is imposed to ISO in certain conditions are considered to be 15 and 20 $/MWh. Moreover, the maximum participation level of customers in DRPs is considered 20%.

4.2. Case studies

The proposed model was solved using CPLEX 12.5.0 [28] on an Intel Core i5-2410 computer at 2.3 GHz and 4 GB of RAM under General Algebraic Modeling System (GAMS) software. In the following numerical illustration sub-sections, several studies are performed and the obtained results are discussed under two main categories:

- **Technical assessment:** The studies mainly focused on evaluating the role of integrated operation of conventional power plants, bulk ESs, and DR programs in systems with high amounts of variable wind generation from technical point of view. In short, this part represents the technical potential benefits of a greater operational flexibility.
- **Economic assessment:** The studies investigate the effectiveness of coordinated scheduling of ESs and different DR strategies from economical perspective. In fact, this part deals with economical potential benefits of a greater operational flexibility.

The simulation results are presented in four cases. The base case is related to conventional scheduling of system without considering any flexible technology. In the first case, the behavior of bulk ESs as independent market participants is investigated. The second case just investigates the role of a typical DR program on optimal generation scheduling so that TOU program as well as EDRP are implemented simultaneously considering $\eta_A = 0.5$. Finally, the impacts of coordinated scheduling of ESs and DR programs (combination of two former mentioned cases) are explored in the third case.

It is noteworthy that the dimensions of the mathematical programming approach have a negligible difference in various case studies. However, in order to clarify the dimension of the mathematical programming problem and convergence performance of the proposed model, the optimization statistics for the mentioned four cases are given in Table 2.

"See Table 2 at the end of the manuscript".

4.3. Simulation results

4.3.1. Day-ahead energy dispatch

Fig. 2 indicates the impact of bulk ESs and DR programs on the day-ahead energy dispatch. According to Fig. 2, in case 1, the day-ahead energy dispatch decreases in peak hours and a part of demand is supplied by discharging the bulk ESs in the hours, as indicated in Fig. 3. On this basis, in hour 18 when the demand is maximum amount, the ESs inject power back to the grid with their maximum capacity. As it can be seen in case 2, DR programs cause that the units generation is increased in the valley period and decreased in the peak hours, and consequently the profile of generation becomes smoother. In case 3, since the total demand in peak period is reduced, the bulk ESs do not inject power back to the grid in hours 17 to 24. Alternatively, bulk ESs are discharged in off-peak period when the new demand is higher than other hours of the day.

"*See Fig. 2 at the end of the manuscript*".

"*See Fig. 3 at the end of the manuscript*".

4.3.2. Ramping capability of conventional power plants

The impact of conventional power plants' ramp rate is illustrated in Fig. 4. In order to study the mentioned impact, the ramp rate of all conventional power plants is multiplied by a ramp rate factor. In addition, effect of implementation of different DRPs is investigated. Meanwhile, for the sake of simplicity of analysing the results, η_A is considered zero, hence, the impact of EDRP is not considered. As can be seen in Fig. 4.a, in operation of power system without implementation of DRPs, the bulk ESs are charged between hours 5 and 9, when the system cost is low. The charged amount is injected back to the grid in hours 10 to 13. Then, the ESs are charged again between hours 13 and 17 in order to have enough charge to inject back to the grid during peak hours. By decreasing the ramp rate of units (i.e. ramp rate factor=0.5), the bulk ESs are charged between hours 20 and 24. The reason is that the conventional power plants cannot decrease their generations to follow the demand reduction, thus, the bulk ESs play the role of demand to compensate the lack of ramp rate down of generators. This can increase the operation cost as indicated in Fig. 5.

As can be seen in Fig. 4.b, implementation of TOU can change the behaviour of bulk ESs in the power system. In this case, the load profile is smoother than base case; hence, the number of charge and discharge cycles of ESs is lower. By increasing the ramp rate of conventional power plants (i.e. ramp rate factor=1.5) the mentioned number of charge and discharge cycle is reduced. This can show that the power system prefers to follow the load changes by conventional power plants rather than the bulk ESs.

"*See Fig. 4 at the end of the manuscript*".

