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A Study on a New Mechanism for Grid Integration of Renewable Energy Based on Forecast Reliability and Energy Storage Configuration

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Abstract: *This paper presents a novel mechanism for integrating renewable energy into the grid by linking forecast reliability with energy storage configuration. A comprehensive reliability score, combining forecast accuracy and energy storage gains, is introduced to determine feed-in tariffs and incentivize optimal energy storage deployment. To address the inherent uncertainty of renewable generation, typical wind power output scenarios are identified using K-means clustering based on the Elbow Method, reducing scenario complexity while preserving statistical characteristics. A genetic algorithm is applied to optimize energy storage capacity and charging/discharging strategies, subject to practical constraints including allocation ratio, storage duration, grid balance, and operational limits. Case studies of two 200 MW wind farms demonstrate that the proposed mechanism significantly reduces output deviations, enhances reliability scores, and increases net revenue. Energy storage exhibits a marginal saturation effect: initial deployment yields substantial improvements, while further expansions provide diminishing incremental benefits. Plants with lower forecast accuracy benefit more from storage optimization, highlighting the value of site-specific strategies. The mechanism also improves system-level stability by smoothing renewable output fluctuations and promoting efficient storage utilization. The framework offers actionable guidance for policymakers and operators to design incentive-based grid-connection mechanisms that align financial rewards with operational performance and is scalable to other renewable sources and hybrid systems, supporting high-penetration renewable energy power systems.*

Keywords: *Renewable Energy, Forecast Reliability, Energy Storage Optimization*

1. Introduction

The development and utilization of traditional fossil fuels have led to increasingly severe environmental pollution and climate change issues, and there is a risk of resource depletion in the future. Consequently, the large-scale development and utilization of renewable energy have become a global consensus [1]. Currently, to actively promote the construction of a new power system, safeguard measures are generally implemented to ensure that renewable energy generation is fully fed into the grid; therefore, a relatively wide margin of error is permitted for renewable energy output forecasts. It is foreseeable that in future power systems with an extremely high proportion of renewable energy, the share of renewable installed capacity will continue to rise, leading to greater power output forecast errors [2]. Due to the inherent characteristics of renewable energy—such as randomness, intermittency, and volatility—this will pose significant challenges to the operation and dispatch of distribution grids and place higher demands on the flexibility and balancing capabilities of the power system [3]. However, the power system cannot indefinitely continue to enhance its flexibility and balancing capabilities. Faced with the significant uncertainty in renewable energy output forecasts, the magnitude of the forecast error will become a key criterion for evaluating the value of renewable energy output, making a feed-in mechanism based on forecast reliability an urgent necessity.

Game theory has been employed to clarify the interaction mechanisms among stakeholders through an economic analysis of institutional arrangements for renewable energy grid integration and a game-theoretic analysis of stakeholder interactions [4]. A pricing and allocation mechanism has also been proposed for an integrated thermal-electric energy market considering renewable energy uncertainty, in which the uncertainty is modeled by a distributionally robust chance constraint based on the Wasserstein distance, and an integrated energy market clearing model is established [5]. In addition, existing studies have summarized market participation models for renewable energy and constructed a frequency regulation market clearing model, where generating units independently incorporate opportunity costs into capacity bidding and the clearing sequence is determined according to declared capacity and ramping bids [6].

Forecast reliability has also been examined in relation to wind power integration. A wind power forecast reliability assessment system and forecast error model have been established, based on which an energy storage cost model incorporating forecast reliability was developed; this model was further combined with a thermal power unit output cost model to formulate an economic dispatch model for systems with wind power [7]. To address wind power uncertainty, a two-level optimization model has been proposed that considers both the temporal characteristics of wind power forecast errors and the reliability of wind power forecasts [8]. Other studies have described the compensation cost of wind power spinning reserve capacity from the perspective of wind farm output forecast reliability, although they do not explicitly define reliability [9,10]. Overall, the above studies have conducted focused and independent investigations into renewable energy grid-connection mechanisms or forecast reliability, yet few have established a link between these two aspects.

This paper investigates a renewable energy grid-connection mechanism based on forecast reliability and energy storage configuration. First, starting from the initial forecast accuracy of renewable energy plants, we introduce a gain term for the comprehensive reliability score derived from energy storage to construct an evaluation model for renewable energy output. Second, we correlate the comprehensive reliability score of renewable energy with the grid-connection tariff criteria. This paper employs the K-means clustering method based on the elbow method to handle the uncertainty of wind power output. It reduces and optimizes the initial scenarios to obtain typical wind power output scenarios, and constructs an optimization model for energy storage configuration at "renewable energy + energy storage" sites. With the goal of maximizing the site's annual net revenue, the model solves for the optimal energy storage configuration and charging/discharging strategies. Finally, a benefit comparison is conducted between two renewable energy sites with different forecast accuracies, and a comparison is made between the benefits before and after energy storage configuration. This demonstrates that under the new grid-connection mechanism, not only can the benefits of the site be effectively enhanced, but the configuration of energy storage can also become an endogenous driving force for renewable energy sites, thereby improving the utilization rate of self-configured energy storage at these sites.

