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Economic Operation Optimization for 2nd Use Batteries in Battery Energy Storage Systems

SUN JINLEI[1], (Member, IEEE), PEI LEI[2], LIU RUIHANG[1], MA QIAN[1], TANG CHUANYU[1], AND WANG TIANRU[1]

[1]School of Automation, Nanjing University of Science and Technology, Nanjing 210094, China
[2]Automotive Engineering Research Institute, Jiangsu University, Zhenjiang 212013, China

Corresponding author: Sun Jinlei (jinlei.sun@njust.edu.cn)

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ABSTRACT The lithium-ion batteries retired from electric vehicles (EVs) and hybrid EVs have been exponentially utilized in battery energy storage systems (BESSs) for 2nd use due to their economic and environmentally friendly benefits. Therefore, research on their aging mechanism and state of health (SOH) has attracted increasing amounts of attention across the world. However, few studies focus on optimizing the economic operation of BESSs that are built by retired batteries with various SOHs. This paper proposes an economic operation optimization method for BESSs comprised of retired batteries with different SOHs, which provides a way for the BESS to operate with new and retired battery systems (BSs) together. An operation cost model is put forward that considers the cost increase caused by aging. This method aims to minimize the operating cost in a time step based on the particle swarm optimization method. To validate the feasibility of the economic operation optimization method, a case was studied using a BESS consisting of four BSs with different SOHs under peak load shifting. Compared with the traditional method, which allocated power according to the available peak power of each BS, the proposed method has advantages in the scheduled number and cost.

INDEX TERMS Battery energy storage system, aging, economic operation, particle swarm optimization.

I. INTRODUCTION

In the past few years, electric vehicles (EVs) and hybrid electric vehicles (HEVs) have been rapidly developed to face energy crises and air pollution problems [1]. Reported sales of EVs in 2017 were 1.1 million worldwide, and it is forecasted that the record will increase to 11 million in 2025 and then surge to 30 million in 2030 as these vehicles become cheaper to make than internal combustion engine (ICE) cars [2]. Moreover, in the next few years, the manufactures and government will face the problem of recycling a large number of lithium-ion batteries retired from EVs. Although retired from EVs, these batteries still possess more than 80% of their initial capacity. They could not meet the power and energy requirement of electric vehicles, but they can still be used in battery energy storage systems (BESSs) with lower current rates [3]. The 2nd use applications not only prolong the battery service life but also reduce energy waste. Therefore, 2nd use applications are a thriving research area for BESSs.

Numerous optimal operation methods for BESSs have been reported in the literature. These methods can mainly be categorized as power and energy optimization control [4], [5] and economic operation control [6]–[11]. Power and energy optimization-based methods focus on charging and discharging control. Reference [4] proposes a novel charging and discharging algorithm to control BESSs for the purpose of peak load shaving, power curve smoothing and voltage regulation. Reference [5] utilizes a fuzzy control based power distribution method to achieve wind power tracking for multiple-type energy storage. Economic operation control based methods focus on cost saving. Reference [6] proposes a novel coordinated control strategy to obtain optimal control parameters and minimize the total cost. Reference [7] proposes a model predictive control based optimization method considering battery degradation caused cost variation. In [8] an optimal decision-making model is developed to perform a trade-off between potential grid revenue that can be collected from

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buying/selling onto the power grid and the effect of degrading the battery. Reference [9] introduces a multi-objective energy management control method considering system reliability and economy. Reference [10] proposes a method to aggregate "gridable vehicles" and second life batteries together in an intelligent way to provide such backup energy can reduce significant storage costs. Reference [11] proposes a model to inform the owners of the revenue potentials, taking cost of battery energy both in automotive and second life into consideration. And further proposed an economic load dispatch model with the inclusion of second life revenue. This method would help earning extra revenue thus contributing to the initial buying price and encouraging more "gridable vehicles" participation in the smart grid. However, none of these studies pay attention to the economic operation of BESSs built by retired batteries, especially for BESS dealing with power scheduling with new and retired BSs working together.

