Energy 253 (2022) 124159

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Potential of electric vehicle batteries second use in energy storage systems: The case of China

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ARTICLE INFO

Article history:
Received 30 December 2021
Received in revised form
27 April 2022
Accepted 28 April 2022
Available online 1 May 2022

Keywords:
Electric vehicle
Energy storage system
Battery second use
Battery degradation

ABSTRACT

Battery second use, which extracts additional values from retired electric vehicle batteries through repurposing them in energy storage systems, is promising in reducing the demand for new batteries. However, the potential scale of battery second use and the consequent battery conservation benefits are largely unexplored. This study bridges such a research gap by simulating the dynamic interactions between vehicle batteries and batteries used in energy storage systems in China's context. Battery supply, use and disposal with and without implementing battery second use are compared. The results show that until 2050, more than 16 TWh of Li-ion batteries are expected to be retired from electric vehicles. If these retired batteries are put into second use, the accumulative new battery demand of battery energy storage systems can be reduced from 2.1 to 5.1 TWh to 0–1.4 TWh under different scenarios, implying a 73–100% decrease. This research justifies the necessity of developing battery second use and calls for joint efforts from the government, industry and academia.

1. Introduction

In the context of global CO_2 mitigation, electric vehicles (EV) have been developing rapidly in recent years. Global EV sales have grown from 0.7 million in 2015 to 3.2 million in 2020, with market penetration rate increasing from 0.8% to 4% [1]. As the world's largest EV market, China's EV sales have grown from 0.3 million in 2015 to 1.4 million in 2020, accounting for over 40% of global total [2]. EV market is expected to continue the growth trend through the coming decades. According to forecast by International Energy Agency, global EV stock is expected to reach 140 million by 2030, 12 times the stock in 2020 [3]. Given this context, it is expected that a large number of EV batteries will reach end-of-life (EOL) stage in the coming decades. As predicted by Bloomberg New Energy Finance, the capacity of retired EV batteries is estimated to be over 150 GWh by 2025 globally [4]. Under such a circumstance, the treatment of retired EV batteries has become a big concern to be addressed.

On the other hand, renewable energy generation has been booming in recent years. According to statistics from IRENA, the installed capacity of renewable energy generation in China has reached 895 GW in 2020, among which variable renewable energy such as wind and solar PV accounted for over 50% [5]. To achieve the integration of variable renewable energy into grid, it is necessary to equip power stations with ESSs to solve the grid fluctuation caused by the intermittency and uncertainty of renewable energy. In addition, residential off-grid renewable energy power systems require ESSs for time shifting while commissioning. According to forecast by IRENA, it is expected that global installed capacity of renewable energy generation will reach over 10,000 GW by 2050 [6]. The growing scale of renewable energy generation increases demand for energy storage batteries and raises concerns on the security of future battery supply.

As defined by USABC, the EOL standard of EV batteries is either a 20% reduction in rated capacity or a 20% reduction in rated power density at 80% DOD, which means that retired EV batteries will still have a high useable capacity and it is wasteful to scrap them for recycling directly [7]. As an emerging technology, B2U provides a

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https://doi.org/10.1016/j.energy.2022.124159
0360-5442/

Acronyms

B2U	Battery second use
BDM	Battery Degradation Model
BESS	Battery energy storage system
BESSDM	Battery Energy Storage System Demand Model
DOD	Depth of discharge
EOL	End-of-life
ESS	Energy storage system
EV	Electric vehicle
GHG	Greenhouse gas
IRENA	International Renewable Energy Agency
LFP	Lithium iron phosphate battery
NCA	Nickel-cobalt-aluminum ternary lithium-ion battery
NCM	Nickel-cobalt-manganese ternary lithium-ion battery
NREL	National Renewable Energy Laboratory
SEI	Solid state interphase
SOH	State of health
TIM	Transport Impact Model
USABC	US Advanced Battery Consortium

promising solution to making maximum utilization of retired EV batteries and increasing the battery value provided over the battery life. B2U refers to the repurposing of retired EV batteries in applications with low battery performance requirements, such as ESSs [8]. Retired EV batteries can be reused after a series of reprocessing, including collecting, performance testing, sorting and grouping, and redesign of battery management system.

Globally, B2U is being demonstrated by a number of pioneering automobile and grid companies. In 2015, Bosch, BMW and Vattenfall cooperated on B2U, building a 2MW/2 MWh ESS for solar PV power station with retired EV batteries, which is the first B2U project in Europe [9]. In 2016, Nissan launched The Mobility House project, applying 280 retired batteries from Nissan Leaf to the xStorage Buildings System as energy storage batteries [10]. In 2017, Daimler launched a demonstration project, in which 1000 retired batteries from Smart Fortwo were repurposed in grid-side ESSs [11]. In 2020, Connected Energy conducted a collaboration with Groupe Renault, using the retired batteries from Renault Kangoo Z.E. to their second-life battery energy storage system E-STOR [12].

In China, the development of B2U is also rapid. China Tower has used the retired Li-ion batteries from electric buses to replace lead-acid batteries as backup power for communication base stations [13]. State Grid Corporation of China has launched demonstration projects in Beijing, Zhejiang, Henan and other regions to reuse retired EV batteries in ESSs, low-speed electric vehicles and other fields [13]. The government has also been actively involved in promoting the development of B2U. In 2019, Ministry of Industry and Information Technology and China Development Bank jointly introduced the Notice on Accelerating Industrial Energy Conservation and Green Development, which stated that the government would promote the development of B2U in Yangtze River Economic Belt, Beijing-Tianjin-Hebei region and Yangtze Delta area [14]. Although the National Energy Administration recently introduced a policy prohibiting the construction of new large-scale ESSs with repurposed EV batteries, its purpose is to emphasize on prohibiting B2U projects until the safety concerns of B2U are addressed instead of banning the development of B2U completely [15].

The concept of B2U has been put forward for a long time with the evolution of battery chemistries from lead-acid to lithium, and the current research focus of B2U mainly lies in its technical and economic feasibility. The main concerns are whether current technologies can enable the commercialization of B2U, and by what business mode can B2U achieve profitability. For technology feasibility, the differences between retired and new Li-ion batteries lie in capacity, power and energy performance and cell-to-cell heterogeneity [10]. Kootstra et al. calculated the optimal battery size for achieving B2U in off-grid residential BESSs, taking into account factors including battery performance, residual capacity, battery degradation and energy management strategy [16]. Hart et al. evaluated the reliability of BESSs composed of retired batteries with two chemistries ($LiNiMnCoO_2$ and $LiFePO_4$), proposing an energy management algorithm to balance the performance of different battery packs [17]. From an economic point of view, Neubauer et al. evaluated the benefits of four groups of B2U applications, among which the combination of power quality and reliability services would be the most promising option [18]. Idjis et al. analyzed the impact of B2U on the costs of EV by 2030 and concluded that B2U could reduce the total EV costs by 6−11% [19]. Kamath et al. analyzed the levelized costs of electricity in three ESS applications using retired EV batteries, and concluded that a 12−57% reduction could be achieved through B2U [20].

In addition to technical and economic viability, another key aspect of concern is B2U's growth potential and future scale, in other words, to what extent retired EV batteries can meet battery needed for BESS deployment, which can provide a basis for future corporate investment and government policy making. However, there are few researches on this aspect. Sathre et al. studied the B2U potential in enabling the integration of renewable energy in California [21]. This study predicted the market penetration and sales of PEV based on s-curve, but lacked a battery degradation model to simulate the battery capacity fade under different operating conditions, and did not consider the impact of battery chemistries on B2U feasibility. Ambrose et al. considered three battery chemistries in their study, predicting global potential of B2U in mini- and micro-grids [22]. While this study just made simple assumptions about battery life and did not consider battery degradation. Neubauer et al. analyzed the potential future scenario of B2U in United States [23]. A battery degradation model was used in this research to distinguish the capacity fade of batteries under different conditions, but the assumptions for EV market prediction were simple.

