frontiers | Frontiers in Energy Research

TYPE Original Research
PUBLISHED 30 May 2024
DOI 10.3389/fenrg.2024.1343879

OPEN ACCESS

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RECEIVED 24 November 2023
ACCEPTED 06 May 2024
PUBLISHED 30 May 2024

CITATION
Yuan Z, He Y and Meng Z (2024), Hybrid energy storage configuration methodology, taking into account the accumulation of wind farm forecast deviations.
Front. Energy Res. 12:1343879.
doi: 10.3389/fenrg.2024.1343879

Hybrid energy storage configuration methodology, taking into account the accumulation of wind farm forecast deviations

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The accumulation of wind power prediction deviations will make it difficult to maintain the long-term stable operation of energy storage. To solve this problem, this paper proposes a hybrid energy storage system configuration method containing second-use batteries. This paper establishes a three-battery hybrid energy storage operation strategy that considers the accumulation of prediction deviation and prevents the accumulation of prediction deviation by changing the energy storage used at the end of the dispatch cycle. It also establishes an optimal allocation model for energy storage capacity, which takes into account the performance parameters and life loss of the second-use batteries and the new power battery. Finally, Gurobi is used to simulate the field data of a wind farm. The simulation results show that this method is effective in preventing the accumulation of prediction deviation while reducing wind power grid deviation and improving the level of energy storage utilization. It can play a certain reference role in the configuration of energy storage for wind farms.

KEYWORDS

wind power forecasts, hybrid energy storage, wind power, planning optimization model, grid connection deviation

1 Introduction

Wind power has entered the era of large-scale grid-connected operations, but the randomness of wind power output and its anti-peaking nature bring great challenges to the power grid (Sepulveda et al., 2021). Hybrid energy storage, combining a power battery and a second-use battery, can effectively solve these problems (Zakeri and Syri, 2015; Guerra et al., 2021; Zou et al., 2023). By using large-capacity second-use batteries as capacity storage for the time-sequence transfer of wind farms and using power batteries as power storage for rapid response to output deviations, the advantages and disadvantages of the two types of storage can be reasonably utilized to complement each other in completing the established work tasks.

Abbreviations: SOC, state of charge; DOD, depth of discharge; BESS, battery energy storage system; WSCS, wind speed curve scoring.

Under the current power market, wind farms need to declare the future wind storage joint output curve based on the wind forecast 1 day in advance according to the consumable target issued by the power grid. The operation process needs to comply with the declared curve, and if it deviates from the declared output curve during operation, it will be penalized according to the degree of deviation (Yu et al., 2022). Due to errors in wind power forecasting, the total intraday output of a wind farm cannot be fully matched with the energy that can be consumed by the grid (Li et al., 2022; Qi et al., 2023). This error will accumulate in the energy storage system. It will gradually increase the degree of deviation from the declared curve. The accumulation of multiple cycles may lead to the inability of the energy storage to operate effectively in conjunction with the wind farm (Lin et al., 2021).

Wind power deviations that are already equipped with peaking energy storage can be achieved by increasing the wind storage capacity to balance the operation cycle of the storage battery. However, this method will produce a large number of duplicate power constructions and capacity redundancies, leading to poor economic efficiency (Nguyen and Lee, 2016). The control strategy can be optimized by changing the energy storage charging and discharging operating states to reduce the likelihood of reaching the limit state. However, although the optimal control strategy can ensure that the energy storage is in a relatively smooth operation state by controlling the energy distribution, the impact on the overall grid connection still exists due to the unchanged total energy input and output (Sewnet et al., 2022).

To reduce the impact of prediction bias, Yang et al. (2023) proposed a wind storage combined system based on a real-time learning prediction model with dynamic error compensation, which improves the accuracy of wind power prediction and reduces the uncertainty of wind farm output through the wind speed curve scoring (WSCS) model. Yuan et al. (2021) proposed a scenario-based prediction method to address the uncertainty of wind farm output; this method involves generating a dataset using the generative adversarial network method and applying a genetic algorithm to predict multi-objective scenarios. Although the above method improves the accuracy of wind power prediction, it still fails to solve the problem of the accumulation of prediction bias. To reduce the accumulation of deviation, Lin et al. (2021) used hybrid energy storage to suppress the wind power output deviation and proposed a storage operation stability index, which allocates the output through the real-time state of storage to prevent the accumulation of prediction deviation from affecting the storage output; Liu et al. (2023) proposed a data-driven energy storage management strategy considering the wind power prediction interval, which focuses on the effect of the wind power prediction on the daily operation of the storage, quantifies the wind power uncertainty, and provides the data management strategy for the wind power prediction. The impact of wind power prediction on the daily operation of energy storage is quantified to obtain long-term stable operation of energy storage; Zhu et al. (2021) also proposed a similar energy storage management strategy, which applies deviation statistics and frequency decomposition to energy allocation and capacity allocation by comparing with the actual power. The abovementioned methods incorporate wind power forecasting and maintain the energy storage energy at a certain interval through energy allocation methods. Still, these methods will affect the energy allocation during the operation cycle, which will generate grid connection deviations and the corresponding penalties. Xu et al. (2023) proposed a day-ahead scheduling method using a trapezoidal fuzzy number equivalence model describing the uncertainty of wind power forecasting and day-ahead scheduling to improve the robustness of wind farms on the grid; Tu et al. (2023) balanced the economics and robustness of day-ahead scheduling for wind farms by fitting three typical features to the wind power output uncertainty and establishing a two-stage day-ahead scheduling model. The abovementioned literature reduces the impact of bias accumulation through the idea of improving the robustness of day-ahead scheduling, but this may lead to a larger amount of wind abandonment as well as the possibility of not being able to meet the intraday scheduling demand when experiencing extreme forecast deviations.

Although much progress has been made in these approaches, the cumulative impact of prediction bias is often not considered or addressed. 1) The method of improving the prediction accuracy can reduce the prediction error and increase the quality of the grid connection. However, the intrinsic prediction error still exists, and the energy storage will continue to accumulate deviations in multi-day operations. 2) Although the method of optimizing energy distribution can solve the problem of accumulation of prediction bias, the energy storage energy is in a relatively stable state. However, in order to maintain the balance of energy storage, this method will inevitably affect the grid-connected quality of wind farms and may cause additional curtailment or grid-connection deviation. 3) The robust scheduling method can slow down the accumulation of prediction bias, but due to the randomness of wind power output, robust scheduling often reduces the economy of wind power grid connections and fails when encountering more extreme cases. These methods can usually only slow down the accumulation rate of prediction deviations or inevitably affect the operation of hybrid energy storage during intraday operation, thus affecting the overall output effect of wind farms to a certain extent.

