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# Real-Time Operation Optimization of Islanded Microgrid with Battery Energy Storage System

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***Abstract*—In islanded microgrids, rechargeable batteries are widely used as storage systems to complement the power imbalance in real-time. Among others, lithium-ion battery is the most popular owing to its high energy density, low self-discharge and long lifespan features. However, the cycle degradation becomes an unavoidable concern in microgrid economic operation. In this paper, a novel degradation model based on online auction and rainflow cycle counting algorithm is proposed for real-time management of lithium-ion batteries. Based on the proposed model, a mixed integer nonlinear problem is formulated for online operation of the islanded microgrid. To confront with the uncertainties involved in a lookahead window, the formulated problem is tackled by weighted model predictive control(MPC). Monte Carlo simulations covering 365 consecutive days verify the effectiveness of the proposed model and its application in real-time microgrid operation concerning degradation cost.**

***Index Terms*—real-time operation, islanded microgrid, weighted model predictive control, battery energy storage system**

## I. Introduction

Various renewable energies such as wind and solar energies provide an efficient way to reduce the fossil fuel dependence and greenhouse gas emissions. Microgrids, as micro distribution power systems, are capable of integrating distributed generators, distributed battery energy storage system (BESS), and local demands. In some cases, microgrids are connected to the main grid, exchanging power energies with the main grid in real time to maintain the power balance. On some other conditions microgrids are constructed to be isolated from the main grid, e.g., in remote communities and islands. They are perceived operating in the standalone mode, or simply mentioned as islanded microgrids [1], [2].

The real-time operation optimization ensures the economic operation between various distributed generators and load demands to reliably reduce the total operation cost. Conventionally, this optimization problem is to determine the optimal schedule or dispatch plan for various microgrid components. However, this becomes challenging for small scale microgrids due to the high intermittency of renewable energies. In addition, the cost of energy storage should never be neglected. Particularly, lithium-ion batteries become popular in recent years, due to their higher energy density and longer lifespan as compared to other batteries [3]. Accurately sensing and calculating their degradation cost is of vital importance for microgrid economic operation, especially the relationship between the power of charge/discharge and the state of charge (SoC) [4].

### A. Related Work

Quite a few methods have been proposed for real time operation of microgrids in recent years. Specifically, stochastic programming is used to deal with the uncertainties of renewable energies power output. In [5] and [6], for instance, the operation problem is formulated as a two-stage stochastic problem, where the first stage determines the optimal dispatch of units while the second stage considers the uncertainty of solar energy and wind energy. However, these scenario based methods require probabilistic distribution of unknown parameters and suffer from a large computation burden in scenarios generation. In addition, to address this drawback, [7] uses robust optimization as an alternative approach to deal with uncertainties. Because of the worst-case consideration, the robust optimization is computationally tractable but provides conservative solution resulting in high operation cost. Distinguished from above methods, the authors in previous works proposed a competitive heuristic algorithm for energy scheduling (CHASE) for microgrids operation in a retroactive fashion instead of using forecasting information [8], [9].

On the other hand, with respect to the degradation model of BESS, most previous literatures assume the energy storage cost as a constant or zero operating cost [5]–[9]. It should be noted that the battery capacity is not a fixed value due to calendar aging and cycle aging of lithium-ion battery cells [4]. Rainflow cycle counting algorithm has been applied to the cycle aging assessment of batteries [10]. It is proved in [11] that this offline cycling counting rule is as accurate as experimental results. However, the cycle depth is impossible to be predicted ahead of time in real-time operation to calculate the cycle aging cost.

### B. Contributions

This paper proposes a novel degradation model for lithium-ion batteries based on online auction and rainflow cycle counting algorithm, which can be integrated to real-time operation of islanded microgrids. This proposed model and approach

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achieve the economic dispatch between generators and BESS in microgrids, taking the health of batteries into account as well. The main contributions of this paper are summarized as follows.

- An online auction based degradation cost model is proposed for lithium-ion batteries accounting for the cycling degradation. This model enables the battery to operate economically without additional constraints.
- A weighted MPC approach is proposed to incorporate the uncertainties of renewable energies and load demands into real-time operation. This approach has a potential to addressing limited forecasting information.

The remainder of this paper is organized as follows: Section II describes the degradation cost model for lithium-ion BESS and the formulation of weighted MPC based operation optimization problem. Section III demonstrates the performance by case studies. Section IV draws conclusions and correlative future work.

