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Sustainability evaluation of second-life battery applications in grid-connected PV-battery systems

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HIGHLIGHTS

- Propose a second-life batteries' performance sustainability evaluation framework.
- Introduce a second-life battery pricing model.
- Batteries with a high initial state of health have better sustainability performance.
- Batteries with a low degradation rate have better sustainability performance.

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ABSTRACT

To open up opportunities for Second-Life Batteries (SLBs), an evaluation framework to evaluate and compare their sustainability performances is required. Accordingly, this paper frames evaluation indexes in line with sustainable development promoted by the United Nations, covering the multidimensional nature of sustainability. Additionally, we propose an SLB pricing model regarding the dynamics of SLB degradation curves to enable economic evaluation. Finally, we investigate SLBs' sustainability performances in grid-connected PV-battery systems with three typical load scenarios (double peak load, stationary load, and single peak load). The results show that their sustainability performances are primarily affected by their degradation curves, particularly the initial State of Health (SOH) and the degradation rate. A higher initial SOH and a slower degradation rate are more favorable with better sustainability performance. However, when considering the SLB purchasing costs, cheaper SLBs can be competitive even with a fast degradation rate.

1. Introduction

The Electric Vehicles (EVs) market is rapidly expanding, thanks to the favoring policy, progressing awareness of environmental sustainability, and declining battery costs [1]. The global EV stock achieved over 11 million in 2020, and its current projection indicates its stock to grow more than ten times to 145 million in 2030 [2]. Despite the contributions that the EVs can lead to the transport sector decarbonization, how to manage the overwhelmingly massive amount of batteries retired from them poses a significant challenge to the industry and government [3]. Since the batteries still have 80% of their designed capacity [4], one prospective solution is to grant them a second life that could not only extend the useful life of the used batteries but also delay or even cancel new battery manufacturing. Besides, these Second-Life Batteries (SLBs) present more affordable energy storage options, which aligns with the United Nations (UN) 2030 Sustainable Development Goal (SDG) 7 [5]. The agenda for the 2030 Sustainable Development is a universal call for action initialized by the United Nations to deliver prosperity and sustainability, covering the substantive field including but not limited to energy, well-being, and climate change. In particular, Goal 7 targets to ensure access to affordable, reliable, sustainable, and modern energy for all in response to the booming energy consumption and depleting natural resources.

Even though the SLB market seems highly appealing given its potential market size and gravity in achieving the 2030 SDGs, investors and consumers are reluctant to jump on board due to the lack of effective pricing models, reliable application evaluation, feasible distribution channels, and appropriate regulation. Consequently, the SLB market development is remarkably lagging the SLBs generation resulting in the piling-up and waste of these retired batteries. As such, ushering in a new era for SLBs market growth to build up sufficient capacity in

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order to accommodate the impending wave of EV battery retirement is an urgent call.

However, these SLBs are inferior in capacity and energy efficiency compared with new batteries due to their exhausting first life service and aging. In addition, they might suffer from more rapid and arbitrary capacity degradation issues. Thus, the SLB application is still at its infancy stage, with only research rather than commercial projects coming out in the last decade [6]. Moreover, most of the cases apply them in a stationary energy storage scenario, which is less demanding and more predictable. GM and ABB have started experimenting EV battery reuse projects for uninterruptible power supply and grid support since 2013; to showcase a sustainable life path for EV batteries, batteries retired from EVs were repurposed for a large stationary storage project with the capacity of 13 MWh by Daimler, The Mobility House, GETEC, and REMONDIS in 2016; a Vattenfall virtual power plant adopted 2600 retired battery modules from BMW's EVs, with a capacity of 2.8 MWh, to grid support in 2016 [7]. In Asia, the SLB projects are dominated by China, South Korea, and Japan [8]. For example, a joint venture called 4R Energy Corporation was founded in 2010 by Nissan and the Sumitomo Corporation to study second-life Nissan Leaf battery packs application; later in 2014, the first large-scale power storage system was established by Sumitomo using sixteen used xEV batteries for a wind farm [7]. And in 2019, a large stationary storage project for China Southern Gird was supported by BAK with the installed power output of 0.15 MW and capacity of 7.27 MWh [9]. Nonetheless, such applications are overly conservative and could not unleash the full potential of these batteries. Hence, it is necessary to explore possibilities of their applications in other scenarios through evaluating and comparing their performances.

Previous studies merely focused on the techno-economic and environmental evaluations of SLBs applications. For instance, the techno-economic model of SLBs assisting utility solar farm was proposed in [10]; the economic value of the SLBs in a hybrid wind battery plant was explored in [11]; the environmental impacts of SLBs are studied in [12]; and the economic profitability of applying retired EV batteries in a second life was investigated in [13]. However, given the unstopping tendency of global sustainable development, the framework of the evaluation needs to cover the full spectrum of sustainability rather than only the technical and economic aspects. The concept of sustainable development can be traced back to thirty years ago when the UN introduced the three pillars structure (social, economic, and environmental) for sustainable development [14]. Nevertheless, such a structure lacks the consideration of the interlinked relationships among the three pillars that include eco-efficiency, socio-environmental, socio-economic [15], and thus fails to draw a complete blueprint for a sustainable future.

Therefore, to measure the sustainability performances of SLBs in a comprehensive and systematic manner, we need to frame evaluation frameworks considering social, economic, environmental, eco-efficiency, and socio-environmental perspectives. Note that the socio-economic impact is in general practiced at a macro level, considering the society development, which is out of the scope of the SLBs application at the end-user level.

The knowledge of SLBs' price plays a vital role in determining their economic value, as indicated in many publications [13,16–18]. However, there are few reasonable SLB market pricing models to date, resulting in no explicitly market price benchmark to facilitate investors in investments and consumers in purchases. The selling price is expected to range from 44 $ to 300 $ per kWh with a high possibility of less than 100 $ per kWh and may vary from country to country [19]. In [20], the cost of used battery reconfiguration was breakdown into direct costs (e.g., battery buy down charges, rent, labor costs) and indirect costs (e.g., insurance and warranty), but its results heavily depended on the assumptions for the key factors influencing each of these costs. In [21], the authors assessed the SLB market with the assumption that the value of the retired battery was simply proportional to its remaining capacity and the new battery price. Later in [22], the authors proposed a model to calculate the time-evolving price for SLBs but neglected the evolving battery technology development's impact on its supply dynamics. Such development majorly influences battery life expectancy distribution [23] and thus the number of retired batteries. Therefore, to accurately capture the market price for SLBs, battery technology development needs to be incorporated into the pricing model. Also, the availability of retired batteries for repurposing is correlated to the price of SLBs, as more retired batteries would lead to less purchase cost based on the principles of microeconomics. As a result, it is necessary to estimate the market size of SLBs, which requires the knowledge of EV market size and battery replacement rate [22].

Empowered by the evaluation framework and SLB pricing model, investors and consumers can gain more confidence in SLB implementation projects, accelerating the completion of the SLB value chain. Such a value chain should be closed-loop, including the upstream and downstream stakeholders from new battery manufacturing to battery application, reuse, and recycling. In this respect, market players and policymakers are allowed to explore market mechanisms, investigate feasible distribution channels, benchmark implementations, and establish policies to further facilitate the market.

Motivated by the challenges mentioned above, this study proposes an evaluation framework of SLBs' sustainability performance and further examines their performance in grid-connected PV-battery systems. Unlike the existing literature, the pricing model proposed in this paper considers the external factors (such as the EV battery resourcing and repurposing costs) and internal factors (including the initial SOH and degradation tendency) affecting the SLB prices in a comprehensive manner. The SLB prices obtained can then be applied in the economic evaluation for SLB applications. Apart from the widely studied economic and environmental impact analysis of SLB applications, we present a sustainability evaluation framework that covers the multidimensionality of sustainability. This evaluation framework is then applied to assess the performances of SLBs in a grid-connected PV-battery system, which are more economically beneficial than solely implementing PV generation or batteries [24]. Moreover, the variations in both load and SLB profiles are incorporated by investigating three typical load scenarios (including stationary load, single peak load, and double peak load scenarios) and SLBs with different degradation curves.

Fig. 1 demonstrates the structure of this paper and the rest of this paper is organized as follows. The following section unfolds the methods, in which Section 2.1 develops the SLB pricing model and Section 2.2 provides the evaluation model. After that, Section 3 demonstrates the case study using the models developed in Section 2. Finally, Section 4 presents the conclusion and future work suggestions.

2. Methods

2.1. SLB pricing model

There are two major costs contributing to the production costs for SLBs. One is the resourcing cost paid for buying retired batteries. This cost is sensitive to the price of new batteries and the condition of these retired batteries. The other cost is the repurposing cost of transforming these retired batteries into SLBs. This cost is affected by labor, capital, and technology costs incurred in the battery repurposing process.

