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Research on the Participation of Household Battery Energy Storage in the Electricity Peak Regulation Ancillary Service Market

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Abstract: Household battery energy storage (HBES) is expected to play an important role in the transition to decarbonized energy systems by enabling the further penetration of renewable energy technologies while assuring power grid stability. However, the hitherto high installation cost is a key barrier for further deployment of HBES. Therefore, in order to improve its economic feasibility, we will study how HBES participates in the electricity peak regulation ancillary service market (PRASM) in China, which can add new sources of income for HBES. When participating in PRASM, the market mechanism first needs to be understood, and the framework for participating in PRASM needs to be established. In this framework, HBES needs to be aggregated into a cluster by the aggregator to participate in PRASM. In this participation process, the aggregator first needs to determine the controllable capacity of HBES and analyze its uncertainty. After the upper limit of the controllable capacity is determined, the aggregator will be able to more accurately formulate the bidding strategy considering the reserve capacity and charging power allocation strategy to maximize the net income. In this paper, particle swarm optimization and chaos optimization are combined to solve this problem, and finally different scenarios are analyzed through example analysis. The results of the case analysis show that the bidding strategy considering the reserve capacity proposed in this paper can effectively reduce the output deviation value and has a relatively higher economy.

Keywords: household battery energy storage; electricity ancillary service market; aggregator; bidding strategy

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1. Introduction

The development of distributed energy resources is strengthened by global initiatives such as the "Paris Agreement", which urges all of its signatories to reduce their greenhouse gas emissions [1,2]. Furthermore, environmental concerns and relative positive returns are identified as major motives for adopting distributed energy resources [3,4]. China, one of the participating countries to the Paris Agreement, has two ambitious goals, namely, to achieve the peak of carbon emissions by 2030 and to achieve carbon neutrality by 2060 [5]. In order to achieve the above two national goals, solar energy is attached with strategic importance and is expected to produce 20–25% of the total electricity by 2050 [6]. Therefore, household solar photovoltaic systems, which mainly comprise residential rooftop solar arrays, has been widely promoted in many areas of China [7]. With the rapid development of household solar photovoltaic systems, household battery energy storage (HBES), especially via Li–ion batteries, has become an increasingly popular piece of residential electrical equipment as it can further increase electricity bill savings and self-consumption of onsite generated solar energy [8], due to the high energy density, power density and conversion efficiency [9].

Therefore, the application of HBES has recently gained increased attention in the literatures. In order to obtain the best performance, when installing HBES for residential buildings, users first need to determine the capacity of energy storage equipment [10]. In reference [11], a method for analyzing the capacity of HBES through the household load profile characteristics was proposed. For the selection of battery types, Li–ion batteries are currently the benchmark technology for residential applications as well as other stationary applications [12–14]. In addition to enhanced lifetime and high round trip efficiency (85–90%), the overall price of Li–ion batteries (at the system level) has dropped by 20% p.a. since 2013, making them more attractive than traditional lead–acid batteries [15,16]. Therefore, in this paper, only Li–ion-based HBES are discussed. In addition to the above literatures on the capacity and types of HBES, there is also some literature that evaluated the economy of HBES [17,18]. The results showed that HBES systems are typically not yet economically viable because their investment cost payback time is still too long, representing the key barrier to further deployment [19]. It is therefore important to find more profit channels to diversify the revenue sources and enhance the feasibility, such as providing multiple power ancillary services [20]. However, there have not been many studies carried out to explore the ways for HBES to participate in ancillary service market.

In China, peak regulation ancillary service market (PRASM), as the most mainstream power ancillary service market, has been studied by many scholars. PRASM is an electricity trading market that encourages coal-fired and nuclear power units to reduce power generation and frees power generation space for renewable energy [21]. References [22–25] summarized the participation mechanism and development status of the peak regulation market in many regions of China. The results showed that with the increasing proportion of renewable energy in China's power system, the peak regulation capacity of traditional thermal power units cannot meet the demand of the power grid [26]. The demand side flexible resources, such as HBES systems and roof solar photovoltaics, have gradually attracted the attention of power grid operators due to their considerable potential peak regulation capacity [27,28]. China's exploration of demand side flexible resources participating in the PRASM began with the "Work Plan for Improving the Market Mechanisms of Electric Power Ancillary Services" issued by the National Energy Administration of China in 2017. This work plan not only enriches the market participants in the PRASM in terms of policy, but also provides a guarantee for demand side flexible resources such as HBES systems to participate in the PRASM in terms of market mechanisms [29–31]. However, the technical difficulty in realizing demand side flexibility resources to participate in PRASM lies in the coordination of demand side resources. The two main problems are that the location of users on the demand side is too scattered and the user's energy consumption is uncertain [32–34]. Therefore, how to aggregate and manage HBES and formulate the optimal bidding strategy to participate in the market are the key research directions to promote HBES to participate in PRASM.

Based on the above research, the research on the participation of HBES in PRASM is very necessary. However, this research needs to face many questions. The capacity of a single HBES is too small, and the positions of each HBES are too scattered. Therefore, HBES cannot directly participate in PRASM. In addition, the manner for household users to implement HBES presents random effect. It is very difficult to determine how much energy the HBES users need to charge at a specified time. This brings great uncertainty to the participation in PRASM. In order to solve the above questions, this paper has carried out some research. Faced with the question that HBES cannot participate directly, based on the market mechanism of PRASM, a framework for HBES to participate in PRASM is designed. Then, considering the user's charging intentions, the aggregation models for the controllable capacity of HBES are established to determine the expected controllable capacity of the HBES aggregation cluster. Facing the uncertainty of HBES, the uncertainty of controllable capacity is also quantified. Then, when the bidding decision models of HBES aggregator participating in PRASM are established, in order to reduce the impact of the uncertainty of HBES controllable capacity, a measure, which is to set the reserve capacity in each bidding period, is proposed.

The rest of this paper is organized as follows. Section 2 describes the framework for HBES to participate in PRASM. In the Section 3, the aggregation models of HBES's controllable capacity are established. Section 4 establishes the bidding decision models for HBES aggregators to participate in PRASM. Section 5 establishes the distribution models of charging power. Section 6 sets up different scenarios to analyze the bidding strategies proposed in this paper. Finally, conclusions are drawn in Section 7.

2. Design of Framework for HBES Participating in the PRASM

With the integration of a high proportion of renewable energy into the power grid, China's deep peak regulation resources can no longer meet the peak regulation demand of the current power grid in the low load period. This means that the power system will face huge challenges. For example, part of the thermal power units will often be in the start–stop state at night, and the amount of unused wind of wind power plants at night will increase. When users use HBES, they always charge HBES at night, because the electricity price at night is lower, so as to meet the use demand of the next day. If these decentralized charging capacities can be aggregated and used to participate in PRASM at night, it will not only create a new source of income for HBES users, but also provide the power grid with scarce peak regulation resources during the low load period. This can achieve a win–win situation for both HBES users and the power grid.

HBES is a typical demand side flexibility resource. Up to now, most PRASM in China stipulate that demand side flexibility resources need to participate in the market through aggregators, such as electric vehicle aggregators and load aggregators. As an emerging power grid service mode, aggregators are responsible for providing aggregation services for decentralized devices and handling their integration with smart grids. Therefore, in this paper, the aggregation and management of HBES will be carried out by aggregators. In this process, the aggregator obtains the control right of HBES by signing online agreements with HBES users, and is also responsible for installing measurement, communication and control equipment for users. Information transmission and equipment control between aggregator and HBES are carried out in an automatic manner. In view of the current electricity market mechanism in China, the charging price of HBES is still in accordance with the price issued by the power company, and the cost arising from HBES charging is still paid by the user to the power company. In this process, the aggregator does not participate in the power purchase behavior of users, and its roles are to effectively integrate the decentralized HBES resources and to provide peak regulation resources for the power grid during the low load period. The aggregator can obtain corresponding remuneration from PRASM, and needs to pay some compensation fees to HBES users.

