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Energy-constrained model for scheduling of battery storage systems in joint energy and ancillary service markets based on the energy throughput concept

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A B S T R A C T

Among different local renewable resources, using battery energy storage (BES) has grown more than other technologies. The main reasons for this growth are flexibility and schedulability of BES. The fast ramp-rate of BES systems provides the opportunity of effective participation of these resources in the regulation ancillary service. However, continuous charging and discharging cycles of BES could decrease its lifetime and the expected profit, consequently. Therefore, the lifespan is a crucial parameter that shall be considered in the scheduling of BES. In this paper, an energy-constrained model is proposed for the scheduling of BES in joint energy and ancillary service markets. Moreover, the Energy Throughput (ET) concept is proposed for modeling the lifetime in the short-term scheduling strategy. In the proposed strategy, the uncertainties of energy prices in energy and regulation markets are modeled by Robust Optimization (RO) methodology. The scheduling problem is linearized and formulated based on the mixed-integer linear programming (MILP) method. The proposed model determines the optimal scheduling of BES based on the profit maximization, operational constraints, lifespan, and the defined risk level. Finally, the performance of model is evaluated vie case study results.

1. Introduction

Increasing the penetration level of variable renewable energy resources in smart grids and dependency of their generating power to uncertain parameters could endanger the stability of grid. Therefore, it is necessary to utilize the flexible resources, which have the ability to adapt to fast variations in power supply and demand. Local grid-connected Battery Energy Storages (BES) as a promising solution can increase the reliability and security of smart grids, significantly. These resources can improve the flexibility of smart grids by storing the excess energy and delivering it within peak periods. Moreover, the fast response BES provides the opportunity for owners to increase the expected profit by participating in regulation ancillary service. However, for participating in these markets, BES owners are faced with various uncertain parameters such as energy prices in energy and regulation markets, and ignoring them may decrease the expected profit or lead additional loss to them. One of the main differences of BES in comparison with other generating resources is the dependency of short-time scheduling program to the expected lifespan [1]. The lifetime of BES is highly dependent to the number of charging/discharging cycles, and the amount of the delivered energy. Therefore, in a comprehensive scheduling model, the dependency of lifetime shall be considered as well as characteristics of batteries and uncertain parameters of different markets.

Different scheduling models are previously proposed in the literature for the optimal scheduling of BES in various markets. In [2–3], the heuristic methods are proposed for scheduling of BES in the presence of demand response resources. The proposed model of [4] provides a coordinated model for the scheduling of BES and thermal generators in the wholesale energy market. Moreover, the dependency of BES lifetime to short-term operation is modeled by the Depth of Discharge (DoD) concept. DoD specifies the battery cycle life based on the depth percentage of the BES capacity that has been discharged from the fully charged state. In [5] a bi-level scheduling framework is proposed for scheduling of BES from viewpoints of the market operator and BES owners. The total energy supply cost of grid and BES profit are minimized and maximized in upper and lower sub-problems, respectively. In this model, DoD method is used to model lifetime of BES in lower sub-problem. The fast ramping capability is one of the main advantages of BES in comparison with thermal generators. Therefore, the energy, spinning reserve, and regulation markets are considered in the bidding

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Nomenclature

Indices and Set

t, T	Index and set of time
j, J	Index and set of intra-hourly
l, NL	Index and set of BES lifetime

Constants and Parameters

E^{Rated}	Rated capacity of BES (MWh)
E^{min}	Minimum capacity of BES (MWh)
π^{SE}	Price of selling to the energy market ($/MWh)
π^{BE}	Price of buying from the energy market ($/MWh)
π^{DR}	Down regulation price in regulation market ($/MWh)
π^{UR}	Up regulation price in regulation market ($/MWh)
π^{CH}	Energy charging price in regulation market ($/MWh)
π^{RT}	Real-time energy price in regulation market ($/MWh)
RR^{Ch}	Charging ramp-rate (MW)
RR^{Dch}	Discharging ramp-rate (MW)
M^{*}	Large enough constant
H^{LT}	Lifetime throughput energy (MWh)
H^{AT}	Annual throughput energy (MWh/year)
ψ	Annual degradation of BES capacity (%)
W	Working days per year (day)
δ	Variation interval of uncertain parameter
ε	Confidence level of uncertain parameter
r	Interest rate (%)

Decision variables

$\Delta E^{E,ch}$	Charging bid in energy market (MWh)
$\Delta E^{E,dch}$	Discharging bid in energy market (MWh)
ΔE^{E}	Energy bid in energy market (MWh)
ΔE^{RS}	Energy bid in regulation service (MWh)
ΔE^{UR}	Energy bid in up-regulation market (MWh)
ΔE^{DR}	Energy bid in down-regulation market (MWh)
E	Stored energy of BES (MWh)
μ, λ	Lagrange multiplier
A^{*}	Auxiliary variable for linearization

Binary Variables

U	Charging/discharging status binary variable ($U = 1$ for discharging, $U = 0$ for down charging)
υ	Regulation service status binary variable ($\upsilon = 1$ for up regulation, $\upsilon = 0$ for down regulation)

strategy of [6]. In the proposed objective function, the decomposition solution is addressed to separate the calculation of hourly energy and intra-hourly regulation markets. According to the bidding strategy in hourly and intra-hourly markets, DoD and consequently the life cycle can be calculated (see Fig. 1).

It shall be noted that DoD is the common method for modeling the lifetime of BES, but sometimes the cycle life cannot be helpful. The main reason is that DoD does not reflect the BES capacity degradation over the lifetime. Moreover, manufacturers provide the allowable life cycle of batteries based on DoD that represents discharged depth from the fully charged state. Evidently, there is no guarantee in hourly scheduling of BES that the discharge cycles are started from the fully charged state. Therefore, the energy throughput concept is proposed by manufacturers to solve this problem. The energy throughput is the total amount of energy that can be charged and discharged within the lifetime of batteries, and it is not affected by the depth of charge or discharge [7]. According to the battery energy throughput and planned lifetime, the energy constraint and optimal scheduling of BES within the planning period can be determined.

As mentioned before, owners of BES face different resources of uncertainty for participating in energy and ancillary service markets. In charging and discharging modes, BES can participate in the energy market as the buyer and seller, respectively. Therefore, uncertainties of selling and buying prices are the main challenge of BES in the energy

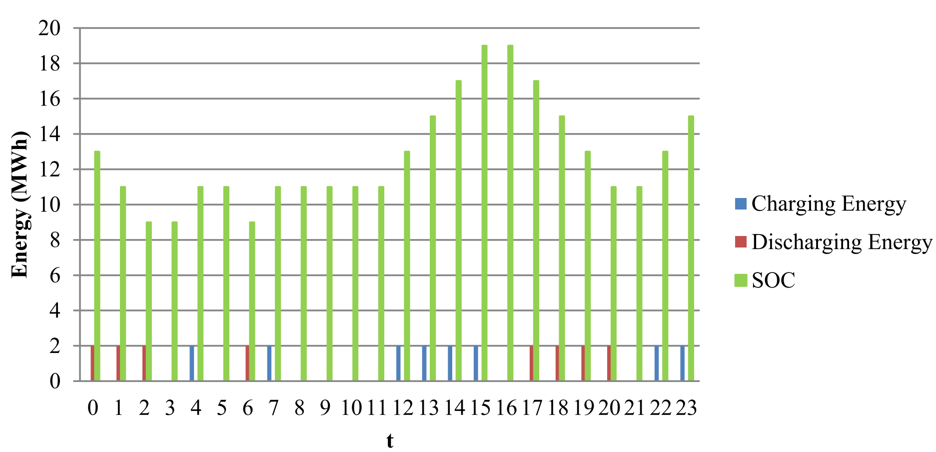

Fig. 1. Scheduling of BES without considering regulation market and energy throughput.