2. Establishing a Feed-in Mechanism for Renewable Energy

This section proposes a grid-connection mechanism that takes into account the reliability of renewable energy output forecasts and energy storage configuration, and presents a model for evaluating the reliability of renewable energy output. Under this new mechanism, renewable energy plants introduce an energy storage gain term in addition to the existing output forecast accuracy term. By configuring energy storage to improve their overall output score, they can secure higher feed-in tariffs, thereby making the deployment of energy storage an intrinsic incentive for renewable energy plants.

2.1. Renewable Energy Output Assessment Model

We propose a new model for evaluating renewable energy output that takes into account forecast reliability and energy storage configuration:

$$C_{cred} = A_{core} + B_{storage}\left(1 - A_{core}\right) \tag{1}$$

$$A_{core} = 1 - \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P_t^{pred} - P_t^{act}}{P_t^{pred}}\right| \tag{2}$$

$$B_{storage} = \lambda B_{alpha} + \mu B_{beta} \tag{3}$$

$$B_{alpha} = \frac{1}{1 + e^{-k_1 \alpha}} - 1 \tag{4}$$

$$B_{beta} = \frac{2}{1 + e^{-k_2 \beta}} - 1 \tag{5}$$

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In the equation: C_{cred} represents the output rating of the wind farm; A_{core} represents the forecast accuracy term of the wind farm; $B_{storage}$ represents the comprehensive gain term for energy storage; B_{alpha} represents the gain term for the energy storage configuration ratio; B_{beta} represents the gain term for the energy storage configuration duration; α represents the energy storage configuration ratio; β represents the energy storage configuration duration; λ and μ are the weighting coefficients for the energy storage configuration ratio and duration, respectively, which are related to the power and capacity costs of the configuration; k_1 and k_2 are shape factors.

2.2. Pricing Model for Feed-in Tariffs at renewable energy Power Stations

After evaluating the predicted output of renewable energy facilities, their feed-in tariffs for the coming year are determined based on their output ratings. Under this mechanism, the results of the comprehensive output reliability assessment for renewable energy facilities correspond to different feed-in tariffs, as shown in Figure 1.

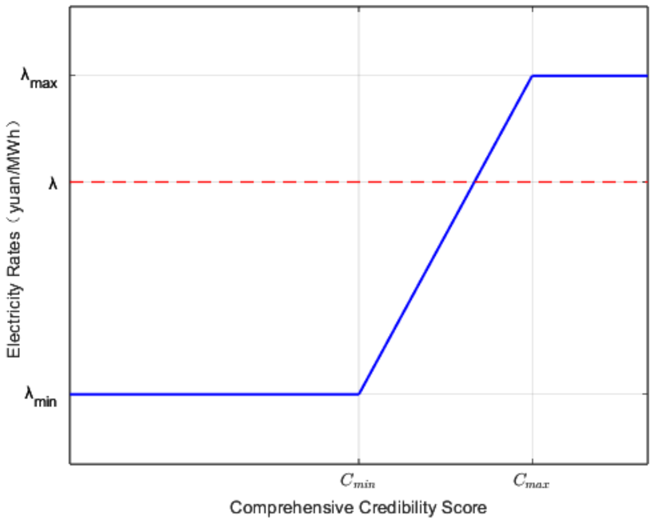

Figure 1: Relationship between Feed-in Tariff and Comprehensive Credibility Score.

3. Optimization Model for Energy Storage Configuration in Power Plants

Within the framework of the aforementioned mechanism for integrating renewable energy into the grid, this study uses typical daily data to optimize energy storage configuration schemes and charging/discharging strategies for renewable energy power plants. The model employs a genetic algorithm to first determine the power and duration of the energy storage configuration, calculate its output score, and subsequently determine the feed-in tariff for the power plant. It then derives the optimal charging/discharging strategy under the optimal energy storage configuration to maximize the economic efficiency of the renewable energy power plant.