In summary, existing researches on the potential scale of B2U tend to only analyze either the availability of retired EV batteries or BESS's demand for batteries, lacking a comprehensive B2U potential analysis from the perspective of the whole B2U industry chain combining the above EV and BESS aspects. Besides, most of existing researches only make simple assumptions about battery life, and rarely consider battery degradation model to distinguish the degrees of battery capacity fade in different applications with different operating conditions, which might have a significant impact on the calculation of battery life. In order to fill these gaps, this study establishes a research framework by using China as the example, comparing the battery supply, use and disposal in EVs and BESSs, which is called battery flows in this study, with and without implementing B2U. The results show that the implementation of B2U could significantly reduce BESS's demand for new Li-ion batteries under a wide range of scenarios. The results of this research can help governments and enterprises have an intuitive understanding on the potential of B2U, and provide a basis for the formulation of policies and corporate strategies.

2. Method

2.1. System definition

Fig. 1 shows the research framework, which consists of two

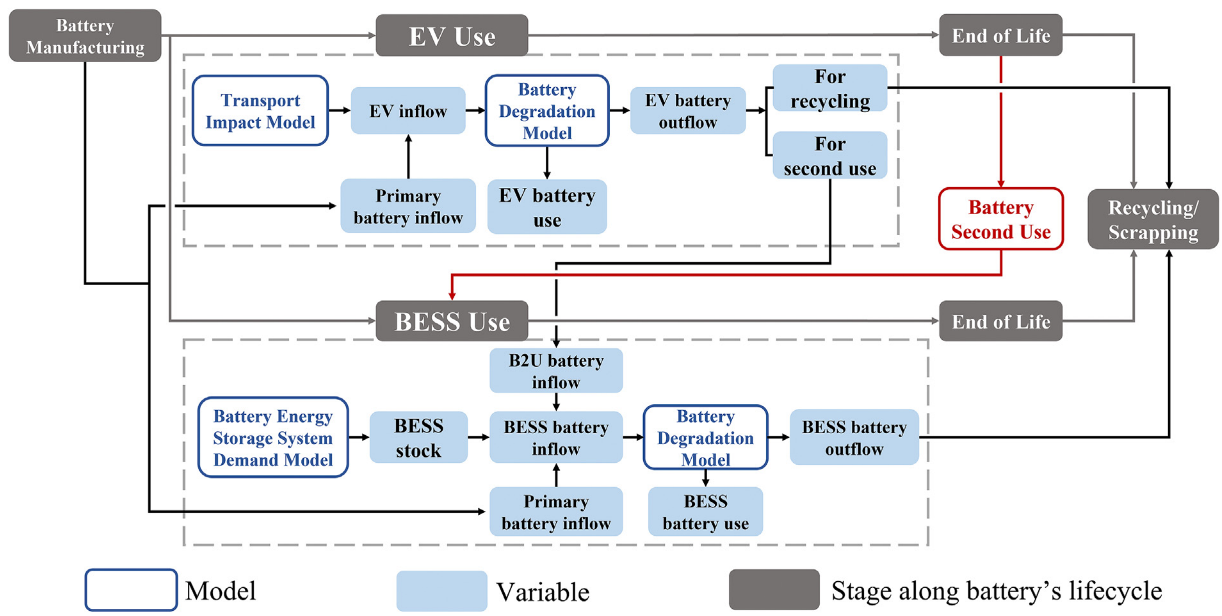

Fig. 1. Schematic diagram of the research framework.

different Li-ion battery lifecycles along the manufacturing, use, and EOL disposal in EVs and BESSs. When B2U is not implemented, retired EV batteries are directly scrapped and recycled, and BESSs can use only new batteries. When implementing B2U, retired EV batteries flow in two different directions, part of them are repurposed to serve as energy storage batteries in BESSs after reprocessing, and the others directly flow into EOL disposal. This research compares the differences of battery flows in EVs and BESSs with and without the implementation of B2U. Considering China's global-leading EV and renewable energy deployment, we conduct a case study by using China in 2000–2050.

Three key models are used to enable the calculation, including Transport Impact Model (TIM), Battery Energy Storage System Demand Model (BESSDM) and Battery Degradation Model (BDM). Fig. 1 illustrates the research framework. The following subsections detail these models.

2.2. Transport Impact Model

The EV sales, scraps and stocks are simulated through TIM. TIM is a technology-rich, bottom-up approached model developed by China Automotive Energy Research Center at Tsinghua University. TIM takes population and GDP as exogenous variables, combined with influencing factors including vehicle scrappage pattern, technology market penetration and vehicle specifications, to predict the EV sales, stocks and retirements under different scenarios. Battery flows associated with electrification of passenger vehicles, light-duty commercial vehicles and heavy-duty vehicles are considered in this model. Structure and calculation of TIM are detailed in relevant references [24,25]. Validation on TIM is shown in Figure A1, [26–28].

2.3. Battery energy storage system deployment model

Prediction on Li-ion batteries needed for BESS deployment in China is analyzed by BESSDM based on historical capacity data [29]. While various predictions have been made by international research institute [30,31], the temporal boundaries of these results are around 2030 to 2040, which cannot meet the requirements of this research. Thus, BESSDM is built to extend prediction on BESS's demand for energy storage batteries to 2050. BESSDM is established based on the Logistic model [32,33]. Logistic model, as one kind of growth curve model, has been widely used in the projections of energy and resource demands [32,34]. The basic formula of Logistic model is shown in equation (1). Q_{max} and t_0 represent the maximum scale that can be achieved and the time it takes to reach half of the maximum scale. k is the shape parameter, which is obtained by regression based on historical data. In this research, considering that China has announced to achieve carbon neutrality by 2060 and that the development of Li-ion BESS is still in its infancy in 2020, t_0 is set to be 2040. The determination of Q_{max} is explained in details below.

$$Q(t) = \frac{Q_{max}}{1 + e^{-k(t-t_0)}} \tag{1}$$

BESSDM takes IMAGE's forecast for China's power generation under the SSP2 baseline scenario as external variable [35]. Since the main purpose of BESSs is to integrate variable renewable energy into grid, the maximum scale of BESSs is predicted according to the future installed capacity of wind and solar PV power generation. We first predict the installed capacity of renewable energy generation in China based on future share of renewable energy generation and corresponding capacity factors [36–38]. Then the installed capacity of BESSs is obtained through the pairing principles between the capacity of power stations and that of corresponding BESSs.

Wind and solar PV power stations require different scales of BESSs. In this research, the pairing principles between power stations and BESSs are described by two parameters: discharge duration DU and pairing coefficient k. The discharge duration refers to the continuous discharge time required for a BESS to run a cycle in a given application. The pairing coefficient refers to the ratio of power output of a power station to that of a BESS. Global Energy Storage Database is an online database of global ESS projects established by U.S. Department of Energy. It gathers relevant information of global grid-connected ESS projects, including technology, main purpose as well as geographic and performance information [39]. According to such statistics, the average discharge durations of BESSs for wind and solar PV power stations in existing projects are 1.58 and 2.51 hours, respectively. The average pairing coefficients of BESSs for wind and solar PV power stations in existing projects are 0.28 and 0.27, respectively. In the aggressive case, the two sets of parameters are set based on the quartiles of available project data. The aggressive discharge durations of BESSs for wind and solar PV are 2 and 4 hours, and the aggressive pairing coefficients are 0.40 and 0.45, respectively. Uncertainty analysis regarding the possible impacts of the uncertainties in these two parameters on the results is conducted and shown in Figure A3-A5. The calculation of BESSDM is shown in equation (2), and the validation on BESSDM is shown in Figure A2, [29–31,40].

$$D_{r,s}(t) = \frac{\max\left\{\frac{EP_{i,r}}{CF_{i,r}*24*365}*1000*k_{r,s}*DU_r\right\}}{1+e^{-k_{0i,s}(t-t_{0i,s})}} \tag{2}$$

where.