## II. Preliminaries and Problem Formulation

An islanded microgrid typically consists of three parts: a) dispatchable generators, i.e., diesel engine (DE) and microgas turbine(MT), b) nondispatchable sources, e.g., photovoltaic (PV) panel and wind turbines (WT), and c) the BESS. The first two parts operate similarly to those in large scale grids, while the BESS has a different characteristic. In this section, we will first prepare the detailed BESS operation model, and then formulate the real-time operation optimization problem including the objective function and constraints.

### A. Battery Operation Model

SoC is regarded as a state variable of the battery and its evolution process can be formulated in a discrete form:

$$\mathrm{SoC}_t = \mathrm{SoC}_{t-1} + \frac{\eta^{\mathrm{ch}}\tau}{B} P_t^{\mathrm{ch}} - \frac{\tau}{\eta^{\mathrm{dis}} B} P_t^{\mathrm{dis}} \tag{1}$$

where $P_t^{\mathrm{ch}}$, $P_t^{\mathrm{dis}}$ are charging/discharging power at $t$, $\eta^{\mathrm{ch}}$,$\eta^{\mathrm{dis}}$ are power transfer efficiency, $B$ is the total capacity of BESS and $\tau$ is the time interval, respectively. Due to the health requirements of battery, it should subject to technical limits such as the capacity range, charging and discharging power output.

$$\mathrm{SoC}_{\min} \le \mathrm{SoC}_t \le \mathrm{SoC}_{\max} \tag{2a}$$

$$0 \le P_t^{\mathrm{ch}} \le P_{\max}^{\mathrm{ch}} \tag{2b}$$

$$0 \le P_t^{\mathrm{dis}} \le P_{\max}^{\mathrm{dis}} \tag{2c}$$

$$P_{\max}^{\mathrm{ch}} \cdot P_{\max}^{\mathrm{dis}} = 0 \tag{2d}$$

Note that the requirement (2d) is to ensure that the battery should be either in a charging mode or a discharging mode during a single period. It is also worth mentioning that this nonlinear requirement can be relaxed since the objective function and problem we formulated in section II-C will avoid the occurrence of charging and discharging simultaneously.

### B. Marginal Degradation Cost Model

In addition to operation behaviors, the degradation cost model is an indispensable part to formulate the real-time operation optimization problem. As mentioned above, cycle aging of BESS is the main element to be considered. Fig. 1 shows an empirical curve of cycle depth aging stress function for lithium-ion batteries. As can be seen, the marginal degradation cost is not fixed, and the life fading effect is less serious at smaller cycle depth.

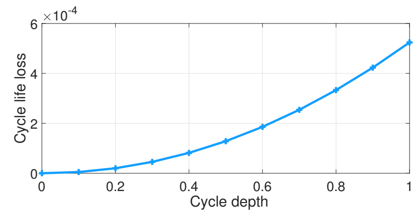



Fig. 1. Cycle life loss of BESS with respect to cycle depth.

Suppose the cycle depth stress function for lithium-ion batteries is defined as follows:

$$\psi(\delta_t) = \alpha \delta_t^{1+\beta} \qquad \delta_t \in [0,1] \tag{3}$$

where $\psi$ is the cycle life loss, $\delta_t$ is the discharging depth and parameters $\alpha$,$\beta \ge 0$ imply the shape of stress function. The marginal degradation can therefore be obtained by taking the derivative of (3) with respect to the discharging power:

$$\frac{\partial \psi(\delta_t)}{\partial P_t^{\mathrm{dis}}} = \frac{\mathrm{d}\psi(\delta_t)}{\mathrm{d}\delta_{\mathrm{t}}} \frac{\partial \delta_t}{\partial P_t^{\mathrm{dis}}} = \frac{1}{\eta^{\mathrm{dis}} B} \frac{\mathrm{d}\psi(\delta_t)}{\mathrm{d}\delta_{\mathrm{t}}} \tag{4}$$

where the second equality holds due to the cycle depth evolution equation in discharging mode. An $N$-segment piecewise linear function is used to approximate the marginal cost in (5), which is accurate as the offline rainflow cycle counting algorithm [11].

$$C^{\mathrm{S}}(\delta_t) = \frac{R}{\eta^{\mathrm{dis}} B} \frac{\psi(\frac{i}{N}) - \psi(\frac{i-1}{N})}{1/N} \qquad \delta_t \in \left[\frac{i-1}{N}, \frac{i}{N}\right) \tag{5}$$

where $C^{\mathrm{S}}$ denotes the segmental cost, $R$ is the replacement money of BESS, segment index $i = 1, 2, ..., N$ and $N$ is the quantity of segments. When addressing the real-time operation problem of islanded microgrids, this marginal cost of battery is compared with that of local generators naturally. However, the system operator can only see the accurate discharging power and cycle depth in the current period, not the final cycle depth. Therefore, to ensure that the storage has enough reserve available, it predicts the final cycle depth based on the current ones and sets prices accordingly.