3.1. Objective Function

Renewable energy power stations aim to maximize their net profits. Revenues include income from electricity sales to the market; costs include energy storage construction costs, energy storage O&M costs, wind power O&M costs, curtailment penalties, and deviation penalties. The formula is as follows:

$$\max f = \sum_{s=1}^{S} \rho_s (C_s - C_{om}^{storage,s} - C_{om}^{wind,s} - C_{up}^{s} - C_{down}^{s}) \cdot 365 - C_{storage} \tag{6}$$

In the equation, ρ_s represents the probability of scenario s occurring; C_s represents the revenue from grid-connected power generation at stations under scenario s; $C_{om}^{storage,s}$ represents the energy storage O&M costs under scenario s; $C_{om}^{wind,s}$ represents the wind power O&M costs under scenario s; C_{up}^{s} represents the curtailment penalty costs under scenario s; C_{down}^{s} represents the deviation penalty costs under scenario s; and $C_{storage}$ represents the energy storage investment costs.

$$C_s = \sum_{t=1}^{T} c_{sw} P_t^{grid} \tag{7}$$

$$C_{om}^{storage,s} = \sum_{t=1}^{T} c_{om}^{storage} P_t^{ess} \tag{8}$$

$$C_{om}^{wind,s} = \sum_{t=1}^{T} c_{om}^{wind} P_t^{act} \tag{9}$$

$$C_{up}^{s} = \sum_{t=1}^{T} c_{up} P_t^{up} \tag{10}$$

$$C_{down}^{s} = \sum_{t=1}^{T} c_{down} P_t^{down} \tag{11}$$

$$C_{storage} = \left(c_e E + c_p P\right) \frac{\left(1+r\right)^Y r}{\left(1+r\right)^Y - 1} \tag{12}$$

In the equation, c_{sw} represents the feed-in tariff per unit; P_t^{grid} represents the feed-in electricity generation at time t under scenario s; $c_{om}^{storage}$ represents the O&M cost per unit of energy storage; P_t^{ess} represents the operating power of energy storage at time t under scenario s; c_{om}^{wind} represents the O&M cost per unit of wind power; P_t^{act} is the actual wind power output at time t under scenario s; c_{up} is the penalty cost per unit of curtailed wind power; P_t^{up} is the curtailed wind power at time t under scenario s; c_{down} is the penalty cost per unit of deviation; P_t^{down} is the deviation power at time t under scenario s; c_e is the capital cost per unit of energy storage capacity; c_p is the capital cost per unit of energy storage power; r is the discount rate; Y is the energy storage lifecycle.

3.2. Constraints

The constraints primarily include the allocation-to-storage ratio constraint, the allocation duration constraint, the grid power balance constraint, and the energy storage operation constraint.

The storage allocation ratio requirement is:

$$\alpha \le \alpha_{\max} \tag{13}$$

In the formula, $\alpha_{\max}$ represents the maximum allocation ratio.

The duration constraint for allocation and storage is:

$$\beta \le \beta_{\max} \tag{14}$$

In the formula, $\beta_{\max}$ represents the maximum allocation duration.

The power balance constraint for the grid connection is:

$$P_t^{grid} = P_t^{act} + P_t^{charge} - P_t^{dischagre} \tag{15}$$

The operational constraints for energy storage are as follows:

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$$\begin{cases} P_{s,t}^{charge} \le P^{charge,\max} u_{s,t}^{charge} \\ P_{s,t}^{discharge} \le P^{discharge,\max} u_{s,t}^{discharge} \\ u_{s,t}^{charge} + u_{s,t}^{discharge} \le 1 \\ 0.1E^{ESS} \le E_{s,t}^{ESS} \le 0.9E^{ESS} \\ E_{s,t}^{ESS} = E_{s,t-1}^{ESS} + \eta_{ESS} P_{s,t}^{charge} \Delta t - \dfrac{P_{s,t}^{discharge}}{\eta_{ESS}} \Delta t \\ E^{ESS} = P_{rated} \cdot \alpha \cdot \beta \end{cases} \tag{16}$$

In the equation, $P^{charge,\max}$ and $P^{discharge,\max}$ represent the rated charging and discharging power of the energy storage system; $P_{s,t}^{charge}$ and $P_{s,t}^{discharge}$ represent the charging and discharging power of the energy storage system at time t in scenario s; $u_{s,t}^{charge}$ and $u_{s,t}^{discharge}$ are 0–1 variables that prevent simultaneous charging and discharging of the energy storage system; η_{ESS} represents the charging and discharging efficiency of the energy storage system; $E_{s,t}^{ESS}$ represents the energy stored in the energy storage system at time t in scenario s; E^{ESS} represents the installed capacity of the energy storage system; and P_{rated} represents the installed capacity of the power station.

4. Case Study Analysis

4.1. Case Description

Taking two wind farms in a certain region, each with an installed capacity of 200 MW, as an example, we assume that their actual power output data are identical but use different forecasting methods to predict their output, thereby resulting in different initial forecast accuracy values. We then analyze their energy storage configurations and economic viability. The remaining parameters are set as follows: the maximum and minimum allowable state of charge (SOC) for energy storage during optimized operation are 0.9 and 0.1, respectively, and the charging and discharging efficiency of the energy storage system is 0.95.

