2019 IEEE PES Innovative Smart Grid Technologies Asia

A Robust Operation Strategy for Energy Storage Considering Uncertainty in Electricity Price

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***Abstract*—Inaccurate price prediction may cause improper charging/discharging schedules of battery energy storage (BES) in electricity market, which further leads to less or even negative market profits of BES. On this condition, uncertainty in market prices should be fully considered when making operation strategies. In this paper, focusing on an independently operated BES in day-ahead and hour-ahead markets, a multi-stage robust optimal operation strategy is formulated considering uncertainty in multi-periods market prices. The robust optimization model is formulated seeking to maximize market revenues of BES within a given confidence level of price deviation. The max-min model can be converted into a mixed-integer linear programming (MILP) problem which can be easily computable. Case study results demonstrated the validity of the presented robust operation strategy of BES.**

***Index Terms*--energy storage, uncertainty, electricity market, robust optimization, max-min model.**

I. INTRODUCTION

With the development of technology of large-scale battery energy storage (BES) and policy support from governments, there is an increasing number of BESs integrated to power grid in many countries and regions. BES contributes to improving reliability of grid or microgird [1], smoothing power output variation of renewable generation [2] and so on. Despite all the valuable functions of BES, however, for the BES investigator and operator, to make maximum benefits is one of the top considerations when making operation strategies.

Temporal variations in multi-type electricity market prices gives BES the arbitrage opportunity [3]. Some researches focus on joint self-schedule strategy of BES in different markets to explore potential profits BES through arbitraging and providing ancillary service, such as participating in day-ahead energy, frequency regulation and reserve market [4], day-ahead market (DAM) and hour-ahead markets (HAM) [5]. All these study results show that, with proper operation schedule, considerable market revenues of BES can be achieved.

However, the arbitrage potential of BES in electricity market is highly influenced by uncertainty in market prices, which may cause improper self-schedule results and further leads to economic loss. Therefore, uncertainty in market prices are considered in a proportion of literatures addressing the optimal schedule strategy of BES. Reference [5] studied the risk-revenue tradeoff of BES in day-ahead and real-time market based on value at risk (VaR). Reference [6] studied a risk-constrained bidding/offering strategy for a merchant compressed air energy storage plant using information gap decision theory (IGDT) based. And in [4] and [7], price uncertainties are dealt with using expected value. By using risk-value indices, the possibility distribution function of market prices is supposed to be known to the decision-maker. However, the distribution probability function of market prices cannot be always precisely described using a deterministic function. Under these circumstances, robust optimization has been adapted in many research fields dealing with uncertainty in market prices. Reference [8] proposed a robust operation strategy for combined wind and energy storage system considering uncertainty in electricity price. Reference [9] proposed a robust bidding strategy model of controllable load aggregator with variable market prices. With robust approach, the schedule result is applicable for all scenarios and no precise price information is needed [9].

BES is especially sensitive to market prices due to its charging/discharging characteristics, thus making a robust operation strategy of BES considering all possible price scenarios more significant. Due to the characteristics of charging and discharging of BES, market revenues of BES composes of both profits of selling energy through discharging behavior and cost of buying energy through charging behavior. If the BES disables to discharge with high prices and charge with low prices, it is likely that the total revenue within certain operation periods is negative. Therefore, to ensure a satisfactory revenue level under uncertain market price, robust optimization contributes a lot.

In this paper, considering uncertainty in electricity market of which the probability distribution function cannot be

978-1-7281-3520-5/19/$31.00 ©2019 IEEE

precisely described, a robust operation strategy of an independently operated BES is presented to ensure a satisfactory market revenue under given confidence interval of market price prediction. Under the framework of day-ahead market and hour-ahead market, the operation strategy model is established at each stage with the objective function of maximizing market revenues among all possible market prediction.

The rest of the paper is organized as follows. Section II presents the problem description, including operational framework and uncertainty in electricity market price. Section III formulates the robust operation strategy model of BES. Case study is discussed in Section IV, and main conclusions are drawn in Section V.

