

Article

Two-Stage Coordinated Bidding and Revenue Sharing Strategies for Wind Farm Consortia

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Abstract

Wind power producers face increasing market risks in electricity spot markets because output uncertainty may lead to large imbalance penalties and unstable revenues. This study aims to improve the market participation performance of wind farm consortia by coordinating day-ahead bidding, real-time deviation correction, and internal revenue allocation. The main novelty of this study is the integration of consortium-level bidding, shared energy storage leasing, and post-settlement revenue-cost allocation within a unified decision-allocation framework. A two-stage coordinated bidding model is developed for a wind farm consortium that leases shared energy storage to mitigate real-time power deviations. A Shapley value-based allocation mechanism is further introduced to distribute consortium revenue, while the shared energy storage leasing cost is allocated using an additional revenue-proportional fairness rule. Case studies show that the proposed strategy can reduce deviation penalties, increase the final net revenue after leasing cost, and maintain fair incentives among consortium members. Sensitivity analyses further demonstrate that the economic performance of the consortium is affected by storage size, charging/discharging efficiency, and wind farm output correlation. The proposed framework provides a practical decision-making reference for wind power aggregation, shared energy storage utilization, and coordinated participation in electricity spot markets.

Keywords: wind farm consortium; shared energy storage leasing; two-stage coordinated bidding; electricity spot market; deviation penalty; Shapley value



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1. Introduction

The large-scale, market-oriented integration of wind power into the power grid is an important pathway for constructing new power systems and achieving low-carbon energy transition goals. However, wind power generation is characterized by strong intermittency, randomness, and volatility. When wind farms participate independently in day-ahead and real-time spot markets, deviations between actual output and contracted power may lead to imbalance penalties and unstable revenues. Recent studies on wind power bidding have shown that day-ahead decisions are strongly affected by real-time imbalance risk, balancing price uncertainty, and the interaction between forecasting errors and market settlement mechanisms [1–3]. Shared energy storage can provide flexible regulation services for renewable energy producers and help mitigate real-time output deviations, while

consortium-based operation can further exploit the spatial complementarity among different wind farms. Therefore, it is necessary to investigate coordinated bidding strategies and fair revenue sharing mechanisms for wind farm consortia that lease shared energy storage in electricity spot markets.

1.1. State of the Art

Research on wind power participation in electricity markets has gradually evolved from deterministic bidding based on point forecasts to uncertainty-aware bidding strategies. Early and recent studies mainly use stochastic optimization, robust optimization, scenario generation, and risk-constrained decision-making to reduce the impact of wind power and price uncertainty on market revenue [4–8]. These studies provide important methodological foundations for renewable energy bidding. Nevertheless, most of them still regard each wind farm or renewable energy producer as an independent market participant. As a result, the complementary output characteristics among multiple renewable energy stations and their potential value in reducing aggregated deviations are not fully exploited.

Energy storage has been widely introduced to improve the market performance of renewable energy producers. Battery energy storage, pumped storage, and other flexible resources can smooth renewable power fluctuations, reduce imbalance penalties, and support multi-stage market participation [9,10]. However, independently configured energy storage may suffer from high investment cost, low utilization rate, and limited regulation flexibility, especially when individual wind farms face intermittent deviation demands. To overcome these limitations, shared energy storage has attracted increasing attention. Recent studies have investigated capacity sharing markets, hybrid self-built and leased modes, shared storage-assisted transaction optimization, market-oriented leasing strategies, and cooperative game-based configuration methods for renewable energy stations and wind farm clusters [11–15]. These studies indicate that shared energy storage can improve resource utilization and reduce configuration costs. However, existing studies mainly focus on capacity planning, storage dispatch, or benefit evaluation, while the joint problem of consortium-level day-ahead bidding, real-time deviation correction, shared storage leasing, and internal revenue allocation remains insufficiently studied.

Revenue allocation is another key issue for maintaining the stability of renewable energy consortia. Proportional allocation and capacity-based allocation are simple to implement, but they may not accurately reflect the marginal contribution of each participant. Cooperative game theory, especially the Shapley value, has been widely applied to benefit allocation in virtual power plants, micro-energy grids, shared storage systems, and heterogeneous energy alliances [16–22]. However, the exact Shapley value calculation becomes computationally expensive as the number of participants increases, and approximation methods have been studied for larger energy communities. For a small wind farm consortium, exact Shapley value calculation remains tractable and can provide a transparent benchmark for fair allocation.

In addition, the effectiveness of consortium operation is closely related to wind power forecasting accuracy and output complementarity. Complementarity is commonly evaluated through correlation-based indicators, and lower correlation generally implies stronger smoothing potential among renewable energy sources [23]. Empirical studies also show that wind power forecast errors can be reduced through geographical aggregation and that forecast accuracy varies with region size, spatial dispersion, and forecasting models [24,25]. Recent forecasting studies further confirm that improvements in wind speed and wind power forecasting can directly affect the value of market participation [26]. Therefore, forecasting accuracy and inter-farm correlation should be explicitly discussed when designing case studies for wind farm consortia.

1.2. Research Gap and Incremental Contributions

Although the above studies have provided valuable insights into renewable energy bidding, storage-assisted market participation, shared energy storage operation, and co-operative game-based benefit allocation, three research gaps remain. First, most wind power bidding studies focus on independent wind farms and pay limited attention to the aggregation benefits of wind farm consortia. Second, shared energy storage studies mainly emphasize planning, capacity leasing, or dispatch optimization, while the coupling between day-ahead bidding decisions and real-time deviation correction under a leasing mechanism has not been sufficiently integrated. Third, existing revenue allocation studies often allocate benefits after operation but do not fully connect the marginal contribution of each wind farm with shared energy storage leasing cost sharing and deviation penalty reduction.

To make the novelty clearer, several closely related studies are further distinguished from the present work. Ju et al. [13] considered shared energy storage-assisted transaction optimization and benefit allocation, but did not focus on a wind farm consortium leasing shared storage for real-time deviation correction in electricity spot markets. Liu et al. [14] studied market-oriented shared storage leasing for wind farm clusters, but did not fully couple post-settlement revenue allocation and leasing-cost sharing with the two-stage bidding process. Zhang et al. [18] investigated shared-storage-assisted virtual power plant bidding and profit allocation, whereas this study focuses on wind farm consortia and explicitly connects day-ahead bidding, real-time imbalance mitigation, leased storage dispatch, and internal revenue-cost allocation. Wu et al. [22] introduced cooperative game theory into wind-storage coalition operation, but did not jointly formulate leasing-based shared storage, two-stage stochastic bidding, and revenue-proportional cost sharing. Therefore, the proposed method advances existing approaches by establishing a unified “bidding–regulation–settlement–allocation” framework for wind farm consortia.

Based on the above comparison and research gaps, this paper proposes a two-stage coordinated bidding and revenue sharing strategy for wind farm consortia participating in electricity spot markets with shared energy storage leasing. The incremental contributions of this paper are summarized as follows:

- A wind farm consortium operation framework with shared energy storage leasing is established, in which multiple wind farms participate in the spot market as a unified market entity while using leased storage resources for real-time deviation correction.
- A two-stage stochastic optimization model is developed to coordinate day-ahead bidding and real-time shared energy storage dispatch, thereby explicitly linking forward-looking bidding decisions with imbalance penalty mitigation.
- A Shapley value-based revenue allocation mechanism is introduced to reflect the marginal contribution of each wind farm, and an additional revenue-proportional fairness rule is used to allocate shared energy storage leasing costs.
- A detailed case study and sensitivity analyses are conducted to examine the effects of shared energy storage size, charging/discharging efficiency, and wind farm output correlation on the economic performance of the consortium. The applicability and limitations of the proposed method are also discussed.

It should be noted that this study focuses on wind farm consortia. Although the proposed modeling framework can provide a reference for other renewable energy aggregation problems, the case study and parameter settings in this paper are designed for wind power plants. Therefore, the scope of the present study is limited to wind farms participating in electricity spot markets with shared energy storage leasing.

The remainder of this paper is organized as follows. Section 2 summarizes the nomenclature and abbreviations used in the mathematical formulations. Section 3 presents the methodology, including the market framework, two-stage coordinated bidding model,

shared energy storage constraints, cooperative game-based allocation mechanism, and solution process. Section 4 presents the case study and analysis, including comparative results and sensitivity analyses. Section 5 discusses the novelty, scientific justification, implications, applicability, and limitations of the proposed strategy. Section 6 concludes the paper and outlines future research directions.

2. Nomenclature and Abbreviations

To improve the readability of the manuscript, the main symbols and abbreviations used in the mathematical formulations are summarized in Table 1.

Table 1. Main nomenclature and abbreviations used in this paper.

Symbol/Abbreviation	Description
t	Index of scheduling period
T	Total number of scheduling periods
s	Index of uncertainty scenario
S	Total number of uncertainty scenarios
i	Index of wind farm
M	Total number of wind farms in the consortium
p_t^b	Day-ahead cleared power at time t
$p_{i,t}^w$	Actual power output of wind farm i at time t
$\hat{p}_{i,t}^w$	Forecasted power output of wind farm i at time t
$\beta_{i,t}$	Day-ahead bid allocation coefficient of wind farm i at time t
p_t^c	Charging power of shared energy storage at time t
p_t^d	Discharging power of shared energy storage at time t
U_t^c	Binary variable indicating the system-level charging status of shared energy storage at time t
U_t^d	Binary variable indicating the system-level discharging status of shared energy storage at time t
E_t	Energy state of shared energy storage at time t
$E_{ess}^{\max}$	Rated capacity of shared energy storage
$p_{ess}^{\max}$	Rated charging/discharging power of shared energy storage
η_c	Charging efficiency of shared energy storage
η_d	Discharging efficiency of shared energy storage
$\rho^{\min}$	Lower operating limit of storage energy state
$\rho^{\max}$	Upper operating limit of storage energy state
λ_t^{da}	Day-ahead market electricity price at time t
λ_t^{bal}	Independent balancing market electricity price at time t
C_l	Shared energy storage leasing cost
C_p	Deviation penalty cost
F	Objective function or total revenue-related function
φ_i	Shapley value allocated to wind farm i
SES	Shared energy storage
SOC	State of charge or state of energy of the storage system
DA	Day-ahead market
RT	Real-time market

3. Methodology

3.1. Market Framework for the Wind Farm Consortium and Shared Energy Storage Leasing

To fully exploit the aggregation benefits of multiple wind farms and the flexible regulation capability of shared energy storage, this paper proposes an operational model in which a wind farm consortium participates in the electricity spot market through unified aggregation and centralized leasing of shared energy storage. Multiple wind farms voluntarily form a wind farm consortium and participate in market bidding and settlement as a unified entity. Acting as a single market participant, the consortium leases regulation power and capacity resources from a shared energy storage operator, and collectively participates in day-ahead bidding, real-time deviation correction, market clearing, and revenue settlement. By utilizing the complementary output characteristics of multiple wind farms and the

flexible regulation capability of leased shared energy storage, the proposed model can smooth wind power output fluctuations, reduce performance deviations, and improve the overall revenue of the consortium while ensuring fair internal allocation. To visually illustrate the relationships among market participants, business processes, and interaction logic of the proposed model, Figure 1 presents the operational architecture of the wind farm consortium and shared energy storage participating in the spot market.

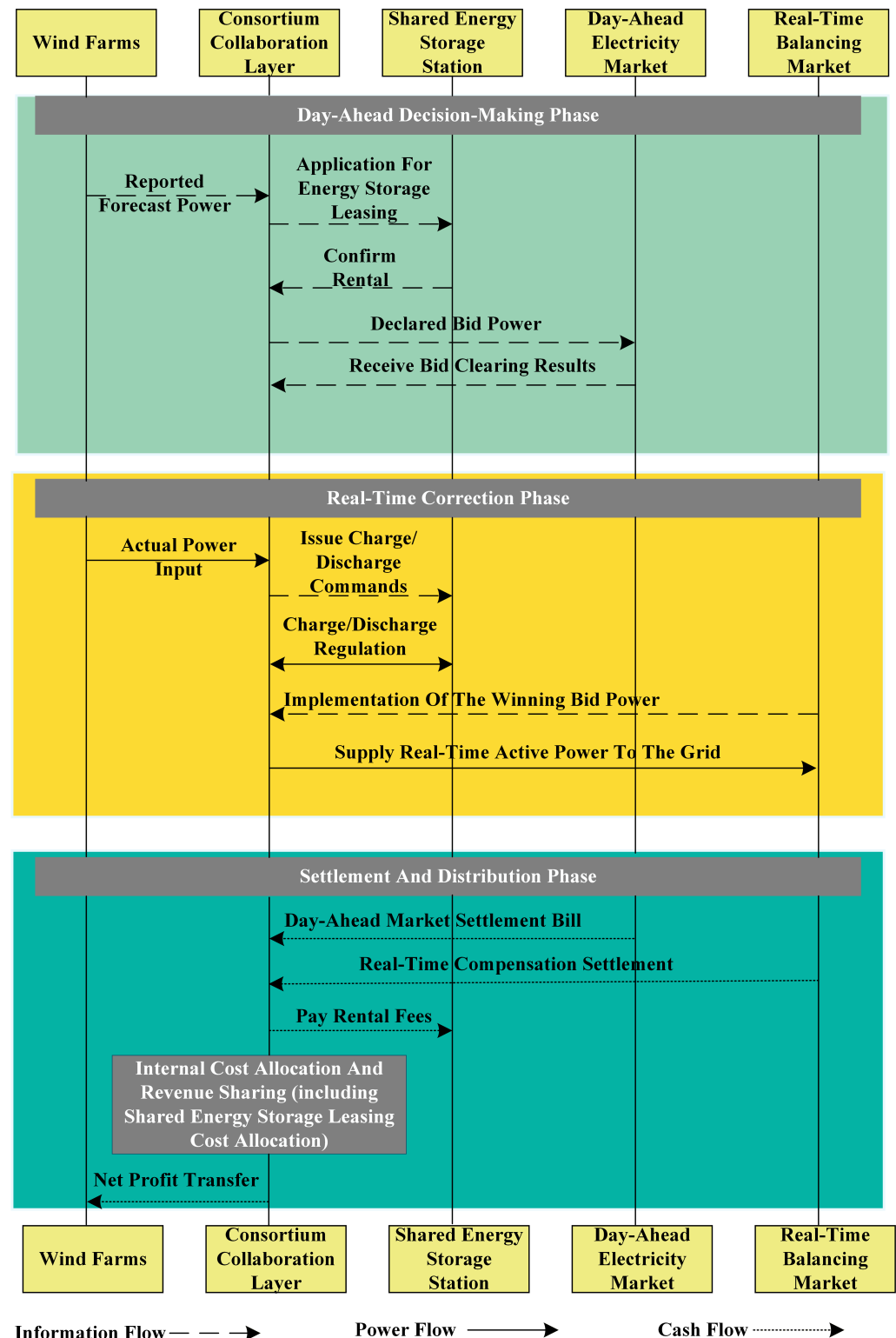


Figure 1. Operational architecture of the wind farm consortium with shared energy storage leasing in the spot market.