4.2. Generation and Reduction in Renewable Energy Scenarios

In the revenue model for renewable energy power stations, typical daily data is required to calculate the operating costs and grid-connected revenue of these facilities. Given the inherent uncertainty in wind power output, this paper employs a K-means clustering method based on the Elbow Method to reduce and optimize the initial set of scenarios. The elbow-based K-means clustering method can extract a representative subset of typical scenarios from a large-scale scenario set while retaining the probability distribution characteristics of the original scenario set as much as possible. Furthermore, it addresses the shortcoming of the general K-means algorithm, which cannot determine the optimal number of clusters. After scenario clustering, several representative wind power output scenarios and their corresponding probabilities can be obtained. This paper uses the clustered wind power output scenarios for the optimization calculations of typical days at renewable energy power stations.

Taking actual wind power output data from a province in southern China as an example, scenario clustering was performed to identify typical days for wind power output. With a total of 365 scenarios throughout the year, the K-means clustering algorithm based on the Elbow Method was applied to the comprehensive dataset of the study subject to perform scenario reduction analysis and construct typical day scenarios. The Elbow Method was used to determine the number of clusters, and the trend in clustering error is shown in Figure 2.

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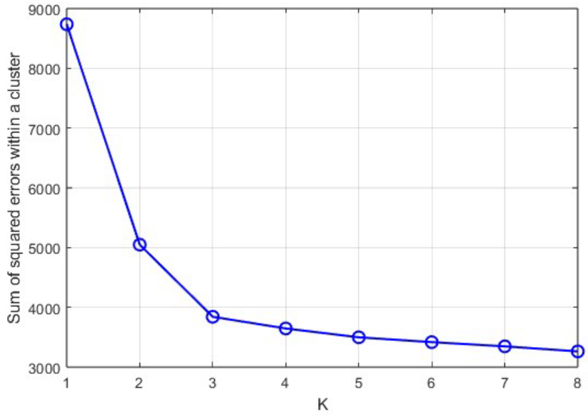

Figure 2: Variation Curve of Clustering Error.

As shown in Figure 2, the intra-cluster error decreases as the number of clusters increases. When the number of clusters is less than 3, the sum of squared intra-cluster errors shows a significant downward trend; when it exceeds 3, the trend in error gradually flattens. Therefore, based on the definition of the elbow method, selecting 3 as the number of clusters is most appropriate.

The typical wind power scenarios obtained after clustering are shown in Figure 3:

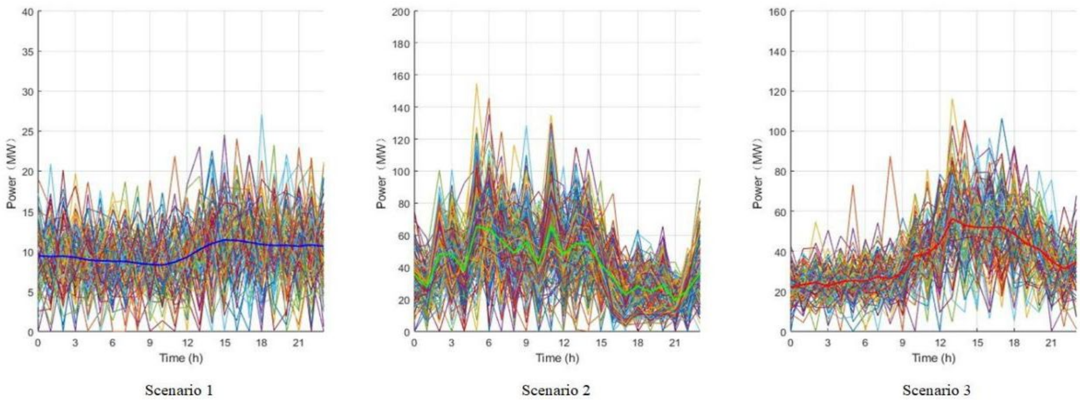

Figure 3: Typical Output Scenarios of Wind Power.

Table 1 shows the number of days on which typical wind power output scenarios occur in this region, along with the corresponding probabilities.

Table 1: Classification Results of Typical Wind Power Output Scenarios.

Typical Output Scenario	Number of days in the scenario	Scenario probability
Scenario 1	100	0.27
Scenario 2	172	0.47
Scenario 3	93	0.26

4.3. Analysis of the Benefits of Energy Storage at Stations

By solving the “renewable energy + energy storage” station energy storage configuration optimization model constructed in Section 3, and setting the energy storage allocation ratio α to increase gradually from 0% to 20% and the energy storage duration β to increase gradually from 0.5 hours to 4 hours, we obtained the net revenue of stations A and B, the three-dimensional relationship plots of α and β, as well as the comprehensive credibility scores and the three-dimensional relationship plots of α and β, as shown in Figures 4 and 5.