After the integration mode of HBES is determined, the market mechanism of PRASM still needs to be fully understood, as the market mechanism is the key to affecting the revenue of market players and the formulation of bidding strategies. In view of the fact that the market mechanism of PRASM in the China Southern Power Grid is relatively mature, this paper will study HBES's participation in PRASM based on the mechanism of this market. The market mechanism of PRASM involved in this paper will be introduced in the following three aspects: market access conditions, bidding methods and settlement rules.

(1) Market access conditions:

The PRASM of the China Southern Power Grid has made the following regulations on the participation form of demand side flexible resources. Demand side resources cannot directly participate in PRASM. They need to be integrated by aggregators before they participate in PRASM. In terms of the categories of aggregated resources, it is more favored by the market to aggregate resources of the same kind. In terms of access technical conditions, the China Southern Power Grid requires the demand side resources integrated by aggregators to have the ability to stably provide at least 2 MW regulated power and 0.5 h regulated time.

(2) Bidding methods:

Aggregators need to declare their bidding capacity of the next day to the trading center every morning, as the PRASM in the China Southern Power Grid is a day-ahead market. Because this market requires aggregators to participate in provincial PRASM as the price-takers of market clearing price, aggregators only need to declare the bidding capacity, but they do not need to carry out bidding price declaration. According to the bid winning capacity of aggregators, the power grid dispatching center will formulate the next day's peak regulation dispatching plan and sign contracts with aggregators to specify the time period, output value and corresponding remuneration for the peak regulation provided by aggregators.

(3) Settlement rules:

The power trading center shall settle the remuneration of aggregators according to the implementation situation of the day-ahead peak regulation dispatching plan by the aggregators. In order to achieve the expected peak regulation effect and reduce the dispatching cost at the same time, when the actual output of aggregators is less than their bid winning capacity, the trading center will impose fines on the output deviation of aggregators.

Based on the above market mechanism of PRASM, the framework of HBES participating in PRASM is shown in Figure 1. First of all, the aggregator signs online contracts with HBES users to obtain users' charging intentions for the next day. Based on these charging intentions, the aggregator determines the controllable charging capacity of HBES on the next day. Secondly, based on the forecast value of PRASM's clearing price, the aggregator formulates the optimal bidding strategy for participating in PRASM with the goal of maximizing market revenue. After the bidding information of all market participants has been declared, the trading center of PRASM will conduct clearing to obtain the unified clearing price and the bid winning situation of each market participant. Then, the power trading center will submit the bid winning situation to the power grid dispatching center for security checks and congestion management, in order to determine the final bid winning capacity of each market participant. Finally, the power grid dispatching center will feed back the bid winning capacity to the aggregator in the form of dispatching commands. The aggregator then controls the charging of each aggregated HBES to respond to these dispatching commands. In this process, the aggregator acts as an intermediary between HBES and PRASM to transfer information flow.

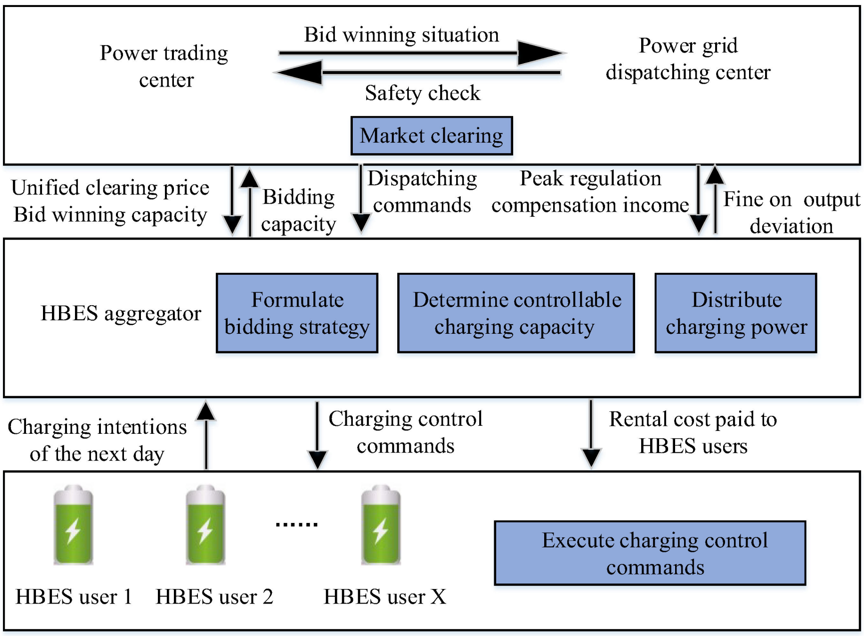

Figure 1. The framework of HBES participating in the PRASM.

3. Aggregation Models of Controllable Capacity of HBES

The controllable capacity of HBES is the power capacity that can be controlled by the aggregator. When the aggregator formulates the bidding strategy for participating in PRASM, the controllable capacity of the HBES aggregation cluster needs to be determined in advance. Therefore, this section establishes the aggregation models of the controllable capacity of HBES to determine the controllable capacity of the HBES aggregation cluster. First, the charging intention of HBES users to participate in peak regulation is introduced. Secondly, based on these charging intentions, the aggregation models of the controllable capacity of HBES are established to calculate the expected controllable capacity of the HBES aggregation cluster in each period. Finally, in order to formulate the optimal bidding strategy for the aggregator to participate in PRASM, the uncertainty of HBES controllable capacity needs to be quantitatively analyzed.

3.1. Charging Intentions of HBES Users to Participate in Peak Regulation

In order to determine the expected controllable capacity of HBES in each period, the aggregator needs to obtain not only the basic equipment parameters of HBES, but also the charging intentions of users to participate in peak regulation, including the total of rentable charging energy, as well as the charging period and charging power that can provide control.

(1) The total of rentable charging energy:

The different power demands of HBES users lead to different charging energy of HBES at night. Therefore, HBES users need to determine their Q^{tot}, which is the total of charging energy that can be leased to the aggregator for control, according to the use demands of HBES equipment.

(2) The charging period and charging power that can provide control:

HBES users have their own preferences for when to charge and at what charging power. In order to enable the control instructions of the aggregator to be executed smoothly, users need to set the charging period, T, and charging power, P^{set}, that can be controlled for the aggregator according to their own use preferences.