As shown in Figure 1, the proposed architecture adopts a horizontal entity partition and a vertical phase partition. Horizontally, the system consists of three major functional modules: the left module is the wind power generation layer, which includes multiple independent wind farms and acts as the sole source of power output and economic revenue for the entire system; the middle module is the consortium coordination layer, which undertakes six core functions: wind power aggregation, energy storage leasing application, day-ahead unified bidding, real-time coordinated dispatch, leasing cost allocation, and consortium revenue distribution, serving as the decision-making and coordination center of the whole model; the right module is the market and energy storage service layer, including three supporting units: the day-ahead electricity market, the real-time balancing market, and the shared energy storage station, which provide a unified trading platform for the consortium. Vertically, the whole operation process is divided into three sequential stages: the day-ahead decision-making stage, the real-time correction stage, and the settlement and allocation stage. The diagram clearly distinguishes power flow, information flow, and capital flow using solid arrows: the actual power output of each wind farm is aggregated upward to the consortium; the consortium issues charge/discharge commands to the shared energy storage system and pays the corresponding leasing fees; the consortium submits bidding power to the day-ahead market and obtains the cleared results; during the real-time stage, the shared energy storage system performs charge/discharge regulation to suppress power output deviations; the market operator completes electricity fee and compensation settlement with the consortium; finally, the consortium finishes internal cost allocation and revenue distribution, and transfers net profits to each wind farm entity separately [14].

This paper adopts a day-ahead and real-time dual-settlement mechanism with two-way imbalance penalties, which is consistent with the proposed two-stage optimization model and the market settings considered in this study. To clearly demonstrate the decision sequence, variable coupling relationships, and algorithm execution flow, Figure 2 illustrates the two-stage coordinated bidding and deviation correction framework for the wind farm consortium in the day-ahead and real-time markets.

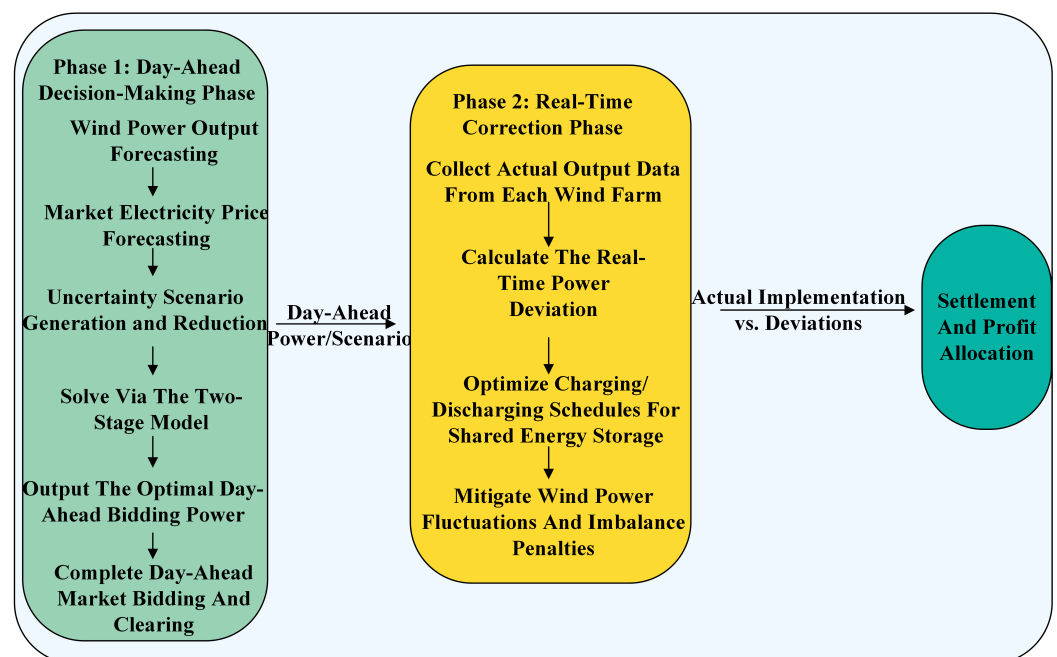


Figure 2. Two-stage coordinated bidding and imbalance correction process for the wind farm consortium in the day-ahead and real-time markets.

Figure 2 illustrates a sequential flowchart that strictly embodies the two-stage stochastic optimization model, following a progressive logic from left to center to right. The left part corresponds to the day-ahead decision-making stage: wind power output forecasting, market electricity price forecasting, and uncertainty scenario generation and reduction are implemented sequentially. These results are then input into the two-stage optimization model to obtain the solution, which outputs the optimal day-ahead bidding power and completes day-ahead market bidding and clearing. The middle part corresponds to the real-time correction stage: actual output data of each wind farm are collected, and real-time power deviations are calculated. Subject to the operational constraints of energy storage, the charge/discharge schedule of shared energy storage is optimized to mitigate wind power fluctuations and deviation penalties. The right part corresponds to the settlement and allocation stage: market electricity revenue settlement, imbalance cost calculation, and shared energy storage leasing cost calculation are completed. Based on the Shapley value, consortium revenue distribution and energy storage cost allocation are implemented, finally yielding the net revenue of each wind farm. The whole process embodies the complete decision-making logic of “forward-looking optimization–rolling correction–revenue allocation”.

3.2. Model Formulation and Solution Method

This section presents the overall methodology of the proposed strategy. The methodology consists of two closely connected parts: the two-stage stochastic optimization coordinated bidding model and the cooperative game-based revenue allocation and leasing cost sharing mechanism. The first part determines the optimal day-ahead bidding power and real-time shared energy storage dispatch strategy, while the second part allocates the consortium revenue and storage leasing cost among wind farms according to their marginal contributions.

3.2.1. Two-Stage Stochastic Optimization Coordinated Bidding Model

This paper adopts a two-stage stochastic optimization framework to characterize the bidding decision timeline of wind farm consortia. With the maximum full-cycle net revenue of the consortium as the core objective, a coordinated optimization model integrating day-ahead bidding and real-time deviation correction is established. The model follows the standard logic of two-stage stochastic programming. In the first stage, the consortium determines the day-ahead bidding power before the realization of wind power and electricity price uncertainties. This first-stage variable belongs to the “here-and-now” decision and must be identical for all uncertainty scenarios. In this paper, the main here-and-now decision variable is the day-ahead cleared power P_t^b . In the second stage, after each uncertainty scenario is realized, the shared energy storage charging/discharging schedule, the storage energy state, and the corresponding deviation penalty variables are adjusted as scenario-dependent recourse decisions. These variables belong to the “wait-and-see” decisions. For notational simplicity, the scenario superscript of some second-stage variables is omitted in the deterministic real-time realization, but their recourse nature is retained in the two-stage formulation.

Accordingly, the relationship between the two objective functions is clarified before presenting the detailed objective functions. Equation (4) gives the first-stage expected objective, in which the expected second-stage deviation penalty under different scenarios is embedded. Equation (6) gives the realized second-stage operating objective after a specific scenario is observed and the first-stage bidding power has been fixed. Therefore, Equation (6) should not be interpreted as an independent objective that conflicts with Equation (4), but as the scenario-wise recourse evaluation used for real-time correction and

subsequent settlement. To show this relationship in a standard stochastic programming form, the compact two-stage formulation is introduced as follows:

$$\begin{aligned} \max_x \quad & \sum_{s=1}^S \gamma_s [f_s(x) + Q_s(x)] \\ \text{s.t.} \quad & Q_s(x) = \max_{y_s} \{g_s(x, y_s) \mid (x, y_s) \in \Omega_s\}, \quad \forall s. \end{aligned} \quad (1)$$

In Equation (1), x denotes the here-and-now bidding decision P_t^b , y_s denotes the wait-and-see recourse decisions under scenario s , $f_s(x)$ represents day-ahead market revenue, $Q_s(x)$ represents the optimized second-stage recourse value, and Ω_s denotes the feasible set of storage operation and market-settlement constraints. This compact formulation is added to clarify the stochastic programming structure of the proposed model before the detailed revenue and penalty expressions are presented.

To improve the tractability of the proposed model while maintaining consistency with practical electricity market operation, the following assumptions are made in this study:

1. The wind farm consortium participates in the day-ahead electricity spot market as a unified market entity. The cleared power is determined in the day-ahead stage, while real-time deviations are settled according to the imbalance penalty mechanism.
2. The output uncertainty of wind farms is represented by a finite number of typical scenarios. In the numerical implementation, $N_0 = 1000$ initial scenarios are generated by Monte Carlo simulation. For wind power uncertainty, the actual output of wind farm i in scenario s is generated around the forecasted output $\hat{P}_{i,t}^w$. To keep the generated wind power within the physical output range, the wind power scenario is generated as follows:

$$P_{i,t}^{w,s} = \min\{\max[\hat{P}_{i,t}^w(1 + \epsilon_{i,t}^s), 0], P_i^{\text{rated}}\}. \quad (2)$$

In Equation (2), $P_{i,t}^{w,s}$ is the generated wind power output of wind farm i at time t under scenario s , $\hat{P}_{i,t}^w$ is the forecasted output, P_i^{rated} is the rated installed capacity, and $\epsilon_{i,t}^s$ is the wind power forecast error. The forecast error follows a zero-mean normal distribution with the forecast-error standard deviations of 5%, 10%, and 15% for Wind Farms 1–3, respectively. The inter-farm error correlation is represented by the covariance matrix, with the baseline correlation coefficient set to 0.1. For electricity price uncertainty, the day-ahead price is generated around the baseline day-ahead price profile. To avoid negative electricity prices in this simplified setting, the price scenario is generated as follows:

$$\lambda_{s,t}^{da} = \max[\bar{\lambda}_t^{da}(1 + \xi_t^s), 0]. \quad (3)$$

In Equation (3), $\lambda_{s,t}^{da}$ is the generated day-ahead price at time t under scenario s , $\bar{\lambda}_t^{da}$ is the baseline day-ahead price profile, and ξ_t^s is a zero-mean normal price error with a standard deviation of 10%. Each initial scenario is assigned an equal probability before scenario reduction.

3. The shared energy storage system provides charging and discharging regulation services to the consortium through a leasing mechanism. Its charging/discharging power, energy state, operating limits, and efficiency constraints are explicitly considered.
4. To simplify the imbalance settlement process, the deviation penalty cost is calculated using the day-ahead market electricity price as the reference price. Although balancing prices may be decoupled from day-ahead prices in practical electricity spot markets, this study adopts the day-ahead price as an explicit modeling assumption. The day-

ahead electricity-price scenarios and the penalty coefficients for over-generation and under-generation are treated as given parameters during the optimization horizon. If an independent balancing market price is available, the proposed model can be directly extended by replacing the day-ahead reference price in the imbalance penalty terms with the balancing price. This change affects the numerical magnitude of deviation penalties and net revenues, but does not change the two-stage decision structure, storage dispatch constraints, or revenue allocation procedure.

5. The internal revenue and cost allocation among wind farms is conducted after market settlement. The Shapley value is used to allocate benefits according to the marginal contribution of each wind farm.

The above assumptions are consistent with the basic operation logic of electricity spot markets and shared energy storage services. First, in practical day-ahead and real-time market mechanisms, renewable energy producers submit bids before actual output is fully realized, and deviations between cleared power and actual output are settled through imbalance penalties. Therefore, representing the market participation process as a day-ahead bidding stage followed by real-time deviation correction is reasonable. Second, wind power uncertainty is commonly described by scenario-based methods, because scenario generation can capture typical fluctuation patterns while keeping the optimization model computationally tractable. Third, shared energy storage is modeled as a flexible regulation resource with power, energy, and efficiency constraints, which reflects the physical operating characteristics of storage systems. Fourth, although balancing prices may be decoupled from day-ahead prices in practical spot markets, the day-ahead market electricity price is adopted as the reference price for imbalance charges in this study to simplify the settlement process and highlight the effects of coordinated bidding and shared energy storage regulation. Finally, since the consortium contains multiple wind farms with different prediction accuracies and marginal contributions, a cooperative game-based allocation method is introduced to ensure the fairness and stability of internal revenue distribution. These assumptions provide the scientific basis for the proposed two-stage coordinated bidding and revenue sharing framework.