The SOH has a significant impact on grid economic operation [12]. A battery ages with the decrease of capacity and increase of internal resistance, which in turn limit the energy and capacity of the BESS and increase the scheduling cost. The published studies focus on studying the aging mechanism [13]–[15] and state estimation methods [16], [17]. While useful for understanding the failure mechanism and predicting the remaining useful life, such detail makes it difficult to extend the models to various use cases. However, in most cases, the researchers merely focus on how a new battery cell ages based on different conditions but ignore the SOH variation. Taking the SOH variation into consideration when dealing with BESS optimal power scheduling is urgently needed.

This paper focuses on economic operation optimization for BESSs built by retired batteries with State of health(SOH) variation. The paper makes the following original contributions:

(1) A BESS cost model considering SOH variation;

(2) A power scheduling optimization method to minimize operation cost;

(3) A performance comparison between traditional and proposed methods.

The remainder of the paper is organized as follows. Section II describes the SOH calculation. Section III formulates the optimal power scheduling strategy, taking SOH variations into consideration. Section IV presents simulation validation, followed by conclusions summarized in Section V.

II. AGING EXPERIMENTS OF LITHIUM-ION BATTERIES

Lithium-ion batteries are popular in the fields of EV and Energy Storage Systems (ESS) due to their high energy and power density, low self-discharge rate and high coulombic efficiency. However, the battery capacity fades with the process of charging and discharging due to the loss of active material (LAM) and the loss of lithium inventory (LLI) [17]. This fading capacity determines the useable life and function of a battery. When batteries are retired from EVs, the capacities have usually faded to 80% of the initial capacities. Although these batteries could not meet the energy and power requirements for vehicular use, they can still be used for energy storage with lower power load, such as load-shifting and frequency regulation. These applications not only prolong the service life but also reduce energy waste. The SOHs of retired batteries are usually approximately 80% according to FreedomCAR [18]. In addition, there is always SOH variation of the BS in BESSs. To ensure the safety of 2nd use BESSs and prolong the service life, the effects of battery aging should be considered.

FIGURE 1. Experimental set up.

TABLE 1. Battery specifications.

Item	Specification
Nominal Capacity	40Ah
Cathode material	LiFePO4
Anode material	Graphite
Battery shape	Prismatic
Weight of battery	1.4 kg
Nominal voltage	3.2V
Charge cutoff voltage	3.65V
Discharge cutoff voltage	2.5V

The instrumentation used to perform the experiments in this paper include an Arbin Testing System, thermostat, and PC. An Arbin Instrument BT-ML (60V/50A, ±10A for the medium current range and ±50A for the high current range) battery tester was used to carry out charge and discharge tests with a voltage measurement accuracy of 0.05% and a current measurement accuracy of 0.05% (on the full-scale value of both ranges). The thermostat temperature range is 223–423K (GDW-50, NJTEST, China). The experimental set up is shown in Fig. 1.

$LiFePO_4$ cathode and graphite anode lithium ion batteries were used in this paper. The detailed parameters are listed in Table 1. The battery was placed in the thermostat to control the temperature with ±2°C variation.

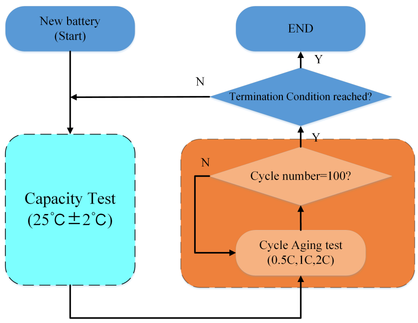

FIGURE 2. SOH test flowchart.

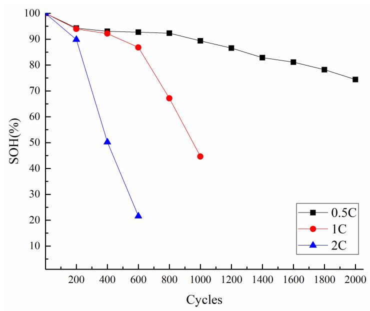

FIGURE 3. Battery SOH measurements at various cycle rates.