The accumulation of prediction deviations will lead to the failure of energy storage operations, which will affect the grid-connected quality of wind farms. In order to solve this problem, this paper proposes an optimal allocation method for hybrid energy storage in the scenario of peak shaving and control output fluctuation energy storage in the scenario of the wind farm, which can effectively prevent the accumulation of wind power prediction bias under the condition that it has a small impact on wind power grid integration. Three groups of energy storage batteries are used for peaking and controlling wind power output fluctuations, and by switching the functions of the battery packs at the end of the operating cycle, it is ensured that the battery packs used for controlling output fluctuations can restore the initial energy to prevent the accumulation of prediction deviations on alternate days. Compared to other methods, the present method combines peaking energy storage with energy storage for controlling power output fluctuations and effectively prevents the accumulation of energy storage prediction deviations by operating at the end of a dispatch cycle; at the same time, it reduces the additional deviations that are generated to maintain the energy balance of the energy storage cycle. In addition, this method can reduce the system's computational complexity by preventing the accumulation of deviations through fixed control. This method can ensure the long-term stable operation of battery energy storage systems (BESS) and reduce the impact of prediction deviation on the combined wind storage output.

2 Integrated hybrid energy storage operation strategy considering the accumulation of forecast bias

The power grid requires wind farms to declare the forecast output before the day of the forecast, and based on the forecast, the wind farms will be issued with consumable targets. After accepting the target, the wind farm declares an output plan for the grid based on the energy storage it has deployed. During the daily operation phase, the wind farms are required to generate electricity according to the declared output plan (Gholami et al., 2018). In cases of severe deviations, economic penalties may result. Given the existence of forecast deviations, energy storage systems need to be configured to smooth out the deviations.

Although energy storage can smooth out the prediction bias at different moments, the total charging and discharging of the energy of the storage battery is often not balanced due to the randomness of wind power output, as shown in Figure 1A (Lin et al., 2021).

Typically, energy storage systems used for peaking are relatively easy to maintain a balance of charge and discharge because the charge and discharge schedules have been developed beforehand. However, energy storage systems used for smoothing forecast deviations tend to experience an accumulation of deviations. With continuous operation for many days, the forecast deviation gradually accumulates, resulting in an extreme situation where the energy storage system used to smooth out the forecast deviation may be depleted or overpowered, failing to meet the wind farm's demand allocation.

The conventional energy storage operating curve for preventing deviation accumulation is shown in Figure 1. The prediction deviation accumulation is prevented by controlling the charging and discharging balance of the energy storage during the operation cycle, and the deviation is eliminated in the output in the form of grid-connected deviation. However, there are two main problems with this approach: on one hand, it fails to fully utilize the energy storage capacity, failing to maximize the economic benefits; on the other hand, it has a certain impact on the operation of the energy storage system, which may limit the flexibility of the energy storage.

In this paper, a three-storage hybrid operation strategy is proposed, which includes three groups of storage batteries called 1, 2, and 3, where battery group 1 is a second-use battery for peak shifting and battery groups 2 and 3 are new power batteries, which have equal capacity.

In the first operating cycle, batteries 1 and 2 are combined for peaking, while battery 3 is used for smoothing out the prediction deviation. At the end of an operating cycle, batteries 1 and 2 maintain a balanced charging and discharging capacity according to the output schedule; however, due to the prediction bias, battery bank 3 is unable to maintain a balanced state of power.

At the beginning of the second operating cycle, the operating functions of batteries 2 and 3 are switched, with batteries 1 and 3 being used for peaking and battery 2 being used for smoothing out

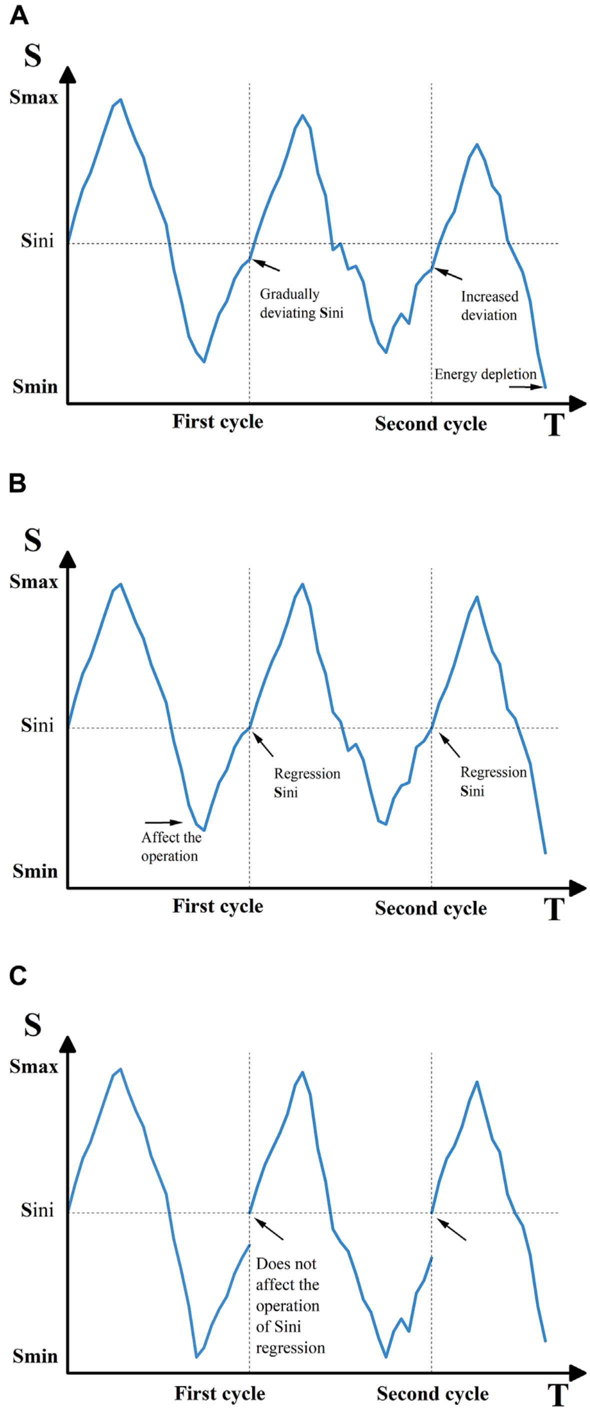

FIGURE 1
Prediction of energy storage charge state under deviation accumulation. **(A)** Unbalanced energy storage cycle charge and discharge energy situation. **(B)** Traditional method of restoring initial energy at the end of the operating cycle. **(C)** The proposed method in this paper does not need to consider the cycle charge and discharge energy balance method. The picture simulates two half-cycle energy storage operations; the vertical axis is the energy storage SOC, where S_{max} and S_{min} are the maximum and minimum safe charge of the energy storage and Sini is the initial SOC state of the energy storage; and the horizontal axis is the time, which spans two and a half energy storage operation cycles, respectively.