market bidding strategy. Moreover, variation of regulation prices is another problem of BES owners for participating in regulation ancillary market. Therefore, the optimal strategy of BES is influenced by the framework, which is used for the modeling of uncertain parameters. The scheduling problem of BES in an uncertain environment is evaluated in different references [8–9]. The presented methodologies for managing the financial risk of uncertain parameters can be categorized as stochastic and deterministic frameworks. In the stochastic framework, the behavior of uncertain parameters is modeled based on the probabilistic distribution functions (PDF) [10–13]. PDF can be approximated according to historical data. This framework is not applicable in all circumstances. For example, the regulation price is highly dependent on demand variations, fluctuations of renewable resources, and unpredicted contingencies of grid. Moreover, the pattern of regulation price is not predictable and historical data is not practical in this case. The deterministic framework such as Robust Optimization (RO) is an effective solution for modeling the uncertain parameters that their behavior cannot be forecasted by the historical data. In RO, a variation interval is specified for the uncertain parameter, and the optimal strategy is determined based on the worst-case realization. Therefore, within the variation interval or confidence interval, the robustness of the optimal strategy against different realizations of the uncertain parameter is guaranteed. In [14–15], a robust model is proposed for scheduling of BES in day-ahead energy, regulation, and reserve markets. The proposed model is formulated as a max–min problem, which the inner minimization represents the worst-case (minimum profit) within the confidence interval, and the outer maximization part determines the optimal values of decision variables that maximize the minimum profit. To solve the presented bi-level optimization models, the strong duality theory is used to convert the Max-Min problem to a Max-Max problem. In [16], a bi-level complementarity model is presented for the scheduling of BES in joint energy and reserve markets. In the proposed bi-level problem, the biding strategies of day-ahead and reserve markets are determined in the upper and lower sub-problems, respectively. To solve the proposed problem, the lower sub-problem is replaced by the Karush-Kuhn-Tucker (KKT) conditions, and the resulting problem is formulated as a single level mathematical program with equilibrium constraints (MPEC). The performance of the proposed model can be improved by modeling the lifetime of batteries. Evidently, the self-scheduling problem of BES is not a new topic, and different stochastic and robust models are proposed for handling the uncertain parameters. However, the modeling of lifetime of batteries is still challenging between researchers and they try to reflect the lifetime of batteries in the self-scheduling problem [17].

This work presents an energy-constrained self-scheduling model for participation of BES's owners in the joint energy and regulation ancillary service markets. The proposed model is formulated based on the profit maximization of BES within the expected lifespan. In the short-term scheduling, the lifetime and capacity degradation of batteries are modeled by the energy throughput concept. Therefore, the optimal scheduling is determined based on the guaranteed storing and delivering energy (which are provided by the manufacturer), the planned lifetime, and the energy constraint of batteries. The buying and selling price of the energy market, incentives, and prices of the regulation market are considered as uncertain parameters. In the next step, RO framework is used to derivate the risk-based model. As mentioned before, in RO framework, the optimal strategy is specified based on the worst-case realization of uncertain parameters. Therefore, a Max-Min problem is suggested for self-scheduling of BES, and according to the worst-case realization of uncertain parameters, it is converted to the Max-Max problem. The model is linearized and formulated based MILP technique that can be solved by the commercial solvers. The main contributions of this paper can be summarized as follows:

- Modeling the lifetime of capacity degradation of batteries in short-term scheduling of BES based on the energy throughput concept, which is not dependent on the depth of charging and discharging.
- Presenting a MILP formulation for the robust self-scheduling of BES according to the expected lifetime and energy constraints of batteries.

The rest of this paper is organized as follows: In Section 2, the deterministic model for scheduling of BES in joint energy and regulation markets is presented. The robust model and the MILP-based formulations are presented in Section 3. The results of simulations are given in Sections 4. Finally, conclusions are presented in Section 5.

2. BES Self-scheduling model

As mentioned before, the focus of this paper is presenting a self-scheduling model for local BES's participation in the energy and regulation ancillary service markets. In the proposed model, it is assumed that BES can buy/sell its energy from the energy market in charging/discharging modes, and bid in energy and regulation markets, simultaneously. Moreover, BES can participate in down and up-regulation services in charging and discharging modes, respectively.

2.1. Energy market

In this work, BES is considered as a price-taker player of the energy market and the market-clearing prices are not affected by its bidding strategy. The hourly energy prices are considered as the uncertain input data of the model. Moreover, the scheduling planning horizon is divided into hourly and intra-hourly categories. In the hourly category, the time step is 1 h and in the intra-hourly category, the time step is 5 min [18]. According to the defined categories, the total traded energy of BES in the operational period t can be formulated by (1). It shall be noted that the binary variable U represents charging ($U = 0$) or discharging mode ($U = 1$) of battery. The second term of (1a) is nonlinear. Therefore, via the auxiliary variable (A^E), and big M theory, ΔE^E is linearized by constraints (1b)–(1e).

$$\begin{aligned}\Delta E_t^E &= \Delta E_t^{E,ch}.(1-U_t) - \Delta E_t^{E,dch}.U_t \\ &= \Delta E_t^{E,ch} - U_t.(\Delta E_t^{E,dch} + \Delta E_t^{E,ch})\end{aligned} \quad : \forall t \tag{1a}$$

$$\Delta E_t^E = \Delta E_t^{E,ch} - A_t^E \quad : \forall t \tag{1b}$$

$$A_t^E \leqslant M^E.U_t \quad : \lambda_t^1, \forall t \tag{1c}$$

$$A_t^E \leqslant \Delta E_t^{E,dch} + \Delta E_t^{E,ch} \quad : \lambda_t^2, \forall t \tag{1d}$$

$$A_t^E \geqslant \Delta E_t^{E,dch} + \Delta E_t^{E,ch} - M^E.(1-U_t) \quad : \lambda_t^3, \forall t \tag{1e}$$

$$A_t^E, \Delta E_t^{E,ch}, \Delta E_t^{E,dch} \geqslant 0 : \ \forall t \tag{1f}$$

It should be noted that charging and discharging efficiencies are fixed terms and they do not have any impact on the optimization procedure. Therefore, without loss of generality it is supposed that charging and discharging efficiencies are equal to one.

In this work, two prices are considered for the selling/buying energy to/from the electricity market in discharging/charging mode. The difference between selling income and purchasing cost represents the payment of BES from the energy market. Same as (1), the energy market payoff is linearized by the auxiliary variable A^{PE} and big valueM^{PE}.

$$\begin{aligned} Pay^{E} &= \sum_{t=1}^{T} \pi_t^{SE}.\Delta E_t^{E,dch}.U_t - \pi_t^{BE}.\Delta E_t^{E,ch}.(1-U_t) \\ &= \sum_{t=1}^{T} \left(\pi_t^{SE}.\Delta E_t^{E,dch} + \pi_t^{BE}.\Delta E_t^{E,ch}\right) U_t - \pi_t^{BE}.\Delta E_t^{E,ch} \end{aligned} \tag{2a}$$

$$Pay^{E} = \sum_{t=1}^{T} A_t^{PE} - \pi_t^{BE}.\Delta E_t^{E,ch} \tag{2b}$$

$$A_t^{PE} \leqslant M^{PE}.U_t \ : \ \lambda_t^4, \forall t \tag{2c}$$

$$A_t^{PE} \leqslant \pi_t^{SE}.\Delta E_t^{E,dch} + \pi_t^{BE}.\Delta E_t^{E,ch} \ : \ \forall t \tag{2d}$$

$$A_t^{PE} \geqslant \pi_t^{SE}.\Delta E_t^{E,dch} + \pi_t^{BE}.\Delta E_t^{E,ch} - M^{PE}.(1-U_t) \ : \ \forall t \tag{2e}$$

$$A_t^{PE} \geqslant 0 \ : \ \forall t \tag{2f}$$

2.2. Regulation ancillary service

The participation level of BES in the regulation ancillary service depends on the regulation incentives and prices. The bidding strategy of BES in the regulation market can be represented as follows:

$$\Delta E_{t,j}^{RS} = \Delta E_{t,j}^{DR}.(1-\upsilon_{t,j}) - \Delta E_{t,j}^{UR}.\upsilon_{t,j} : \ \forall t, \ \forall j \tag{3a}$$

$$\Delta E_{t,j}^{DR}, \Delta E_{t,j}^{UR} \geqslant 0 : \ \forall t, \ \forall j \tag{3b}$$

