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Optimization Configuration of Leasing Capacity of Shared-Energy-Storage Systems in Offshore Wind Power Clusters

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Abstract: A double-layer robust optimization method for capacity configuration of shared energy storage considering cluster leasing of wind farms in a market environment is proposed based on the autonomy and profitability of shared energy storage. The feasibility of the leasing model of shared energy storage in the current market environment in China is discussed, and a commercial operation model for shared energy storage to provide leasing services and participate in spot market transactions is proposed. A robust optimization model of a master—slave game for the capacity configuration of shared energy storage is constructed, considering output uncertainties of wind-driven generators and spot prices at multiple time scales. The upper layer of the model aims to minimize the annual cost of shared energy storage and determines the leasing prices and capacity-planning schemes for each period of shared energy storage in the scenario of an interactive game of wind farm clusters. The lower level of the model aims to minimize the assessment cost of the wind farm cluster and updates the leasing capacity for each time period by utilizing the leasing prices and the leasing demand of the wind turbine output power in the worst scenario. By comparing and analyzing multiple scenarios, the master–slave-game-formed lease improves the shared-storage lease benefit by $1.46 million compared to the fixed tariff, and the multi-timescale uncertainty promotes the shared-storage cost-effectiveness to be reduced by 8.7%, while the configuration result is more robust, providing new ideas for optimizing the capacity configuration of shared energy storage in multiple application scenarios.

Keywords: market environment; offshore wind power clusters; shared-energy-storage systems; leasing capacity; optimization configuration; master–slave game

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1. Introduction

Currently, research on optimizing the configuration of shared energy storage (SES) mainly focuses on scenarios such as microgrids at user side [1–12], big data centers [13], and demand response [14,15], with less involvement in power generation resources such as wind farms. With the large-scale integration of new energy into the grid, the randomness and volatility of its output power will significantly reduce the stability of the power system. Wind farms will face stricter assessment requirements in terms of grid-connected power fluctuations and prediction deviations, leading to the generation of large-capacity, high-frequency energy storage configurations and operational needs in wind farms. In addition, as new energy gradually replaces the power generation capacity of traditional coal-fired generators, the scarcity of grid regulatory resources will force market trading institutions to design market mechanisms and trading varieties that are more suitable for energy storage

participation, encouraging high-quality regulatory resources such as energy storage to participate in market transactions. Therefore, this article aims to study the optimization configuration of shared energy storage in the leasing scenario of wind farm clusters (WFCs) in a market environment.

The energy storage system can effectively smooth the fluctuation of new energy through flexible charging and discharging characteristics, which is conducive to promoting the consumption of new energy [16–20]. There are significant differences in the capacity and operational requirements for energy storage in different application scenarios. For optimizing the configuration of shared energy storage, multiple application scenarios should be explored, and the complementary space of shared-energy-storage capacity in different application scenarios should be deeply explored to improve its utilization rate. Reference [21] focuses on the optimization configuration of shared energy storage in photovoltaic communities, introduces a capacity leasing model, and constructs a master–slave game model to describe the interactive game process between shared energy storage and photovoltaic communities. Reference [22] considers load demand response within microgrids and constructs a two-layer model for energy storage configuration and operation. To quantify the impact of energy storage sharing on new energy stations, reference [23] explored the coupling relationship between new energy penetration rate, power generation prediction accuracy, and shared-energy-storage capacity based on an evolutionary game mechanism. With the gradual improvement of the electricity market construction, the market mechanism of multiple trading varieties provides new profit margins and business models for shared energy storage. For example, the literature [24] introduces shared energy storage into the spot market, peak shaving, and frequency regulation markets and establishes a master–slave game model to achieve capacity configuration and optimized operation in different markets. To improve the frequency stability of the power system with wind power clusters, reference [25] uses shared energy storage to assist in supporting the primary frequency regulation demand of the regional power grid and invests the remaining capacity in the electricity market to participate in various auxiliary service transactions in order to enhance its economic benefits. The above research focuses more on the optimization configuration and economic operation of energy storage for a single service scenario. In a few multi-application scenarios, service actors are forcibly bound, that is, shared energy storage needs to prioritize meeting the needs of service actors before the surplus can be used to participate in market-oriented auxiliary service transactions or provide other regulatory services. However, shared energy storage has independent and autonomous characteristics. While considering participating in multiple service scenarios to improve its utilization, it is necessary to consider its economic benefits for more reasonable decision-making in order to achieve capacity configuration and optimization in different application scenarios and form more reasonable and economical configuration results.

The uncertainty factors in different application scenarios will significantly affect the configuration results of energy storage [26–29]. The optimization configuration of shared energy storage should take into account and quantify the uncertainty impact in different application scenarios to ensure the effectiveness of the configuration scheme of energy storage. To reduce the impact of uncertainty on configuration results of energy storage, reference [30] established a “source-load” uncertainty model based on robust optimization and then optimized the energy storage configuration and capacity sharing of various interest actors. Reference [31] uses robust optimization methods to characterize the impact of uncertain electric prices in the spot market on peak-valley arbitrage of shared energy storage, effectively optimizing the operational strategy of shared energy storage. Reference [32] quantifies the risk-scheduling cost brought about by the uncertainty of wind power through conditional value at risk. The above research quantifies the impact of

uncertain factors on the optimization configuration of energy storage capacity in different application scenarios from the perspectives of uncertainty modeling and conditional risk, improving the effectiveness and accuracy of energy storage configuration results. However, energy storage may face many uncertain factors in different application scenarios, and these uncertain factors have the characteristics of multiple time scales. It is necessary to consider more uncertain factors at different time scales in different application scenarios to further improve the rationality of the configuration results of energy storage.

To enrich the service models of shared energy storage, improving its utilization and economic benefits, this paper proposes a double-layer robust optimization method for the capacity configuration of shared energy storage considering the cluster leasing of wind farms in a market environment. The main contributions of this paper are as follows:

(1) An overall framework for shared energy storage is established to provide capacity-leasing services and participate in spot market transactions, and the feasibility and superiority of leasing-service models in the current market environment in China are discussed.
(2) To improve the universality and economy of the configuration results of shared energy storage, improved K-means-clustering and robust optimization methods are adopted to depict the uncertainty of the output power of wind power clusters and the clearing prices of spot markets at multiple time scales.
(3) Considering the energy sharing and interactive game between wind farm clusters and shared energy storage, a double-layer robust optimization model for the capacity configuration of shared energy storage is constructed. The upper layer of the optimization model aims to minimize the annual cost of shared energy storage to develop a plan for energy storage capacity. It determines the leasing prices for each time period using leasing demand and leasing income and transmits them to the lower layer of the optimization model. At the same time, the plan for energy storage capacity is modified. The lower level of the optimization model aims to minimize the assessment cost of the wind farm cluster and updates the leasing capacity of each time period by utilizing the leasing prices of each time period and the leasing demand in the worst scenario of the output power of the wind farm cluster.
(4) Multiple scenarios are set up for analysis and comparison to verify the effectiveness and rationality of the optimization results of capacity configuration of shared energy storage.

2. The Proposed Optimization Model

The overall structure of the double-layer robust optimization model considering the capacity configuration of shared energy storage for cluster leasing of wind farms is shown in Figure 1. In the first stage of the upper-level model, using the predicted data of clearing prices in various time periods of the spot market, considering the investment and construction costs, operating costs, and the uncertainty of clearing prices in the spot market of shared energy storage, the optimization model of the first stage of the upper-level model is constructed with the objective function of maximizing the cost-effectiveness of shared energy storage. The planning scheme for the initial capacity of shared energy storage (initial capacity and power) and the initial operating strategy of shared energy storage (charging and discharging power in each time period) are determined. In the second stage of the upper-level model, an optimization model is constructed to modify the initial operating strategy and planning scheme of shared energy storage, determine the leasing prices for each period of shared energy storage, develop a planning scheme for the initial capacity of shared energy storage, and form the initial operating strategy for shared energy storage and the leasing capacity for each period of the wind farm cluster.

In the lower-level model, using the leasing prices of shared energy storage at different time periods, considering the assessment costs of grid-connected power fluctuations and the impact of predicted deviations in power generation, considering the uncertainty of the output power of the wind farm cluster based on the leasing demand at different time periods, with the objective function of minimizing the total assessment cost of the wind farm cluster (including the leasing cost of shared energy storage), a lower level optimization model is constructed to update the leasing capacity of the wind farm cluster at different time periods and determine the leasing cost of shared energy storage and the total assessment cost of the wind farm cluster.