A series of tests were conducted to investigate SOH under different C-rates. Fig. 2 shows the experimental flow chart including capacity and cycle aging tests.

Fig. 2 shows the two-step flow chart including (1) the capacity and cycle aging tests under different C-rates. Both experiments are performed under room temperature (25°C ± 2°C). The performance testing is conducted every 100 cycles to obtain the characteristic battery parameters during the process of aging under a certain C-rate. The aging test is conducted under different C-rates with constant current charging and discharging. Data analysis takes place after both experiments are complete to derive mathematical functions that represent the impact of C-rates on the SOH. Finally, the functions are directly embedded into the optimal BESS operation cost function. Fig. 3 shows the SOH degeneration of batteries at 0.5C, 1C, and 2C. From Fig. 3, it can be seen that higher cycle rate leads to larger SOH decrease under room temperature.

III. FORMULATION OF POWER SCHEDULING OPTIMIZATION

The BESS power scheduling optimization is developed by first introducing a scheduling cost model, and then calculating the optimal power allocation with the target of minimizing operation costs.

A. OPERATION COST MODEL

To simplify the analysis, the following assumptions are made.

1) The cell inconsistencies in a BS are ignored, including the SOC, SOH, and charge/discharge efficiency.
2) BS parameters are considered unchanged during each time step.
3) The dispatching task is within the acceptance range of the battery energy storage system.
4) Battery self-discharging is ignored.

The BESS operation cost includes three parts, and can be expressed as follows:

$$C = C_{fix} + C_{loss} + C_f \tag{1}$$

where C is the operation cost, C_{fix} is the maintenance cost, C_{loss} is the loss cost, and C_f is the fixed cost.

1) MAINTENANCE COST

During the operation of BESSs, regular maintenance should be carried out to improve reliability, and the resulting cost is recorded as the BESS maintenance cost. The maintenance cost can be calculated using (2).

$$C_{fix} = T \sum_{i=1}^{n} K_i^f P_i \tag{2}$$

where C_{fix} is the maintenance cost (CNY), T is the time per operation cycle (hour), K_i^f is the operation and maintenance cost coefficient of the ith BS (CNY/kWh), P_i is the allocated power of the ith BS (kW), and n is the number of BSs in the BESS.

2) LOSS COST

The internal resistance consists of ohmic resistance and polarization resistance. Ohmic resistance is composed of resistance of electrode material, electrolyte and separator and contact resistance of other battery parts. The polarization resistance refers to the polarization between positive electrode and negative electrode during electrochemical reaction [19]. And both kinds of resistance lead to energy losses when charging or discharging. Additionally, the Power Conversion System (PCS) and battery system have losses during operation. Thus, such cost is recorded as the loss cost and is considered separately in charging and discharging, and the loss cost is calculated according to the power loss in a step time, as is shown in equation (3):

$$C_{loss} = \begin{cases} T \sum_{i=1}^{n} K_i^l \left(1 - \eta_i^c\right) P_i & \text{charge} \\ T \sum_{i=1}^{n} K_i^l \left(\dfrac{1}{\eta_i^d} - 1\right) P_i & \text{discharge} \end{cases} \tag{3}$$

where C_{loss} is the loss cost (CNY), K_i^l is the power loss coefficient (CNY/kWh), $(1 - \eta_i^c)$ and $(\frac{1}{\eta_i^d} - 1)$ are charging and discharging loss efficiency, respectively. T is the step time(hour). n is the number of BS.

3) FIXED COST

The BS charges or discharges according to the power allocation of the BESS, and a battery SOH degenerates with charging or discharging, especially for high current rate and high temperature. The end of life for the BESS is determined by the $\mathrm{SOH}_{\mathrm{i}}^{\min}$, which is the BS with the worst SOH. The BESS cannot complete the scheduling task and needs to be replaced when any BS reaches the SOH lower limit.