The status of BES in up regulation/down regulation service is specified by the binary variable υ (for $\upsilon = 1$ up-regulation, and $\upsilon = 0$ for down-regulation), and$\Delta E_{t,j}^{RS}$is linearized as follow:

$$\begin{aligned} \Delta E_{t,j}^{RS} &= \Delta E_{t,j}^{DR} - \upsilon_{t,j}.(\Delta E_{t,j}^{DR} + \Delta E_{t,j}^{UR}) \\ &= \Delta E_{t,j}^{DR} - A_{t,j}^{RS} \end{aligned} \quad : \ \forall t, \ \forall j \tag{4a}$$

$$A_{t,j}^{RS} \leqslant M^{RS}.\upsilon_{t,j} : \ \lambda_{t,j}^5, \forall t, \ \forall j \tag{4b}$$

$$A_{t,j}^{RS} \leqslant (\Delta E_{t,j}^{DR} + \Delta E_{t,j}^{UR}) : \ \lambda_{t,j}^6, \forall t, \ \forall j \tag{4c}$$

$$A_{t,j}^{RS} \geqslant (\Delta E_{t,j}^{DR} + \Delta E_{t,j}^{UR}) - M^{RS}.(1-\upsilon_{t,j}) : \ \lambda_{t,j}^7, \forall t, \ \forall j \tag{4d}$$

$$A_{t,j}^{RS} \geqslant 0 : \ \forall t, \ \forall j \tag{4e}$$

In regulation service, BES receives the capacity and deployment payments, which are calculated based on the accepted capacity and deployed energy in the ancillary service market, respectively. In this work, it is supposed that all the capacity of regulation bid will be deployed by the local market operator in the real-time operation. Moreover, it is supposed that BES can participate in up and down-regulation services by discharging and charging of energy, respectively. Therefore, BES income in from the regulation market is:

$$Pay^{RS} = \sum_{t=1}^{T}\sum_{j=1}^{J}\left(\left(\pi_{t,j}^{DR} - \pi_{t,j}^{CH}\right)\Delta E_{t,j}^{DR}.(1-\upsilon_{t,j}) + \left(\pi_{t,j}^{UR} + \pi_{t,j}^{RT}\right)\Delta E_{t,j}^{UR}.\upsilon_{t,j}\right) \tag{5}$$

In (5), the first and second terms represent the BES income from down and up regulation services, respectively. BES receives π^{DR} and π^{UR} for providing down or up regulation services, respectively. In down regulation service, the market operator faces with the over-generation. Therefore, the consumption (or charging of BES) should be increased to maintain the balance of generation and consumption. In down regulation service, BES should pay π^{CH} for charging of batteries. Without loss of generality π^{CH} can be equal to real-time prices. Similarly, in case of under-generation, the generating should be increased to maintain the balance of generation and consumption. Therefore, BES receives π^{RT} for discharging.

Since (5) is nonlinear, it is rewritten as follow:

$$\begin{aligned} Pay^{RS} = \sum_{t=1}^{T}\sum_{j=1}^{J} &\left(\pi_{t,j}^{DR} - \pi_{t,j}^{CH}\right)\Delta E_{t,j}^{DR} - \left(\pi_{t,j}^{CH} - \pi_{t,j}^{DR}\right)\Delta E_{t,j}^{DR}.\upsilon_{t,j} + \left(\pi_{t,j}^{UR}\right. \\ &\left. + \pi_{t,j}^{RT}\right)\Delta E_{t,j}^{UR}.\upsilon_{t,j} \end{aligned} \tag{6}$$

and the nonlinear parts are linearized via big M reformulations.. Therefore:

$$Pay^{RS} = \sum_{t=1}^{T}\sum_{j=1}^{J}\left(\pi_{t,j}^{DR} - \pi_{t,j}^{CH}\right)\Delta E_{t,j}^{DR} - A_{t,j}^{DR} + A_{t,j}^{UR} \tag{7a}$$

$$A_{t,j}^{DR} \leqslant M^{RG}.\upsilon_{t,j} : \ \lambda_{t,j}^8, \forall t, \ \forall j \tag{7b}$$

$$A_{t,j}^{UR} \leqslant M^{RG}.\upsilon_{t,j} : \ \lambda_{t,j}^9, \forall t, \ \forall j \tag{7c}$$

$$A_{t,j}^{DR} \leqslant \left(\pi_{t,j}^{CH} - \pi_{t,j}^{DR}\right)\Delta E_{t,j}^{DR} : \ \forall t, \ \forall j \tag{7d}$$

$$A_{t,j}^{UR} \leqslant \left(\pi_{t,j}^{UR} + \pi_{t,j}^{RT}\right)\Delta E_{t,j}^{UR} : \ \forall t, \ \forall j \tag{7e}$$

$$A_{t,j}^{DR} \geqslant \left(\pi_{t,j}^{CH} - \pi_{t,j}^{DR}\right)\Delta E_{t,j}^{DR} - M^{RG}.(1-\upsilon_{t,j}) : \ \forall t, \ \forall j \tag{7f}$$

$$A_{t,j}^{UR} \geqslant \left(\pi_{t,j}^{UR} + \pi_{t,j}^{RT}\right)\Delta E_{t,j}^{UR} - M^{RG}.(1-\upsilon_{t,j}) : \ \forall t, \ \forall j \tag{7g}$$

$$A_{t,j}^{DR}, A_{t,j}^{UR} \geqslant 0 : \ \forall t, \ \forall j \tag{7h}$$

It shall be noted that the charging price is specified based on the real-time price, which is greater than the regulation capacity price ($\pi^{CH} > \pi^{DR}$).

2.3. Lifetime modeling based on energy throughput

The common methodology to model the lifetime of batteries is the life estimation based on DoD concept. DoD is the percentage of the energy that has been discharged from the fully rated capacity [4]:

$$DOD_t\% = \frac{E^{Rated} - E_t}{E^{Rated}} \times 100 \tag{8}$$

According to the relation between DOD and battery life cycle (which is presented by the manufacturers), the lifetime of BES can be estimated. However, sometimes using the DOD method cannot be helpful. As seen in (8), the reference (or initial) value to calculate the deviation of energy is the full rated capacity. For example, if the following values are considered for the stored energy of BES:

$$E_0 = E^{Rated}, \ E_1 = 0.7E^{Rated}, \ E_2 = 0.8E^{Rated}, \ E_3 = 0.7E^{Rated}$$

The values of DOD for $t = 1$ and $t = 3$ are 30%. However, the discharged energy in $t = 1$ and $t = 3$ are $0.3E^{Rated}$ and $0.1E^{Rated}$, respectively. Considering the variation of energy in each time interval ($E_{t-1} - E_t$) is not an appropriate solution. The main reason is the battery life cycle curve, which is presented based on the deviation from the rated capacity. Moreover, DoD does not reflect the impact of lifetime degradation of E^{Rated}. Another solution to estimate the BES lifetime is using the energy throughput concept. The energy throughput is the total amount of energy that cycles through BES in charging and discharging modes within its lifetime. In Energy throughput framework, instead of DoD, the total amount of deliverable energy of BES is considered. This parameter is independent of the depth of charge and discharge. According to the throughput concept, the lifetime of BES can be calculated as follow:

$$NL = \frac{H^{LT}}{H^{AT}} \tag{9}$$

where H^{LT} and H^{AT} are the lifetime energy and the annual energy throughputs, respectively.

