energies

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Cooperative Construction of Renewable Energy and Energy Storage System: Research on Evolutionary Game Model Based on Continuous Strategy and Random Disturbance

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Abstract: As the global push toward carbon neutrality accelerates, cooperation between power generation enterprises and energy storage companies plays a crucial role in the low-carbon transition of energy systems. However, there remains a lack of research on the stochastic dynamic mechanisms of cooperation evolution. This paper develops a stochastic evolutionary game model to analyze the cooperation evolution pathways between power generation enterprises and energy storage companies under different market parameter conditions. Sensitivity analysis is conducted to reveal the impact of factors such as market prices and power capacity on cooperation willingness. The results indicate that the dispatch optimization capability of storage technology and policy incentives significantly influence the willingness to cooperate. The study suggests that governments should enhance policy support and technological innovation to promote the sustainable development of energy systems.

Keywords: cooperative development; energy storage; renewable energy; stochastic evolutionary game

Citation: He, W.; Liu, R.; Han, T.; Zhang, J.; Lei, Y.; Xu, S.; Yu, H.; Li, Z. Cooperative Construction of Renewable Energy and Energy Storage System: Research on Evolutionary Game Model Based on Continuous Strategy and Random Disturbance. *Energies* **2024**, *17*, 5858. https://doi.org/10.3390/en17235858

Academic Editor: Ahmed Abu-Siada

Received: 29 October 2024
Revised: 9 November 2024
Accepted: 20 November 2024
Published: 22 November 2024

1. Introduction

Achieving global carbon neutrality has become one of the most critical objectives in combating climate change. In recent years, major economies have committed to reducing greenhouse gas emissions and transitioning to more sustainable energy systems, with targets set for reaching peak emissions and carbon neutrality within the next few decades [1,2]. This transition involves a large-scale deployment of renewable energy sources, such as wind, solar, and hydropower, driven by the need to reduce fossil fuel dependency and enhance energy security. However, renewable energy is inherently variable and intermittent, making it challenging to maintain a stable energy supply. These challenges manifest in several critical areas, including the efficient absorption of energy into the grid, the balancing of power supply and demand, and the overall reliability of power systems [3,4]. As the share of renewables increases globally, addressing these challenges has become a focal point for both policymakers and industry stakeholders.

Energy storage systems are widely recognized as a key solution to these issues, as they provide flexibility in energy systems by storing excess energy during periods of low demand and releasing it when demand peaks. This capability not only helps balance supply and demand but also enhances grid stability, making energy storage essential for integrating renewable sources into the power system [5,6]. In addition, energy storage can help reduce grid congestion, improve the efficiency of power generation, and provide ancillary services to the grid, further supporting the transition to low-carbon energy systems [7]. However, despite these benefits, energy storage investments are often constrained by several barriers. High initial capital costs, uncertain long-term returns, and regulatory complexities create significant risks for investors and limit the willingness of renewable energy enterprises to incorporate storage solutions [8]. Consequently, the deployment of storage systems is often inadequate, leading to missed opportunities for optimizing renewable integration and achieving sustainable energy transitions [9].

To address these issues, this study develops an evolutionary game model involving renewable energy generation enterprises and energy storage companies. The model employs continuous strategy sets and Gaussian white noise stochastic disturbances to analyze cooperation dynamics under varying market conditions. The continuous strategy set captures the gradual and flexible nature of cooperation decisions, while the stochastic disturbances simulate the uncertainty caused by market fluctuations. It is important to note that the entities in this study represent a class of market participants rather than individual companies. Evolutionary game theory is particularly well-suited for multi-agent systems, as it analyzes the strategic interactions and evolutionary processes among different groups of entities, revealing the dynamic trends of overall market behavior. This modeling approach provides a more comprehensive representation of the cooperation mechanisms between renewable energy generation and energy storage enterprises, offering theoretical support for optimizing market operations and enhancing system efficiency [10].

The findings suggest that cooperation between renewable energy enterprises and energy storage providers can be significantly enhanced through market incentives and improved collaboration mechanisms. However, without sustained incentives, cooperation willingness declines over time, illustrating the complexities of maintaining long-term cooperation. Sensitivity analysis reveals that factors such as higher electricity prices, increased generation capacity, and effective cooperation mechanisms positively impact cooperation sustainability.

The paper is structured as follows: Section 2 reviews the current literature on renewable energy and energy storage cooperation; Section 3 presents the model and its evolutionary dynamics; Section 4 conducts simulation analyses under different parameters; Section 5 provides further discussion on the power levels of renewable energy, the power levels of energy storage, and the location of energy storage; and Section 6 concludes with key findings and policy recommendations for optimizing cooperation between the renewable energy and energy storage sectors.

2. Literature Review

Driven by global carbon neutrality goals and the transition to sustainable energy, the integration of renewable energy into power systems has been widely studied. This integration poses unique challenges, as renewable sources like wind, solar, and hydropower are inherently intermittent and variable. Addressing these challenges requires the development of reliable balancing mechanisms to ensure energy stability and reliability. Among these mechanisms, energy storage systems (ESSs) have garnered significant attention due to their flexibility in storing surplus energy and releasing it during peak demand. Several studies emphasize the crucial role of energy storage in enhancing grid stability, optimizing energy dispatch, and supporting large-scale renewable integration.

Despite the potential advantages of energy storage systems, they face significant economic barriers. High upfront costs, uncertain returns, and policy risks make it difficult for renewable energy enterprises to widely adopt storage solutions. Steckel [11] studied the levelized cost of storage (LCOS), finding that while storage technologies are becoming increasingly cost competitive, economic obstacles still hinder large-scale deployment. The International Renewable Energy Agency (IRENA) [5] also points out that while storage costs are decreasing, economic feasibility remains a critical bottleneck for many investors.

To overcome these barriers, several researchers have proposed different economic models. For instance, Ning et al. [12] analyzed the economic impact of energy storage under various pricing mechanisms, finding that dynamic pricing can enhance the economic attractiveness of storage investments. Additionally, Hoang and Nguyen [13] proposed a mechanism combining government subsidies with market-driven rewards to improve the economic viability of storage projects. These models suggest that effective economic incentives are essential for overcoming the financial barriers faced by storage investors and renewable energy generators.

Collaboration between renewable energy generation enterprises and energy storage companies is considered a key factor in optimizing storage utilization and improving system efficiency [14]. Korpaas et al. [15] developed a game-theoretic model to explore the cooperative behavior between wind farms and storage providers. The study found that cooperation can significantly reduce wind power variability and enhance grid reliability. Similarly, Nazari et al. [16] proposed a joint investment strategy for renewable energy and storage enterprises, demonstrating how joint investment can maximize utilization while improving the profitability of renewable-generation assets. He et al. [17] examined the willingness of renewable energy enterprises and storage companies to cooperate under different market mechanisms. Their findings indicate that in competitive markets, firms are more likely to cooperate if there are clear economic benefits, such as reduced dispatch costs or increased peak revenues. These studies underscore the importance of designing cooperation models that align the interests of both parties, thereby promoting more efficient integration of the energy storage systems.

Game theory has been widely applied to analyze strategic interactions in energy markets, including cooperation between renewable energy generators and energy storage companies [18]. Evolutionary game theory (EGT), which models the dynamic adaptation of strategies over time, has become an effective tool for understanding the gradual and complex evolution of cooperative behavior in energy systems [19]. Sun et al. [20] applied evolutionary game theory to simulate interactions between solar power enterprises and battery storage providers, considering factors like capacity constraints, market fluctuations, and strategic uncertainty. Their study indicates that when strong market incentives and stable policy frameworks are present, the cooperation evolution between solar generators and storage providers is smoother. Introducing stochastic disturbances into evolutionary models is another area of research. Wang et al. [21] used Gaussian white noise to simulate unpredictable market fluctuations, demonstrating how randomness affects cooperation dynamics. Their findings reveal that while stochastic disturbances may disrupt cooperation stability in the short term, they also create opportunities for adaptation and learning, potentially leading to more resilient cooperation in the long run. This approach is particularly relevant in the context of renewable energy, where market conditions are inherently uncertain.

Compared with traditional binary strategy models, continuous strategy models provide a more realistic depiction of cooperative behavior in energy markets [22]. Continuous strategies allow players to adopt varying levels of effort in cooperation, reflecting the flexibility and gradual nature of decision making in energy systems. Zhou et al. [23] developed a continuous strategy model to study interactions between wind farms and storage companies, finding that such models capture a wider range of strategic behaviors and more accurately predict outcomes in real-world scenarios. Policy support is a critical driver for the successful integration of renewable energy and energy storage systems [24]. Studies have shown that subsidies, tax incentives, and regulatory frameworks can significantly enhance the economic feasibility of energy storage [25]. For instance, Bian [26] found that targeted subsidies for joint renewable-storage projects can increase cooperation rates and improve system efficiency. Additionally, Abolhosseini and Heshmati [27] emphasized the importance of carbon trading mechanisms and renewable portfolio standards in incentivizing energy storage deployment.