 10.3389/fenrg.2024.1343879

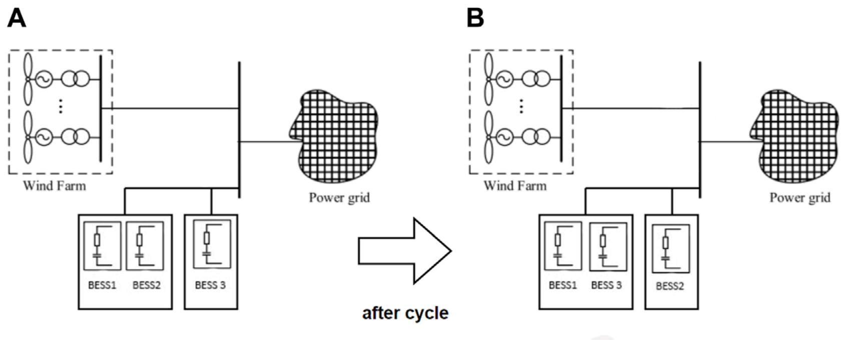

FIGURE 2
Diagram of the operation strategy of the energy storage device. **(A)** Electricity distribution method during the operation cycle of the energy storage device. **(B)** Electricity distribution method after the cycle of the energy storage device. Switching the BESS2 and BESS3 functions after an operating cycle allows the smoothing of the prediction deviation storage to be stabilized for a long period.

the prediction deviation. This ensures that the prediction deviation does not accumulate in the second operating cycle. At the same time, in the operation strategy of battery packs 2 and 3 is that battery pack 2 is used for smoothing out the prediction deviation and battery pack 3, which is not required to be used for smoothing out the prediction deviation, can balance the charging and discharging energies during the operation cycle. Its operating curve is shown in Figure 1C.

This hybrid operation strategy utilizes the characteristics and advantages of different types of energy storage batteries to achieve the goals of peaking and smoothing forecast deviations by switching battery bank functions. Through rational battery bank scheduling and energy management strategies, grid connection deviation is minimized while the overall performance and sustainability of the wind farm configuration of energy storage are improved. Figure 2 shows a schematic of this hybrid operation strategy.

3 Mathematical model of energy storage configuration for the hybrid energy storage system considering grid-connected characteristics

3.1 Analysis of hybrid energy storage utilization

After the retirement of lithium-ion batteries, the second use of the power grid under simulated load conditions has good life characteristics. According to experiments by power battery manufacturers, second-use of the power battery pack (48V50Ah) undergoes 1C/1C and 100% depth of discharge (DOD) charging and discharging at 45°C and room temperature (RT) conditions, respectively, after the rated capacity is below 80%. The experimental results show that before reducing to 60% of the rated capacity, it will undergo between 3,000 and 6,000 cycles (BYD, 2016). In addition, experiments have found that the battery life exceeds 3,000 times under simulated load conditions [RT, 0.5C, 80% (DOD)] in the power grid (Lai, 2020). The battery has a significant price advantage, with a price of about 60% that of new batteries, which can greatly improve the efficiency of energy storage configurations (Dong et al., 2023). However, the second use of batteries will deteriorate after cyclic use and is not suitable for high-power charging. In addition, stricter state-of-charge (SOC) restrictions need to be implemented. This will, to some extent, have an impact on the configuration of second-use batteries.

For the second use of lithium-ion batteries, it is necessary to evaluate their initial operating conditions. Currently, lithium-ion batteries are mainly used in electric vehicles and electric bicycles. Electric bicycles have good operating conditions, but their individual capacity is low, making it difficult to scale their second use. The operating conditions of electric vehicles are complex, and lithium-ion batteries may experience significant degradation during operation. Due to the concentrated energy storage configuration in wind farms, safety requirements are high. When using second-use batteries, careful screening should be carried out in conjunction with battery recycling enterprises. For example, when grouping and classifying electric vehicles into different types and operating conditions, it is important to consider not only the number of cycles and service life of lithium-ion batteries but also the operating conditions of electric vehicles. Special treatment should be given to categories with high operating temperatures and frequencies of use.

Extensive research has been conducted on the application of cascading battery energy storage (Deng et al., 2021; Zhang et al., 2021; Yang et al., 2021). By utilizing batteries in communities, microgrids, smart grids, and other application scenarios, the economic efficiency of energy storage configurations can be improved while meeting performance requirements. In addition, a large number of cascade utilization battery energy storage demonstration projects have been built for peak shaving, frequency regulation, arbitrage, backup energy, and other purposes (Look, 2017; Gjerløw, 2018; ELSA Consortium, 2020; Mosbæk, 2020; Faessler, 2021).

The demand for high-power fast charging and discharging cannot be met using the second-use battery alone, so an additional new power battery needs to be configured to provide supplementary power. By combining the characteristics of the two batteries, good performance complementarity can be achieved, which together prevents the accumulation of prediction bias (Guerra et al., 2020).

3.2 Hybrid energy storage lifetime loss modeling

3.2.1 Energy storage lifetime depletion modeling

Wind energy storage faces complex working conditions. The depth of charging and discharging, the charging and discharging power, and the number of cycles all impact the life of the storage battery. The irregularity of charging and discharging for energy storage batteries cannot be solely accounted for based on the manufacturer's standard factory life, necessitating a separate assessment. The National Renewable Energy Laboratory of the United States has proposed a battery damage life model based on experimental data (Drouilhet and Johnson, 1997). It considers that under rated operating conditions, the total discharge of the battery throughout its entire lifecycle is referred to as the total effective discharge (in units of A.h). This is expressed as (Eq.s 1-3)

$$A_{11} = L_{R1} D_{R1} C_{R1}, \tag{1}$$

$$A_{12} = L_{R2} D_{R2} C_{R2}, \tag{2}$$

$$A_{13} = L_{R3} D_{R3} C_{R3}. \tag{3}$$

Among them, A_{11}, L_{R1}, D_{R1}, and C_{R1} represent the total effective discharge, rated cycle life, rated depth of discharge, and rated capacity of the second-use battery, respectively. A_{12}, L_{R2}, D_{R2}, and C_{R2} denote the total effective discharge, rated cycle life, rated depth of discharge, and rated capacity of the new power battery used for peaking, respectively. A_{13}, L_{R3}, D_{R3}, and C_{R3}, respectively, stand for the total effective discharge capacity, rated cycle life, rated discharge depth, and rated capacity of the new power battery used for smoothing out the prediction deviation.