The impact of ramp rate of conventional power plants on the total operation cost is indicated in Fig. 5. As it can be seen, by increasing the ramp rate, the operation cost is decreased in all cases. However, the reduction is not linear and higher amount of ramp rate has no significant impact on the operation cost. It should be noted that, the cases with implementing TOU and RTP have the highest sensitivity to the ramp rate of conventional power plants. In these cases, by decreasing the ramp rate of units, the bulk ESs have to be charged in hours 20 to 24 in order to compensate the lack of ramp rate down of generators. Another key factor of operation cost is the start-up cost. As indicated in Fig. 6, a lower amount of ramp rate causes that the start-up cost of generation units is significantly increased in cases that TOU and RTP are implemented.

"*See Fig. 5 at the end of the manuscript*".

"*See Fig. 6 at the end of the manuscript*".

4.3.3. Evaluation of DR strategies

In this section, the different DR strategies are evaluated. The impact of different DRPs on the different terms of operation cost and the hourly amount of energy stored in the bulk ESs is studied. On this basis, three cases are considered based on the implementation of TOU, RTP and CPP. In all the cases, EDRP is implemented simultaneously by considering $\eta_A = 0.5$. The terms of operation cost is presented in Table 1.As it can be seen, implementation of TOU and EDRP has the lowest start-up cost and up/down reserve capacity cost. However, the cost of bulk ESs for supplying energy and reserve is the highest. The incentive cost in the case of implementing RTP and EDRP is the highest. It can be concluded that the tendency of responsive customers for participating in EDRP is higher when they have RTP as the TBRDRP option.

"*See Table 1 at the end of the manuscript*".

The amount of stored energy in the bulk ESs is illustrated in Fig. 7. According to Fig. 7.a and Fig. 7.c, in cases TOU+EDRP and CPP+EDRP, the bulk ESs are charged during hours 5 and 9, in order to supply a part of demand between hours 10-14. However, according to Fig. 7.b, in case RTP+EDRP, the only participation of the bulk ESs during valley and off-peak periods is related to a 34.8 MW discharge at hour 12. It can be concluded that, the participation of bulk ESs in the electricity market is significantly high in both cases TOU+EDRP and CPP+EDRP during valley and off-peak hours.

"*See Fig. 7 at the end of the manuscript*".

4.3.4. Evaluation of customer behaviour

In order to investigate the customer behavior, the demand profile is studied for different types of DRPs as well as different amounts of incentive factor. On this basis, η_A is changed between 0 and 1 and the amount of demand is obtained for each DRP as shown in Fig. 8. As it can be observed from Fig. 8.a, in the case of implementing TOU+EDRP, by increasing the incentive factor the amount of demand is decreased in the valley period, but the load does not have significant changes in other periods. In the case of implementation of RTP+EDRP, increasing the incentive factor has a significant impact on the peak demand. It should be noted that RTP has a lower impact on the peak shaving compared to TOU, CPP (as can be seen in $\eta_A = 0$) and EDRP (as can be seen in $\eta_A = 1$). In the case of implementation of CPP+EDRP, by increasing the incentive factor the peak demand is decreased, but the load does not change in other periods meaningfully.

"*See Fig. 8 at the end of the manuscript*".

4.3.5. System operation cost

The daily operation cost in different cases is indicated in Fig. 9. As it can be seen, the case 3 is the most effective case and can decrease 7.2% of the total operation cost of the system. Following case 3, case 2 has the highest impact on reducing the cost. As it can be seen, case 1 that denotes presence of bulk ESs without implementation of DRPs has significantly lower effect on the system operation cost.

"*See Fig. 9 at the end of the manuscript*".

5. Conclusion

This paper investigated the role of coordinated scheduling of bulk ESs and different DR strategies as two emerging flexible options in order to achieve a greater operational flexibility in systems with high amount of variable wind generation. Regarding this matter, a robust optimization problem was proposed to derive an optimal unit commitment in co-optimized energy and reserve markets. The numerical results showed that the coordinated dispatch of bulk ESs and DR programs can bring significant benefits for grid operators from economic and technical points of view. Complementary case studies revealed that implementation of different DR strategies can change the optimal scheduling of bulk ESs as well as conventional generation units in market environment. Moreover, the results achieved in this study confirmed that the type of obligatory TBRDRPs can affect the customer's participation in voluntary IBDRPs, remarkably. More exact modeling of DR programs and even investigating the effectiveness of other types of flexible technologies such as electric vehicles are interesting directions for future researches.