Given the variety in size, chemistry, and shape of EV batteries in the market, it is arduous to construct production cost models for every one of them. A more realistic way is to develop a general production cost model that offers the average cost per KWh (AC) for SLB production with the unit of $ per kWh, which can be then adopted as the benchmark unit price for SLB selling.

Unlike new batteries, SLBs may have different aging tendencies. Degradation curves of SLBs can describe the process of their aging, and can be well predicted using the techniques in [25–28]. Thus, in calculating a specific SLB's price c_i, we incorporate the degradation curve

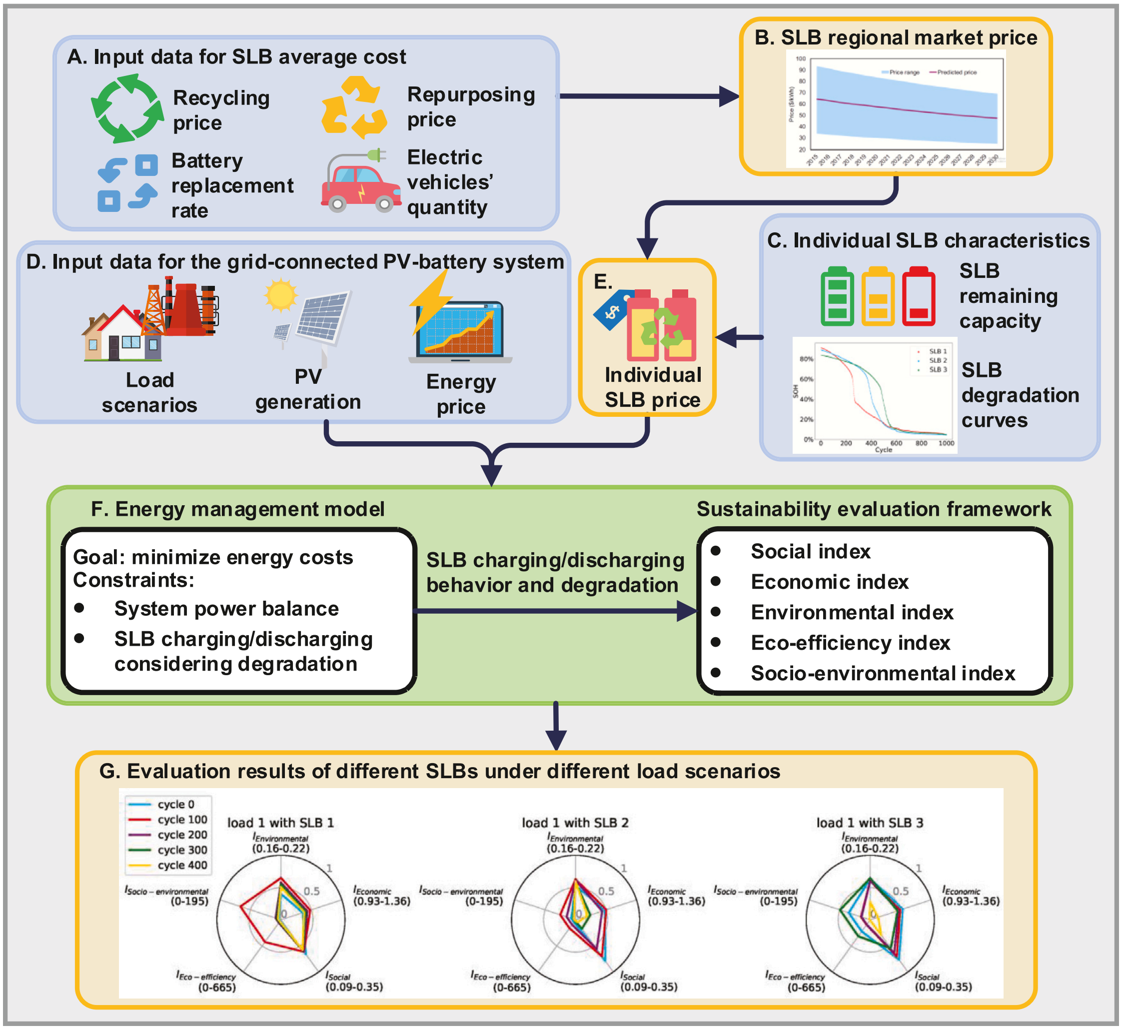


Fig. 1. Structure of the sustainability evaluation of second-life battery applications in grid-connected PV-battery systems.

factor $\alpha_{\mathrm{dc,i}}$ to account for the heterogeneity in the aging tendencies among SLBs as in (1):

$$c_i = AC \times \alpha_{\mathrm{dc,i}} \times Q_i, \tag{1}$$

where Q_i is the remaining capacity for SLB i, $\alpha_{\mathrm{dc},i}$ is defined as the ratio of accumulated State of Health (SOH) for SLB i $SOH_{i,cycle}$ during its second life to the accumulated SOH for the market average SLBs $SOH_{av,cycle}$ during their second life, and can be written as

$$\alpha_{\mathrm{dc},i} = \frac{\sum_{cycle=1}^{K_i} SOH_{i,cycle}}{\sum_{cycle=1}^{K} SOH_{av,cycle}}, \tag{2}$$

where K_i is the cycle number when the value of SOH reduces to 40% for SLB i (note that the useful life a SLB starts at the initial SOH inherited from its first life and ends when its SOH drops to 40% [29]). Likewise, K is the cycle number when the value of SOH reduces to 40% for the market average SLBs. Therefore, $\alpha_{\mathrm{dc},i}$ measures the relative capability of an individual SLB i during its second life to that of the market's average.

2.1.1. SLB production costs

In this subsection, we introduce an SLB production model to obtain the AC that appeared in (1). Here, we consider the two key factors contributing to the SLBs' production costs: resourcing costs and repurposing costs for the retired batteries. We recognize that other factors may affect production costs, such as the supply chain condition and labor costs. Nevertheless, we consider these two factors for the sake of simplicity since it is not difficult to add other factors into the model. And the SLB production total cost ($TC(t)$) in the tth year can be written as

$$TC(t) = \omega_1(t)Q_r(t) + \omega_2(t)Q_{SLB}(t), \tag{3}$$

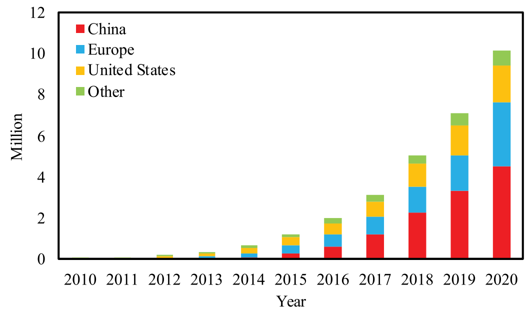
where $Q_r(t)$ is the capacity of retired batteries available for a second-life, $Q_{SLB}(t)$ is the capacity of the SLBs, $\omega_1(t)$ is the unit price for resourcing the retired batteries, and $\omega_2(t)$ is the unit price for repurposing them in the tth year.

A Cobb–Douglas production function describes the relationship between the production outputs and inputs [30]. In our case, we assume that there are two input factors affecting $Q_{SLB}(t)$, including $Q_r(t)$ and the battery repurposing technology efficiency $T(t)$. $Q_{SLB}(t)$ can be calculated as

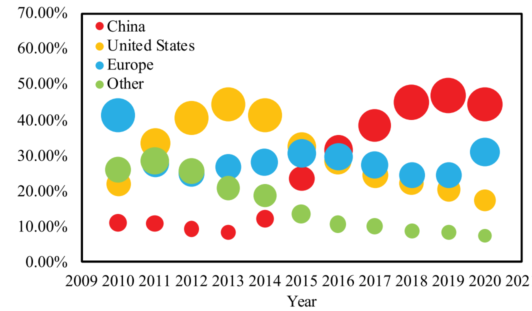
$$Q_{SLB}(t) = Q_r(t)^a T(t)^b, \tag{4}$$

where $a > 0$ and $b > 0$ are the elasticity parameters accounting for the quantity of retired batteries and repurposing technology efficiency. $T(t)$ ranges from 0 to 1, with its value of 1 suggesting that the technology is completely ideal with a 100% success rate of turning the retired batteries into SLBs. On the contrary, 0 implies no successful SLBs repurposed from the retired ones. From (3) and (4) we can rewrite Eq. (3) as