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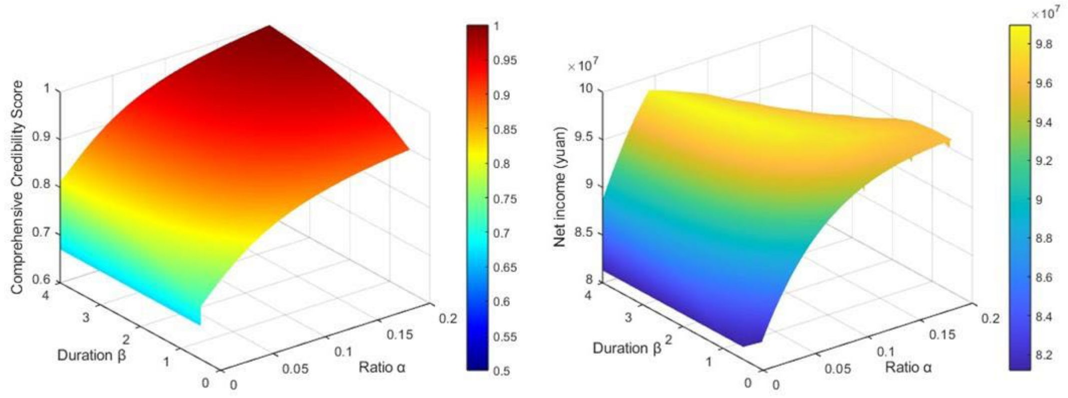
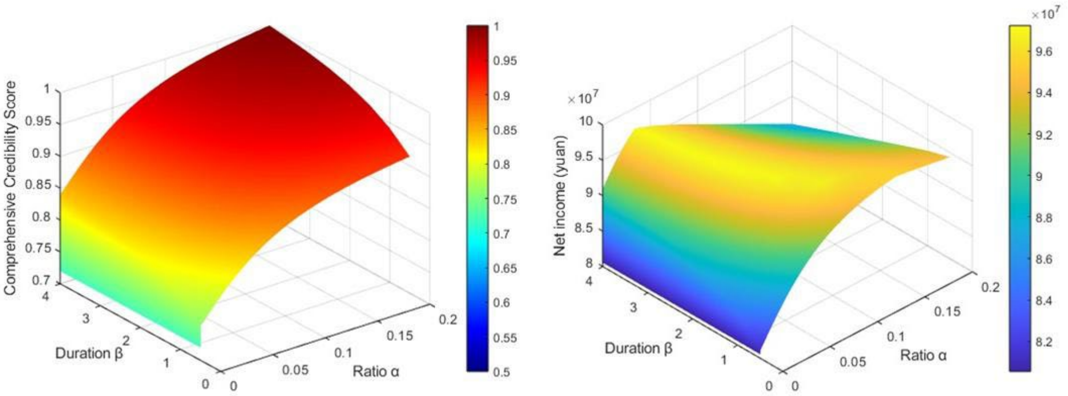


(a)3D Distribution Map of the Comprehensive Credibility Score for Station A

(b)3D Distribution Map of Net Income for Station A

Figure 4: 3D Relationship Diagram of Comprehensive Credibility Score and Net Profit for Power Station A.



(a)3D Distribution Map of the Comprehensive Credibility Score for Station B

(b)3D Distribution Map of Net Income for Station B

Figure 5: 3D Relationship Diagram of Comprehensive Credibility Score and Net Profit for Power Station B.

As shown in Figures 4(a) and 5(a), the comprehensive reliability score of the station exhibits a monotonically increasing trend as α and β increase, reaching a maximum when α = 20% and β = 4 h. As shown in Figures 4(b) and 5(b), the net revenue of the power station exhibits a pattern of "initial increase followed by stabilization" as α and β vary. At the stage where distribution storage capacity is low (α < 5%, β < 2 h), net revenue increases significantly with increases in α and β; during this stage, the gain effect of energy storage on output reliability dominates the change in revenue. Once the storage capacity reaches a critical threshold, the gain in output reliability from energy storage tends to saturate, while the cost of energy storage continues to increase monotonically with capacity. If α and β are further increased, the cost of energy storage will exceed the incremental benefit, leading to a decline in net revenue.

Based on the principle of "marginal benefit-cost equilibrium," the optimal storage configuration for Station A in the first year under the new grid-connection mechanism is determined to be: α = 4.51%, β = 2.5 h, corresponding to a storage capacity of 9.02 MW/22.55 MWh; The optimal energy storage configuration for Station B is: α = 5.77%, β = 2.5h, corresponding to an energy storage capacity of 11.54 MW/28.85 MWh. Under this scheme, the costs and benefits of the stations' energy storage configurations achieve an optimal balance, maximizing net revenue.