The price scheme of BESS has two major goals: a) the marginal gain is larger than the degradation cost; b) keep some storage remaining as a spinning reserve for emergency condition. In light of the online auction method in [12], the system operator predicts the final cycle depth to be $\gamma$ times larger than its current cycle depth if the predicted final cycle depth does not exceed the range. If the above predicted final cycle depth exceed the maximal range $\delta_{\max}$, the operator needs to increase the marginal price exponentially. In summary, the auction based marginal degradation cost is defined as a function of current level of cycle depth:

$$C^{\mathrm{A}}(\delta_t) = \begin{cases} C^{\mathrm{S}}(\gamma\delta_t) & \delta_t \leq \frac{\delta_{\max}}{\gamma}, \\ C^{\mathrm{S}}(\delta_{\max}) \exp\left(\theta(\delta_t - \frac{\delta_{\max}}{\gamma})\right) & \text{otherwise} \end{cases} \tag{6}$$

where the parameter $\gamma$ and $\theta$ are determined by

$$\gamma = \max\left\{2, (1+\beta)^{1/\beta}\right\} \tag{7}$$

$$\theta = \max\left\{\frac{\gamma\beta}{\delta_{\max}}, \frac{\gamma}{\delta_{\max}(\gamma-1)}\ln\left(\frac{C^{M}_{\max}}{\alpha(1+\beta)\delta_{\max}}\right)\right\} \tag{8}$$

where $C^{M}_{\max}$ denotes the upper bound of marginal cost of local generators which could be derived since the cost function is known. It is worth noting that the cost model $C^{\mathrm{A}}$ divides the whole capacity of BESS into $N'$ (which depends on $\gamma$ and $N$) heterogeneous segments. Energies stored in the same segment will share the same degradation cost, i.e., the cost of BESS power energy is dependent on which segment it belongs to. This segmental characteristic plays a key role in problem formulation as discussed next.

### C. Cost Function

The cost function of operation optimization in an islanded microgrid includes the fuel cost of dispatchable generators and cycle degradation cost of BESS as in (9). A quadratic cost function is used to model the fuel consumption cost of $M$ local generators. The proposed $N'$ segmental degradation cost model is used for BESS. Here we neglect the network power loss.

$$F_t = \sum_{j=1}^{M} u_{j,t}(a_j(P^{\mathrm{gen}}_{j,t})^2 + b_j P^{\mathrm{gen}}_{j,t} + c_j) + \sum_{i=1}^{N'} C^{\mathrm{A}} P^{\mathrm{dis}}_{i,t} \tag{9}$$

where $a_j, b_j, c_j$ are parameters of cost function for generator $j$, $P^{\mathrm{gen}}_{j,t}$ denotes the power output of generator $j$ at time $t$, $u_{j,t}$ is the binary variable indicating the on/off state of $j$-th generator at time $t$.

### D. Constraints

Besides constraints (1) and (2) of BESS, constraint (10) is added since the battery is evenly divided into $N'$ segments in section II-B.

$$\mathrm{SoC}_t = \sum_{i=1}^{N'} \mathrm{soc}_{i,t}, P^{\mathrm{ch}}_t = \sum_{i=1}^{N'} p^{\mathrm{ch}}_{i,t}, P^{\mathrm{dis}}_t = \sum_{i=1}^{N'} p^{\mathrm{dis}}_{i,t} \tag{10}$$

where $\mathrm{soc}_{i,t}$ denotes the state of charge of $i$-th segment among all $N'$ segments of BESS, $p^{\mathrm{ch}}_{i,t}$ and $p^{\mathrm{dis}}_{i,t}$ are charging/discharging power of $i$-th segment at time $t$. Other technical constraints should be considered in real-time operation, including power balance, power limits, ramping rates and minimal on-time/off-time duration limits of dispatchable generators.