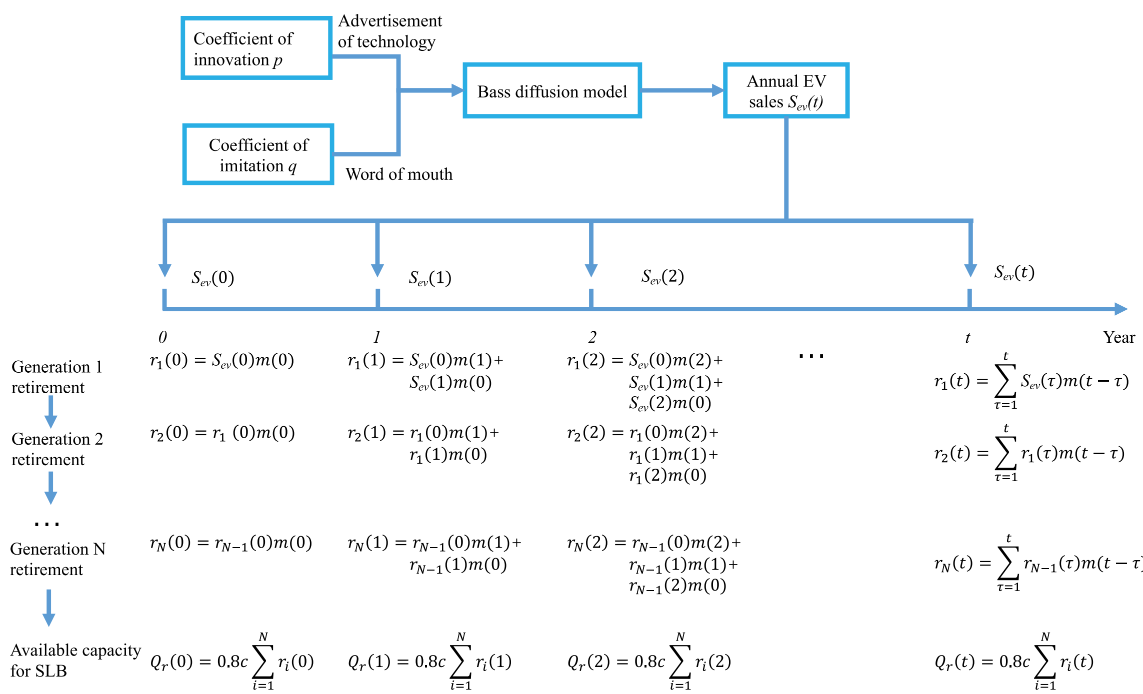
$$TC(t) = \omega_1(t)Q_r(t) + \omega_2(t)Q_r(t)^a T(t)^b. \tag{5}$$



(a) The global EV sales from 2010 to 2020 .



(b) The market share of the global EV sales .



(c) Illustration of the battery replacement model.

Fig. 2. The global EV annual sales, market share, and the battery replacement model. The global EV annual sales data and market share data are obtained from [2].

Then, the average cost per KWh in the tth year $AC(t)$ can be calculated as

$$AC(t) = \frac{TC(t)}{Q_r(t)} = \omega_1(t) + \omega_2(t)Q_r(t)^{a-1}T(t)^b. \tag{6}$$

And $AC(t)$ can be adopted as the unit selling price for SLBs in the market in the tth year.

2.1.2. SLB capacity prediction model

This subsection develops a prediction model to estimate the retired batteries' available capacity for a second life $Q_r(t)$ appeared in (6). $Q_r(t)$ is primarily influenced by EVs' quantity and battery replacement frequency in the tth year. The EV's quantity can be calculated by fitting the historical EV sales data into the Bass model, which is a widely implemented model that describes the process of a new product getting accepted in a population [31]. And a battery replacement model is developed to estimate the battery replacement frequency.

2.1.3. Global EV annual sales

The knowledge of the global EV sales is required to estimate the annual batteries retired from them. Fig. 2(a) demonstrates the yearly global EV sales growth from 2010 to 2020, revealing an exponentially growing tendency. Such aggressive expansion of the EV market is triggered by global concerns about climate change and fossil fuel depletion.

Regardless, the progress of regional EV market development varies due to different local levels of public acceptance and policy support as shown in Fig. 2(b), where the bubble size represents the market share of that region. China's position appears firmer with its dedicated commitment to hitting its carbon peak no later than 2030 [32], making it the largest EV market globally today. The second-largest market is Europe, where the growth is relatively steady compared to China. However, the United States witnessed a shrinking market share at the global level as fossil-fueled cars still dominate the automobile market in that region. And the rest of the world is falling behind, owning less than 10% market share in 2020.

Transportation costs come to play a primary role in determining the profitability margin for SLBs. In addition to distance, the safety risks associated with the degraded batteries demand extra maintenance costs making it less economical. On top of this, the Covid-19 pandemic has significant adverse effects on the global supply chain, accelerating and magnifying its existing problems. Thus, we expect the SLBs to be circulated at a regional level, with local players largely impacting their prices. In this regard, the information of previous analyzed regional EV annual sales is very important.

2.1.4. Bass model

The Bass model or Bass diffusion model, a widely used model to describe the process of a new technology/product adopted by the population [22,31], can describe the EV adoption process. Two groups of players, namely the imitators (those who have not adopted EVs yet) and the innovators (the existing EV users), interact with each other to stimulate the process. Such interactions can be described as below:

$$\frac{a(t)}{1-A(t)} = p + qA(t), \tag{7}$$

where $a(t)$ is the proportion of the population that adopts EVs in the tth year, $A(t)$ is the accumulated fraction of the population that has adopted EVs in the tth year, p is the coefficient of innovation, and q is the coefficient of imitation (the extent that the new adopters are influenced by the old users). If we denote $N(t)$ as the proportion of the remaining non-adopters for EVs in the tth year, then

$$N(t) + A(t) = 1. \tag{8}$$

Also, the relationship between $a(t)$ and $A(t)$ is

$$a(t) = \frac{\mathrm{d}A(t)}{\mathrm{d}t} = -\frac{\mathrm{d}N(t)}{\mathrm{d}t}. \tag{9}$$

From (7) and (9), we can obtain [31]

$$N(t) = \frac{e^{-(p+q)t} + \frac{q}{p}e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}, \tag{10}$$

$$A(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}, \tag{11}$$

$$a(t) = \frac{\frac{(p+q)^2}{p}e^{-(p+q)t}}{(1 + \frac{q}{p}e^{-(p+q)t})^2}. \tag{12}$$

Then, the annual EV sales $S_{ev}(t)$ in the tth year can be defined as [22]

$$S_{ev}(t) = a(t) \cdot S, \tag{13}$$

where S is the all-time total amount of EV sales. And the value of p, q, and S can be determined through fitting historical EV sales data to Eq. (13).

2.1.5. Battery replacement model

Since batteries' capacity would deteriorate during usage, as a result, the EV owners might consider replacing inefficient batteries with new ones to ensure their experience. Such replacements are common regarding electronic devices when buying a new one would cost more than replacing the old one. As a result, the retired batteries for a second life in the tth year needs to take account of all the battery replacements occur in that year. These replacements are affected by the previous EV sales $S_{ev}(i), i = 0, 1, 2, \ldots, t$ and the corresponding battery replacement rate. In this respect, we develop a battery replacement model to calculate the replacement rates.

The replacement rate of the batteries evolves along with the battery technology development. To account for the changing replacement rate, we use the survival function demonstrated in [33], which has an average service life μ and a replacement rate determined by the value of the shape parameter h. Such survival function $M(t)$ refers to the proportion of survivors remaining at time t, from an original installation of unit amount at time zero [34]. Here, $M(t)$ is adopted to describe the probability that a battery remains in use until the tth year after purchase.

$$M(t) = \frac{\Phi(\omega t/\mu - h)}{\Phi(-h)}, \tag{14}$$

$$\omega = h + \phi(-h)/\Phi(-h), \tag{15}$$

where $\phi(.)$ denotes the standard normal probability density function, and

$$\Phi(x) = \int_{z=x}^{\infty} \phi(z)\mathrm{d}z. \tag{16}$$

Then $f(t)$ is introduced as the unconditional probability that a battery is retired and replaced in the tth year after purchase. Thus, its relationship with the survival function $M(t)$ is

$$M(t) = 1 - \int_{x=0}^{t} f(x)\mathrm{d}x. \tag{17}$$

Derived from (14) and (17), we can obtain

$$f(t) = \frac{\omega\phi(\omega t/\mu - h)}{\mu\Phi(-h)}. \tag{18}$$

Furthermore, another relationship between $M(t)$ and $f(t)$ is

$$f(t) = M(t) \times m(t), \tag{19}$$

where $m(t)$ is the replacement rate in the tth year after purchase. In general, $m(t)$ is monotonically increasing, but can also be constant when h tends to $-\infty$. And it can be written as

$$m(t) = \frac{\omega\phi(\omega t/\mu - h)}{\mu\Phi(\omega t/\mu - h)}. \tag{20}$$

Finally, the accumulated retired batteries for each year can be calculated through the process demonstrated in Fig. 2(c). $r_i(t)$ measures the quantity of retired batteries, while $Q_r(t)$ represents the capacity of these batteries in the tth year. Thus, the parameter c is adopted to convert the quantity of retired batteries to their capacity with the unit of kWh per battery. Assume that the ith generation batteries would be replaced immediately after retirement with those of the $(i+1)$th generation. And generation 0 batteries are the original ones that come with the EVs, suggesting that the quantity of these batteries in one year is equal to the quantity of the EV sales in that year. The EV itself would be retired after a number of battery replacements, which indicates that the number of battery replacements is finite. Last but not least, a discounted factor 0.8 is added in the $Q_r(t)$ calculation to account for capacity degradation, as most batteries would be retired when their capacities drop to 80% of their designed values [4].