The energy storage charging and discharging strategies under the optimal charging and discharging scheme are shown in Figures 6 and 7.

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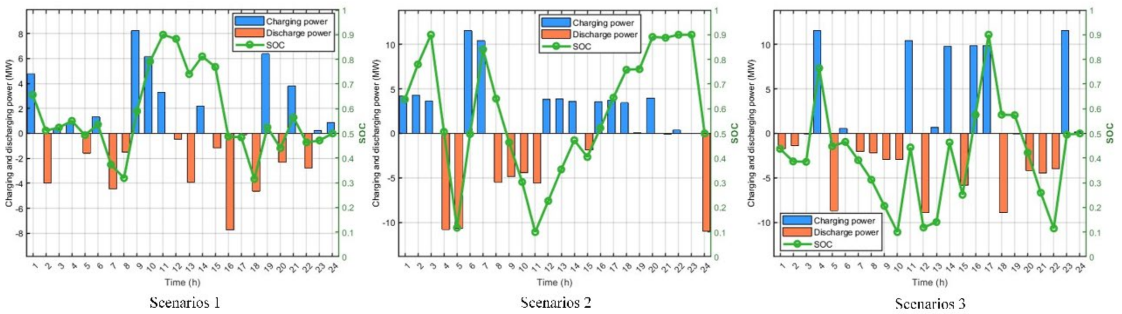

Figure 6: Energy Storage Charging-Discharging Strategy for Typical Scenarios of Power Station A.

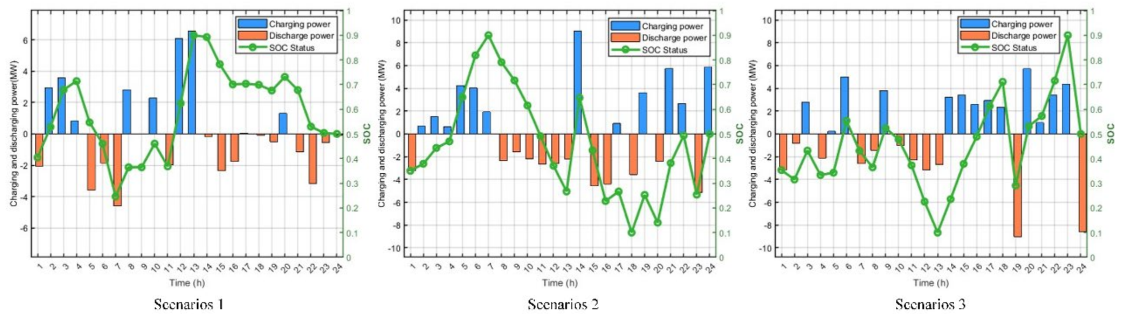

Figure 7: Energy Storage Charging-Discharging Strategy for Typical Scenarios of Power Station B.

Scenarios 1 through 3 represent typical wind power output scenarios, with Scenario 1 corresponding to a low-output period and Scenarios 2 and 3 corresponding to high-output periods. According to the power sign convention established in this paper, when the energy storage power is on the negative half-axis, it indicates that the energy storage system is discharging; conversely, when it is on the positive half-axis, it indicates that the energy storage system is charging. Taking Station A as an example, as shown in Figure 6, during periods of peak wind power output accompanied by curtailment—such as 0:00–3:00 and 6:00–7:00 in Scenario 3—the energy storage system operates at positive power, effectively absorbing the curtailed electricity; during periods of low wind power output resulting in a deviation shortfall—such as 4:00–5:00 and 8:00–11:00 in Scenario 3—the energy storage system operates at negative power, flexibly discharging electricity to compensate for the deviation; simultaneously, the energy storage system's SOC is consistently maintained within the reasonable range of 0.1–0.9, balancing battery cycle life with charging and discharging efficiency.

Figures 8 and 9 show the comparison of wind power output deviations at Sites A and B under three typical scenarios before and after the installation of energy storage.

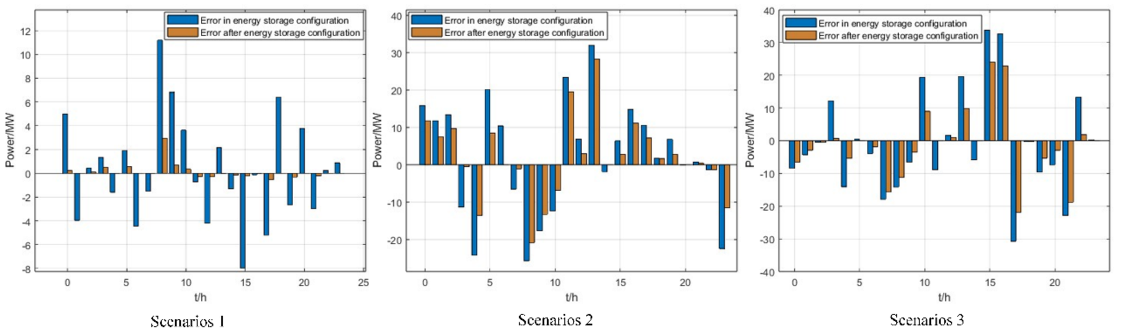

Figure 8: Output Deviation of Power Station A under Typical Scenarios Before and After Energy Storage Configuration.