3.2. Aggregation Models of the Controllable Capacity of HBES

Based on the above users' charging intentions, the aggregator can determine the expected controllable capacity of each HBES and aggregate them to obtain the expected controllable capacity of the HBES aggregation cluster in each period. They can be expressed as:

$$E_{\text{all},t}^{\text{ant}} = \sum_{x=1}^{X} E_{x,t}^{\text{ant}} \tag{1}$$

$$E_{x,t}^{\text{ant}} = \begin{cases} P_{x,t}^{\text{ant}} & , t \in T_x \\ 0 & , t \notin T_x \end{cases} \tag{2}$$

In the above formulas: $E_{\text{all},t}^{\text{ant}}$ is the expected controllable capacity of the HBES aggregation cluster in period t (KW); X is the number of HBES users participating in aggregation; $E_{x,t}^{\text{ant}}$ is the expected controllable capacity of HBES user x in period t (KW); T_x is the charging period that HBES user x can provide control; $P_{x,t}^{\text{ant}}$ is the upper limit of the expected controllable charging power of HBES user x in period t (KW), and its value depends on both the boundary of charging energy and the boundary of charging power. The boundary of charging energy is the remaining amount of charging energy leased by HBES user x to the aggregator in period t. The boundary of charging power is the power of HBES user x that can be controlled by the aggregator in period t. The expression of $P_{x,t}^{\text{ant}}$ is as follows:

$$P_{x,t}^{\text{ant}} = \min\left[\frac{Q_{x,t}^{\text{sur}}}{\eta \cdot \Delta t}, P_{x,t}^{\text{set}}\right] \tag{3}$$

In the above formula: $P_{x,t}^{\text{set}}$ is the power of HBES user x that can be controlled by the aggregator in period t (KW); η is the charging efficiency of HBES equipment; Δt is the length of one period (h); $Q_{x,t}^{\text{sur}}$ is the remaining amount of charging energy leased by HBES user x to the aggregator in period t (KWh), and it can be obtained by subtracting the total of charging energy leased by HBES user x to the aggregator from the amount of charging energy used by the aggregator in the past period. The expression of $Q_{x,t}^{\text{sur}}$ is as follows:

$$Q_{x,t}^{\text{sur}} = Q_x^{\text{tot}} - \sum_{r=1}^{t-1} q_{x,r} \tag{4}$$

$$q_{x,r} = \eta \cdot p_{x,r} \cdot \Delta t \tag{5}$$

In the above formulas: Q_x^{tot} is the total of charging energy leased by HBES user x to the aggregator (KWh); r period is the period before the t period; $q_{x,r}$ is the consumption of charging energy leased by HBES user x to the aggregator in period r (KWh); $p_{x,r}$ is the charging power of HBES user x controlled by the aggregator in period r (KW), and its value will be determined in the power distribution models below.

3.3. Quantitative Analysis of Uncertainty of HBES Controllable Capacity

The uncertainty of HBES controllable capacity is reflected in the deviation between the actual controllable capacity and the expected controllable capacity. Therefore, this paper will forecast the deviation rate of the controllable capacity to quantify the uncertainty of HBES controllable capacity. First, this paper determines the controllable capacity deviation rate of HBES users, and its expression is as follows:

$$\phi_{x,t} = \frac{E_{x,t}^{\text{ant}} - E_{x,t}^{\text{real}}}{E_{x,t}^{\text{ant}}} \tag{6}$$

In the above formula: $\phi_{x,t}$ is the controllable capacity deviation rate of HBES user x in period t; $E_{x,t}^{\text{real}}$ is the actual controllable capacity of HBES user x in period t (KW).

In order to reduce the calculation difficulty, this paper chooses normal distribution $N(\mu_{x,t}, \sigma_{x,t}^2)$ to simulate the probability distribution of controllable capacity deviation rate $\phi_{x,t}$. $\mu_{x,t}$ is the expectation of probability distribution function of controllable capacity deviation rate $\phi_{x,t}$. It can be seen from the nature of normal distribution that the probability is maximum when the controllable capacity deviation rate, $\phi_{x,t}$, is $\mu_{x,t}$. Therefore, this paper will calculate $\mu_{x,t}$ according to the historical data of controllable capacity deviation rate $\phi_{x,t}$ and take $\mu_{x,t}$ as the prediction value of controllable capacity deviation rate $\phi_{x,t}$.

Before formulating the bidding strategy of the HBES aggregator, in addition to the controllable capacity deviation rate of HBES users, the controllable capacity deviation rate of the HBES aggregation cluster should also be predicted. The controllable capacity deviation of the HBES aggregation cluster is superposed by the deviation of the aggregated HBES users, and the influence of the deviation of each HBES user on the deviation of the HBES aggregation cluster is different. The influence of HBES user x depends on the weight of $E_{x,t}^{\text{ant}}$ in $E_{\text{all},t}^{\text{ant}}$. Therefore, the controllable capacity deviation rate of the HBES aggregation cluster can be derived from all users' $\phi_{x,t}$, and its expression is as follows:

$$\phi_{\text{all},t} = \sum_{x=1}^{X} \frac{\phi_{x,t} \cdot E_{x,t}^{\text{ant}}}{E_{\text{all},t}^{\text{ant}}} \tag{7}$$

In the above formula: $\phi_{\text{all},t}$ is the controllable capacity deviation rate of HBES aggregation cluster in period t.

According to the nature of normal distribution, the random variable formed by the linear combination of several independent normal random variables still obeys normal distribution. Because HBES users are independent from each other during actual operation, $\phi_{\text{all},t}$, a random variable formed by linear combination of normal random variables $\phi_{x,t}$, also obeys normal distribution, and the expectation of probability distribution of $\phi_{\mathrm{all},t}$ can be derived from the expectation of $\phi_{x,t}$, and its expression is as follows:

$$\mu_{\mathrm{all},t} = \sum_{x=1}^{X} \frac{\mu_{x,t} \cdot E_{x,t}^{\mathrm{ant}}}{E_{\mathrm{all},t}^{\mathrm{ant}}} \tag{8}$$

In the above formula: $\mu_{\mathrm{all},t}$ is the expectation of the probability distribution of $\phi_{\mathrm{all},t}$. It can be seen from the nature of normal distribution that the probability is maximum when the controllable capacity deviation rate, $\phi_{\mathrm{all},t}$, is $\mu_{\mathrm{all},t}$. Therefore, this paper will take $\mu_{\mathrm{all},t}$ as the prediction value of controllable capacity deviation rate, $\phi_{\mathrm{all},t}$, and input it into the bidding decision models below.

4. Bidding Decision Models for HBES Aggregator to Participate in PRASM

Because the manner for household users to implement HBES presents random effects, the controllable capacity of HBES is uncertain. When the HBES aggregator participates in the PRASM, this uncertainty may cause output deviation between the actual delivered capacity and the bid winning capacity of the aggregator. The aggregator will face high fines from the power trading center due to the output deviation. Therefore, in the process of formulating the bidding strategy, this paper will set a certain reserve capacity for each bid winning capacity and divide the expected controllable capacity of HBES into two parts: one is the bidding capacity, and the other is the reserve capacity. The reserve capacity and the bidding capacity are both provided by HBES. When the actual delivered capacity of the HBES aggregator is lower than its bid winning capacity, the aggregator can use the reserve capacity to eliminate the output deviation and reduce the penalty cost caused by the output deviation.

4.1. Objective Function

The decision objective of formulating the bidding strategy of the HBES aggregator is to maximize the net income of the HBES aggregator [35,36]. Therefore, both the benefit and the cost in the transaction process should be taken into account in the objective function. The benefit is the peak regulation compensation income given by the power trading center. The cost includes the penalty cost of output deviation and the rental cost paid to HBES users [37]. The net income of the HBES aggregator is the peak regulation compensation income minus the penalty cost of output deviation and the rental cost of HBES [38]. Therefore, with the objective of maximizing the net income of the HBES aggregator, bidding decision models for the HBES aggregator to participate in PRASM are established. The objective function is as follows:

$$\max F = \sum_{t \in \mathrm{TL}} (C_t - L_t - W_t) \tag{9}$$

In the above formula: F is the net income of the HBES aggregator (China Yuan); TL is the peak regulation period announced by the power trading center; C_t is the peak regulation compensation income of the HBES aggregator in period t (China Yuan); L_t is the penalty cost of output deviation in period t (China Yuan); W_t is the rental cost paid to HBES users in period t (China Yuan). C_t, L_t and W_t will be described in detail in the following paragraphs.