3.2.2. Objective Function

This paper takes the maximization of the full-cycle net revenue of the wind farm consortium as the optimization objective and establishes a two-stage objective function. The optimal day-ahead bidding model aims to maximize the expected revenue under various scenarios, where the decision variables are the day-ahead bidding power of each time period. The real-time penalty cost is directly embedded into the modeling process to realize effective two-stage coupling [4]. The corresponding objective function is formulated as follows.

$$\max F_1 = \sum_{s=1}^S \gamma_s \sum_{t=1}^T \left(\lambda_{s,t}^{da} P_t^b \Delta t - R_{s,t}^{re} \right), \quad (4)$$

where F_1 is the expected total net revenue of the consortium in the day-ahead scenario; S is the total number of uncertainty scenarios; γ_s is the occurrence probability of scenario s , which satisfies $\sum_{s=1}^S \gamma_s = 1$; T is the total number of scheduling periods; Δt is the duration of a single time period; $\lambda_{s,t}^{da}$ is the day-ahead market clearing price at time t under scenario s ; P_t^b is the day-ahead bidding power of the consortium at time t under deterministic scenarios, which is a first-stage here-and-now decision variable and does not vary with scenarios; $R_{s,t}^{re}$ is the scenario-dependent real-time deviation penalty cost at time t under scenario s , which reflects the second-stage recourse consequence after the day-ahead bidding power has been fixed. Thus, the nonanticipativity requirement of standard two-

stage stochastic programming is satisfied because P_t^b is common to all scenarios, whereas the real-time penalty and storage-dispatch-related decisions are evaluated separately under each scenario.

The real-time deviation penalty adopts a piecewise two-way penalty mechanism to reflect the differentiated penalty rules for over-generation and under-generation, which is expressed as:

$$R_{s,t}^{re} = \begin{cases} k^+ \lambda_{s,t}^{da} (P_{s,t}^w - P_t^b) \Delta t, & P_{s,t}^w \geq P_t^b \\ k^- \lambda_{s,t}^{da} (P_t^b - P_{s,t}^w) \Delta t, & P_{s,t}^w < P_t^b \end{cases} \quad (5)$$

where k^+ is the penalty coefficient for over-generation deviation; k^- is the penalty coefficient for under-generation deviation; $P_{s,t}^w$ is the actual total wind power output of the consortium at time t under scenario s . It should be noted that the day-ahead market electricity price $\lambda_{s,t}^{da}$ is used as the reference price for imbalance charges in Equation (5). This is a simplifying assumption adopted in this study, while balancing prices may be independently determined in practical electricity spot markets. When independent balancing market prices are considered, the imbalance penalty formulation remains the same except that the day-ahead price is replaced by the balancing price, i.e., $\lambda_{s,t}^{da}$ in Equation (5) can be replaced by $\lambda_{s,t}^{bal}$. Under this setting, higher balancing prices increase the marginal cost of power deviations, and lower balancing prices reduce the numerical value of imbalance penalties. However, the role of shared energy storage in reducing the residual deviation $|P_{s,t}^w - P_t^b|$ remains unchanged. Therefore, the proposed model remains applicable under independent balancing-price settlement.

The real-time market deviation correction stage is the optimization layer of the second stage. Given the fixed day-ahead bidding power, this stage aims to maximize the actual net revenue of the consortium by optimizing the charging and discharging schedule of shared energy storage to mitigate deviations between wind power output and cleared power. The objective function is formulated as follows:

$$\max F_2 = \sum_{i=1}^M \sum_{t=1}^T \lambda_t^{da} P_{i,t}^b \Delta t - \sum_{i=1}^M \sum_{t=1}^T r_{i,t}^{re} - C_l, \quad (6)$$

where F_2 is the actual net revenue of the consortium in the real-time stage, which is the realized value of the first-stage objective under a deterministic scenario; M is the number of wind farms; $P_{i,t}^b$ is the allocated bidding power of the i -th wind farm at time t under the deterministic scenario; $r_{i,t}^{re}$ is the real-time deviation penalty cost of the i -th wind farm at time t under the deterministic scenario; C_l is the total leasing cost of shared energy storage. In the two-stage stochastic programming interpretation, F_2 corresponds to the realized second-stage recourse objective after the scenario is observed. The first-stage variable P_t^b is fixed when Equation (6) is evaluated, while the storage dispatch and deviation penalty terms are adjusted according to the realized wind power and price conditions. Therefore, Equations (4) and (6) describe the expected planning objective and the realized recourse objective, respectively, and they are linked through the fixed first-stage bidding decision.

The expression for $r_{i,t}^{re}$ is given as follows:

$$r_{i,t}^{re} = \begin{cases} k^+ \lambda_t^{da} (P_{i,t}^w - P_{i,t}^b) \Delta t, & P_{i,t}^w \geq P_{i,t}^b \\ k^- \lambda_t^{da} (P_{i,t}^b - P_{i,t}^w) \Delta t, & P_{i,t}^w < P_{i,t}^b \end{cases} \quad (7)$$

Consistent with Equation (5), the day-ahead market electricity price λ_t^{da} is also adopted as the reference price for imbalance settlement in Equation (7). If the balancing market price is independently determined, λ_t^{da} in Equation (7) can be replaced by λ_t^{bal} . This modification

changes the settlement amount of each wind farm but preserves the linearity of the penalty term and the solvability of the proposed mixed-integer linear model. To calculate the entity-level settlement and deviation penalty in the second stage, the total day-ahead cleared power of the consortium needs to be disaggregated into entity-specific bidding powers. In this study, the total day-ahead bid P_t^b is allocated to each wind farm according to its forecasted power output share at time t . This rule reflects the expected generation contribution of each wind farm and ensures consistency between consortium-level bidding and entity-level settlement. The relationships are expressed as follows:

$$\begin{cases} \sum_{i=1}^M P_{i,t}^w = P_t^w \\ P_{i,t}^b = \beta_{i,t} P_t^b, \quad \forall i, t \\ \beta_{i,t} = \frac{\hat{P}_{i,t}^w}{\sum_{j=1}^M \hat{P}_{j,t}^w}, \quad \forall i, t' \\ \sum_{i=1}^M \beta_{i,t} = 1, \quad \forall t \end{cases} \quad (8)$$

where $P_{i,t}^b$ is the day-ahead bidding power allocated to the i -th wind farm at time t ; $\hat{P}_{i,t}^w$ is the forecasted power output of the i -th wind farm at time t ; and $\beta_{i,t}$ is the corresponding allocation coefficient. When the total forecasted output of all wind farms at a certain time period is zero, the allocation coefficient can be determined according to the installed-capacity proportion to avoid division by zero. With this allocation rule, the entity-level bidding power $P_{i,t}^b$ used in Equation (7) is explicitly determined, and the sum of all entity-specific bidding powers is equal to the consortium-level cleared power P_t^b .

Shared energy storage adopts a real-time charging mode based on the actual charge and discharge power, where the leasing cost is directly linked to the regulation intensity. The calculation formula is as follows:

$$C_l = \sum_{i=1}^M \sum_{t=1}^T \mu (P_{i,t}^c + P_{i,t}^d) \Delta t, \quad (9)$$

where μ is the unit power leasing price; $P_{i,t}^c$ is the leased charging power of the i -th wind farm at time t ; $P_{i,t}^d$ is the leased discharging power of the i -th wind farm at time t . The leasing cost is calculated based on the gross regulation power provided by the shared energy storage operator. To avoid simultaneous charging and discharging at the physical storage terminal, a system-level mutually exclusive charging/discharging constraint is further imposed in Equation (11).

3.2.3. Constraints

Constraints on Consortium Bidding Power and Market Rules

The model must satisfy the constraints on power bounds and penalty coefficients. The consortium's bidding power is non-negative and cannot exceed the maximum technical output limit, while the penalty coefficients comply with market settlement rules, as follows:

$$\begin{cases} 0 \leq P_t^b \leq P_t^{\max} \\ 0 < k^+ < 1, k^- > 1' \end{cases} \quad (10)$$

where $P_t^{\max}$ is the maximum technical output of the consortium at time t .

3.2.4. Charging and Discharging Power Constraints of Shared Energy Storage Power Station Leased by Wind Farms

To ensure the physical consistency of shared energy storage operation, the charging and discharging behaviors of the shared energy storage system should be mutually exclusive at each time period. Different wind farms may lease charging or discharging regulation services from the same shared energy storage operator, but the physical storage terminal cannot charge and discharge simultaneously. Therefore, a system-level binary charging/discharging status variable is introduced for each time period to prohibit cross-entity simultaneous charging and discharging [27], as expressed below:

$$\begin{cases} P_t^c = \sum_{i=1}^M P_{i,t}^c, & \forall t \\ P_t^d = \sum_{i=1}^M P_{i,t}^d, & \forall t \\ 0 \leq P_t^c \leq P_{ess}^{\max} U_t^c, & \forall t \\ 0 \leq P_t^d \leq P_{ess}^{\max} U_t^d, & \forall t \\ 0 \leq P_{i,t}^c, & 0 \leq P_{i,t}^d, \quad \forall i, t \\ U_t^c + U_t^d \leq 1, & \forall t \\ U_t^c \in \{0, 1\}, & \forall t \\ U_t^d \in \{0, 1\}, & \forall t \end{cases} \quad (11)$$

where P_t^c and P_t^d are the total charging and discharging powers of the shared energy storage system at time t , respectively; $P_{i,t}^c$ and $P_{i,t}^d$ are the leased charging and discharging powers allocated to the i -th wind farm at time t , respectively; $P_{ess}^{\max}$ is the rated charging/discharging power of the shared energy storage system; U_t^c and U_t^d are system-level binary variables representing the charging and discharging status of the shared energy storage system at time t , respectively. The constraints ensure that the aggregate charging and discharging powers leased by all wind farms do not exceed the physical power limit of the shared energy storage station. In addition, $U_t^c + U_t^d \leq 1$ ensures that the shared energy storage system cannot charge and discharge simultaneously at the same physical time, even when multiple wind farms lease regulation services from the same storage operator.

3.2.5. Shared Energy Storage Operation Constraints

The state of charge of the energy storage system should ensure safe operation and daily cycling [28]. The constraints are given as follows:

$$\begin{cases} \rho^{\min} E_{ess}^{\max} \leq E_t \leq \rho^{\max} E_{ess}^{\max} \\ E_t = E_{t-1} + \eta_c P_t^c \Delta t - \frac{P_t^d}{\eta_d} \Delta t, \\ E_0 = E_T \end{cases} \quad (12)$$

where $E_{ess}^{\max}$ is the rated capacity of the shared energy storage system; E_t is the state of charge of the shared energy storage system at time t ; $\rho^{\min}$ and $\rho^{\max}$ are the lower and upper operating limits of the energy state of the storage system, respectively; η_c is the charging efficiency of the shared energy storage system; η_d is the discharging efficiency of the shared energy storage system; P_t^c is the total charging power of the shared energy storage system at time t ; P_t^d is the total discharging power of the shared energy storage system at time t ; E_0 is the initial state of charge of the shared energy storage system; and E_T is the final-period state of charge of the shared energy storage system.

3.3. Revenue Allocation and Leasing Cost Sharing Based on Cooperative Game Theory

3.3.1. Revenue Allocation and Cost Allocation Model Based on Shapley Value

The operation mode of the wind farm consortium participating in the spot market and leasing shared energy storage is essentially a cooperative game problem. All members obtain higher overall revenue through coordinated operation than under independent operation, while jointly bearing the leasing cost of shared energy storage. It should be noted that deviation penalty costs are settled with the real-time market at the consortium level. Individual wind farms do not directly settle imbalance penalties with the market operator; instead, their effects are reflected in the coalition characteristic function and the subsequent internal revenue allocation. To ensure the stable operation of the alliance, the revenue allocation must satisfy both collective rationality and individual rationality, i.e., the total revenue of the alliance is maximized, and the net revenue of each member after joining the alliance is not lower than its independent operation revenue. Cooperative game theory provides a rigorous solution framework for revenue allocation and cost sharing in multi-agent alliances. Among them, the Shapley value method allocates revenue based on each agent's marginal contribution to the alliance, possessing the properties of fairness, uniqueness, and efficiency, which can well meet the allocation requirements of the wind farm consortium.

The wind farm consortium is defined as a cooperative game $\langle I, V \rangle$, where $I = \{1, 2, \dots, M\}$ is the set of all wind farms in the alliance, and V is the characteristic function. $V(K)$ is strictly defined as the optimal net revenue obtained by a sub-alliance K when it independently participates in the spot market and leases shared energy storage to mitigate deviations using the two-stage stochastic optimization bidding model proposed in this paper. This revenue includes the day-ahead market income and deducts the deviation penalty cost, but excludes the shared energy storage leasing cost, which is allocated separately using the revenue-proportional fairness rule after the Shapley value-based revenue allocation. The characteristic function satisfies:

$$\begin{cases} V(\emptyset) = 0 \\ V(I) \geq \sum_{i \in I} V(\{i\}) \end{cases} \quad (13)$$

where $\emptyset$ denotes the empty set; $V(\{i\})$ is the optimal net revenue of the i -th agent when participating in the market independently; $V(I)$ is the optimal net revenue of the grand alliance formed by all agents. The above equation indicates that the total revenue of the consortium under coordinated operation is no less than the sum of the revenues of each agent under independent operation, providing a basis for cooperation.

