Embedding Lithium-ion Battery Scrapping Criterion and Degradation Model in Optimal Operation of Peak-shaving Energy Storage

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Abstract—Lithium-ion battery systems have been deployed in practical power system for peak-shaving, demand response, and frequency regulation. The lithium-ion battery is degrading while cycling and would be scrapped when the capacity is reduced to a certain threshold (e.g. 80%). Such scrapping criterion may not explore maximum benefit from the battery storage. In this paper, we propose a novel scrapping criterion for peak-shaving energy storage based on battery efficiency, time-of-use prices, and arbitrage benefit. Using this scrapping criterion to determine the end of battery life, a new lithium-ion battery life model with scrapping parameters is then derived. Embedded with the degradation model, an optimal operation method for peak-shaving energy storage system is presented. The results of case study show that the operation method could maximize the benefits of peak-shaving energy storage while delaying battery degradation. Compared with the traditional 80% capacity-based scrapping criterion, the proposed efficiency-based scrapping criterion can improve lifetime benefit of battery by 100%.

Index Terms—energy storage operation optimization, lithium-ion battery life model, battery lifetime benefit, battery scrapping criterion, battery degradation.

I. INTRODUCTION

The burden of power system peak-shaving is sharply increasing due to the mismatch between peak load and renewable energy generation and the shortage of flexible resources [1]. More energy storage systems are needed for power system peak-shaving [2] and improving power system flexibility [3]. Lithium-ion battery systems have been deployed in practical power system for peak-shaving, demand response, frequency regulation, and suppress renewable energy fluctuations [4], [5]. However, the lithium-ion battery is degrading while cycling and with calendar time, which are called cycle life and calendar life, respectively. The degradation is mainly caused by two factors: 1) decreasing lithium-ions consumed by the formation of solid electrolyte interface (SEI); 2) loss of electrode sites [6]. These, in turn, result in increasing internal resistance, decreasing capacity and efficiency of the battery, and thus shortened its life [7], [8].

Many researchers develop different models to uncover the complex battery degradation mechanism. Xu, et al. classify the lithium-ion battery life model into theoretical models and empirical models. The theoretical models focus on the loss of active materials and try to explain the degradation mechanism while the empirical models are easier to be embedded in operation and planning research. They further propose a new empirical stress model for cycle loss of three types of lithium-ion batteries [9]. Wang, et al. establish a capacity loss model for graphite-LiFePO4 battery. The capacity loss is power-law function for charge throughput and Arrhenius function for temperature [6]. Redondo-Iglesias, et al. find that there is high dependent between efficiency decreasing and capacity fade in calendar life of lithium-ion battery for electric vehicles. They propose two efficiency degradation models based on the Eyring relationship and correlation between capacity and efficiency, respectively [10].

However, due to the difficulty of embedding the battery life model in optimization, the degradation of lithium-ion battery is usually ignored in previous researches in energy storage operation [4], [11]. Recently, many researchers integrate battery life model into different power system applications. Liu, et al. introduce the capacity loss model about time, depth of discharge (DOD), and charge throughout. They further simplify the model to incorporate it in optimal size planning of lithium-ion battery considering PV generation [12]. Shi, et al. assume that the lithium-ion battery has a constant marginal degradation cost. The degradation cost is included in the objective of battery operation model for peak shaving and frequency regulation. They conclude that the benefit of joint optimization is higher than the sum of individual benefits from peak shaving and frequency regulation [13]. He, et al. use power function to model the relationship between maximum battery cycle number and DOD, and then derive the loss of battery life. They apply the model into battery operation for frequency regulation on electricity market [14]. Tran, et al. propose a battery life model for micro-grid application based on lifetime energy throughput. The results show the model could improve both the energy storage efficiency and battery life [5]. Shi, et al. apply Rainflow algorithm to identify battery cycle number and embed the cycle-based cost into operation optimization model. They proved the model is convex and can extend the lifetime of battery [15].