II. Problem Description

A. Operational Framework

BES can achieve economic operation and make considerable profits if given access to multiple markets [10]. In this paper, day-ahead market and hour-ahead market are considered. In day-ahead market, BES operator decides and submits its energy offer/bid for the 24 hours in the next day while possible power output adjustment in hour-ahead markets are considered. In each hour-ahead market in operating day, BES could choose to increase or decrease its power output at each time interval to make more profits according to new price forecast, as well as its actual charging/discharging rate and stored energy level, as shown in Fig. 1.

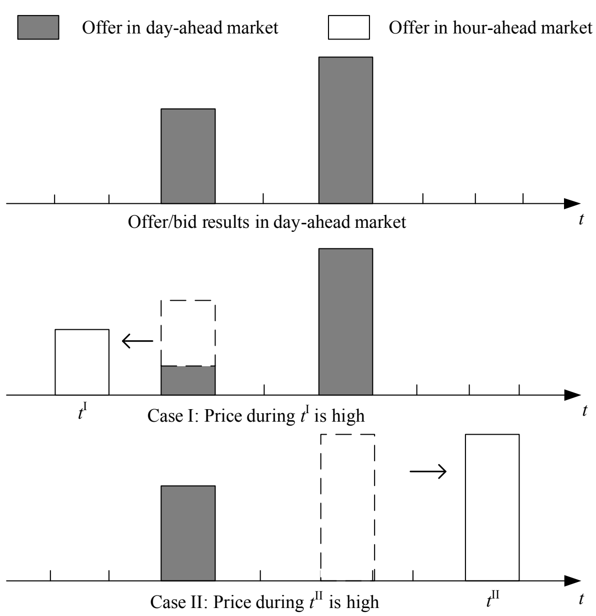

Figure 1. Diagram of changing reserved capacity responding to RTM price.

To make the proposed strategy more reasonable, some assumptions are made:

- Prices in day-ahead market are more trustable compared with hour-ahead market when making decisions for day-ahead market and thus treated as determined [5];
- Prediction errors of hour-ahead market prices are within a certain confidence level;
- The BES is a price-taker and its offer/bid are fully accepted.

B. Uncertainties in Price Prediction

Due to prediction errors, market prices in hour-ahead market t is a parameter with uncertainty. Price prediction errors at different time may be different and always fall within a given upper and lower bounds, which is the confidence interval [11], as shown in Fig. 2.

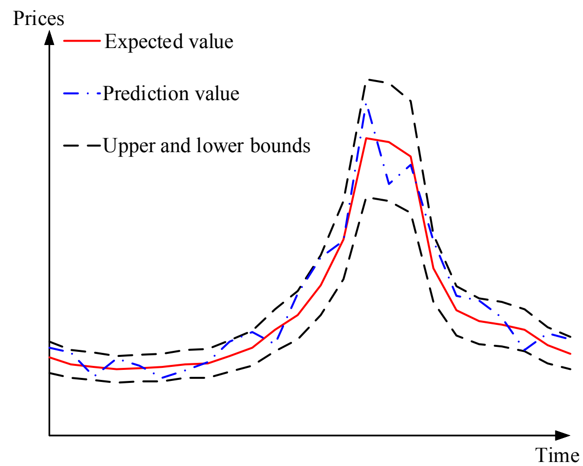

Figure 2. Diagram of price prediction within given confidence interval.

The model of uncertain prediction prices is supposed as follows:

$$r_t^{\mathrm{HAM}} = \tilde{r}_t^{\mathrm{HAM}}\left(1+\delta_t\right) \tag{1}$$

$$-\delta^{\max} \le \delta_t \le \delta^{\max} \tag{2}$$

where, $\tilde{r}_t^{\mathrm{HAM}}$ is the expected price; r_t^{HAM} is the predicted price; δ_t is the prediction error coefficient and $\delta^{\max}$ is the confidence level of prediction error, denoting the maximum prediction error range.

III. Robust Operation Strategy of BES

Robust optimization is adapted to guarantee that the formulated operation schedule brings BES maximum market revenue even under the worst-case of market price prediction. For the BES participating in day-ahead market and hour-ahead markets, the robust optimization is used when making operation strategy in day-ahead market and operation strategy in each hour-ahead market, aiming at maximizing expected market revenues in all following time intervals.