The literature on renewable energy and energy storage integration covers a wide range of economic, technical, and policy-related studies. Economic models highlight the financial incentives needed to overcome investment barriers, while cooperation models emphasize the importance of aligning the interests of renewable energy enterprises and storage providers. Evolutionary game theory and continuous strategy models provide valuable insights into the dynamics and gradual evolution of cooperation in energy systems. Finally, policy studies underscore the critical role of regulatory frameworks in supporting storage deployment and sustaining renewable integration. Based on existing research, this study constructs an evolutionary game model that incorporates continuous strategies and stochastic disturbances to better understand the dynamics of cooperation between renewable energy generators and storage companies. This approach aims to provide a comprehensive analysis of the factors driving long-term cooperation and proposes policy recommendations to enhance the effectiveness of renewable–storage integration strategies.

3. The Model

3.1. Model Assumptions

Assumption 1. *Both renewable energy power generation companies and energy storage companies are composed of multiple companies of the same type, each representing a type of market entity. The decision variable for each type of company is defined as its degree of cooperation. Specifically, the effort level of the power generation enterprise is represented by a, and the effort level of the energy storage company is represented by b. Both a and b are continuous variables within the range [0, 1], with probability densities $f(a)$ and $f(b)$, respectively, capturing the gradual effort levels of both parties in cooperation. When $a = 1(b = 1)$, the renewable energy generation enterprise (or energy storage company) fully opts for cooperation; when $a = 0(b = 0)$, they completely choose not to cooperate, interacting through capacity leasing. In this model, both parties can adjust their respective degrees of cooperation to optimize their revenues and costs. The use of continuous variables allows for a realistic depiction of the flexible choices and transition states between joint construction and capacity leasing as two extreme strategies.*

Assumption 2. *In the electricity market, a company's revenue is closely related to its production capacity. Power generation enterprises earn revenue by selling electricity to the market, while energy storage companies generate income by storing and releasing electricity based on peak–valley price differences. Therefore, the revenue of power generation enterprises depends on the amount of electricity generated, whereas the revenue of energy storage companies depends on their capacity to store and release electricity. Meanwhile, the power output of renewable energy enterprises is often influenced by natural conditions, such as wind speed and solar radiation, which introduces significant volatility [28]. Through cooperation, energy storage companies can help power generation enterprises balance their electricity output, thus reducing the risks associated with price fluctuations in the electricity market. Both the market revenue of power generation enterprises and that of energy storage companies are linked to their production capacity, which can be further optimized through increased cooperation willingness. The market revenue of power generation enterprises, $R_{renewable}$, is related to the power generation capacity Q and the market electricity price P. Cooperation willingness a increases power generation capacity, and thus, the revenue can be expressed as*

$$R_{renewable} = PQ(1 + \kappa_1 a), \tag{1}$$

where the parameter κ_1 represents the impact of cooperation willingness a on increasing power generation capacity. As a increases, power generation enterprises improve their power output capacity through optimized dispatch. Similarly, the market revenue of energy storage companies, $R_{storage}$, is related to the peak–valley price difference ΔP, and cooperation willingness b increases storage capacity, thus enhancing revenue.

$$R_{storage} = \Delta PQ(1 + \kappa_2 b), \tag{2}$$

where the parameter κ_2 represents the impact of cooperation willingness b on optimizing storage capacity.

Assumption 3. *When power generation enterprises and energy storage companies cooperate, their revenues are no longer independent, but generate incremental benefits through synergy. Cooperation allows power generation enterprises to better handle market fluctuations, while energy storage* *companies can fully utilize the storage facilities and optimize their charging and discharging strategies [29]. This process effectively increases the market value of electricity, resulting in additional market revenue, expressed as follows:*

$$S_{joint} = \alpha_1 ab \tag{3}$$

where α_1 is the coefficient of additional market revenue from cooperation, and ab reflects the interaction of both parties' cooperation willingness. Maximum cooperative benefits can be achieved only when both parties exhibit a high willingness to cooperate.

Assumption 4. *To promote the development of clean energy, governments often provide policy subsidies, especially for projects that integrate renewable energy generation with energy storage technology. These subsidies aim to increase the share of renewable energy in the energy mix and facilitate the transition of the power sector toward low-carbon and environmentally friendly development. Additionally, these subsidy policies are closely linked to the level of cooperation between enterprises, as cooperation enables better resource integration and improved renewable energy utilization. The amount of government subsidies depends on the cooperation willingness of both power generation enterprises and energy storage companies. Therefore, the subsidy is expressed as*

$$C_{subsidy} = \beta_1 ab, \tag{4}$$

where β_1 is the government subsidy coefficient. As the cooperation willingness a and b increase, the subsidies received by the enterprises also increase. These subsidies not only enhance the enterprises' revenue but also strengthen their motivation for sustained cooperation.

Assumption 5. *In the process of electricity dispatch, power generation enterprises often encounter dispatch costs due to the imbalance between electricity supply and demand. This is particularly evident in renewable energy generation, where the instability of wind and solar power leads to greater fluctuations in power output, thereby increasing dispatch costs. By cooperating with energy storage companies, power generation enterprises can better balance their power output, using storage systems to store electricity during price troughs and release it during peaks, thus reducing high dispatch costs. The dispatch cost decreases as cooperation willingness increases and is expressed as*

$$C_{dispatch} = \gamma_1 (1 - ab) Q, \tag{5}$$

where γ_1 is the dispatch cost coefficient, and as the cooperation willingness ab increases, the dispatch costs decrease.

Assumption 6. *For renewable energy generation enterprises, revenue is derived not only from electricity sales but also from the trading of green certificates. Green certificates are a policy tool designed to promote the production and use of renewable energy, providing an additional income source for renewable energy projects. When power generation enterprises produce clean energy, they earn green certificates, which can then be sold to other enterprises or individuals (typically, electricity companies or large customers with renewable energy quota obligations) to generate additional revenue. The number of green certificates obtained by a power generation enterprise is proportional to the amount of renewable energy it produces, and an increase in cooperation willingness a enhances power output, enabling the enterprise to obtain more green certificates. The market price of green certificates fluctuates with market supply and demand, so revenue is also affected by price changes. As cooperation willingness a increases, the production of renewable energy rises, resulting in a corresponding increase in the number of green certificates obtained, and thus, an increase in green certificate market revenue. The green certificate market revenue can be expressed as*

$$R_v = \theta_1 a + \theta_2 \ln(1 + a), \tag{6}$$

where θ_1 and θ_2 are the revenue coefficients for the green certificate market. As cooperation willingness a increases, power generation enterprises can obtain more green certificates and sell them in *the market, thus increasing green certificate market revenue. The logarithmic function $ln(1+a)$ is introduced to reflect the incremental effect of increased cooperation willingness on revenue growth.*

Assumption 7. *If the energy storage company chooses not to cooperate with the power generation enterprise, it can earn revenue by leasing storage capacity to other enterprises or entities in the market. The capacity of storage systems is limited, making storage leasing highly profitable during periods of peak electricity demand. The leasing market provides an alternative revenue source for energy storage companies, especially when their cooperation willingness with power generation enterprises is low. In such cases, leasing becomes particularly important. When cooperation willingness is low, energy storage companies are more inclined to earn revenue through leasing storage systems. As cooperation willingness increases, more storage capacity is allocated to cooperation with power generation enterprises, reducing leasing income. The deeper the cooperation, the lower the leasing demand of energy storage companies. The revenue from capacity leasing can be expressed as*

$$C_{lease} = \beta_3(1 - ab), \tag{7}$$

where β_3 is the leasing income coefficient, and as cooperation willingness ab increases, the storage capacity available for leasing decreases, leading to a reduction in leasing income.

Assumption 8. *The construction and operation costs of storage systems are high, but cooperation with power generation enterprises enables the optimized management of storage systems, reducing operational costs. In particular, with high cooperation willingness, the storage system can adopt more efficient dispatch strategies, reducing the frequency of charging and discharging, optimizing the utilization of storage equipment, and lowering depreciation and maintenance costs. Therefore, there is a negative relationship between cooperation willingness and storage costs, expressed as*

$$C_{storage} = \gamma_2 \frac{1}{1+\lambda b}, \tag{8}$$

where γ_2 is the storage cost coefficient, and λ is the dispatch optimization coefficient. As cooperation willingness b increases, storage costs decrease.

Based on the above assumptions, the revenue functions of renewable energy generation enterprises and energy storage companies, given a and b, are as follows:

$$\pi_1(a,b) = R_{renewable} + S_{joint} + C_{subsidy} - C_{dispatch} + R_v \tag{9}$$

$$\pi_2(a,b) = R_{storage} + S_{joint} - C_{lease} - C_{storage} \tag{10}$$

3.2. Analysis of the Binary Strategy Set Game Model

In the traditional binary strategy set context, the strategy choices of renewable energy generation enterprises and energy storage companies are characterized as "either-or", i.e., $a \in \{0,1\}, b \in \{0,1\}$. Assume that the probability of cooperation for renewable energy generation enterprises is x, and the probability of cooperation for energy storage companies is y.

Evolutionary Game Model with Binary Strategy Set

Substituting $a = \{0,1\}$ and $b = \{0,1\}$ into Equations (9) and (10), we obtain the payoff matrix for the evolutionary game model, as shown in Table 1.