In summary, the previous researches about battery degradation mainly focus on capacity decrease. The efficiency decrease, especially for cycle life, is rarely studied [10]. For example, Ahmadi et al. apply used lithium-ion battery pack for power system application and conclude that the efficiency is important for re-used lithium-ion battery. Due to the lack of efficiency data, they strongly assume that efficiency decrease has the same trend as capacity fade [8]. In addition, the scrapping criterion for grid-connected energy storage system is seldom discussed and most of the current researches use capacity scrapping criterion such as 80% capacity to determine...
the end of life (EOL) of lithium-ion battery [7]. This scrapping criterion may be suitable for electrical vehicles because high power is necessary to handle all kinds of extreme traffic scenarios. However, the criterion is empirically obtained and is hardly effective for grid-connected battery. After reaching 80% capacity, the grid-connected battery can still benefit from electricity market for peak-shaving and frequency regulation.

In this paper, we propose a novel lithium-ion battery scrapping criterion for peak-shaving energy storage system based on battery efficiency, time-of-use prices and arbitrage benefit of energy storage. The contributions of this paper are as follows: 1) Propose a novel efficiency-based battery scrapping criterion. This criterion can be used for both new and re-used battery in power system applications. 2) Introduce a lithium-ion battery life model considering decreasing capacity and efficiency. The maximal cycle number is derived as the function of DOD and scrapping parameters to make the life model easy to be embedded in optimization. 3) Propose an operation optimization model for peak-shaving energy storage system embedding the degradation model. The objective is to maximize the benefit of peak-shaving while minimizing the cost of battery degradation.

The remainder of the paper is organized as follows. Section II presents the framework of the methodology, introduces the new scrapping criterion and battery life model, and proposes an optimal operation method for lithium-ion battery. Section III provides a case study based on Jiangsu province data in China to validate the life model and operation method. Section IV concludes the paper and describes future work.

II. METHODOLOGY

A. Framework

There are three main issues in the lithium-ion battery optimal operation: 1) how to quantify the EOL of lithium-ion battery for peak shaving? 2) how to model the battery life and embed it in battery operation optimization considering the new scrapping criterion? 3) how to make the battery operation optimization model easy to solve. To this end, Fig. 1 shows the framework of the proposed three-stage method. First, we propose a new scrapping criterion using the battery efficiency to determine EOL of battery. The scrapping criterion is defined as the arbitrage benefit of energy storage for peak-shaving cannot support the O&M cost:

\[
\pi^s E \eta^{dis} - \pi^s E / \eta^{chs} < \pi^c (E \eta^{dis} + \pi^s E / \eta^{chs})
\]

where \( E \) is the average O&M cost for unit charge or discharge.

B. Efficiency-based Scrapping Criterion

Instead of using 80% of rated capacity, we propose a novel lithium-ion battery scrapping criterion for peak-shaving energy storage based on battery efficiency, time-of-use prices, and arbitrage benefit. The efficiency-based scrapping criterion is defined as the arbitrage benefit of energy storage for peak-shaving cannot support the O&M cost:

\[
\pi^s E \eta^{dis} - \pi^s E / \eta^{chs} < \pi^c (E \eta^{dis} + \pi^s E / \eta^{chs})
\]

where \( \eta^{dis} \) and \( \eta^{chs} \) are the discharge and charge efficiency of the battery, respectively. \( \pi^s \) is the average O&M cost for unit charge or discharge.