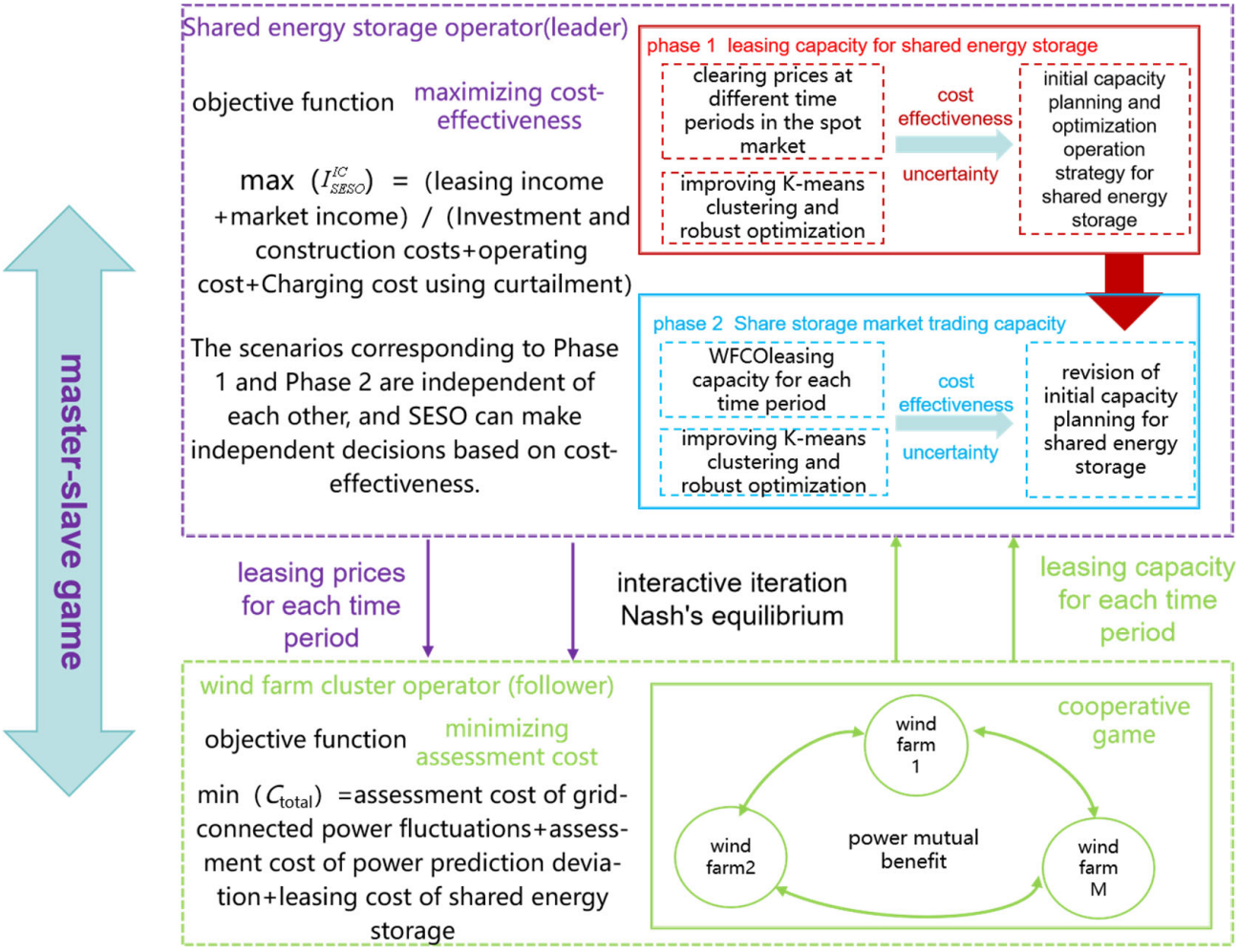


Figure 1. Architecture diagram of a two-layer robust optimization model for the capacity configuration of shared energy storage considering wind farm cluster leasing.

2.1. Uncertainties on Multiple Time Scales

Multi-scenario applications reduce the idle rate of shared-energy-storage operators (SESOs), which is beneficial for cost recovery. However, the uncertainty factors of multiple scenarios have also intensified the difficulty of formulating SESO-capacity-planning schemes. The uncertainty of the output power of wind farm clusters requires dynamic adjustment of assessment costs, which leads to fluctuations in leasing capacity at different time periods, thereby affecting the capacity configuration of SESO in leasing service scenarios. Meanwhile, the uncertainty of clearing prices in the spot market will significantly alter SESO arbitrage behavior using pricing difference, directly affecting capacity configuration in market-trading scenarios.

The capacity planning of shared energy storage is a relatively long-term consideration (usually measured on an annual or full lifecycle basis), which needs to ensure the economic viability of the SESO configuration results and meet the energy storage capacity requirements of the configuration actors under different operating states as much as possible. The uncertainty of the output power of wind farm clusters and the uncertainty of clearing prices in the spot market have an impact on the capacity planning of shared energy storage mapped on multiple time scales. On a long-term scale, factors such as natural environment and seasons will affect wind power output (presenting typical daily characteristics of different seasons). With the large-scale integration of new energy into the grid, the uncertainty of wind power will have an impact on the clearing results of the spot market. The uncertainty on a long-term scale will lead to a decrease in the universality of the SESO-capacity-planning scheme. On a short-term scale, the uncertainty of wind power output and spot prices often increases the difficulty of predicting power generation. The resulting prediction bias will change the operating strategy of shared energy storage and the leasing capacity of wind farm clusters. The impact of short-term uncertainty often leads to a decrease in the economic efficiency of SESO-capacity-planning schemes. Therefore, this article introduces an improved K-means-clustering method (for scenario analysis) and a robust optimization method to characterize the uncertainty of wind power output and spot prices in the long and short time scales in a multi-stage manner.

In view of the uncertainty of long-term wind power output and spot price, a scenario analysis method based on K-means clustering can be adopted to reduce scenarios and improve the versatility and economy of SESO capacity allocation results [33]. Considering the correlation between wind farm output and spot clearing price, the K-means-clustering method is used to cluster the forecast results of wind power output and spot price in the future long-term scale (1 year in this paper) together to form a typical scenario and its occurrence probability, thereby reducing the workload and redundancy caused by separate clustering of wind power output and spot price. The typical uncertainty scenario set of long-term joint clustering of wind power output and spot price can be expressed as follows:

$$\Omega_1 = \left\{ \pi_i, \left(\boldsymbol{P}_{\mathrm{w},i}, \boldsymbol{p}_{\mathrm{EP},i} \right) \right\} \tag{1}$$

$$\text{s.t.} : i = 1, 2, \ldots, G_{I1} \tag{2}$$

where Ω_1 is a typical scenario set of uncertainty in the joint clustering of wind power output and spot prices over a long time scale; π_i is the probability that the uncertainty scenario set of wind power output and spot prices in the joint clustering occurs in the BIth typical scenario; and $\boldsymbol{P}_{\mathrm{w},i}$ and $\boldsymbol{p}_{\mathrm{EP,i}}$, respectively, represent the vectors of wind power output and spot prices in the i th typical scenario.

In terms of the uncertainty of wind power output and spot prices on a short time scale, this paper uses robust optimization methods to construct uncertainty sets in typical scenarios to characterize the prediction deviation range of power generation, improving the effectiveness of capacity configuration results for shared energy storage. Taking the typical scenario as an example, robust parameters are introduced to construct an uncertain set of wind power output and spot prices.

$$\sum_{t=1}^{T} \left| \frac{P_{\mathrm{w}}(t) - P_{\mathrm{w}}^{\mathrm{r}}(t)}{\hat{P}_{\mathrm{w}}^{\mathrm{b}}(t)} \right| = \sum_{t=1}^{T} y_{\mathrm{w}}(t) \le \Gamma_{\mathrm{w}} \tag{3}$$

$$\sum_{t=1}^{T} \left| \frac{p_{\mathrm{EP}}(t) - p_{\mathrm{EP}}^{\mathrm{r}}(t)}{\hat{p}_{\mathrm{EP}}^{\mathrm{b}}(t)} \right| = \sum_{t=1}^{T} y_{\mathrm{EP}}(t) \le \Gamma_{\mathrm{EP}} \tag{4}$$

where $P_{\mathrm{w}}(t)$ and $p_{\mathrm{EP}}(t)$ are the actual values of the output power and spot price of the wind farm cluster in the t th time period, respectively; $P_{\mathrm{w}}^{\mathrm{r}}(t)$ and $p_{\mathrm{EP}}^{\mathrm{r}}(t)$ are the predicted values of the output power and spot price of the wind farm cluster in the t th time period, respectively, which are the wind power values and clearing price values of the i th typical scenario that are jointly clustered and reduced by improving the K-means-clustering method; $y_{\mathrm{w}}(t)$ and $y_{\mathrm{EP}}(t)$ are the values of the uncertain sets of the output power and spot prices of the wind farm cluster in the t th time period, respectively; Γ_{w} and Γ_{EP} are robust parameters for the output power of the wind farm cluster and the uncertainty set of spot prices, respectively; and $\hat{P}_{\mathrm{w}}^{\mathrm{b}}(t)$ and $\hat{p}_{\mathrm{EP}}^{\mathrm{b}}(t)$, respectively, represent the maximum deviation range of the predicted output power and spot price of the wind farm cluster in the t th time period.

$$P_{\mathrm{w}}(t) \in \left[P_{\mathrm{w}}^{\mathrm{r}}(t) - \hat{P}_{\mathrm{w}}^{\mathrm{b}}(t), P_{\mathrm{w}}^{\mathrm{r}}(t) + \hat{P}_{\mathrm{w}}^{\mathrm{b}}(t)\right] \tag{5}$$

$$p_{\mathrm{EP}}(t) \in \left[P_{\mathrm{EP}}^{\mathrm{r}}(t) - \hat{p}_{\mathrm{EP}}^{\mathrm{b}}(t), P_{\mathrm{EP}}^{\mathrm{r}}(t) + \hat{p}_{\mathrm{EP}}^{\mathrm{b}}(t)\right] \tag{6}$$

The robust indicator parameters represent the degree of uncertainty in the output power and spot prices of wind farm clusters, as well as the conservatism of the capacity-planning scheme for shared energy storage. The increase in robust parameters means that the prediction deviation scenarios faced by the output power and spot prices of wind farm clusters are more severe, and the formulated capacity-planning scheme of shared energy storage is more conservative. In addition, for any typical scenario, with the selection of robust parameters for the output power and spot prices of the wind farm cluster, an uncertainty set Ω_2 containing G_{J1} uncertain scenarios can be generated, thus forming the uncertainty scenario set G of the output power and spot prices of the wind farm cluster on multiple time scales.

$$G = G_{\mathrm{I1}} \times G_{\mathrm{J1}} \tag{7}$$

$$\pi_{i,j} = \pi_i / G_{\mathrm{J1}} \tag{8}$$

where G represents the number of uncertain scenarios for the output power and spot prices of the wind farm cluster at multiple time scales; $\pi_{i,j}$ is the probability of the joint scenario of the output power and spot prices of the wind farm cluster occurring under the uncertainty scenario j th in the i th typical scenario.

2.2. SESO Model

2.2.1. The Pricing Mechanism of SESO Leasing Services

The leasing service of shared energy storage can reasonably avoid the construction costs of high initial investment in storage configuration of wind farm energy, while enriching its own business model and improving energy storage utilization efficiency. The current mainstream shared energy storage leasing mainly consists of the following two business models: (1) A paid model based on energy storage capacity, abbreviated as the capacity-leasing model. This model starts from the perspective of the overall capacity of shared energy storage, dividing the storage capacity into multiple parts based on user leasing needs and allowing users to freely control the leasing capacity. The characteristic of this model is that it has advantages such as simple leasing methods and convenient cost settlement. However, the capacity-leasing model is difficult to effectively map the actual charging and discharging behavior of leasing users. In this leasing model, there is often a significant difference in the frequency of charging and discharging energy storage among different leasing users after leasing the same energy storage capacity, resulting in biased behavior towards shared energy storage (inclined towards leasing users with lower charging and discharging behavior), which is unfair to both shared energy storage and leasing users. (2) The leasing payment model based on energy storage charging and

discharging services is abbreviated as the charging and discharging demand-leasing model. This model starts from the perspective of diversified leasing needs of users and charges based on the real-time charging and discharging behavior of leasing users, effectively meeting personalized leasing needs of users. It has advantages such as high transparency and clear settlement processes. However, the charging and discharging demand-leasing model usually only considers the operating cost of shared energy storage, making it difficult to effectively measure the opportunity cost of shared energy storage. With the application of shared energy storage in multiple scenarios and the diversification of profit channels, it is necessary to reflect the profit losses faced by shared energy storage in providing leasing services through opportunity costs.