In practice, different charging depths and charging power will cause different losses in battery life, so converting the actual discharge amount into the effective discharge amount A2 is necessary. . The battery's lifespan will be counted as a cut-off when the accumulated A2 = A1 after N cycles.

The charging and discharging losses of each storage battery are equivalent to the standard loss, represented as follows in Eqs 4-6:

$$A_{21,t} = \frac{L_{R1} P_{R1} d^{\,a}_{1,t}}{a D^{-b}_{1,t}\, e^{-CD_{1,t}} P^{\,dc}_{1,\ t}}, \tag{4}$$

$$A_{22,t} = \frac{L_{R2} P_{R2} d^{\,a}_{2,t}}{a D^{-b}_{2,t}\, e^{-CD_{2,t}} P^{\,dc}_{2,\ t}}, \tag{5}$$

$$A_{23,t} = \frac{L_{R3} P_{R3} d^{\,a}_{3,t}}{a D^{-b}_{3,t}\, e^{-CD_{3,t}} P^{\,dc}_{3,\ t}}, \tag{6}$$

where a, b, and c are constants, which are 694, 1.98, and 0.016, respectively; $A_{21,t}$, $A_{22,t}$, and $A_{23,t}$ are the equivalent standard losses of the second-use battery at time t, the new power battery used for peaking, and the new power battery used for smoothing out the prediction deviation, respectively; $d^{\,a}_{1,\ t}$, $d^{\,a}_{2,\ t}$, and $d^{\,a}_{3,\ t}$ are the actual Ah values of discharging of the second-use battery at time t, new power battery used for peaking, and new power battery used for smoothing out the prediction deviation, respectively. $D_{1,t}$, $D_{2,t}$, and $D_{3,t}$ are the discharge depths of the second-use battery at time t, the new power battery used for peaking, and the new power battery used for smoothing out the prediction deviation, respectively; and $P^{\,dc}_{1,\ t}$, $P^{\,dc}_{2,\ t}$, and $P^{\,dc}_{3,\ t}$ are the power absorbed by the grid from the second-use battery, new power battery used for peaking, and new power battery used for smoothing out the prediction deviation at time t, respectively.

3.2.2 Economic discounting of energy storage losses

Converting the lifetime loss per charge/discharge into cost consumption. As shown in Eqs. 7-10

$$C_a = \frac{(1+r)^{T^{eye}}}{r(1+r)^{T^{eye}} - 1}, \tag{7}$$

$$C_{loss1,t} = \frac{\left[\left(C_{battery1} + C^{\,eqip}_{1}\right) E_1 A_{21,t} C_a + W_1 C_{power}\right]}{A_{11}}, \tag{8}$$

$$C_{loss2,t} = \frac{\left[\left(C_{battery2} + C^{\,eqip}_{2}\right) E_2 A_{22,t} C_a + \frac{W_2 C_{power}}{2}\right]}{A_{12}}, \tag{9}$$

$$C_{loss3,t} = \frac{\left[\left(C_{battery2} + C^{\,eqip}_{2}\right) E_2 A_{23,t} C_a + \frac{W_2 C_{power}}{2}\right]}{A_{13}}. \tag{10}$$

C_a represents the discount factor of the lithium battery system. $C_{loss1,t}$, $C_{loss2,t}$, and $C_{loss3,t}$ denote the cost consumption of the second-use battery at time t, the new power battery for peaking, and the new power battery for smoothing out the prediction deviation, respectively. r is the discount rate, and Teye is the planned service life of the lithium battery system; $C_{battery1}$ represents the unit price of the second-use battery, while $C_{battery2}$ represents the price of the power battery; $C^{\,eqip}_{1}$, $C^{\,eqip}_{2}$ are the peripheral equipment costs of the second-use battery and new power battery, respectively. W_1 and W_2 denote the rated power of the second-use battery system and the new power battery system, respectively. C_{power} represents the cost of the energy storage inverter of the energy storage station. E_1, E_2, and E_3 are the installed capacities of the second-use battery, the new power battery used for peaking, and the new power battery used for smoothing out the prediction deviation, respectively.

3.3 Economic modeling of hybrid energy storage for wind farm deployment

Optimization aims at wind farms achieving the maximum economic benefit from the deployment of energy storage; this benefit includes the daily income from electricity sales, the daily carbon emission benefit, as well as battery charging and discharging losses and deviation penalties due to non-compliance with the grid connection curve submitted a few days ago (Chen et al., 2022). The objective function is determined by the above factors and is formulated below in Eq. 11:

$$\mathrm{Max}C = \left(C^{sell} + C^{carbon} - C^{maintain} - C^{bias}\right), \tag{11}$$

where C^{sell} represents the daily electricity sales revenue. C^{carbon} is the daily carbon emission revenue. $C^{maintain}$ is the daily operation and maintenance expenditure and C^{bias} is the daily deviation penalty.

3.3.1 Revenue from electricity sales

The main means by which wind farms make a profit is by delivering electricity to the grid according to a predetermined output curve. The energy storage absorbs the portion of the actual output that exceeds the predefined output curve or generates wind abandonment; the energy storage uses the portion that is below the predefined output curve to release energy or generates an economic output deviation as shown in Eq. 12

$$C^{sell} = \sum_{t=0}^{n} \left(P_t - P_t^{abandon} - P_{1,t}^{ch} + P_{1,t}^{dc} - P_{2,t}^{ch} + P_{2,t}^{dc} - P_{3,t}^{ch} + P_{3,t}^{dc} - P_t^{deviation}\right) C^{price} \quad , \tag{12}$$

where Pt is the actual output of the electric wind farm at time t; $P_t^{abandon}$ is the abandoned wind at time t; $P_{1,t}^{ch}$, $P_{2,t}^{ch}$, and $P_{3,t}^{ch}$ are the power released by the grid for the second-use of battery, new power battery for peaking, and new power battery for smoothing out the prediction deviation at time t, respectively; $P_{1,t}^{dc}$, $P_{2,t}^{dc}$, and $P_{3,t}^{dc}$ are the power absorbed by the grid at time t from the second-use of battery, new power battery for peaking, and new power battery for smoothing out the prediction deviation. $P_t^{deviation}$ is the grid integration deviation of wind power at time t. C^{price} is the feed-in tariff.