A. Operation Strategy in Day-ahead Market

1) Objective Function

When making offer/bid decisions in the day-ahead market for each hour in the following day, possible power output adjustment in hour-ahead markets in operating day is considered. Therefore, the expected market revenue when making decision for day-ahead market composes of revenue B^{DAM} in day-ahead market, expected revenue B_D^{HAM} in hour-ahead market and expected operation cost C_D.

$$\max \min_{\delta_t \in \Omega_t} \left(B_D = B^{\mathrm{DAM}} + B_D^{\mathrm{HAM}} - C_D \right) \tag{3}$$

$$B^{\mathrm{DAM}} = \sum_{t=1}^{T} \left(-r_{t,\mathrm{c}}^{\mathrm{DAM}} P_{t,c}^{\mathrm{DAM}} - r_{t,\mathrm{d}}^{\mathrm{DAM}} P_{t,\mathrm{d}}^{\mathrm{DAM}} \right) \Delta t \tag{4}$$

$$\underset{\delta_t \in \Omega_t}{B_D^{HAM}} = \sum_{t=1}^{T} \left(-r_{D,t,\mathrm{c}}^{\mathrm{HAM}} \Delta P_{D,t,-}^{\mathrm{HAM}} - r_{D,t,\mathrm{d}}^{\mathrm{HAM}} \Delta P_{D,t,+}^{\mathrm{HAM}} \right) \Delta t \tag{5}$$

$$C_D = c_{\mathrm{o}} \sum_{t=1}^{T} \left| \Delta E_t \right| \tag{6}$$

where, B_D is the expected revenue when making operation strategy for day-ahead market; B^{DAM}, $B_{\mathrm{D}}^{\mathrm{HAM}}$ and C_{D} are the expected revenue from day-ahead market, hour ahead markets and expected operation cost, respectively; Ω_t is the set of uncertain parameter δ_t; $r_{t,\mathrm{c}}^{\mathrm{DAM}}$ and $r_{t,\mathrm{d}}^{\mathrm{DAM}}$ are day-ahead market prices for charging and discharging at time *t*, respectively; $P_{t,\mathrm{c}}^{\mathrm{DAM}}$ and $P_{t,\mathrm{d}}^{\mathrm{DAM}}$ are the charging and discharging rate for day-ahead market at time *t*, respectively; $r_{\mathrm{D},t,\mathrm{c}}^{\mathrm{HAM}}$ and $r_{\mathrm{D},t,\mathrm{d}}^{\mathrm{HAM}}$ are respectively the hour-ahead market prices for increasing and decreasing power output at time *t*, and they are related to uncertain parameter δ_t; $\Delta P_{\mathrm{D},t,-}^{\mathrm{DAM}}$ and $\Delta P_{\mathrm{D},t,+}^{\mathrm{DAM}}$ are the expected decreased and increased power output at time *t* in hour-ahead market, respectively; Δt is the time interval, which is usually set 1 hour; c_{o} is the unit operation cost; ΔE_t is the expected change of energy of BES at time *t*. Note that increasing power output means increasing discharging rate or decreasing charging rate, while decreasing power output means decreasing discharging rate or increasing charging rate.

2) Constraint Conditions

a) Constraint of Charging/Discharging Rate

At each time, the overall charging/discharging rate of BES must be within its allowable charging/discharging rate range.

$$0 \le P_{t,\mathrm{c}}^{\mathrm{DAM}} \le \left(1 - u_t^{\mathrm{DAM}}\right) P^{\mathrm{N}} \tag{7}$$

$$-P^{\mathrm{N}} u_t^{\mathrm{DAM}} \le P_{t,\mathrm{d}}^{\mathrm{DAM}} \le 0 \tag{8}$$

$$0 \le P_{\mathrm{D},t,-}^{\mathrm{HAM}} \le \left(1 - u_t^{\mathrm{HAM}}\right) P^{\mathrm{N}} \tag{9}$$

$$-P^{\mathrm{N}} u_t^{\mathrm{DAM}} \le P_{\mathrm{D},t,+}^{\mathrm{HAM}} \le 0 \tag{10}$$

