An Energy Management System For Second-Life Battery In Renewable Energy Systems Considering Battery Degradation Costs

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Title page

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ORIGINAL ARTICLE

An Energy Management System For Second-Life Battery In Renewable Energy Systems Considering Battery Degradation Costs

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Abstract: The proportion of renewable energy sources in the power generation has gradually increased. However, due to the variation and intermittency of renewable energy sources such as wind and solar energy, energy storage system must be integrated in the microgrid to ensure the power balance between the load and the generating end. At the same time, economic benefits must be considered due to the introduction of energy storage systems. Secondary utilization of power batteries is considered to be an effective solution to the above-mentioned problems. This paper proposes an energy storage management system composed of second life batteries. Comprehensively considering battery lifetime loss costs and system operating costs, and to conduct the dispatch of energy in the lowest cost way. Considering battery degradation, remaining capacity, and cost, and comparing the performance of second life batteries with new batteries. Based on simulation results, the effectiveness of the method is verified.
Keywords: Second Life Battery, Battery ageing, Energy storage, Power management, Electric Vehicle

1 Introduction

At present, greening in the transportation industries is considered a necessary prerequisite to achieve carbon neutrality to cope with the threat of global climate change [1]. As a result, new energy vehicles represented by electric vehicles (EV) have owned larger and larger share in vehicle market. However, the current power batteries used in EVs still have some shortcomings, such as high cost and short life, and large-scale EV applications will inevitably cause problem that how to deal with large retired batteries [2]. Therefore, exploring the cascade utilization of retired batteries has become an essential for stakeholders and government [3].

EV manufactories widely agree that 80% of the rated capacity is the retirement standard for EV batteries. Some studies have shown that the retired batteries still have the potential to be reused in other less-demand fields [4]. Abdel-Monem's technical analysis of application of second life battery (SLB) showed that SLB can still have the competence to be used in stationary energy storage applications at the expense of some performance requirements [5]. Furthermore, Cready's research showed that SLB not only have the potential for reusing, but can even be profitable in some applications [6]. In addition, due to the volatility of renewable energy, energy storage facilities are needed to cater large-scale penetration of renewable energy including wind and solar energy without negatively affecting the grid [7-9]. In this way, the use of lower-cost SLB nor new batteries in combination with renewable energy sources may generate additional benefits in certain areas.

Since SLB has experienced a period of use, it is necessary to pay attention to the degradation of SLB during the secondary application. Tong et al, introduced the use of SLB for solar energy time shifting and demand side management in a single residence [10]. In the energy management system (EMS) proposed in ref.46, the worst-difference state-of-charge estimation scheme for battery pack is introduced, in which more computing resources are allocated to the battery cells with the worst health condition. However, the objective of this system is to maximize economic benefits and minimize energy consumption from grid, and does not take into account the degradation cost of SLB. As a result, the system verified that a system with 10kWh battery pack and 2.16kW PV arrays can reduce the dependence of the power grid by more than 64%. To optimize the operation cost of microgrids, Chen et al, proposed a smart EMS which is commonly composed of power prediction modules, energy storage system management and optimization modules [11].

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There is also a lack of consideration of the degradation cost of battery. Ju et al. considered the degradation cost of the battery in their two-layer energy management system for microgrids with hybrid energy storage, but the model used considered relatively few factors [12].

This paper proposes an EMS for SLB and renewable energy integration that can be applied to household demand side management. In order to improve the accuracy of SLB degradation prediction, this study uses the battery capacity prediction method mentioned in [13]. PV, wind energy and an SLB pack with an initial capacity of 20kWh will form an energy system connected to the grid to meet the load of a single family. The proposed energy management system aims at minimizing system operating costs, and a typical time-of-use pricing scheme will be used in this system.

2 Mathematical model of EMS

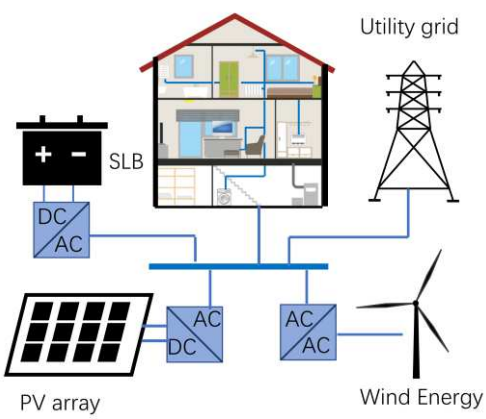

Figure 1 Configuration of the EMS

As depicted in Figure 1, the system used in this work is connected to the utility grid, which consists of a hybrid ESS, a RES system at the supply side and the aggregate load at the demand side. Similar to other microgrid systems, surely, the microgrid introduced in this paper can operate either as an islanded grid or in the grid-connected mode, which is determined by the requirements of power dispatch. This work will mainly focus on the grid-connected mode.