In this work, it is supposed that initial and final energy levels of BES are equal within the daily planning period. Therefore, the daily energy constraint can be represented as follows:

$$E_{t=0} = E_{t=T} \tag{10a}$$

$$\sum_{t=1}^{T}\left(\Delta E_t^{E,ch}.(1-U_t) + \sum_{j=1}^{J}\Delta E_{t,j}^{DR}.(1-\upsilon_{t,j})\right) = \sum_{t=1}^{T}\Delta E_t^{E,dch}.U_t + \sum_{j=1}^{J}\Delta E_{t,j}^{UR}.\upsilon_{t,j} \tag{10b}$$

$$\sum_{t=1}^{T}\left(\Delta E_t^{E,ch} - A_t^E + \sum_{j=1}^{J}\Delta E_{t,j}^{DR} - A_{t,j}^{RS}\right) = 0 \ : \ \mu^1 \tag{10c}$$

Therefore, the annual throughput energy or delivered energy can be calculated as follow:

$$H^{AT} = W.\sum_{t=1}^{T}\Delta E_t^{E,dch}.U_t + \sum_{j=1}^{J}\Delta E_{t,j}^{UR}.\upsilon_{t,j} \tag{11a}$$

$$H^{AT} = W.\sum_{t=1}^{T}\left(A_t^{EAT} + \sum_{j=1}^{J}A_{t,j}^{RAT}\right) \ : \ \mu^2 \tag{11b}$$

$$A_t^{EAT} \leqslant M^{AT}.U_t \ : \ \lambda_t^{10}, \forall t, \forall j \tag{11c}$$

$$A_{t,j}^{RAT} \leqslant M^{AT}.\upsilon_{t,j} \ : \ \lambda_{t,j}^{11}, \forall t, \forall j \tag{11d}$$

$$A_t^{EAT} \leqslant \Delta E_t^{E,dch} \ : \ \lambda_t^{12}, \forall t, \forall j \tag{11e}$$

$$A_{t,j}^{RAT} \leqslant \Delta E_{t,j}^{UR} \ : \ \lambda_{t,j}^{13}, \forall t, \forall j \tag{11f}$$

$$A_t^{EAT} \geqslant \Delta E_t^{E,dch} - M^{AT}.(1-U_t) \ : \ \lambda_t^{14}, \forall t, \forall j \tag{11g}$$

$$A_{t,j}^{RAT} \geqslant \Delta E_{t,j}^{UR} - M^{AT}.(1-\upsilon_{t,j}) \ : \ \lambda_{t,j}^{15}, \forall t, \forall j \tag{11h}$$

$$A_t^{EAT}, A_{t,j}^{RAT} \geqslant 0 \ : \ \forall t, \forall j \tag{11i}$$

where W is average working days per year.

2.4. Operational constraints

The main operational constraints of BES are capacity and ramp-rate. The stored energy of BES can be represented as follow:

$$\begin{aligned} E_{t,j} &= E_{t,j-1} + \left(S_{t,j} - S_{t,j-1}\right)\Delta E_t^E + \Delta E_{t,j}^{RS} \\ &= E_{t,j-1} + (S_{t,j} - S_{t,j-1}).(\Delta E_t^{E,ch} - A_t^E) + \Delta E_{t,j}^{DR} - A_{t,j}^{RS} \end{aligned} \ : \ \forall t, \ \forall j \tag{12}$$

where $S_{t,j}$ - $S_{t,j-1}$ represents the duration of intra-hourly time step. The maximum and minimum capacity limitations of BES are represented by (13a) and (13b), respectively. Moreover, the annual degradation of BES capacity is modeled by (13c).

$$E_{t,j-1} + (S_{t,j} - S_{t,j-1}).(\Delta E_t^{E,ch} - A_t^E) + \Delta E_{t,j}^{DR} - A_{t,j}^{RS} \leqslant E_l^{Rated} \ : \ \lambda_{t,j}^{16}, \forall t, \ \forall j \tag{13a}$$

$$E^{min} \leqslant E_{t,j-1} + (S_{t,j} - S_{t,j-1}).(\Delta E_t^{E,ch} - A_t^E) + \Delta E_{t,j}^{DR} - A_{t,j}^{RS} \ : \ \lambda_{t,j}^{17}, \forall t, \ \forall j \tag{13b}$$

$$E_l^{Rated} = E_{l-1}^{Rated}(1 - \psi.l) \ : \ \forall l = 1, ..., NL \tag{13c}$$

The annual degradation depends on the characteristics of batteries. This parameter is specified based on the lifetime of batteries, and in this work it is supposed that the degradation is a fixed term within the considered year.

The operation of BES can be limited by the ramp-rate constraint. As mentioned before, in this work the time interval of energy market is 1 h ($\Delta E_t^E = P_t^E$). Therefore, charging and discharging ramp-rate constraints are represented by (14a) and (14b), respectively.

$$\Delta E_t^{E,ch} - A_t^E + \frac{\Delta E_{t,j}^{DR} - A_{t,j}^{RS}}{S_{t,j} - S_{t,j-1}} \leqslant RR^{Ch} \ : \ \lambda_{t,j}^{18}, \forall t, \ \forall j \tag{14a}$$

$$A_t^E - \Delta E_t^{E,ch} - \frac{\Delta E_{t,j}^{DR} - A_{t,j}^{RS}}{S_{t,j} - S_{t,j-1}} \leqslant RR^{Dch} \ : \ \lambda_{t,j}^{19}, \forall t, \ \forall j \tag{14b}$$

2.5. Deterministic objective function

According to the presented payment functions, the deterministic object function or overall profit can be written as follow:

$$\begin{aligned} &Max \ \ W.\frac{1-(1+r)^{-NL}}{r}\left(\sum_{t=1}^{T}A_t^{PE} - \pi_t^{BE}.\Delta E_t^{E,ch} + \sum_{j=1}^{J}(\pi_{t,j}^{DR} - \pi_{t,j}^{CH}).\Delta E_{t,j}^{DR} - A_{t,j}^{DR} + A_{t,j}^{UR}\right) \\ &s.t.: \ (1c)-(1e), (2c)-(2e), (4b)-(4d), (7b)-(7g), (10c), (11b)-(11h), (13), and (14). \\ &\Delta E_t^{E,ch}, \Delta E_t^{E,dch}, A_t^E, A_t^{PE}, A_t^{EAT}, \Delta E_{t,j}^{DR}, \Delta E_{t,j}^{UR}, A_{t,j}^{RS}, A_{t,j}^{DR}, A_{t,j}^{UR}, A_{t,j}^{RAT} \geqslant 0 : \ \forall t, \ \forall j \\ &U_t, \upsilon_{t,j} \in [0,1] : \ \forall t, \ \forall j \end{aligned} \tag{15}$$

The overall profit is the net presented value of profit (income minus cost), within the lifetime of batteries, and it is calculated based on the energy throughput constraint that depends on the characteristics of batteries and it is presented by the manufacturer. Effects of uncertain parameters are modeled in next section by RO methodology.