$$\sum_{j=1}^{M} u_{j,t} P^{\mathrm{gen}}_{j,t} + P^{\mathrm{dis}}_t - P^{\mathrm{ch}}_t \geq P^{\mathrm{Lnet}}_t \tag{11}$$

$$u_{j,t} P^{\mathrm{gen}}_{j,\min} \leq P^{\mathrm{gen}}_{j,t} \leq u_{j,t} P^{\mathrm{gen}}_{j,\max} \tag{12}$$

$$P^{\mathrm{gen}}_{j,t} - P^{\mathrm{gen}}_{j,t-1} \leq P^{\mathrm{RU}}_j, \quad P^{\mathrm{gen}}_{j,t-1} - P^{\mathrm{gen}}_{j,t} \leq P^{\mathrm{RD}}_j \tag{13}$$

$$u_{j,t} - u_{j,t-1} \leq u_{j,t'}, \quad u_{j,t-1} - u_{j,t} \leq 1 - u_{j,t'} \tag{14}$$

where $P^{\mathrm{RU}}_j$ and $P^{\mathrm{RD}}_j$ are ramping-up/ramping-down rates of generator $j$. Note that the net load $P^{\mathrm{Lnet}}_t$ in (11) is defined as the local load demands subtracted by total power output of distributed renewable energies. In addition, (14) captures the minimal on/off period constraints, $t' = t+1, ..., \min(t + T^{\mathrm{on(off)}}_j - 1, H)$, where $T^{\mathrm{on(off)}}_j$ denotes the minimal on-time/off-time of $j$-th generator, $H$ is the horizon window.

### E. Weighted MPC Approach

In this section, we formulate the real-time operation problem in a weighted MPC fashion (15). In each current time period $t$, an optimal decision is obtained by solving the optimization problem over a predefined time horizon $H$ using the near future forecasting information. However, only the first element in the optimal solution is implemented and then the horizon window is rolling forward. In the next time period $t+1$, the optimization process is repeated using the newly measured states and forecasting information. By doing so, a feedback is designed. In this receding horizon strategy, the optimal strategy can potentially compensate for the uncertainty that acts on the model. Given the load demands and BESS states, in each time period $t$, the system operator minimizes the weighted total cost (15a) with a discount rate $r$ in the time horizon $H$.

$$\min \sum_{t'=t}^{t+H-1} r^{t'-t} F_{t'} \tag{15a}$$

$$\text{s.t.}(1), (2), (10) - (14) \tag{15b}$$

Note that the time interval $\tau$ is 15 minutes in this paper, which is adequate for real-time scheduling and dispatching.

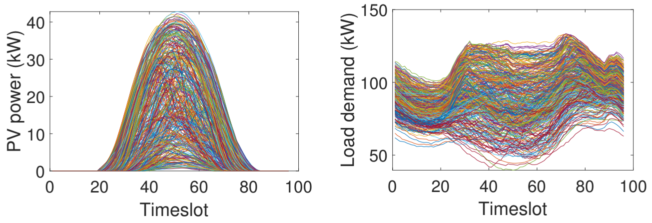
## III. Case Study

In this section, to validate the proposed BESS degradation cost model in real-time operation optimization problem, a simplified small scale islanded microgrid is studied. All simulations are conducted using MATLAB 2019b on an Intel(R) Xeon(R) CPU E5-2650 v4 @ 2.2GHz 2.2GHz 2-processor computer with a 64.0 GB memory. The formulated mixed integer nonlinear problem is solved by the solver 'scip'.

### A. Case Configuration

Table I provides parameters of two dispatchable generator units [14], with minimal on/off duration constraint $T^{\mathrm{on}} = T^{\mathrm{off}} = 1$h. The generator G1 is set always on to guarantee the reliability. One PV panel with maximal power output of 45 kW, and one BESS with parameters shown in Table II are included. Parameters of the cycle depth stress function are $\alpha = 5.24 \times 10^{-4}$, $\beta = 1.03$ [3]. In the weighted MPC optimization problem (15), the horizon window $H = 4$, and the discount rate $r = 0.9$, respectively.

It is also noted in Table II that for simplicity the efficiency and maximal power of BESS in charging and discharging




(a) (b)

Fig. 2. PV power output and load demand profile during 365 consecutive days.

modes are equal. Fig. 2 shows the solar and load demand data during 365 days from the realistic data in Belgium grid in 2014-2015. Moreover, the positive property of the net load holds for all cases.