According to Table 1, the replication dynamic equations of renewable energy power generation companies and energy storage companies are as follows:

$$dx = x(1-x)(PQ\kappa_1 + Q\gamma_1 y + \alpha_1 y + \beta_1 y + \theta_1 + \theta_2 \log(2))dt \tag{11}$$

$$dy = \frac{y(1-y)(\Delta PQ\kappa_2\lambda + \Delta PQ\kappa_2 + \alpha_1\lambda x + \alpha_1 x - \beta_3\lambda x - \beta_3 x + \gamma_2\lambda)}{\lambda+1}dt \tag{12}$$

The dynamic system analysis of the replication dynamic Equations (11) and (12) shows that there are five stationary points in the game system: $(1,1)$, $(1,0)$, $(0,1)$, $(0,0)$, $\left(x^{*}, y^{*}\right)$. Among them,

$$x^{*} = \frac{\Delta PQ\kappa_2\lambda + \Delta PQ\kappa_2 + \gamma_2\lambda}{\alpha_1\lambda + \alpha_1 + \beta_3\lambda + \beta_3} \tag{13}$$

$$y^{*} = \frac{PQ\kappa_1 + \theta_1 + \theta_2\log(2)}{Q\gamma_1 + \alpha_1 + \beta_1} \tag{14}$$

Let $A = PQ\kappa_1 + \theta_1 + \theta_2\log(2) > 0$, $B = \Delta PQ\kappa_2\lambda + \Delta PQ\kappa_2 + \gamma_2\lambda > 0$, $C = \alpha_1\lambda + \alpha_1 + \beta_3\lambda + \beta_3 > 0$, $D = Q\gamma_1 + \alpha_1 + \beta_1 > 0$. Next, we analyze the equilibrium situation based on the eigenvalues of the five stationary points.

Table 1. Payoff matrix for the evolutionary game model with binary strategy set.

Both Parties in the Game		**Renewable Energy Generation Companies**	
		Cooperation (x)	**Non-Cooperation ($1-x$)**
Energy Storage Companies	Cooperation (y)	$PQ(1+\kappa_1) + \alpha_1 + \beta_1 + \theta_1 + \theta_2\ln(2)$ $\Delta PQ(1+\kappa_2) + \alpha_1 - \gamma_2\frac{1}{1+\lambda}$	$PQ - \gamma_1 Q$ $\Delta PQ(1+\kappa_2) - \beta_3 - \gamma_2\frac{1}{1+\lambda}$
	Non-cooperation ($1-y$)	$PQ(1+\kappa_1) - \gamma_1 Q + \theta_1 + \theta_2\ln(2)$ $\Delta PQ - \beta_3 - \gamma_2$	$PQ - \gamma_1 Q$ $\Delta PQ - \beta_3 - \gamma_2$

From Table 2, it can be observed that the only Evolutionarily Stable Strategy (ESS) is $(1,1)$, indicating that the system reaches a stable state when both renewable energy generation enterprises and energy storage companies choose to cooperate. All other equilibrium points—$(1,0)$, $(0,1)$, $(0,0)$, $\left(x^{*}, y^{*}\right)$—are unstable, implying that if either or both parties do not cooperate, the system will deviate from these equilibrium points. Overall, the system tends to move toward the cooperative equilibrium $(1,1)$, suggesting that in the evolutionary process, both power generation enterprises and energy storage companies will ultimately choose to cooperate. This is the only stable state in the evolutionary game model with a binary strategy set.

Table 2. The payoff matrix of the evolutionary game model determined by the binary strategy set.

Stationary Point	**Eigenvalue**	**ESS**
$(1,1)$	$-A-D, -\frac{B+C}{\lambda+1}$	Yes
$(1,0)$	$A+D, -\frac{B}{\lambda+1}$	No
$(0,1)$	$-A, \frac{B+C}{\lambda+1}$	No
$(0,0)$	$A, \frac{B}{\lambda+1}$	No
(x^*, y^*)	$-\frac{1}{\lambda+1}\sqrt{\frac{AB(A+D)(B-C)}{(\alpha_1-\beta_3)D}}$, $\frac{1}{\lambda+1}\sqrt{\frac{AB(A+D)(B+C)}{(\alpha_1-\beta_3)D}}$	Yes

3.3. Stochastic Evolutionary Game Model with Continuous Strategy Set

To better reflect the uncertainty of the real world and the bounded rationality of players in adjusting their strategies, this study incorporates Gaussian white noise as a stochastic disturbance into the traditional replicator dynamic equations. Moreover, evolutionary game theory treats the players as populations rather than individuals, where members within the population continuously adjust their strategy choices to optimize their own payoffs. Thus, the probability of adopting a specific strategy within the population essentially follows a continuous distribution.

Since there are many implicit factors in the cooperation process between renewable energy generation enterprises and energy storage companies, their decisions often transition from no cooperation to full cooperation as continuous variables rather than a binary relationship. The diversity in strategy choices among players also increases the complexity of the game. In this section, we assume that $a \in [0,1], b \in [0,1]$, with their probability densities represented as $f(a)$ and $f(b)$, respectively, providing a more realistic depiction of the gradual changes in cooperation levels between both parties. This enables the analysis of the evolutionary pathway of cooperation between renewable energy generation enterprises and energy storage companies under a continuous strategy set.

Furthermore, this section introduces a stochastic disturbance term B_t into the replicator dynamic equations, where $\forall s, t > 0, B_{s+t} - B_t \sim N(0,t)$, representing the impact of random disturbances on the evolutionary speed of strategies. The stochastic disturbance is expressed as $x(1-x)dB_t$ and $y(1-y)dB_t$, minimizing the impact of external random disturbances when the probability of strategy choice for renewable energy generation enterprises and energy storage companies is at extreme values.

In evolutionary game models, the introduction of stochastic disturbances aims to more accurately reflect the uncertainties present in complex market environments. These disturbances simulate how firms adjust their strategies in dynamic settings, helping to analyze the evolutionary pathways of the system under varying conditions. In reality, firms not only operate in stable market environments but must also contend with fluctuations and shocks stemming from policies, market dynamics, and natural factors. Therefore, the inclusion of stochastic disturbances enriches the model's dynamic characteristics and provides decision makers with more valuable analytical tools.

Gaussian white noise is a typical form of stochastic disturbance that simulates continuous small-scale market fluctuations. Its theoretical significance lies in capturing frequent and minor changes, such as intraday electricity price volatility or variations in renewable energy output due to weather changes. These disturbances generally do not affect the overall stability of the system, but they have a persistent impact on firms' short-term profitability and strategic choices. In practice, Gaussian white noise reflects how firms adjust their strategies incrementally under normal market conditions to optimize cooperation levels and adapt to minor market fluctuations. It can be expressed as

$$B_t^G \sim N\left(0, \sigma^2 t\right), \tag{15}$$

where σ^2 is the noise intensity controlling the amplitude of the disturbances. The increment $B_{s+t} - B_t$ over each time step is independent and follows $N(0,t)$.

Poisson noise is mainly used to describe sparse, discrete, and sudden events, such as sudden policy changes, equipment failures, or spikes in demand during peak periods. The theoretical significance of Poisson noise lies in capturing the severe disruptions caused by low-frequency, high-impact events. Although these events occur infrequently, each occurrence can have a significant impact on cooperative strategies. In practice, firms need to quickly adjust their strategies following such sudden events to mitigate losses and maintain market competitiveness. Thus, the introduction of Poisson noise helps to study firms' response mechanisms and the evolutionary pathways of cooperation under abrupt environmental changes. It can be expressed as

$$B_t^P \sim Poisson(\lambda t), \tag{16}$$

where λ is the average number of events occurring per unit of time. The increment of the disturbance within the time interval $[t, t+\Delta t]$ is $\Delta B_t = N(t+\Delta t) - N(t)$, where $N(t)$ is a Poisson process.

Laplacian noise is suitable for simulating extreme market fluctuations, such as a sudden drop in wind or solar power output due to extreme weather or drastic price changes caused by supply–demand imbalances. Laplacian noise is characterized by its sharp peaks and long tails, and its theoretical significance lies in revealing the profound impact of extreme events on system stability and strategic choices. In practice, this noise helps analyze how firms adjust their cooperation strategies under extreme conditions to minimize the risks of market volatility. It can be expressed as

$$B_t^L \sim Laplacian(\mu, b), \tag{17}$$

where μ is the mean and b is the scale parameter controlling the amplitude of the disturbances.

The introduction of stochastic disturbances allows the model to simultaneously account for routine fluctuations, sudden events, and extreme conditions in system evolution. Different types of disturbances provide theoretical support for studying strategy evolution in diverse market environments and offer practical guidance for decision making under uncertainty. For instance, policymakers can simulate various disturbance scenarios to evaluate the effectiveness of different market mechanisms and incentive policies, while firms can use the model to predict optimal cooperation strategies and risk response measures under specific market conditions. Ultimately, these analyses provide systematic tools to enhance market resilience and optimize cooperation frameworks.