To balance the fairness and economy of both parties in the leasing model, this article comprehensively considers the operating and opportunity costs of shared energy storage and proposes a pricing mechanism for shared energy-storage-leasing services based on a two-part electricity price system, which includes two parts: capacity price and electricity (charging and discharging power) price. The capacity price ensures that shared energy storage faces profit losses due to opportunity costs in reserving leasing capacity for wind farm clusters. The electricity price reflects the actual demand for charging and discharging of wind farm clusters and the operating cost of shared energy storage.

The two-part leasing price for shared energy storage considering cluster leasing of wind farms can be expressed as follows:

$$\zeta_t = \zeta_t^{\text{cap}} + \zeta_t^{\text{mail}} \tag{9}$$

where t is the period during which shared energy storage provides leasing services to wind farm clusters, in hour, $t \in \{1, 2, \ldots, 24\}$; ζ_t is the leasing price for shared energy storage in the wind farm cluster during the t th time period; ζ_t^{cap} is capacity-leasing price for the shared energy storage of the wind farm cluster during the t th time period; ζ_t^{mail} is the electricity-leasing price for shared energy storage of the wind farm cluster in the t th time period.

2.2.2. SESO Model

The shared energy storage model needs to consider the cost or benefit in the leasing-service scenario and price difference scenario in spot markets in order to form an objective function. It is worth noting that in a price difference arbitrage scenario in the spot market, as the shared-energy-storage capacity increases, the returns will also increase. Only considering the maximum economic benefits or the lowest cost makes it difficult to effectively map the actual cost of shared energy storage in unit revenue, resulting in difficulty or no solution for the configuration of energy storage capacity. Therefore, this article adopts the minimization of annual cost-effectiveness as the objective function of the upper level model for optimizing the capacity configuration of shared energy storage.

The objective function of the upper level model for optimizing the capacity configuration of shared energy storage:

$$\min I_{\text{SESO}}^{\text{IC}} = \frac{C_{\text{inv}} + C_{\text{loss}} + C_{\text{w}}}{I_{\text{SESO}}^{\text{R}} + I_{\text{SESO}}^{\text{EP}}} \tag{10}$$

$$I_{\text{SESO}}^{\text{R}} = \sum_{d=1}^{D} \sum_{t=1}^{24} \left(\zeta_t^{\text{cap}} R_t + \zeta_t^{\text{mail}} S_t \right) \tag{11}$$

$$I_{\text{SESO}}^{\text{EP}} = \sum_{d=1}^{D} \sum_{t=1}^{24} \left(p_{\text{EP},t}^{d} P_{\text{EP},t}^{d} - p_{\text{EP},t}^{c} P_{\text{EP},t}^{c} \right) \tag{12}$$

$$C_{\text{inv}} = \psi_E \frac{r(1+r)^{N_y} E_N}{(1+r)^{N_y} - 1} \tag{13}$$

$$C_{\text{loss}} = \sum_{d=1}^{D} \sum_{t=1}^{24} \lambda \left(P_{\text{SES},t}^{c} + P_{\text{SES},t}^{d} \right) \tag{14}$$

$$C_{\text{w}} = \sum_{d=1}^{D} \sum_{t=1}^{24} p_t^s Q_{\text{w},t}^{c} \tag{15}$$

where $I_{\text{SESO}}^{\text{IC}}$ is the annual cost benefit of shared energy storage; $I_{\text{SESO}}^{\text{R}}$ is annual leasing income for shared energy storage leasing services; $I_{\text{SESO}}^{\text{EP}}$ is the annual market-trading income of price differences arbitrage in the spot market for shared energy storage; C_{inv} is the annual investment and construction cost of shared energy storage over its entire lifecycle; C_{loss} is the annual operating cost discount of shared energy storage; C_{w} is the annual cost of purchasing electricity for wind farm cluster abandonment through shared energy storage; D is the annual operating days of shared energy storage, and it is necessary to consider the maintenance status of shared energy storage; R_t is the leasing capacity of shared energy storage of the wind farm cluster in the t th time period; S_t is the total charging and discharging power of shared energy storage of the wind farm cluster in the t th time period; $P_{\text{EP},t}^{d}$ and $P_{\text{EP},t}^{c}$, respectively, are the online power and charging power of the price difference arbitrage of shared energy storage participating in the spot market during the t th time period; $p_{\text{EP},t}^{d}$ and $p_{\text{EP},t}^{c}$, respectively, are the on-grid electric price and charging electric price for the price difference arbitrage of shared energy storage participating in the spot market during the t th time period; ψ_{E} is the unit capacity cost of shared energy storage; E_{N} is the rated capacity of the configured shared energy storage; N_{y} is the planning period for configured shared energy storage; r is the discount rate; λ is the discounted cost per unit of charging and discharging power for shared energy storage; $P_{\text{SES},t}^{c}$ and $P_{\text{SES},t}^{d}$ are the charging and discharging power of the shared energy storage in the t th time period, respectively; p_t^s is the purchasing price of wind power for shared energy storage during the t th time period; $Q_{\text{w},t}^{c}$ is the curtailment electricity purchased by shared energy storage from the wind farm cluster during the t th time period.

Constraint conditions include the following:

(1) **Power balance relationship of shared energy storage**

In shared energy storage, there are the following powers: the difference between the charging power and discharging power of the leased capacity of the wind farm cluster that calls for shared energy storage, the charging power of the abandoned wind power of the wind farm cluster purchased by shared energy storage, the difference between the grid power and charging power of the price difference arbitrage of shared energy storage participating in the spot market, and the difference between the charging power and discharging power of shared energy storage. These four power values should maintain the following balance relationship:

$$P_{\text{W},t}^{c} - P_{\text{W},t}^{d} + P_{\text{W},t}^{\text{Q},c} + P_{\text{EP},t}^{c} - P_{\text{EP},t}^{d} = P_{\text{SES},t}^{c} - P_{\text{SES},t}^{d} \tag{16}$$

where $P_{\text{W},t}^{c}$ and $P_{\text{W},t}^{d}$, respectively, represent the charging and discharging power of the shared-energy-storage-leasing capacity called by the wind farm cluster during the t th time period, while $P_{\text{W},t}^{\text{Q},c}$ represents the charging power of the shared energy storage purchased from the wind farm cluster during the t th time period.

The interaction between shared energy storage and the charging and discharging power of wind farm clusters and power grids meets the following conditions:

$$\begin{cases} S_t = \left|P^c_{\mathrm{W},t}\right| + \left|P^d_{\mathrm{W},t}\right| \\ P^c_{\mathrm{SES},t} = P^c_{\mathrm{W},t} + P^c_{\mathrm{EP},t} + P^{Q,c}_{\mathrm{W},t} \\ P^d_{\mathrm{SES},t} = P^d_{\mathrm{W},t} + P^d_{\mathrm{EP},t} \end{cases} \tag{17}$$

In addition, the charging and discharging power of shared energy storage in different application scenarios meets the following conditions:

$$\begin{cases} P^c_{\mathrm{W},t} \perp P^d_{\mathrm{W},t} = 0 \\ P^c_{\mathrm{EP},t} \perp P^d_{\mathrm{EP},t} = 0 \\ P^c_{\mathrm{SES},t} \perp P^d_{\mathrm{SES},t} = 0 \end{cases} \tag{18}$$

where $\perp$ is the operator, indicating that at least one of the left and right parameters will be 0.

(2) **Constraints on the charging and discharging power of shared energy storage**

The charging and discharging power of shared energy storage cannot exceed its maximum allowable value, nor be less than its minimum allowable value:

$$0 \le P^c_{\mathrm{SES},t} \le P^c_{\mathrm{N}} \tag{19}$$

$$0 \le P^d_{\mathrm{SES},t} \le P^d_{\mathrm{N}} \tag{20}$$

where P^c_{N} and P^d_{N}, respectively, represent the rated values of the charging and discharging power for the configured shared energy storage.

(3) **Constraints on the state of charge of shared energy storage**

The state of charge value of shared energy storage is closely related to the operating state of the previous period and cannot exceed its allowed maximum value or be less than its allowed minimum value:

$$k_{\mathrm{SOC},t} = k_{\mathrm{SOC},t-1} + \frac{\left(P^c_{\mathrm{SES},t}\eta_c - P^d_{\mathrm{SES},t}/\eta_d\right)}{E_N}\Delta t \tag{21}$$

$$\underline{k}_{\mathrm{SOC},i} \le k_{\mathrm{SOC},i} \le \overline{k}_{\mathrm{SOC},i} \tag{22}$$

$$k_{\mathrm{SOC,o}} = k_{\mathrm{SOC,e}} \tag{23}$$

where $k_{\mathrm{SOC},t}$ and $k_{\mathrm{SOC},t-1}$ are the state of charge values of shared energy storage during the t th and $(t-1)$ th time period, respectively; η_c and η_d represent the charging and discharging efficiency of shared energy storage, respectively; E_N is the rated capacity of shared energy storage; Δt is the time interval, and in this article, 1 h is taken; $k_{\mathrm{SOC},i}$, $\overline{k}_{\mathrm{SOC},i}$, and $\underline{k}_{\mathrm{SOC},i}$ are the actual, maximum, and minimum values of the state of charge set for shared energy storage, respectively; $k_{\mathrm{SOC,o}}$ and $k_{\mathrm{SOC,e}}$ are the initial state of charge values for shared energy storage and the state of charge values at the end of one operating cycle (24 h), respectively.

2.2.3. A Robust Optimization Model for SESO Considering Electricity Price Uncertainty

The uncertainty of clearing prices in the spot market will affect the capacity configuration of shared energy storage in the price difference arbitrage scenario. By using an uncertainty modeling method on multiple time scales to analyze the uncertainty of clearing prices in the spot market, a planning scheme for the capacity configuration of shared energy storage can be established. In the first stage, the upper level model of the two-stage

robust optimization model in the price difference arbitrage scenario of the spot market can be established:

$$\max_{\phi} \min_{\varphi \in \Omega_2} \sum_{i=1}^{G_{I1}} I_i I_{\mathrm{SESO}}^{\mathrm{EP}} \tag{24}$$

where I_i is the i th typical joint scenario considering uncertainty over a long time scale; φ is the worst-case scenario that considers the uncertainty of clearing prices in the spot market on a short-term scale (with the smallest price difference), including the actual clearing price $p_{\mathrm{EP},t}$ in the spot market and the actual charging price $p_{\mathrm{EP},t}^{c}$ for shared energy storage; ϕ represents the charging and discharging power of shared energy storage in the worst-case scenario, including the actual charging power $P_{\mathrm{EP},t}^{c}$ and discharging power $P_{\mathrm{EP},t}^{d}$ of shared energy storage.

$$\varphi = \left[p_{\mathrm{EP},t}, p_{\mathrm{EP},t}^{c}\right]^{\mathrm{T}} \tag{25}$$

$$\phi = \left[P_{\mathrm{EP},t}^{c}, P_{\mathrm{EP},t}^{d}\right]^{\mathrm{T}} \tag{26}$$

The outer objective function is to minimize the cost-effectiveness of price difference arbitrage in typical scenarios for shared energy storage. The inner objective function is to maximize the profit of price difference arbitrage in the worst scenario of clearing prices in the spot market for shared energy storage.