The BS construction cost is recorded as a fixed cost, and it is evenly distributed to the SOH attenuation of the BS in this paper. Thus, the fixed cost loss can be written as (4).

$$C_f = \sum_{i=1}^{n} \frac{\Delta \mathrm{SOH}_i}{1-\mathrm{SOH}_i^{\min}} f_i^B \tag{4}$$

where C_f represents the fixed cost loss (CNY), $\Delta\mathrm{SOH}_i$ represents the SOH variation of the ith BS in a time step, $\mathrm{SOH}_i^{\min}$ represents the SOH lower limit of the ith BS, and f_i^B represents the construction cost of the ith BS (CNY).

The SOH can be calculated by (5):

$$\mathrm{SOH} = \frac{C_{bat}}{C_{bat,0}} = 1 - \frac{C_l}{C_{bat,0}} \tag{5}$$

where C_{bat}, $C_{bat,0}$ *and* C_l, respectively, indicate the current capacity (Ah), initial capacity (Ah) and capacity loss (Ah) of the BS.

A multiple stress coupling capacity loss model for lithium ion batteries is used, which takes the loss of lithium inventory and the loss of active materials into consideration [17]. The mode is expressed as follows.

$$\begin{cases} \mathrm{SOH} = 1 - \dfrac{C_l}{C_{bat,0}} \\ C_l = LLI + LAM \\ LLI = \left[k_{SEI} \times \exp\left(\dfrac{-E_{a,SEI}}{RT^{std}}\right) \times \sum \left\{ \exp\left(-\dfrac{E_{a,SEI}}{R} \right.\right.\right. \\ \quad \left.\left.\left. \times \dfrac{T^{std}-T_k}{T^{std}T_k}\right) \Delta t_{cyc,k} \right\}\right]^{1/2} - LLI_0 \\ LAM = \dfrac{2}{3} \times C_{bat,0} \displaystyle\int_0^{\exp\left[k_{crk}\cdot\left(I_{cyc}^{std}\right)^2 \cdot \sum\left\{\left(I_{cyc,k}/I_{cyc}^{std}\right)^2\right\}\right]} \\ \quad \times \dfrac{1}{\sqrt{2\pi}\sigma_a} \exp\left(-\dfrac{(a-\mu_a)^2}{2\sigma_a^2}\right) da \end{cases} \tag{6}$$

In equation (6), R is the gas constant 8.314 J/(mol · K), T is the working temperature (K); T^{std} is the standard working temperature, 298 (K), k_{SEI} and $E_{a,SEI}$ are the correlation coefficients to characterize the formation rate of SEI, with units A^2h and J/mol, respectively, LLI_0 is the LLI (Ah) in the formation process of new batteries; Δt_{cyc} is the cycle time (h); and I_{cyc} is the cycle current (A). k_{crk}, μ_a, and σ_a are taken as the correlation coefficients describing the fatigue cracking process of electrode particles. The unit of the former is A^{-2}, and the latter is m. It should be noted that the lower-angle mark k denotes the relevant parameters taking the specific value of the k_{th} cycle, and the above parameters are obtained by the corresponding previous experiments.

The objective function is to minimize the operation cost of the BESS, and can be expressed as follows.

$$\min C = C_{fix} + C_{loss} + C_f$$
$$= \begin{cases} T\displaystyle\sum_{i=1}^{n} K_i^f P_i + T\sum_{i=1}^{n} K_i^l \left(1-\eta_i^c\right) P_i \\ \quad + \displaystyle\sum_{i=1}^{n} \frac{\Delta\mathrm{SOH}_i}{1-\mathrm{SOH}_i^{\min}} f_i^B \qquad \text{charging} \\ T\displaystyle\sum_{i=1}^{n} K_i^f P_i + T\sum_{i=1}^{n} K_i^l \left(\frac{1}{\eta_i^d} - 1\right) P_i \\ \quad + \displaystyle\sum_{i=1}^{n} \frac{\Delta\mathrm{SOH}_i}{1-\mathrm{SOH}_i^{\min}} f_i^B \qquad \text{discharging} \end{cases} \tag{7}$$