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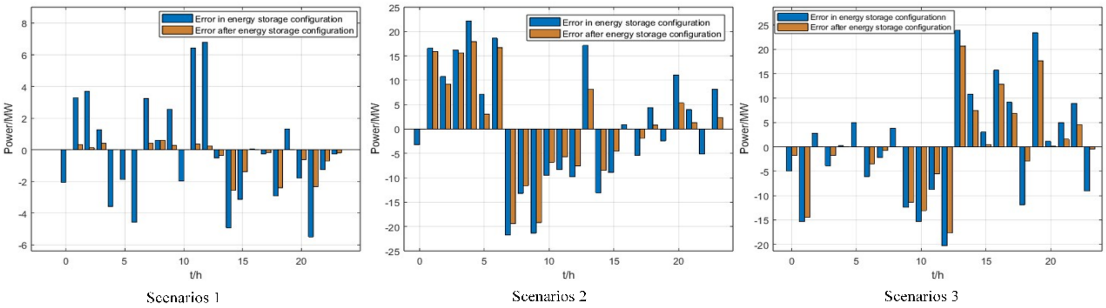

Figure 9: Output Deviation of Power Station B under Typical Scenarios Before and After Energy Storage Configuration.

As shown in Figure 8, under the optimal storage allocation scheme, station A still exhibits a slight output deviation, but the overall mitigation effect is significant: in Scenario 1, the output deviation decreased from 27.99% before storage allocation to 5.42%; in Scenario 2, it decreased from 27.06% to 18.37%; in Scenario 3 from 25.03% to 15.76%, and the overall output deviation from 26.69% to 13.18%. As shown in Figure 9, the overall output deviation at Station B was higher than that at Station A before storage allocation, and the suppression effect was even more pronounced after allocation: in Scenario 1, the deviation decreased from 34.14% to 7.42%, Scenario 2 decreased from 32.12% to 20.96%, Scenario 3 decreased from 32.85% to 18.52%, and the overall output deviation decreased from 33.03% to 14.30%. The above results indicate that a reasonable energy storage allocation strategy under the new grid connection mechanism can effectively mitigate fluctuations in wind power output, improve energy storage utilization, and avoid redundant energy storage capacity.

Building on the first year's energy storage allocation, the new grid-connection mechanism further raises the scoring criteria for the feed-in tariffs of the two power stations. Based on the optimization results achieved after the first year's allocation, the criteria are increased by 5% compared to the first year to strengthen incentives for energy storage allocation at the power stations and enhance the reliability of their long-term power output. By re-solving the energy storage configuration optimization model, the optimal additional storage configuration for Station A in the second year was determined to be: α = 4.00%, β = 3h, corresponding to an additional storage capacity of 8 MW/24 MWh; the optimal additional storage configuration for Station B was determined to be: α = 4.50%, β = 3h, corresponding to an additional storage capacity of 9 MW/27 MWh. This scheme continues to aim for "marginal cost-benefit balance," ensuring the maximization of the power plant's net revenue.

Compared to the pre-storage configuration and the first year, the output deviation at Power Plant A has further decreased. The average output deviations for Scenarios 1, 2, and 3 have dropped to 3.23%, 13.14%, and 12.64%, respectively, while the overall output deviation has decreased from 13.18% in the first year to 9.67%; For Plant B, the average output deviation in Scenarios 1, 2, and 3 decreased to 3.58%, 12.69%, and 13.07%, respectively, while the overall output deviation dropped from 14.30% in the first year to 9.78%. It should be noted that the reduction in deviation in the second year was significantly lower than in the first year. The primary reason is that the deployment of energy storage in the first year had already mitigated approximately 80% of the "low-cost, optimizable deviations"—such as significant wind power curtailment and large output shortfalls. The remaining deviations were mostly minor fluctuations with strong randomness, requiring a higher capacity of energy storage to further suppress them. This led to a further increase in energy storage costs, while the marginal benefit of deviation mitigation gradually approached saturation.

The comparison of annual revenue metrics for Power Stations A and B before and after energy storage deployment is shown in Tables 2 and 3.

Table 2: Annual Profit of Power Station A Before and After the Participation of Energy Storage.