3.3.2 Revenue from carbon emissions

Additional revenue from energy storage by discharging instead of peaking in conventional thermal power plants is an important part of the revenue from deploying energy storage. It will be composed of the energy discharged from storage and the price of carbon emissions as shown in Eq. 13

$$C^{carbon} = \sum_{t=0}^{n} \left(P_{1,t}^{dc} + P_{2,t}^{dc} + P_{3,t}^{dc}\right) P_{price}^{carbon} , \tag{13}$$

where P_{price}^{carbon} is the carbon price.

3.3.3 Battery depletion costs

Energy storage battery charging and discharging will produce life loss; too much charging and discharging will affect the wind farm configuration of energy storage revenue as shown in Eq. 14

$$C^{maintain} = \sum_{t=0}^{n} \left(C_{loss1,t} + C_{loss2,t} + C_{loss2,t}\right). \tag{14}$$

3.3.4 Grid deviation penalty

The wind power fluctuation will lead to a deviation between the grid connection and forecast curves, and the grid will penalize the plant according to the deviation when the deviation at time t exceeds the permissible amount as shown in Eq. 15

$$C^{bias} = \left(\sum_{i=0}^{n} P_t^{deviation} - P_{permit}^{deviation}\right) P_{check}^{deviation} C^{price}, \tag{15}$$

where $P_{permit}^{deviation}$ is the permitted value of grid-connection deviation and $P_{check}^{deviation}$ is the penalty value of grid-connection deviation.

3.4 Hybrid energy storage system constraints

3.4.1 Power capacity constraints

Power capacity is the total maximum amount of energy released by a storage battery per unit of time and is limited according to the nature of the storage battery. The power capacity of the battery needs to be limited to a lower level of 15 percent of its capacity. The power capacity of a new power battery can be relatively large, up to 25 percent of its capacity as shown in Eq. 16-19

$$0 \le P_{1,t}^{ch} \le 15\% E_1, \tag{16}$$

$$0 \le P_{1,t}^{dc} \le 15\% E_1, \tag{17}$$

$$0 \le P_{2,t}^{ch} \le 25\% E_2, \tag{18}$$

$$0 \le P_{2,t}^{dc} \le 25\% E_2. \tag{19}$$

3.4.2 Maximum and minimum SOC constraints

SOC is the ratio of energy to total energy capacity at time t. Limiting the maximum and minimum SOC of a storage battery prevents overcharging and overdischarging and improves battery life. Because of poor consistency, high internal resistance, and other reasons, the SOC of the battery needs to be limited more conservatively as shown in Eq. 20-22

$$10\% \le SOC_{1,t} \le 90\%, \tag{20}$$

$$5\% \le SOC_{2,t} \le 95\%, \tag{21}$$

$$5\% \le SOC_{3,t} \le 95\%, \tag{22}$$

where $SOC_{1,t}$, $SOC_{2,t}$, and $SOC_{3,t}$ are the SOC power of the second-use battery, new power battery for peaking, and new power battery for smoothing out the prediction deviation at time t, respectively.

3.4.3 Energy storage system energy balance constraints

To maintain the energy balance of the energy storage, the energy storage charge is equal to its discharge after one cycle. However, if the proposed method is used, there is no need for Batteries B or C to maintain an operating cycle energy balance as shown in Eq. 23-25

$$\sum_{t=0}^{n} P_{1,t}^{ch} \eta_1 = \sum_{t=0}^{n} \frac{P_{1,t}^{dc}}{\eta_1}, \tag{23}$$

$$\sum_{t=0}^{n} P_{2,t}^{ch} \eta_2 = \sum_{t=0}^{n} \frac{P_{2,t}^{dc}}{\eta_2}, \tag{24}$$

$$\sum_{t=0}^{n} P_{3,t}^{ch} \eta_2 = \sum_{t=0}^{n} \frac{P_{3,t}^{dc}}{\eta_2}, \tag{25}$$

where η_1 and η_2 are the charging and discharging power of the battery system for the second-use battery and the new power battery system, respectively. The charge/discharge efficiency includes the integration of the charge/discharge efficiency of the power conversion system and the storage battery. The efficiency is 0.9 for the second-use battery and 0.95 for the conventional power battery.

3.4.4 Constraints on charging and discharging energy storage in the same group

Energy storage battery packs must not be discharged while being charged as shown in Eq. 26-34

$$P^{ch,co}_{1,\ t} = 1, \tag{26}$$

$$P^{dc,co}_{1,\ t} = 1, \tag{27}$$

$$P^{ch,co}_{1,\ t} + P^{dc,co}_{1,\ t} \leq 1, \tag{28}$$

$$P^{ch,co}_{2,\ t} = 1, \tag{29}$$

$$P^{dc,co}_{2,\ t} = 1, \tag{30}$$

$$P^{ch,co}_{2,\ t} + P^{dc,co}_{2,\ t} \leq 1, \tag{31}$$

$$P^{ch,co}_{3,\ t} = 1, \tag{32}$$

$$P^{dc,co}_{3,\ t} = 1, \tag{33}$$

$$P^{ch,co}_{3,\ t} + P^{dc,co}_{3,\ t} \leq 1, \tag{34}$$

where $P^{ch,co}_{1,\ t}$, $P^{ch,co}_{2,\ t}$, and $P^{ch,co}_{3,\ t}$ represent the state representations at time t of the second-use of battery, the new power battery used for peaking, and the new power battery used for smoothing out forecast deviations are in the charging state, respectively. $P^{dc,co}_{1,\ t}$, $P^{dc,co}_{2,\ t}$, and $P^{dc,co}_{3,\ t}$ represent the state representations in the discharge state at time t for the second-use battery, the new power battery used for peaking, and the new power battery used for smoothing out forecast deviations, respectively.

3.4.5 Constraints on charging and discharging heterogeneous energy storage

To reduce energy storage life consumption, different groups of energy storage cannot be in different charging and discharging states as shown in Eq. 35-38

$$P^{ch,co}_{1,\ t} + P^{dc,co}_{3,\ t} \leq 1, \tag{35}$$

$$P^{ch,co}_{3,\ t} + P^{dc,co}_{1,\ t} \leq 1, \tag{36}$$

$$P^{ch,co}_{2,\ t} + P^{dc,co}_{3,\ t} \leq 1, \tag{37}$$

$$P^{ch,co}_{3,\ t} + P^{dc,co}_{2,\ t} \leq 1. \tag{38}$$

3.5 Wind abandonment constraints

To prevent the waste of resources, a wind farm shall not abandon more than 5 percent of its total electricity production per day as shown in Eq. 39

$$\sum\nolimits_{\mathrm{i}=0}^{\mathrm{n}} P_t^{\mathrm{abandon}} \leq 5\% \sum\nolimits_{t=0}^{n} P_t. \tag{39}$$

TABLE 1 Wind farm techno-economic assumptions.