2.2. SLB sustainability evaluation framework

This section aims to develop a sustainability evaluation framework to evaluate SLB applications. First, we demonstrate a general operation model to enable the simulation of SLB performances under different load scenarios. Then, we unfold the sustainability evaluation framework by framing indexes to measure SLB applications' social, economic, environmental, eco-efficiency, and socio-environmental impacts. It is worth noting that multiple evaluation indexes may emerge from SLB application practice with improved availability of industry data. This study endeavors to introduce one index for each sustainability aspect. Also, the socio-economic aspect is excluded since it is generally practiced at a macro level regarding social development, which is out of the SLB applications' scope.

2.2.1. SLB operation modeling

Perspective application scenarios for SLBs include but are not limited to energy arbitrage, peak load shaving, and stationary storage, presenting massive value in the global energy transition into a carbon-neutral future. Since renewables would be the leading driving force in this transition, it is desirable to implement SLBs to support the power grid and hedge the uncertainty with renewable generation. Accordingly, we develop an SLB operation model with the existence of PV generation. Assume that the SLBs are positioned as energy storage systems for end-users, whose primary goal is to minimize the energy costs associated with buying power from the power grid. Moreover, these end-users have stand-by solar generation and can trade power with the grid, including buying and selling power.

Practically, techniques such as Model Predictive Control (MPC) are needed to manage the uncertainty in operation with the renewable generation and power demand [35,36]. Nevertheless, for the sake of evaluating these SLBs' performance, we adopt the average curves of renewable generation and power demand so that the average performance under these known information can be pre-checked. In this respect, minimizing the daily energy costs is equivalent to solving the following optimization problem:

$$\min \quad \sum_{t=0}^{23} c_{\text{power}}(t) \cdot P_{\text{grid}}(t), \tag{21}$$

$$\text{s.t.} \tag{22}$$

$$P_{\text{grid}}(t) + P_{\text{PV}}(t) + P_{\text{dis}}(t) = P_{\text{d}}(t) + P_{\text{ch}}(t), \tag{23}$$

$$P_{\text{b}}(t) = \eta\left(SOH(0)\right) \cdot P_{\text{ch}}(t) - \frac{P_{\text{dis}}(t)}{\eta\left(SOH(0)\right)}, \tag{24}$$

$$E(t+1) = E(t) + P_{\text{b}}(t), \tag{25}$$

$$0 \le P_{\text{ch}}(t) \le \frac{1}{3} \cdot SOH(0) \cdot Q_{\text{rated}}\lambda(t), \tag{26}$$

$$0 \le P_{\text{dis}}(t) \le \frac{1}{3} \cdot SOH(0) \cdot Q_{\text{rated}}\left(1 - \lambda(t)\right), \tag{27}$$

$$SOC(t) = \frac{E(t)}{Q_{\text{rated}} \cdot SOH(0)}, \tag{28}$$

$$SOC_{\min} \le SOC(t) \le SOC_{\max}, \tag{29}$$

where $\lambda(t)$, $P_{\text{ch}}(t)$, $P_{\text{dis}}(t)$ and $E(t)$ are the decision variables. $c_{\text{power}}(t)$ is the power cost at time t, $P_{\text{grid}}(t)$ is the power imported from or sold back to the grid, $\lambda(t)$ is a binary variable to indicate the charging status of the SLB at time t (with the value of one indicating charging and zero indicating not charging), $P_{\text{PV}}(t)$ is the solar generation at time t, $P_{\text{d}}(t)$ is the load at time t, $P_{\text{dis}}(t)$ and $P_{\text{ch}}(t)$ are the discharging/charging power at time t, $SOH(0)$ is the SOH at the beginning of the day (SOH is the State of Health of the battery representing the ratio of the available capacity to the original capacity, and its value remains unchanged during the day and is updated every other day), $\eta\left(SOH(0)\right)$ is the roundtrip efficiency, $P_{\text{b}}(t)$ is the SLB power output ($P_{\text{b}}(t) > 0$ suggests charging power and $P_{\text{b}}(t) < 0$ suggests discharging power), Q_{rated} is the original capacity value, SOC is the State of Charge (SOC) at time t as defined in (28), $SOC_{\min}$ and $SOC_{\max}$ are the lower and upper SOC limits, $E(t)$ is the energy level of the SLB at time t, and 23 is the end time of the operation period. Different from the unit of t in Section 2.1, i.e., a year, here the unit of t is an hour.

Note that the degradation also has an adverse impact on the battery's roundtrip efficiency, since the associated increased internal resistance would cause energy loss during the charging/discharging process. To incorporate this dynamic in roundtrip efficiency, the relationship between it and the SOH is given in Table 1, in which two commonly used Li-ion battery types are presented, including Lithium Nickel Manganese Cobalt oxide (NMC) and Lithium Iron Phosphate (LFP). We adopt the LFP as the battery type in this study as LFP batteries have superior cycle life compared with NMC batteries and are more promising for a second life.

The balance between the energy supply and demand is expressed in (23). The energy level at time $t+1$ $E(t+1)$ equals to its previous value $E(t)$ plus the amount of the charged power $\eta\left(SOH(0)\right)P_{\text{ch}}(t)$ minus the amount of the discharged power $\frac{P_{\text{dis}}(t)}{\eta(SOH(0))}$ as shown in (25). Eqs. (26) and (27) restrict the charging and discharging power of the battery from exceeding 1/3 of its available capacity as required by battery manufacturers [37].

The operation (charging/discharging) of these batteries would cause their capacity degradation [38], which affects their available energy capacity and the maximum capability in charging/discharging as shown in constraints (26)–(28). Assume that we know the SOH of an SLB before it is put into operation as $SOH(0)$, then we can estimate the corresponding cycle number $cycle(t = 0)$ given by the degradation curves in Fig. 3. Meanwhile, we define the incremental cycle occurred during the operation as $\Delta cycle$, which can be calculated by dividing the accumulated charging/discharging values of the batteries by the throughout power of a full charge–discharge cycle in (30). The throughout power of a full charge–discharge cycle is defined as two times the value of its available capacity. Then, the accumulated number of cycles at time $t = 24$ $cycle(t = 24)$ is calculated by adding the incremental cycle $\Delta cycle$ to $cycle(t = 0)$ as presented in (31).

Table 1
Polynomial round-trip efficiency model [39].

NMC	$-0.2303(1 - SOH) + 0.9582$
LFP	$-0.1532(1 - SOH)^2 + 0.003923(1 - SOH) + 0.9530$

$$\Delta cycle = \frac{\sum_{t=0}^{23}|P_{\text{b}}(t)|}{2 \cdot Q_{\text{rated}} \cdot SOH(0)}, \tag{30}$$

$$cycle(t = 24) = \Delta cycle + cycle(t = 0). \tag{31}$$

Finally, we can obtain the updated value of SOH for the next day with the value of $cycle(t = 24)$ and the degradation curves shown in Fig. 3. Also, the capacity degradation ΔQ due to the operation can be calculated as the Q_{rated} multiplied with the difference of $SOH(24)$ and $SOH(0)$ in (32).

$$\Delta Q = Q_{\text{rated}} \times (SOH(24) - SOH(0)). \tag{32}$$

2.2.2. The sustainability evaluation framework for SLBs

This subsection illustrates the sustainability evaluation framework for SLBs using the operation data offered by the optimization model from the previous subsection. Such a framework integrates five indexes measuring the social, economic, environmental, eco-efficiency, and socio-environmental impacts.