The Shapley value allocates the total alliance revenue from the perspective of marginal contribution. Its core idea is that the allocated revenue of a player is equal to the weighted average of its marginal contributions to all possible sub-alliances, assuming that all permutations of players occur with equal probability [22]. Let φ_i be the total revenue allocated to the i -th player, then the Shapley value is calculated as:

$$\varphi_i = \sum_{K \subseteq I \setminus \{i\}} \frac{|K|!(M - |K| - 1)!}{M!} [V(K \cup \{i\}) - V(K)], \quad (14)$$

where K is any sub-alliance not containing player i ; $|K|$ is the number of members in sub-alliance K ; M is the total number of members in the alliance; $V(K)$ is the optimal net revenue of sub-alliance K ; $V(K \cup \{i\})$ is the optimal net revenue of the new alliance formed after player i joins sub-alliance K .

It should be noted that the exact Shapley value calculation requires evaluating the characteristic function $V(K)$ for all possible sub-alliances. In the proposed framework, each

characteristic value $V(K)$ is obtained by solving the two-stage optimization model for the corresponding coalition. Therefore, the computational complexity of the exact Shapley calculation can be expressed as $\mathcal{O}((2^M - 1)C_{\text{MILP}})$, where M is the number of wind farms and C_{MILP} denotes the computational cost of solving one coalition-level mixed-integer linear programming model. The empty coalition satisfies $V(\emptyset) = 0$ and does not require optimization, while all $2^M - 1$ non-empty coalitions need to be evaluated. In the present case with $M = 3$, only seven non-empty coalitions are optimized, so the exact Shapley value can be calculated directly and used as a transparent benchmark for fair allocation.

For larger consortia, the exact enumeration burden increases exponentially. Table 2 summarizes the number of coalition optimization calls and the expected scalability of exact Shapley value calculation. Here, $\bar{T}_{\text{coal}}$ denotes the average execution time for solving one coalition-level optimization model; thus, the total execution time is approximately $(2^M - 1)\bar{T}_{\text{coal}}$. This expression is used because the actual execution time depends on the solver, hardware, scenario number, and coalition size. The coalition optimization problems are mutually independent and can be parallelized; nevertheless, when the number of wind farms becomes large, sampling-based or approximation-based Shapley value methods should be adopted. In practical applications, exact enumeration is suitable for small consortia, while approximate Shapley methods are recommended when the number of wind farms exceeds about 10–12 or when each coalition optimization model is computationally heavy.

Table 2. Scalability of exact Shapley value calculation.

Number of Wind Farms M	Required Non-Empty Coalition Optimizations	Expected Total Execution Time	Scalability Implication
3	7	$7 \bar{T}_{\text{coal}}$	Baseline case; exact calculation is tractable
5	31	$31 \bar{T}_{\text{coal}}$	Small consortium; exact calculation is generally feasible
10	1023	$1023 \bar{T}_{\text{coal}}$	Medium consortium; parallel computation is recommended
15	32,767	$32,767 \bar{T}_{\text{coal}}$	Large consortium; approximation is recommended
20	1,048,575	$1,048,575 \bar{T}_{\text{coal}}$	Very large consortium; exact enumeration is generally impractical

The Shapley value allocation satisfies the properties of efficiency, symmetry, dummy axiom, and additivity, which can ensure fair and reasonable allocation results: the sum of the allocated revenues of all players equals the total alliance revenue; players with the same contribution receive equal revenues; players with no marginal contribution to the alliance receive zero revenue; and the alliance revenues are additive with linear additivity of the allocation results.

After the optimal revenue of the consortium is allocated using the Shapley value, the leasing cost of shared energy storage needs to be further shared among the participating wind farms. It should be emphasized that the cost-sharing rule used in this paper is not directly derived from cooperative game theory. Instead, it is an additional fairness rule introduced after the Shapley value-based revenue allocation. Specifically, this paper adopts a revenue-proportional cost-sharing heuristic, under which wind farms receiving higher allocated revenues bear a larger share of the shared energy storage leasing cost. This rule follows the practical principle of “who benefits more, who bears more”, and ensures full recovery of the total leasing cost without surplus or deficit. Let $C_{l,i}$ be the leasing cost to be borne by the i -th wind farm, and α_i be its cost-sharing coefficient. The calculation formulas for the sharing coefficient and shared cost are:

$$\begin{cases} \alpha_i = \frac{\varphi_i}{\sum_{j=1}^M \varphi_j}; \\ 0 \leq \alpha_i \leq 1 \end{cases} \quad (15)$$

$$\begin{cases} C_{l,i} = \alpha_i C_l \\ \sum_{i=1}^M C_{l,i} = C_l' \end{cases} \quad (16)$$

where C_l is the total cost incurred by the consortium for leasing shared energy storage; $\sum_{i=1}^M \varphi_i$ is the total allocated revenue of the alliance. Since the Shapley value allocation satisfies the efficiency property, the sum of the allocated revenues of all entities equals the total alliance revenue. Based on the additional revenue-proportional cost-sharing rule adopted in this paper, the cost-sharing coefficient can be expressed as:

$$\alpha_i = \frac{\varphi_i}{V(I)}. \quad (17)$$

Equation (17) should therefore be understood as an additional revenue-proportional fairness rule for allocating the shared energy storage leasing cost, rather than as a direct theoretical result derived from the Shapley value. This treatment links the cost burden to the allocated benefit of each entity, so that members receiving higher Shapley-based revenues bear a larger proportion of the leasing cost.

After deducting the allocated leasing cost, the final net revenue of the i -th wind farm is obtained, expressed as:

$$R_i^{net} = \varphi_i - C_{l,i}. \quad (18)$$

To assess coalition stability after leasing-cost sharing, the net characteristic value of a sub-alliance is further defined as

$$\tilde{V}(K) = V(K) - C_l(K), \quad \forall K \subseteq I, \quad (19)$$

where $C_l(K)$ denotes the shared energy storage leasing cost incurred when sub-alliance K independently participates in the market and uses the leased storage service. Compared with $V(K)$, which is used for Shapley revenue allocation before leasing-cost sharing, $\tilde{V}(K)$ represents the net payoff that a sub-alliance can obtain after considering its own storage leasing cost.

The individual rationality constraint is then expressed as

$$R_i^{net} \geq \tilde{V}(\{i\}), \quad \forall i \in I, \quad (20)$$

which means that each wind farm should obtain no less final net revenue in the grand consortium than it can obtain by operating independently. Meanwhile, the collective rationality constraint is expressed as

$$\sum_{i=1}^M R_i^{net} = \tilde{V}(I) = V(I) - C_l(I). \quad (21)$$

This equality ensures budget balance after revenue allocation and leasing-cost sharing.

In addition to individual and collective rationality, the core condition is introduced to evaluate whether any subset of wind farms has an incentive to leave the grand consortium

and operate as a smaller sub-alliance. The allocation vector $R^{net} = (R_1^{net}, \dots, R_M^{net})$ belongs to the core if

$$\sum_{i \in K} R_i^{net} \geq \tilde{V}(K), \quad \forall K \subseteq I, K \neq \emptyset. \quad (22)$$

For $K = I$, Equation (22) reduces to the collective rationality condition. For any proper sub-alliance $K \subset I$, it means that the members of K cannot obtain a higher total net payoff by leaving the grand consortium. Therefore, the core condition provides a stronger game-theoretic stability check than individual rationality alone. It should also be noted that Shapley value allocations do not necessarily belong to the core for all cooperative games. Therefore, this study explicitly checks the core condition for the three-wind-farm case rather than assuming core membership automatically.

3.3.2. Solution Procedure and Computational Implementation

The solution process of the two-stage model and the Shapley value-based revenue allocation is shown in Figure 3. The proposed model contains piecewise imbalance penalty terms and binary charging/discharging status variables. To avoid relying on heuristic algorithms and improve solution reproducibility, the piecewise penalty functions are reformulated using non-negative auxiliary variables and linear inequality constraints. The mutually exclusive charging/discharging behavior of shared energy storage is modeled using system-level binary variables and big-M constraints. Therefore, both the day-ahead bidding model and the real-time shared energy storage dispatch model can be formulated as mixed-integer linear programming problems and solved by CPLEX. Monte Carlo simulation is adopted to generate $N_0 = 1000$ initial scenarios for wind power output and electricity prices. Each scenario contains the 24 h wind power outputs of all wind farms and the corresponding day-ahead price profile. To reduce the computational burden, the initial scenario set is reduced to five representative scenarios based on the Kantorovich distance. Specifically, the distance between two scenarios is calculated from the normalized wind power and price trajectories over the full scheduling horizon. A forward selection procedure is then used to retain the scenarios that minimize the probability-weighted distance between the original scenario set and the reduced scenario set. The probabilities of the deleted scenarios are reassigned to their nearest retained scenarios, so that the final probabilities of the five typical scenarios still sum to one. This scenario generation and reduction procedure improves the reproducibility of the uncertainty modeling process while keeping the optimization problem computationally tractable.

After completing the two-stage optimization and obtaining the day-ahead bidding power of each wind farm and the real-time energy storage charging/discharging schedule, the process enters the cooperative game allocation stage. First, based on the actual operational revenues of each wind farm and the alliance, the alliance characteristic function is constructed, and the net revenues under different sub-alliance combinations are calculated as the basis for subsequent allocation. Then, the Shapley value method is used to allocate the total consortium revenue according to the marginal contribution of each wind farm. After that, the shared energy storage leasing cost is allocated using the revenue-proportional fairness rule. This sequence is consistent with the theoretical distinction between endogenous cooperative revenue allocation and exogenous leasing-cost sharing discussed above.

To verify the stability and rationality of the allocation scheme, three levels of checks are performed: individual rationality, collective rationality, and core stability. The individual rationality check ensures that each wind farm obtains no less final net revenue in the grand consortium than it can obtain independently. The collective rationality check ensures that the total final net revenue after cost sharing equals the net value of the grand consortium.

The core-stability check further verifies all proper sub-alliances and examines whether any subset of wind farms could obtain a higher net payoff by leaving the grand consortium. If the core condition is satisfied, the allocation is regarded as stable for the considered cooperative game. If the core condition is violated in a different case, additional side-payment adjustment, alternative allocation rules, or stability-constrained allocation methods would be required. In the present three-wind-farm case, all possible proper sub-alliances can be enumerated directly.

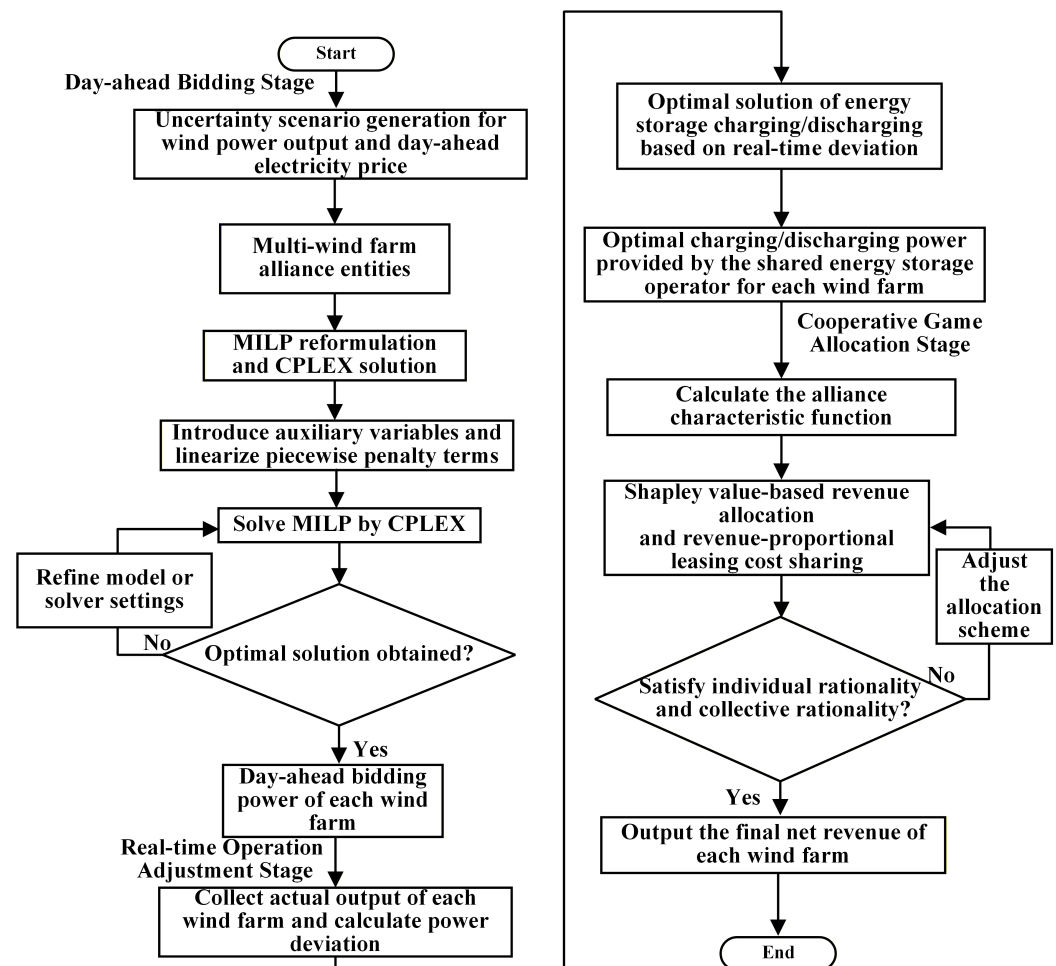


Figure 3. Joint Solution Process of Two-Stage Optimization and Cooperative Game Allocation.