Type	Value
Maximum abandoned wind value %	5
Feed-in tariff/yuan	0.4
Carbon emission price/(yuan)	1.2
Deviation assessment coefficient/	3
Deviation allowable value/percent	5
Price of second-use battery/(yuan/Wh)	0.65
Price of new power battery/(yuan/Wh)	1.1
New power battery integrated system price/(yuan/Wh)	0.25
Price of the integrated battery system for second-use/(yuan/Wh)	0.31
Energy storage inverter price/(yuan/Wh)	0.1
Charge/discharge efficiency of decommissioned power battery system/%	90
New power battery system efficiency/%	95
Design life of energy storage power station/year	5
Rated power of new power battery/Wh	1x battery installed energy
Rated power of second-use battery/Wh/	0.8x battery installed energy
Rated discharge depth of energy storage battery/	0.8
Rated life of energy storage battery/times	2000
Annual discount rate/%	5

4 Analysis of examples

The techno-economic assumptions for the wind farm are shown in Table 1.

Taking the data of a certain day in a wind farm in China as an example, two configuration methods are simulated in this simulation. By comparing it with the traditional method, the effectiveness of the proposed method in this paper is proved.

Scenario 1: operate according to the hybrid energy storage configuration method proposed in this paper.

Scenario 2: use the traditional hybrid configuration method, but also set up three groups of energy storage; however, it is necessary to keep the storage balanced between charging and discharging during the operating cycle.

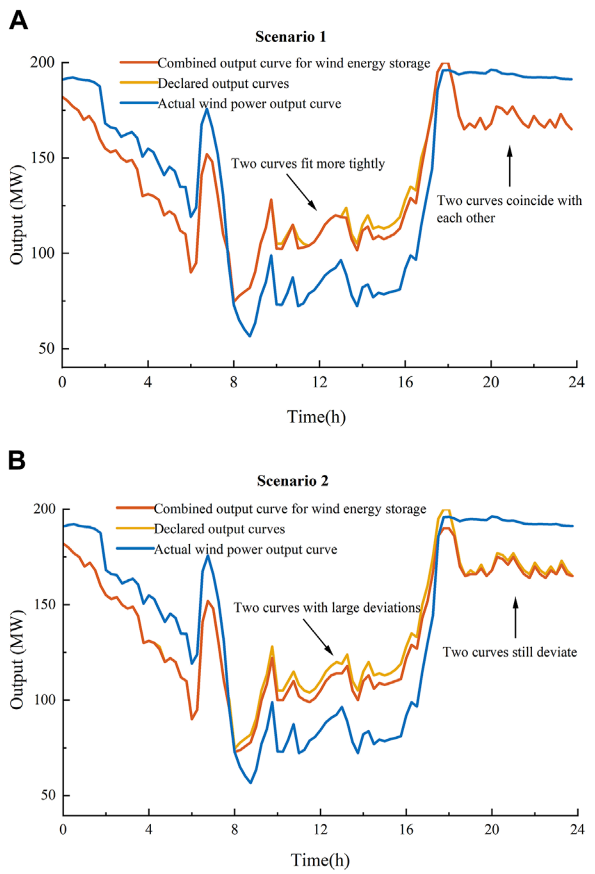

FIGURE 3
Combined output curves of wind storage under different scenarios: **(A)** Scenario 1 and **(B)** Scenario 2.

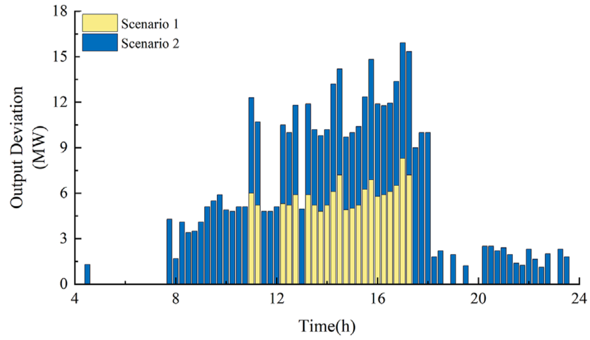

FIGURE 4
Grid connection deviation of wind farms under different scenarios.

After linearizing the battery life loss model, the scenarios were solved in Python using Gurobi.

4.1 Hybrid energy storage grid integration effect

As shown in Figure 3, the power curves of Scenarios 1 and 2 are similar in the 0–8 h period, and there is no obvious power deviation, during which the wind power output is larger than the grid's consumption target and the energy storage is in the charging state. However, after 8 h, the power curves of different scenarios are quite different. Scenario 2 has a continuous deviation from the grid from 8 h until the end of 24 h and always has a certain deviation from the pre-declared curve. The deviation time of Scenario 1 is shorter, and the magnitude is lower than that of Scenario 2.

No matter whether the scenario proposed in this paper is used or not, grid connection deviation will be generated, but the grid connection deviation generated by this scenario is smaller, the duration is lower, and the wind farm grid connection is more effective.

These data can be better analyzed through the wind farm grid integration deviation.

Figure 4 shows the grid connection deviation under both scenarios.

From Figure 4, it is clear that the grid connection deviation of Scenario 2 is larger in duration and power than that of Scenario 1. Scenario 1 grid connection deviation occurs only during 11–17 h, i.e., the second half of the time when storage discharge is required, whereas Scenario 2 grid connection deviation occurs during the whole period of storage operation.

With the same total generation, this may be because Scenario 1 storage can release more energy to smooth out grid connection deviations at different moments in time. The reasons for this situation are further explained below.

As can be seen in Figure 5, the energy storage outputs of the two scenarios are close to each other in the 0–9 h period; in the remaining period, the battery pack of Scenario 1 used to control the output fluctuation releases more energy in the 9–18 h period while absorbing less energy in the 18–24 h period compared to that of Scenario 2. This proves the previous conjecture because the storage battery in Scenario 1 can release more energy to compensate for the grid deviation.

In addition, Scenario 2 releases less energy while preemptively absorbing some of the energy used for the peaking battery bank during the charging period. This will cause a difference in the capacity of the energy storage configuration under the two scenarios.

Combining the wind farm forecast-actual output curves, we can find that these differences occur because the total amount of power generated on the day is lower than the total amount predicted, which creates a scarcity of power due to the prediction deviation. In contrast, Scenario 2 needs to control the charging/discharging balance of the energy storage and can only release as much energy as it can be replenished; therefore, it can only reduce the amount of power out and increase the energy absorption at the moment of recharging. In contrast, Scenario 1 does not need to take this into account and only needs to ensure that the energy is not at its limit at the end of the operating cycle.This conjecture can be further proved by combining the variation of the storage SOC used to control the power output fluctuation under different scenarios.