When considering the scrapping criterion in the battery life model, the most difficult part is to model the efficiency decrease of lithium-ion battery, which is seldom studied, especially for the cycle life [10]. Thus, we try to establish the relationship among average efficiency, capacity, and resistance. Fig. 2 illustrates the equivalent circuit of the lithium-ion battery and how the lithium-ion battery connected to the grid by inverter. Assuming the lithium-ion battery charges and discharges with \( n^{cha} \) and \( n^{dis} \) C current, respectively, \( V^{cha} \) and \( V^{dis} \) are average voltage of charge and discharge, respectively, then the scrapping criterion can be expressed by internal resistance \( R \) and capacity \( C_L \) (with the unit of Ah) as follows:

\[
\eta_{total} = \eta_{inv} \eta_{dis} \eta_{cha} = \eta_{inv} \frac{P^{dis}}{P^{cha}}
\]

\[
= \eta_{inv} \frac{n^{dis} C_L V^{dis} - (n^{cha} C_L)^3 R}{n^{cha} C_L V^{cha} + (n^{cha} C_L)^3 R}
\]

\[
= \eta_{inv} \frac{n^{dis} V^{dis} - n^{cha} C_L R}{n^{cha} V^{cha} + n^{cha} C_L R} < \frac{\pi^s + \pi^c}{\pi^s - \pi^c}
\]
where the $\eta_{\text{inv}}$ is the average overall efficiency of the inverter. $\eta_{\text{total}}$ is the total efficiency of inverter and battery. It should be noted that $n^b C_1 V_{\text{ele}} = n^b C_1 V_{\text{inv}}$ should be held in (2).

Figure 2. Illustration of lithium-ion battery connected to the grid.

Simplifying equation (2), the lithium-ion battery reaches EOL when:

$$C_1 R > \frac{V_{\text{dis}} - V_{\text{charge}}}{\eta_{\text{total}}}$$

Equation (3) indicates that the increasing speed of internal resistance is much higher than the decreasing speed of capacity during the degradation, which causes efficiency decrease.

C. Lithium-ion Battery Life Model

According to [16], the degradation of normalized capacity $C_1$ and normalized resistance $R'$ of lithium-ion battery due to cycle is the function of DOD and charge throughput as follows:

$$C_1' = 1 - (\beta_0 V + \beta_1 d) \cdot \sqrt{Q}$$

$$R' = 1 + (\alpha_0 V + \alpha_1 d) \cdot Q$$

where $V$ is the average voltage of charge and discharge. $d$ is the DOD. The $Q$ is the charge throughput. $\beta_0$, $\beta_1$, $\alpha_0$, $\alpha_1$ are the parameters, which can be calculated as:

$$\beta_0(V) = 7.348 \cdot 10^{-3} \cdot (V - 3.667)^2 + 7.600 \cdot 10^{-4}$$

$$\beta_1 = 4.081 \cdot 10^{-3}$$

$$\alpha_0(V) = 2.153 \cdot 10^{-4} \cdot (V - 3.725)^2 - 1.521 \cdot 10^{-5}$$

$$\alpha_1 = 2.798 \cdot 10^{-4}$$

To derive the battery life using maximum cycle number, we can express the $Q$ by cycle number and DOD:

$$Q = N \cdot 2d \cdot C_{\text{aux}}$$

where $N$ is the cycle number, $C_{\text{aux}}$ is the battery initial capacity.

1) Life model with capacity-based scrapping criterion

Substituting (7) into (4), the function between cycle number $N$ and capacity degradation is derived as:

$$N = \frac{(1 - C_1')^2}{2C_{\text{aux}} (\beta_0 + \beta_1 d)^2}$$

Thus, the maximum cycle number $N^{\text{end}}$ with capacity degradation criterion $C_{\text{end}}^{\text{end}}$ such as 80% is:

$$N^{\text{end}} = \frac{(1 - C_1')^2}{2C_{\text{aux}} (\beta_0 + \beta_1 d)^2}$$

Multiplying (4) and (5), the function between $C_1' R'$ and $Q$ is derived as:

$$C_1' R' = 1 - (\beta_0 V + \beta_1 d) \cdot \sqrt{Q} + (\alpha_0 V + \alpha_1 d) \cdot Q$$

Equation (10) shows that $C_1' R'$ and $\sqrt{Q}$ have a cubic relationship. Thus, there is an analytical-form solution for $\sqrt{Q}$ expressed by $C_1' R'$, denoted as:

$$\sqrt{Q} = f_{\text{cubic}} \left( R' C_1', d \right)$$

where $f_{\text{cubic}}$ is real and positive solution of cubic function, which can be found in [17]. In this paper, the solution is derived by Mathematica.