2.3. WFCO Model

2.3.1. WFCO Model

Based on the predicted power generation results, the assessment cost of grid-connected power fluctuations and the assessment cost of generating power prediction deviations can be calculated. Consider capacity leasing for shared energy storage and construct a WFCO model with the objective function of minimizing annual assessment costs.

The objective function of the WFCO model:

$$\min C_{\mathrm{total}} = C_{\mathrm{PG}}^{\mathrm{a}} + C_{\mathrm{PG}}^{\mathrm{y}} + C_{\mathrm{SESO}}^{\mathrm{R}} \tag{27}$$

$$C_{\mathrm{PG}}^{a} = \sum_{d=1}^{D} \sum_{t=1}^{24} C_{\mathrm{PG},t}^{a} \tag{28}$$

$$C_{\mathrm{PG}}^{y} = \sum_{d=1}^{D} \sum_{t=1}^{24} C_{\mathrm{PG},t}^{y} \tag{29}$$

$$C_{\mathrm{SESO}}^{R} = \sum_{d=1}^{D} \sum_{t=1}^{24} \left(\zeta_t^{\mathrm{cap}} R_t + \zeta_t^{\mathrm{mail}} S_t\right) \tag{30}$$

where C_{PG}^{a}, C_{PG}^{y}, and C_{SESO}^{R}, respectively, represent the annual assessment costs for grid connected power fluctuations of wind farm clusters, the annual assessment costs for predicted deviations in power generation, and the annual leasing costs for shared energy storage; $C_{\mathrm{PG},t}^{a}$ and $C_{\mathrm{PG},t}^{y}$ are the assessment costs for grid connected power fluctuations and predicted deviations in power generation during the t th period of the wind farm cluster, respectively. The specific calculation methods are shown in Appendix A.

Constraints of WFCO model

(1) **Constraints on the output power of wind farm clusters**

The output power of a wind farm cluster cannot exceed its allowed maximum value or be less than its allowed minimum value:

$$0 \le P_t^{\mathrm{B}} \le P_t^{\mathrm{L}} \tag{31}$$

where P_t^{L} is the maximum allowable power of the grid-connected nodes of the wind farm cluster during the t th time period.

(2) **Constraints on the output power of each member of the wind farm clusters**

The output power of each member of the wind farm cluster cannot exceed its allowed maximum value or be less than its allowed minimum value:

$$0 \le P_{m,t}^{\mathrm{B}} \le P_{m,t}^{\mathrm{F}} \tag{32}$$

where $P_{m,t}^{\mathrm{B}}$ and $P_{m,t}^{\mathrm{F}}$, respectively, represent the dispatchable and predicted output power of the m th wind farm in the wind farm cluster during the t th time period.

(3) **Constraints on the abandoned wind power of a wind farm cluster**

The output power of a wind farm cluster can be predicted. Therefore, the abandoned wind power of a wind farm cluster cannot exceed the difference between its predicted and actual values:

$$0 \le P_{\mathrm{W},t}^{\mathrm{Q},c} \le \max\left(P_t^{\mathrm{F}} - P_t^{\mathrm{L}}, 0\right) \tag{33}$$

where P_t^{F} is the predicted output of the wind farm cluster during the t th time period.

2.3.2. A Robust Optimization Model for WFCO Considering Wind Power Uncertainty

Considering the impact of uncertainty in the output power of wind farm clusters on the capacity configuration leasing scenarios of shared energy storage, an uncertainty modeling method at multiple time scales is adopted to analyze the uncertainty of the output power of wind farm clusters. This article will construct a two-stage robust optimization model as follows. The objective function of the first stage is to minimize the assessment cost of grid-connected power fluctuations in typical scenarios of wind farm clusters. The objective function of the second stage is to minimize the leasing cost of shared energy storage in the wind farm cluster, taking into account the assessment cost of the predicted deviation of output power in the worst scenario of cluster output.

$$\sum_{i=1}^{G_{\mathrm{I1}}} I_i \left(\min_{I_i \in \Omega_1} C_{\mathrm{PG}}^{\mathrm{a}} + \max_{\tau \in \Omega_2} \min_{\mu} \left(C_{\mathrm{PG}}^{\mathrm{y}} + C_{\mathrm{SESO}}^{\mathrm{R}} \right) \right) \tag{34}$$

where τ is the worst-case scenario that considers the uncertainty of the output power of a wind farm cluster on a short time scale, including the actual output power $P_{\mathrm{w},t}$ of the wind farm cluster; μ is the leasing demand of shared energy storage in the worst-case scenario, including the actual leasing capacity demand R_t and the actual charging and discharging power demand S_t

$$\tau = [P_{\mathrm{w},t}] \tag{35}$$

$$\mu = [R_t, S_t]^{\mathrm{T}} \tag{36}$$

2.4. A Double-Layer Robust Optimization Model for Capacity Configuration in the Master–Slave Game of SESO

The double-layer robust optimization model for capacity configuration in the master–slave game of shared energy storage SESO can be composed of Equations (35)–(37), which include three elements: participants, strategies, and benefits.

$$G = \left\{ N; S_{\mathrm{SESO}}; S_{\mathrm{WFCO}}; I_{\mathrm{SESO}}^{\mathrm{IC}}; C_{\mathrm{total}} \right\} \tag{37}$$

The above master–slave game model specifically includes the following three elements:

(1) Participant: The participants in the master–slave game are wind farm clusters and shared energy storage, with a set of $N = \{\text{SESO} \cup \text{WFCO}\}$.

(2) Strategy: The strategy for sharing energy storage among actors is the following:

$$S_{\text{SESO}} = \begin{pmatrix} \zeta_t^{\text{cap}}, \zeta_t^{\text{mail}}, P_{\text{EP},t}^{d}, P_{\text{EP},t}^{c}, \\ P_{\text{W},t}^{\text{Q},c}, p_{\text{EP},t}^{d}, p_{\text{EP},t}^{c}, p_t^{s}, \forall t \end{pmatrix} \tag{38}$$

The strategy for the wind farm cluster as a sub actors is the following:

$$S_{\text{WFCO}} = \left(R_t, S_t, C_{\text{PG},t}^{a}, C_{\text{PG},t}^{\text{y}}, C_{\text{SESO},t}^{\text{R}}, \forall t \right) \tag{39}$$

(3) Benefits: The benefits of SESO and WFCO are calculated using Equations (2), (12), and (22), respectively.

Considering the autonomy and profit-driven nature of shared energy storage and wind farm clusters, which may lead to unsolvable Nash equilibrium in the master–slave game process, a constraint on the upper and lower limits of the leasing price of shared energy storage, taking into account the bilateral benefits of interactive games, is proposed (see Appendix B).

It is worth noting that the upper and lower limits of the leasing price for shared energy storage are not strictly constrained, and both sides of the game can timely cross, based on the overall leasing benefits and assessment costs.

3. The Solving Steps

For the double-layer robust optimization model for capacity configuration of shared energy storage considering cluster leasing of wind farms constructed in this article, the upper and lower models, respectively, consider the uncertainty of clearing prices in the spot market and the output power of wind farm clusters at multiple time scales, and use robust optimization methods to reconstruct the configuration model. The upper layer model of the robust optimization model for shared energy storage and the lower layer model of the robust optimization model for wind farm clusters are split into two-stage optimization problems. When applied to this optimization problem, it is difficult to achieve good results with the traditional and typical solution approach of transforming a double-layer model into a single-layer model. In addition, shared energy storage and wind farm clusters form leasing prices and leasing capacity at different time periods through a master–slave game, and the interactive game process is difficult to effectively map through a single-layer model. Therefore, this article adopts a particle swarm optimization algorithm to solve the dual layer optimized mixed linear programming model for capacity configuration of shared energy storage constructed in this article. The particle swarm optimization algorithm has the characteristics of simple structure and few core parameters and can characterize the interactive game process through iterative optimization, achieving effective solution of the master–slave game model [34–36].

It is worth noting that the upper and lower layers of the dual layer optimization model for capacity configuration of shared energy storage are split into two-stage optimization problems, which greatly increases the workload of the particle swarm optimization algorithm in calculating the benefits and costs of the upper- and lower-layer models, and significantly reduces the accuracy, speed, and convergence of the solution. Therefore, this article introduces the Column and Constraint (C and CG) algorithm [35] and the CPLEX commercial solver for solving and embeds them into the particle swarm optimization algorithm to improve the efficiency of the solution. The solution process of the robust optimization model of SESO's double-layer master–slave game is shown in Figure 2. The

current use of C and CG algorithm to solve two-stage optimization problems is relatively mature, and the specific solution process will not be elaborated here.