$$P_{\mathrm{D},t} = P_{t.\mathrm{c}}^{\mathrm{DAM}} + P_{t.\mathrm{d}}^{\mathrm{DAM}} + P_{\mathrm{D},t,-}^{\mathrm{HAM}} + P_{\mathrm{D},t,+}^{\mathrm{HAM}} \tag{11}$$

$$-P^{\mathrm{N}} \le P_{\mathrm{D},t} \le P^{\mathrm{N}} \tag{12}$$

where, P^{N} is the rated charging/discharging power of the BES; $P_{\mathrm{D},t}$ is the total charging/discharging rate at *t*; u_t^{DAM} and u_t^{HAM} are respectively Boolean variables representing charging and discharging status of BES at *t* in day-ahead market and the status of increasing and decreasing power output in hour-ahead *t*.

b) Constraint of State of Charge

State of charge (SOC) of BES at each time interval should be limited within allowable range.

$$\Delta E_t = \left(1 - u_t\right) P_{\mathrm{D},t} \Delta t \eta_{\mathrm{c}} - u_t P_{\mathrm{D},t} \Delta t / \eta_{\mathrm{d}} \tag{13}$$

$$E_t = E_{t-1} + \Delta E_t \tag{14}$$

$$SOC_t = E_t / E^{\mathrm{N}} \tag{15}$$

$$SOC^{\min} \le SOC_t \le SOC^{\max} \tag{16}$$

where, u_t is a Boolean variable denoting the actual charging/discharging status of BES at *t*; η_{c} and η_{d} are charging and discharging efficiency, respectively; E^{N} is the rated capacity of BES; $SOC^{\max}$ and $SOC^{\min}$ are the maximum and minimum value of SOC.

c) Constraint of Residual Energy

To ensure that the SOC of BESS is kept within a certain level at the final time interval, SOC_T should be limited [2].

$$\left| SOC_0 - SOC_T \right| \le \Delta S \tag{17}$$

where, SOC_0 is the initial SOC. ΔS is a very small constant.

3) Solving Approach

With variable u_t, (6) can be written as:

$$C_{\mathrm{D}} = c_{\mathrm{o}} \sum_{t=1}^{T} \left[\left(1 - u_t\right) P_{\mathrm{D},t} \Delta t \eta_{\mathrm{c}} - u_t P_{\mathrm{D},t} \Delta t / \eta_{\mathrm{d}} \right] \tag{18}$$

Use a robust parameter $\gamma \in [0,1]$ to represent the BES operator's preference of risk level, where the lager γ is, the more risk-averse the operator is. Then (2) is modified as:

$$-\gamma \delta^{\max} \le \delta_t \le \gamma \delta^{\max} \tag{19}$$

Set $y_D = \min_{\delta_t \in \Omega_t} \left(B_D \right)$, then the whole mathematical model of operation strategy in day-ahead market is:

$$\begin{cases} \max\ y_D \\ \text{s.t.} \begin{cases} y_D \le B_{\mathrm{D}}, \forall \delta_t \in \Omega_t \\ (1) \sim (5) \\ (7) \sim (19) \end{cases} \end{cases} \tag{20}$$

Using McCormick envelopes [12], the established models with nonlinear elements $u_t P_{\mathrm{D},t}$ can be converted into a mixed-integer linear programming (MILP) problem.

B. Operation Strategy in Operating Day

As time goes forward, at each hour-ahead market *i*, BES operator updates its power adjustment $\Delta P_{\mathrm{D},t,+}^{\mathrm{DAM}}$ and $\Delta P_{\mathrm{D},t,-}^{\mathrm{DAM}}$ in the periods $t=i,i+1,\ldots,T$ on the basis of newly received price prediction information, so that maximum market profits can be achieved.

The mathematical model of operation strategy in each hour-ahead market is similar to that in day-ahead market, only that the charging/discharging power at each time in day-ahead market is already known, and power adjustment and prices in in $i=1,2,\ldots,t$-1 are determined.

IV. Case Study

A battery energy storage participating in day-ahead and hour-ahead markets are taken as an example. Parameters of the BES are shown in Table I. The MILP problem is coded and solved using MATLAB 2018.