Substituting (7) into (10), the maximum cycle number $N_{\text{end}}$ with new scrapping criterion $C_{\text{end}}^{\text{end}} R_{\text{end}}$ is:

$$N_{\text{end}} = \frac{f_{\text{cubic}} \left( C_{\text{end}}^{\text{end}} R_{\text{end}}, d \right)}{2d \cdot C_{\text{aux}}}$$

where the $C_{\text{end}}^{\text{end}} R_{\text{end}}$ is determined by (3).

D. Degradation Cost of Lithium-ion Battery

Equation (8) and (11) shows that there exists a complex relationship between the maximum cycle number and depth of discharge in the battery life model. This makes it difficult to embed the life model in battery optimal operation. To this end, we express battery degradation as loss rate of battery life [14]. The loss rate of battery life $f_{\text{cycle}}(n,d)$ after $n$ times cycles with DOD $d$ can be derived as:

$$f_{\text{cycle}}(n,d) = \frac{n}{N_{\text{end}}(d)}$$

Therefore, the battery cycle degradation cost $J^{\text{inv}}(n,d)$ can be represented as the product of the loss rate and the total investment cost:

$$J_{\text{cycle}}(n,d) = f_{\text{cycle}}(n,d) \cdot \eta_{\text{inv}}$$

where $\eta_{\text{inv}}$ is the investment cost of the lithium-ion battery.

Similarly, the calendar life loss rate $f_{\text{cal}}$ and corresponding degradation cost $J_{\text{cal}}$ in an operation day can be calculated as follows:

$$f_{\text{cal}} = \frac{1}{T_{\text{end}}}$$

$$J_{\text{cal}} = f_{\text{cal}} \cdot \eta_{\text{inv}}$$

where the $T_{\text{end}}$ is constant calendar life. The calculation method can be found in [16].

E. Operation Optimization Model

1) Objective function

The aim of our model is to maximize the peak-shaving benefit of energy storage system with PV and load while delaying the battery degradation. Therefore, the objective of our operation optimization model, taking the form as (16), is to
minimize four terms at the same time: 1) the cost of energy, 2) the cost of peak capacity, 3) the O&M cost of lithium-ion battery, and 4) the degradation cost of lithium-ion battery. The benefits of peak-shaving energy storage are from reducing the cost of the first term and second term.

\[
J^{\text{day}} = \min \left( \sum_{i=1}^{M} \pi_i^g P_{i}^g + \pi_i^p P_{i}^p \right) + \sum_{i=1}^{K} \left( \sum_{i=1}^{M} \pi_i^g \left( P_{i}^{\text{dis}} + P_{i}^{\text{cha}} \right) \right) + \sum_{i=1}^{K} J_{i}^{\text{cycle}} (0.5, d_i) + J_{i}^{\text{cal}} \right) 
\]

where \( J^{\text{day}} \) is the daily total cost. \( M, K \) are the numbers of time intervals and batteries, respectively. \( \pi_i^g \), \( \pi_i^p \) are the time-of-use electricity price at time \( t \) and the peak capacity price, respectively. \( P_{i}^g \), \( P_{i}^p \) are the power from the grid at time \( t \) and peak capacity during a day, respectively. \( P_{i}^{\text{dis}}, P_{i}^{\text{cha}}, d_i \) are the discharge output, charge output, DOD, cycle degradation cost, and calendar degradation cost of \( i \)-th battery at time \( t \), respectively.

2) Constraints

The operation optimization model considers several constraints, including energy storage, renewable energy, and power balance.