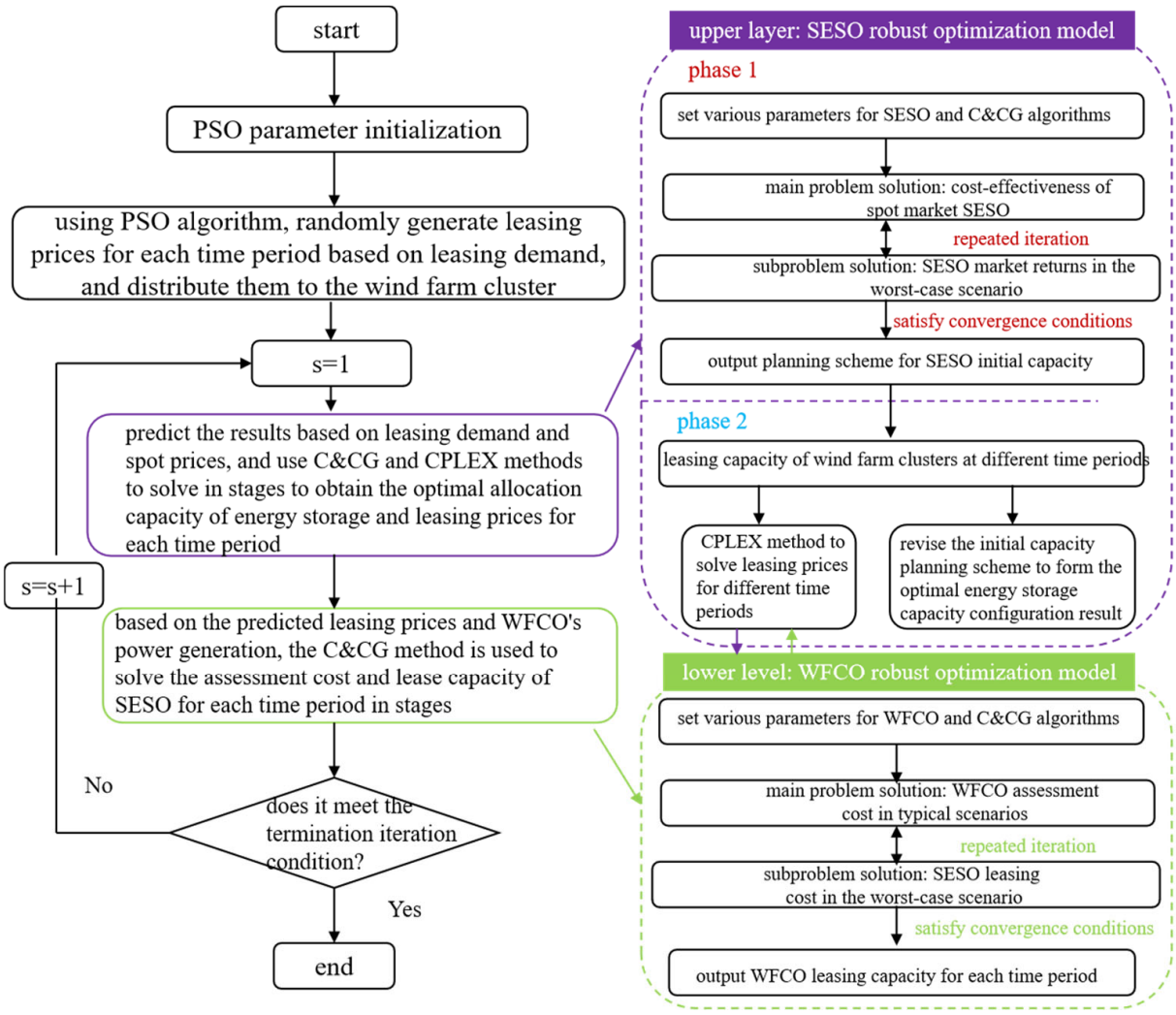


Figure 2. A flowchart for solving the dual layer robust optimization problem of capacity configuration for shared energy storage in cluster leasing of wind farms.

(1) At the upper level of the two-layer optimization configuration model, multi-stage solutions are carried out based on diverse application scenarios. In the first stage, targeting the arbitrage scenario of price differences in the spot market, the C and CG algorithm is used to split the robust optimization model of shared energy storage into a main problem and a sub problem, achieving iterative solution of upper and lower bounds in two stages, forming an initial planning scheme for shared energy storage in the worst-case scenario of clearing prices in the spot market. In the second stage, aimed at providing leasing service scenarios, the initial planning scheme for shared energy storage formed in the first stage is utilized, combined with the leasing needs of wind farm clusters in different time periods. The CPLEX commercial solver is used to directly solve the leasing prices for shared energy storage in each time period, and the initial planning scheme for shared energy storage is modified to form the optimal capacity configuration for shared energy storage.

(2) At the lower level of the two-layer optimization configuration model, the C and CG algorithm is used to split the robust optimization model of the wind farm cluster into a main problem and a sub problem, achieving two-stage iterative solution of upper

and lower bounds, and forming leasing capacity for each time period in the worst output power scenario of the wind farm cluster.

4. Study Cases

4.1. Data and Scene Settings

This article sets up three wind farms to form a wind farm cluster. Through cooperative games, interact with one shared energy storage power station. Based on the historical trial operation settlement data of a certain node in the Guangdong electricity spot market, predict the clearing price of the spot market. Based on the historical power curves and related influencing factors of each wind farm [37], predict the output power of the wind farm. The prediction curves for the output power of each wind farm in the next year, the prediction curves for the output power of wind farm clusters in the next year, the maximum capacity power curve of wind farm cluster at the grid-connected node, and the prediction curves for the clearing price in the spot market in the next year are shown in Figures A1–A4 in Appendix C. The relevant parameters of the wind farm cluster are as follows: the installed capacity of wind farms 1–3 is 75 MW, 80 MW, and 90 MW, respectively. The assessment cost for unit grid-connected power fluctuation is 0.3654 yuan/kWh, and the assessment cost for unit power prediction deviation is 0.1250 yuan/kWh. Assuming that the price of wind power curtailment and sale of the wind farm cluster in each time period is 50% of the clearing price in the corresponding time period in spot market. The relevant parameters of the power grid are as follows: set the clearing price of the spot market of the power grid to 80% of the selling price (charging price for shared energy storage) [36].

The parameters related to shared energy storage are as follows: the investment and construction cost per unit capacity of shared energy storage λ = 600 yuan/kWh, the discount cost per unit charging and discharging power λ = 0.1542 yuan/kWh, the discount rate r = 5%, the charging and discharging efficiency $\eta_c = \eta_d = 95\%$, the planning period N_y = 15 years, the leasing price per unit capacity ζ_t^{cap} = 0.3142 yuan/kWh, and the conversion coefficient κ = 0.85. The initial value of state of charge (SOC) for shared energy storage is 0.2, with maximum and minimum values of 0.9 and 0.1, respectively. Shared energy storage participates in spot market trading as a price receiver [38,39].

The parameters related to robust optimization are set as follows: the robust indicators for the output power of the wind farm cluster and the clearing price in the spot market are 6 and 6, respectively, and $G_{J1} = 5$ is taken for uncertain scenarios. The relevant parameter settings for improving K-means clustering are as follows: the total number of clusters (typical scenarios) is taken as $k = 4$, and the minimum value is $\delta = 0.1$.

To analyze the optimization effect of capacity configuration for shared energy storage considering cluster leasing of wind farms, multiple cases were set up for comparative analysis, as shown in Table 1.

Table 1. Case scenario settings.

Case Scenario	Leasing Services	Autonomous Decision-Making	Robust Optimization	Scene Reduction	Reference
Case1	×	×	×	×	[31]
Case2	√	×	×	×	[38]
Case3	√	√	×	×	[3,21]
Case4	√	√	√	×	[1,29,32]
Case5	√	√	√	√	/

Note: √ represents considering the element; × represents not considering the element.

4.2. Optimization Results and Analysis

The optimization results, cost-effectiveness, leasing costs, and assessment costs of the shared-energy-storage capacity configuration in cases 1–5 are shown in Table 2. The optimization results of typical scenarios obtained by using the improved K-means joint clustering method are shown in Table 3.

Table 2. Optimization results of capacity configuration for shared energy storage, cost-effectiveness, leasing costs, and assessment costs of wind farm clusters in different cases.

Case Scenario	The Configuration Results of Shared Energy Storage/MWh	The Cost-Effectiveness of Shared Energy Storage/$	The Leasing Cost of Wind Power Gathering Stations/$10^4$$	Assessment Costs for Wind Farm Clusters/$10^4$$
Case1	30	0.1172	/	0.8988
Case2	40.62	0.0402	0.3824	0.3824
Case3	45.68	0.0368	0.3242	0.4223
Case4	52.47	0.0414	0.3767	0.4756
Case5	56.23	0.0378	0.4300	0.5477

Table 3. Typical scenario results of joint clustering.

Typical Scenarios	Number	Probability
1	119	32.60%
2	68	18.63%
3	94	25.75%
4	84	23.02%

4.2.1. Impact Analysis of Leasing Models for Shared Energy Storage

The leasing model of shared energy storage is an effective way to enrich the business model of shared energy storage and improve utilization efficiency. Case 1 only considers the price difference arbitrage model of shared energy storage for the spot market, while case 2 considers the leasing service scenario proposed in this article to provide capacity support for the wind farm cluster. In case 2, a fixed electric price model is used for the leasing price, taking the average value of the upper limit and lower limit of the average price in the master–slave game as the fixed electric price. The output power prediction curve and actual curve of the wind farm cluster are taken from the first typical scenario and the first uncertain scenario under the first typical scenario, respectively. The clearing price in the spot market is also calculated using the same method. The operational results of shared energy storage in typical daily scenarios for case 1 and case 2 are shown in Figure 3.

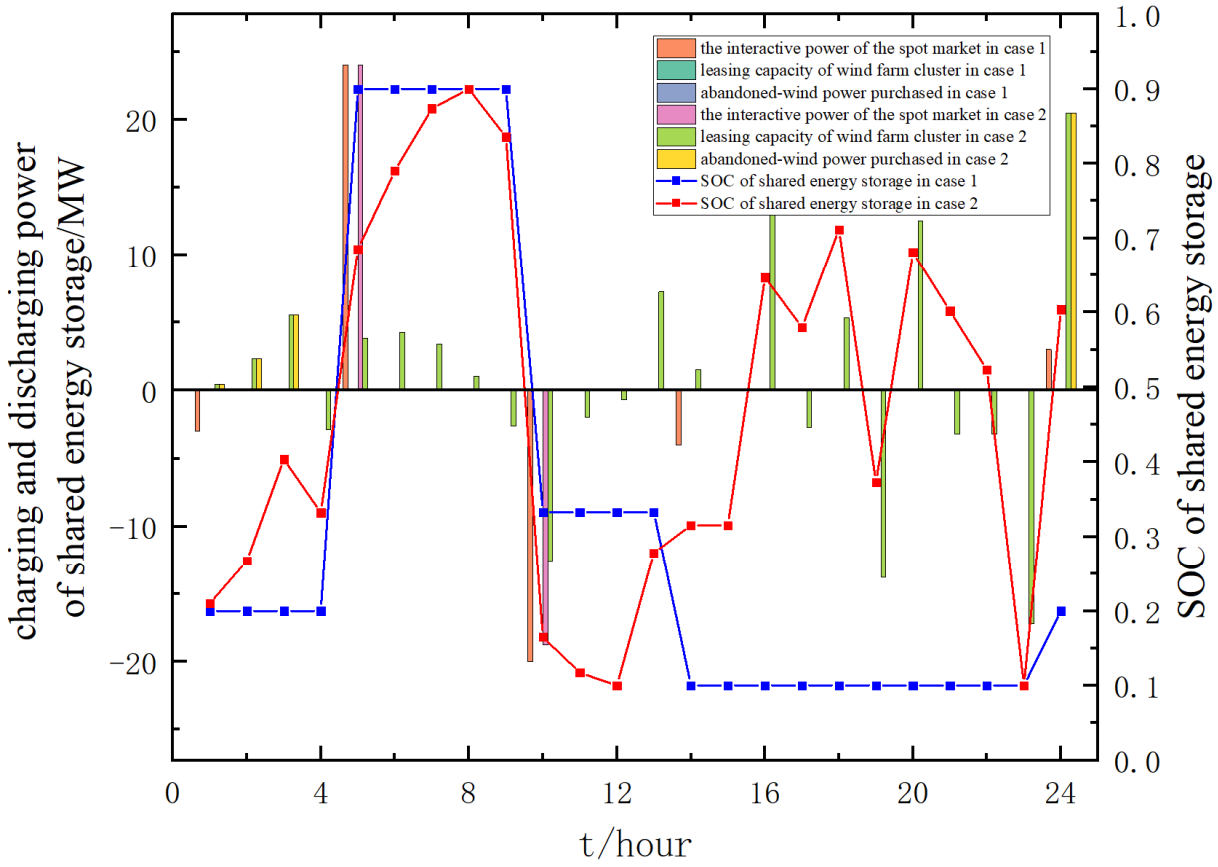


Figure 3. The operational results of shared energy storage in typical scenarios for case 1 and case 2.