Nomenclature

Indices

b, b'	Index of system buses
i	Index of generating unit
j	Index of bulk energy storage units
l	Index of transmission line
m	Segment index for linearized fuel cost
$Tpeak$	Index of peak hours
ω	Index of worst case
t, t'	Index of hours
NM	Number of segments for the piecewise linearized emission and fuel cost curves of units
NG	Number of generation units
NES	Number of bulk energy storage units
NT	Number of hours under study
NB	Number of network buses

Parameters

d_t^0	Initial electricity demand at hour *t* (MW)
LD_b	Demand contribution of bus *b* (MW)
C_{itm}^e	Slope of segment *m* in linearized fuel cost curve of unit *i* at hour *t* (\$/MWh)
MPC_i	Minimum production cost of unit *i* (\$)

ρ_t^0	Initial electricity price at hour t (\$/MWh)
ρ_t	Electricity tariff in TBRDRPs at hour t (\$/MWh)
C_{it}^{UC}	Offered capacity cost of up-spinning reserve provision of unit i in hour t (\$/MW)
C_{it}^{DC}	Offered capacity cost of down-spinning reserve provision of unit i in hour t (\$/MW)
C_{it}^{NSR}	Offered capacity cost of non-spinning reserve provision of unit i in hour t (\$/MW)
C_{it}^{UE}	Offered energy cost of up-spinning reserve provision of unit i in hour t (\$/MWh)
C_{it}^{DE}	Offered energy cost of down-spinning reserve provision of unit i in hour t (\$/MWh)
$C_{jt}^{ES,Energy}$	Offered energy cost of bulk energy storage j at hour t (\$/MWh)
$C_{jt}^{ES,U}$	Offered capacity cost of up-spinning reserve provision of bulk ES j at hour t (\$/MW)
$C_{jt}^{ES,D}$	Offered capacity cost of down-spinning reserve provision of bulk ES j at hour t (\$/MW)
$C_{jt}^{ES,NSR}$	Offered capacity cost of non-spinning reserve provision of bulk ES j at hour t (\$/MW)
C_{jt}^{UE}	Offered energy cost of up-spinning reserve provision of bulk ES j at hour t (\$/MWh)
C_{jt}^{DE}	Offered energy cost of down-spinning reserve provision of bulk ES j at hour t (\$/MWh)
C_b^{wind}	Offered energy cost of wind power producer of bus b (\$/MWh)
$C^{spillage}$	Cost of wind power curtailment (\$/MWh)
$VOLL_{bt}$	Value of lost load in bus b at hour t (\$/MWh)
A_t	Incentive payment at hour t (\$/MWh)
η_A	Incentive's weighting coefficient
W_{bt}^*	Forecasted value of wind generation in bus b at hour t (\$/MWh)
η_{Ch} / η_{DeCh}	Charge/discharge efficiency of bulk ES
$Elas_{tt'}$	Price elasticity of demand
$P_i^{\min} / P_i^{\max}$	Minimum/ Maximum output limit of generation unit i (MW)
RU_i / RD_i	Ramp up/down of generation unit i (MW/h)

SC_i	Start-up cost of generation unit *i* ($)
MUT_i / MDT_i	Minimum up/down time of generation unit *i* (h)
$P_j^{ChES,\max}$ / $P_j^{DeES,\max}$	Maximum charging/discharging power of bulk ES *j* (MW)
$E_j^{ES,\min}$ / $E_j^{ES,\max}$	Minimum/Maximum energy limit of bulk ES *j* (MWh)
α_j	Percent of initial energy level of bulk ES *j*
$E_{j,initial}^{ES}$	Initial state of the charge of bulk ES *j* at the beginning of scheduling horizon
X_l	Reactance of line *l*
$F_l^{\max}$	Maximum capacity of transmission line *l* (MW)
τ	Spinning reserve market lead time (h)

Variables

δ_{bt}^0 / $\delta_{bt\omega}$	Voltage angle at bus *b* in hour *t* (rad)
F_{lt}^0 / $F_{lt\omega}$	Power flow through line *l* in hour *t* (MW)
U_{it}	Binary status indicator of generation unit *i* in hour *t*
I_{jt}^{DeBatt} / I_{jt}^{ChBatt}	Binary indicator of net discharge/charge status of bulk BES *j*
$LS_{bt\omega}$	Involuntary load shedding in bus *b* at hour *t* of worst case (MWh)
$WS_{bt\omega}$	Wind power spillage in bus *b* at hour *t* of worst case (MWh)
P_{itm}^e	Generation of segment *m* in linearized fuel cost curve (MW)
d_t	Modified demand of hour *t* after simultaneous IBDR and TBRDR programs (MW)
d_t^{TBRDRP}	Modified demand of hour *t* after implementing only TBRDRPs (MW)
P_{it}	Total scheduled power of unit *i* in hour *t* (MW)
SUC_{it}	Start-up cost of generation unit *i* at hour *t* ($)
P_{it}^{usr} / P_{it}^{dsr}	Scheduled up- and down-spinning reserve capacity of unit *i* in hour *t* (MW)
P_{it}^{nsr}	Scheduled non-spinning reserve capacity of unit *i* in hour *t* (MW)