4.1.1. The Peak Regulation Compensation Income, C_t

$$C_t = \pi_t \cdot E_t^{\mathrm{win}} \cdot \Delta t \tag{10}$$

$$E_t^{\mathrm{win}} = \omega \cdot E_t^{\mathrm{bid}} \tag{11}$$

In the above formulas: π_t is the forecast value of the clearing price of PRASM in period t (China Yuan/KWh); E_t^{win} is the bid winning capacity of the HBES aggregator in period t (KW); E_t^{bid} is the bidding capacity of the aggregator in period t (KW); ω is the probability of winning the bid of the aggregator. When the aggregator bids in PRASM, the aggregator is the price-taker, and the bidding capacity of the aggregator is very small compared with the total market capacity. This means that the power trading center will accept all the bidding capacity of the aggregator. Therefore, the value of ω is taken as 1.

4.1.2. The Penalty Cost of Output Deviation, L_t

$$L_t = k \cdot \pi_t \cdot E_t^{\text{loss}} \cdot \Delta t \tag{12}$$

$$E_t^{\text{loss}} = \begin{cases} 0, E_t^{\text{win}} \leq E_t^{\text{real}} \\ E_t^{\text{win}} - E_t^{\text{real}}, E_t^{\text{win}} > E_t^{\text{real}} \end{cases} \tag{13}$$

In the above formulas: k is the penalty coefficient of output deviation; E_t^{loss} is the output deviation of the HBES aggregator in period t (KW); E_t^{real} is the capacity actually delivered by the HBES aggregator in period t (KW), and its expression is as follows:

$$E_t^{\text{real}} = (1 - \phi_{\text{all},t}^{\text{fore}}) \cdot E_t^{\text{con}} \tag{14}$$

In the above formula: $\phi_{\text{all},t}^{\text{fore}}$ is the predictive value of controllable capacity deviation rate of the HBES aggregation cluster in time period t; E_t^{con} is the total charging capacity of the HBES aggregation cluster controlled by the aggregator in period t (KW), and its expression is as follows:

$$E_t^{\text{con}} = \min[E_t^{\text{win}} + E_t^{\text{res}}, E_{\text{all},t}^{\text{ant}}] \tag{15}$$

$$E_t^{\text{res}} = \gamma_t \cdot E_t^{\text{win}} \tag{16}$$

In the above formulas: E_t^{res} is the reserve capacity set by the aggregator for the bid winning capacity in period t (KW); γ_t is the proportion of reserve capacity in period t.

4.1.3. The Rental Cost Paid to HBES Users, W_t

$$W_t = \sum_{x=1}^{X} q_{x,t} \cdot \zeta_x \tag{17}$$

In the above formula: $q_{x,t}$ is the consumption of charging energy leased by HBES user x to the aggregator in period t (KWh), and its value can be determined by Formula (5); ζ_x is the rental price of charging energy of HBES user x (China Yuan/KWh). Because HBES users have different controllable capacity deviation rates, it is extremely unfair for HBES users with a lower controllable capacity deviation rate to give all HBES users the same charging energy rental price. Therefore, based on the controllable capacity deviation rate of HBES users, this paper will set different charging energy rental prices for each HBES user, so that HBES users with a lower controllable capacity deviation rate can obtain higher charging energy rental prices. The derivation process is as follows:

$$\zeta_x = (1 - \hat{\phi}_x^{\text{aver}}) \cdot Y_{\max} \tag{18}$$

$$\hat{\phi}_x^{\text{aver}} = \frac{\phi_x^{\text{aver}}}{\max[\phi_1^{\text{aver}}, \cdots, \phi_X^{\text{aver}}]} \tag{19}$$

In the above formulas: ϕ_x^{aver} is the average of the historical data of HBES user x's controllable capacity deviation rate; $\hat{\phi}_x^{\text{aver}}$ is the normalized result of ϕ_x^{aver}, and this normalization refers to dividing ϕ_x^{aver} by the maximum of all ϕ_x^{aver}; $Y_{\max}$ is the maximum charging energy rental price given to users by the aggregator (China Yuan/KWh).

4.2. Constraint Conditions

The objective function of the bidding decision model of the HBES aggregator participating in PRASM is Equation (9). The decision variables of the model are the bidding capacity, E_t^{bid}, and the reserve capacity, E_t^{res}, and they need to meet the following constraints:

$$0 \le E_t^{\text{bid}} \le \sum_{x=1}^{X} P_{x,t}^{\max} \tag{20}$$

$$0 \le E_t^{\text{res}} \le \sum_{x=1}^{X} P_{x,t}^{\max} - E_t^{\text{win}} \tag{21}$$

In the above formulas: $P_{x,t}^{\max}$ is the maximum charging power of HBES user x that can be controlled by the aggregator in period t (KW), and its expression is as follows:

$$P_{x,t}^{\max} = \begin{cases} P_{x,t}^{\text{set}} & ,t \in T_x \\ 0 & ,t \notin T_x \end{cases} \tag{22}$$

In conclusion, when formulating the optimal bidding strategy for the aggregator to participate in PRASM, we need to determine the benefits and costs of different bidding strategies. When calculating the penalty cost of output deviation in each period, we need to determine the expected controllable capacity of the HBES aggregation cluster in each period through the models in Section 3. In this process, $p_{x,t}$, the charging power of each HBES user controlled by the aggregator, needs to be determined. This means that we need to allocate the charging power corresponding to E_t^{con} (the total charging capacity of each period), and this allocation process will be described in detail below.

5. Distribution Models of Charging Power

In the process of charging power distribution, this paper will give priority to the users with a lower controllable capacity deviation rate based on the difference of each user's controllable capacity deviation rate. The charging power distribution process will be described below, and the distribution strategy is as follows.

First, $p_{\text{tot},t}$ is determined; $p_{\text{tot},t}$ is the total charging power that the HBES aggregation cluster needs to be controlled by the aggregator in period t (KW), and its expression is as follows:

$$p_{\text{tot},t} = E_t^{\text{con}} \tag{23}$$

According to the predicted value of each user's controllable capacity deviation rate, the distribution order of charging power is generated in a way that users with lower $\phi_{x,t}^{\text{fore}}$ can obtain a higher priority distribution order. Then, $p_{\text{tot},t}$ will be separated in this distribution order. First, the charging power controlled by the aggregator for the user with the highest priority is determined, and its distribution model is as follows:

$$p_{x,t} = \min[p_{\text{tot},t}, P_{x,t}^{\text{ant}}] \tag{24}$$

Then, it must be judged whether $p_{\text{tot},t}$ is completely separated. If $p_{\text{tot},t}$ is not completely separated, the next distribution will be performed. The multi-layer cycle distribution process of charging power is as follows:

Step 1: Calculate $p_{\text{sum},t}$; $p_{\text{sum},t}$ is the cumulative distribution of charging power (KW), and its expression is as follows:

$$p_{\text{sum},t} = \sum_{x=1}^{X} p_{x,t} \tag{25}$$

Step 2: Calculate $p_{\text{dif},t}$; $p_{\text{dif},t}$ is the unallocated charging power (KW), and its expression is as follows:

$$p_{\text{dif},t} = p_{\text{tot},t} - p_{\text{sum},t} \tag{26}$$

Step 3: judge whether $p_{\mathrm{tot},t}$ is completely separated.