Social index. The social impact evaluation quantifies the effects of SLB application on the people and community's well-being. Regarding battery operation, safety is a primary concern as fires and explosions accidents might occur, posing significant threats to the users and local communities. Particularly, extra caution is required for the operation of SLB regarding their deteriorated capacity and compromised capability. Thus, we develop an index that measures the SLBs' safety to facilitate end-users adopting SLBs. This index could reflect the social impacts of SLBs since a low battery safety level could indicate a negative social impact on people and the community. The less frequently changes between charging/discharging status and the lower power output magnitude, the safer the batteries are. And it is defined as the accumulated absolute value of an SLB's power output divided by its flipping frequency during a particular operation period:

$$\begin{aligned} I_{social} &= \frac{\text{accumulated SLB output power}}{\text{flipping frequency} \cdot Q_{\text{rated}}} \\ &= \frac{\sum_{t=0}^{23}|P_{\text{b}}(t)|}{\frac{1}{2} \cdot \sum_{t=0}^{22}\left(1 - \frac{P_{\text{b}}(t)P_{\text{b}}(t+1)}{|P_{\text{b}}(t)P_{\text{b}}(t+1)|}\right) \cdot Q_{\text{rated}}}, \end{aligned} \tag{33}$$

where flipping frequency is the number of changes between charging and discharging states.

Economic index. The economic impact evaluation assesses the economic benefits gained by adopting SLBs. SLBs function as standby energy storage in the PV-battery energy system to support load shifting and accommodate renewable generation (solar power in this case) in the energy system since this study takes the end-user's perspective. Accordingly, the cost for the system with an SLB consists of energy cost and battery degradation cost. Comparatively, the system without the SLB only owes the energy cost. And the economic index is defined as the ratio of cost without an SLB to that with an SLB as shown below:

$$I_{economic} \tag{34}$$

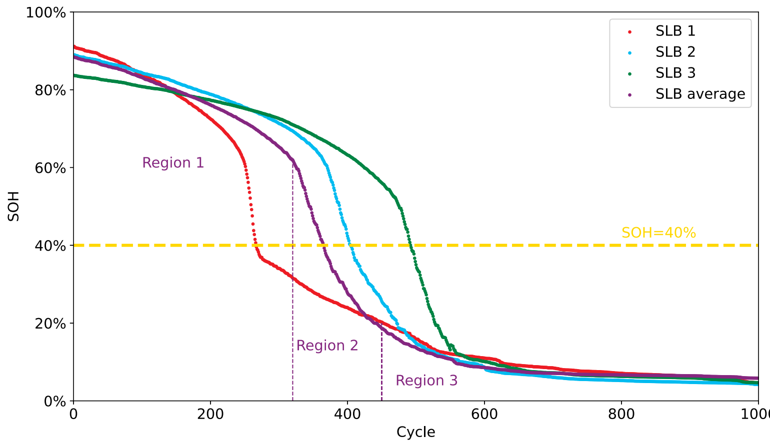


Fig. 3. Three representative commercial battery degradation curves from the industry. These batteries (SLB 1, SLB 2, and SLB 3) are retired LFP batteries. And assume that the SLB average is the average degradation curve in the market. Each degradation curve can be approximately divided into three regions by the two turning points. For instance, the three regions for the SLB average are demonstrated. The end of the second life for SLB 1, SLB 2, and SLB 3 comes around cycle 266, cycle 403, and cycle 491, respectively, when their SOHs reduce to 40%.

$$= \frac{\text{energy cost without SLB}}{\text{energy cost with SLB} + \text{degradation cost}}$$
$$= \frac{\sum_{t=0}^{23} c_{\text{power}}(t) \cdot P'_{\text{grid}}(t)}{\sum_{t=0}^{23} c_{\text{power}}(t) \cdot P_{\text{grid}}(t) + AC \cdot \alpha_{\text{dc}} \cdot \Delta Q},$$

where AC is the market unit selling price for SLBs in the operating year, α_{dc} is the degradation curve factor, ΔQ is the capacity loss, and $P'_{\text{grid}}(t)$ is the grid cost that occurs at time t in case of no SLBs that complies with the following equation:

$$P'_{\text{grid}}(t) + P_{\text{PV}}(t) = P_{\text{d}}(t). \quad (35)$$

Environmental index. The environmental impact evaluation measures the influence of SLBs adoption on the environment (i.e., water, air, and land). In our case, the explicit environmental impact stems from Green House Gas (GHG) emissions. Thus, the environmental index is defined as the reduction of GHG emissions realized by adopting SLBs, and can be written as

$$I_{environmental} \quad (36)$$
$$= \frac{\text{GHG savings -GHG emission}}{\text{GHG emission}}$$
$$= \frac{\sum_{t=0}^{23} P_{\text{PV}}(t) \cdot \epsilon_{fossil} - \Delta Q \cdot \epsilon_{battery}}{\Delta Q \cdot \epsilon_{battery}},$$

where ϵ_{fossil} is the unit GHG emission for power generation by fossil fuels and $\epsilon_{battery}$ is the unit GHG emission for new battery production.

Social, economic and environmental cross indexes. The nexus between economic and environmental impacts results in eco-efficiency, suggesting a highly efficient utilization of environmental resources during economic activities. Regarding SLBs, the energy efficiency can be used to evaluate their eco-efficiency impact, defined as the ratio of energy stored to its degraded capacity.

$$I_{eco-efficiency} = \frac{\sum_{t=0}^{23} P_{\text{dis}}(t)}{\Delta Q}. \quad (37)$$

$$I_{socio-environmental} \quad (38)$$
$$= \frac{\text{renewable energy utilized by the SLB}}{\text{battery degradation}}$$
$$= \frac{\sum_{t=0}^{23} P_{\text{ch\_PV}}(t) \cdot \eta\,(SOH(0))^2}{\Delta Q},$$

where $P_{\text{ch\_PV}}(t)$ is the amount of PV power charged into the SLB, and $\eta\,(SOH(0))^2$ is added to account for the energy loss during the charging and discharging process. $P_{\text{ch\_PV}}(t)$ can be calculated by

$$P_{\text{ch\_PV}}(t) \quad (39)$$

$$= \begin{cases} \max\left(P_{\text{PV}}(t) - P_{\text{d}}(t), 0\right) \cdot \lambda(t) & P_{\text{grid}}(t) > 0 \\ \max\left(P_{\text{PV}}(t) - P_{\text{d}}(t) + P_{\text{grid}}(t), 0\right) \cdot \lambda(t) & P_{\text{grid}}(t) < 0. \end{cases}$$

Table 2
The parameters of the Bass model.

Region	China	Europe	USA
S	1.98e+08	1.815e+08	5.931e+09
p	0.002737	0.001476	0.0001107
q	0.449	0.4854	0.1684
R^2	0.9972	0.9986	0.9948
Quantity of retired batteries for a second life in 2030	13702379	12093245	3831920