4. Results and Analysis

To verify the effectiveness and rationality of the proposed two-stage coordinated bidding model and the revenue-cost linkage allocation mechanism, three wind farms are selected in this section to form a wind farm consortium. The consortium leases shared energy storage and participates in the electricity spot market for case simulation. The case is set with reference to the operation rules of domestic spot market pilots and the commercial operation model of shared energy storage. The three wind farms have similar installed capacities but obvious differences in output prediction accuracy, which can fully reflect the fairness and rationality of the Shapley value method in allocating revenue based on marginal contribution and sharing costs based on revenue proportion.

4.1. Analysis Framework and Evaluation Indicators

To clearly separate the methodological formulation from the results interpretation, this subsection is added to define the analysis framework used in the case study. Section 3 fo-

cuses on the proposed methodology, including the market framework, two-stage stochastic optimization model, shared energy storage constraints, cooperative game-based allocation mechanism, and solution process. In contrast, the present section focuses on analyzing the numerical results and verifying the economic effectiveness, deviation mitigation capability, parameter sensitivity, and allocation fairness of the proposed strategy.

The analysis in this section follows a progressive procedure. First, the baseline case parameters, data source, and validation scope are defined, and the applicability of the case study is explained. Second, three comparative scenarios are constructed to distinguish the effects of consortium operation, independently configured energy storage, and shared energy storage leasing. Third, the economic indicators and power deviation curves are analyzed to evaluate the deviation mitigation effect of the proposed method. Fourth, sensitivity analyses are conducted for storage size, charging/discharging efficiency, wind farm output correlation, and balancing-price level. Finally, the Shapley value-based allocation results are analyzed to verify fairness, individual rationality, collective rationality, and core stability. In response to the uncertainty of scenario generation, an additional statistical robustness consideration is also added to explain how variability and confidence intervals can be evaluated under multiple Monte Carlo realizations.

To support the above analysis, the main evaluation indicators include the virtual income, deviation penalty cost, shared energy storage leasing cost, optimal net revenue before leasing cost, final net revenue after leasing cost, maximum absolute power deviation, accumulated absolute power deviation, Shapley value-based allocated revenue, allocated leasing cost, and final net revenue of each wind farm. These indicators are used to evaluate the proposed method from three complementary perspectives: economic performance, deviation correction performance, and internal allocation fairness.

4.2. Case Study Design and Parameter Settings

The case system in this paper includes three independent wind farms forming a wind farm consortium, with one centralized shared energy storage station providing leasing and regulation services. The case study is used for two reasons. First, it provides a representative small-scale consortium in which the exact Shapley value can be calculated without approximation, making the fairness of revenue allocation transparent and verifiable. Second, it allows the effects of forecasting accuracy, shared energy storage size, and wind farm output complementarity to be examined under controlled boundary conditions. Therefore, the case study is not intended to represent a single physical project only; rather, it is used as a numerical test system to verify the proposed methodology and to demonstrate how the model can be applied to wind farm consortia participating in electricity spot markets.

The proposed methodology can also be extended to other scenarios, such as larger wind farm clusters, wind-solar hybrid renewable energy portfolios, different shared energy storage sizes, and alternative imbalance settlement rules. In such applications, the model structure remains unchanged, while the wind power scenarios, market price scenarios, storage parameters, and allocation participants need to be updated according to the target system. For larger consortia, approximate Shapley value methods may be adopted to reduce computational burden.

The main parameters are selected with reference to typical operating characteristics of wind farms, shared energy storage stations, and electricity spot market pilots, so that the case settings are representative of practical market operation conditions. The installed capacities of the three wind farms participating in the consortium are 105 MW for Wind Farm 1, 100 MW for Wind Farm 2, and 95 MW for Wind Farm 3, respectively. Therefore, the total installed capacity of the wind farm consortium is 300 MW. There are differences in output characteristics and prediction levels: Wind Farm 1 has stable output with a

prediction error standard deviation of 5%; Wind Farm 2 has moderate output fluctuations with a prediction error standard deviation of 10%; and Wind Farm 3 has relatively large output fluctuations with a prediction error standard deviation of 15%. These three levels are used to represent high-, medium-, and low-forecasting-accuracy wind farms. Empirical studies have shown that regional day-ahead wind power forecast errors can differ significantly with aggregation scale and geographical dispersion, and that forecast accuracy is strongly affected by the quality of wind speed prediction and forecasting models [24,26]. Therefore, the 5%, 10%, and 15% settings are used as representative scenario parameters rather than fixed universal values. The output correlation between wind farms is set to 0.1 in the baseline case to represent a weakly correlated wind farm portfolio with strong complementarity. Correlation-based indicators are commonly used to evaluate renewable energy complementarity, and studies on wind power aggregation have shown that spatial dispersion can reduce forecast-error correlation and smooth aggregated output [23,25]. To avoid relying on a single correlation assumption, additional sensitivity analysis with correlation coefficients of 0.5 and 0.9 is conducted in Section 4.4.5.

The shared energy storage station adopts a centralized electrochemical energy storage configuration with a rated charging/discharging power of 5 MW and a rated capacity of 10 MWh. This configuration should be interpreted relative to the 300 MW total installed capacity of the wind farm consortium. The rated storage power accounts for 1.67% of the total installed wind capacity, and the rated storage energy accounts for 3.33% of the one-hour full-load energy production of the consortium. Therefore, the baseline shared energy storage system is not designed for long-duration energy shifting of the entire wind farm output, but for short-term real-time deviation correction and imbalance-penalty mitigation. Its 2 h duration enables the storage station to continuously absorb or supply the rated regulation power for two hours, which is consistent with the short-term fluctuation mitigation role considered in this study. In addition, a previous study on wind power participation in day-ahead and real-time markets based on shared energy storage also adopted a 5 MW/10 MWh storage configuration, indicating that this scale has practical reference value for similar simulation scenarios [4]. Therefore, the 5 MW/10 MWh configuration is adopted as the baseline configuration in this study to provide moderate regulation capability while avoiding excessive leasing cost. The relationship between the baseline storage size and the wind farm consortium capacity is summarized in Table 3.

Table 3. Relationship between the baseline shared energy storage size and wind farm consortium capacity.

Item	Value	Explanation
Total installed capacity of wind farms	300 MW	105 MW + 100 MW + 95 MW
Rated power of shared energy storage	5 MW	1.67% of the total installed wind capacity
Rated energy capacity of shared energy storage	10 MWh	3.33% of one-hour full-load wind energy production
Storage duration	2 h	Suitable for short-term deviation correction rather than bulk energy shifting
Main functional role	Real-time regulation	Used to reduce residual deviations and imbalance penalties

In the baseline case, the shared energy storage operating range is set as $\rho^{\min} = 0.1$ and $\rho^{\max} = 0.9$, and both the charging and discharging efficiencies are set to 0.95. These values are used as the baseline parameters for the electrochemical shared energy storage system considered in the case study. It should be noted that the proposed model is not limited to a specific storage technology. For different types of storage systems, such as lithium-ion batteries, compressed air energy storage, or pumped storage, the operating energy limits and charging/discharging efficiencies can be adjusted by changing $\rho^{\min}$, $\rho^{\max}$,

η_c , and η_d without modifying the model structure. Therefore, the conversion losses of different storage technologies can be represented through the corresponding efficiency parameters in the SOC transition equation. The shared energy storage adopts a real-time charging/discharging power-based billing model, with a unit power leasing price of 0.33 CNY/(kW·h). The leasing cost is settled uniformly by the consortium and reasonably allocated internally.

In terms of market operation and scenario settings, the scheduling cycle is one natural day, divided into 24 scheduling periods to meet the day-ahead and real-time two-stage decision-making timing requirements. The benchmark forecasted wind power profiles and day-ahead price profile used for scenario generation are synthetically generated representative 24 h normalized profiles constructed from public electricity spot-market information and wind power operating characteristics reported in the cited literature, rather than direct measurements from a specific wind farm project. Therefore, the data period considered in the case study corresponds to a representative one-day scheduling horizon, and the Monte Carlo process is used to generate uncertainty around these baseline profiles. This clarification is added to ensure that the scenario-generation procedure is reproducible and to avoid implying the use of undisclosed plant-level historical measurements. The detailed uncertainty modeling settings are summarized in Table 4.

Table 4. Scenario generation and reduction settings for uncertainty modeling.

Item	Setting
Scheduling horizon	One representative operating day with 24 hourly scheduling periods
Initial scenario number	$N_0 = 1000$ Monte Carlo scenarios
Reduced scenario number	Five typical scenarios retained after scenario reduction
Wind power uncertainty	Correlated zero-mean normal forecast-error model around the forecasted wind power profile, with output truncated within $[0, P_i^{rated}]$
Wind forecast-error standard deviation	5%, 10%, and 15% for Wind Farms 1–3, respectively
Baseline inter-farm correlation coefficient	0.1, with additional sensitivity analysis for 0.5 and 0.9
Price uncertainty	Zero-mean normal multiplicative error around the baseline day-ahead price profile, with a standard deviation of 10% and non-negative truncation
Scenario reduction method	Kantorovich-distance-based forward selection; probabilities of deleted scenarios are reassigned to the nearest retained scenarios
Data source and period	Synthetically generated representative 24 h simulation profiles constructed from public market information and literature-based wind power characteristics; not direct measurements from a specific wind farm

Data Source and Validation Scope

To further clarify the data basis of the numerical study, the wind power and electricity price data used in Section 4 are not direct measured datasets from a specific wind farm project. Instead, they are synthetically generated representative datasets constructed around normalized 24 h benchmark profiles and literature-supported uncertainty parameters. This choice is adopted because plant-level SCADA data, actual settlement records, and confidential market bidding data are usually not publicly available for wind farm consortia. Therefore, the purpose of the case study is to verify the modelling logic, solution process, economic comparison, and allocation mechanism under reproducible representative conditions, rather than to conduct an empirical back-test for one particular operating project.

Although direct validation against real operational data is not performed in this study, several consistency checks are used to improve the credibility of the numerical case. First, the installed capacities, forecast-error levels, and inter-farm correlation assumptions are selected according to typical wind farm operating characteristics and related literature. Second, all generated wind power scenarios are constrained within physical output limits and all electricity price scenarios are non-negative. Third, sensitivity analyses are conducted

for storage size, charging/discharging efficiency, wind farm correlation coefficient, and balancing-price level to examine whether the conclusions depend on a single synthetic dataset. Finally, the scenario generation and reduction settings are fully reported so that the numerical study can be reproduced. The data source and validation scope are summarized in Table 5.

Table 5. Data source and validation scope of the case study.

Item	Description
Wind power data type	Synthetically generated representative profiles, not direct plant-level measurements
Price data type	Representative day-ahead price profile with Monte Carlo price perturbations
Parameter basis	Typical wind farm operating characteristics, public market information, and cited literature
Physical consistency check	Wind power is truncated within $[0, P_i^{rated}]$ and electricity prices are constrained to be non-negative
Robustness check	Sensitivity analyses are performed for storage size, efficiency, correlation coefficient, and balancing-price multiplier
Validation limitation	No confidential SCADA or real settlement data are used; empirical validation with long-term operational data is left for future work

The real-time market adopts a two-way imbalance penalty mechanism: the penalty coefficient for over-generation deviation is 0.5, and the penalty coefficient for under-generation deviation is 1.5, which conforms to the general settlement rule of “severe punishment for under-generation and mild punishment for over-generation” in domestic spot markets.

4.3. Comparative Scenario Design

To comprehensively verify the superiority of the “wind farm consortium + shared energy storage leasing” mode proposed in this paper, three typical comparative scenarios are designed from three dimensions: whether to operate in a consortium, whether to deploy energy storage, and the energy storage configuration mode. The boundary conditions of all scenarios are kept consistent to ensure the comparability of the results.

Scenario 1 is the consortium mode without energy storage support: three wind farms form a consortium to participate in the day-ahead and real-time markets in a unified manner, but do not lease shared energy storage. They rely entirely on their own output complementarity to smooth deviations, without incurring any energy storage regulation or leasing costs.

Scenario 2 is the distributed operation mode with independent energy storage: each wind farm does not form a consortium, participates in the spot market independently, and is equipped with its own energy storage system. It should be emphasized that Scenario 2 is designed as an operation-side benchmark to show the deviation penalty reduction effect of independently configured storage. Because the storage assets in Scenario 2 are independently owned by each wind farm, their annualized investment cost, fixed operation and maintenance cost, replacement cost, and financing cost belong to long-term asset-cost items. These costs are different in nature from the short-term shared energy storage leasing payment in Scenario 3. Therefore, Scenario 2 reports the market income and deviation penalty after independent storage dispatch, but it does not calculate the final net revenue after storage-related life-cycle costs. This treatment avoids mixing a long-term self-owned storage investment model with a one-day leasing-service settlement model.