The objective function is subject to several constraints. The battery operation voltage range is between 2.5V and 3.65V. And the other constraints are shown in (8).

$$\begin{cases} P_{total} = \displaystyle\sum_{i=1}^{n} P_i \\ -\hat{P}_{dis,i} \le P_i \le \hat{P}_{chg,i} \\ \mathrm{SOC}_i^{\min} \le \mathrm{SOC}_i \le \mathrm{SOC}_i^{\max} \end{cases} \tag{8}$$

The definition of SOC is as follows

$$\mathrm{SOC} = \frac{\mathrm{Q}_C}{\mathrm{Q}_{rate}} \times 100\% \tag{9}$$

where, Q_C is the current quality of charge(Ah), Q_{rate} is the rated capacity(Ah).

The SOC must lie within the bounds and is formulated as

$$\mathrm{SOC}_i^{\min} \le \mathrm{SOC}_i \le \mathrm{SOC}_i^{\max} \tag{10}$$

where SOC_i is the SOC of the ith BS, $\mathrm{SOC}_i^{\min}$ is the lower limit of the ith BS, and $\mathrm{SOC}_i^{\max}$ is the upper limit of the ith BS. In this study, the SOC operation range is between 20% and 100%. It is because that the battery voltage would drop rapidly when the SOC is below 20%. In order to ensure that the battery voltage can satisfy the rated level demand, the minimum value of SOC is set to 20%.

In addition to the SOC being within limits, the charging and discharging power must also be within limits, which is expressed as (11)

$$-\hat{P}_{dis,i} \le P_i \le \hat{P}_{chg,i} \tag{11}$$

where $\hat{P}_{dis,i}$ and $\hat{P}_{chg,i}$ are the maximum discharge and charge power (kW), respectively. $\mathrm{P_i}$ is the power allocated to the ith BS (kW). The maximum charging and discharging power decreases proportionally with the degenerates of SOH. In this paper, the absolute value of maximum charge and discharge power are equal.

B. OPTIMAL POWER SCHEDULING METHOD BASED ON PARTICLE SWAM OPTIMIZATION METHOD

Particle Swarm Optimization (PSO) is a computational method that optimizes a problem by trying to improve a candidate solution with regard to a given measure of quality.

The idea of the PSO algorithm is inspired by the behavior of birds. Kennedy and Elberhart [20], [21] proposed this method for the first time in 1995. The PSO algorithm has advantages such as simple coding, and few parameters, and has been widely used for function optimization. The main idea is to generate a population of candidate solutions, and move these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position but is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

It can be observed in equation (7), the operation cost contains fixed cost, loss cost and maintenance cost and all these costs are functions of allocated power of each BS. When a scheduling task is sent to BESS, the crucial issue is to obtain a set of power that allocated to BSs to minimize operation cost. This is an optimization problem, and an optimization method is needed to obtain solutions. PSO method is a simple coding implementation and is able to perform exploration in a high dimension searching space for optimum solution. Specifically, PSO is able solve the problem with high complexity where many variables are involved.

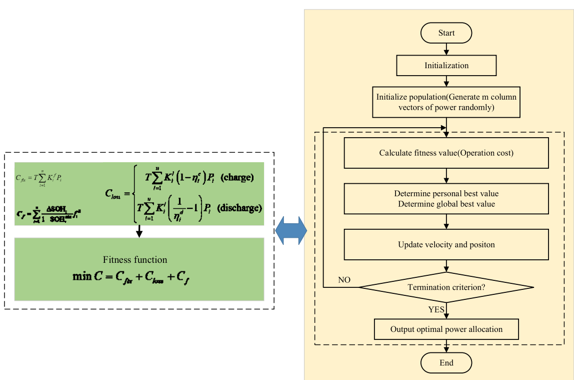

FIGURE 4. Flowchart of the proposed economic operation optimization method.