If $p_{\mathrm{dif},t} = 0$, it indicates that $p_{\mathrm{tot},t}$ is completely separated, and the distribution process of charging power is over.

If $p_{\mathrm{dif},t} > 0$, it indicates that $p_{\mathrm{tot},t}$ is not completely separated, and the distribution process of charging power needs to be continued.

Step 4: Calculate $p_{\mathrm{tot\_re},t}$; $p_{\mathrm{tot\_re},t}$ is the total amount of charging power to be allocated in the next layer (KW), and its expression is as follows:

$$p_{\mathrm{tot\_re},t} = p_{\mathrm{tot},t} - p_{\mathrm{sum},t} \tag{27}$$

Step 5: Calculate $p_{x,t}$ of the next HBES user according to the power allocation order, and its expression is as follows:

$$p_{x,t} = \min[p_{\mathrm{tot\_re},t}, P_{x,t}^{\mathrm{ant}}] \tag{28}$$

Then, return to Step 1 and execute the cycle from Step 1 to Step 5. When $p_{\mathrm{dif},t} = 0$, this cycle ends, and $p_{\mathrm{tot},t}$ is completely separated.

6. Case Analysis

6.1. Model Solving Process

The solution of the model in this paper mainly focuses on the determination of the optimal bidding strategy of the HBES aggregator. The content of the bidding strategy is the bidding capacity and the reserve capacity in each period. In this paper, the chaotic particle swarm optimization algorithm based on the Cat chaotic sequence will be used to solve the optimal bidding strategy [39], and the specific solution process is shown in Figure 2.

Particle Swarm Optimization (PSO) originates from the study of the predation behavior of birds. First, a group of random particles (random solutions) is initialized, and then the particles make the movement of the whole group generate an evolution process from disorder to order in the problem-solving space through the information sharing mechanism, so as to obtain the optimal solution [40]. The particle swarm optimization algorithm has less adjustment parameters and a fast optimization speed and is easy to implement, but its disadvantage is that it can easily fall into the local optimum and the search accuracy is not high. To solve these problems, we have combined chaos optimization with particle swarm optimization to improve the solution process. Chaos is a universal nonlinear phenomenon with ergodicity, randomness and sensitivity to initial value. The search process corresponds to the ergodic process of chaotic orbits, which can avoid falling into the local optimal solution and improve the accuracy and convergence speed of the algorithm [41,42].

6.2. Parameter Setting

In order to verify the validity of the models, this paper takes Guangxi PRASM of the China Southern Regional Power Grid as the research background to carry out case analysis. Based on the equipment parameters of Tesla's HBES product (Power Wall), some reasonable assumptions regarding HBES are as follows:

(1) The number of HBES users participating in aggregation is 2000.
(2) Each HBES use's total charging energy that can be leased to aggregator obeys the uniform distribution of [5, 10] kWh.
(3) The charging period that each HBES user can provide is the same as the peak regulation period published by the trading center.
(4) The charging power that each HBES user can provide obeys the uniform distribution of [3, 6] kW.
(5) The HBES user's controllable capacity deviation rate in each period obeys the uniform distribution of [0, 0.1].

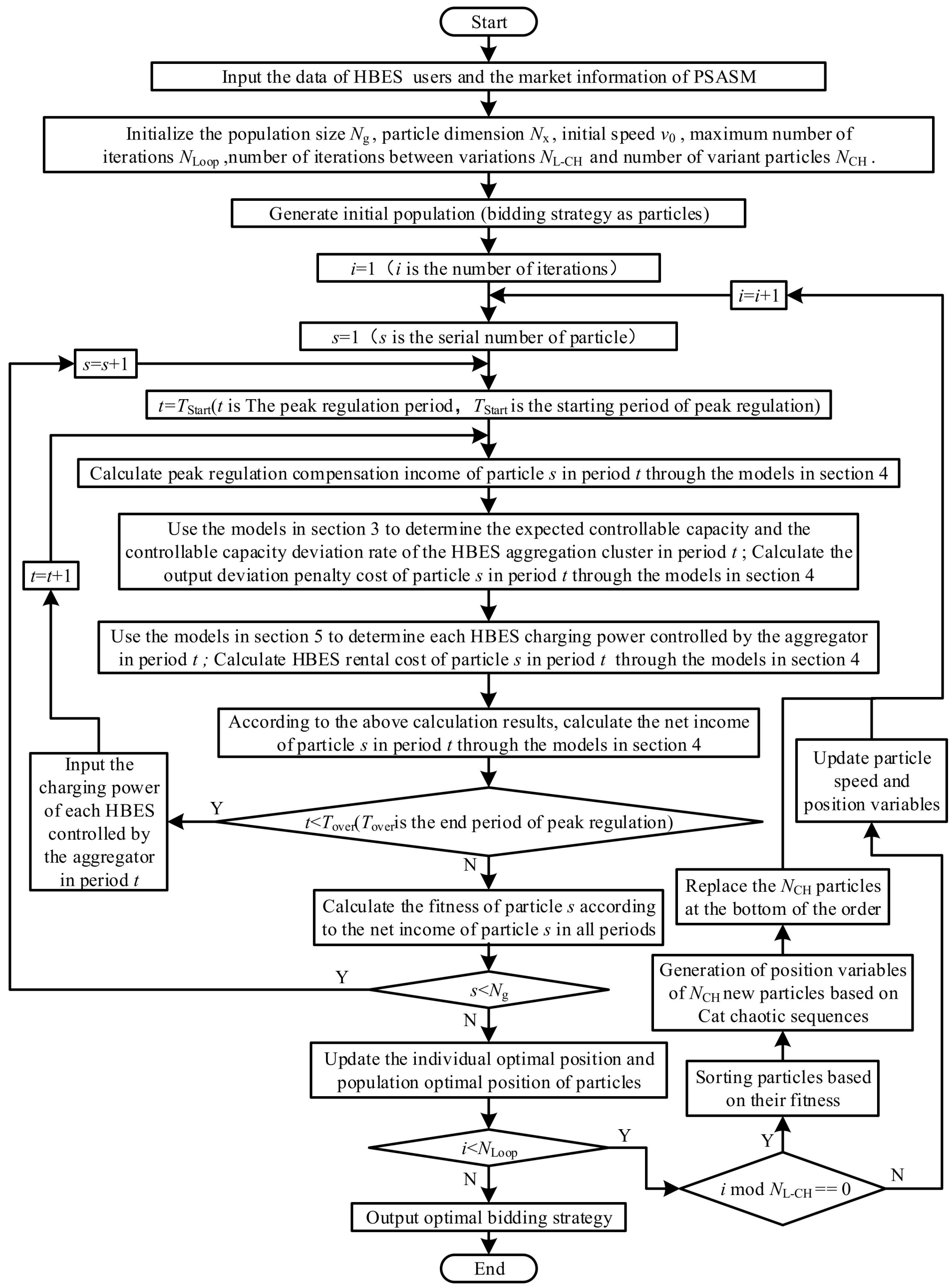

Figure 2. The solution flow chart of the optimal bidding strategy.

In order to ensure the applicability of the models, the market transaction data of a certain month in the PRASM of China's Guangxi Province will be randomly selected as the input parameter of the models in this case analysis. Based on the weighted average of this month's price data, the forecast value of clearing price in the bidding decision model is generated. The power trading center takes 15 min as the length of a trading period and divides 24 h into 96 periods. The peak regulation period in this case analysis is from period 1 to period 16. In addition, the other parameters required for solving the bidding decision model are shown in Table A1 of Appendix A.