The power from the grid \( P_{i}^g \), PV generation \( P_{i}^r \), and energy storage output \( P_{i}^{\text{dis}} - P_{i}^{\text{cha}} \) should meet the load demand \( L_i \) at time \( t \).

\[
P_{i}^g + P_{i}^r + \sum_{i=1}^{K} \left( P_{i}^{\text{dis}} - P_{i}^{\text{cha}} \right) = L_i \forall t = 1 \cdots M \quad (17)
\]

The energy storage has constraints of SOC and power output.

\[
P_i^g = P_i^{\text{dis}} / \eta_{i}^{\text{dis}} - P_i^{\text{cha}} / \eta_{i}^{\text{cha}} \quad S_i = S_{i-1} - \left| P_i^{\text{dis}} - P_i^{\text{cha}} \right| \quad 0 \leq S_i \leq C_i \quad 0 \leq P_i^{\text{dis}} \leq P_i^{\text{max}} \quad 0 \leq P_i^{\text{cha}} \leq P_i^{\text{max}} \quad \forall t = 1 \cdots M , i = 1 \cdots K \quad (18)
\]

where \( C_i, P_i^{\text{dis}}, P_i^{\text{cha}} \) are capacity, maximum discharge power, and maximum charge power of \( i \)-th battery. \( S_i, P_i^{\text{dis}}, \eta_{i}^{\text{dis}}, \eta_{i}^{\text{cha}} \) are the SOC, net output, discharge efficiency, charge efficiency of \( i \)-th battery at time \( t \), respectively.

The DOD is defined as follows:

\[
d_i = \left| P_i^{\text{dis}} / C_i \right| \quad \forall t = 1 \cdots M , i = 1 \cdots K \quad (19)
\]

The output of renewable energy should be less than day-ahead prediction \( \overline{P} \).

\[
0 \leq P_i^r \leq \overline{P}_i \quad \forall t = 1 \cdots M \quad (20)
\]

The peak load at time \( t \) is the maximum load from the grid during a day:

\[
L^* = \max \left( P_i^g \right) \quad (21)
\]

For real-world power system in Jiangsu, injecting net power to power system from the battery-PV system is not allowed currently.

\[
P_i^g \geq 0 \quad \forall t = 1 \cdots M \quad (22)
\]

F. Solving Method

Assuming capacity and efficiency during a day is fixed, only the degradation loss of the model is nonlinear. Therefore, we linearize (13) using the piece-linearized technique in order to solve the problem with software Gurobi. The solving method is listed in Algorithm 1.

Algorithm 1: Optimal operation of peak-shaving storage

| Input | Battery parameters (such as initial capacity and efficiency, average discharge and charge voltage, rated charge and discharge current), load, PV prediction, time-of-use prices |
|-------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Step 1 | Determine the EOL using (2)-(3) or 80% capacity |
| Step 2 | Determine parameters of life model using (9) or (12) |
| Step 3 | Derive the degradation cost using (13)-(15) and piece-linearize degradation function |
| Step 4 | Solve the linear operation optimization model (16)-(22) with Gurobi |
| Output | Battery output, PV generation, Cost of energy, peak load, O&M, and degradation |

G. Lifetime Benefit Estimation

According to (13)-(15), the battery reaches EOL when the sum of loss rate is 1. Therefore, the lifetime \( T^{\text{total}} \) (with the unit of day) of battery can be expressed as:

\[
T^{\text{total}} = \frac{1}{\sum_{i=1}^{M} J_{i}^{\text{cycle}} (0.5, d_i) + J_{i}^{\text{cal}}} \quad (23)
\]

Then, the total benefit \( J^{\text{total}} \) of the battery can be estimated as typical daily benefit product lifetime:

\[
J^{\text{total}} = \left( J^0 - J^{\text{day}} \right) \cdot T^{\text{total}} \quad (24)
\]

where \( J^0 \) is the daily operation cost without battery.

It should be noted that (23) is an estimation of battery lifetime when using average capacity and efficiency in daily operation. The accurate lifetime should simulate battery operation iteratively until the battery reaches the EOL, which computation burden is much heavier and can not be considered in the operation optimization model.