2.1 ESS

It is generally believed that battery used in the EVs should be retired when the capacity of the battery reaches below 80% of the initial capacity. Of course, there are still some doubts about this end of life (EOL) standard. Limited by the actual diverse driving conditions and the lack of firmness in implementing the standards by car manufacturers, the capacity of the battery at the time of retirement may be in a relatively large range [14]. The 10-30% interval of capacity loss should be a reasonable assessment range, however, 80% of the remaining capacity is still a good indicator of the capacity of SLB [15]. This article uniformly adopts this standard for the capacity of SLB.

Another important issue to considerate for SLBs is the efficiency of charging and discharging. When used in EVs, the charging and discharging efficiency of the battery is relatively high (nearly 98%) due to good operating conditions. However, the operating conditions of stationary energy storage system are relatively poor, and the charging and discharging efficiency is relatively lower than it applicated in EVs. Most of the charging and discharging efficiency of new batteries are set to 95% in the research about stationary energy storage. After several years of operation, the secondary battery has already undergone a certain degradation, so that the charge and discharge efficiency has dropped more significantly. This article refers to Heymans' research data [16] on SLBs and sets 80% as the charging and discharging efficiency.

Table 1 SLB pack parameters

SOH	80%
Charge efficiency	80%
Discharge efficiency	80%
Overall cycle efficiency	64%

2.2 Time-of-use pricing and house load

Time-of-use electricity pricing is adopted in this work. The time-of-use pricing refers to dividing the 24 hours a day into several periods according to the operating conditions of the system, and the electric price is set into different levels. Time-of-use pricing contributes to encourage users to shift peaks load demand into the low load demand period, and optimize grid power supply. It is generally accepted that 17-20h is the peak-price period, 6-17h and 21h is middle-price period and low-price period in other time period. As showed in Figure 2, The time-of-use pricing scheme adopted in this work is divided into three levels, which is 0.25$ per kWh during peak price period, 0.18$ per kWh during middle-price period and 0.10$ per kWh during low-price period. Changes in pricing strategies brought about by season changes are not considered in this study.

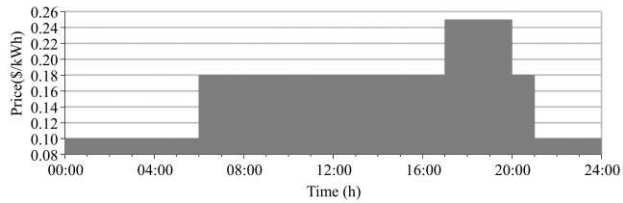

Figure 2 Time-of-use scheme

The function of ESS is to shift energy from high price period to lower price period so that the consumer's cost will be minimized. The house hold load is a typical electricity consumption mode that conforms to the time-of-use pricing, that is, more electricity energy is used during peak period and less electricity energy is used during low-price periods. In order to utilize the electric energy during peak periods, ESS will store the excess electric energy provided by RES and release it during peak hours.

2.3 RES

Volatility of power generation is the typical characteristic of RES. Wind power generated is related to wind speed and turbine height, and PV power generated is related to solar light intensity. Apart from this, the power generation of RES will have obvious seasonal variability in different regions and season. The power volatility brought by seasons is particularly obvious in PV system (more power generation in spring and summer, less power generation in winter). For the energy management of microgrid, it is necessary to predict the power generation of RES for a period of time in the future. This paper does not make specific discussion on the prediction of RES, and utilizes the data generated by RES modelling. In order to confirm to the circumstance of most regions, the solar light data used in this paper will be two sunny days and one cloudy day, but the volatility brought by season change is not take into consideration.