$D_{r,s}(t)$ is the capacity of BESSs for power stations in energy source r in year t under scenario s;
$EP_{i,r}$ is the electricity generated in energy source r in year i;
$CF_{i,r}$ is capacity factor of power station in energy source r in year i;
$k_{r,s}$ is the pairing coefficient for BESS and power station in energy source r under scenario s;
DU_r is the discharge duration for BESS and power station in energy source r;
$k_{0i,s}$ and $t_{0i,s}$ are parameters of Logistic model as explained above.

2.4. Battery degradation model

Considering that different applications of BESS correspond to different battery operating conditions which will directly affect the capacity fade performances and life of Li-ion batteries, it is necessary to distinguish battery degradation in different BESS applications. Degradation of Li-ion batteries are simulated by BDM in this research. Due to the requirements for calculation complexity and data availability, a multi-factor empirical model is chosen in this study to calculate battery capacity fade. The variable used to measure battery degradation in this model is battery's SOH, which refers to the ratio of residual battery capacity relative to nominal capacity [41].

Li-ion battery capacity fade includes two parts: cycle aging and calendar aging. Cycle aging refers to capacity fade caused by the charge-discharge process of batteries in use, which is proportional to the full equivalent cycle or Ah throughput. Ah throughput represents the amount of charge transferred by the battery in cycling [41]. The main influencing factors on cycle aging include C-rate and DOD [42]. In this study, the cycle aging model is established based on the battery degradation model developed by NREL, which has been widely used in researches on EV and energy storage batteries [43,44]. NREL model assumes that a battery has a finite cycle life, i.e., the rated Ah throughput, which means that a battery will reach its EOL stage when the effective Ah throughput reaches the rated value. The relevant parameters in this model are recalibrated based on the experimental data of Li-ion batteries [45]. The calculations of capacity loss caused by cycle aging are shown in equations (3)–(5).

$$d_{eff_{t,a}} = \left(\frac{D_A}{D_R}\right)^{u_0} * \exp\left(u_1 * \left(\frac{D_A}{D_R} - 1\right)\right) * \left(\frac{C_R}{C_A}\right) * d_{actual} \tag{3}$$

$$Q_{losspercycle}(n) = \frac{d_{eff}}{L_R * D_R * C_R} * EOL_{rate} \tag{4}$$

$$Q_{loss_{cyc}}(t) = Q_{loss_{percycle}} * f_{B2U} * t \tag{5}$$

where.

$d_{eff_{t,a}}$ is the effective Ah-throughput per cycle of batteries with chemistry t in application a;
D_{A_a} is the actual DOD of batteries in application a, varying in different applications;
D_R is the rated DOD of batteries under rated operating condition, corresponding to the rated battery cycle life, which is set as 80% in this study [7];
C_{A_a} is the actual C-rate of batteries in application a, varying in different applications;
C_R is the rated C-rate of batteries under rated operating condition, corresponding to the rated battery cycle life, which is set as 1C in this study [42];
$d_{actual_{t,a}}$ is the actual Ah-throughput per cycle of batteries with chemistry t in application a;
$Q_{losspercycle_{t,a}}$ is the capacity loss caused by cycle aging per cycle of batteries with chemistry t in application a;
L_{R_t} is the rated cycle life of batteries with chemistry t under rated operating condition;
EOL_{rate_t} is the rated SOH of batteries with chemistry t representing the end of battery life, which is set as 80% in this study [7];
f_{B2U_a} is the annual use frequency of batteries in application a;
$Q_{loss_{cyc_{t,a}}}(t)$ is the capacity loss caused by cycle aging per year of batteries with chemistry t in application a.

Regarding calendar aging, this part of capacity fade is mainly up to irreversible self-discharge capacity loss caused by the lithium loss during the formation of solid-state-interphase (SEI) on the negative electrode [46]. The operating condition of batteries in BESSs is relatively stable, as the air-conditioning system of BESSs can stabilize the operating environment at room temperature, for which the influence of temperature on battery calendar aging can be ignored in this study [47,48]. The capacity loss caused by calendar aging is demonstrated to be proportional to the square root of time [48–50]. Equation (6) shows the calculation of capacity loss caused by calendar aging, $Q_{loss_{cal}}$. Parameter C is the calendar aging characteristic parameter of a given battery, referring to the capacity loss after first five years of placement.

$$Q_{loss_{cal}}(t) = C * \sqrt{t} \tag{6}$$

For a given battery chemistry and application, battery capacity fade is calculated as the sum of capacity loss caused by cycle aging and calendar aging [49], as shown in equation (7).

$$Q_{loss}(t) = Q_{loss_{cyc}} + Q_{loss_{cal}} \tag{7}$$

2.5. B2U feasibility for different Li-ion battery chemistries

The performance requirements for batteries in BESSs include long cycle life, high safety and low cost. For LFP batteries, the advantages exactly meet BESS's requirements for energy storage batteries, and the shortcomings include low energy density and poor performance at low temperature can be ignored in BESSs [42]. From this perspective, retired LFP batteries are suitable for further work as energy storage batteries through B2U. In contrast, although

NCM/NCA batteries have better power and energy performances, they have poor durability and safety performances. In addition, due to the high recycling value of critical metals such as nickel and cobalt in NCM and NCA batteries, industry currently considers that directly recycling without B2U is a better solution to the disposal of NCM and NCA batteries. For the above reasons, battery repurposing is only considered for retired LFP batteries, and retired NCM and NCA batteries are assumed to be directly scrapped and recycled. In the case without B2U, battery needed for BESS deployment is fully met by new LFP batteries as well.

2.6. Scenarios

There are three influencing factors that are critical to assessing the impact of B2U, including the implementation of B2U, BESS scale, and the mix of EV battery chemistries. Two cases are set for each of the above-mentioned factors.

Regarding the implementation of B2U, two cases are established, distinguished by whether B2U becomes technologically and commercially feasible. The B2U-feasible (W–B2U) case reflects the condition under which the safety and cost concerns of B2U are well addressed with efforts from the government, industry and academia. Such case is supported by the assumption that all LFP batteries retired from the EV fleet can be repurposed in BESSs. The B2U-non-feasible (W/O–B2U) case reflects the possibility under which the implementation of B2U is consistently impeded by safety and cost issues. Under this case, no B2U is considered.

Regarding BESS scale, two cases are established reflecting different degrees of renewable energy generation's dependence on BESSs. In moderate case (MOD-BESS), the variability of renewable energy generation is comprehensively addressed by a wide range of measures, with energy storage making moderate contribution. Such case is supported by using the average of pairing coefficient and discharge duration mentioned above. While in aggressive case (AGG-BESS), BESS is considered as the dominating solution to renewable energy variability, which would require more BESS for renewable energy generation. Correspondingly, the aggressive settings regarding pairing coefficient and discharge duration are used.

Regarding the mix of EV battery chemistries, two cases are established reflecting the dominance of different battery chemistries. In NCM/NCA dominating case (NCM/NCA-DOM), EVs tend to use NCM and NCA batteries pursuing for high energy density. While in LFP dominating case (LFP-DOM), low cost and high safety are the main considerations for choosing batteries. Market penetrations of different battery chemistries in two cases are shown in Table 1.