From Figure 3, it can be observed that compared to case 1, in case 2, the charging and discharging operations of shared energy storage are more frequent at each time period. There is no zero charging and discharging period, and the state of charge curve is closer to the upper and lower limits in some time periods. In other time periods, it fluctuates up and down, indicating that leasing services provided by shared energy storage significantly reduces the idle rate, and the SOC value is closer to 0.5, which improves utilization while ensuring its safety. Based on Table 1, it can be seen that compared to case 1, due to the consideration of the cluster leasing model of the wind farm, the configuration capacity of shared energy storage in case 2 has increased by 23.61 MWh. Although the configuration cost of shared energy storage has been increased, the benefits brought by the leasing model not only cover the configuration cost but also have remaining space. The cost-effectiveness of shared energy storage has been reduced by 43.17%, confirming the effectiveness of the capacity-leasing model of shared energy storage. While reducing the idle rate of shared energy storage, it has also improved the economy. For wind farm clusters, although the leasing cost of shared energy storage increases the overall assessment cost, its capacity support effectively offsets the assessment cost of most grid-connected power fluctuations and the assessment cost of generation power prediction deviations. The overall assessment cost of wind farm clusters has decreased by 247.46 million yuan, a decrease of 38.72%, indicating that leasing services for shared energy storage can help alleviate the assessment costs faced by wind farm clusters. Without the need for large-scale investment in energy storage construction in the early stage, the energy storage configuration requirements formulated by relevant policies can be met, and wind farm clusters have sufficient motivation to participate in capacity leasing services for shared energy storage.

4.2.2. Impact Analysis of Autonomous Decision-Making on Shared Energy Storage

In case 3, the autonomy of shared energy storage is fully considered, and the restriction in case 2 on prioritizing shared energy storage to meet the leasing needs of wind farm clusters is lifted. The impact of clearing prices in the spot market on leasing prices is taken into account. Based on the economic benefits, the capacity configuration of shared energy storage in multiple scenarios and the capacity configuration in different scenarios are determined.

Figure 4 shows the electric leasing prices of shared energy storage in case 3 and case 2 at different time periods. From Figure 4, it can be observed that there is a certain degree of difference in the leasing prices of shared energy storage between case 2 and case 3 at different time periods. Case 3 shows greater volatility in most time periods, especially during periods with larger price differentials in the spot market. In addition, the leasing-price difference is more significant, with a maximum of 0.5858 yuan/kWh. According to Table 1, it can be seen that the capacity configuration of shared energy storage is reduced by 5.06 MWh in case 4 compared to in case 3. Due to the prioritization of meeting the leasing needs of wind farm clusters, the cost-effectiveness increases by 0.0246, and the economic effect of capacity configuration is relatively poor, confirming the impact of clearing prices on the leasing service of shared energy storage in the spot market scenario. In the scenario of pricing-difference arbitrage, shared energy storage performs more actively and invests more capacity in case 3, especially between time periods 5 and 10. There is basically no charging or discharging behavior for shared energy storage in case 3 (only charging during time period 6), and more capacity is used for pricing difference arbitrage in the spot market to improve economic benefits. The analysis data show that shared energy storage, as an independent actor, prioritizing the leasing setting of the wind farm cluster in case 4 will limit its optimal decision-making, resulting in shared energy storage not being able to develop optimization operation strategies and capacity-planning schemes solely based on profitability. As a result, shared energy storage generates large-capacity idleness for some periods of time in the scenario of providing leasing services, resulting in poor overall cost-effectiveness. In addition, case 2 prioritizes meeting the leasing setting of the wind farm cluster, separating the leasing-service scenario from pricing-difference arbitrage scenario in the spot market. The impact of the clearing price in the spot market on the electric-leasing price of shared energy storage in different time periods is ignored, especially in some time periods where the price difference in spot market is relatively large. Shared energy storage is more inclined to invest capacity into market transactions, resulting in a further increase in the leasing price in case 3 compared to that in case 2, which more effectively maps the capacity supply and demand relationship of shared energy storage. Therefore, considering the impact of clearing prices in the spot market on leasing prices is beneficial for assisting shared energy storage in forming more reasonable and economical leasing prices for various time periods in diverse scenarios and improving the independence and autonomy of shared energy storage.

With the gradual optimization and improvement of China's electricity spot market, the upper and lower limits of clearing prices will be further widened, and the arbitrage space of price differences for shared energy storage in the spot market will be enlarged. The impact of clearing prices on lease prices will become more important. Considering the correlation between clearing prices and lease prices in advance is beneficial to help shared energy storage allocate storage capacity reasonably during the planning stage and improve the utilization rate and economic benefits of storage capacity.

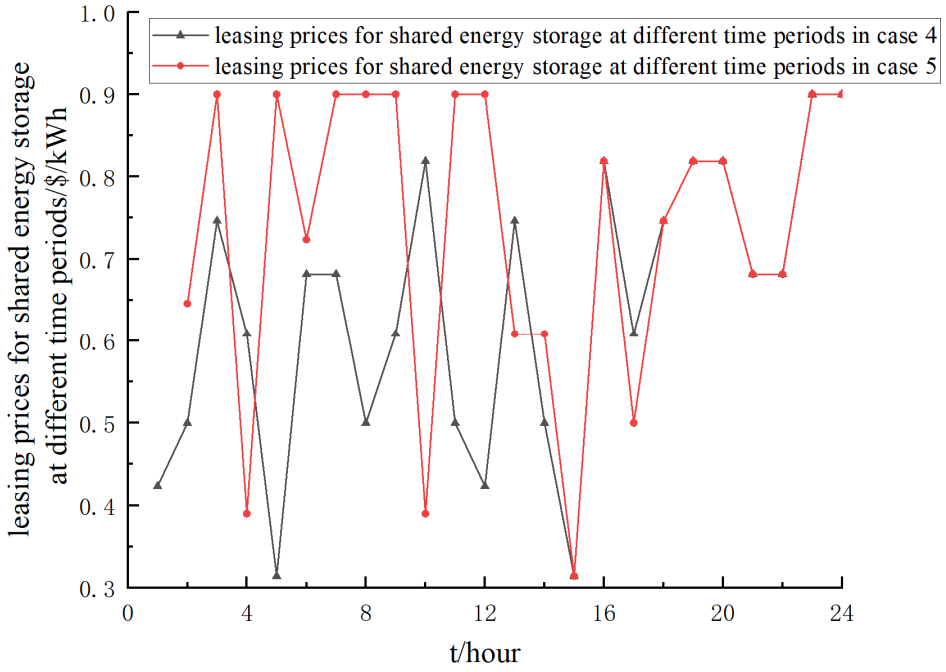


Figure 4. The leasing prices for shared energy storage at different time periods in case 5 and case 4.

4.2.3. Impact Analysis of Short-Term Uncertainty

In case 4, the uncertainty of the output power of wind farm clusters and clearing prices in the spot market on a short-term scale was considered. Robust optimization methods were used to construct uncertainty sets to characterize typical potential scenarios, effectively achieving optimal configuration of shared energy storage in the worst-case scenario. To further verify the impact of considering short-term uncertainty, new cases 4–1 and 4–2 were added. Case 4–1: optimization operation of the capacity configuration scheme for shared energy storage in case 4 scenario; case 4–2: optimization operation of the capacity configuration scheme for shared energy storage in case 4 scenario; and the cost-effectiveness of case 4–1 and case 4–2 are shown in Table 4. It can be observed that the cost-effectiveness of shared energy storage in case 4–1 increased by 6.25% compared to that in case 4, while the cost-effectiveness of shared energy storage in cases 4–2 decreased by 0.7% compared to that in case 3. This is because case 4 is the worst-case scenario in a typical scenario, and compared to case 5, the output power of the wind farm cluster and the clearing price in the spot market fluctuate more frequently, resulting in the need to allocate more capacity for shared energy storage in case 4 to cope with the fluctuation of clearing prices. At the same time, in this scenario, the leasing-service income and pricing-difference arbitrage income of shared energy storage increase with the severity of the severity. Therefore, in case 4–1, without the adverse scenario in case 4, the charging and discharging power reduced and the cost-effectiveness increased, while in case 4–2, the opposite is true. Case 4–1 can effectively respond to the scenario of case 3 and have remaining capacity in some periods. An analysis of the data shows that considering the uncertainty impact of key elements in the application scenarios of shared energy storage on a short-term scale is beneficial for improving the effectiveness and practicality of capacity configuration, enhancing the ability of shared energy storage to cope with uncertainty scenarios, and promoting wind power consumption while ensuring its own configuration benefits.

Table 4. Optimization operation results of shared energy storage in different cases.