3 Modeling

3.1 Degradation cost model of battery

As the battery is used, the battery will gradually begin to age. The external manifestations include capacity power decay, decrease in charge and discharge efficiency, and increase in battery inconsistency. For secondary batteries, after one use, they have experienced a period of attenuation. Under the same conditions, the battery is more prone to attenuation. The use of secondary batteries must consider battery degradation, and discuss the feasibility of battery reuse from the perspective of battery degradation. The capacity loss of a battery is affected by many factors (including time, temperature, DOD, rate, etc.), of which the number of cycles and temperature have the greatest impact on the battery [17]. For a certain DOD condition, the number of cycles of the battery is almost certain. The cycling conditions of the battery also have a great impression on the attenuation of the battery, and some unreasonable attenuation often leads to an increase in the attenuation of the battery. Temperature will also affect the attenuation of the battery, which will increase at high temperatures. However, this study does not consider the impact of ambient temperature on battery life. It is assumed that the battery's thermal management system is good and can maintain a temperature of 298.15K.

For energy management in the microgrid, the SOC and SOH of the battery should be predicted to ensure safe and efficient operation. The battery state of health (SOH) directly denotes the ratio of the remaining capacity of the battery to the initial capacity. Taking battery capacity degradation into consideration, the SOH of the battery can be defined as follows:

$$S_{\mathrm{b}}(t)=\frac{Q_{cb}(t)}{Q_{rb}}\times 100\% \tag{1}$$

Where S_b represents SOH of battery, Q_{cb} denotes the current capacity of battery and Q_{rb} denotes the initital capacity of battery in kWh. Considering the capacity degradation value Q_{loss} of the battery, S_b can be expressed as:

$$S_b(t)=\frac{Q_{rb}-Q_{loss}(t)}{Q_{rb}}\times 100\% \tag{2}$$

Then the capacity loss ratio R_c can by expressed as:

$$R_c(t)=1-S_b(t)=\frac{Q_{loss}(t)}{Q_{rb}}\times 100\% \tag{3}$$

SOC which represents the proportion of the current stored energy of the battery to the maximum storage capacity is another important parameter. The SOC of the battery at a certain moment can be expressed as follows:

$$SOC_b(t)=SOC_b(t-1)-\frac{P_b(t)T_s\eta_b}{Q_{rb}S_b} \tag{4}$$

Where $P_b(t)$ is the battery average power during the time t - 1 to t，Ts is the time interval, SOC(t) represents the actual capacity at time t, and η_b is the battery charge or discharge efficiency. The loss of recyclable lithium and the growth of the solid electrolyte interface (SEI) constitute the two main causes of battery degradation. To estimate the lifetime of the battery, it is not necessary to know the exact change amount of these physical parameters in the battery. Drouilhet et al, proposed a method for estimating the lifetime of batteries subjected to depth of discharge (DOD) [18]. This method indicates that the battery life is related to the depth of discharge of the battery, and the lifetime of battery will decrease as the battery DOD increases. To use the above

method to estimate the remaining lifetime of the battery, however, the degradation process of the battery must be considered as a time-linear process through the entire life cycle of batteries. In order to minimize the prediction error, more factors should be considered to estimate the remaining lifetime of battery. The method [19] used in this study considers cycling time, test temperature, DOD and discharge rate for the cycle, which can be expressed as follows:

$$Q_{loss} = A\exp(-\frac{E_a + B\cdot C_{rate}}{RT})t^z \tag{5}$$

Where Q_{loss} is the capacity loss of battery, B is the pre-exponential factor, E_a is the activation energy in J, R denotes the gas constant, T is the absolute temperature, Crate is the charge or discharge current of battery, t is the time and z the exponent of time. Ah-throughput, which represents amount of charge through the battery, is directly proportional to t. while using Ah-throughput to replace t, Q_{loss} can be expressed as follows [17]:

$$Q_{loss} = A\exp(-\frac{E_a + B\cdot C_{rate}}{RT})A_h^{\ z} \tag{6}$$

Where Ah denotes Ah-throughput and can be expressed as (cycle number)×(DOD)×Cc. However, eq.6 is applied to 1/2 C-rate. In order to change the application field of the battery degradation model from the fixed charge and discharge mode to dynamic processes, this research refers to the approach in [20]. Q_{loss} can be expressed as follows [20]. First, after transforming eq.6, Ah can be expressed as:

$$A_h = \left[Q_{loss}\exp(\frac{E_a + B\cdot C_{rate}}{RT})/A\right]^{1/z} \tag{7}$$

And the derivative of Q_{loss} to Ah can be derived as [20]:

$$dQ_{loss}/dA_h = zA\exp(-\frac{E_a + B\cdot C_{rate}}{RT})A_h^{\ z-1} \tag{8}$$