The flowchart of optimal power allocation for this work is shown in Fig.4, and the specific procedure is summarized as follows. A pool of candidate solutions is randomly generated and in this process, m column vectors with N allocated power are randomly generated based on the total power limit. Then fitness values are calculated, in which the operation cost is taken as the optimization objective. Third, calculate and update the personal best solution (P_{best}) and the global best solution (G_{best}), and then update the velocity and position. Finally, G_{best} is the location with the best global fitness value. Actually, each element of vector G_{best} represents the corresponding power allocation of each BS.

IV. CASE STUDY

Generally, the proposed optimization method can be applied to any BESS power allocation with the goal of minimizing operation cost. The BESS strategy is to act as a load when the grid needs to discharge and as a supply when the grid needs energy injected back into it. When the power generation is insufficient, the BESS provides power output. When power generation is in surplus, the BESS stores energy. For a BESS built by BSs with retired batteries, the SOH consistency is difficult to maintain, because not all the retired batteries could be used in 2nd use application. In addition, the rated power and capacity could even be different. This is the situation that 2nd use application usually faces. The proposed economic operation optimization method solves the power scheduling problem of a BESS built by BSs with different SOHs.

A. BESS PARAMETERS

The BESS operates to release and absorb energy, with the goal of meeting the power exchange between production and total grid demand. The typical peak load shifting power curve takes the power curve of a period of time, derived from [22], as shown in Fig. 5.

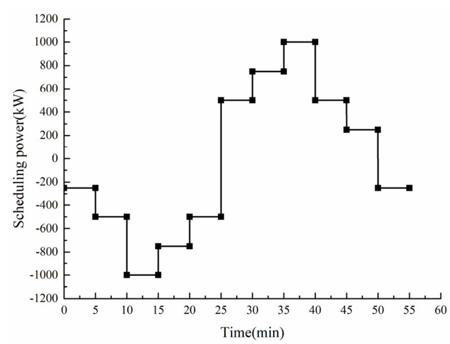

FIGURE 5. Typical peak load shifting power curve.

The BESS was rated at 1 MWh, and was compromised of four BSs. The rated energy of the BSs was 250kWh, 200kWh, 300kWh, and 150kWh, and the rated voltage of each system was 400V. The BSs were connected in parallel and series with LFP batteries mentioned in Section II, and the detailed parameters are shown in TABLE 2. The temperature is assumed to be controlled at 25°C ± 2°C. The detailed parameters of the BSs in the BESS are shown in TABLE 2.

TABLE 2. Initial parameters of storage energy station.

Related parameters	B1	B2	B3	B4
Rated voltage (kV)	0.4	0.4	0.4	0.4
Rated power (kW)	250	200	300	150
Rated energy (kWh)	250	200	300	150
Charging efficiency	95%	95%	95%	95%
Discharge efficiency	95%	95%	95%	95%
Operation and maintenance cost (CNY/kWh)	0.1	0.1	0.1	0.1
Power loss coefficient (CNY/kWh)	0.5	0.5	0.5	0.5
Construction cost (10^4CNY)	40	30	42	19.5
Initial SOC (%)	60	60	60	60
Initial SOH (%)	100	95	90	85

The charging and discharging efficiency are assumed to be 95% in this paper, because the main loss is the heat during charging and discharging. According to the previous experimental results, the efficiency is assumed to be 95% during constant current charging and discharging, and to ease analysis the charging and discharging efficiency are assumed to be the same. The BS prices were set to 40, 30, 42, and 19.5 (10^4CNY), respectively, according to the power level. The operation and maintenance cost and power loss coefficient are set to 0.1 CNY/kWh and 0.5 CNY/kWh, respectively. The initial SOCs are all set to 60% to simulate the actual situation, because it is convenient for absorbing and releasing energy. The initial SOHs are set to 100%, 95%, 90%, and 85%, respectively, to simulate the SOH variation, and the terminate SOH in this simulation is 40%.