Case	The Cost-Effectiveness of Shared Energy Storage
4–1	0.3127
4–2	0.2593

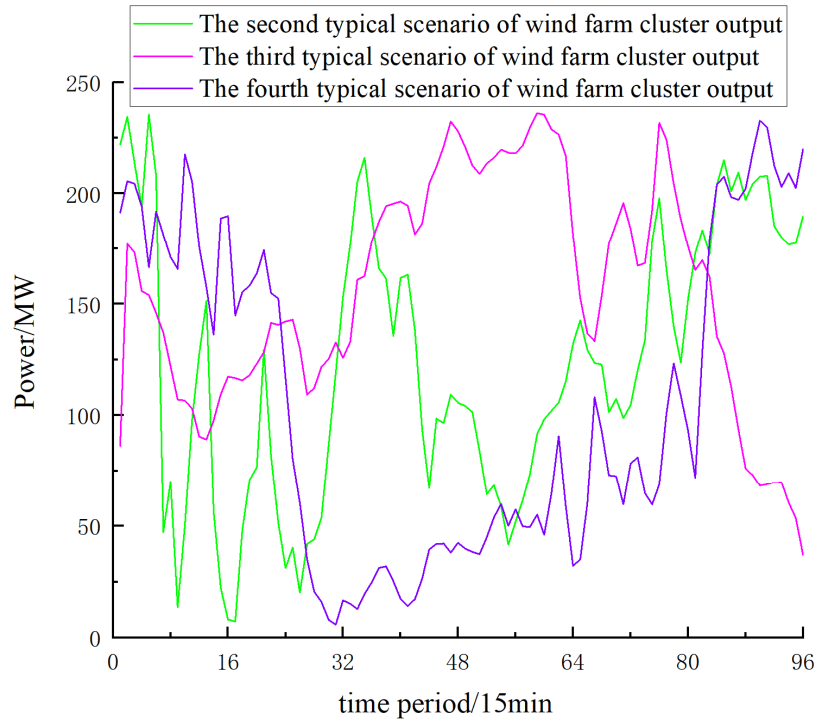
4.2.4. Impact Analysis of Long-Term Uncertainty

In case 5, the uncertainty of the output power of the wind farm cluster and the clearing prices in the spot market over a long period of time is considered, and an improved K-means-clustering method is used to enhance the universality and effectiveness of the configuration results. To verify the robustness of the optimization results of energy storage configuration in case 5, new cases 5–1, 5–2, and 5–3 are added. Cases 5–1, 5–2, and 5–3 represent the second, third, and fourth typical scenarios, respectively. The configuration results and cost-effectiveness of shared energy storage in different cases are shown in Table 5. The leasing demand for wind farm clusters in different time periods in typical scenarios 2–4 can be found in Figure 5.

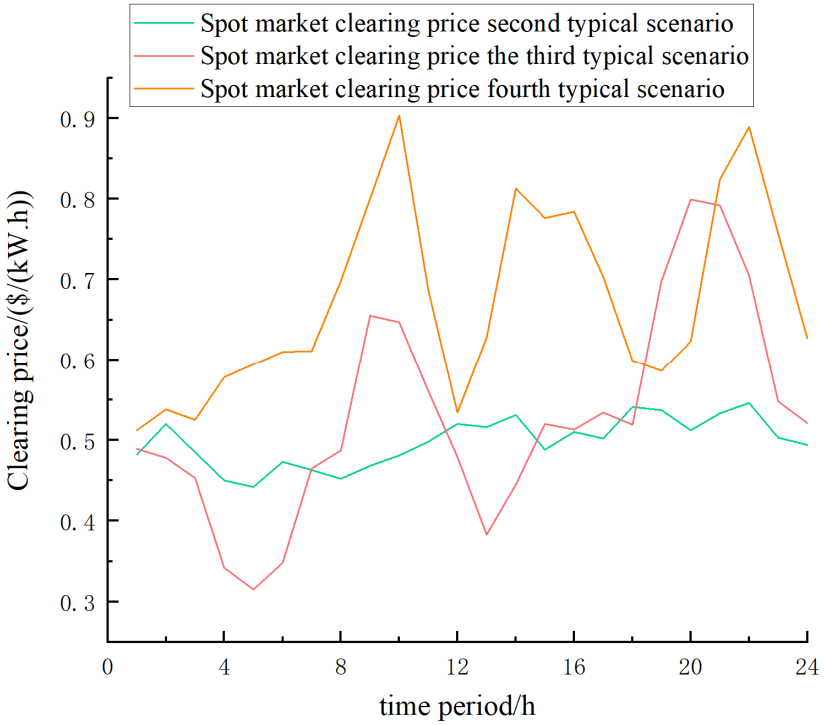
Table 5. Optimization results of shared energy storage configuration in different cases.

Case Scenario	The Configuration Results of Shared Energy Storage/MWh	The Cost-Effectiveness of Shared Energy Storage
Case4	52.47	0.2943
Case5–1	77.61	0.2409
Case5–2	46.83	0.2845
Case5–3	54.77	0.2781
Case5	56.23	0.2686

From Table 5, it can be seen that in different typical scenarios, the configuration results of shared energy storage in case 4, case 5–1, case 5–2, case 5–3, and case 5 are not the same. Case 5–1 has the highest capacity configuration result, while case 5–2 has the lowest capacity configuration result, with a difference of 30.78 MWh between the two. The capacity configuration result of case 5 is in the middle. In terms of cost-effectiveness, as case 4, case 5–1, case 5–2, and case 5–3 all allocate shared-energy-storage capacity based on different typical scenarios; their configuration results significantly reduce cost-effectiveness in other typical scenarios, making it difficult to cope with the uncertainty impact brought by other scenarios. Due to the consideration of the uncertainty impact in different typical scenarios, the capacity-planning scheme in case 5 is developed based on the lowest cost-effectiveness. The capacity configuration results have good adaptability in different typical scenarios and have better universality and economy. It can be observed that due to the significant differences in output curves among different typical scenarios, there are significant differences in leasing demand for wind farm clusters in different cases at different time periods. The capacity configuration results of shared energy storage in a single typical scenario are difficult to effectively balance with other typical scenarios. The difference in clearing prices in the spot market further exacerbates the limitations of capacity configuration results in a single scenario. Therefore, it is necessary to consider the impact of uncertainty elements in the diversified scenarios of shared energy storage providing leasing services and participating in pricing-difference arbitrage in the spot market on a long-term scale and adjust the capacity configuration of shared energy storage reasonably to improve the robustness and economy of the capacity configuration results of shared energy storage in different scenarios.



(**a**) Output power curves of wind farm clusters in typical scenarios 2–4



(**b**) The clearing-price curve of the spot market in typical scenarios 2–4

Figure 5. The output power curve of wind farm clusters and the clearing-price curve of spot markets in typical scenarios 2–4.

5. Conclusions

(1) A reasonable leasing price is the key to ensuring the continuous operation of shared-energy-storage-leasing services. By constructing a master–slave game model to depict the interactive game between the leasing demand of wind farm clusters and the

capacity configuration of shared energy storage, the formation process of leasing prices reflects the supply–demand balance on both sides of the game. Compared with the fixed electric price of shared energy storage, the leasing income has increased by $1.46 million, which is conducive to guiding wind farm clusters to lease shared energy storage according to demand.

(2) Fully considering the autonomy of shared energy storage, the setting of prioritizing shared energy storage to meet the leasing needs of wind farm clusters is canceled, and the clearing price of the spot market is included in the formation process of leasing prices. The configured capacity of shared energy storage is increased by 5.06 MWh, and the cost-effectiveness is significantly reduced by 8.6%. This is conducive to improving the independent decision-making ability of shared energy storage in multi coupling scenarios, thereby optimizing the rationality and economy of capacity configuration.

(3) The capacity configuration of shared energy storage tends towards long-term planning, and the impact of uncertainty elements on the configuration results includes both long-term and short-term scales. The uncertainty on a long-term scale takes into account the limitations of optimizing typical scenarios, reducing cost-effectiveness by 8.7%. The uncertainty on a short-term scale takes into account the impact of accommodating extreme scenarios, resulting in more robust configuration results. Taking into account the uncertainty impact of key elements in multiple application scenarios at multiple time scales is beneficial for improving the response capacity and adequacy of shared energy storage in various potential scenarios, ensuring the effectiveness and economy of capacity configuration results.

In the current market environment in our country, this article only considers the mature business model of pricing difference arbitrage for shared energy storage participating in the spot market and does not involve regulatory services in the auxiliary service market with higher returns. With the continuous increase in the proportion of new energy and the gradual improvement of the electricity market, the insufficient regulatory resources of the power grid will guide market management institutions to include high-quality regulatory resources such as shared energy storage in the auxiliary service market, and lower the entry threshold. Subsequent research can consider the participation of shared energy storage in auxiliary service market transactions such as frequency regulation and peak shaving. Frequent frequency fluctuations and peak loads will provide more diverse commercial operation models and profit channels for shared energy storage, further improving utilization and economic benefits.

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Abbreviations

Symbol	Definition
WFCO	Wind farm cluster operator
WF	Wind farm
SESO	Shared energy storage operator
SES	Shared energy storage
PG	Power grid
K-means	k-means clustering algorithm
SOC	State of Charge
C&CG	column-and-constraint generation
Ω_1	a typical scenario set of uncertainty in the joint clustering of wind power output and spot prices over a long time scale
Ω_2	an uncertainty set
π_i	the probability that the uncertainty scenario set of wind power output and spot prices in the joint clustering occurs in the i typical scenario
Γ_{w}	robust parameters for the output power of the wind farm cluster
Γ_{EP}	robust parameters for the output power of the uncertainty set of spot prices
$P_{\mathrm{w}}(t)$	the actual values of the output power of the wind farm cluster in the t th time period
$p_{\mathrm{EP}}(t)$	the actual values of the spot price in the t th time period
ζ_t	the period during which shared energy storage provides leasing services to wind farm clusters, in hour, $t \in \{1, 2, \ldots, 24\}$
ζ_t^{cap}	capacity leasing price for the shared energy storage of the wind farm cluster during the t th time period
ζ_t^{mail}	electricity leasing price for shared energy storage of the wind farm cluster in the t th time period
$I_{\mathrm{SESO}}^{\mathrm{IC}}$	the annual cost benefit of shared energy storage
$I_{\mathrm{SESO}}^{\mathrm{R}}$	annual leasing income for shared energy storage leasing services
$I_{\mathrm{SESO}}^{\mathrm{EP}}$	the annual market trading income of price differences arbitrage in the spot market for shared energy storage
C_{inv}	the annual investment and construction cost of shared energy storage over its entire lifecycle
C_{loss}	the annual operating cost discount of shared energy storage
C_{w}	the annual cost of purchasing electricity for wind farm cluster abandonment through shared energy storage
D	the annual operating days of shared energy storage, and it is necessary to consider the maintenance status of shared energy storage
R_t	the leasing capacity of shared energy storage of the wind farm cluster in the t th time period
S_t	the total charging and discharging power of shared energy storage of the wind farm cluster in the t th time period
$Q_{\mathrm{w},t}^c$	the curtailment electricity purchased by shared energy storage from wind farm cluster during the t th time period
$\perp$	the operator, indicating that at least one of the left and right parameters will be 0
$P_{\mathrm{EP},t}^d$	the online power of the price difference arbitrage of shared energy storage participating in the spot market during the t th time period
$P_{\mathrm{EP},t}^c$	The charging power of the price difference arbitrage of shared energy storage participating in the spot market during the t th time period