In addition, in Figure A4 of Appendix A, a one-line diagram to present the grid topology/configuration that we used for simulation and analysis in the Case Analysis section is given [43,44].

6.3. Analysis of HBES Aggregator's Bidding Strategy

6.3.1. Optimal Bidding Strategy Considering Reserve Capacity

Through the solution process shown in Figure 2, the optimal bidding strategy considering the reserve capacity is determined, and its content is shown in Figure 3:

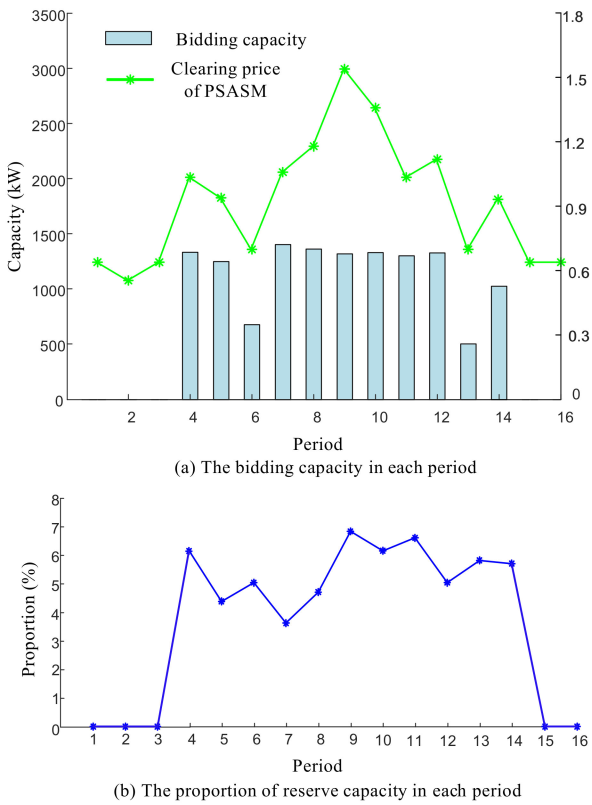

Figure 3. The optimal bidding strategy considering reserve capacity.

It can be seen from Figure 3a that the selection of bidding period of the HBES aggregator is related to the forecast value of the clearing price of PRASM. Because the periods from period 4 to period 14 have higher market clearing prices than other periods, the HBES aggregator chooses to bid from period 4 to period 14. However, the market clearing prices of the periods from period 4 to period 14 are also different from each other. For example, the market clearing prices of period 6 and period 13 are relatively lower. Therefore, in order to obtain higher peak regulation compensation income, the HBES aggregator chooses to conduct relatively fewer bids in period 6 and 13.

It can be seen from Figure 3b that the periods for setting reserve capacity are the same as the bidding periods. The periods for setting reserve capacity are also from period 4 to period 14. This achieves the goal of setting up reserve capacity in each bidding period. By comparing Figures 3b and A1 of Appendix A, it can be seen that the proportion value of reserve capacity in each period is affected by the predicted value of the controllable capacity deviation rate. The larger the predicted value of the controllable capacity deviation rate, the greater the proportion of reserve capacity to be set.

6.3.2. The Effect of Setting Reserve Capacity on Optimization of Transaction Results

In order to verify that the setting of reserve capacity can have a positive effect on the transaction results, this section will solve the optimal bidding strategy without reserve capacity and calculate the corresponding transaction results of this bidding strategy. Then, this transaction results is compared with that of the bidding strategy shown in Figure 3.

Based on the same market clearing price forecast value as in Figure 3a, the optimal bidding strategy without considering the reserve capacity is solved, and the results are shown in Figure A3 of Appendix A. Then, based on the actual value of controllable capacity deviation rate shown in Figure A2 of Appendix A, this section calculates the transaction results of the above two bidding strategies, respectively. Finally, the output deviation value corresponding to the above two bidding strategies, as shown in Figure 4, and the income situation corresponding to the above two bidding strategies, as shown in Table 1, are obtained.

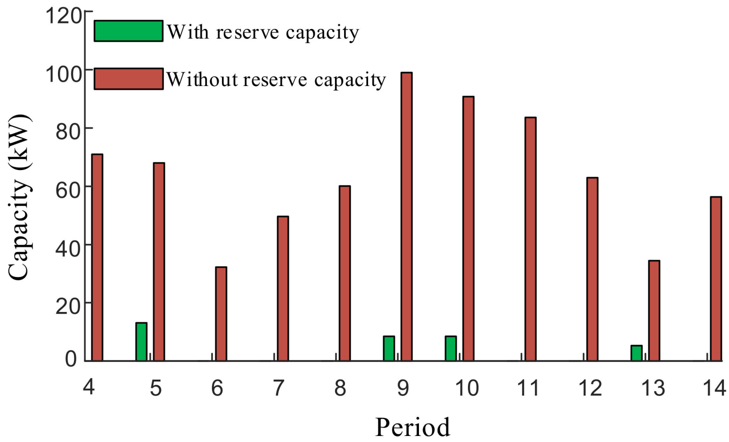

Figure 4. The capacity deviation value under two bidding strategies.

Table 1. The income and cost under the two bidding strategies.

With or without Reserve Capacity	Rental Cost Paid to HBES Users (Yuan)	Penalty Cost of Output Deviation (Yuan)	Peak Regulation Compensation Income (Yuan)	Net Income (Yuan)
with	2073	198	11,746	9475
without	2073	2145	12,525	8307

It can be seen from Figure 4 that considering the reserve capacity in the bidding decision model can effectively reduce the output deviation value. However, there is always a gap between the predicted value and the actual value of the controllable capacity deviation rate. When the actual deviation rate of the controllable capacity in some periods is relatively large, the reserve capacity in these periods will not be enough to compensate for the output deviation. Therefore, when the bidding strategy with reserve capacity is implemented, there will still be output deviation values in some periods, such as periods 5, 9, 10, 13.

It can be seen from the analysis of Table 1 that considering the reserve capacity in the bidding decision model can effectively reduce the deviation penalty cost of the transaction. Although the peak regulation compensation income decreases due to the reduction of bidding capacity, the reduction of peak regulation compensation income is smaller than the reduction of deviation penalty cost. Therefore, formulating a bidding strategy considering the reserve capacity can enable the aggregator to obtain more net income.

6.4. The Influence of Different Proportion of Reserve Capacity on Income and Cost

Through the above case analysis, it can be seen that the proportion of reserve capacity is an important factor affecting income and cost. Therefore, this section will study the influence of different proportions of reserve capacity on income and cost. In order to facilitate the analysis of the calculation results, this case sets the reserve capacity of each period as a similar proportion and takes this proportion from 0% to 10% at 1% intervals. The change curves of income and cost under different proportions of reserve capacity are shown in Figure 5.