Historical prices in September 2018 from New England electricity market [13] are adapted, as are shown in Fig. 3. Based on actual real-time prices, the uncertainty set of predicted real-time prices at each time is formulated with the prediction error of 20%, and the robust parameter γ is set to 1.

TABLE I. Parameters of Battery Energy Storage

P^N	E^N	η_c	η_d	c_0
10MW	40MWh	0.95	0.95	1.5 \$/(MWh)
P_c^{max}	P_c^{min}	P_d^{max}	P_d^{min}	SOC_0
10MW	0	0	-10	0.5
SOC^{max}	SOC^{min}	ΔS		
1.0	0.1	0.1		

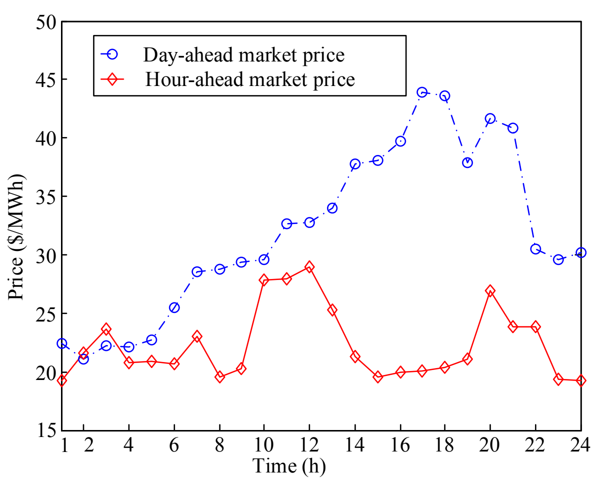

Figure 3. Actual day-ahead and hour-ahead market prices.

A. Case Study Results

The whole operation strategy can be seen as two satages. At Stage I, the operation strategy for day-ahead markets is formulated considering possible changes in hour-ahead markets; at Stage II, the final self-scheduling results are obtained through rolling operation in 24 hour-ahead markets. Results of operation strategy at Stage I and Stage II are respectively shown in Fig. 4 and Fig. 5, and corresponding market revenues are presented in Table II, where expected revenue means the minimum revenue BES can have with robust optimization, actual revenue means revenue that BES can have with schedulue results under proposed operation strategy, and maximum revenue means the revenue BES can have with schedulue made under complete accurate prices.

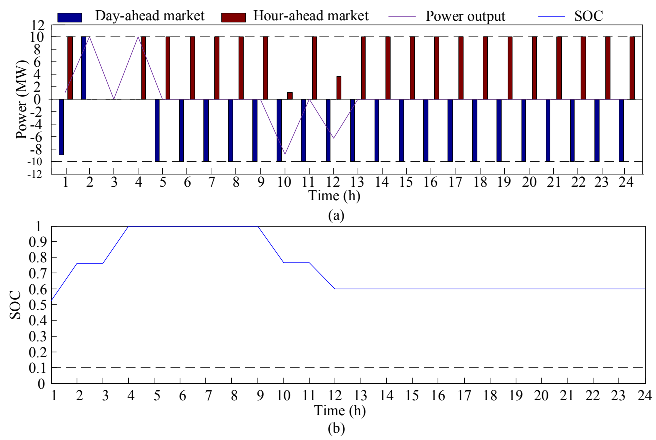

Figure 4. Self-scheduling results of Stage I. (a) results of charging/discharging power at Stage I; (b) results of SOC at Stage II.

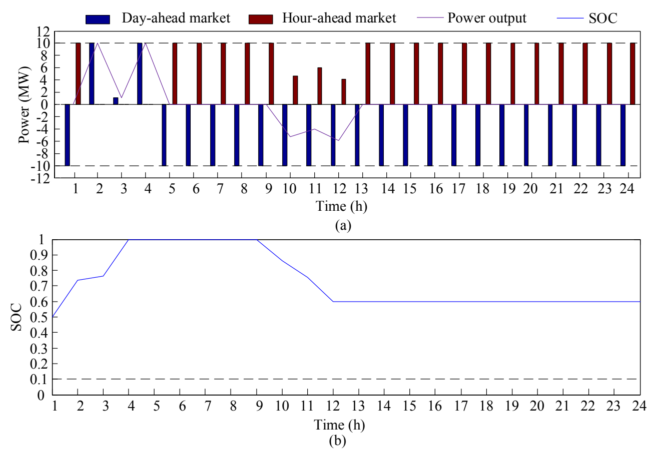

Figure 5. Self-scheduling results of Stage II. (a) results of charging/discharging power at Stage II; (b) results of SOC at Stage II.