3. Robust self-scheduling model

As mentioned before, in this work, RO methodology is used for modeling the uncertain parameters. In RO methodology, the optimal strategy is specified based on the worst-case realization of uncertain parameters. As mentioned before, the prices of energy, regulation, and real-time markets (π_t^{SE},π_t^{BE},$\pi_{t,j}^{DR}$,$\pi_{t,j}^{UR}$,$\pi_{t,j}^{RT}$ and $\pi_{t,j}^{ER}$) are considered as the uncertainty resources. The realizations of uncertain parameters or confidence intervals are represented by (16).

$$-\varepsilon^{SE}.\pi_t^{SE}\leqslant\delta_t^{SE}\leqslant\varepsilon^{SE}.\pi_t^{SE} : \forall t \tag{16a}$$

$$-\varepsilon^{BE}.\pi_t^{BE}\leqslant\delta_t^{BE}\leqslant\varepsilon^{BE}.\pi_t^{BE} : \forall t \tag{16b}$$

$$-\varepsilon^{DR}.\pi_{t,j}^{DR}\leqslant\delta_{t,j}^{DR}\leqslant\varepsilon^{DR}.\pi_{t,j}^{DR} : \forall t,\ \forall j \tag{16c}$$

$$-\varepsilon^{UR}.\pi_{t,j}^{UR}\leqslant\delta_{t,j}^{UR}\leqslant\varepsilon^{UR}.\pi_{t,j}^{UR} : \forall t,\ \forall j \tag{16d}$$

$$-\varepsilon^{CH}.\pi_{t,j}^{CH}\leqslant\delta_{t,j}^{CH}\leqslant\varepsilon^{CH}.\pi_{t,j}^{CH} : \forall t,\ \forall j \tag{16e}$$

$$-\varepsilon^{RT}.\pi_{t,j}^{RT}\leqslant\delta_{t,j}^{RT}\leqslant\varepsilon^{RT}.\pi_{t,j}^{RT} : \forall t,\ \forall j \tag{16f}$$

$$0\leqslant\varepsilon^{SE},\varepsilon^{BE},\varepsilon^{DR},\varepsilon^{UR},\varepsilon^{CH},\varepsilon^{RT}\leqslant 1 \tag{16g}$$

According to the concept of RO methodology, objective function (15) can be reformulated as follows:

$$Max\,Min\ \ W.\frac{1-(1+r)^{-NL}}{r}\left(\begin{array}{c}\sum_{t=1}^{T}A_t^{PE}-(\pi_t^{BE}+\delta_t^{BE}).\,\Delta E_t^{E,ch}\\ +\sum_{j=1}^{J}(\pi_{t,j}^{DR}+\delta_{t,j}^{DR}-\pi_{t,j}^{CH}-\delta_{t,j}^{CH}).\Delta E_{t,j}^{DR}-A_{t,j}^{DR}+A_{t,j}^{UR}\end{array}\right) \tag{17a}$$

$$s.t.:\ (1c)-(1e),(2c),(4b)-(4d),(7b)-(7c),(10c),(11b)-(11h),(13),and(14).$$

$$A_t^{PE}\leqslant(\pi_t^{SE}+\delta_t^{SE}).\,\Delta E_t^{E,dch}+(\pi_t^{BE}+\delta_t^{BE}).\,\Delta E_t^{E,ch}\ \ :\ \forall t \tag{17b}$$

$$A_t^{PE}\geqslant(\pi_t^{SE}+\delta_t^{SE}).\,\Delta E_t^{E,dch}+(\pi_t^{BE}+\delta_t^{BE}).\,\Delta E_t^{E,ch}-M^{PE}.(1-U_t)\ :\ \forall t \tag{17c}$$

$$A_{t,j}^{DR}\leqslant\left(\pi_{t,j}^{CH}+\delta_{t,j}^{CH}-\pi_{t,j}^{DR}-\delta_{t,j}^{DR}\right)\Delta E_{t,j}^{DR}:\ \forall t,\ \forall j \tag{17d}$$

$$A_{t,j}^{UR}\leqslant\left(\pi_{t,j}^{UR}+\delta_{t,j}^{UR}+\pi_{t,j}^{RT}+\delta_{t,j}^{RT}\right)\Delta E_{t,j}^{DR}:\ \forall t,\ \forall j \tag{17e}$$

$$A_{t,j}^{DR}\geqslant\left(\pi_{t,j}^{CH}+\delta_{t,j}^{CH}-\pi_{t,j}^{DR}-\delta_{t,j}^{DR}\right)\Delta E_{t,j}^{DR}-M^{RG}.(1-\upsilon_{t,j}):\ \forall t,\ \forall j \tag{17f}$$

$$A_{t,j}^{UR}\geqslant\left(\pi_{t,j}^{UR}+\delta_{t,j}^{UR}+\pi_{t,j}^{RT}+\delta_{t,j}^{RT}\right)\Delta E_{t,j}^{DR}-M^{RG}.(1-\upsilon_{t,j}):\ \forall t,\ \forall j \tag{17g}$$

In the presented objective function, the lower bound of minimization is achieved for the minimum selling prices (π_t^{SE},$\pi_{t,j}^{DR}$,$\pi_{t,j}^{UR}$, and $\pi_{t,j}^{RT}$) and maximum buying and charging prices (π_t^{BE} and $\pi_{t,j}^{CH}$). Therefore, the worst-case realizations of uncertain parameters within the variation interval are as follows:

$$\delta_t^{SE}=-\varepsilon^{SE}.\pi_t^{SE};\forall t \tag{18a}$$

$$\delta_t^{BE}=\varepsilon^{BE}.\pi_t^{BE};\forall t \tag{18b}$$

$$\delta_{t,j}^{DR}=-\varepsilon^{DR}.\pi_{t,j}^{DR};\forall t,\ \forall j \tag{18c}$$

$$\delta_{t,j}^{UR}=-\varepsilon^{UR}.\pi_{t,j}^{UR};\forall t,\ \forall j \tag{18d}$$

$$\delta_{t,j}^{CH}=\varepsilon^{CH}.\pi_{t,j}^{CH};\forall t,\ \forall j \tag{18e}$$

$$\delta_{t,j}^{RT}=-\varepsilon^{RT}.\pi_{t,j}^{RT};\forall t,\ \forall j \tag{18f}$$

Accordingly, the Max-Min problem (17) can be converted to the Max optimization problem, as follows:

$$Max\ \ W.\frac{1-(1+r)^{-NL}}{r}\left(\begin{array}{c}\sum_{t=1}^{T}A_t^{PE}-(\pi_t^{BE}+\varepsilon^{BE}.\pi_t^{BE}).\Delta E_t^{E,ch}\\ \sum_{j=1}^{J}\left(\pi_{t,j}^{DR}-\varepsilon^{DR}.\pi_{t,j}^{DR}-\pi_{t,j}^{CH}-\varepsilon^{CH}.\pi_{t,j}^{CH}\right)\Delta E_{t,j}^{DR}-A_{t,j}^{DR}+A_{t,j}^{UR}\end{array}\right) \tag{19a}$$

$$s.t.:\ (1c)-(1e),(2c),(4b)-(4d),(7b)-(7c),(10c),(11b)-(11h),(13),and(14).$$

$$A_t^{PE}\leqslant\pi_t^{SE}.(1-\varepsilon^{SE}).\,\Delta E_t^{E,dch}+\pi_t^{BE}.(1+\varepsilon^{BE}).\,\Delta E_t^{E,ch}\ :\ \lambda_t^{20},\forall t \tag{19b}$$

$$A_t^{PE}\geqslant\pi_t^{SE}.(1-\varepsilon^{SE}).\,\Delta E_t^{E,dch}+\pi_t^{BE}.(1+\varepsilon^{BE}).\,\Delta E_t^{E,ch}-M^{PE}.(1-U_t)\ :\ \lambda_t^{21},\forall t \tag{19c}$$