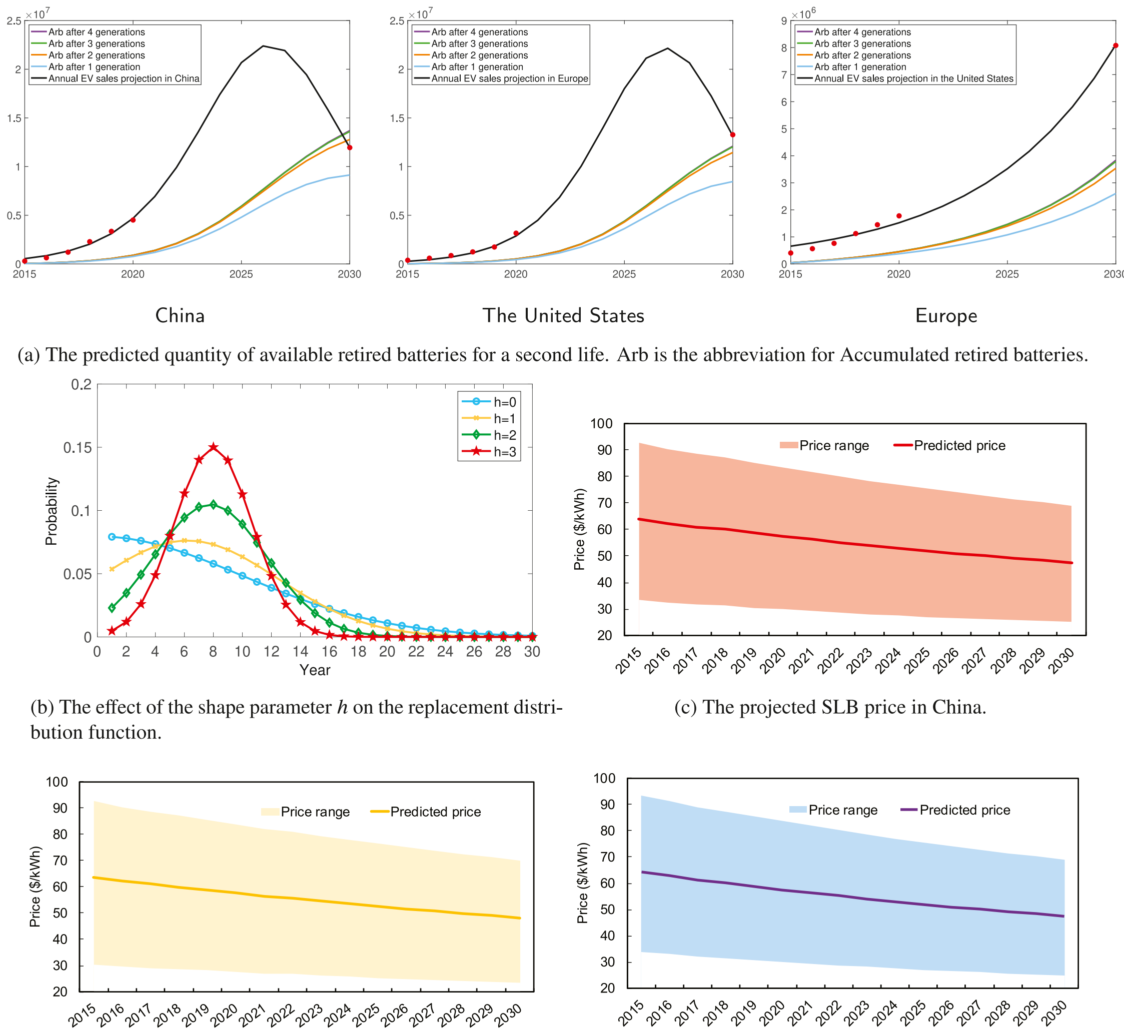
When $P_{\text{grid}}(t) > 0$ (the end-user buys power from the grid) and $\lambda(t) = 1$ (SLB charges power at time t), the excessive power from the PV generation after meeting the end-user's demand would all be charged into the SLB. In this case, $P_{\text{ch\_PV}}(t) = P_{\text{PV}}(t) - P_{\text{d}}(t)$ if $P_{\text{PV}}(t) - P_{\text{d}}(t) > 0$, otherwise, it is equal to 0. When $P_{\text{grid}}(t) < 0$ (the end-user sells power to the grid) and $\lambda(t) = 1$ (SLB charges power at time t), the excessive power from the PV generation after meeting the end-user's demand would partially be charged into the SLB and partially sold to the grid. In this case, the value of $P_{\text{ch\_PV}}(t) = P_{\text{PV}}(t) - P_{\text{d}}(t) + P_{\text{grid}}(t)$ if $P_{\text{PV}}(t) - P_{\text{d}}(t) + P_{\text{grid}}(t) > 0$, otherwise, it is equal to 0.

3. Results and discussion

This section demonstrates and analyzes the simulation results based on the previous sections. First, the SLB price in 2030 is estimated, since year 2030 marks a turning point for global sustainable development given the UN 2030 SDGs. After knowing the price, we apply the sustainability evaluation framework to evaluate the SLBs' performance under different load scenarios.

3.1. 2030 SLB price estimation

We predict the SLBs capacity in China, Europe, and the USA in 2030. They are the primary market players with growing solid momentum regarding the previous global EV market sales analysis. Considering the profound impact of the 2030 SDGs, we assume that the International Energy Agency (IEA) sustainable development scenario is more likely to happen [2]. Thus we adopt the predicted annual sales in the IEA sustainable development scenario to fit the EV sales development curves in Fig. 4(a). The year 2015 marks the turning point for EV sales, which had a relatively small market before 2015 but witnessed exponential



(a) The predicted quantity of available retired batteries for a second life. Arb is the abbreviation for Accumulated retired batteries.

(b) The effect of the shape parameter h on the replacement distribution function.

(c) The projected SLB price in China.

(d) The projected SLB price in the United States.

(e) The peojected SLB price in Europe.

Fig. 4. Properties of the 2030 SLB price estimation parameters and simulation results.

growth afterward. Accordingly, we adopt the historical annual sales data from 2015 to 2020 to fit the development curve in Fig. 4(a) (the black lines), where the exact values of the parameters are presented in Table 2. The red dots are the historical annual sales data from 2015 to 2020 and the 2030 annual sales in the IEA sustainable development scenario from [2].

Next, to obtain the replacement rate of these EV batteries, we need to determine the values of the two parameters in the battery replacement model. Fig. 4(b) shows the flexibility in the replacement distribution shape provided by the shaping factor h, where the average service life is set to be eight years (μ=8, which is the commonly expected life expectancy of EV batteries [6]) and the shape factor h ranges from 0 to 3. As the value of h increases, the distribution function concentrates more around the average service life, and the probability of retiring at the average service life is higher. Assume that a higher value of h represents a more advanced battery technology since the battery's reliability is more guaranteed with a lower possibility of retiring at either an earlier or a later stage. The knowledge of EV battery full lifecycle data covering the whole industry is required to obtain accurate values of the shape factor, which is challenging to acquire at the current stage due to the lack of data recording. Thus, we consider a linear series of values for the shape factors regarding different generations to achieve an acceptable approximation, which are 0, 1, 2, and 3 for generation 1, 2, 3, and 4.

Finally, the accumulated quantity of retired batteries prediction can be estimated through the replacement model along with the knowledge of annual EV sales and battery replacement rates as presented in Fig. 4(a) (the colored curves). For all three regions, the accumulated quantity tends to converge after three generations of replacements in 2030. For the sake of simplicity, assume that each battery pack has a capacity of 80 kWh (c = 80 kWh per battery), then we can anticipate roughly 1096, 967, and 307 GWh retired batteries for second-life usage in China, Europe, and the USA, respectively.

The value of ω_1 and ω_2 can be easily observed and extracted from the market once the digitalization of the market is achieved, making the transaction information along the SLB value chain available. Factors such as the new battery price fluctuation and battery technology development may affect the unit price for resourcing retired batteries. Here, we assume that the primary factor is the new battery price fluctuation since it can reflect the battery technology development and market dynamics. As a result, the evolving rate of ω_1 is consistent with the new battery price dropping rate in this study. We adopt 2% as the dropping rate since the battery price reduction will significantly slow down since 2020 [40]. The unit price for repurposing retired batteries consists of labor, factory operation, and other costs that occurred during the process. These costs are more or less affected by the inflation rate. Thus, we assume the changing rate of ω_2 in a specific region is consistent with the inflation rate of that region [41–43]. Given that the range of used battery salvage value is 19–72 \$/kWh and the range of repurposing costs is 25–36 \$/kWh with the new battery price as 150 \$/kWh [44], we consider three scenarios: a base scenario with $\omega_1(0) = 50$ \$ and $\omega_2(0) = 30$ \$, a low price scenario with $\omega_1(0) = 19$ \$ and $\omega_2(0) = 25$ \$, and a high price scenario with $\omega_1(0) = 72$ \$ and $\omega_2(0) = 36$ \$ (note that the starting year is 2015 in our prediction model as shown in Fig. 4 and the number 0 in $\omega_1(0)$ and $\omega_2(0)$ marks the year 2015). Assume that the values of T, a, and b are fixed from 2015 to 2030 with $T = 0.6$, $a = 0.95$, and $b = 0.05$. More accurate T, a, and b can be obtained through fitting Eq. (4) with available data on Q_r and Q_{SLB}.

The market average price evolutions of SLBs in China, the United States, and Europe are given in Fig. 4, where the price range spreads between the price projections in high and low price scenarios and the predicted price in the base scenario is depicted as the line in the middle. The results show that the price ranges from 23 \$/kWh to 67 \$/kWh under different scenarios in 2030. The predicted price agrees with the selling price in [19], which is expected to range from 44 \$/kWh to 300 \$/kWh with a high possibility of less than 100 \$/kWh and may vary from country to country. And in the base scenario, the price is approximately 48 \$/kWh for all three regions in 2030. Without compromising the accuracy of our evaluation, we select 48 \$/kWh as the SLB unit price for the subsequent economic evaluation.

3.2. SLB sustainability performance under different load scenarios

Fig. 5(a) presents three typical load scenarios [45], including scenario 1 as a double peak load (commercial users), scenario 2 as a stationary load (light industries), and scenario 3 as a single peak load (large industries and government utilities). And Fig. 5(b) shows the hourly solar generation and energy price. The weighted average Green House Gas (GHG) emissions per kWh during EV battery production is approximately 65 kg per KWh [46]. Electricity consumed at the low voltage level produces 447 gCO2eq/kWh [47] in average. Assume that Q_{rated} is 15 kWh in our case, $SOC(0)$ is 0.5, $SOC_{\min}$ is 0.2, and $SOC_{\max}$ is 0.8. Provided the degradation curves in Fig. 3, we can obtain $\alpha_{\text{dc},SLB1} = 0.7665$, $\alpha_{\text{dc},SLB2} = 1.1289$, and $\alpha_{\text{dc},SLB3} = 1.3058$.