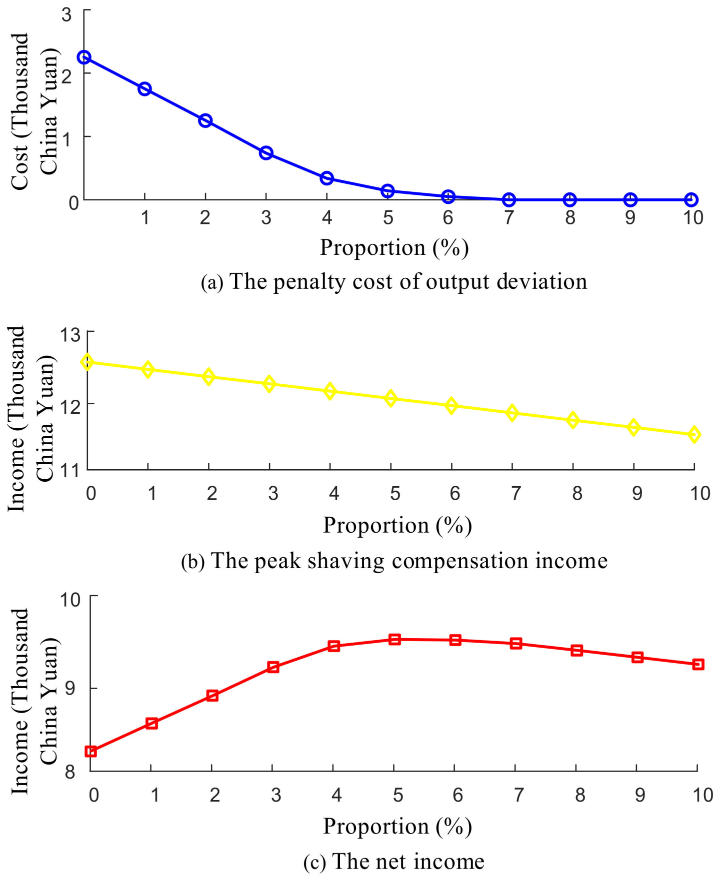

Figure 5. The change curves of income and cost under different proportions of reserve capacity.

It can be seen from Figure 5a that with the increasing proportion of reserve capacity, the penalty cost of the aggregator's output deviation will gradually decrease. However, the reduction speed of deviation penalty cost will also gradually decrease. When the proportion of reserve capacity is relatively low, such as 0% to 4%, the deviation penalty cost will be reduced rapidly. However, with the increase of the proportion of reserve capacity, there will be a surplus of reserve capacity in some periods, and the deviation penalty cost in these periods will not decrease with the increase of the reserve capacity's proportion. Therefore, the reduction speed of deviation penalty cost will gradually decrease until it is zero at a certain node.

It can be seen from Figure 5b that the peak regulation compensation income of the aggregator will decrease with the increase of the proportion of reserve capacity. The reasons are as follows. The value of peak regulation compensation income depends on the value of bidding capacity. If the proportion of reserve capacity is set too high, the value of bidding capacity will be reduced, which will lead to the reduction of peak regulation compensation income. As shown in Figure 5c, the net income of the aggregator will gradually increase and then decrease, for the following reasons. In the transaction process, the HBES rental cost will not change with the increase of the proportion of reserve capacity, and the change of the aggregator's net income is only related to the peak regulation compensation income and the deviation penalty cost. By comparing Figure 5a,b, it can be seen that before the proportion of reserve capacity reaches 5%, the reduction of deviation penalty cost is always higher than the reduction of peak regulation compensation income, and the net income of the aggregator will increase with the increase of the proportion of reserve capacity. Then, after the proportion of reserve capacity reaches 5%, the reduction of deviation penalty cost is lower than the reduction of peak regulation compensation income, and the net income of the aggregator will decrease with the increase of the proportion of reserve capacity.

Therefore, the proportion of reserve capacity needs to be set reasonably when formulating the bidding strategy considering reserve capacity.

7. Conclusions

Based on the market mechanism of the China Southern Power Grid PRASM, this paper designs a framework for HBES to participate in PRASM. Then, according to this operation framework, this paper establishes the aggregation models of HBES's controllable capacity, the bidding decision models for the HBES aggregator to participate in PRASM and the distribution models of charging power in turn. In order to reduce the impact of the uncertainty of HBES's controllable capacity, the setting of reserve capacity is considered in the formulation of the aggregator's bidding strategy, and some discussions on the results achieved are as follows:

(1) Aimed at the problem that a single HBES cannot directly participate in PRASM, this paper designs an aggregation framework for HBES to participate in PRASM. In this framework, by aggregating a large number of HBES, the controllable capacity of the HBES aggregation cluster can meet the admission conditions of PRASM, thus realizing indirect participation in PRASM.
(2) Faced with the problem that the capacity of HBES is too small and its location is too scattered, this paper establishes an aggregation model of HBES controllable capacity considering the user's charging intention. By analyzing the charging intention of each HBES user, the controllable capacity of HBES can be evaluated more accurately, thus providing a more accurate capacity basis for the formulation of bidding strategy in the next stage.
(3) Aimed at the large uncertainty of the controllable capacity of HBES, this paper first quantifies this uncertainty. Then, in the process of formulating the optimal bidding strategy of the HBES aggregator, this paper sets the reserve capacity in each bidding period. The results show that the setting of reserve capacity can reduce the impact of the uncertainty of HBES's controllable capacity and have a positive effect on the transaction results. The reserve capacity can reduce the output deviation of the aggregator and improve the net income of the aggregator to a certain extent.

This paper conducts a preliminary exploration and research on the HBES's participation in PRASM, but there is still room for improvement in the design of a specific operation framework and the formulation of bidding strategy. In the future, the following aspects will be studied:

(1) When studying HBES's participation in PRASM, this paper only focuses on HBES's participation in PRASM through its charging capacity. However, HBES sometimes has idle discharge capacity during operation. Therefore, in future research, we can explore how to aggregate the idle discharge capacity of HBES to participate in PRASM.
(2) As for the selection of ancillary service market type, this paper only considers the peak regulation ancillary service market. However, HBES can also participate in the frequency modulation ancillary service market. Therefore, in future research, we can explore how HBES participates in the frequency modulation ancillary service market.

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Nomenclature

Abbreviations	
HBES	Household battery energy storage
PRASM	Peak regulation ancillary service market
Indices	
x	HBES user
t	time period
Parameters	
X	The number of HBES users participating in aggregation
Q_x^{tot}	The total charging energy leased by HBES user x to the aggregator (KWh)
T_x	The charging period where HBES user x can provide control
$P_{x,t}^{\text{set}}$	The power of HBES user x that can be controlled by the aggregator in period t (KW)
η	The charging efficiency of HBES equipment
Δt	The length of one period, t (h)
TL	The peak regulation period announced by the power trading center
π_t	The forecast value of the clearing price of PRASM in period t (China Yuan/KWh)
ω	The probability of winning the bid of the aggregator
k	The penalty coefficient of output deviation
$\phi_{\text{all},t}^{\text{fore}}$	The predictive value of controllable capacity deviation rate of the HBES aggregation cluster in time period t
ζ_x	The rental price of charging energy of HBES user x (China Yuan/KWh)
ϕ_x^{aver}	The average of the historical data of HBES user x's controllable capacity deviation rate
$Y_{\max}$	The maximum charging energy rental price given to users by the aggregator (China Yuan/KWh)
Variables	
$E_{\text{all},t}^{\text{ant}}$	The expected controllable capacity of the HBES aggregation cluster in period t (KW)
$E_{x,t}^{\text{ant}}$	The expected controllable capacity of HBES user x in period t (KW)
$P_{x,t}^{\text{ant}}$	The upper limit of the expected controllable charging power of HBES user x in period t (KW)
$Q_{x,t}^{\text{sur}}$	The remaining amount of charging energy leased by HBES user x to the aggregator in period t (KWh)
F	The net income of the HBES aggregator (China Yuan)
C_t	The peak regulation compensation income of the HBES aggregator in period t (China Yuan)
L_t	The penalty cost of output deviation in period t (China Yuan)
W_t	The rental cost paid to HBES users in period t (China Yuan)
E_t^{win}	The bid winning capacity of the HBES aggregator in period t (KW)
E_t^{bid}	The bidding capacity of the aggregator in period t (KW)
E_t^{loss}	The output deviation of the HBES aggregator in period t (KW)
E_t^{real}	The capacity actually delivered by the HBES aggregator in period t (KW)
E_t^{con}	The total charging capacity of the HBES aggregation cluster controlled by the aggregator in period t (KW)
E_t^{res}	The reserve capacity set by the aggregator for the bid winning capacity in period t (KW)
γ_t	The proportion of reserve capacity in period t
$q_{x,t}$	The consumption of charging energy leased by HBES user x to the aggregator in period t (KWh)
$p_{x,t}$	The charging power of each HBES user controlled by the aggregator in period t (KW)

$p_{\text{tot},t}$	The total charging power that the HBES aggregation cluster needs to be controlled by the aggregator in period t (KW)
$p_{\text{sum},t}$	The cumulative distribution of charging power (KW)
$p_{\text{dif},t}$	The unallocated charging power (KW)
$p_{\text{tot\_re},t}$	The total amount of charging power to be allocated in the next layer (KW)

Appendix A

Table A1. Parameters setting.