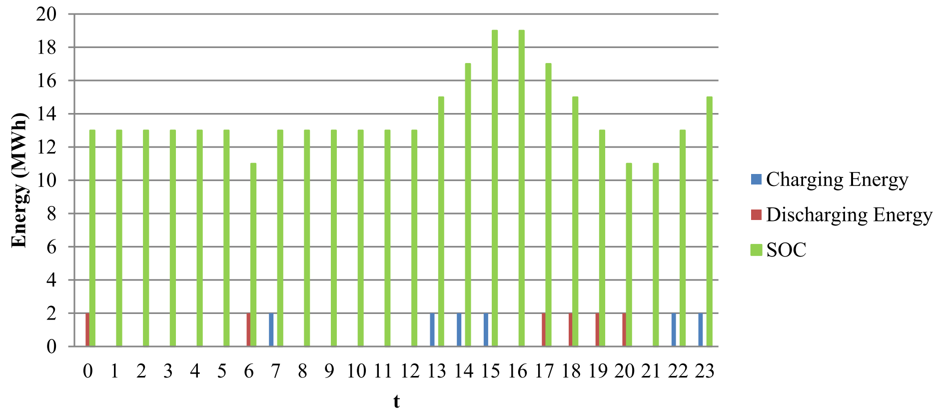

Fig. 2. Impact of energy throughput on scheduling of BES without considering regulation market.

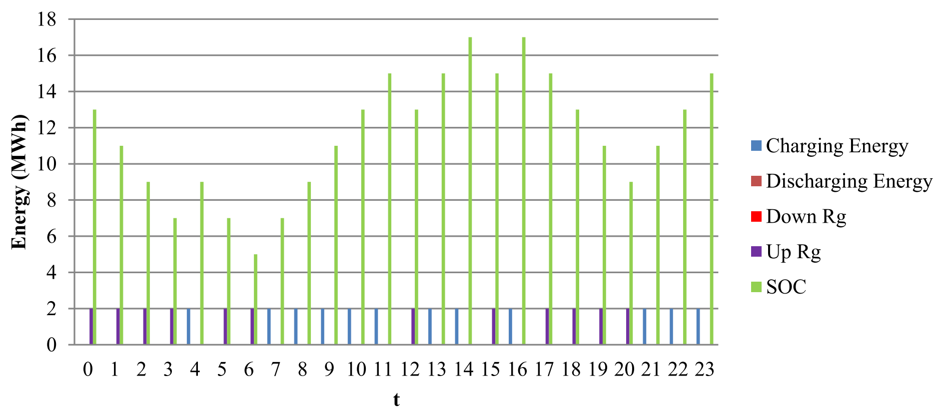

Fig. 3. Scheduling of BES in joint energy and regulation markets without considering the uncertainty of prices.

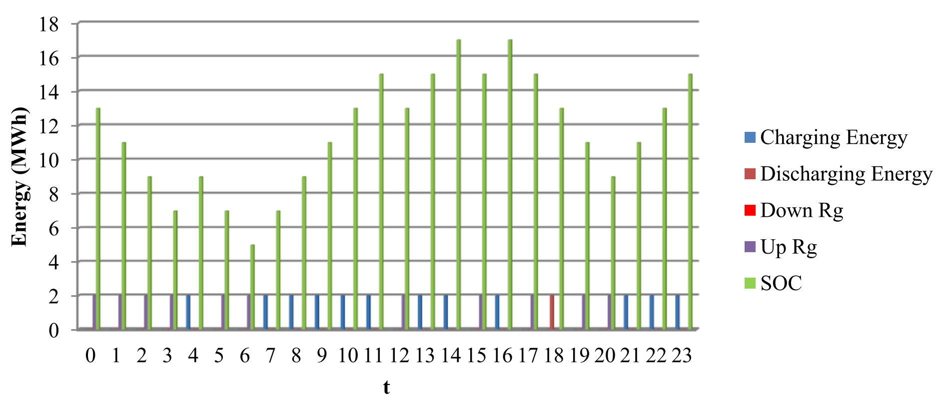

Fig. 4. Scheduling of BES for real-time price variation interval 20%.

$$A_{t,j}^{DR} \leqslant \left(\pi_{t,j}^{CH}.(1+\varepsilon^{CH}) - \pi_{t,j}^{DR}.(1-\varepsilon^{DR})\right) \Delta E_{t,j}^{DR} : \quad \lambda_{t,j}^{22}, \forall t, \ \forall j \tag{19d}$$

$$A_{t,j}^{UR} \leqslant \left(\pi_{t,j}^{UR}.(1-\varepsilon^{UR}) + \pi_{t,j}^{RT}.(1-\varepsilon^{RT})\right) \Delta E_{t,j}^{UR} : \quad \lambda_{t,j}^{23}, \forall t, \ \forall j \tag{19e}$$

$$A_{t,j}^{DR} \geqslant \left(\pi_{t,j}^{CH}.(1+\varepsilon^{CH}) - \pi_{t,j}^{DR}.(1-\varepsilon^{DR})\right) \Delta E_{t,j}^{DR} - M^{RG}.(1-\upsilon_{t,j}) : \quad \lambda_{t,j}^{24}, \forall t, \ \forall j \tag{19f}$$

$$A_{t,j}^{UR} \geqslant \left(\pi_{t,j}^{UR}.(1-\varepsilon^{UR}) + \pi_{t,j}^{RT}.(1-\varepsilon^{RT})\right) \Delta E_{t,j}^{UR} - M^{RG}.(1-\upsilon_{t,j}) : \quad \lambda_{t,j}^{25}, \forall t, \ \forall j \tag{19g}$$

The proposed formulation of (19) is linear and can be solved by commercial optimization solvers. The KKT equations are presented in Appendix A. The numerical simulations are presented in the next section.

4. Numerical simulations

The proposed model is used in a simulation using a BES with the capacity 30 MWh, and initial power 15 MWh [14]. The charging and discharging ramp-rates are 2 MW [19]. Moreover, working days per year, lifetime, annual degradation, and interesting rate are 300 days, 10 years, 1%, and 2%, respectively. In this work, data of 24th of January 2016 of New York electricity market is used [14]. The day-ahead and regulation prices are considered for the energy buying/selling and up/down-regulation capacity prices, respectively. Moreover, the real-time prices are considered for charging of BES in down regulation service

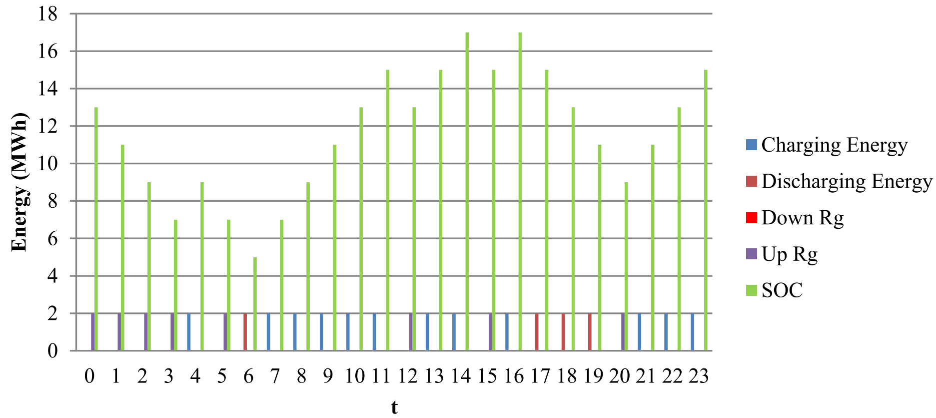

Fig. 5. Scheduling of BES for real-time price variation interval 40%.