TABLE I
GENERATOR DATA

| **Gen** | $a$**(\$/(kW)$^2$h)** | $b$**(\$/kWh)** | $c$**(\$)** |
|---|---|---|---|
| G1 | 0.0013 | 0.062 | 1.34 |
| G2 | 0.0010 | 0.057 | 1.14 |
| **Gen** | $P^{\mathrm{RU(RD)}}$**(kW)** | $P_{\max}$**(kW)** | $P_{\min}$**(kW)** |
| G1 | 240 | 50 | 6 |
| G2 | 280 | 92 | 16.4 |

TABLE II
BESS DATA

| $B$**(kWh)** | $R$**(\$)** | $\mathrm{SoC}_{\min}$ | $\mathrm{SoC}_{\max}$ | $P_{\max}$**(kW)** | $\eta$ |
|---|---|---|---|---|---|
| 600 | 120000 | 20% | 90% | 120 | 0.95 |

## B. Simulation and Analysis

*a) Performance of the degradation cost model for BESS:* Fig. 3 compares the results of rainflow algorithm based cost model $C^{\mathrm{S}}$ in blue and proposed cost model $C^{\mathrm{A}}$ in red with $N = 10$, $\delta_{\max} = 0.8$. Note that the parameter $\gamma = 2$ in (6) accordingly. As for the curve of $C^{\mathrm{S}}$, the capacity of BESS is evenly divided into 10 segments (sub capacity = 60 kWh), each of which shares a single degradation cost. This blue curve reveals that the marginal degradation cost series for ten segments are quasi-linear, since the life cycle loss function for lithium-ion battery is quasi-quadratic with respect to the cycle depth.

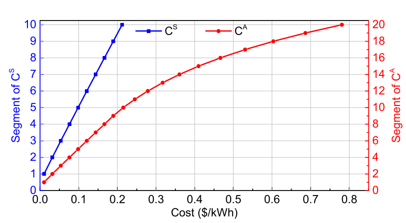
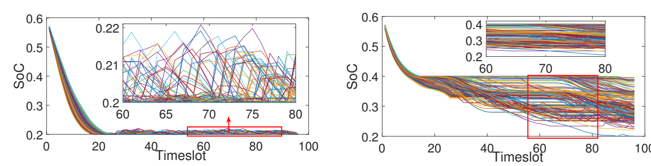



Fig. 3. Segmental marginal cost of two models for the BESS.

However, the red curve of proposed cost model $C^{\mathrm{A}}$ lies in the right side to that of $C^{\mathrm{S}}$, which means the marginal cost is higher by auction method. Meanwhile, the quantity of segments increases to $N' = 20$, which is equal to $\gamma N$. It implies that the sub capacity of each segment is half of that in $C^{\mathrm{S}}$ model. Both these two models share the same marginal cost for the first 8 ($= N\delta_{\max}$) segments. For the next 12 segments in $C^{\mathrm{A}}$ model, the marginal cost increases exponentially. This incremental cost gap between curves ensures not only the price will cover the degradation cost but also the BESS can provide spinning reserve automatically without additional constraints. This advantage can explain the operation features in following results.

*b) Performance of real-time operation:* Fig. 4 illustrates the SoC level profile of the BESS in the 365 cases with the initial SoC = 60%. Fig.4(a) shows that with $C^{\mathrm{S}}$ model, BESS discharges at a fast rate and ends with SoC = 20%. The BESS charges and discharges frequently to suppress high frequency fluctuations of load demand after the SoC reaches the lower bound.

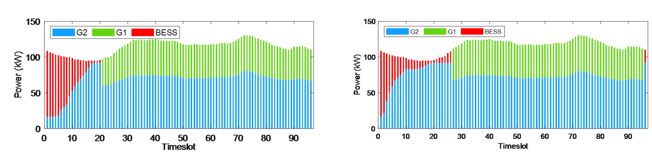
However, the BESS discharges at a slower rate and the terminal SoC is between 22% and 40% in most cases with the proposed $C^{\mathrm{A}}$ model in Fig.4(b). This indicates the advantage in automatically providing spinning reserve for islanded microgrids in case of some emergency conditions. Note that there is no need to add additional constraints of SoC.




(a) (b)

Fig. 4. SoC profile of BESS during the real time optimization. (a) With $C^{\mathrm{S}}$ model. (b) With proposed $C^{\mathrm{A}}$ model.