As a result, the average expected payoffs for renewable energy generation enterprises and energy storage companies are as follows:

$$\overline{EX} = \int_0^1 \int_0^1 \Big(R_{renewable} + S_{joint} + C_{subsidy} - C_{dispatch} + R_v\Big) f(b) f(a) dbda \tag{18}$$

$$\overline{EY} = \int_0^1 \int_0^1 \big(R_{storage} + S_{joint} - C_{lease} - C_{storage}\big) f(a) f(b) dadb \tag{19}$$

Therefore, the replication dynamic equations of renewable energy power generation companies and energy storage companies are

$$dx(a,t) = f(a)\big[EX(a) - \overline{EX}\big]dt + [1 - f(a)]f(a)dB_t \tag{20}$$

$$dy(b,t) = f(a)\big[EY(b) - \overline{EY}\big]dt + [1 - f(b)]f(b)dB_t \tag{21}$$

where

$$X(a) = \int_0^1 \Big(R_{renewable} + S_{joint} + C_{subsidy} - C_{dispatch} + R_v\Big) f(b) da \tag{22}$$

$$EY(b) = \int_0^1 \big(R_{storage} + S_{joint} - C_{lease} - C_{storage}\big) f(a) db \tag{23}$$

Due to the introduction of stochastic disturbance terms, it becomes challenging to use stochastic differential equations to analyze the stability of the evolutionary game system. Therefore, this section applies the Lyapunov stability criterion from stochastic dynamical systems to assess the stability of the equilibrium solution, exploring the evolutionary pathway of cooperation between renewable energy generation enterprises and energy storage companies. The mathematical foundation is as follows.

Let the stochastic process $X = \{X(t), t > 0\}$ be represented by the differential equation

$$\begin{cases} dX(t) = f(t, X(t))dt + g(t, X(t))dB_t \\ X(t_0) = x_0 \end{cases} \tag{24}$$

where there exist a continuously differentiable function $V(t, x)$ and constants c_1 and c_2, such that $c_1|x|^k \leq V(t, x) \leq c_2|x|^k$. If there exists a constant γ, such that $LV(t, x) \leq -V(t, x)$, then the solution to the initial value problem of this differential equation is k-th moment exponentially stable, where

$$LV(t, x) = V_t(t, x) + V_x(t, x) f(t, x) + \frac{1}{2} g^2(t, x) V_{xx}(t, x). \tag{25}$$

In this study, we set $V(t,x) = x^2$ and $V(t,y) = y^2$. For the equilibrium solution of the stochastic evolutionary game with continuous strategies to achieve exponential stability, the following conditions must be satisfied:

$$2\left[EX(a) - \overline{EX}\right] + (1-a)^2 < 0 \tag{26}$$

$$2\left[EY(b) - \overline{EY}\right] + (1-b)^2 < 0 \tag{27}$$

Assuming that a and b follow a normal distribution within the interval $[0,1]$, these conditions can be simplified as follows:

$$\begin{aligned} 2PQa\kappa_1 - PQ\kappa_1 \quad & + Qa\gamma_1 - \frac{Q\gamma_1}{2} + a\alpha_1 + a\beta_1 + 2a\theta_1 - \frac{\alpha_1}{2} - \frac{\beta_1}{2} - \theta_1 + 2\theta_2\log(a+1) - 4\theta_2\log(2) + 2\theta_2 \\ & + (1-a)^2 < 0 \end{aligned} \tag{28}$$

$$\begin{aligned} -\Delta PQ\kappa_2 - 2\Delta Q \quad & + \alpha_1 b - \frac{\alpha_1}{2} + b\beta_3 + \frac{3\beta_3}{2} + \frac{2\gamma_2\log(\lambda+1)}{\lambda} + (1-b)^2 \\ & + \frac{2\left(\Delta PQb^2\kappa_2\lambda + \Delta PQb\kappa_2 + \Delta PQb\lambda + \Delta PQ - b\beta_3\lambda - \beta_3 - \gamma_2\right)}{b\lambda+1} < 0 \end{aligned} \tag{29}$$

From the simplified equations, it is evident that the core of the conditions lies in the fulfillment of the two inequalities. These inequalities correspond to the strategy choices and cooperation levels of the power generation enterprises and energy storage companies under stochastic disturbances, affecting the overall system stability.

In the first inequality, the cooperation improvement coefficient of the power generation enterprise, κ_1, and the dispatch cost, γ_1, play key roles. The inequality can hold only if the increase in revenue is sufficient to offset the negative impact of non-cooperation or insufficient cooperation under stochastic disturbances. Thus, the impact of stochastic disturbances on the power generation enterprise is minimal when the cooperation willingness is near 0 or 1, but disturbances may have a greater impact at intermediate cooperation levels (partial cooperation).

In the second inequality, the cooperation improvement coefficient of the energy storage company, κ_2, and the operational cost of storage equipment, γ_2, are critical factors. Similarly, the system is less affected by external disturbances when the energy storage company's cooperation willingness is low or high, while system volatility may be greater at moderate cooperation levels. Therefore, additional subsidies or revenue increases are needed to counterbalance the impact of disturbances.

4. Simulation Analysis

4.1. Parameter Settings and Simulation Process

For the simulation analysis, this study uses data from the International Renewable Energy Agency (IRENA) and the National Energy Administration. The electricity market price P is set at 0.08 USD/kWh, and the generation capacity Q is set at 100 MW. The cooperation improvement coefficient for power generation enterprises κ_1 is 0.15, while the cooperation improvement coefficient for energy storage companies κ_2 is 0.1. The government subsidy coefficient for cooperative projects β_1 is set at 0.12, the dispatch cost coefficient γ_1 is set at 0.07, and the operational cost coefficient for energy storage γ_2 is 0.05; these values are based on studies in energy economics and storage market reports. The peak–valley price difference ΔP is set at 0.05 USD/kWh according to data from the State Grid Corporation of China, and the leasing income coefficient for energy storage companies β_3 is set at 0.2. The cooperation optimization coefficient λ is 0.1, reflecting the optimization effects of cooperation on dispatch. The stochastic disturbance term B_t is modeled as a standard Gaussian process, $B_t \sim N(0,t)$, representing the impact of external uncertainties on the game process. These parameters provide a realistic representation of the cooperation dynamics between renewable energy generation enterprises and energy storage companies (Table 3). The data sources for this study are provided in Appendix A.

Table 3. Simulation parameters.

Parameter Name	Parameter	Parameter Value
Electricity Market Price	P	0.08 USD/kWh
Generation Capacity	Q	100 MW
Cooperation Improvement Coefficient for Power Generation Enterprises	κ_1	0.15
Cooperation Improvement Coefficient for Energy Storage Companies	κ_2	0.1
Government Subsidy Coefficient	β_1	0.12
Dispatch Cost Coefficient	γ_1	0.07
Operational Cost Coefficient for Energy Storage	γ_2	0.05
Peak–Valley Price Difference	ΔP	0.05 USD/kWh
Leasing Income Coefficient	β_3	0.2
Cooperation Optimization Coefficient	λ	0.1
Stochastic Disturbance Term	B_t	$N(0,t)$

The simulation process depicted in Figure 1 involves an iterative approach to analyze the evolution of cooperation strategies between power generation enterprises and energy storage companies under various stochastic disturbance scenarios. Initially, the system defines decision variables, cooperation levels, and corresponding objective functions for both entities. The process starts by generating random disturbances B_t to simulate market uncertainties. In each iteration, the model updates the cooperation strategies (a and b) based on the replicator dynamic equations, which consider both the expected payoffs and the impact of stochastic disturbances. The updated strategies are then evaluated against the model's constraints, including the non-negativity of profits and the stability criterion. This process continues until convergence is achieved, where both entities reach a stable cooperation level or the system reaches the defined simulation time limit. The results provide insights into how different types of stochastic disturbances affect the cooperation dynamics and the overall system stability.

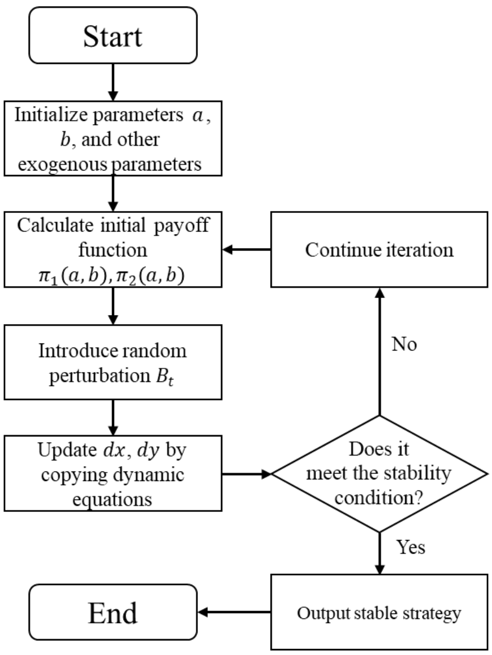

Figure 1. Simulation process.

4.2. Simulation Analysis of the Stochastic Evolutionary Game Model with a Continuous Strategy Set

Based on the parameter settings in Section 4.1, this study presents simulation results depicting the evolution of cooperation willingness between power generation enterprises and energy storage companies over time. The dynamics of this cooperation willingness are influenced by market factors and internal cooperation incentives. Figure 1 illustrates the dynamic evolution of cooperation willingness between power generation enterprises and energy storage companies under four different scenarios: No Noise, Gaussian Noise, Poisson Noise, and Laplacian Noise. Each subplot represents the impact of a specific type of stochastic disturbance on the cooperation dynamics over time. The figure aims to highlight how different types of market uncertainties and external shocks influence the stability and trajectory of cooperative behavior, providing insights into the robustness and adaptability of collaboration strategies in varying market conditions.