III. Case Study

We consider a 4 MW / 4 MWh lithium-ion energy storage system with 12 MW PV and load. In the rest of the section, we will implement and validate the proposed battery life and operation optimization model with analysis and comparison of case study results.
A. Data Description

Real-world data from Jiangsu Province of China such as time-of-use prices, PV generation, and load profile are used in this case study. The load profile and typical PV prediction are shown in Fig. 3. The load mainly has two peaks during 9:00-17:00 and 20:00-22:00. The PV generation peak at 13:00. It should be noted that the uncertainty of PV prediction can be considered using stochastic programing with typical generation scenarios [13]. The time-of-use prices and peak capacity price for industrial load are listed in Table I. The parameters of calculating EOL of lithium-ion battery are shown in Table II. We assuming the battery pack has the same degradation trend as a single battery. Thus, the average voltage and current in Table II are parameters of a single battery in the battery pack. The investment cost of lithium-ion battery pack is 176 $/kWh.

To study how the degradation and scrapping criterion affect the operation and peaking-shaving benefits of battery, four scenarios are shown in Table III. Scenario 1 without energy storage and Scenario 2 without degradation are set as base scenario. Scenario 3 with 80% capacity-based scrapping criterion and Scenario 4 with efficiency-based scrapping criterion are also compared. Calculated by (2) with parameters in Table I, the scrapping efficiency of battery is 61.6%.

B. Results of Battery Life Model

Fig. 4 and Fig. 5 show how capacity and efficiency degrade with cycle number given a certain DOD, respectively. Both the capacity and efficiency of lithium-ion battery will decrease with increasing cycle numbers while the efficiency is decreasing much slower than capacity. For example, after 2000 full DOD cycles, the capacity decreases from 100% to 50% while the efficiency decreases from about 80% to 60%. Besides, reducing the DOD can significantly delay the decreasing speed of capacity and efficiency.

Fig. 6 and Fig. 7 further display the relationship between maximum cycle number and DOD given capacity-based and efficiency-based scrapping criterion, respectively. Under 50% capacity-based or 60% efficiency-based scrapping criterion, reducing DOD from 1 to 0.5 can extend the battery lifetime approximately four times and two times, respectively. The maximum cycle number is strongly affected by the scrapping...
standard. For example, both reducing the scrapping capacity from 80% to 50% and reducing scrapping efficiency from 75% to 60% can extend the lifetime of battery nearly five times. It should be noted that the relationship between maximum cycle number and DOD is convex as shown in Fig. 6 and Fig. 7. This feature makes the maximum cycle number easier to be linearized and embedded in the optimization model.

C. Results of Optimal Operation

Fig. 8 shows the battery output, load, PV generation, power from grid, PV prediction of four scenarios. In Scenario 1, the local load mainly served by power from grid and PV generation. Due to the overgeneration, some PV generation will be curtailed at noon. When battery considered in Scenario 2, the battery mainly charges during valley load time (3:00-7:00) and PV overgeneration time (10:00-16:00). In Scenario 3 and 4, the charge and discharge time are similar to Scenario 2. However, considering the trade-off between peak-shaving benefit and battery degradation, the batteries in Scenario 3 and 4 tend to charge and discharge with much smaller DOD and less frequently in order to extend lifetime of battery. Fig. 9 further shows the DOD of Scenarios 2, 3, 4. The DOD in Scenario 2 is predominantly between 0.3-0.9, while DOD in Scenarios 3 and 4 are mainly between 0.1-0.6 and 0.1-0.5, respectively. The number of high DOD cycles is also reducing in Scenario 3 and 4.