Scenario 3 is the consortium + shared energy storage leasing mode, which is the operation mode proposed in this paper: three wind farms form a unified consortium, centrally lease a shared energy storage station to provide regulation services, participate in market bidding, settle accounts, and distribute revenues and allocate leasing costs in a unified manner.

4.4. Comparative Results and Sensitivity Analysis

4.4.1. Comparative Analysis of Economic Results Under Different Scenarios

To quantitatively verify the economic advantages of the proposed “consortium + shared energy storage leasing” mode over the no-energy-storage mode and the independent energy storage mode, the economic results under the three scenarios are compared. Here, the virtual income refers to the market income before deducting the deviation penalty cost. The optimal net revenue before leasing cost is obtained by deducting the deviation penalty cost from the virtual income. The final net revenue after leasing cost is obtained by further deducting the storage leasing cost from the optimal net revenue before leasing cost. The storage leasing cost represents the payment made by the consortium to the shared energy storage operator for providing regulation services. For Scenario 2, the independently owned storage systems are treated as self-built assets. Their life-cycle investment and operation costs are not included in the one-day operational comparison; therefore, the final net revenue after storage-related long-term costs is not reported. The comparison involving Scenario 2 should be interpreted as an operation-level comparison before storage life-cycle cost accounting, rather than as a complete investment-cost comparison. The corresponding results are shown in Table 6.

Table 6. Comparison of economic results under different scenarios.

Scenario	Virtual Income (CNY)	Deviation Penalty Cost (CNY)	Storage Leasing Cost (CNY)	Optimal Net Revenue Before Leasing Cost (CNY)	Final Net Revenue After Leasing Cost (CNY)
Scenario 1	410,580	66,161	0	344,419	344,419
Scenario 2	376,273	14,186	–	362,087	–
Scenario 3	383,363	6750	5654.4	376,613	370,958.6

The symbol “–” in Table 6 indicates that the corresponding storage-related long-term cost is outside the boundary of the one-day operational comparison. In Scenario 1, no storage cost is incurred. In Scenario 3, the storage cost is explicitly represented by the shared energy storage leasing payment. In Scenario 2, the cost of self-owned storage would require additional assumptions on investment cost, depreciation period, replacement cycle, financing rate, and fixed operation and maintenance cost. Since these parameters are not the focus of the proposed leasing-based framework, they are not included in the present comparison.

As shown in Table 6, the additional economic indicators make the comparison among the three scenarios clearer. In Scenario 1, although the virtual income reaches 410,580 CNY, the deviation penalty cost is as high as 66,161 CNY due to the lack of energy storage regulation. Since no storage leasing cost is incurred, both the optimal net revenue before leasing cost and the final net revenue after leasing cost are 344,419 CNY.

In Scenario 2, independently configured energy storage reduces the deviation penalty cost to 14,186 CNY, and the optimal net revenue before storage-related long-term costs reaches 362,087 CNY. This result shows the operational value of storage dispatch in reducing imbalance penalties. However, the independently owned storage systems in Scenario 2 would require additional life-cycle cost accounting, including investment cost, depreciation or annualization, fixed operation and maintenance cost, replacement cost, and financing cost. Since the present study focuses on short-term market operation and shared energy storage leasing, these long-term self-owned storage costs are not included. Therefore, Scenario 2 is used only as an operational benchmark, and its final net revenue after storage-related long-term costs is not reported.

In contrast, Scenario 3, namely the proposed “consortium + shared energy storage leasing” mode, achieves the lowest deviation penalty cost of 6750 CNY. Its optimal net

revenue before leasing cost reaches 376,613 CNY, which is 32,194 CNY higher than that of Scenario 1. After deducting the storage leasing cost of 5654.4 CNY, the final net revenue after leasing cost is 370,958.6 CNY, which is still 26,539.6 CNY higher than that of Scenario 1. The storage leasing cost of 5654.4 CNY also represents the service income obtained by the shared energy storage operator from providing regulation services. This value provides a useful reference for further evaluating the investment return and payback performance of the shared energy storage system. Overall, Table 6 demonstrates that the proposed operation mode can effectively reduce deviation penalties, improve the economic performance of the consortium, and provide economic incentives for shared energy storage operation.

To further address the possible impact of independent balancing market prices, an additional robustness discussion is conducted by varying the balancing price around the day-ahead reference price. The balancing price is represented as $\tau\lambda_t^{da}$, where τ denotes the balancing-price multiplier. This setting is used to examine whether the economic advantage of the proposed strategy is sensitive to the imbalance-price level. The corresponding results for Scenario 3 are shown in Table 7.

Table 7. Robustness results under different balancing-price multipliers in Scenario 3.

Balancing-Price Multiplier τ	Deviation Penalty Cost (CNY)	Optimal Net Revenue Before Leasing Cost (CNY)	Storage Leasing Cost (CNY)	Final Net Revenue After Leasing Cost (CNY)
0.8	5400	377,963	5654.4	372,308.6
1.0	6750	376,613	5654.4	370,958.6
1.2	8100	375,263	5654.4	369,608.6

Table 7 shows that when the independent balancing price is lower than, equal to, or higher than the day-ahead reference price, the deviation penalty cost and final net revenue change accordingly. A higher balancing-price multiplier increases the deviation penalty cost and reduces the final net revenue, while a lower multiplier has the opposite effect. However, the proposed framework remains robust because the optimization structure, shared energy storage dispatch logic, and revenue-cost allocation mechanism do not depend on whether the imbalance price is represented by the day-ahead price or by an independently determined balancing price. In particular, when balancing prices are higher, the economic value of reducing real-time deviations through shared energy storage becomes more important. Therefore, considering independent balancing prices would mainly change the numerical settlement results, rather than invalidating the proposed coordinated bidding and shared energy storage leasing framework.

4.4.2. Statistical Robustness Consideration Under Multiple Scenario Realizations

The economic values reported in Tables 6 and 7 are deterministic optimization results obtained from the retained representative scenario set. To avoid overinterpreting a single reduced scenario set, this revision further clarifies how variability and confidence intervals can be evaluated when multiple independent uncertainty realizations are generated. Specifically, the Monte Carlo scenario generation and Kantorovich-distance-based reduction procedure described in Section 3 can be repeated N_r times using different random seeds. In each repetition, $N_0 = 1000$ initial scenarios are generated and reduced to five typical scenarios, and the proposed two-stage optimization and allocation model is solved again. For an economic or deviation indicator z , such as deviation penalty cost, final net revenue, maximum absolute deviation, or accumulated absolute deviation, the repeated results can be denoted by $z_1, z_2, \dots, z_{N_r}$.

The sample mean, sample standard deviation, and 95% confidence interval of the mean can then be calculated as

$$\bar{z} = \frac{1}{N_r} \sum_{r=1}^{N_r} z_r, \quad \sigma_z = \sqrt{\frac{1}{N_r - 1} \sum_{r=1}^{N_r} (z_r - \bar{z})^2}, \quad CI_{95\%} = \left[\bar{z} - 1.96 \frac{\sigma_z}{\sqrt{N_r}}, \bar{z} + 1.96 \frac{\sigma_z}{\sqrt{N_r}} \right]. \quad (23)$$

This formulation provides a reproducible way to report statistical variability when repeated scenario realizations are available. In the present numerical study, the main conclusions are further checked through sensitivity analyses on storage size, charging/discharging efficiency, wind farm correlation coefficient, and balancing-price level. Therefore, the baseline deterministic values should be interpreted together with these sensitivity and robustness results, rather than as single-sample empirical estimates. The statistical robustness reporting framework used in this revision is summarized in Table 8.

Table 8. Statistical robustness reporting framework for repeated uncertainty realizations.

Indicator	Baseline Value in This Study	Statistical Robustness Interpretation Under Repeated Realizations
Deviation penalty cost in Scenario 3	6750 CNY	Mean, standard deviation, and 95% confidence interval can be calculated from repeated Monte Carlo scenario-generation runs
Final net revenue after leasing cost in Scenario 3	370,958.6 CNY	The conclusion is robust if the confidence interval remains higher than the final net revenue of the no-storage benchmark
Maximum absolute deviation in Scenario 3	4.63 MW	The conclusion is robust if repeated realizations consistently show a lower maximum deviation than the comparison scenarios
Accumulated absolute deviation in Scenario 3	32.95 MWh	The conclusion is robust if repeated realizations consistently show reduced accumulated deviation energy
Shapley-based final allocation	Core-stability satisfied	The allocation is considered robust if individual rationality and core-stability inequalities remain satisfied across repeated realizations

Table 8 provides a statistical robustness reporting framework for future repeated-scenario implementations. In the present case study, the baseline results are obtained from a retained representative scenario set generated from synthetic wind power and electricity-price profiles. Therefore, these deterministic values are interpreted together with the sensitivity analyses on shared energy storage size, charging/discharging efficiency, wind farm output correlation, and balancing-price level. When repeated Monte Carlo scenario realizations or long-term operational datasets are available, Equation (23) can be used to calculate the sample mean, sample standard deviation, and 95% confidence interval of key economic and deviation-mitigation indicators. This treatment provides a reproducible basis for evaluating statistical variability while maintaining consistency with the data availability and validation scope of the present study.

To further clarify the deviation mitigation effect of different operation modes, Figure 4 is redrawn by presenting the residual power output deviation over the complete 24-period scheduling horizon. Compared with the original figure, the revised figure not only shows the time-series variation in power deviation under the three scenarios, but also adds key statistical indicators, including the maximum absolute deviation and the accumulated absolute deviation. These indicators can more directly reflect the amount of residual deviation that cannot be covered by the available regulation capability, thereby helping to evaluate whether the storage configuration is adequate for the wind farm portfolio.

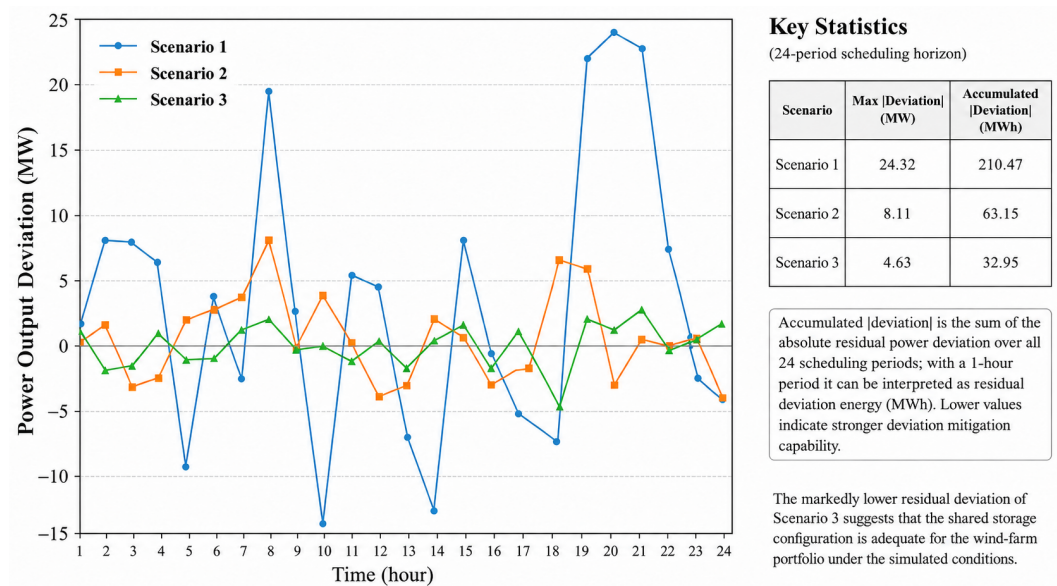


Figure 4. Comparison of power output deviation curves and key statistics under different scenarios.

The power output deviation in Figure 4 refers to the difference between the actual wind power output and the day-ahead cleared power. A positive deviation indicates that the actual output is greater than the cleared power, while a negative deviation indicates that the actual output is lower than the cleared power. The closer the deviation is to zero, the stronger the ability of the operation mode to track the cleared power curve and reduce imbalance penalties.

As shown in Figure 4, Scenario 1 presents the largest fluctuation because no energy storage is available for real-time deviation correction. Its maximum absolute deviation reaches 24.32 MW, and the accumulated absolute deviation reaches 210.47 MWh, indicating a large amount of uncovered deviation energy. Scenario 2 reduces the power deviation to a certain extent through independently configured energy storage, with the maximum absolute deviation and accumulated absolute deviation decreasing to 8.11 MW and 63.15 MWh, respectively. However, due to the limited coordination capability of distributed storage, residual deviations still exist in several periods.

In contrast, Scenario 3, namely the proposed “consortium + shared energy storage leasing” mode, shows the smallest residual deviation among the three scenarios. The maximum absolute deviation is reduced to 4.63 MW, and the accumulated absolute deviation is reduced to 32.95 MWh. This indicates that the centralized shared energy storage and unified consortium dispatch can effectively cover most output deviations and significantly improve the tracking ability of renewable energy with respect to the day-ahead cleared power. Therefore, the revised Figure 4 provides a clearer quantitative basis for demonstrating that the selected shared energy storage configuration is adequate for the wind farm portfolio under the simulated conditions.