Energy Storage Participation	Net Income (10,000 yuan)	Variance Cost (10,000 yuan)	Total power deviation	Energy Storage Revenue (10,000 yuan)	Percentage of Revenue from Energy Storage
Before Participating	9215.88	2318.68	26.69%	0	0
First year of participation	9723.20	2065.61	13.18%	530.15	4.39%
Participating for the second year	9897.85	1862.90	9.67%	781.10	6.49%

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Table 3: Annual Profit of Power Station B Before and After the Participation of Energy Storage.

Energy Storage Participation	Net Income (10,000 yuan)	Variance Cost (10,000 yuan)	Total power deviation	Energy Storage Revenue (10,000 yuan)	Percentage of Revenue from Energy Storage
Before Participating	9139.54	2693.42	33.03%	0	0
First year of participation	9695.43	2312.96	14.30%	596.68	4.83%
Participating for the second year	9807.16	1999.67	9.78%	890.29	7.29%

As shown in Table 2, Station A’s deviation costs decreased significantly in the first year of the allocation and reserve program, falling from 23.1868 million yuan to 20.6561 million yuan, a decrease of 10.91%; net revenue increased from 92.1588 million yuan to 97.2320 million yuan, an increase of 5.51%. As shown in Table 3, after the first year of energy storage deployment, Station B’s deviation costs decreased from 26.9342 million yuan to 23.1296 million yuan, a reduction of 14.13%; net revenue increased from 91.3954 million yuan to 96.9543 million yuan, an increase of 6.08%. These results validate the dual benefits of energy storage deployment: on the one hand, by smoothing output fluctuations, it improves the comprehensive reliability score of wind power output, thereby securing a higher feed-in tariff; on the other hand, by reducing output deviations, it lowers penalty costs, ultimately increasing the power plant’s revenue. Furthermore, the greater the initial forecast inaccuracy of a power plant, the more significant the improvement in benefits. This also addresses the industry’s current situation where energy storage systems are often built but not utilized, or used inefficiently.

In the second year, the deviation costs for both power stations decreased further compared to the first year. Power Station A’s deviation cost dropped to 18.629 million yuan, a decrease of 9.38%, while Station B’s costs dropped to 19.9967 million yuan, a decrease of 13.54%. The rate of decrease for both stations was slightly lower than in the first year. On the other hand, the growth in net revenue significantly narrowed: Station A’s net revenue increased to 98.9785 million yuan, a rise of only 1.79%, while Station B’s net revenue increased to 98.0716 million yuan, representing a growth of only 1.15%. This further validates the marginal saturation characteristic of energy storage on power plant profitability.

Under the new grid-connected mechanism, the improvement in power plant profitability resulting from energy storage configuration exhibits a significant “marginal saturation effect”: in the first year, the deployment of energy storage can achieve a substantial reduction in deviation costs and a significant increase in net revenue, marking a critical phase for optimizing power plant profitability; In the second year, the energy storage configuration plan must be dynamically optimized in conjunction with adjustments to the feed-in tariff standards—such as extending the duration of energy storage deployment or adjusting the proportion of energy storage—to balance the costs of energy storage with the additional revenue generated. In the future, by further integrating iterative changes in electricity pricing policies, a dynamic optimization model for energy storage configuration at power stations can be established, providing more precise decision-making support for energy storage deployment at renewable energy power stations.

5. Conclusions

This study introduces a mechanism linking forecast reliability with energy storage configuration to enhance renewable energy integration into the grid. By combining forecast accuracy and storage gains into a comprehensive reliability score, renewable energy plants can optimize energy storage deployment and secure higher feed-in tariffs, transforming storage from a passive support into an active operational and economic tool. The methodology integrates K-means clustering based on the Elbow Method to generate typical wind power scenarios, reducing uncertainty while preserving statistical characteristics. A genetic algorithm is employed to optimize storage capacity and charging/discharging strategies under constraints of allocation ratio, storage duration, grid balance, and operational limits. Case studies of two 200 MW wind farms show significant reductions in output deviations, improved reliability scores, and increased net revenue. The results reveal a marginal saturation effect of energy storage: initial deployment provides substantial benefits, while further expansion yields smaller incremental gains. Plants with lower initial forecast accuracy experience greater improvements, emphasizing the need for site-specific storage strategies. Beyond economic benefits, this mechanism enhances system-level stability by mitigating renewable output fluctuations and promoting efficient

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utilization of installed storage capacity. It provides practical guidance for policymakers and operators to design incentive-based grid-connection mechanisms that align financial rewards with operational performance and is scalable to other renewable sources and hybrid systems, offering a robust approach to high-penetration renewable energy power systems. In summary, linking forecast reliability with energy storage deployment establishes a proactive, market-driven strategy for renewable energy integration, improving profitability, reducing output uncertainty, and strengthening grid stability while providing a practical model for optimizing renewable energy utilization in future power systems.

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