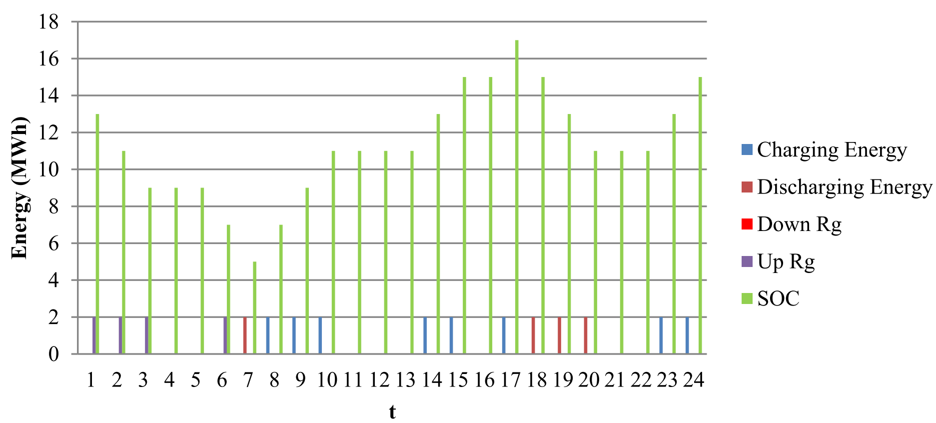

Fig. 6. Impact of energy throughput constraint on scheduling of BES for real-time price variation interval 40%.

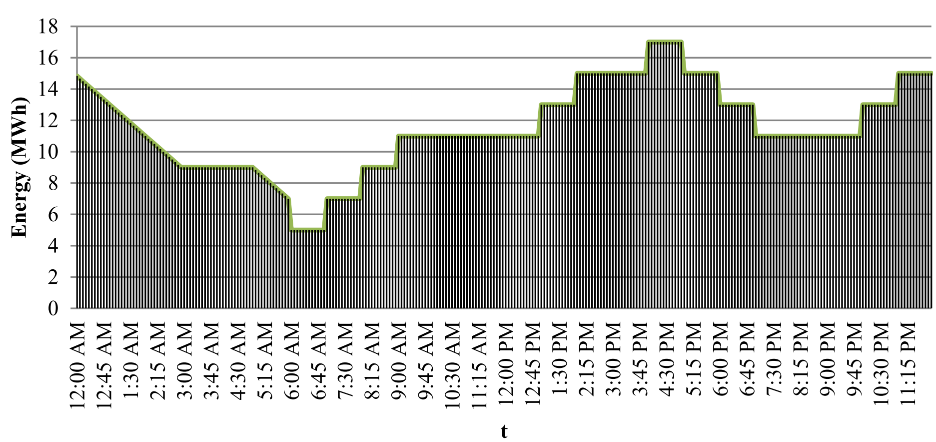

Fig. 7. Energy level of BES in regulation service.

Table 1
Comparison of results in different case studies.

Case Number	Energy Price Uncertainty (%)	Real-time Price Uncertainty (%)	Energy Throughput (MWh)	Participation level in Energy	Participation level in Regulation	Profit ($)
Base	0%	0%	48,000	–	Not considered	306,126
1	3%	0%	48,000	Increased	Not considered	238,881
2	3%	0%	36,000	Decreased	Not considered	229,904
3	3%	0%	72,000	Increased	–	1,312,926
4	3%	20%	66,000	Decreased	Decreased	707,111
5	3%	40%	72,000	Increased	Decreased	356,007
6	3%	40%	48,000	Decreased	Decreased	290,285

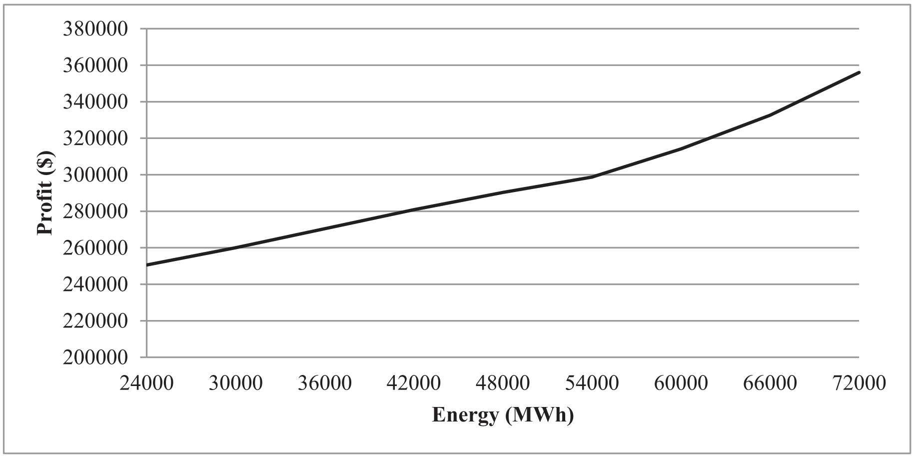

Fig. 8. Profit of BES vs. the Energy Throughput.

[14].

In the first case study, the proposed model is simulated without considering the regulation market and energy throughput constraint. The uncertainty of energy prices in this case study is 3%. Evidently, within the high-price period BES participates in the energy market as a seller energy, and vice-versa. In this case, the expected profit and delivered energy within the defined lifetime are 238,881 $ and 48,000 MWh, respectively. It shall be noted that the expected profit without considering the uncertainty of the energy price is 306,126 $.

To evaluate the effect of energy throughput on the scheduling of BES, it is limited to 36,000 MWh. Fig. 2 shows the optimal scheduling of BES. The expected profit for this case study is 229,904 $. In other words, the profit is decreased to 96.25% by a 25% reduction in traded energy. It shall be noted that one of the main parameters that could decrease the lifetime of batteries is the traded energy. Therefore, a tradeoff between the traded energy and expected profit is necessary in the scheduling of BES. The scheduling of BES in joint energy and regulation markets is shown in Fig. 3. Usually, the energy price in the real-time market is higher than the day-ahead market. Therefore, BES prefers to buy energy from the day-ahead market, and resell it in the regulation market. However, the uncertainty of real-time prices is very higher than the day-ahead market. The expected profit and traded energy in this case study are 1,312,926 $ and 72,000 MWh, respectively. Additionally, the higher prices of real-time market (in comparison with the day-ahead market) could increase the expected profit, significantly. However, increasing of energy throughput and consequently decreasing the lifetime is a critical parameter that shall be considered.

It should be noted that the variation of energy state of BES represents the charging/discharging power that is equal to participation level in the energy and regulation markets. Therefore, the differences between charging and discharging levels and the participation level in regulation service demonstrates the participation level in the energy market.

As mentioned before, the uncertainty of real-time price is the main parameter that limits the participation level of BES in the regulation market. In Figs. 4 and 5, the scheduling of BES for real-time price variation intervals 20% and 40% are represented. Simulation results show that increasing the uncertainty of real-time price reduces the expected profit from 707,111 $ to 356,007 $. Moreover, the traded energy for variation interval of 20% and 40% are 66,000 and 72,000 MWh, respectively. As mentioned before, in robust optimization, the optimal strategy is specified based on the worst case. Therefore, the higher variation interval leads to higher/lower buying/selling prices. In other words, BES prefers to sell its power in the energy market, which has more certain prices.