4.4.3. Sensitivity Analysis of Shared Energy Storage Size

To further investigate the impact of the shared energy storage size on the economic performance of the proposed strategy, a sensitivity analysis is conducted by varying the rated power and rated capacity of the shared energy storage system while keeping the storage duration unchanged at 2 h. Four shared energy storage configurations are considered in this study, namely 2.5 MW/5 MWh, 5 MW/10 MWh, 7.5 MW/15 MWh, and 10 MW/20 MWh. Relative to the 300 MW wind farm consortium, these configurations correspond to storage-power ratios of 0.83%, 1.67%, 2.50%, and 3.33%, respectively. Among them, the 5 MW/10 MWh configuration is selected as the baseline scenario because it rep-

resents a moderate short-term regulation capacity rather than an oversized energy-shifting resource. The corresponding results are shown in Table 9.

Table 9. Sensitivity analysis results under different shared energy storage sizes.

Storage Size	Optimal Net Revenue Before Leasing Cost/CNY	Deviation Penalty Cost/CNY
2.5 MW/5 MWh	368,920	10,480
5 MW/10 MWh	376,613	6750
7.5 MW/15 MWh	378,120	5120
10 MW/20 MWh	376,980	4380

As shown in Table 9, increasing the size of the shared energy storage system can effectively reduce the deviation penalty cost and improve the optimal net revenue before leasing cost of the consortium. When the storage size increases from 2.5 MW/5 MWh to 5 MW/10 MWh, the deviation penalty cost decreases from 10,480 CNY to 6750 CNY, while the optimal net revenue before leasing cost increases from 368,920 CNY to 376,613 CNY. This indicates that insufficient energy storage capacity limits the regulation capability of the shared energy storage system, thereby weakening its ability to mitigate wind power output deviations.

When the storage size further increases to 7.5 MW/15 MWh and 10 MW/20 MWh, the deviation penalty cost continues to decrease. This is because a larger shared energy storage system can provide stronger charging and discharging regulation capability, thereby further reducing the mismatch between the actual wind power output and the day-ahead cleared power. However, as the storage size increases, the improvement in optimal net revenue before leasing cost gradually diminishes. In particular, although the deviation penalty cost is the lowest under the 10 MW/20 MWh configuration, its optimal net revenue before leasing cost is slightly lower than that under the 7.5 MW/15 MWh configuration. This indicates that blindly increasing the energy storage size does not necessarily lead to a continuous increase in the optimal net revenue before leasing cost.

Overall, the sensitivity analysis shows that the selection of the shared energy storage size should not be determined solely according to the maximum deviation mitigation capability. Instead, the relationship between the storage-to-wind capacity ratio, the improvement in optimal net revenue before leasing cost, and the reduction in deviation penalty cost should be comprehensively considered. Under the simulation conditions of this study, although the 7.5 MW/15 MWh configuration achieves the highest optimal net revenue before leasing cost, the 5 MW/10 MWh configuration can already significantly reduce the deviation penalty cost from 10,480 CNY to 6750 CNY compared with the smaller 2.5 MW/5 MWh configuration. Meanwhile, its storage-power ratio is only 1.67% of the total installed wind capacity, indicating that a relatively small short-term regulation resource can provide an effective deviation-mitigation effect for the 300 MW consortium. Therefore, the 5 MW/10 MWh configuration is adopted as the baseline shared energy storage configuration in this study to balance regulation effectiveness, leasing cost, and the relative scale of storage to wind generation capacity.

4.4.4. Sensitivity Analysis of Charging and Discharging Efficiencies

To further investigate the impact of charging and discharging efficiencies on the economic performance of the proposed strategy, a sensitivity analysis is conducted by varying the charging efficiency η_c and discharging efficiency η_d of the shared energy storage system. The baseline case adopts $\eta_c = 0.95$ and $\eta_d = 0.95$. Three lower or asymmetric-efficiency cases are also considered: $\eta_c = 0.85$, $\eta_d = 0.90$; $\eta_c = 0.90$, $\eta_d = 0.90$; and $\eta_c = 0.90$, $\eta_d = 0.95$. The corresponding results are summarized in Table 10.

Table 10. Sensitivity analysis results under different charging and discharging efficiencies.

Efficiency Setting	Optimal Net Revenue Before Leasing Cost/CNY	Deviation Penalty Cost (CNY)
$\eta_c = 0.85, \eta_d = 0.90$	372,860	8420
$\eta_c = 0.90, \eta_d = 0.90$	374,310	7860
$\eta_c = 0.90, \eta_d = 0.95$	375,480	7210
$\eta_c = 0.95, \eta_d = 0.95$	376,613	6750

As shown in Table 10, decreasing the charging efficiency from 0.95 to 0.85 and the discharging efficiency from 0.95 to 0.90 increases the deviation penalty cost from 6750 CNY to 8420 CNY, while the optimal net revenue before leasing cost decreases from 376,613 CNY to 372,860 CNY. Lower efficiencies result in higher energy losses during storage operation, thereby reducing the effective regulation capability of the shared energy storage system.

The results also demonstrate that the proposed strategy does not require equal charging and discharging efficiencies. Even under asymmetric or lower efficiencies, the shared energy storage system can still effectively reduce deviation penalties and maintain relatively high optimal net revenue before leasing cost. Therefore, the model is applicable to storage systems with asymmetric efficiencies, and the corresponding conversion losses are directly reflected through the efficiency parameters in the energy state transition equation.

4.4.5. Sensitivity Analysis of Wind Farm Correlation Coefficient

To further verify the influence of wind power output complementarity on the economic performance of the wind farm consortium, a sensitivity analysis is conducted by changing the correlation coefficient among wind farms. A lower correlation coefficient indicates stronger output complementarity, whereas a higher correlation coefficient indicates more synchronous output fluctuations and weaker complementarity. The corresponding results are shown in Table 11.

Table 11. Sensitivity analysis results under different wind farm correlation coefficients.

Correlation Coefficient	Maximum Absolute Deviation/MW	Accumulated Absolute Deviation/MWh	Deviation Penalty Cost/CNY	Storage Leasing Cost/CNY	Final Net Revenue After Leasing Cost/CNY
0.1	4.63	32.95	6750	5654.4	370,958.6
0.5	6.72	48.86	9410	6180.0	367,773.0
0.9	9.38	69.74	14,280	7070.0	362,013.0

As shown in Table 11, the correlation coefficient among wind farms has a significant influence on the deviation mitigation effect of the consortium. When the correlation coefficient is 0.1, the output fluctuations of different wind farms are weakly correlated, and the aggregation of multiple wind farms provides a strong complementary smoothing effect. In this case, the maximum absolute deviation and accumulated absolute deviation are only 4.63 MW and 32.95 MWh, respectively. The deviation penalty cost is 6750 CNY, and the final net revenue after leasing cost reaches 370,958.6 CNY.

When the correlation coefficient increases from 0.1 to 0.5 and 0.9, the output fluctuations of different wind farms become more synchronous, and the natural complementarity among wind farms is gradually weakened. As a result, the accumulated absolute deviation increases from 32.95 MWh to 48.86 MWh and 69.74 MWh, respectively, while the deviation penalty cost increases from 6750 CNY to 9410 CNY and 14,280 CNY. Meanwhile, the final net revenue after leasing cost decreases from 370,958.6 CNY to 367,773.0 CNY and 362,013.0 CNY.

These results confirm that the economic advantage of consortium-based coordinated bidding is closely related to the output complementarity among wind farms. A lower correlation coefficient allows the consortium to better smooth the aggregated output fluctuation and reduce the regulation burden of shared energy storage. Conversely, when the wind farms are highly correlated, output deviations tend to occur in the same direction, which weakens the smoothing effect of aggregation and increases the deviation penalty cost. Therefore, the proposed consortium operation mode is particularly beneficial when the participating wind farms have relatively strong output complementarity.

4.4.6. Analysis of Revenue Distribution and Cost Allocation Results for the Consortium Based on the Shapley Value

To verify the fairness, rationality, and alliance stability of the revenue distribution and cost allocation linkage mechanism based on the Shapley value proposed in this paper, the optimal revenue distribution and energy storage leasing cost allocation under three allocation methods for each wind farm are calculated based on the optimal operation results of Scenario 3. Since the installed capacities of the wind farms are different, only the optimal net revenue and energy storage leasing cost per 1 MW of installed capacity for the three wind farms are calculated. First, the optimal net revenue is calculated, and the results are shown in Table 12.

Table 12. Optimal revenue allocation per 1 MW for each wind farm under three allocation methods.

Wind Farm	Average Allocation (CNY/MW)	Shapley Allocated Revenue (CNY/MW)	Allocation Based on Installed Capacity (CNY/MW)
Wind farm 1	1195.60	1271.71	1255.38
Wind farm 2	1255.38	1255.60	1255.38
Wind farm 3	1321.45	1239.63	1255.38

Table 12 compares the three allocation methods for optimal net revenue. A vertical comparison reveals that average allocation is clearly unreasonable. Wind Farm 1 has the largest installed capacity and the smallest prediction error standard deviation, making average allocation the most unfavorable for it, while Wind Farm 3 can easily free-ride. Wind Farm 3 has the smallest installed capacity and the largest prediction error, yet it receives 1321.45 CNY/MW under average allocation. Under such an allocation, Wind Farm 1 may consider participating in the market independently with its own energy storage, which is detrimental to the long-term stability of the alliance. Allocation based on installed capacity seems reasonable at first glance, as each of the three wind farms receives 1255.38 CNY/MW. However, Wind Farm 1 and Wind Farm 2 have larger installed capacities and lower prediction error standard deviations than Wind Farm 3. This allocation is unfavorable to Wind Farm 1 and Wind Farm 2, especially to Wind Farm 1. Under this scheme, Wind Farm 1 and Wind Farm 2 might also consider leaving the alliance to operate independently. In contrast, the Shapley value allocation is the most reasonable and fair approach. Wind Farm 1, with the largest capacity and the smallest prediction error, obtains the highest revenue; Wind Farm 3, with the smallest capacity and the largest prediction error, obtains the lowest revenue; and Wind Farm 2 falls in between. Therefore, the consortium should adopt the Shapley value method for allocating the optimal net revenue.

Subsequently, the cost allocation method based on marginal contribution is adopted to share the leasing cost, and the allocation results are shown in Table 13.

Comparing Table 12 and Table 13, it can be observed that a wind farm with a higher Shapley value per unit bears a higher energy storage leasing cost. The positive correlation between revenue and allocated cost conforms to the principle of “who benefits, who bears”

and is consistent with the marginal contribution logic of the Shapley value, thereby ensuring the stable operation of the alliance.

Table 13. Leasing cost allocation per 1 MW for each wind farm.

Wind Farm	Allocated Leasing Cost (CNY/MW)
Wind farm 1	19.08
Wind farm 2	18.84
Wind farm 3	18.60

To guarantee the stable operation of the alliance, the individual rationality constraint must be satisfied, i.e., the final net revenue of each entity participating in the alliance should be higher than its net revenue under independent operation. Here, the final net revenue refers to the optimal net revenue after deducting the leasing cost. To more intuitively demonstrate the final net revenue of each wind farm before and after joining the consortium, the final net revenue per 1 MW for each wind farm is plotted, as shown in Figure 5.

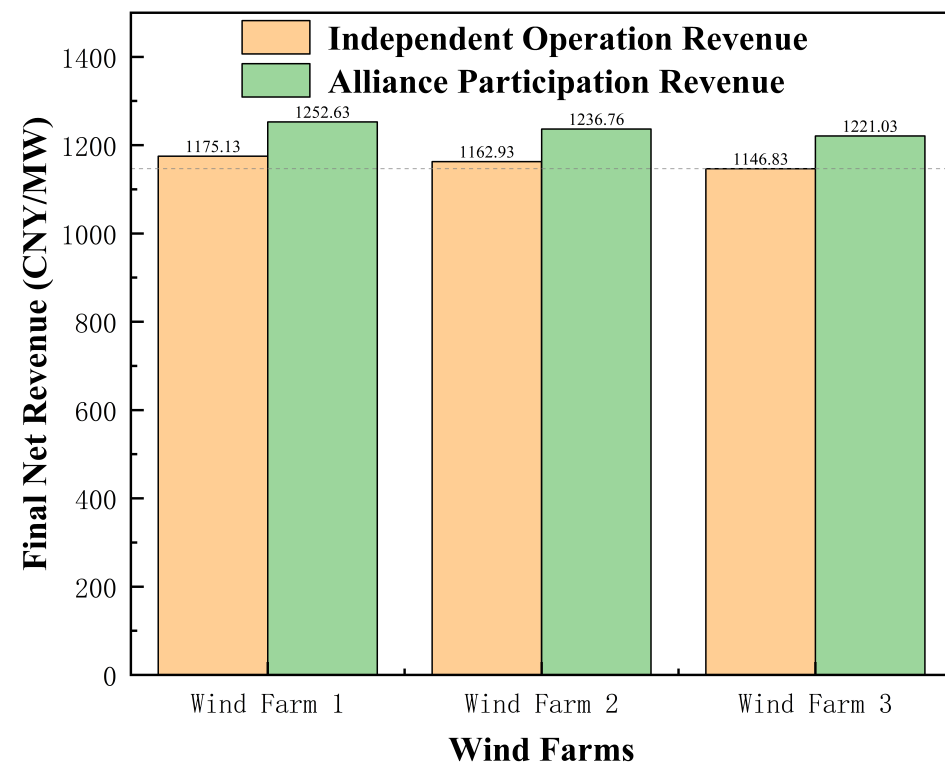


Figure 5. Comparison of final net revenue per 1 MW for each wind farm before and after joining the consortium.