Parameters	Value
k	3
$\Upsilon_{\max}$ (yuan/KWh)	0.5
η	95%

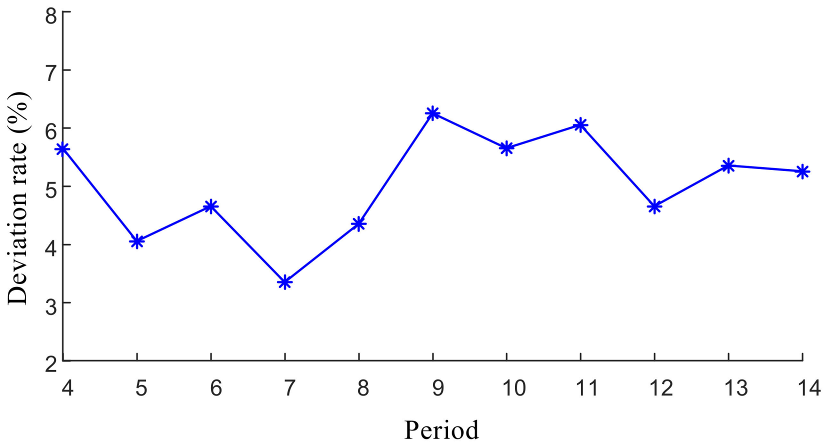

Figure A1. The predicted value of controllable capacity deviation rate of the HBES aggregation cluster.

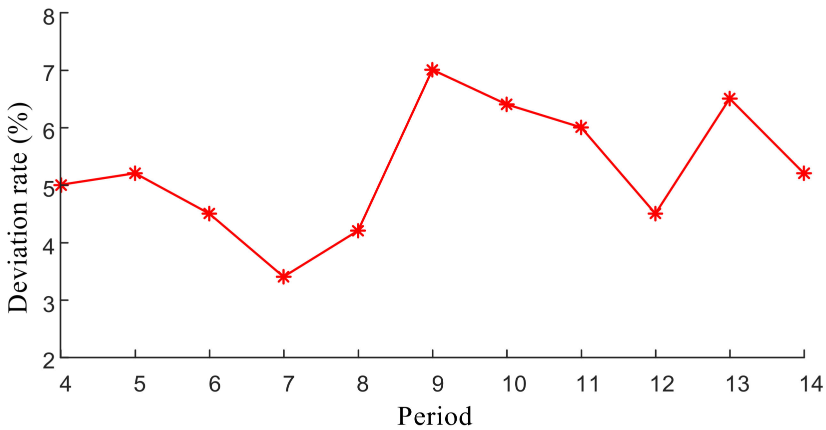

Figure A2. The actual value of controllable capacity deviation rate of the HBES aggregation cluster.

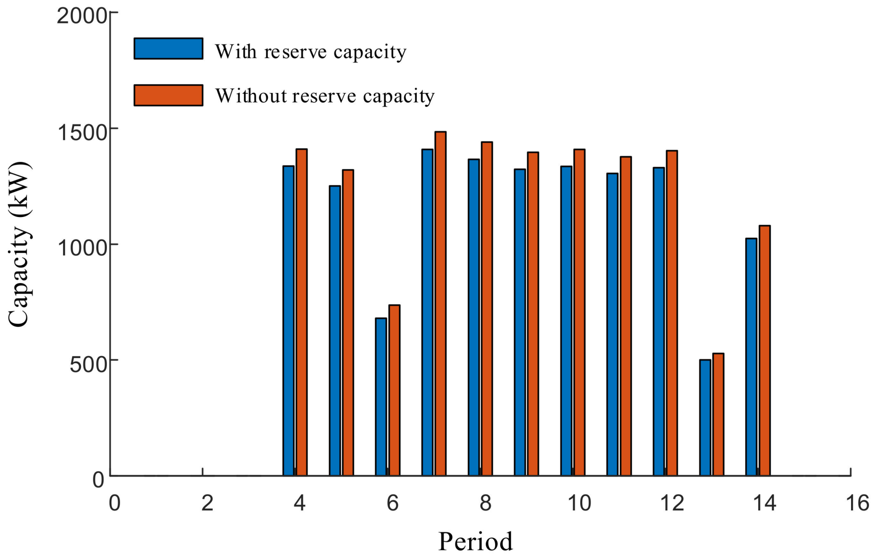

Figure A3. The optimal bidding strategy with and without reserve capacity.

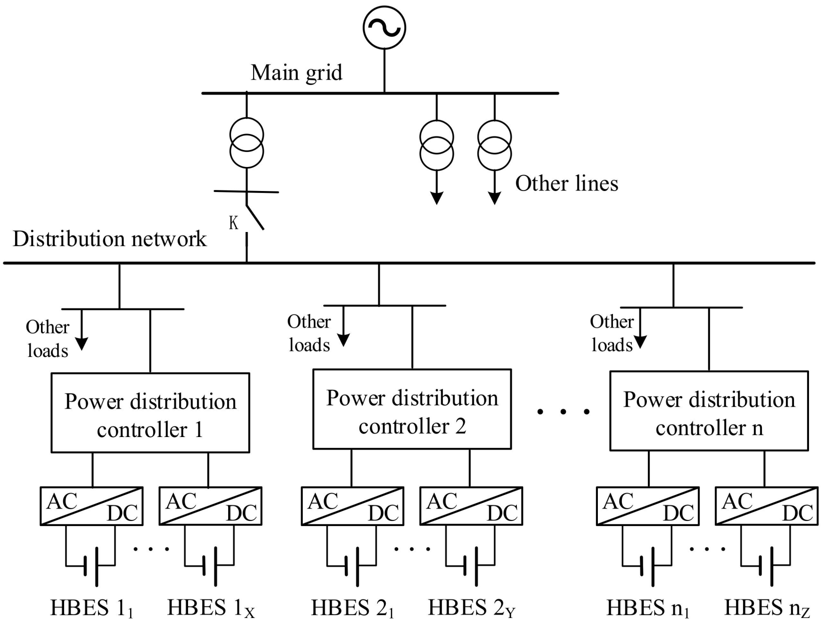

Figure A4. One-line diagram to present the grid topology.

In Figure A4 of Appendix A, the aggregator controls HBES in a "central-distributed" architecture. When using this architecture, the HBES participating in the aggregation will be divided into n groups based on their location, and each group is configured with a power distribution controller. The charging behavior of HBES is controlled by this power distribution controller, and the number of HBES controlled by each controller is different.

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