From Figure 2, it can be observed that the evolution of cooperation willingness between power generation enterprises and energy storage companies varies significantly under different stochastic disturbance scenarios. In the No Noise scenario, cooperation willingness (a and b) quickly rises to 1, indicating that in a fully deterministic environment, both parties can rapidly achieve a high level of cooperation. In this stable context, collaboration efficiently optimizes their revenues, and policymakers do not need to intervene, allowing firms to maximize profits autonomously. In the Gaussian Noise scenario, continuous small fluctuations cause cooperation willingness to rapidly decline to zero, destabilizing the system. The unpredictability of profits weakens the motivation to cooperate, highlighting the need for policy measures such as price stabilization mechanisms or risk subsidies to mitigate the impact of persistent market volatility. In the Poisson Noise scenario, despite discrete, infrequent shocks such as equipment failures or sudden policy changes, cooperation willingness quickly recovers and converges to 1, demonstrating that low-frequency events have limited impact on long-term cooperation. Managers can rely on contingency plans, while short-term policy support helps firms navigate these disruptions. Conversely, in the Laplacian Noise scenario, extreme events result in a sharp decline in cooperation willingness, with the system struggling to recover. This underscores the severe impact of rare, high-magnitude shocks such as extreme weather or drastic market price changes. In such cases, policymakers must implement strong interventions, including price protection mechanisms or long-term subsidies, while firms should enhance their risk management strategies, such as investing in insurance and disaster preparedness, to cope with extreme volatility.

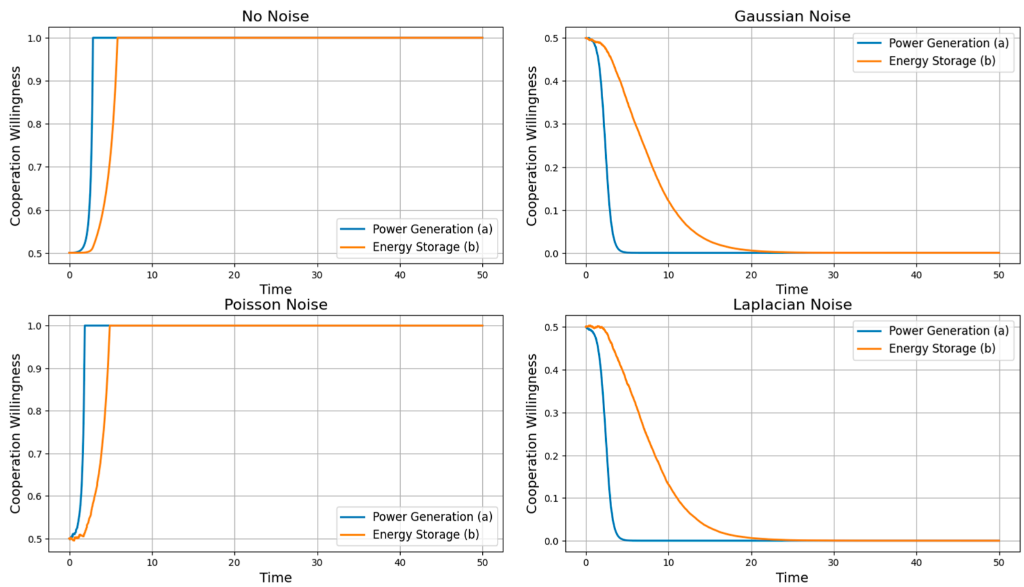

Figure 2. Simulation of the stochastic evolutionary game model with continuous strategy set.

To further analyze the pathways for promoting cooperation between renewable energy generation enterprises and energy storage companies, this study conducts sensitivity analysis on parameters such as electricity market prices.

1. Sensitivity Analysis of Electricity Market Price

Figure 3 shows the sensitivity analysis results of the evolution of cooperation willingness between power generation enterprises (a) and energy storage companies (b) over time under different values of the electricity market price P. The left panel illustrates the evolution of cooperation willingness a of power generation enterprises, while the right panel shows the evolution of cooperation willingness b of energy storage companies. The analysis covers a range of P values, from 0.04 to 0.12 USD/kWh, allowing us to observe the impact of electricity price changes on the cooperation willingness of both parties.

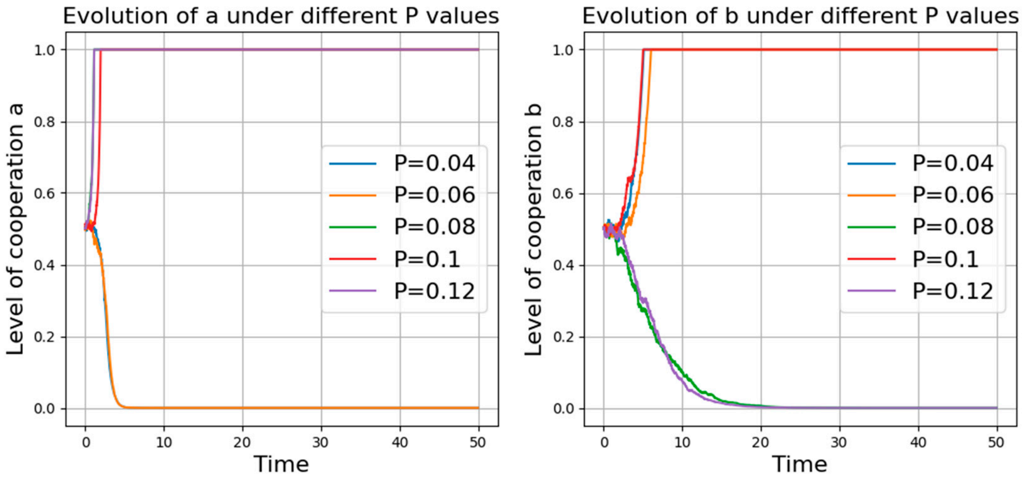

Figure 3. Sensitivity analysis of electricity market price.

As depicted in the Figure 3, an increase in electricity market price P leads to varying degrees of fluctuation in the cooperation willingness of both power generation enterprises and energy storage companies. However, the overall trend is that cooperation willingness declines to zero over time. When P is higher (e.g., 0.12 USD/kWh), the cooperation willingness remains more stable in the early stages, while lower P values result in a faster decline in cooperation willingness. This indicates that higher electricity prices provide greater motivation for cooperation, likely due to the short-term economic benefits derived from elevated market prices.

Nevertheless, relying solely on market prices to drive cooperation is unsustainable in the long run. This finding highlights the significant influence of electricity market prices on the cooperative behavior of renewable energy generation enterprises and energy storage companies. Although higher prices can stimulate short-term cooperation, sustained cooperation requires additional policy interventions and incentives, such as government subsidies or carbon-trading mechanisms, to effectively enhance synergy during the energy transition. This analysis also underscores the importance of enterprises developing flexible cooperation strategies in dynamic market conditions.

2. Sensitivity Analysis of Generation Capacity

Figure 4 presents the sensitivity analysis results of cooperation willingness between power generation enterprises (a) and energy storage companies (b) over time under different levels of generation capacity Q. The left panel shows the evolution of cooperation willingness a for power generation enterprises, while the right panel illustrates the changes in cooperation willingness b for energy storage companies. The analysis covers a range of generation capacity from 50 to 250 MW, aiming to study the impact of changes in generation capacity on the cooperation willingness of both parties.

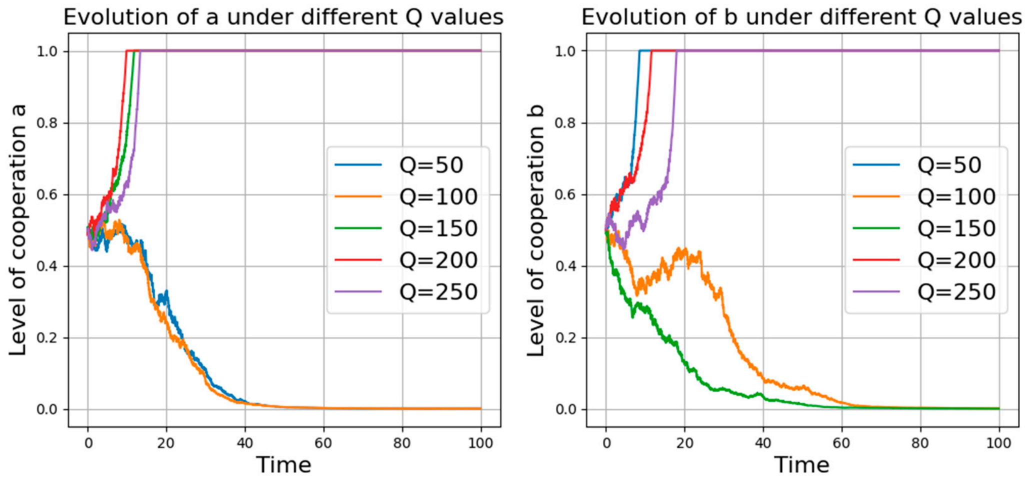

Figure 4. Sensitivity analysis of generation capacity.

From the figure, it is evident that the impact of generation capacity Q on cooperation willingness exhibits a clear nonlinear pattern. As the generation capacity increases, the cooperation willingness of both power generation enterprises and energy storage companies initially shows greater stability, particularly when Q is larger (e.g., $Q = 250$). In such cases, cooperation willingness is maintained for a longer period, with a slower rate of decline. This indicates that higher generation capacity enhances the synergy between power generation enterprises and energy storage companies, leading to stronger cooperation motivation.