Extending the micro-element scale to the time interval [t, t+1], eq.8 becomes:

$$\Delta Q_{loss} = Q_{loss}(t+1) - Q_{loss}(t) = \Delta A_h zA\exp(-\frac{E_a + B\cdot C_{rate}}{RT})A_h^{\ z-1} \tag{9}$$

And substituting A_h in eq.9 with eq.7, the following equation can be got:

$$\Delta Q_{loss} = \Delta A_h zA^{\frac{1}{z}}\exp(-\frac{E_a + B\cdot C_{rate}}{RT})Q_{loss}(t-1)^{\frac{z-1}{z}} \tag{10}$$

ΔA_h is the Ah-throughput during the time interval [t-1, t], which can be defined as:

$$\Delta A_h = \int_t^{t+1}|I|dt \tag{11}$$

Note that in the process of energy management is to control the dispatch of power. Therefore, we consider a charge or discharge event with the average power $P_b(t)$ during the time interval [t, t+1] and substitute voltage U (300V in the system of this paper) of the battery and the relationship between power and current into eq.11, which can be calculated as:

$$\Delta A_h = \frac{|P_b(t)|}{U}T_s\eta_b \tag{12}$$

After every time interval, we can get the corresponding battery degradation cost by simply multiplying the ratio of capacity loss to rated capacity with battery cost, which can be calculated as:

$$C_{DOB}(t) = \frac{|P_b(t)|}{U}T_s\eta_b zA^{\frac{1}{z}}e^{-\frac{E_a + B\cdot C_{rate}}{zRT}}Q_{loss}(t-1)^{\frac{z-1}{z}}C_B/Q_{rb} \tag{13}$$

Where C_B denotes initial cost of battery.

The degradation cost of the battery expressed by Eq.13 applies to both charge and discharge process. It is worth noting that the capacity loss expressed in Eq.6 is applicated at C/2 rate [17]. Considering that the volatility of the load and renewable energy is only reflected in a large time scale, such fade caused by the high C-rate in a short term would be insignificant.

3.2 EMS

The EMS of this microgrid system includes SLB. The main goal of the proposed energy management system is to coordinate the relationship of renewable energy power generation and grid power consumption for a period of time in the future, and complete the dispatch of power between grid and SLB. Generally, EMS is based on economic considerations to optimize the costs incurred during system operation. In this system, if the supply of renewable energy power generation cannot meet its demand, and the energy in the battery cannot also support the system, the excess power must be purchased from the grid. In order to establish a reliable economic analysis, the optimized objective function takes into account the degradation of the battery and the purchase cost of energy from utility grid.

This EMS consists of a nonlinear model predictive controller with the time horizon $t_n \in \{T1, T2,\ldots, TN\}$. It is easy to calculate the purchase cost of grid electricity，which only need to multiply the total amount of electricity purchased by the current electricity price. Therefore, the electricity cost within a time horizon can be expressed as:

$$C_g = \sum_n^N P_g(t_n)C_g(t_n)T_s \tag{14}$$

Where $P_g(t_n)$ is the power from the utility grid, $C_g(t_n)$ denotes the price at time tn.

The degradation cost of the battery in a time horizon can be expressed by the cumulative degradation cost of the battery in each time period, which is recorded as:

$$C_b = \sum_{n}^{N} C_{DOB}(t_n) \tag{15}$$

For the system, power balance must be maintained at all time periods. The power balance at any time can be expressed as:

$$P_g(t) + P_b(t) = P_L(t) - (P_{PV}(t) + P_W(t)) \tag{16}$$

For the power balance, $P_{PV}(t)+P_W(t)$ is the power of renewable energy generation, and $P_L(t)$ is the load power. Notes that although the power balance expressed by eq.16 is applied to any time t, t must not exceed the predefined time horizon, that is to say, $t \in \{T1, T2, \ldots, TN\}$. There is an upper limit for the power of batteries. At the same time, the power of the grid is not unlimited. The power of batteries and grids must be limited respectively:

$$P_{g,\min} \le P_g(t) \le P_{g,\max} \tag{17}$$

$$P_{b,\min} \le P_b(t) \le P_{b,\max} \tag{18}$$

At the same time, in order to smooth the battery and grid power, constraining the ramp rate of P_g and P_b:

$$LP_g \le \left|P_g(t) - P_g(t-1)\right| \le UP_g \tag{19}$$

$$LP_b \le \left|P_b(t) - P_b(t-1)\right| \le UP_b \tag{20}$$

Where:

- $P_{g,max}$ and $P_{g,min}$ is the maximum and minimum power obtained from utility grid;
- $P_{b,max}$ and $P_{b,min}$ is the maximum and minimum power generated from SLB;
- UP_g and LP_g is the maximum and minimum ramp up and down rates of power obtained from utility grid;
- UP_b and LP_b is the maximum and minimum ramp up and down rates of power generated from SLB;

The SOC limits of the battery must be restricted to prevent over-charge and over-discharged:

The SOC limits of the battery must be restricted to prevent over-charge and over-discharged:

$$SOC_{b,\min} \le SOC_b \le SOC_{b,\max} \tag{21}$$

Combining various costs and the above constraints, the optimization problem of the system at this time can be formulated as follows:

$$\begin{aligned} &\min\ C_g + C_b, t \in \{T_1, T_2, \ldots, T_N\} \\ &s.t.(16)-(20) \\ &\text{variables}: \{P_g(t_n), P_b(t_n)\} \end{aligned} \tag{22}$$

4 Simulations and discussion

In this section, the proposed EMS will be combined with case studies to analyse the performance of SLB applicated in household applications. The optimized method uses the interior-point algorithm integrated in MATLAB. The system includes one wind generator, one PV generator, an optimization period of 12h, and one hour interval will be considered. Table 2 lists the decision variables related to EMS constrains. The duration of this case is five days. The five-day PV and wind power generation, and load demand are shown in Figure 3. The relevant parameters of batteries are listed in Table 3. And the initial capacity of SLB is 20 kWh. Therefore, the actual capacity of SLB is 16 kWh. There may be different battery recycling prices under different market mechanisms. The price of SLB is in a market with great variability. This study selects 150$/kWh as the price of SLB, however, in the practice, there may be multiple SLB prices, which will be analysed later.

Table 2 Data of constrains in EMS

$P_{g,max}$, $P_{g,min}$	4, 0
$P_{b,max}$, $P_{b,min}$	5, -5
LP_g, UP_g	0, 3
LP_b, UP_b	0, 4
$SOC_{b,max}$, $SOC_{b,min}$	10, 90

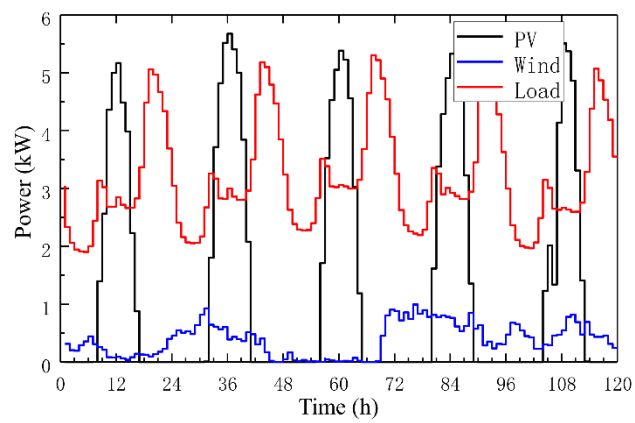

Figure 3 Power of load, PV, and wind in 120h

Figure 4 presents the system operation results over the course of five days. Normally the peak pricing period occurs briefly in the evening, in which is also the peak load demand period. During the day time, PV generator produces the adequate electric energy, for which a part is used to supported the load demand and the rest of energy is stored by the battery. It can be seen that the most expensive electric price of the whole day is in 19:00 to 21:00, and SLB releases the stored energy as much as possible during this time period. However, due to the limited size-set of battery and PV, SLB lacks more energy to support the subsequent load demand after the battery releases energy during peak hours. Figure 3 also verifies that the BMS proposed by this paper has the ability to conduct the energy dispatch between battery and utility grid with the goal of minimizing operation costs under the situation of time-of-use pricing, in which the operation cost consists of electricity cost and battery degradation cost.