3. Results

3.1. EV and BESS battery flow

Fig. 2 shows prediction on EV battery flows in Chinese EV market in two cases of battery chemistries. Under NCM/NCA dominating case, the batteries inflowing to EVs increase rapidly over the next decades, reaching 2.1 TWh in 2050. Scrapping batteries from EVs also increase rapidly with a ten-year lag compared with inflow, reaching 1.5 TWh in 2050. In this case, the share of LFP batteries is relatively small. The accumulative batteries inflow and outflow between 2020 and 2050 are 39.1 TWh and 16.0 TWh respectively, including 9.9 TWh of LFP batteries for inflow and 5.4 TWh for outflow. If LFP becomes the dominating battery chemistry, the overall development of batteries in EVs are basically similar to that in NCM/NCA dominating case, while the share of LFP batteries increases significantly. In 2050, LFP batteries inflow and outflow are 1.8 TWh and 1.0 TWh. The accumulative inflow and outflow of LFP batteries till 2050 are 26.2 TWh and 8.9 TWh, 3 and 2 times higher than those in NCM/NCA dominating case.

The estimated SOH of retired EV batteries in each year is shown in Fig. 3, where the area and corresponding color in the graph represent the market share of retired batteries with different SOH, and the red line represents the average SOH of retired EV batteries for each year. In both cases, the SOH of retired EV batteries is concentrated between the range of 80%–90%. Considering the future improvement of battery life, the average SOH shows an upward trend. In NCM/NCA dominating case, the average SOH increases from 81.1% in 2020 to 84.8% in 2050. In LFP dominating case, the average SOH increases from 81.1% in 2020 to 86.3% in 2050. As the Ah throughput of LFP batteries along the life is greater than that of NCM/NCA batteries, retired batteries' average SOH in LFP dominating case is slightly higher than that in NCM/NCA dominating case.

Fig. 4 shows prediction on Li-ion batteries needed for BESS deployment without B2U. In the case of moderate BESS deployment, installed BESS capacity is expected to increase rapidly over the next few decades and level off by around 2050. The BESS installation reaches 2.0 TWh by 2050, with a peak annual new installation of 0.2 TWh in around 2040. While in the case of aggressive deployment, the installed BESS capacity increases by three times to 5.0 TWh by 2050, and annual new installation peaks at 0.4 TWh in around 2040. This prediction is compelling given the Chinese target of achieving carbon neutrality before 2060, as well as the significant role of renewable energy and BESS in emission mitigation.

Table 1
Market penetrations of different battery chemistries in two cases.

			2020	2030	2040	2050
LDV	NCM/NCA-DOM	LFP	30%	20%	10%	0%
		NCM523	45%	20%	10%	0%
		NCM811	10%	40%	57.5%	75%
		NCA	15%	20%	22.5%	25%
	LFP-DOM	LFP	30%	40%	60%	80%
		NCM523	45%	20%	10%	0%
		NCM811	10%	25%	17.5%	10%
		NCA	15%	15%	12.5%	10%
HDV		LFP	100%	100%	100%	100%

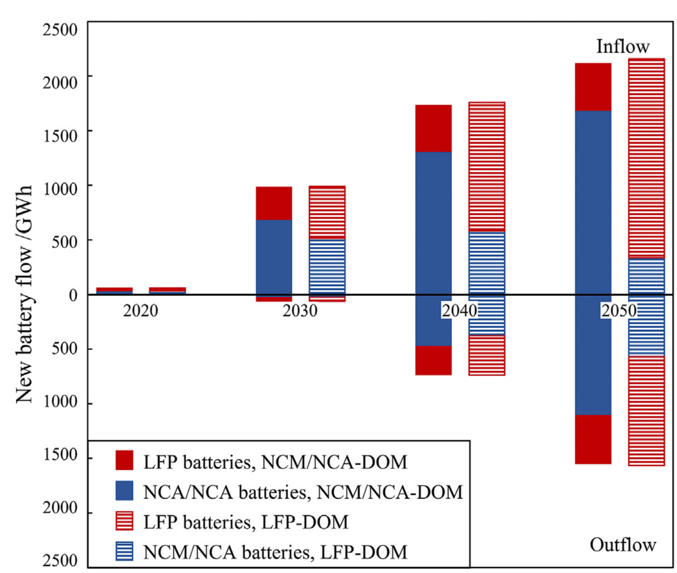

Fig. 2. Prediction on Chinese EV battery flows in two cases of battery chemistries. Note: The bars above horizontal axis represent Li-ion batteries inflowing to EVs and the bars below horizontal axis represent batteries outflows.

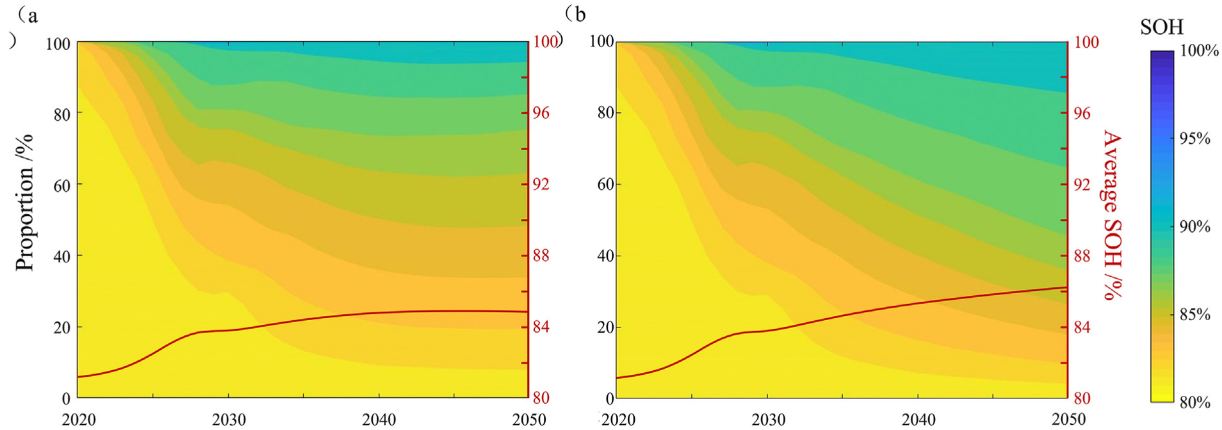

Fig. 3. The estimated SOH of retired EV batteries in (a) NCM/NCA dominating case and (b) LFP dominating case.

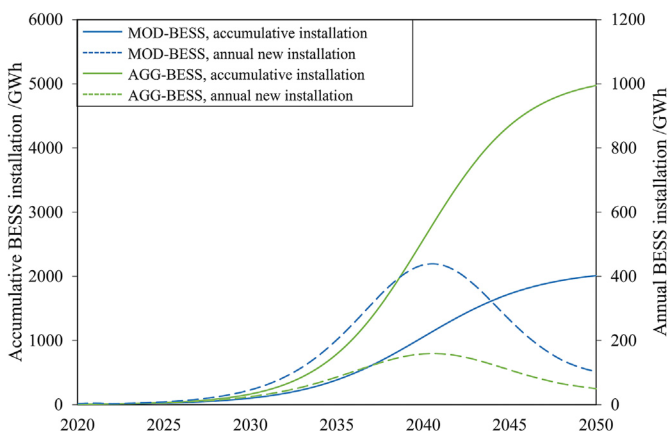

Fig. 4. Prediction on accumulative and annual BESS installed capacity.

3.2. Impact of B2U on BESS market

This section focuses on the impact of B2U implementation on the battery flow in BESS market. Fig. 5 shows prediction on new Li-ion batteries needed for BESS deployment with the implementation of B2U. As mentioned above, the implementation of B2U can significantly reduce the demand for new batteries in BESS. In moderate case, regardless of which type of battery dominates the future EV use, retired EV batteries are able to fully cover BESS's battery demand, reducing the future peak demand for new Li-ion batteries from 159 GWh to basically none. While in the case of aggressive BESS deployment, the implementation of B2U can reduce peak annual demand from 436 GWh to 190 GWh in NCM/NCA dominating case and to 108 GWh in LFP dominating case. Regarding accumulative demand, B2U can cover 75% of it in NCM/NCA dominating case and 88% in LFP dominating case.