To evaluate the impact of energy throughput, the delivered power is limited to 48,000 MWh. Comparing the results of Figs. 5 and 6 shows that the traded powers in the regulation and energy market are reduced by decreasing the delivered energy, which is expectable. The net present value of profit in this case is 290,285 $. The impact of regulation market on the energy level of BES is demonstrated in Fig. 7.

The comparison of simulation results in different case studies are represented in Table 1. As seen in this table, considering the regulation market could increase the expected profit of BES. Moreover, increasing the uncertainty price reduces the profit and participation level in the energy market. The energy throughput limits the traded energy and profit of BES. Finally, increasing the uncertainty of real-time prices could decrease the profit and increase the participation level of BES in the energy market. The sensitivity of BES profit to variation of energy throughput is demonstrated in Fig. 8. It shall be noted that the energy throughput is one of the most important factors that reflects the quality of batteries and according to Fig. 8, the expected profit is increased by improving the quality of batteries. However, the relation between the energy throughput and expected profit is not linear and it depends on the energy prices in different markets.

5. Conclusions

This paper presents an energy-constrained model for scheduling of BES in joint energy and regulation markets. The energy and regulation prices as uncertainty resources are modeled by RO. In this work, the new concept of energy throughput is proposed to evaluate the impact of lifetime limitation in short-term scheduling of BES. The proposed Max-Min problem is converted to a Max optimization with the concept of worst-case realization. The final linear model specifies the optimal scheduling of BES based on the defined confidence level and delivered energy limitation.

Simulation results show that the profit of BES can be increased by participation in regulation service. However, the main problem of this market is the uncertainty of real-time prices that could decrease the expected profit dramatically. Moreover, by increasing the confidence level, the participation levels in regulation and energy markets are decreased and increased, respectively. The lifetime of BES can be controlled by the delivered energy. However, decreasing the delivered energy will reduce the expected profit. The relation of traded energy and lifetime is not linear, and in some presented case study, it is possible to increase 25% of lifetime by a 3.75% reduction in the profit. As a part of future work, the authors are going to model the tradeoff between the lifetime and expected profit in the short-term scheduling of BES.

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Declaration of Competing Interest

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

Appendix A. KKT equation

According to the proposed objective function and constraints, the KKT equations can be represented as follows [20]:

$$W.\frac{1-(1+r)^{-NL}}{r}(\pi_t^{BE}+\varepsilon^{BE}.\pi_t^{BE})-\lambda_t^2+\lambda_t^3+(S_{t,j}-S_{t,j-1})(\lambda_{t,j}^{16}-\lambda_{t,j}^{17}) \\ +\lambda_{t,j}^{18}-\lambda_{t,j}^{19}-(\pi_t^{BE}+\varepsilon^{BE}.\pi_t^{BE})(\lambda_t^{20}-\lambda_t^{21})=0: \ ,\forall t,\ \forall j \tag{1A}$$

$$-\lambda_t^2+\lambda_t^3-\lambda_t^{12}+\lambda_t^{14}-(\pi_t^{SE}-\varepsilon^{SE}.\pi_t^{SE})\lambda_t^{20}+(\pi_t^{SE}-\varepsilon^{SE}.\pi_t^{SE})\lambda_t^{21}+\mu^1=0: \ ,\forall t,\ \forall j \tag{2A}$$

$$-\lambda_{t,j}^6+\lambda_{t,j}^7-(\pi_{t,j}^{UR}-\varepsilon^{UR}.\pi_{t,j}^{UR}+\pi_{t,j}^{RT}-\varepsilon^{RT}.\pi_{t,j}^{RT})\lambda_{t,j}^{23} \\ -\lambda_{t,j}^{13}+\lambda_{t,j}^{15}+(\pi_{t,j}^{UR}-\varepsilon^{UR}.\pi_{t,j}^{UR}+\pi_{t,j}^{RT}-\varepsilon^{RT}.\pi_{t,j}^{RT})\lambda_{t,j}^{25}=0: \ ,\forall t,\ \forall j \tag{3A}$$

$$-W.\frac{1-(1+r)^{-NL}}{r}\left(\pi_{t,j}^{DR}-\varepsilon^{DR}.\pi_{t,j}^{DR}+\pi_{t,j}^{CH}+\varepsilon^{CH}.\pi_{t,j}^{ER}\right)-\lambda_{t,j}^6+\lambda_{t,j}^7+\lambda_{t,j}^{16}-\lambda_{t,j}^{17} \\ +\frac{1}{S_{t,j}-S_{t,j-1}}(\lambda_{t,j}^{18}-\lambda_{t,j}^{19})-(\varepsilon^{DR}.\pi_{t,j}^{DR}-\pi_{t,j}^{DR}+\pi_{t,j}^{CH}+\varepsilon^{CH}.\pi_{t,j}^{CH})(\lambda_{t,j}^{22}-\lambda_{t,j}^{24})+\mu^1=0: \ ,\forall t,\ \forall j \tag{4A}$$

$$\lambda_t^1+\lambda_t^2-\lambda_t^3-(S_{t,j}-S_{t,j-1})\lambda_{t,j}^{16}+(S_{t,j}-S_{t,j-1})\lambda_{t,j}^{17}-\lambda_{t,j}^{18}+\lambda_{t,j}^{19}-\mu^1=0: \ ,\forall t,\ \forall j \tag{5A}$$

$$-W.\frac{1-(1+r)^{-NL}}{r}+\lambda_t^4+\lambda_t^{20}-\lambda_t^{21}=0: \ ,\forall t,\ \forall j \tag{6A}$$

$$\lambda_{t,j}^5+\lambda_{t,j}^6-\lambda_{t,j}^7-\lambda_{t,j}^{16}+\lambda_{t,j}^{17}-\frac{1}{S_{t,j}-S_{t,j-1}}\lambda_{t,j}^{18}+\frac{1}{S_{t,j}-S_{t,j-1}}\lambda_{t,j}^{19}-\mu^1=0: \ ,\forall t,\ \forall j \tag{7A}$$

$$W.\frac{1-(1+r)^{-NL}}{r}+\lambda_{t,j}^8+\lambda_{t,j}^{22}-\lambda_{t,j}^{24}=0: \ ,\forall t,\ \forall j \tag{8A}$$

$$W.\frac{1-(1+r)^{-NL}}{r}+\lambda_{t,j}^9+\lambda_{t,j}^{23}-\lambda_{t,j}^{25}=0: \ ,\forall t,\ \forall j \tag{9A}$$

$$\lambda_t^{10}+\lambda_t^{12}-\lambda_t^{14}+W\mu^2=0: \ ,\forall t,\ \forall j \tag{10A}$$

$$\lambda_{t,j}^{11}+\lambda_{t,j}^{13}-\lambda_{t,j}^{15}+W\mu^2=0: \ ,\forall t,\ \forall j \tag{11A}$$

$$-M^E\lambda_t^1+M^E\lambda_t^3-M^{PE}\lambda_t^4-M^{AT}\lambda_t^{10}+M^{AT}\lambda_t^{14}+M^{PE}\lambda_t^{21}=0: \ ,\forall t,\ \forall j \tag{12A}$$

$$-M^{RS}\lambda_{t,j}^5+M^{RS}\lambda_{t,j}^7-M^{RG}\lambda_{t,j}^8-M^{RG}\lambda_{t,j}^9 \\ -M^{AT}\lambda_{t,j}^{11}+M^{AT}\lambda_{t,j}^{15}+M^{RG}\lambda_{t,j}^{24}+M^{RG}\lambda_{t,j}^{25}=0: \ ,\forall t,\ \forall j \tag{13A}$$

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