$p^{d}_{\mathrm{EP},t}$	the on-grid electric price for price difference arbitrage of shared energy storage participating in the spot market during the t th time period
$p^{c}_{\mathrm{EP},t}$	the charging electric price for price difference arbitrage of shared energy storage participating in the spot market during the t th time period
ψ_{E}	the unit capacity cost of shared energy storage
E_{N}	the rated capacity of the configured shared energy storage
N_{y}	the planning period for configured shared energy storage
r	the discount rate
λ	the discounted cost per unit of charging and discharging power for shared energy storage
$P^{c}_{\mathrm{SES},t}$	the charging power of the shared energy storage in the t th time period
$P^{d}_{\mathrm{SES},t}$	the discharging power of the shared energy storage in the t th time period
p^{s}_{t}	the purchasing price of wind power for shared energy storage during the t th time period
$P^{c}_{\mathrm{W},t}$	the charging power of the shared energy storage leasing capacity called by the wind farm cluster during the t th time period
$P^{d}_{\mathrm{W},t}$	The discharging power of the shared energy storage leasing capacity called by the wind farm cluster during the t th time period
$P^{\mathrm{Q},c}_{\mathrm{W},t}$	the charging power of the shared energy storage purchased from the wind farm cluster during the t th time period
$k_{\mathrm{SOC},t}$	the state of charge values of shared energy storage during the t th time period, respectively
η_{c}	the charging efficiency of shared energy storage
η_{d}	the discharging efficiency of shared energy storage
$k_{\mathrm{SOC,o}}$	the initial state of charge values for shared energy storage
$k_{\mathrm{SOC,e}}$	the state of charge values at the end of one operating cycle (24 h)
φ	the worst-case scenario that considers the uncertainty of clearing prices in the spot market on a short-term scale (with the smallest price difference)

Appendix A

Calculation of Assessment Costs and Leasing Needs for Wind Farm Clusters

The assessment cost of wind farm clusters comes from the volatility and randomness of wind power output. In this article, the assessment cost of wind farm clusters mainly includes two aspects: assessment of grid-connected power fluctuations and assessment of predicted deviations in power generation. Based on the implementation rules for grid-connected operation and auxiliary service management of wind power in the southern region, the assessment standards for the grid-connected power of wind farms and the assessment standards for the predicted deviation of generated power in the document will be used as the basis. Any part of the predicted output of wind farms that exceeds the actual output by 20% will be subject to deviation assessment. The assessment amount for wind farms due to grid-connected power fluctuations during the 15 min period is set as:

$$P_{w,\mathrm{limit}} = \begin{cases} 3 & E_{\mathrm{W,N}} \le 30 \\ \frac{E_{\mathrm{W,N}}}{10} & 30 < E_{\mathrm{W,N}} \le 100 \\ 10 & 100 < E_{\mathrm{W,N}} \end{cases} \tag{A1}$$

where $P_{\mathrm{w,limit}}$ is the upper limit value of the power fluctuation of the wind farm during the grid-connection process; $E_{\mathrm{W,N}}$ is the rated capacity of the wind farm.

The fluctuation cost $C^a_{\mathrm{PG},t}$ of grid connected power for wind farm clusters is:

$$C^a_{\mathrm{PG},t} = \varepsilon_a \sum_{h=1}^{4} \max\left(\left|P^r_{t,h} - P^r_{t,(h-1)}\right| - P_{\mathrm{limit}}, 0\right)\Delta h \tag{A2}$$

where ε_a is the assessment cost of unit grid connected power fluctuations for wind farm clusters; $P^r_{t,h}$ and $P^r_{t,(h-1)}$ represent the predicted output of the wind farm cluster of time h and $h-1$ at t th time periods, respectively; Δh is the time interval, 15 min.

The predicted deviation cost C^r_y is:

$$C^y_{\mathrm{PG},t} = \varepsilon_y \sum_{h=1}^{4} \max\left(|P^r_{t,h} - P_{t,h}| - 0.2P_{t,h}, 0\right)\Delta h \tag{A3}$$

where ε_y is the assessment cost of unit prediction deviation for shared energy storage; $P_{t,h}$ is the actual output of the wind farm cluster at the t th time period and the h th time period.

Considering that the assessment values for the fluctuation of grid connected power and the prediction deviation of power generation in the wind farm cluster are both assessed based on the time period (15 min), while the interactive game between the wind farm cluster and shared energy storage forms a leasing capacity that is carried out based on the time period (1 h). Therefore, the assessment power of the wind farm cluster needs to be converted at various times, in order to form the leasing demand for shared energy storage at different time periods:

$$R_t = \frac{1}{4}\sum_{h=1}^{4} [\max(|P^r_{t,h} - P^r_{t,(h-1)}| - P_{\mathrm{limit}}, 0) + \max(|P^r_{t,h} - P^r_{t,(h-1)}| - 0.05P_h, 0)] \tag{A4}$$

Appendix B

Constraints on the Upper and Lower Limits of Leasing Prices in a Master-Slave Game Model for Shared Energy Storage

(1) Constraints on the upper limit of leasing prices

This constraint takes into account the limitation of the assessment cost of the leasing subordinate WFCO, and sets that the total leasing cost of each period formed by the master–slave game is not higher than the overall assessment cost.

$$\sum_{t=1}^{24}\left(\zeta^{\mathrm{cap}}_t H_t + \zeta^{\mathrm{mail}}_t S_t\right) \le \sum_{t=1}^{24}\left(C^a_{\mathrm{PG},t} + C^y_{\mathrm{PG},t}\right) \tag{A5}$$

where $C^a_{\mathrm{PG},t}$ is the assessment cost for the grid connected power fluctuations of the wind farm cluster during the t th time period; $C^y_{\mathrm{PG},t}$ is the assessment cost for the prediction deviation of the power generation of the wind farm cluster during the t th time period.

(2) Constraints on the lower limit of leasing prices

This constraint takes into account the constraints of operating costs and opportunity costs for the leasing entity SESO, and sets that the total leasing costs for each period formed by the master–slave game are not less than the shared energy storage costs.

$$\sum_{t=1}^{24}\lambda\left(P^c_{\mathrm{SES},t} + P^c_{\mathrm{SES},t}\right) + \sum_{t=1}^{24} S_t\kappa\overline{p}_{\mathrm{EP},t} \le \sum_{t=1}^{24}\left(\zeta^{\mathrm{cap}}_t H_t + \zeta^{\mathrm{mail}}_t S_t\right) \tag{A6}$$

where κ is the conversion coefficient; $\overline{p}_{\mathrm{EP},t}$ is the maximum price difference in the spot market during the t th time period, which is the difference between the maximum and minimum clearing prices in the spot market during each period.

Appendix C

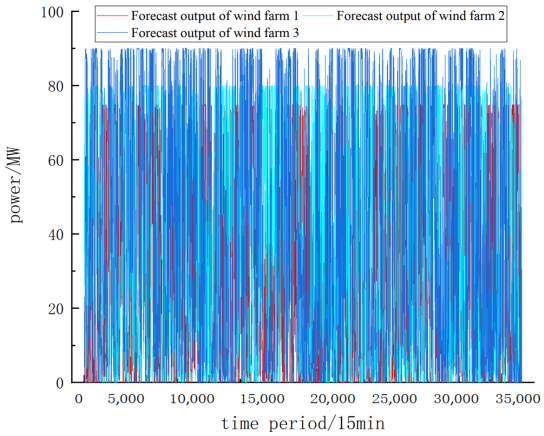


Figure A1. Prediction value of output power of wind farms 1–3.

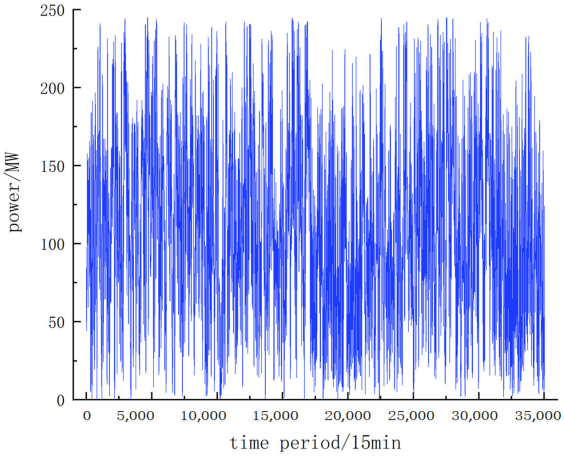


Figure A2. Prediction value of output power of wind farm clusters.

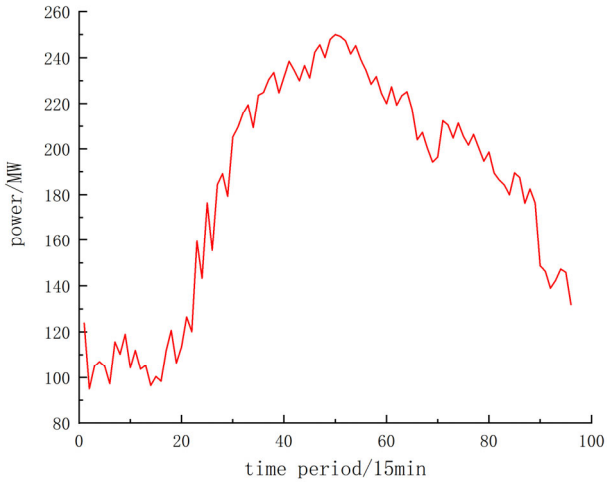


Figure A3. The maximum capacity power value of grid connected nodes in wind farm clusters.

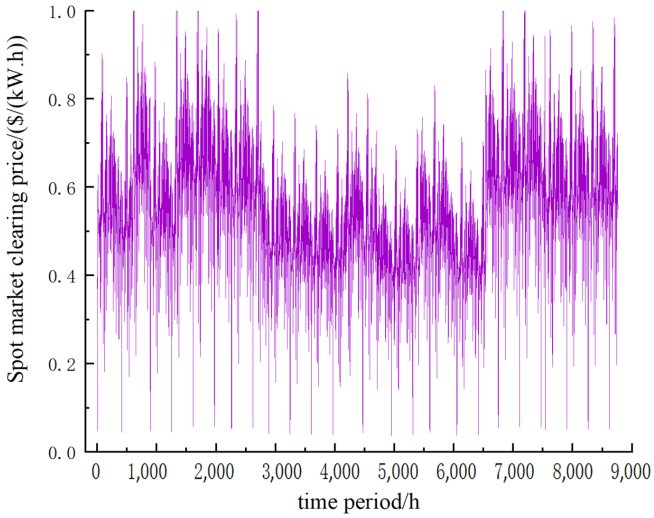


Figure A4. Predicted clearing prices in the spot market.

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