From the perspective of the future source of batteries used in BESS, Fig. 6 shows the comparison between repurposed EV batteries supply and BESS's battery demand as well as the share of new and repurposed Li-ion batteries inflowing to BESSs under different scenarios. In the cases of moderate BESS deployment, retired EV batteries can meet all the battery demand of BESS, and it can be seen that the future batteries in BESS will be 100% sourced from retired EV batteries. If BESS deployment is aggressive, repurposed batteries are able to meet 58–81% of the demand in 2040 and totally cover it in 2050.

3.3. Impact of B2U on the whole market

Fig. 7 shows the new Li-ion batteries inflowing to EVs and BESSs in China until 2050. In the case of moderate BESS deployment, the annual battery demand is expected to continue to grow and slows down after 2040, reaching 2.1–2.2 TWh in 2050. The accumulative battery demand from 2020 to 2050 reaches 41.1–41.7 TWh without B2U, and B2U can reduce it to 39.1–39.6 TWh with a decrease of 5%. In the case of aggressive BESS deployment, the overall trend of new Li-ion battery demand is similar to that in moderate BESS deployment case. The difference in new battery demand between the two cases comes mainly from the increase in BESS scale, and B2U can significantly mitigate this increase. From the accumulation perspective, demand for new batteries till 2050 reaches 44.2–44.7 TWh without B2U, while B2U can reduce it to 40.2–40.4 TWh with a decrease of 9–10%.

Fig. 8 shows the scrapped Li-ion batteries from EVs and BESSs in China with battery SOH characterized. Results show that the implementation of B2U can effectively reduce the accumulative scrapped Li-ion batteries. In NCM/NCA dominating case, B2U can reduce the accumulative scrapped batteries between 2020 and 2050 from 16.0 to 16.1 TWh to 12.4–14.0 TWh with a decrease of 13–23%. If LFP batteries dominate EV battery market, B2U can reduce the accumulative scrapped batteries from 16.2 TWh to 11.8–14.1 TWh with a decrease of 13–27%. This decrease can be attributed to the reduction of new batteries inflowing to EVs and BESSs, as well as that B2U can prolong battery's lifetime and delay the battery scrapping.

4. Discussion

B2U provides a promising solution for making maximum utilization of retired EV batteries and can decrease tera-watt hours of new Li-ion batteries needed for BESS deployment in China. Based on the above results, over 80% of new Li-ion batteries for BESS deployment can be covered by repurposed EV batteries in the case of aggressive BESS deployment and LFP dominating EV market. From an environmental point of view, such reduction of new Li-ion batteries through B2U can bring considerable environmental benefits. Calculated with the GHG emissions intensity of higher than 100 kg of CO_2 equivalent for per kWh of Li-ion battery manufacturing [51], the implementation of B2U in China leads to a reduction of GHG emissions on the magnitude of hundreds of megatons. Besides, collecting each ton of lithium-ion corresponds to 250 tons of mineral ore spodumene or 750 tons of mineral-rich brine in the mining process while consuming 1900 tons of water,

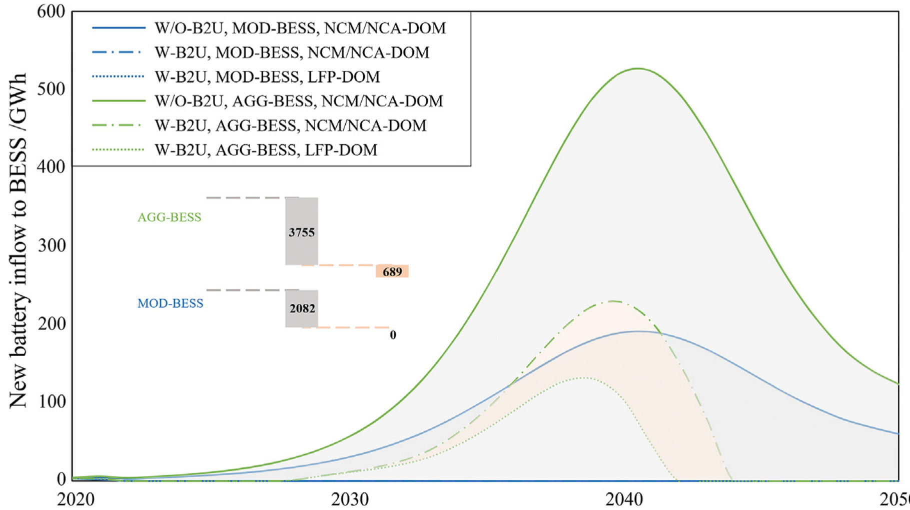

Fig. 5. Prediction on new batteries needed for BESS deployment under different scenarios.

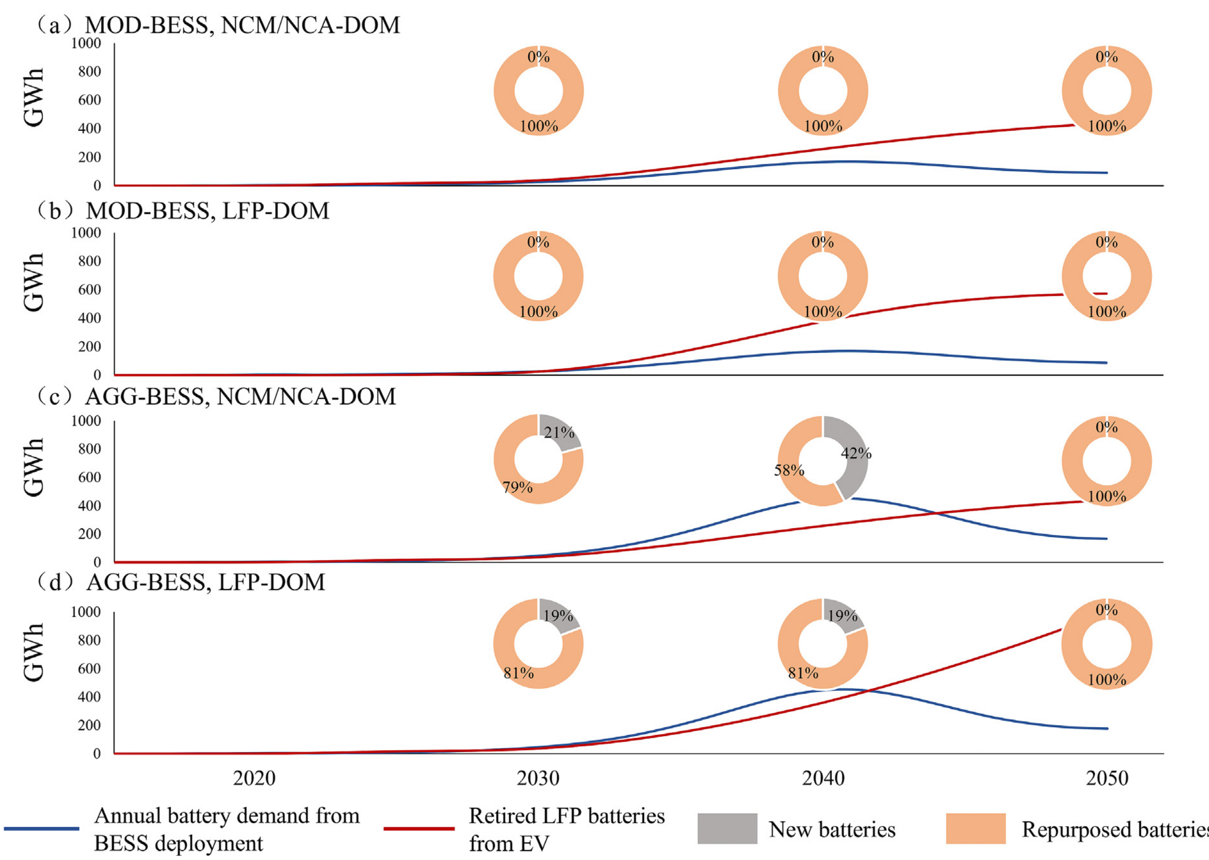

Fig. 6. Comparison between repurposed batteries supply and BESS's demand as well as the share of new and repurposed Li-ion batteries inflowing to BESSs under different scenarios.

which imposes a significant burden on the environment [52]. The decline of new Li-ion batteries demand also implies reduction in critical resource demand. Taking lithium for example, the lithium intensity for the current generation of Li-ion batteries is about 0.11 kg per kWh [53]. This implies a conservation of million tons of lithium with B2U implementation, which is beneficial to mitigate the supply risk of lithium resources. Although this demand can theoretically be made up by recycling retired Li-ion batteries, the current recycling rate of lithium that is close to zero still leads to a low resource efficiency [54].