When a scheduling order is sent to the BESS, the proposed optimal operation method searches for the optimal current for each BS in a single time step with the target of minimizing operation cost using the PSO method. Then, it updates the SOH of each BS and prepares for the optimal power scheduling of the next time step. The operation cost calculation shown in (7) is a function of the allocated current for each BS. In addition, the SOH calculation is also a function of current. High current rate leads to large capacity loss. As the BESS operates, the SOHs of the BSs go down in case any BS reaches the terminal SOH condition.

B. RESULTS AND DISCUSSION

To demonstrate the superiority of the algorithm, the proposed method is compared with a traditional method, in which the power allocation strategy is according to the actual acceptable maximum power ratio of each BS. The initial simulation parameters are the same and the simulation comparison is shown in Fig. 6.

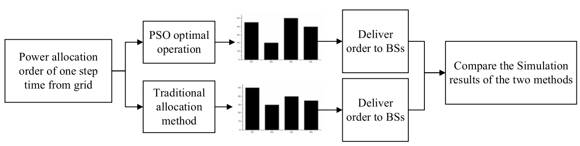

FIGURE 6. Simulation comparison between two methods.

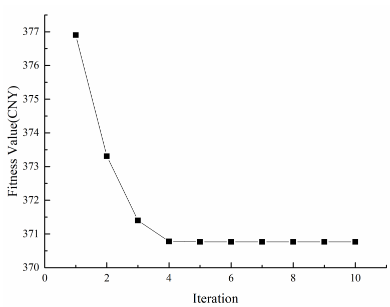

FIGURE 7. The PSO convergence rate of the objective function.

The Fig.7 shows the PSO based convergence rate of the objective function.

It is obvious that the proposed PSO-based scheduling method in a time step is converged to its final state approximately after 4th iterations.

The power allocations of both methods are shown in Fig. 8.

The proposed PSO based optimal operation method allocated power according to the calculated optimal operation cost, which takes SOH and rated power into consideration. In the first 500 scheduling times, the first BS undertook more power in the BESS to achieve cost optimization in each time step, and that in turn accelerated its aging. Meanwhile, the aging of the other BSs was relatively slower. After 2000 scheduling times, the power allocation ratio was stable. The proposed method had a profound effect on protecting the SOH variation from worsening. The SOH variation during scheduling is shown in Fig. 9.

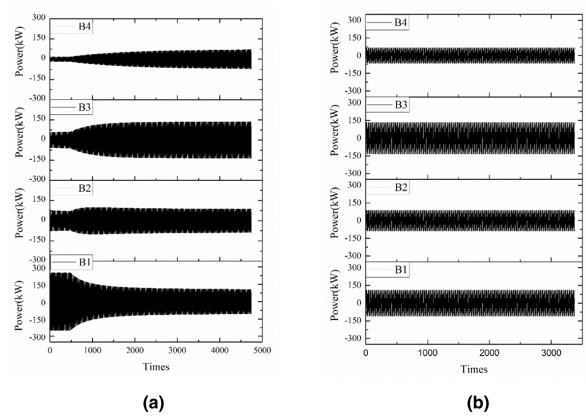

FIGURE 8. Power allocation method comparison. (a) Power allocation of PSO method. (b) Power allocation of traditional method.

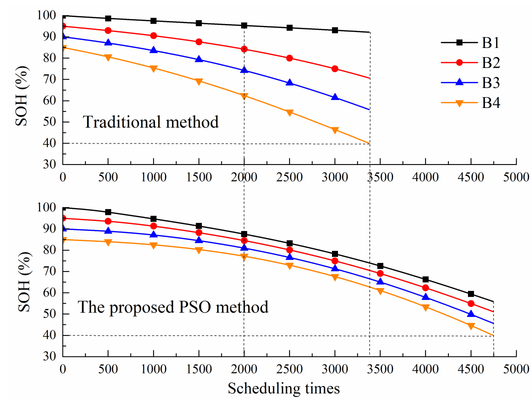

FIGURE 9. SOH variation during operation.