Fig. 5 displays the power output results of local generators and the BESS on day 23, when the total net demand is the largest among those in all 365 cases. As can been seen, the output profile of G2 is similar in both models. This may be attributed to its large capacity and fundamental share of the whole demand. It is also found that G1 starts up at $t = 27$ when the battery storage reaches the minimal limit value of SoC 20% in Fig. 5(a). However, the SoC of battery is 34.75% when G1 starts up with $C^{\mathrm{A}}$ model in Fig. 5(b).



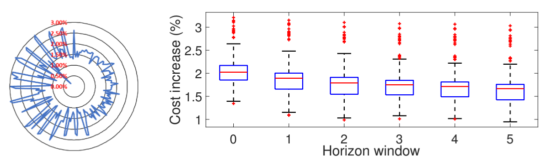

(a) (b)

Fig. 5. Power output results on day 23. The BESS is modeled with (a) $C^{\mathrm{S}}$ model (b) proposed $C^{\mathrm{A}}$ cost model.

Table III compares quantitatively the total energy output and cost between two models on day 23. The cheaper generator G2 in $C^{\mathrm{A}}$ model is scheduled to generate more power energies. As the results summarizes, even though the price is higher in proposed model, the total cost increases only by 0.85% and the final storage of BESS increases by 50% compared to that in $C^{\mathrm{S}}$ model. More generally, the radar map in Fig. 6(a) illustrates that the total cost increases by proposed $C^{\mathrm{A}}$ model are below 3.1% for all cases. This incremental cost is reasonable due to the auction method, where more energies are scheduled from generators.

TABLE III
TOTAL ENERGY OUTPUT AND COST ON DAY 23

| Cost Model | G1(kWh) | G2(kWh) | BESS(kWh) | Cost($) |
|---|---|---|---|---|
| $C^{\mathrm{S}}$ | 697.43 | 1620.81 | 233.96 | 233.10 |
| $C^{\mathrm{A}}$ | 573.40 | 1799.28 | 171.32 | 235.09 |




(a) (b)

Fig. 6. The total cost increase by proposed $C^{\mathrm{A}}$ model with discount rate $r = 0.9$. (a) On day 23. (b) In 365 days under different sizes of horizon window.

*c) Impacts of horizon window and discount rate:* The weighted MPC method is used within the horizon window $H$ with discount rate $r$. Here we assess the impacts of these two parameters. Fig. 6(b) and Fig. 7 show the total cost increase percentage of proposed $C^{\mathrm{A}}$ model from Monte Carlo simulations of 365 consecutive days with $r = 0.9$ and $r = 0.6$.

It can be observed from both two boxplots that as the size of horizon window increases, the total cost increase is bounded between 1% and 3.5%, and its mean value decreases from 2% to 1.5%. Even with no accurate forecasting information, this proposed method can still reach acceptable operation instructions with small values of $H$ and $r$. Another finding is that a smaller discount rate in Fig. 7 incurs a slower decreasing rate with $H$ than in Fig. 6(b). This is attributed to the resulting small weights of future cost functions as in (15a). An inspiration from this finding is to adjust the discount rate $r$ accordingly in specific microgrids with forecasting system. Specifically, larger $r$ is desirable for the case with large prediction accuracy to fully exploit the benefit of MPC, while smaller $r$ is preferable for the case where forecasting errors are large.

## IV. CONCLUSION

This paper proposes a degradation cost model for BESS based on online auction and rainflow cycle counting algorithm. A weighted model predictive control approach is proposed

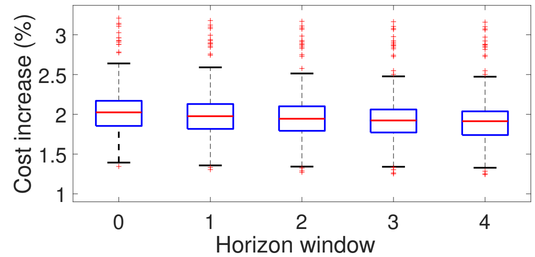



Fig. 7. The total cost increase by proposed $C^{\mathrm{A}}$ model in 365 days with discount rate $r = 0.6$.

to deal with real-time operation considering the uncertainties. Results of numerous cases show that the proposed BESS cost model takes the health of batteries into account. The final SoC of BESS is increased from 20% up to 40% with no need for additional constraints, while keeping the total cost increase upper bounded only by 3.5%. Sensitivity tests of the horizon window and discount rate show that the proposed weighted MPC approach has a potential to addressing the condition of limited forecasting information.

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