The main technical obstacles restricting the development of B2U are the difficulty in ensuring battery safety and the lack of accurate and simple model to predict battery's residual life [10]. The cell-to-cell heterogeneity of battery packs caused by different automotive use histories not only reduces their secondary life, but also raises safety concerns. It requires the joint efforts from the government,

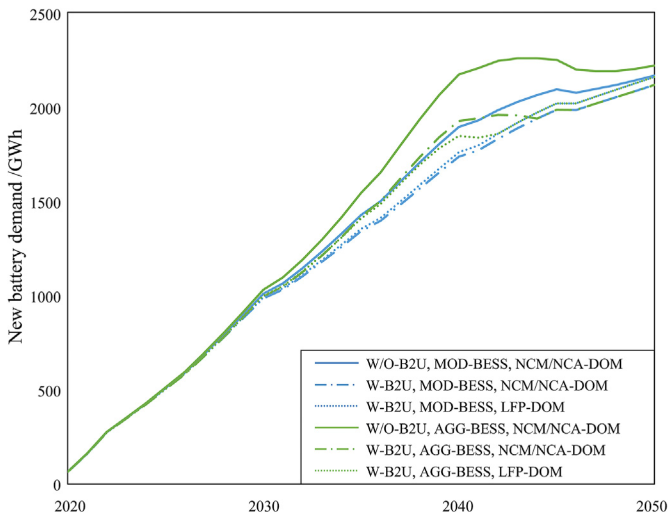

Fig. 7. Prediction on new Li-ion batteries inflowing to EVs and BESSs in China under different scenarios.

industry and academia to solve this problem. For industry and academia, it is necessary to promote researches on on-board battery monitoring system and battery degradation model, tracking the automotive use data of batteries and predicting their degradation in both primary and secondary life based on these data. For the government, regulations should be introduced to promote enterprises to jointly establish a transparent automotive battery use database. Transparent automotive use data are helpful for B2U companies to identify the residual value of retired batteries and optimize strategies, improving the safety of repurposed batteries. In addition, unified standards including physical parameters as well as packaging and chemistry for EV batteries are crucial to reducing B2U costs and improving safety. This can only be promoted by strong codes and standards from the government.

Necessity of BESS in integrating renewable energy into grid also provides opportunities for emerging energy storage technologies. Besides Li-ion batteries, many emerging energy storage technologies are also gaining momentum, such as sodium-ion batteries. Sodium-ion batteries work similarly to Li-ion batteries. Sodium-ion batteries promise lower cost and higher safety than Li-ion batteries, while low specific energy and energy density are major barriers. Based on these characteristics, it is generally believed that sodium-ion batteries are more suitable for stationary energy storage systems which are insensitive to battery size and energy density. While technological and commercial progresses have been made, sodium-ion batteries are still in the early stage of development and still need a long time to competitive [55]. Thus, it should be noted that this study might represent an overestimation of B2U's benefits if emerging technologies other than Li-ion batteries become the dominating technologies for energy storage systems.

5. Conclusion

With the development of EVs, there is expected to be a large number of retired EV batteries still with considerable residual value. B2U provides a solution to making maximum utilization of these batteries. This study focuses on the potential of B2U implementation in China, exploring to what extent retired EV batteries can meet batteries needed for BESS deployment. The results show that until 2050, more than 16 TWh of Li-ion batteries are expected to be retired from EVs. If these retired batteries are put into second use, the accumulative new battery demand of BESSs can be reduced from 2.1 to 5.1 TWh to 0–1.4 TWh under different scenarios, implying a 73–100% decrease. This study proves that B2U has considerable market potential, which provides a basis for the formulation of policies and corporate strategies.

This study provides a methodological framework about B2U that can be extended for future research on the economic or environmental impacts of B2U. Limited by data and modeling, a few weaknesses exist in the current study. For example, the competition among various energy storage technologies in the future has not been modeled in this study. Besides, other factors influencing the supply of retired EV batteries for B2U, e.g., possible battery damage, are not considered. Such limitations need to be addressed in subsequent studies.

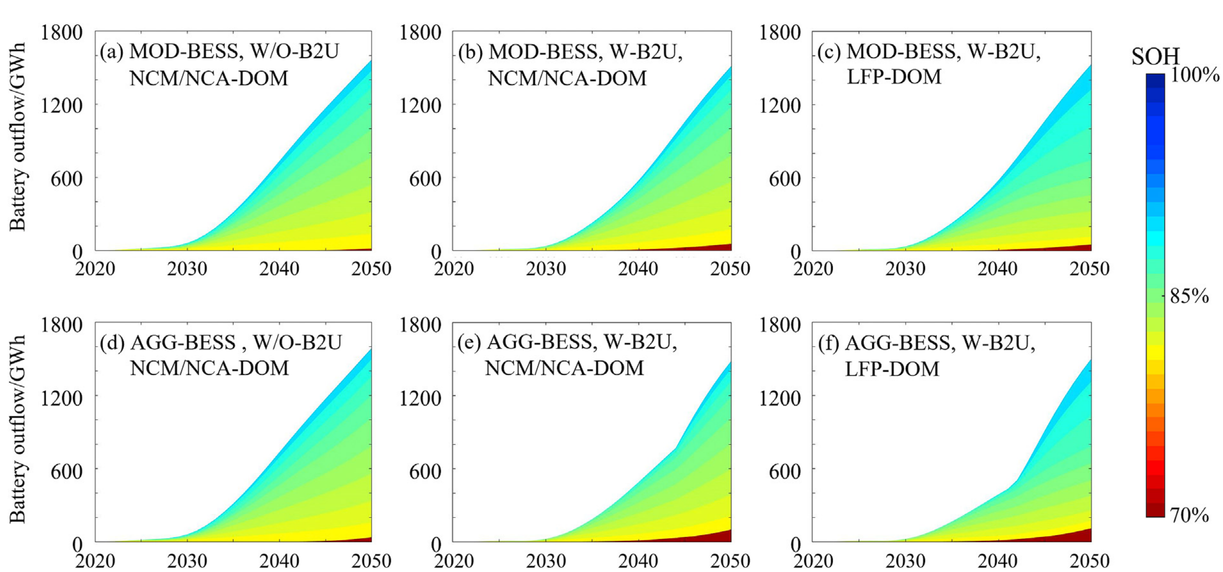

Fig. 8. Prediction on scrapped batteries with different SOH from EVs and BESSs under the case of moderate and aggressive BESS deployment.

Credit author statement

Jingxuan Geng: Methodology, Investigation, Formal analysis, Writing – original draft. Suofen Gao: Methodology, Writing – review & editing. Xin Sun: Methodology, Writing – review & editing. Zongwei Liu: Conceptualization. Fuquan Zhao: Conceptualization. Han Hao: Conceptualization, Methodology, Writing – review & editing, Project administration, Supervision, Funding acquisition.

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.

Acknowledgements

This study is sponsored by the National Key R&D Program of China (2019YFC1908501), National Natural Science Foundation of China (72122010, 71774100).