P_{jt}^{ChES} / P_{jt}^{DeES}	Scheduled charge/discharge power of bulk ES j at hour t (MW)
P_{jt}^{usr} / P_{jt}^{dsr}	Scheduled up- and down-spinning reserve capacity of bulk ES j in hour t (MW)
P_{jt}^{nsr}	Scheduled non-spinning reserve capacity of bulk ES j in hour t (MW)
$sr_{it\omega}^{U}$ / $sr_{it\omega}^{D}$	Deployed up- and down spinning reserve of unit i at hour t of worst case (MWh)
$sr_{jt\omega}^{ES,U}$ / $sr_{jt\omega}^{ES,D}$	Deployed up- and down spinning reserve of bulk ES j at hour t of worst case (MWh)
E_{jt}^{ES}	Energy stored in bulk ES j at hour t (MWh)

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Figure captions

Fig. 1. Schematic representation of proposed robust scheduling problem.

Fig. 2. Units generation in different cases.

Fig. 3. Bulk ESs injection to the grid in different cases.

Fig. 4. Impact of ramp rate on the stored energy in the bulk ESs, (a) without implementation of DRPs (b) with implementation of TOU program.

Fig. 5. Impact of ramp rate on the operation cost.

Fig. 6. Impact of ramp rate on the start-up cost.

Fig. 7. Stored energy in the ESs, (a) TOU+EDRP (b) RTP+EDRP (c) CPP+EDRP.

Fig. 8. Impact of incentive factor on the demand profile, (a) TOU+EDRP (b) RTP+EDRP (c) CPP+EDRP.

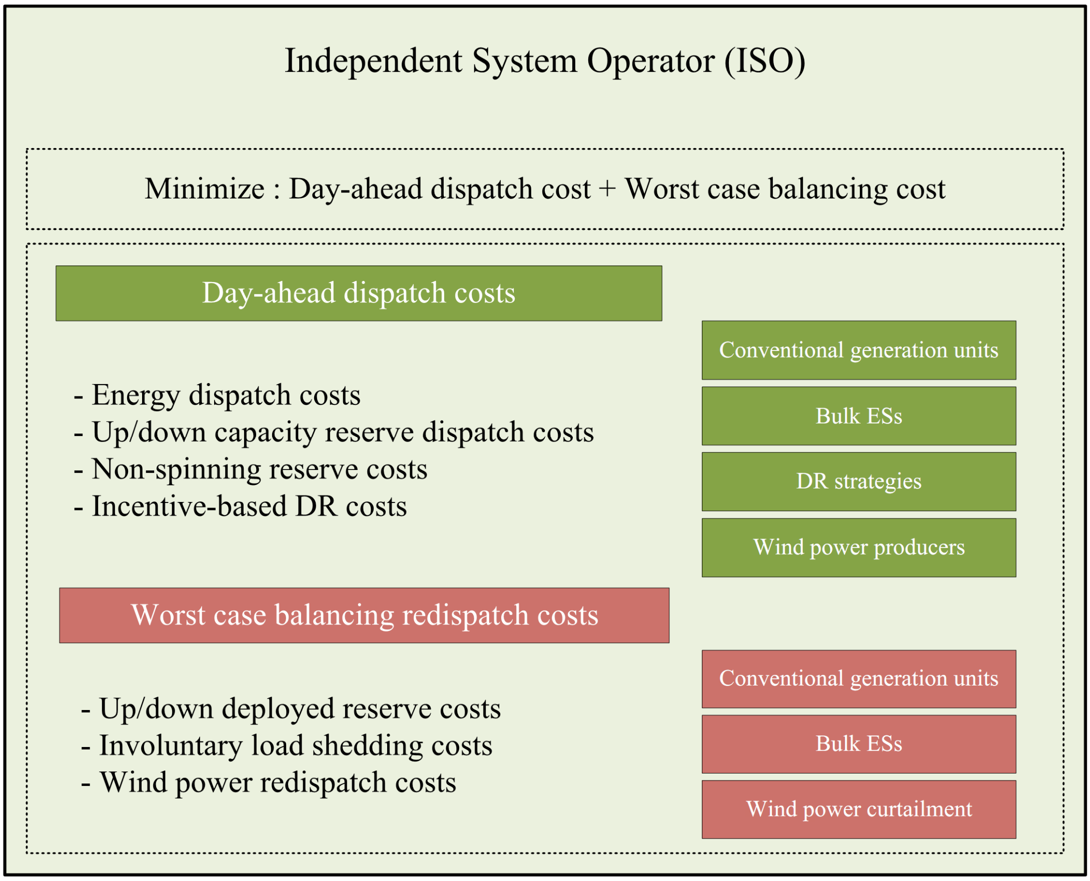
Fig. 9. Operation cost in different cases.