Conversely, when the generation capacity is lower (e.g., $Q = 50$), cooperation willingness declines rapidly, suggesting that under low generation capacity, the market and enterprises lack sufficient incentives to maintain long-term cooperation. An increase in generation capacity directly boosts the market competitiveness and revenue potential of power generation enterprises, while stronger cooperation willingness reflects the economies of scale in a high-capacity environment. For energy storage companies, higher generation capacity means more electricity is available for storage and dispatch, leading to greater economic returns. Therefore, increased generation capacity positively influences the profitability of both parties, extending the sustainability of cooperation.

This finding suggests that enterprises should prioritize expanding generation capacity in energy cooperation projects or improving the utilization rate of existing equipment through technological innovation to achieve greater cooperative benefits. It also implies that when selecting cooperation partners, enterprises should prioritize power generation enterprises or energy storage companies with larger capacities to enhance the stability of cooperation. Additionally, enterprises need to optimize internal resource allocation to better cope with potential market fluctuations, ensuring sustained cooperation willingness at a higher level.

3. Sensitivity Analysis of Cooperation Improvement Coefficients

Two sets of figures illustrate the sensitivity analysis results for the cooperation improvement coefficients of power generation enterprises (κ_1) and energy storage companies (κ_2). These coefficients represent the capacity or efficiency improvements achieved through cooperation. By adjusting the values of κ_1 from 0.1 to 0.3 and of κ_2 from 0.05 to 0.25, we can visually observe the evolution of cooperation willingness under different levels of cooperation improvement coefficients.

From Figures 5 and 6, it is clear that as the cooperation improvement coefficients κ_1 and κ_2 increase, the cooperation willingness of both power generation enterprises and energy storage companies demonstrates greater stability and persistence. When κ_1 or κ_2 is high, the cooperation willingness of both parties increases significantly in the initial stages and is maintained for a longer period. Conversely, when κ_1 or κ_2 is low, the cooperation willingness declines rapidly, indicating that it is difficult for both parties to sustain cooperation over the long term. This phenomenon suggests that higher cooperation improvement coefficients directly enhance the cooperative capacity of power generation enterprises and energy storage companies. With higher coefficients, both parties can achieve greater production gains or reduced dispatch costs in a shorter time, providing stronger motivation for sustained cooperation. This not only helps improve operational efficiency for both sides but also reduces market risks to some extent. When cooperation improvement coefficients are low, the cooperative benefits for both parties are minimal, making it difficult to maintain long-term cooperation effectively.

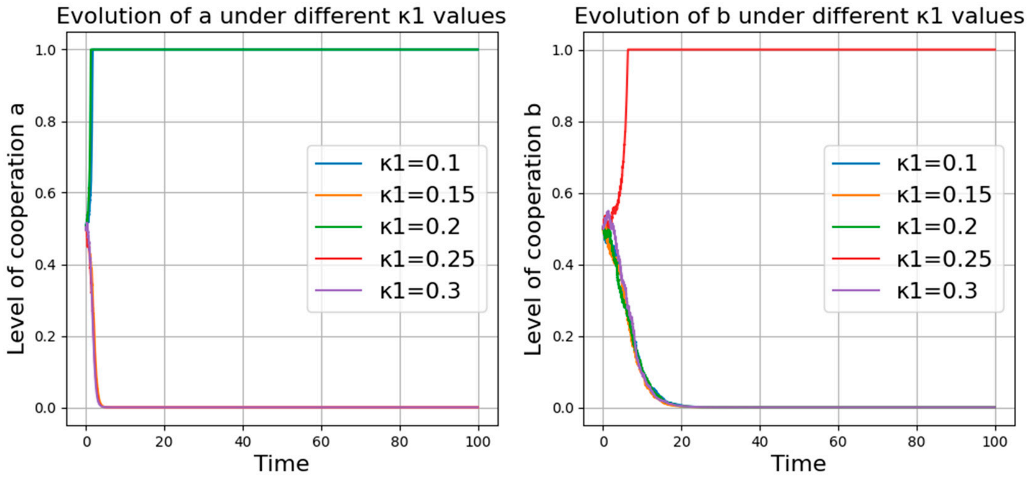

Figure 5. Sensitivity analysis of cooperation improvement coefficient κ_1.

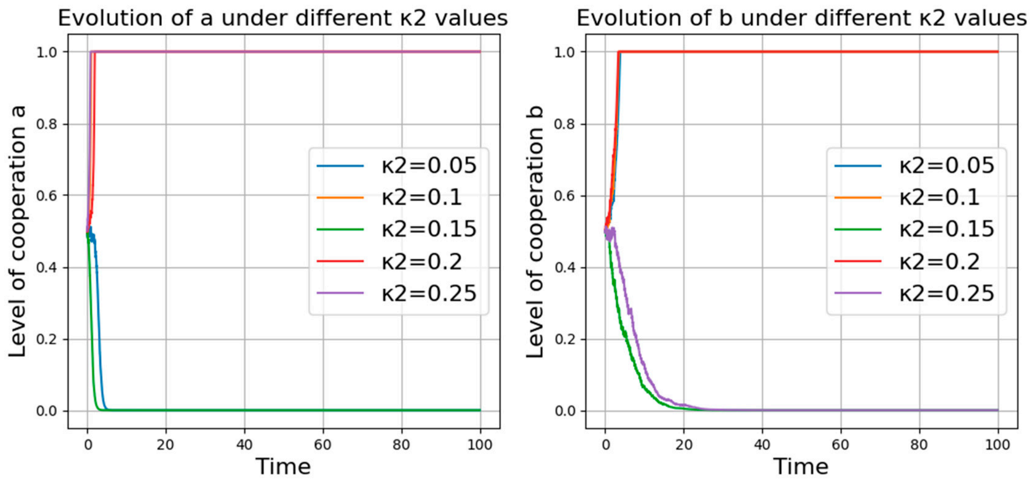

Figure 6. Sensitivity analysis of cooperation improvement coefficient κ_2.

Increasing cooperation coefficients can promote long-term cooperation among enterprises and enhance market competitiveness. Companies should focus on investing in technologies and management practices that improve cooperation efficiency, optimizing their overall resource allocation, and maximizing the gains from cooperation. Meanwhile, policymakers can encourage technological innovation and the establishment of cooperation mechanisms to further promote industry-wide synergy, strengthening the stability of the energy market. This cooperative model is instrumental in driving the low-carbon economy, improving energy utilization efficiency, and increasing the proportion of renewable energy in power systems.

4. Sensitivity Analysis of Market Gain Coefficient

Figure 7 presents the sensitivity analysis results for the joint market revenue increment coefficient α_1 and its impact on the cooperation willingness of power generation enterprises

(a) and energy storage companies (b). The coefficient α_1 represents the additional market revenue generated through cooperation between power generation enterprises and energy storage companies. By varying α_1 from 0.05 to 0.25, the left panel shows the evolution of cooperation willingness a over time, while the right panel illustrates the evolution of cooperation willingness b.

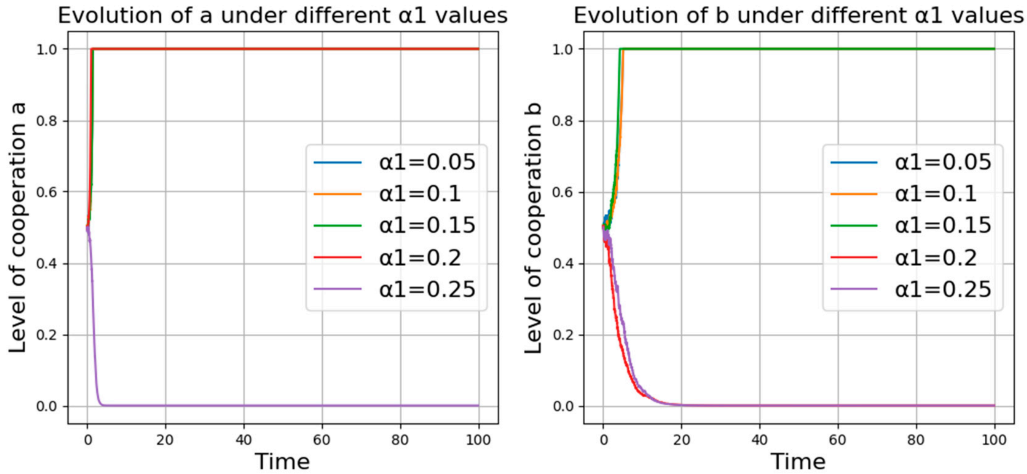

Figure 7. Sensitivity analysis of market gain coefficient α_1.

The figure shows that as the value of α_1 increases, the cooperation willingness of both power generation enterprises and energy storage companies improves during the early stages of cooperation. When α_1 is high (e.g., 0.25), cooperation willingness rises rapidly at the start and remains at a high level, with a slower rate of decline, indicating relatively stable motivation for cooperation. Conversely, when α_1 is low (e.g., 0.05), cooperation willingness declines rapidly, making it challenging for both parties to sustain long-term cooperation. This demonstrates that the joint market revenue increment coefficient α_1 significantly influences the cooperation motivation of both parties. An increase in α_1 means greater additional market revenue from cooperation, providing strong economic incentives for power generation enterprises and energy storage companies. In particular, during periods of energy market volatility, the incremental market gains from cooperation help both parties mitigate risks and achieve additional economic returns. Thus, a higher α_1 can support long-term cooperation stability, whereas a lower α_1 results in limited cooperative benefits, making sustained cooperation more difficult.