Appendix

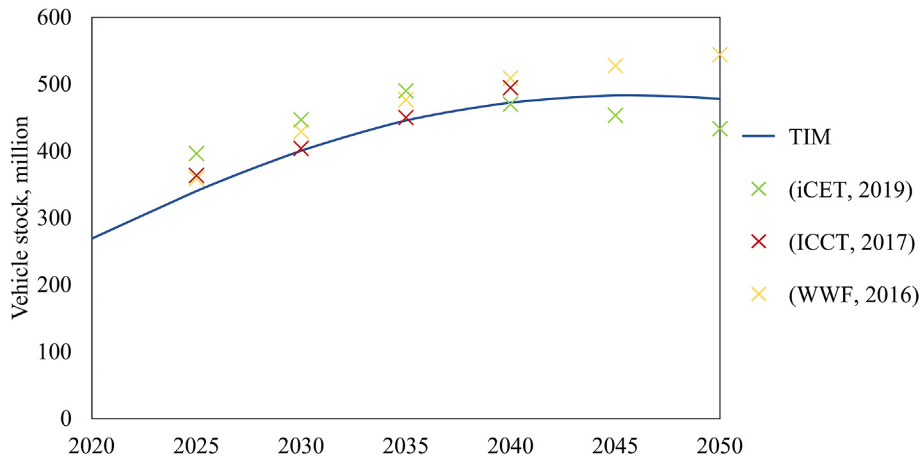

Fig. A1. Comparison of prediction on Chinese vehicle stock by TIM with existing studies.

Figure A1 shows the prediction on Chinese vehicle stock by TIM and the comparison with other representative studies. The future vehicle stock in China predicted in this study is generally in line with the results in existing studies.

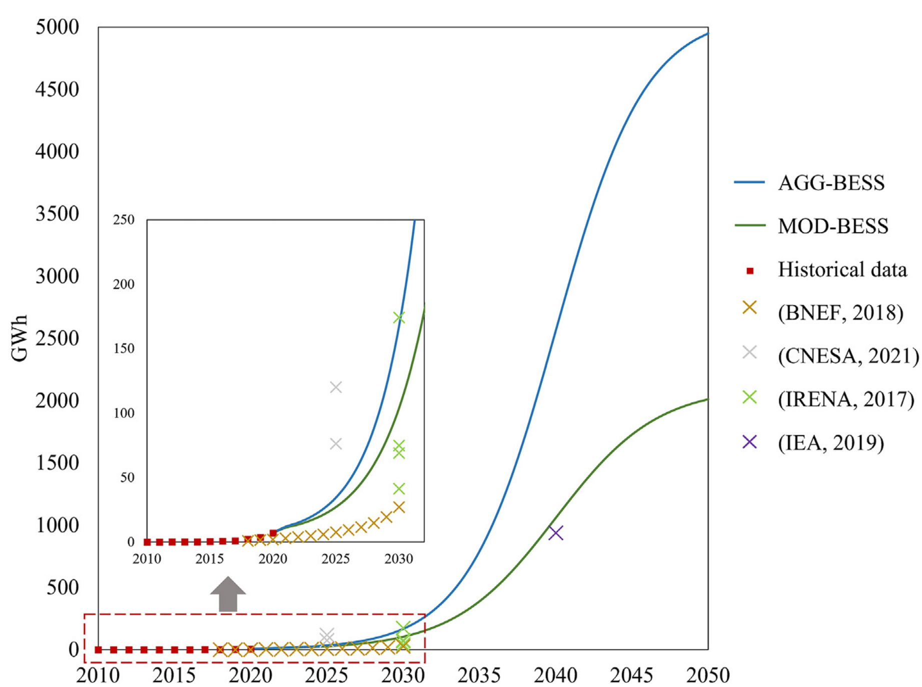

Fig. A2. Comparison of prediction on installed BESS capacity by BESSDM with existing studies.

Figure A2 shows the comparison of prediction on installed BESS capacity by BESSDM with the results in other existing studies. It should be noted that the results of BESS scale from different studies are showing large disparity. The results in earlier studies tended to be lower than the actual development. Overall, the future BESS capacity in China predicted by BESSDM is in line with the results in existing studies.

Figure A3 shows the impact of ± 10% changes in *DU* or *k* from reference values on the new Li-ion battery demand of BESS deployment. Without B2U, it would have an impact of 4.3–12.9% on BESS's new battery demand. While in the aggressive scenarios with B2U, a 10% change in *DU* or *k* would lead to a 57.1% change in the results. This is mainly because the results are obtained by subtracting retired batteries from total annual battery demand, and in the case that B2U cannot satisfy the battery demand, the changes in *DU* or *k* would result in a larger change in new battery demand. Even with wide changes, the new battery demand values remain low.

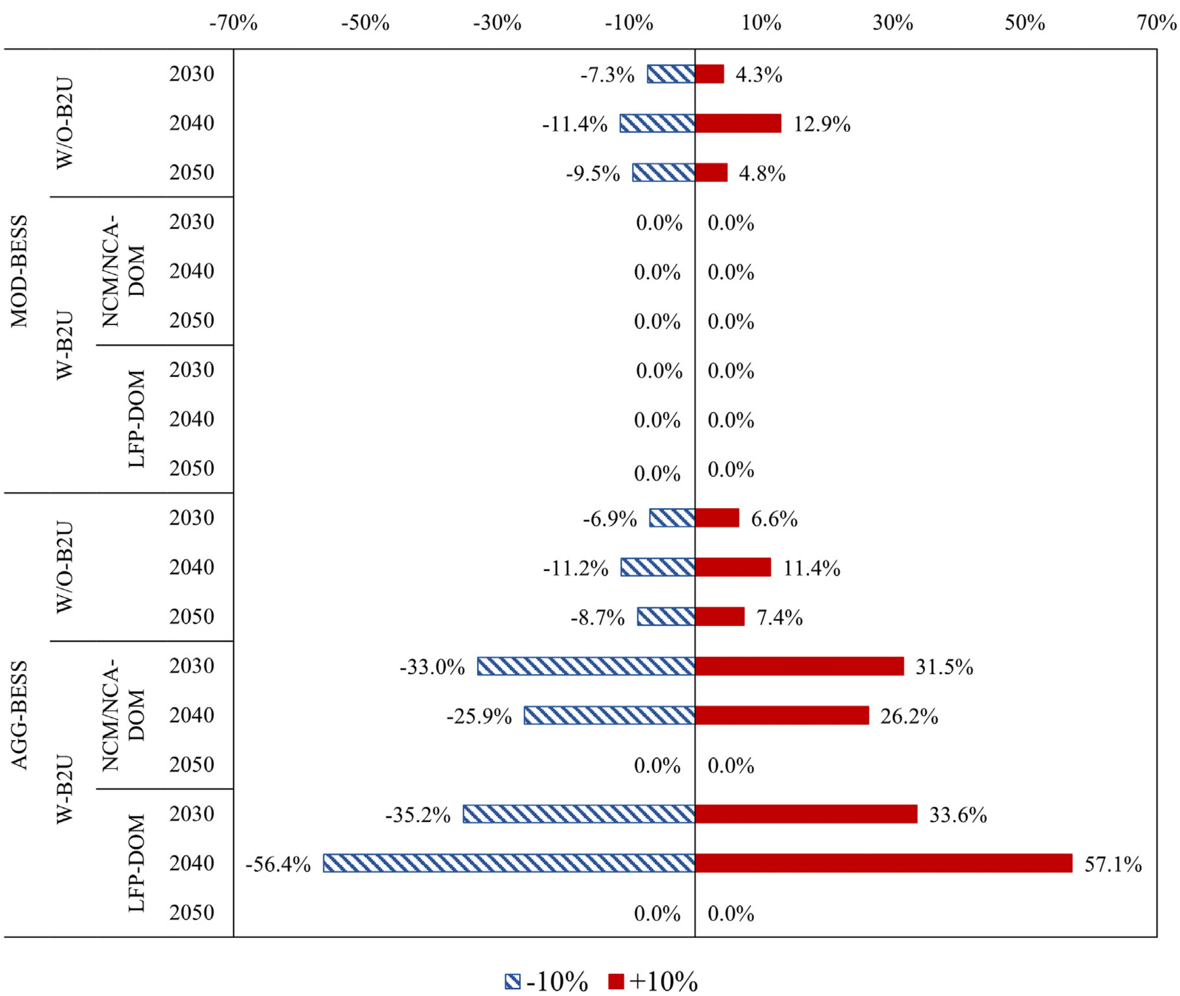

Fig. A3. Uncertainty analysis for ± 10% changes from reference values for discharge duration (*DU*) or pairing coefficient (*k*) in the prediction on new Li-ion battery demand of BESS deployment under different scenarios.