Table captions

Table 1. Comparison of different energy storage technologies rating power [14]

Table. 2. Optimization statistics for considered case studies

Table 3. Terms of operation cost in different DR strategies ($)



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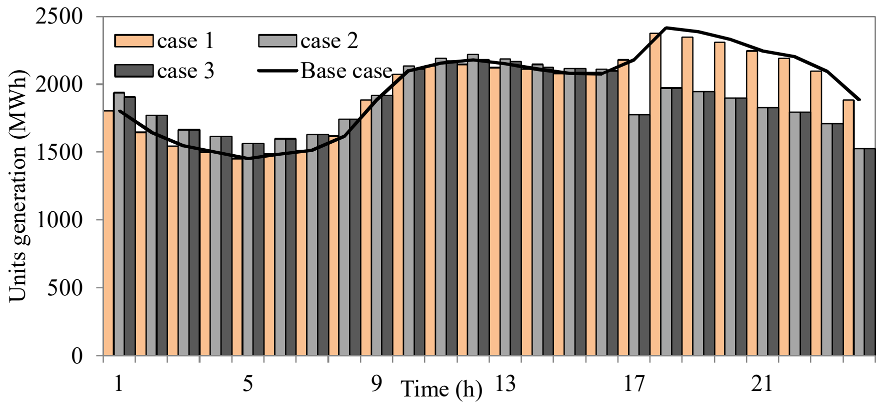

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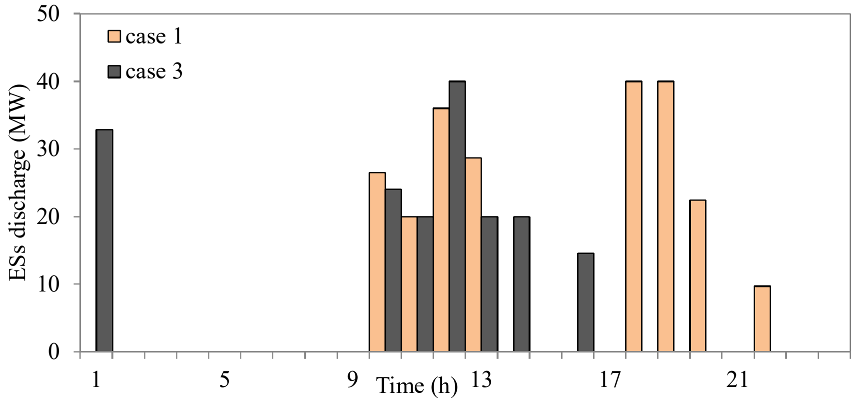