Whereas the traditional method took maximum power as the principle to schedule power, regardless of SOH, and the power allocation ratio of different BSs are the same. As shown in Fig. 9, that in return led to the result that the BS with low SOH undertook more power, which is the reason for SOH uniformity deterioration. The SOH of the 4th BS reached 40% and terminated the simulation only after 3377 scheduling times. Compared with the traditional method, the PSO based optimal operation method prolonged the scheduling by 1367 times (40.5%) and maintained SOH consistency. The SOH consistency and scheduling times of both methods when the termination condition is met are shown in TABLE 3.

Different power scheduling methods correspond to different scheduling costs, and the cumulative scheduling cost is an important factor to reflect the overall economic effect in application. The cumulative scheduling cost comparison of both methods for 3377 times is shown in Fig. 10.

TABLE 3. Simulation results.

Method	Total number of dispatches (times)	The maximum difference of SOH at the simulation end
Traditional proportional allocation	3377	52.2%
PSO optimal allocation	4744	15.9%

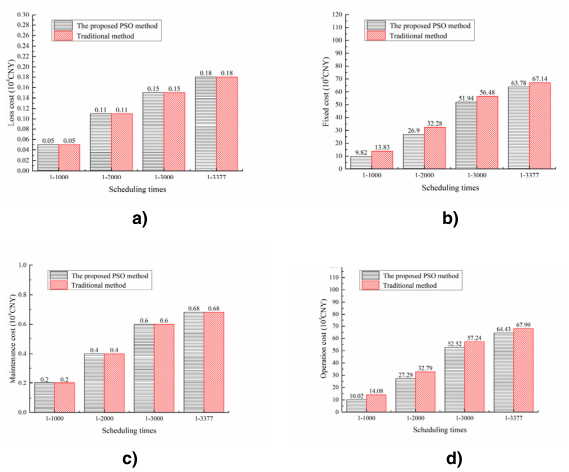

FIGURE 10. Cumulative scheduling cost comparison. (a) Loss cost comparison. (b) Fixed cost comparison. (c) Maintenance cost comparison. (d) Operation cost comparison.

As is shown in Fig. 10 the cumulative scheduling cost of the PSO optimal and traditional equal proportion allocation schemes are 272,900 and 327,900 CNY, respectively, in the first 2000 times, and the scheduling cost is reduced by 55,000 CNY (16.8%). After 3,377 cumulative dispatches by the traditional equal-proportion allocation, the life of the BESS terminates and the total dispatching cost is 679,900 CNY, whereas the cumulative dispatching cost of PSO optimal allocation for the same number of dispatches is 644,300 CNY, which is 35,600 CNY (5.24%) lower than the traditional dispatching method.

It can be seen that the maintenance cost and loss cost are the same for the two methods. And the fixed cost is the main part for operation cost. With the increase of BESS dispatching times, the aging rate of batteries gradually accelerates, and the increment of dispatching cost increases. Additionally, the proposed method is obviously superior to the traditional method for economic operation under the same scheduling cost calculation method. This occurs because the fixed cost and loss cost are functions of allocated power, which occupies a small proportion. For the fixed cost mainly caused by the SOH, the proposed method limited the BESS construction cost to the SOH operation range, which occupied main part of the total cost. Thus, the more SOH changes in a time step, the greater the scheduling cost with the same SOH operation range.

In summary, it is of benefit to implement the proposed cost optimization method taking SOH into consideration so that minimizing operation cost is achieved in return for prolonging BESS scheduling times in peak shaving operation condition. This method provides an optimal economic operation power scheduling method for BSs with different SOHs and capacities.

V. CONCLUSIONS

A BESS operation cost model is put forward that takes the aging-caused cost increase into consideration. The proposed method aims to minimize the time step operation cost using the PSO based optimization method. The results show that the BESS scheduling cost is optimized under peak load shifting and the SOH variation between BSs improves compared with the traditional power allocation method. This method provides an optimal power allocation method for BESS with new and retired BSs working together.

The proposed economic operation optimization method can be effectively embedded in current BESS scheduling methods to minimize scheduling cost for applications such as EV charging stations and energy trading in the electricity market.

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Authors' photographs and biographies not available at the time of publication.