Enterprises should focus more on developing incremental revenues through cooperation. For example, they can enhance α_1 by leveraging technological innovation, policy collaboration, and market resource integration, thereby achieving greater economic benefits from long-term cooperation. Policymakers, in turn, can promote cooperation between power generation enterprises and energy storage companies through incentive mechanisms and policy support, facilitating the optimization and sustainable development of the energy system. Maximizing joint revenue not only boosts market competitiveness but also effectively reduces energy market risks, supporting the healthy development of a low-carbon economy.

5. Sensitivity Analysis of Dispatch Optimization Coefficient

Figure 8 presents the sensitivity analysis results for the dispatch optimization coefficient λ and its impact on the cooperation willingness of power generation enterprises (a) and energy storage companies (b). The dispatch optimization coefficient λ reflects the ability of energy storage companies to reduce operating costs through optimized system dispatch via cooperation. By simulating different values of λ ranging from 0.05 to 0.25, the left panel shows the evolution of cooperation willingness a over time, while the right panel illustrates the changes in cooperation willingness b.

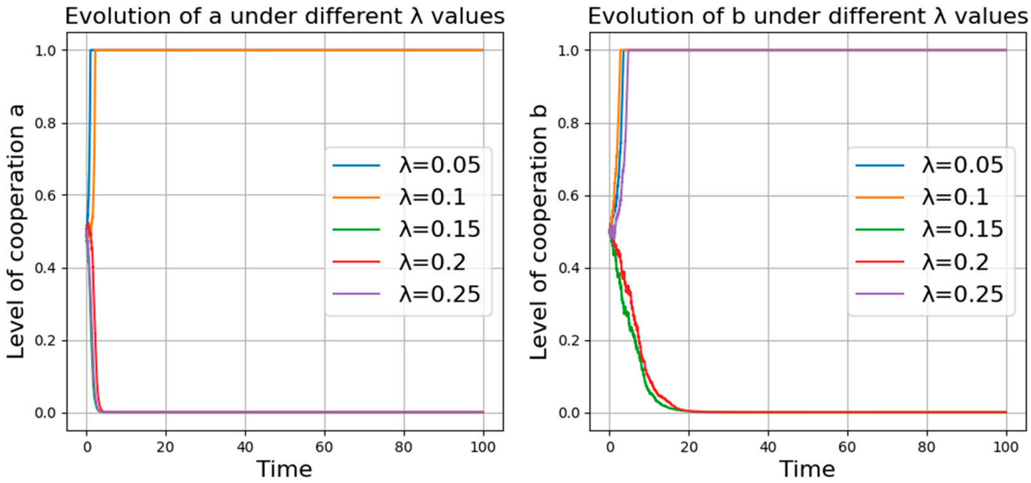

Figure 8. Sensitivity analysis of dispatch optimization coefficient λ.

The figure indicates that as the dispatch optimization coefficient λ increases, the initial rise in cooperation willingness b of energy storage companies is slightly faster, and the overall level of cooperation willingness improves. This suggests that when energy storage companies achieve greater cost savings through more efficient dispatch optimization, their motivation for cooperation also strengthens. However, the cooperation willingness of energy storage companies gradually decreases over longer time periods, indicating that, while optimized dispatch can lower costs, cooperation willingness is still affected by other factors and may decline over time.

The cooperation willingness a of power generation enterprises shows relatively stable trends in relation to changes in λ, maintaining a generally high level. This indicates that the cooperation motivation of power generation enterprises is less sensitive to the dispatch optimization of energy storage companies. A higher λ implies that energy storage companies can effectively lower operating costs through optimized dispatch, providing stronger economic incentives for cooperation. For energy storage companies, improving dispatch optimization not only reduces costs but also enhances their market competitiveness and increases their ability to survive and grow in the market.

Meanwhile, power generation enterprises' cooperation motivations are primarily driven by other factors, such as market revenues or government policy support, due to their lower dependence on dispatch optimization. Companies should focus on improving energy storage dispatch optimization through technological innovation and management improvements to reduce costs and enhance market competitiveness. Policymakers can further promote energy storage technology upgrades and encourage cooperation by implementing incentive measures to optimize energy dispatch mechanisms, fostering deeper cooperation between renewable energy generation enterprises and energy storage companies. This not only helps improve the efficiency of the overall energy market but also supports the adoption and development of renewable energy, facilitating the achievement of dual carbon goals.

5. Extended Discussion

The power level plays a crucial role in shaping the dynamics of cooperation between power generation enterprises and energy storage companies, as it directly affects their operational efficiency and economic outcomes. Discussing power levels provides deeper insights into how actual power output, as opposed to theoretical capacity, influences strategic decisions. Considering the inherent uncertainties in power generation and storage, such as market fluctuations and intermittent renewable output, we have extended the model to incorporate stochastic disturbances in power levels. This enhancement allows us to better capture the impact of real-world variability and explore its effects on cooperation strategies. The following simulations are designed to analyze system behavior under these extended conditions.

To account for real-world uncertainties, we model the power level $P_{level}(t)$ as a dynamic variable that is influenced not only by the maximum power generation capacity Q and cooperation efforts a and b, but also by stochastic disturbances B_t. Specifically, the power level is defined as follows:

$$P_{level}(t) = Q\phi(a,b) + \varpi B_t \tag{30}$$

where Q represents the fixed power generation capacity, and $\phi(a,b)$ captures the effect of cooperation on power utilization, reflecting how the cooperation efforts a and b improve power efficiency. For instance, $\phi(a,b)$ can be defined as $\phi(a,b) = 1 + \kappa_1 a + \kappa_2 b$. B_t is a stochastic disturbance term, modeled using various types of noise, and ϖ is the disturbance intensity coefficient controlling the magnitude of the stochastic impact on the power level.

Incorporating this dynamic power level into the profit function allows the model to capture the impact of power-level fluctuations on enterprise performance. The profit function for power generation enterprises and energy storage enterprises are updated as follows:

$$\pi_1(a,b) = \left[R_{renewable} + S_{joint} + C_{subsidy} - C_{dispatch} + R_v\right]\frac{P_{level}(t)}{Q} \tag{31}$$

$$\pi_2(a,b) = \left[R_{storage} + S_{joint} - C_{lease} - C_{storage}\right]\frac{P_{level}(t)}{Q} \tag{32}$$

This formulation ensures that the profit dynamically reflects the influence of power level variability, providing a more realistic representation of the system's behavior under uncertain conditions.

We set the stochastic disturbance term in the power level to different intensity parameters of ϖ and conducted simulation analyses. Figure 9 shows the dynamic evolution of the cooperation willingness of power generation enterprises and energy storage companies under different values of ϖ, thereby revealing the impact of power-level fluctuations on the cooperation willingness of these two types of entities.

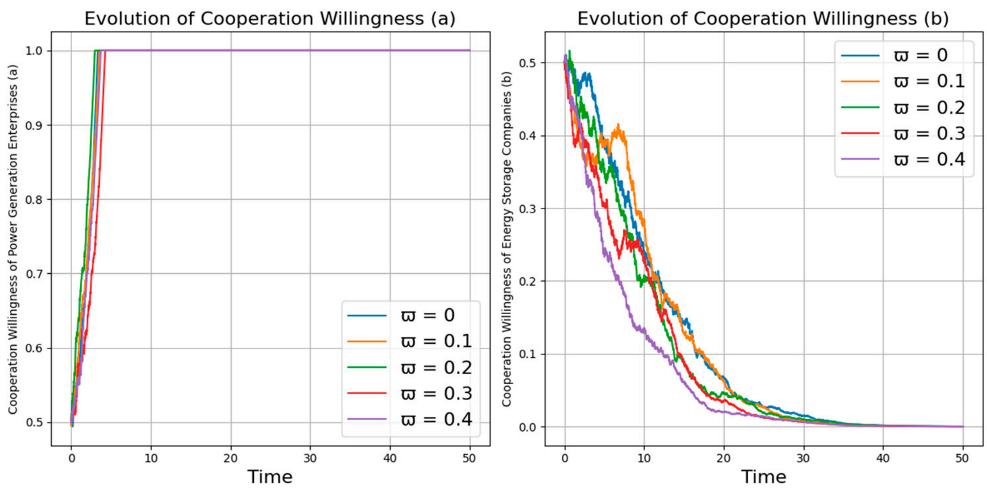

Figure 9. Sensitivity analysis of power level.

From Figure 9, it can be observed that the left panel illustrates how the cooperation willingness of power generation enterprises quickly stabilizes over time. The increase in ϖ has little impact on them, as their cooperation willingness remains high even under stronger disturbance intensities. In contrast, the right panel shows that the cooperation willingness of energy storage companies is more sensitive to stochastic disturbances. As the value of ϖ increases, their cooperation willingness decreases more rapidly and approaches zero earlier. This indicates that stochastic disturbances pose a higher uncertainty risk to energy storage companies. The relatively stable cooperation willingness of power generation enterprises demonstrates their stronger resilience to external fluctuations, enabling them to maintain cooperation better during market volatility. However, energy storage companies face higher cooperation risks, as increased stochastic disturbances may hinder their ability to sustain long-term cooperation, thereby affecting their revenue stability. Policymakers should provide more targeted support for energy storage companies, such as risk subsidies or volatility buffering mechanisms, to enhance their willingness to cooperate in highly uncertain markets. Additionally, corporate managers should optimize internal risk management to effectively respond to market fluctuations and ensure the sustained stability of cooperative relationships.