Fig. 5 gives the evaluation results of the SLBs under the three load scenarios. We consider the operation of SLB 1, SLB 2, and SLB 3 from Fig. 3 under the three load scenarios with initial cycle numbers equal to 10, 100, 200, 300, and 400. Based on the definition of the five indexes, a higher value indicates a better performance. Cycle number 10 is selected instead of 0 since it takes a few cycles for the battery's cycling performance to start to stabilize. And for SLB 1, we only consider the operation from cycle number 10 to 200 since its SOH reduces to 40% at cycle number 266 and will be retired from its second life.

For load scenario 1 (double peak load), SLB 1 has a relatively consistent performance, with all the five indexes decreasing in response to the increase of the initial cycle. Such consistency in performance occurs as the operation is within the first region of its degradation curve. Regarding SLB 2, the overall trend of its performance is to deteriorate with the increase of the initial cycle number. Nevertheless, the performance around cycle number 300 is improved as the degradation curve is entering the transition from region 1 to region 2 with a lower degradation rate. Such degradation rate results in a smaller ΔQ and thus larger values in $I_{environmental}$, $I_{eco-efficiency}$, and $I_{socio-economic}$. Also, around cycle number 400, its performance worsens drastically due to the plummet of its degradation curve in region 2. SLB 3 also operates in region 1 of its degradation curve, leading to a consistent performance with all the five indexes decreasing in response to the increase of the initial cycle. It is worth noting that its performance considering the environmental, eco-efficiency and socio-efficiency aspects around cycle 10 is considerably better than that at cycle 100, as the degradation rate is slower.

The overall performance trend for load scenario 2 (stationary load) is similar to that in load scenario 1 case. However, the performance of SLB in the social aspect fluctuates due to the fluctuation in flipping frequency.

For load scenario 3 (single peak load), all three SLBs have more satisfactory performances. The power demand is low when PV generation is available. The excessive PV generation is charged into the battery for later use (note that the energy price at that time is not high enough to sell the energy back to the grid). Thus, the socio-environmental index has larger values compared to the other two load scenarios. And the higher values in the economic index are induced by the lower total energy demand in this case, as the area below the load curve is the smallest in Fig. 5(a).

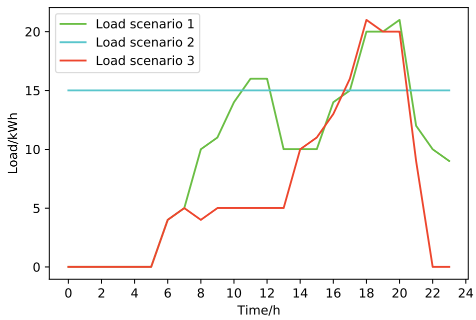
Fig. 6(a) shows the averaged performance of the three SLBs from cycle 10 to 200 under different load scenarios. SLB 3 has the best performance in all three load scenarios thanks to its slow degradation rate. SLB 1 and SLB 2 have similar performance under load 1 and 2 scenarios, driven by the tradeoff between the initial value of SOH and its degradation rate. Even though the SLB 1 starts with a higher SOH, its SOH deteriorates fast and compromises its overall performance. Fig. 6(b) shows the averaged performance of the three SLBs from cycle 10 to 400 under different load scenarios. SLB 3 excels in the environmental, economic, eco-efficiency, and socio-efficiency aspects with a slower degradation rate. A slower degradation rate allows less degradation ΔQ in the operation process and thus less degradation costs and energy loss. However, if we consider the different purchase prices for the three SLBs ($c_{SLB1} = 502$ \$, $c_{SLB2} = 723$ \$, and $c_{SLB1} = 789$ \$), SLB 1 has improved performance thanks to its low cost, as shown in Fig. 6(c). Again, Fig. 6(d) reveals that the sustainability performance of SLB 2 is more comparable to that of SLB 3 due to its lower price.

The cycles expensed for a one-day operation at cycle j $\Delta cycle_j$ can be calculated by Eq. (30) with the initial cycle number at the beginning of the day as $cycle(t = 0) = cycle_j$. Correspondingly, $\frac{1}{\Delta cycle_j}$ implies the days that the SLB takes to experience one complete cycle starting from $cycle_j$. Further, the remaining life of this SLB can be obtained by summing up $\frac{1}{\Delta cycle_j}$ throughout its useful life (j is from 0 to the cycle number when SOH reduces to 40%). For simplicity, we sample every 20 cycles starting from cycle 20 to obtain the corresponding $\frac{1}{\Delta cycle_j}$ and approximate the data with a polynomial function. Then, the remaining life can be estimated as the integral of the polynomial function over the SLB's useful life. The results show that SLB 1, SLB 2, and SLB 3 have a remaining life of 204, 309, and 375 days on average, given the three load scenarios.

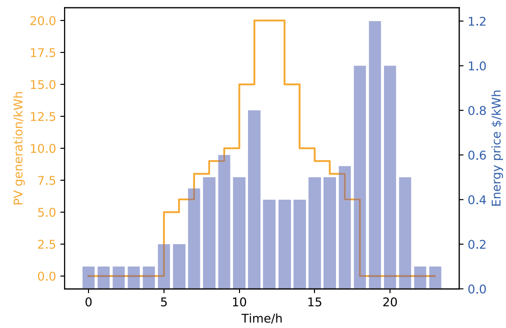
To sum up, the sustainability performances of SLBs are primarily affected by their degradation curves, in which the initial SOH and the degradation rate are the key factors. A higher SOH indicates fewer restrictions on SLB charging and discharging actions, leading to more aggressive exploitation of them and thus more flexibility provided by them. Such flexibility allows users to reduce their energy costs from buying/selling energy from/to the power grid. A slower degradation rate enables less degradation in the operation process for providing the same level of service, resulting in a more satisfactory performance with less degradation cost and energy loss. In this regard, the degradation curves play an essential role in determining the sustainability value of these SLBs and need to be incorporated into their pricing model. Nevertheless, SLBs with a fast degradation rate are more affordable, making them more competitive when considering the purchasing costs. Hence, we need to estimate not only the SLBs' remaining capacity but also their degradation curves before they enter the market.

4. Conclusions

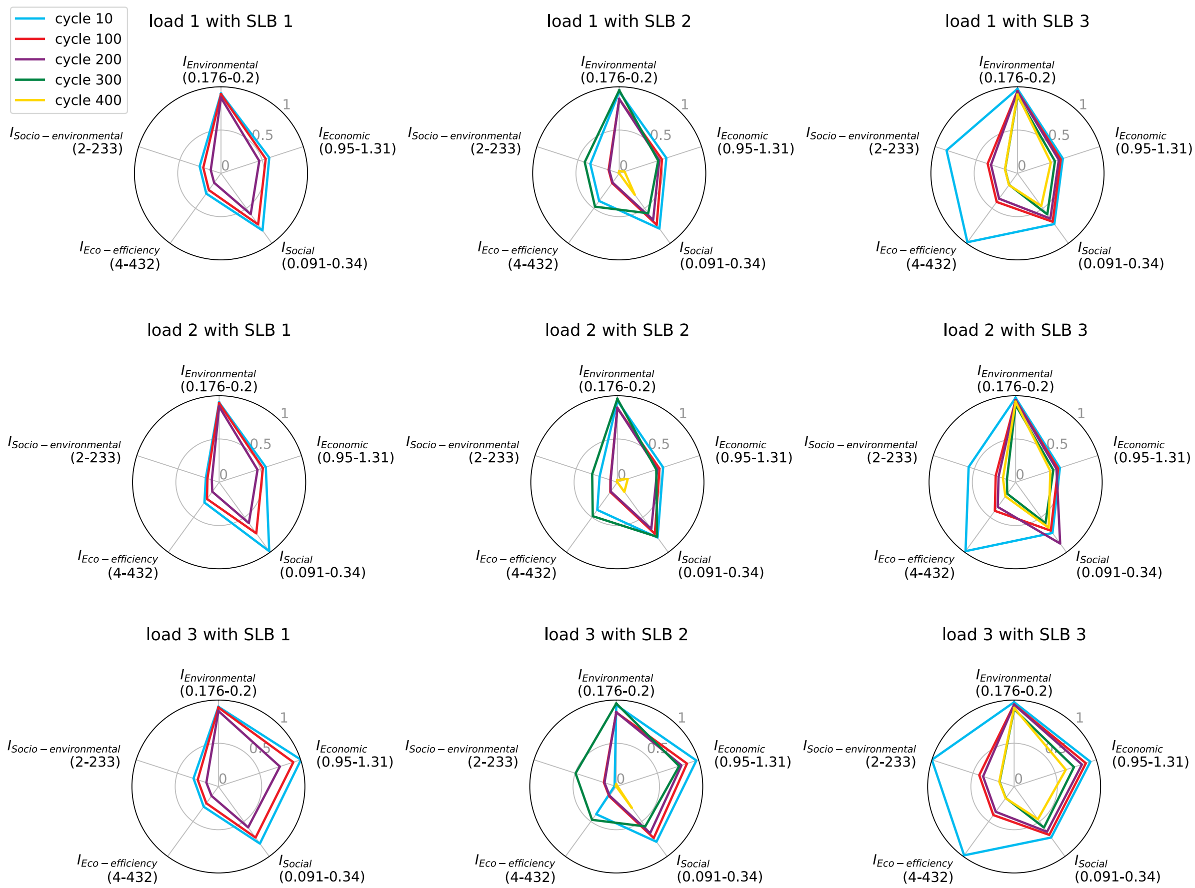
Second-life Battery (SLB) applications would reshape the landscape of the end-of-life for those retired EV batteries with relatively high remaining capacities. Except for the explicit economic and environmental benefits of giving these batteries a second life, the implications for the other aspects of sustainability should also be recognized. As such,



(a) Three load scenarios.