Table IV shows the daily and lifetime benefits of battery in four scenarios. Comparing Scenario 2 with Scenario 1, the daily cost decreases from $12918 to $12150 by $768. The benefit in Scenario 2 mainly comes from reducing energy cost ($689) and peak capacity cost ($236) due to peak-shaving energy storage. The peak capacity is reduced by 0.7 MW from 7.66 MW to 6.96 MW. However, when the investment cost is considering, the lifetime benefit of the battery reducing to $-315161$. This means the benefits from arbitrage and peak-shaving even cannot cover the cost of the investment. The main reason is a short lifetime (506 days) due to high DOD cycles and thus fast degradation speed. Comparing Scenario 3 with Scenario 2, the daily benefit reduces from $768 to $580 due to lower DOD cycles, higher energy cost, and considering degradation cost in daily operation. However, the lifetime benefit increases from $-315161$ to $690380$ because the lifetime increases by nearly 100% to 1052 days. Therefore, more benefits can be earned to cover the cost of investment cost. This means that considering the proposed degradation model in battery optimal operation can extend the battery lifetime and lifetime benefit. Comparing Scenario 4 with Scenario 3, the daily benefit in Scenario 4 slightly increases from $580 to $670$. The lifetime benefit sharply increases by nearly 100%, from $609380$ to $1199935$. The daily benefit increase is mainly due to decreasing degradation cost from $167$ to $98$. The main reasons for increasing lifetime benefit are both higher daily

\[ \text{Figure 6. The relationship between maximum cycle number and depth of discharge given capacity scrapping criterion} \]

\[ \text{Figure 7. The relationship between maximum cycle number and depth of discharge given efficiency scrapping criterion} \]

\[ \text{Figure 8. The battery output, load, PV generation, power from grid, PV prediction of four scenarios.} \]

\[ \text{Figure 9. The depth of discharge of scenarios 2, 3 and 4.} \]
benefit and much longer lifetime, which increases from 1052 days to 1792 days. This means that the proposed efficiency criterion can extend battery lifetime while improving daily operation benefit.

| Scenario  | Scenario 2 | Scenario 3 | Scenario 4 |
|-----------|------------|------------|------------|
| Daily total cost/$ | 12918 | 12150 | 12338 | 12248 |
| Daily energy cost/$ | 10363 | 9674 | 9704 | 9674 |
| Daily O&M cost/$ | 0 | 157 | 148 | 157 |
| Daily degradation cost/$ | 0 | 0 | 167 | 98 |
| Daily peak load cost/$ | 2555 | 2319 | 2319 | 2319 |
| Daily benefit of battery/$ | -768 | 580 | 670 | - |
| Lifetime estimation/day | -506 | 1052 | 1792 | - |
| Lifetime benefit of battery/$ | -315161 | 609380 | 1199935 | - |
| Peak capacity/MW | 7.66 | 6.96 | 6.96 | 6.96 |

**IV. CONCLUSION AND FUTURE WORK**

In this paper, we propose a novel lithium-ion battery scrapping criterion for peak-shaving energy storage based on energy efficiency, time-of-use prices and arbitrage benefit of energy storage. This criterion can be used for both new and reused battery in power system applications. Using this scrapping criterion to determine EOL of battery, the maximal cycle number is derived as the function of DOD and the scrapping parameters to make the life model easy to be embedded in battery operation optimization model. The results of the case study validate the proposed method and show that battery life is significantly affected by DOD and scrapping criterion. Embedding the battery degradation model in operation optimization model could maximize the lifetime benefit of the lithium-ion energy storage system while delaying the battery degradation by less frequent high DOD cycles. Compared with 80% capacity-based scrapping criterion, the proposed efficiency-based scrapping criterion could increase the battery lifetime benefit by 100% with extending battery lifetime and improving daily operation benefit.

It should be noted that the cycle number in this paper is not counted by Rainflow algorithm because time granularity for peak-shaving is an hour. The cycle in an hour can be approximated as a half cycle with different DOD. This may not hold for frequency regulation due to frequent and variable cycles in short time interval. Future work aims at embedding the Rainflow algorithm in the battery optimal operation with the proposed life model.

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