As shown in Figure 5, after the Shapley value-based revenue allocation and cost sharing, the net revenue of all wind farms is significantly higher than their independent operation revenue, demonstrating that the consortium mode can achieve Pareto improvement for all members. A comparison of the final net revenue per unit for the three wind farms reveals that Wind Farm 1 has the largest revenue increase, followed by Wind Farm 2, while Wind Farm 3 has the smallest increase. The allocation results are consistent with the relative contribution of each entity, reflecting the rationality of the proposed allocation mechanism. Figure 5 further illustrates that the proposed allocation mechanism not only ensures the overall revenue optimality of the consortium but also achieves fair individual allocation.

To further strengthen the game-theoretic stability analysis, the core condition is checked for the final allocation result. Since the case study contains three wind farms,

all six proper non-empty sub-alliances can be enumerated directly. For each sub-alliance K , the total final net revenue allocated to the members of K in the grand consortium is compared with the net characteristic value $\tilde{V}(K)$ that the same sub-alliance can obtain by operating independently. The verification results are summarized in Table 14.

Table 14. Core-stability check for the Shapley-based final allocation.

Sub-Alliance K	Core-Stability Condition	Verification Result
$\{1\}$	$R_1^{net} \geq \tilde{V}(\{1\})$	Satisfied
$\{2\}$	$R_2^{net} \geq \tilde{V}(\{2\})$	Satisfied
$\{3\}$	$R_3^{net} \geq \tilde{V}(\{3\})$	Satisfied
$\{1, 2\}$	$R_1^{net} + R_2^{net} \geq \tilde{V}(\{1, 2\})$	Satisfied
$\{1, 3\}$	$R_1^{net} + R_3^{net} \geq \tilde{V}(\{1, 3\})$	Satisfied
$\{2, 3\}$	$R_2^{net} + R_3^{net} \geq \tilde{V}(\{2, 3\})$	Satisfied

Table 14 shows that the final allocation satisfies the core-stability inequalities for all proper non-empty sub-alliances in the three-wind-farm case. Therefore, no individual wind farm or pair of wind farms can obtain a higher total net payoff by leaving the grand consortium and forming a smaller coalition under the simulated conditions. This result indicates that the proposed Shapley-based revenue allocation combined with the revenue-proportional leasing-cost sharing rule not only satisfies individual and collective rationality, but also belongs to the core of the cooperative game in this case.

4.4.7. Analysis of the Influence of Forecasting Accuracy on Marginal Contribution and Allocation Results

To further reveal the intrinsic relationship among prediction accuracy, marginal contribution, and allocation results, and to strengthen the rationality of the proposed allocation mechanism, an impact analysis is carried out based on the case results.

As can be seen from Table 12 and Figure 5, the higher the prediction accuracy of a wind farm, the greater its contribution to reducing the deviation penalty of the consortium, and consequently, the higher the allocated revenue it receives, with a more pronounced increase in net revenue. Comparing the net revenue of each wind farm, the revenue increase rate of Wind Farm 1, which has the smallest prediction error, reaches 6.60%, slightly higher than the 6.47% of Wind Farm 3, demonstrating that the Shapley value can accurately identify differences in contributions among entities. Prediction accuracy affects the level of output deviation, which in turn influences the total revenue of the consortium and ultimately manifests as differences in allocated revenue. In summary, the proposed framework can create a positive incentive for wind farms to improve their forecasting accuracy and enhance the overall competitiveness of the consortium. This also indicates that, in electricity spot markets, wind farms should improve their power forecasting capability to strengthen their market competitiveness.

Although the numerical differences among wind farms appear relatively small, this is mainly because the results are normalized on a per-MW basis. In long-term market operation, such per-unit differences will accumulate into a significant total revenue difference. Moreover, Wind Farm 3, which has the largest prediction error, obtains the lowest Shapley-based allocated revenue per unit capacity, indicating that its lower forecasting accuracy reduces its marginal contribution to the consortium. Therefore, improving the forecasting tool would help Wind Farm 3 increase its contribution to deviation reduction and obtain a higher allocated revenue. This demonstrates that the proposed allocation mechanism can still provide a positive incentive for wind farms with poorer forecasting accuracy to improve their prediction performance.

5. Discussion

5.1. Novelty and Scientific Justification

To further justify the novelty of this study, the proposed method is compared with existing research from the perspectives of modeling scope and coordination mechanism. Existing studies usually focus on independent wind farm bidding, storage-assisted dispatch, or cooperative benefit allocation separately. In contrast, this study considers a wind farm consortium as a unified market entity and combines day-ahead bidding, real-time shared energy storage regulation, and post-settlement allocation in a single framework.

The proposed framework therefore provides a complete chain of “bidding–regulation–settlement–allocation”. The two-stage stochastic optimization model determines consortium-level bidding and shared energy storage dispatch, while the Shapley value and revenue-proportional rule allocate revenues and leasing costs among wind farms. This integrated treatment distinguishes the proposed method from studies that analyze only one of these components separately.

5.2. Implications, Limitations, and Differences from Existing Methods

The results demonstrate that the proposed consortium-based coordinated bidding strategy can effectively reduce deviation penalties and improve the final net revenue of wind farms participating in the electricity spot market. The economic advantage mainly comes from two aspects. First, the aggregation of multiple wind farms provides output complementarity, which reduces the overall deviation between actual output and day-ahead cleared power. Second, shared energy storage provides flexible real-time regulation, which further mitigates imbalance risks and improves market participation performance.

Compared with existing methods that mainly focus on independent renewable energy bidding or independently configured energy storage, the proposed approach combines consortium-based coordinated bidding, shared energy storage leasing, real-time deviation correction, and cooperative game-based revenue allocation in a unified framework. This makes the proposed method different from traditional independent bidding strategies, because it not only optimizes the bidding decision of the wind farm consortium, but also considers the internal allocation of benefits and leasing costs among wind farms. In addition, the Shapley value-based allocation mechanism reflects the marginal contribution of each wind farm and provides incentives for improving forecasting accuracy and reducing deviation risks.

The sensitivity analyses show that the performance of the proposed strategy depends on key system and market factors. A larger shared energy storage size can reduce deviation penalties, but the marginal economic benefit may decrease as the storage size continues to increase. The baseline 5 MW/10 MWh storage configuration corresponds to only 1.67% of the 300 MW wind farm consortium in terms of rated power, which indicates that the shared storage is used as a short-term regulation resource rather than as a large-scale energy-shifting unit. Lower charging and discharging efficiencies reduce the effective regulation capability of the storage system and increase energy losses. Stronger output correlation among wind farms weakens the smoothing effect of aggregation and reduces the economic benefit of consortium operation. These findings indicate that the proposed strategy is particularly suitable for wind farm portfolios with strong output complementarity and moderate shared energy storage regulation capacity.

For practical implementation, the proposed approach can be applied by establishing a wind farm consortium or an aggregation platform that is responsible for unified day-ahead bidding, real-time deviation monitoring, shared energy storage leasing, and internal revenue settlement. In practice, the consortium operator should collect wind power forecasts, market price information, storage leasing prices, and real-time output data from

participating wind farms. The two-stage optimization model can then be solved before market bidding and updated during real-time operation. After market settlement, the Shapley value-based allocation mechanism can be used to distribute revenues and leasing costs among the participating wind farms.

However, several limitations should also be noted. First, the imbalance settlement price is simplified by using the day-ahead market price as the reference price, while practical balancing prices may be independently determined. As discussed in the robustness analysis, the model can be extended by replacing the day-ahead reference price with an independent balancing price, but more detailed balancing-price forecasting and market-rule modeling should be considered in future applications. Second, the case study uses synthetically generated representative simulation profiles rather than confidential plant-level measured data. Although the Monte Carlo scenario generation and Kantorovich-distance-based reduction procedure have been clarified to improve reproducibility, the present numerical results should be interpreted as model verification under representative operating conditions rather than as project-specific empirical validation. The statistical robustness framework in Section 4 indicates how repeated scenario-generation and optimization experiments can be used to calculate sample means, standard deviations, and 95% confidence intervals. In future empirical applications, long-term wind farm measurements, plant-level SCADA records, actual day-ahead bidding data, and real market clearing and settlement records should be incorporated to quantify the variability of economic and deviation-mitigation indicators under practical operating conditions. Third, the case study only considers three wind farms. Although this size allows exact Shapley value calculation, the number of coalition optimization calls increases as $2^M - 1$ when the number of members increases. Therefore, exact Shapley value calculation is mainly suitable for small or medium-sized consortia, while sampling-based approximation, clustering, or parallel computation should be used for larger wind farm portfolios. In addition, Shapley value allocation is not guaranteed to lie in the core for every cooperative game. Therefore, the core condition should be checked explicitly when applying the proposed allocation framework to other systems, especially when participant heterogeneity or storage-cost differences become more significant. Fourth, the comparison with independently owned storage in Scenario 2 is an operation-level comparison before storage life-cycle cost accounting. A complete comparison between self-owned storage and leased shared storage would require additional assumptions on annualized investment cost, fixed operation and maintenance cost, replacement cost, and financing rate. Fifth, the long-term investment recovery of the shared energy storage system is not fully modeled, because this study mainly focuses on short-term market operation and leasing-based regulation services.

5.3. Future Research Directions

Future research can be extended in several directions. First, the proposed framework should be validated using long-term measured wind farm output, SCADA data, and real electricity-market settlement records when such data become available. Second, more realistic balancing price mechanisms should be considered to better reflect the operation rules of practical electricity spot markets. Third, larger-scale wind farm consortia and geographically dispersed wind farm portfolios can be studied to further evaluate the influence of spatial complementarity on deviation mitigation and storage leasing demand. Fourth, sampling-based or approximation-based Shapley value methods can be introduced to improve computational scalability when the number of consortium members increases. Fifth, hybrid renewable energy portfolios, such as wind–solar complementary systems, can be considered to analyze the coordination characteristics of different stochastic renewable energy sources. Finally, long-term investment recovery, payback period, storage ownership

cost, and pricing mechanisms of shared energy storage services should be further investigated to support a complete life-cycle economic comparison between self-owned storage and leased shared storage business models.

6. Conclusions

This paper proposes a two-stage coordinated bidding and revenue sharing strategy for wind farm consortia participating in electricity spot markets with shared energy storage leasing. The proposed framework integrates day-ahead coordinated bidding, real-time deviation correction, shared energy storage regulation, and Shapley value-based revenue allocation. In addition, a revenue-proportional fairness rule is introduced to allocate the shared energy storage leasing cost among the participating wind farms.

The case study results show that the proposed strategy can effectively reduce deviation penalties and improve the final net revenue of the wind farm consortium. Compared with the case without shared energy storage regulation, the introduction of shared energy storage reduces the deviation penalty cost and increases the final net revenue after leasing cost. Under the baseline shared energy storage configuration of 5 MW/10 MWh, the optimal net revenue before leasing cost reaches 376,613 CNY, and the final net revenue after leasing cost reaches 370,958.6 CNY, while the deviation penalty cost is reduced to 6750 CNY. This indicates that shared energy storage can provide effective real-time regulation support for mitigating wind power uncertainty.

The sensitivity analysis on shared energy storage size further verifies the economic effect of storage configuration. When the storage size increases from 2.5 MW/5 MWh to 7.5 MW/15 MWh, the deviation penalty cost decreases from 10,480 CNY to 5120 CNY, and the optimal net revenue before leasing cost increases from 368,920 CNY to 378,120 CNY. However, when the storage size further increases to 10 MW/20 MWh, although the deviation penalty cost continues to decrease to 4380 CNY, the optimal net revenue before leasing cost decreases slightly to 376,980 CNY. This shows that blindly increasing the storage size does not necessarily lead to continuous economic improvement.

The efficiency sensitivity analysis shows that charging and discharging efficiencies also affect the economic performance of the consortium. Lower charging and discharging efficiencies reduce the effective regulation capability of shared energy storage and increase energy losses, which further affects deviation penalty costs and final net revenue. Therefore, both storage size and operation efficiency should be considered when determining the shared energy storage leasing scheme.

The Shapley value-based allocation results show that the proposed allocation mechanism can reflect the marginal contribution of each wind farm to the consortium. Wind farms with larger contributions to deviation reduction and revenue improvement receive higher allocated revenues, which helps maintain fairness and participation incentives within the consortium. Meanwhile, the revenue-proportional cost-sharing rule ensures that the total shared energy storage leasing cost is fully recovered without surplus or deficit. The core-stability check further shows that, under the simulated three-wind-farm case, no individual wind farm or pairwise sub-alliance has an incentive to leave the grand consortium, which strengthens the game-theoretic foundation of the proposed allocation mechanism.

Overall, the proposed method provides a practical decision-making reference for wind farm consortium bidding, shared energy storage utilization, and internal revenue allocation in electricity spot markets. Because the present case study is based on synthetically generated representative profiles rather than direct measured wind farm data, the current results provide reproducible numerical validation under representative scenarios. Future work will extend the validation using long-term operational measurements, plant-level SCADA records, actual day-ahead bidding results, and real market settlement records. Repeated

scenario-generation experiments and repeated optimizations across multiple random seeds or real operating days will be used to calculate sample means, standard deviations, and 95% confidence intervals according to Equation (23). This extension will further quantify the statistical variability of revenues, penalty costs, deviation-mitigation indicators, and allocation-stability results under practical operating conditions. Future research will also consider independently determined balancing prices, larger-scale wind farm consortia, sampling-based Shapley value approximation methods, and the long-term investment recovery mechanism of shared energy storage systems.

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