(b) The PV generation and energy unit price.



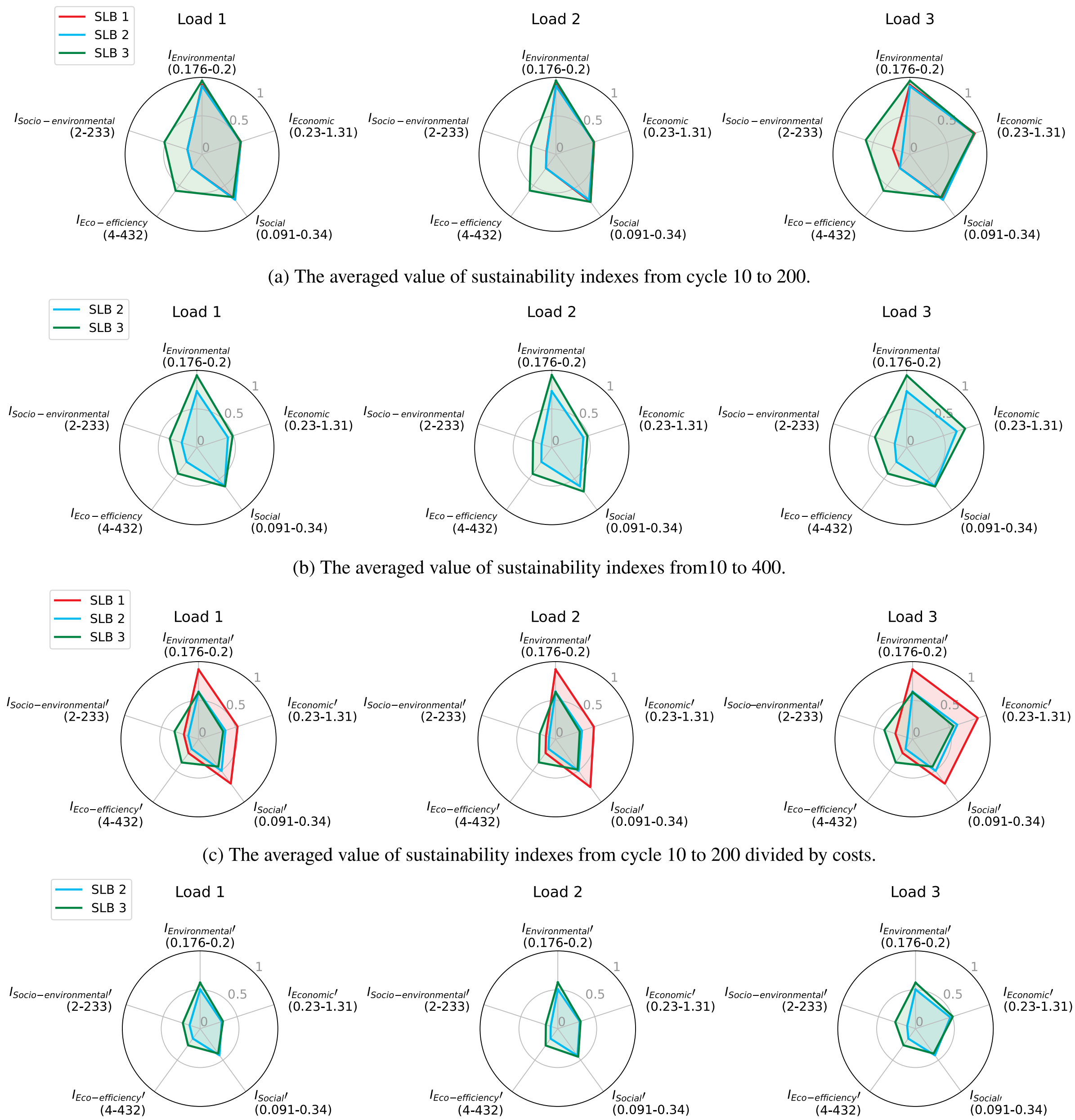
(c) The sustainability performances of SLBs at various cycle numbers under different load scenarios.

Fig. 5. Properties of the sustainability performance evaluation parameters and simulation results.

this paper aims to develop a sustainability evaluation framework to measure the social, economic, environmental, eco-efficiency, and socio-environmental impacts of SLB applications. Also, an SLB cost-based pricing model is proposed to enable economic evaluation. This model carefully considers external and internal factors affecting the SLB prices by incorporating the market information (retired EV battery resourcing cost, retired EV battery repurposing cost, and SLB market size) and the individual characteristics of SLBs (initial SOH and degradation tendency). The prices for SLBs in 2030 are predicted to range from 23 to 67 $/kWh in China, Europe, and the United States. Furthermore, the performances of SLBs in grid-connected PV-battery systems under different load scenarios (double peak load, stationary load, and single peak load) are measured.

The sustainability performances of SLBs are primarily affected by their degradation curves, in which the initial SOH and the degradation rate are the key factors. As a result, it is necessary to consider these two factors in the previous pricing model (note that the degradation tendency reflects the degradation rate). SLBs with a high initial SOH and a slow degradation rate are desirable in terms of sustainability performances since they enjoy a relatively high and stable round-trip efficiency and thus suffer less from energy loss and capacity degradation. However, when considering the capital investments in these SLB purchases, cheaper SLBs can be competitive even with a fast degradation rate.

The lack of available data throughout the SLB value chain remains a challenge to the SLB pricing model. Future research may look into the



(a) The averaged value of sustainability indexes from cycle 10 to 200.

(b) The averaged value of sustainability indexes from10 to 400.

(c) The averaged value of sustainability indexes from cycle 10 to 200 divided by costs.

(d) The averaged value of sustainability indexes from cycle 10 to 400 divided by costs.

Fig. 6. The averaged sustainability performances of SLBs under different load scenarios. In (c) and (d), the averaged values of sustainability indexes are divided by the SLB costs to incorporate the purchase costs of adopting these SLBs, where $I_{Environmental,i}{\prime} = 500 \times I_{Environmental,i}/c_{SLB,i}$, $I_{Economic,i}{\prime} = 500 \times I_{Economic,i}/c_{SLB,i}$, $I_{Social,i}{\prime} = 500 \times I_{Social,i}/c_{SLB,i}$, $I_{Eco-efficiency,i}{\prime} = 500 \times I_{Eco-efficiency,i}/c_{SLB,i}$, $I_{Socio-environmental,i}{\prime} = 500 \times I_{Socio-environmental,i}/c_{SLB,i}$, and $c_{SLB,i} = AC \times \alpha_{SLB,i} \times SOH_{\text{initial,i}} \times Q_{\text{rated,i}}$. Here i indicates the SLB i, $c_{SLB,i}$ is the cost of SLB i, and $SOH_{\text{initial,i}}$ is the initial SOH of SLB i. Additionally, a scaling factor of 500 is added to the modified indexes to achieve the same scale as before.

digitalization of the SLB value chain and develop effective methods to extract valuable information from it. Another research direction is to extend this paper's sustainability indexes and establish a comprehensive sustainability matrix system. Again, with the availability of SLB data, we can further validate the effectiveness of SLBs' performances in practical applications.

CRediT authorship contribution statement

Ming Cheng: Conceptualization, Methodology, Software, Writing – original draft. **Aihua Ran:** Data curation, Writing – review & editing. **Xueling Zheng:** Data curation, Writing – review & editing. **Xuan Zhang:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Guodan Wei:** Validation. **Guangmin Zhou:** Resources, Writing – review & editing, Funding acquisition. **Hongbin Sun:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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