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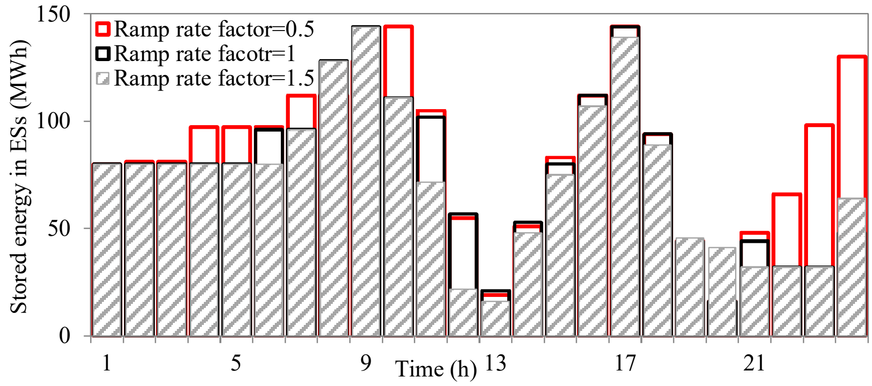
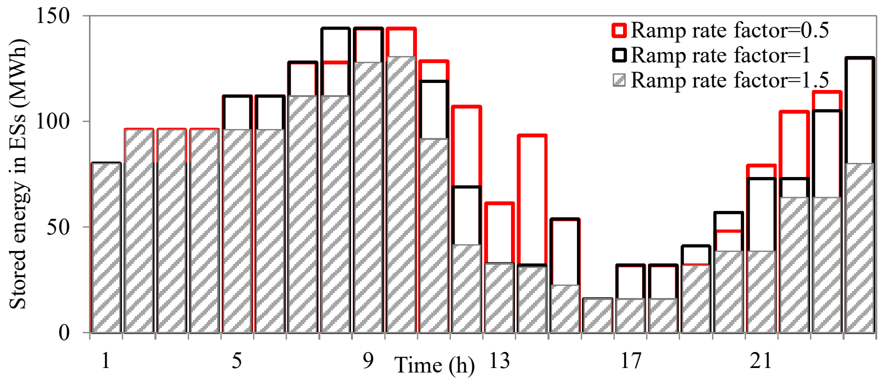


(a)



(b)

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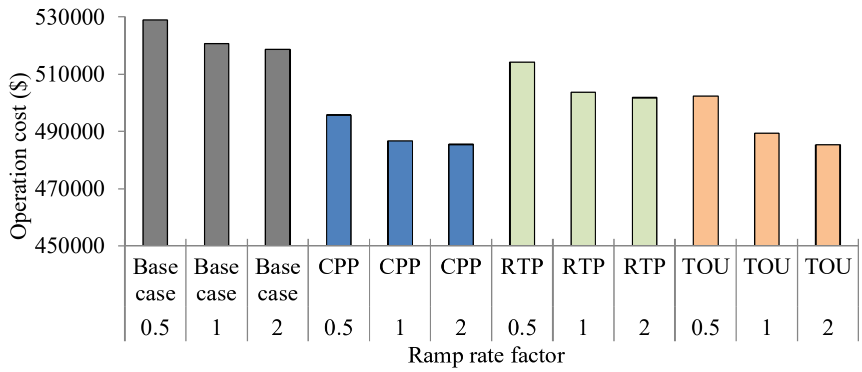