As shown in Figure 6.

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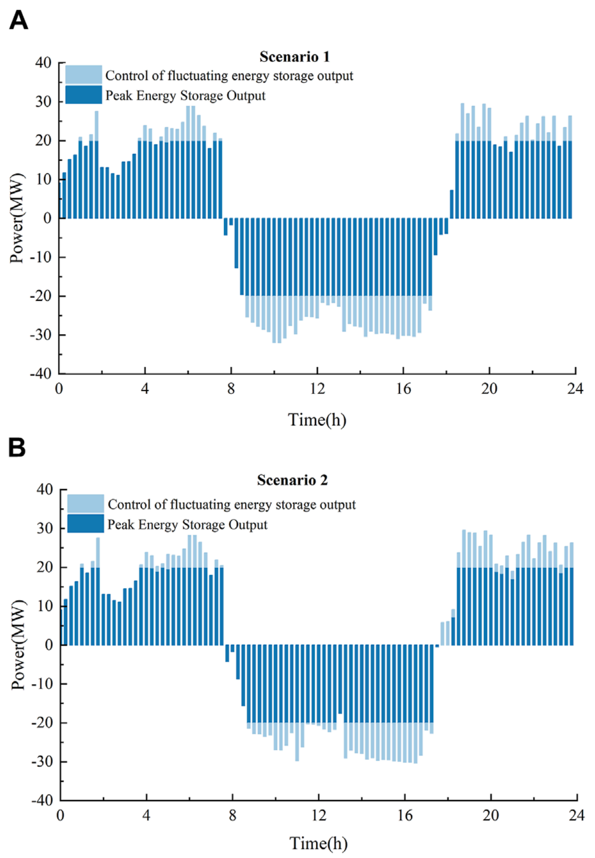

FIGURE 5
Energy storage output curves under different scenarios: **(A)** Scenario 1 and **(B)** Scenario 2.

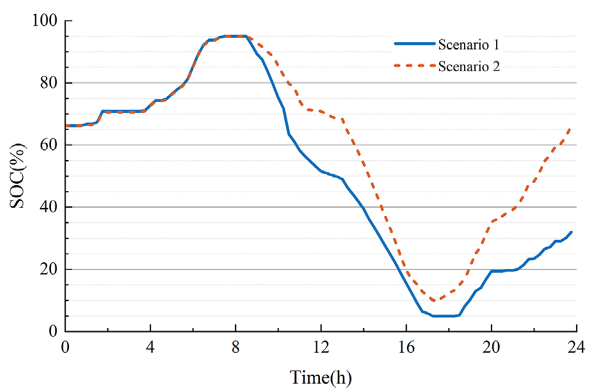

FIGURE 6
Variation of energy storage SOC used to smooth out the prediction deviation under different scenarios.

From Figure 6, we can see that the charging curves of the energy storage under the two scenarios at 0–8 h coincide with each other, and both of them reach 95% of the limit power state. However, Scenario 1 finally discharges to 5% of the limit power, while Scenario 2 finally discharges to 10% of the SOC; and after reaching 10%, Scenario 2 starts to charge rapidly, restoring the initial 66% SOC state; in contrast, Scenario 1 restores to an arbitrary SOC state, arbitrarily charging and discharging to 30% SOC state.

Zhao et al. (2023) suggested that the efficiency of energy storage is not only affected by the configured capacity but also by the net charge/discharge amount of energy storage and the maximum discharge depth. Compared with the 85% discharge depth in Scenario 2, the discharge depth of Scenario 1 reaches 90%, which is a more effective use of the battery capacity; at the same time, the net discharge of energy storage in Scenario 2 is 0, which means that the energy consumed and released in one cycle is the same, while the net discharge energy of Scenario 1 is 36% SOC, which means that the energy storage provides an additional 36% SOC energy to the grid for smoothing the fluctuation of the power output.

This curve also confirms the previous finding that the lack of power reduces the net discharge in Scenario 2, causing additional grid connection deviations. In addition, Scenario 2 is not able to fully utilize the storage capacity and stops discharging before the minimum SOC is reached.

Compared to Scenario 2, the method of Scenario 1 allows the energy storage to have a deeper depth of discharge during a charge/discharge cycle and allows for a net charge/discharge. Therefore, the energy storage under Scenario 1 can work better with the wind farm to smooth out the output fluctuation and not produce an accumulation of prediction deviation.

The above analysis shows that in Scenario 1, compared to Scenario 2, the energy storage has a deeper depth of discharge and net discharge, which allows more energy to be released and reduces the deviation from the grid, improving the utilization of the storage capacity. Wind farms can achieve a higher quality of grid connection using the configuration of Scenario 1.

4.2 Hybrid energy storage economic effects

Table 2 shows a comparison of the economic benefits of wind farms under different configuration options.

According to Table 2, the daily revenue of Scenario 1 is about 3% higher than that of Scenario 2; i.e., the allocation method proposed in this paper can increase the revenue of wind farms with energy storage by about 3%. This enhancement is because Scenario 1 has higher revenue from electricity sales and carbon emissions, as well as lower penalties for grid connection deviation.Combined with the conclusions above, it can be shown again that this is because Scenario 1 does not need to maintain the energy balance during the operating cycle, so the energy storage has a larger discharge space to release more energy and use this energy for the smoothing of the grid deviation; therefore, the configuration of energy storage in wind farms needs to be concerned not only with the configured capacity but also with the net energy released or absorbed during a cycle when configuring the energy storage.A better understanding of the operating modes under different scenarios can be obtained by comparing the relationship between lifetime loss cost and capacity allocation under different scenarios, as shown in Figure 7.

TABLE 2 Comprehensive allocation of energy storage revenue.