TABLE II. Market Revenues

	Only Stage I	**Stage I and Stage II**
Expected revenues (\$)	2167.6	2225.0
Actual revenues (\$)	2243.1	2245.6
Maximum revenue (\$)	2248.3	2248.3

From Fig. 4 and Fig. 5, since for most of time the day-ahead prices are higher than those of hour-ahead prices, BES discharges in day-ahead market and charges in hour-ahead markets. The schedule results of BES in joint different markets are influenced by price differences in different markets. From Table II, we can see that, at both Stage I and Stage II, the expected revenues are less than the actual revenues. Meanwhile, through constantly updating operation strategy at each hour in operating day, the final actual revenue is larger than that of Stage I. That is because updating operation strategy according to more accurate newly received price information helps reduce the impacts of price prediction error. However, since price prediction errors always exist at each decision-making time point and the robust operation schedule is very conservative, the actual revenue is always less than the maximum revenue that BES can achieve. It should be noted that, since the difference between day-ahead marke price and hour-ahead market price is remarkably distinguashable, the revenue with operation strategy including only ofirst stage and revenue with two-stage operation strategy is not very obvious. The proposed operation strategy can also be applied in more complictaed consideration.

B. *Analysis of Impact of Prediction Errors*

Expected revenues and actual revenues under different confidence interval of price prediction is shown in Fig. 6.

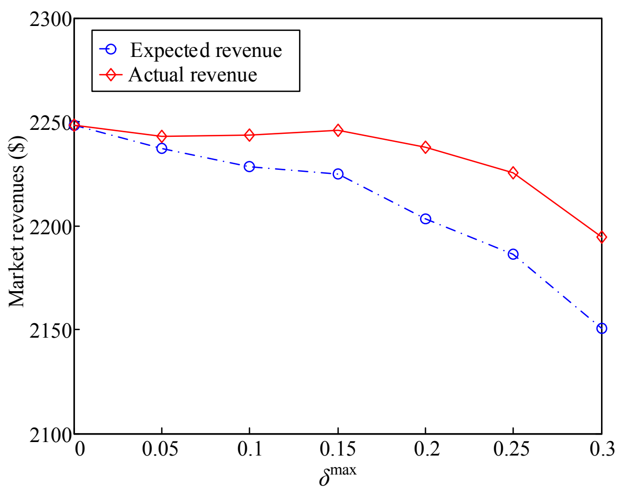

Figure 6. Expected and actual market revenues under different price prediction confidence intervals.

According to Fig. 6, we can see that, with price prediction confidence interval increases, the expected market revenue and corresponding actual revenue generally decrease. That is because the larger prediction errors are, the more conservative the schedule is to avoid possible economic loss caused by charging with high prices and discharging with low prices. Therefore, corresponding expected revenues and actual revenues are less than those with smaller confidence level. Besides, the actual revenues are always lager than the expected ones and the larger confidence level is, the larger differences between actual and expected revenues are. This is because the expected revenue obtained using robust operation strategy is related to worst case and actual revenues are always lager than the expected ones, and as the confidence level getting larger, the price errors in worst case.

V. Conclusion

Considering uncertainties in electricity market, in this paper, a robust optimal operation strategy of an independent battery energy storage (BES) is formulated participating in both day-ahead market and hour-ahead market. Case study proves that robust optimal operation strategy can guarantee BES a certain profit level even under worst case of price prediction. To make more market revenues, prediction errors should be decreased and multi-stage self-scheduling contributes. This work may provide reference for operators of independent BES to make operation decisions facing incomplete market information.

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