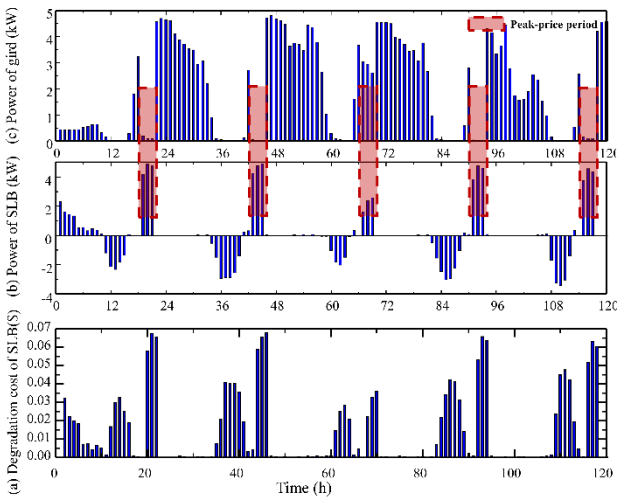

Figure 4 Results in case study

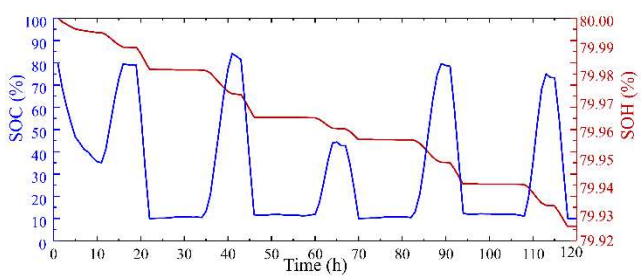

Figure 5 SOC and SOH change of SLB

As showed in Figure 4 (c) and Figure 5, the overall capacity loss of the battery reaches 0.0742% in five days. If other factors are ignored, and the battery loss is regarded as a linear process and taking 40% SOH as the EOL of the SLB, the battery will have a service life of more than 7.38 years in this application. And the electricity cost saved from the grid will reach 15.3805$. Have a certain profitability. In this paper, the total investment of the battery has reached 2400$. If the cost of other equipment and operation is ignored, it will take a total of 2.14 years to recover the cost of the battery. There is 5.24 years of profit time left. In the life cycle of the battery, this is a considerable profit time.

As summarized in Figure 6, the SLB with actual 16 kWh capacity, the energy supplied by the SLB and renewable energy reaches 19.14% during the peak period and 20.7% during off-peak period. These energy accounts for total 39.84% of load demand. Although, 60.16% load demand is supported by utility grid, only 2.48% is used in peak period. The system will reduce the dependence of the grid by approximately 40%. This research shows that SLB can be used in household energy applications and is profitable. However, evaluating the profitability of the battery requires further evaluation of the price of SLB. Now the price difference between new batteries and secondary batteries is getting smaller and smaller and the initial battery capacity decay is slower than the subsequent degradation process, so the economic advantage of SLB is relatively small compared with new batteries. However, based on this research, an important conclusion can be drawn: SLB is profitable when used in household applications connected with renewable energy.

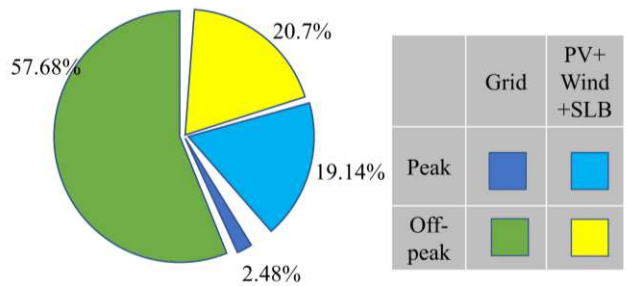

Figure 6 Energy supply source percentage in Peak and Off-peak period.

5 Conclusion

In this paper, economic and technical performance of SLB for stationary energy storage systems used in a single house is analysed. The system uses SLB to compensate for the volatility of renewable energy and to shift the load of peak hours. And EMS applied to the system considering the degradation of SLB is proposed. The EMS aims at minimizing system power costs and battery degradation costs. Based on a five-day case in time-of-use electricity price scheme and with an actual capacity of 16kWh SLB is studied. The profitability and performance of secondary batteries are studied. The final result shows that the selected configuration can reduce the dependence of the power grid by about 40%. The service life of the secondary battery can be as long as 7.38 years. And SLB is profitable when used in household applications connected with renewable energy. In future work, we will continue to analyse performance of SLB applicated in more scenarios.

6 Declaration

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Availability of data and materials

The datasets supporting the conclusions of this article are included within the article.

Authors' contributions

The author' contributions are as follows: **Jianwei Li**: Methodology, Conceptualization, Supervision, Validation. **Shucheng He** : original draft, Software, Data curation. **Qingqing Yang**: Conceptualization, Supervision, **Hongwen He**: Conceptualization, Supervision. **Zouwei Tao**: Software. **Wanke Cao**: Validation.

Competing interests

The authors declare no competing financial interests.

Consent for publication

Not applicable

Ethics approval and consent to participate

Not applicable

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