	Gross daily revenue of wind farm/10,000 yuan	Revenue of daily electricity sales/10,000 yuan	Daily carbon emissions revenue/10,000 yuan	Daily grid connection deviation penalties/10,000 yuan	Daily operation and maintenance cost/10,000 yuan
Scenario 1	126.94	132.12	29.21	0	34.39
Scenario 2	122.41	130.88	27.69	2	34.16

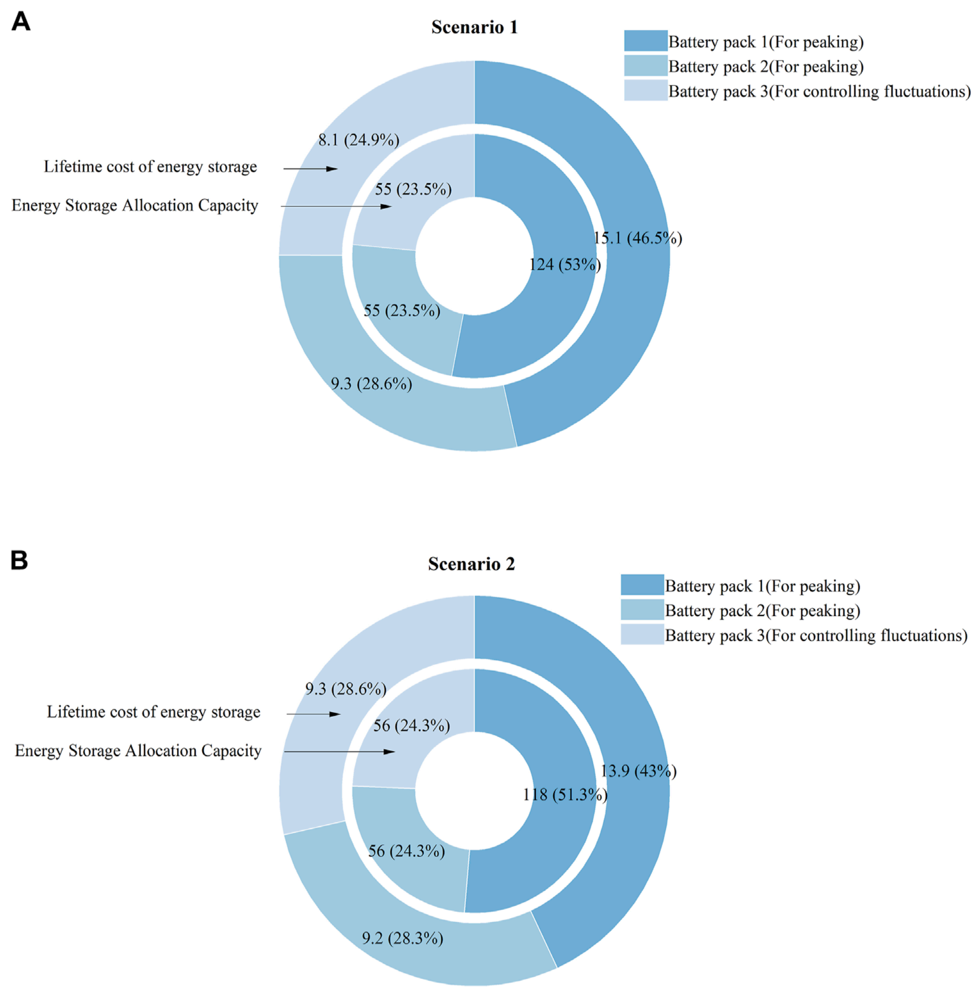

FIGURE 7
Capacity and lifetime loss cost of energy storage configuration under different scenarios: **(A)** Scenario 1 and **(B)** Scenario 2.

From Figure 7, it can be seen that the percentage of second-use batteries used for peaking is more than 50% in both scenarios, but the incurred energy storage lifetime cost is only 46.5% and 43% of the total consumption cost. This is because hybrid energy storage is configured in this paper, and the total lifetime consumption cost can be reduced through the second use of batteries.In addition, we can see that the life loss of the new power battery used to control the output fluctuation under Scenario 1 is significantly lower than that of Scenario 2. This is because Scenario 1 can end the operation in any energy state without additional charging action, thereby reducing the energy storage action and, at the same time, reducing its life loss.

We also find that Scenario 1 has an additional capacity of about 3% over Scenario 2, but its daily revenue from electricity sales increases by only 1%, while the carbon revenue increases by 9%. It can be inferred that the main revenue of wind farms currently deployed with energy storage comes from carbon revenue rather than from shifting the generation schedule. This is similar to the conclusion of Guerra et al. (2020).

The above simulation results can prove that the proposed method can avoid the accumulation of wind power prediction bias and improve the economic performance of wind farms while improving the grid-connected performance of wind farms with energy storage.

5 Conclusion

This paper proposes a hybrid energy storage configuration method to prevent the accumulation of wind power prediction bias, with special consideration of the intraday energy storage operation charging and discharging energy balance. By switching the energy storage use at the end of the operation cycle, it has a larger charging and discharging space, does not need to maintain the charging and discharging energy balance within the cycle, and does not generate bias accumulation. Through the field data simulation, results show that

1) Energy storage in the control of output fluctuations, such as the consideration of Sunday energy balance, may affect the overall grid integration effect, resulting in grid integration deviation and reducing the quality of wind farms connected to the grid.
2) Energy storage needs to be deployed not only in terms of the capacity it is deployed for but also in terms of the net energy it can release or absorb during each operating cycle.
3) The main way for wind farms to profit from the deployment of energy storage is through carbon revenue rather than through the transfer of wind power in a time series.

The study in this paper starts with the current situation, but it will have different variations under different prediction-output curves, different grid connection policies, and different prices of new and second-use batteries. In addition, in future research, it is also possible to combine standby units and different robust scheduling methods to further reduce the capacity of energy storage allocation and prevent the accumulation of prediction bias.

In addition, the energy storage of second-use batteries is not yet mature, and the standards for retired power batteries that can be used for energy storage are not yet standardized. When seamlessly integrating second-use batteries, wind farms may need to limit the service life, operating time, battery performance indicators, etc. of second-use batteries due to safety, economy, and other reasons. However, such restrictions may affect the interests of the first user (the electric vehicle owner). After the electric vehicle battery deteriorates to a certain extent, using it according to old driving habits will accelerate battery aging. Second users (wind farms) and intermediaries (car companies, second-use battery service providers) can consider setting recycling ramp prices on old power batteries to incentivize the first user to retire the batteries early when they still have operation life left. The goal should be to have a second-use lifetime before sending the dead batteries to the recycling facilities. In future research, attention should be directed toward enhancing the coordination between the first and second users to maximize the utilization of key components.

Data availability statement

The datasets presented in this article are not readily available because these data are confidential and the authors cannot provide it to others. Requests to access the datasets should be directed to 858400082@qq.com.

Author contributions

ZY: writing–review and editing and writing–original draft. YH: writing–review and editing. ZM: writing–review and editing.

Funding

The authors declare that financial support was received for the research, authorship, and/or publication of this article. The National Natural Science Foundation of China (52061001); Guangxi Science and Technology Major Special Project (2021AA08001); Soft Science Project of Guangxi Branch of China Huaneng Group Co., Ltd. “Development and Exploration of Offshore Wind Power Planning in Beibu Gulf (Guangxi)” (2020623).

The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article, or the decision to submit it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher’s note

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