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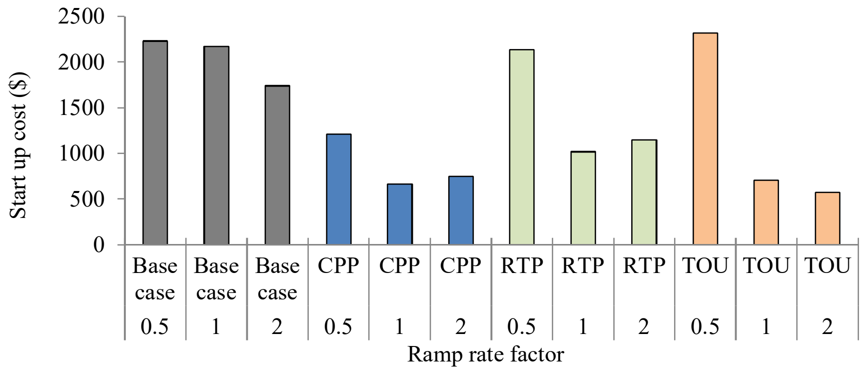
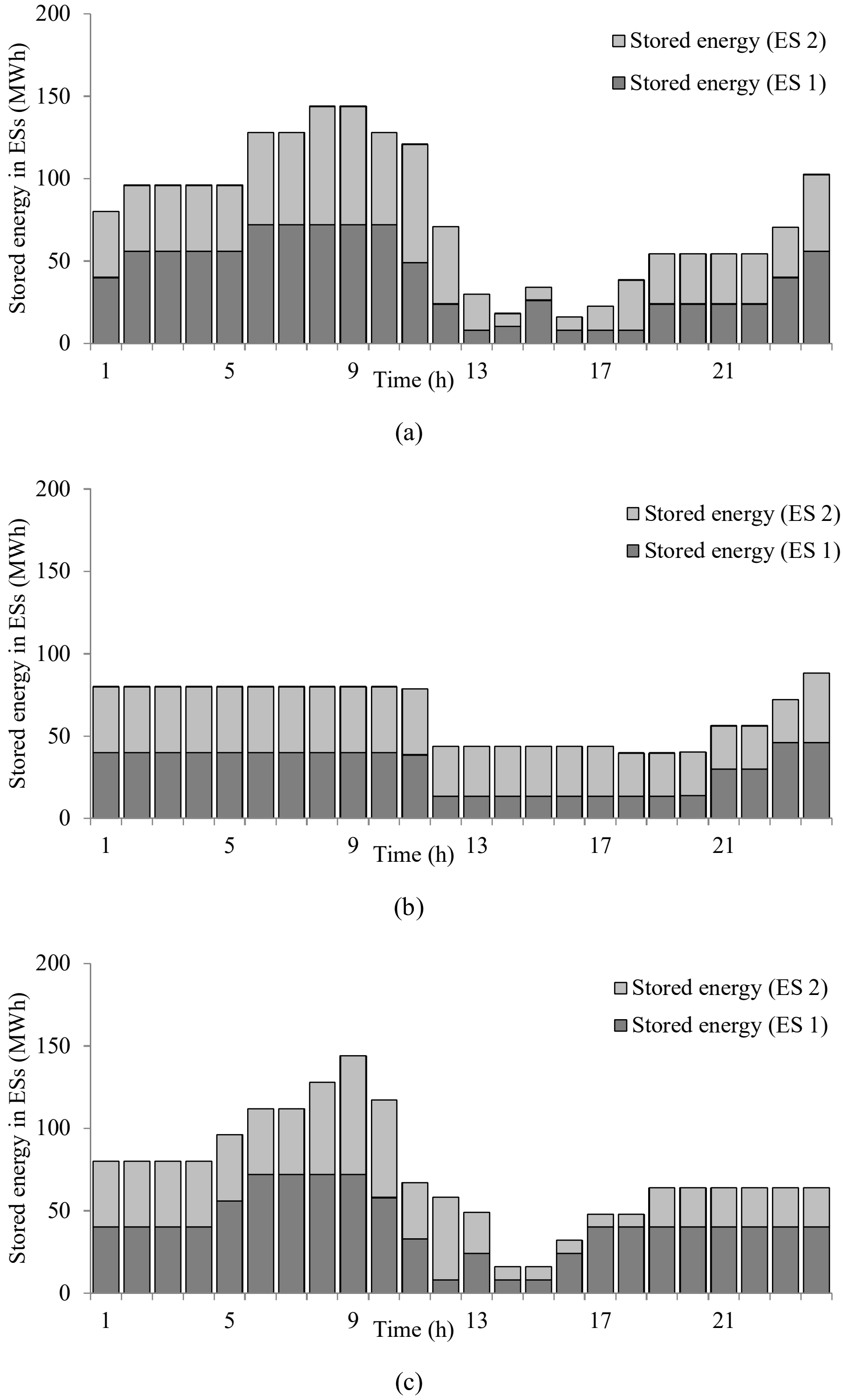


Fig. 6. Impact of ramp rate on the start-up cost.



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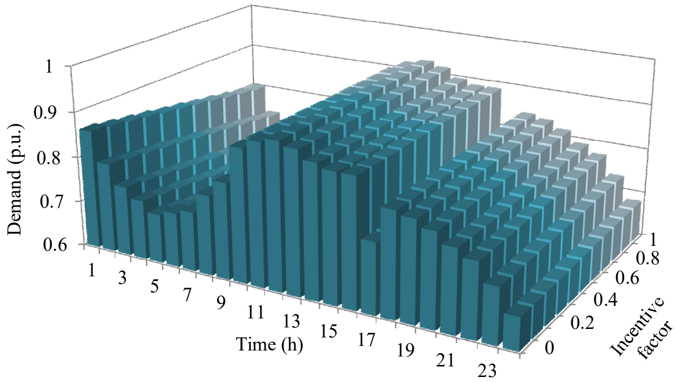
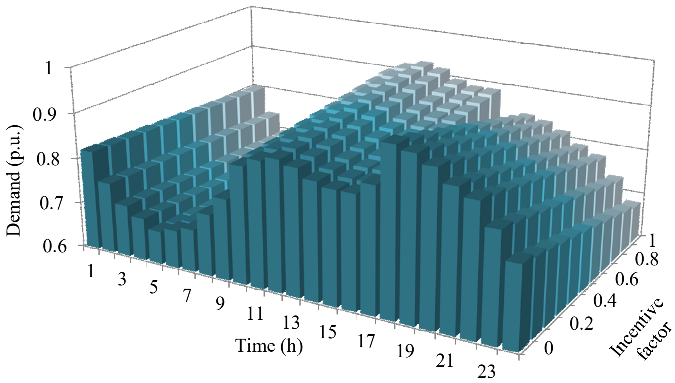