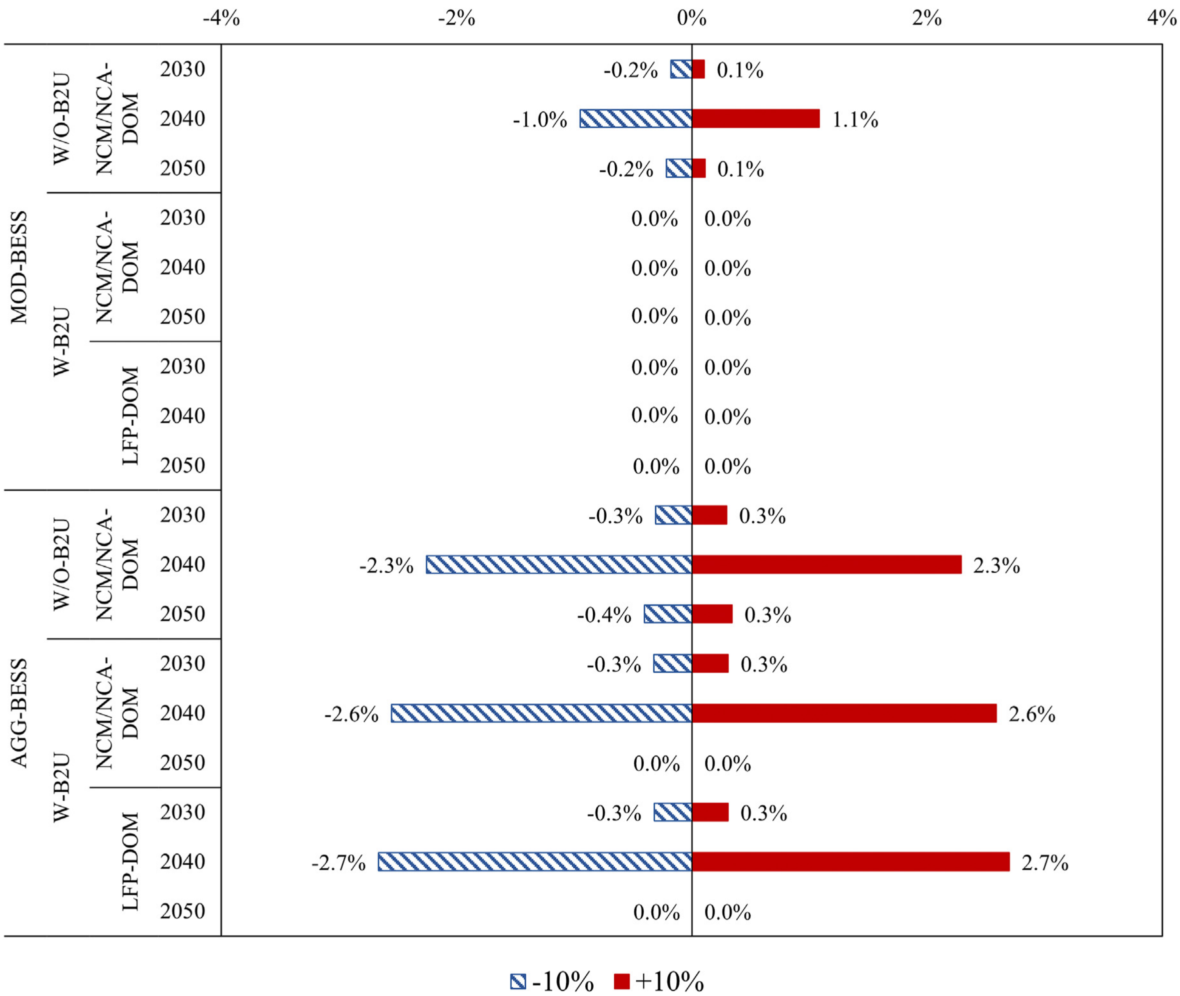

Fig. A4. Uncertainty analysis for ± 10% changes from reference values for *DU* or *k* in the prediction on new Li-ion batteries inflowing to EVs and BESSs under different scenarios.

Figure A4 shows the uncertainty analysis for ± 10% changes from reference values for *DU* or *k* in the prediction on new Li-ion batteries inflowing to EVs and BESSs. Compared to the results in figure A3, the uncertainty in EV and BESS battery demands caused by *DU* or *k* is smaller. A 10% change for *DU* or *k* would lead to a 2.7% change in the new Li-ion batteries consumption in EVs and BESSs.

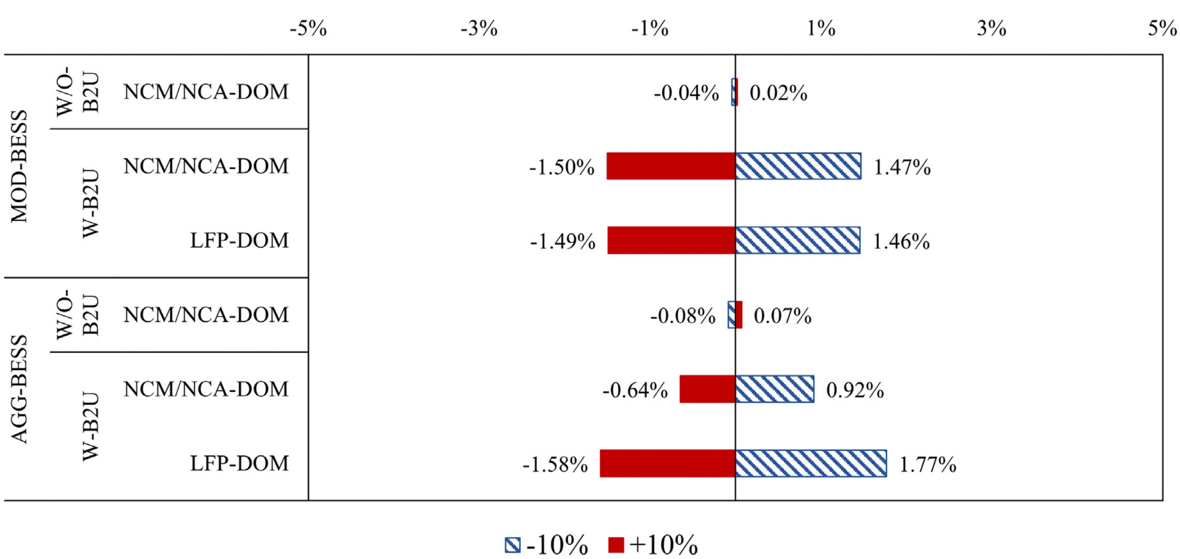

Fig. A5. Uncertainty analysis for ± 10% changes from reference values for *DU* or *k* in the prediction on scrapped batteries from EVs and BESSs under different scenarios.

Figure A5 shows the uncertainty analysis for ± 10% changes from reference values for *DU* or *k* in the prediction on scrapped batteries from EVs and BESSs. Since an increase in *DU* or *k* would lead to more retired EV batteries consumption through B2U, an increase for *DU* or *k* would lead to the opposite change in the accumulative scrapped batteries. A 10% change for *DU* or *k* would result in a 1.8% change in the results.

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