(a)



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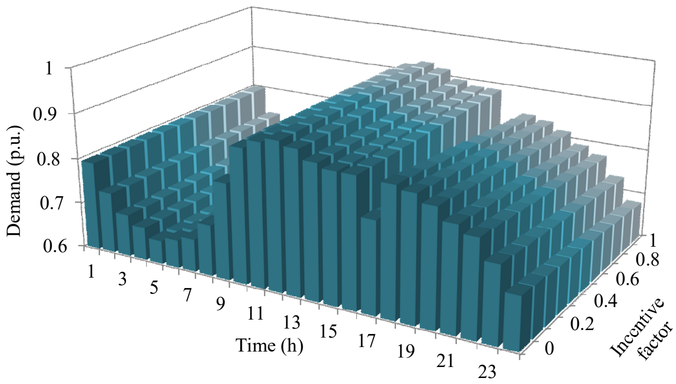

(c)

Fig. 8. Impact of incentive factor on the demand profile, (a) TOU+EDRP (b) RTP+EDRP (c) CPP+EDRP.

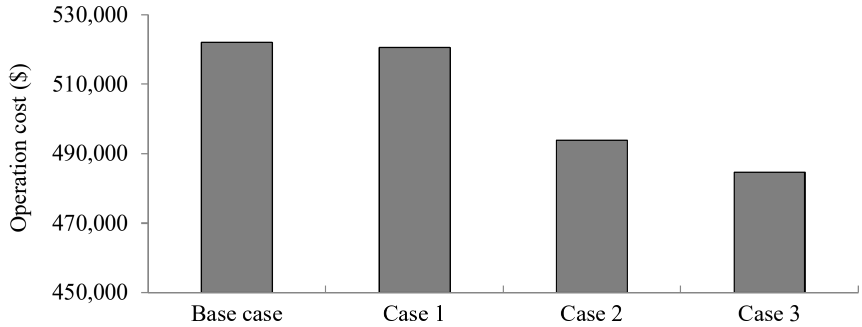

Fig. 9. Operation cost in different cases.

Table 1. Comparison of different ES technologies rating power [14]

Energy storage technology	Rating power range (MW)
Pumped Hydro Storage (PHS)	100-5000
Compressed Air Energy Storage (CAES)	5-300
Flywheel Energy Storage (FES)	0-0.25
Lead Acid (LA) battery	0-20
Nickel Cadmium (NiCd) battery	0-40
Lithium Ion (Li-ion) battery	0-0.1
Sodium Sulphur (NaS) battery	0.05-8
Vanadium Redox Battery (VRB)	0.03-3
Zinc Bromine (ZnBr)	0.05-2
Superconducting Magnetic Energy Storage (SMES)	0.1-10
Super-Capacitor (SC)	0-0.3
Fuel Cell (FC)	0-50

Table. 2. Optimization statistics for considered case studies

Case No.	No. of iterations	Solution time
Base-case	4417	3.73 sec
Case 1	4979	5.09 sec
Case 2	4518	3.79 sec
Case 3	6505	8.49 sec

Table 3. Terms of operation cost in different DR strategies ($)

	TOU+EDRP+ES	RTP+EDRP+ES	CPP+EDRP+ES
Start-up cost	677.4	1018.9	1150
Generation unit production cost	393440	401520	393120
Up/down reserve capacity cost	1223.02	2031.45	2976.93
ES energy cost	1477.26	387.75	1280
ES capacity reserve cost	923.29	242.34	800
Incentive cost	949.67	8725.13	2967.7
FIT cost	91633.95	91633.95	91633.95
Worst case cost	-4843.07	-6065.79	-7865.44
Optimal operation cost	485481.52	499493.73	486063.14