In the cooperation between renewable energy producers and energy storage companies, geographical differences significantly impact the efficiency and cost of collaboration. The greater the distance, the more challenging it becomes to transmit information, manage energy dispatch, and maintain equipment, leading to higher cooperation costs. Therefore, it is essential for the model to account for the spatial distribution of the two parties, linking cooperation costs to their distance to more accurately reflect the geographical constraints in real-world collaborations. To this end, we have redefined the cooperation cost function, incorporating both distance and cooperation willingness as influencing factors to further explore the role of location in cooperative behavior.

Therefore, this paper further extends the model. The profit functions for power generation enterprises and energy storage enterprises are updated as follows:

$$\pi_1(a,b) = R_{renewable} + S_{joint} + C_{subsidy} - C_{dispatch} + R_v - aC_{distance} \tag{33}$$

$$\pi_2(a,b) = R_{storage} + S_{joint} - C_{lease} - C_{storage} - bC_{distance} \tag{34}$$

$$C_{distance}(a,b) = \frac{\gamma_3 d}{1+\theta_1 a + \theta_2 b} \tag{35}$$

where d represents the distance between the renewable energy producer and the energy storage company, γ_3 is the unit distance coefficient for cooperation cost, and θ_1 and θ_2 represent the contributions of cooperation willingness a and b to reducing costs, respectively. By integrating distance d and cooperation willingness, the model provides a more comprehensive reflection of geographical constraints and efficiency improvements in collaboration.

We then assigned different values to distance d and conducted simulation analyses. Figure 10 illustrates the dynamic evolution of cooperation willingness for power generation enterprises and energy storage companies under various values of d, revealing the impact of distance on the cooperation willingness of both parties.

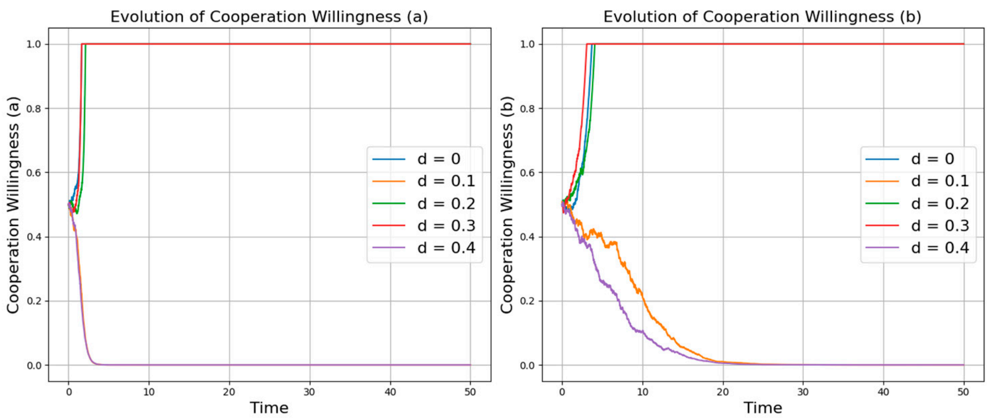

Figure 10. Sensitivity analysis of distance.

From Figure 10, it can be observed that the cooperation willingness a of power generation enterprises and b of energy storage companies gradually decrease as the distance d increases, although their sensitivities to distance differ. When the distance is small (e.g., $d = 0$ or $d = 0.1$), both power generation enterprises and energy storage companies quickly stabilize their cooperation willingness at high levels. However, as the distance increases (e.g., $d = 0.3$ or $d = 0.4$), cooperation willingness significantly declines, especially for energy storage companies, whose cooperation willingness rapidly approaches zero within a short period. This indicates that the increased cooperation cost caused by greater distances has a more pronounced impact on energy storage companies, significantly weakening their motivation to cooperate. Cooperation between geographically distant enterprises faces higher transportation, communication, and management costs, which in turn affect the stability of returns and the sustainability of cooperation. Policymakers should offer subsidies or tax incentives to geographically distant partners to alleviate cost pressures. Meanwhile, enterprise managers should optimize the geographic layout of their partners and leverage technological solutions to reduce operational costs caused by distance, thereby enhancing cooperation efficiency and long-term profitability.

To further explore the significance of energy storage companies in the overall evolution of cooperation, this study treats the cooperation willingness b of energy storage companies as an exogenous parameter for simulation analysis. When $b = 0$, it represents a scenario without the participation of energy storage companies; when $b > 0$, it reflects scenarios with varying degrees of participation from energy storage companies. By comparing the evolutionary trajectories of the cooperation willingness a of renewable energy generation companies under these different scenarios, the critical role of energy storage companies in the cooperation mechanism can be visually demonstrated. The simulation results are as follows.

Figure 11 shows clear evolutionary trends in the cooperation willingness a of renewable energy generation companies under different cooperation willingness levels b of energy storage companies over time. When $b = 0$, the cooperation willingness a of generation companies rapidly declines and approaches zero, indicating that, in the absence of energy storage participation, generation companies lack the motivation to cooperate. Conversely, when $b > 0$, the cooperation willingness a gradually increases and stabilizes as b rises. Notably, at $b = 0.8$, cooperation willingness reaches its highest level.

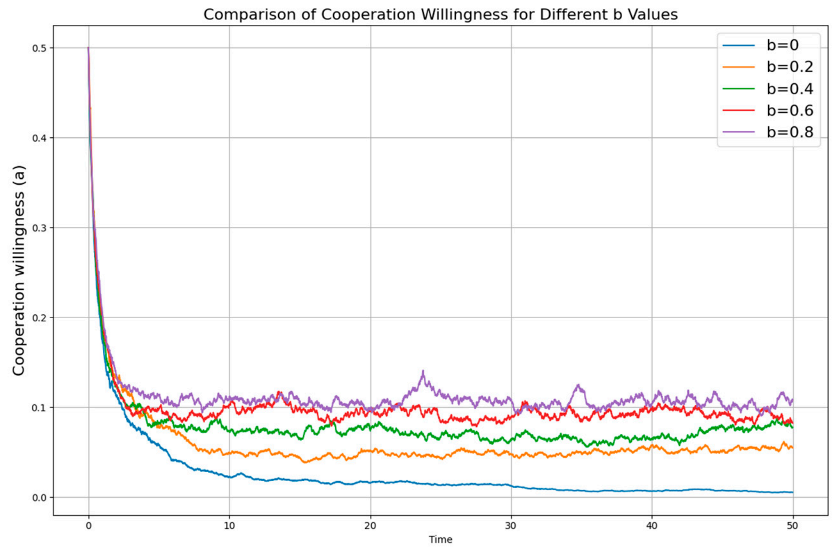

Figure 11. Sensitivity analysis of willingness b.

At the same time, the volatility of cooperation willingness varies with different b values: under higher b values (e.g., $b = 0.8$), the fluctuations are more pronounced, indicating that generation companies are more sensitive to market conditions and cooperation terms when the level of energy storage participation is high. In contrast, under lower b values (e.g., $b = 0.2$), the fluctuation amplitude is smaller, but the overall cooperation level is also lower.

The participation of energy storage companies significantly enhances the cooperation willingness of generation companies, highlighting the crucial role of energy storage in smoothing power fluctuations, reducing market risks, and improving revenue stability. When energy storage companies exhibit a higher cooperation willingness, the system's potential for revenue optimization increases, encouraging generation companies to actively participate in market cooperation. On the other hand, in scenarios without energy storage participation ($b = 0$), generation companies miss out on benefits such as peak–valley price arbitrage, leading to a lack of cooperation incentives, which ultimately affects the overall efficiency and stability of the market.

This result also underscores the importance of policy design and incentive mechanisms. Governments and market regulators should implement measures such as subsidies and tax incentives to encourage energy storage companies to participate in cooperation, thereby not only increasing the cooperation willingness b of energy storage companies but also indirectly boosting the cooperation willingness a of generation companies, enhancing the overall system efficiency. Moreover, while higher energy storage cooperation willingness improves overall cooperation levels, it also introduces greater volatility, highlighting the need for strengthened market coordination and risk management to ensure system stability.

6. Conclusions

Amid the global response to climate change, achieving carbon neutrality has become a core focus of national energy policies. Accelerating the low-carbon transition of energy systems and promoting the integration of renewable energy generation with energy storage technologies has emerged as a key strategy. The widespread adoption of energy storage technologies not only addresses the intermittency and instability of renewable energy generation but also enhances the flexibility and reliability of power systems. At the same time, how to facilitate deep cooperation between power generation enterprises and energy storage companies through effective market mechanisms and policy support has become a critical research topic for achieving energy structure transformation.

This study developed a cooperative model based on a stochastic evolutionary game to analyze the dynamic evolution of cooperation willingness between power generation enterprises and energy storage companies under various market conditions and parameter settings. The model incorporates Gaussian white noise as a stochastic disturbance, accounting for the bounded rationality of the players in uncertain market environments. Sensitivity analysis of key exogenous parameters, such as electricity market price, generation capacity, cooperation improvement coefficients (e.g., the synergy between power generation enterprises and energy storage companies), and dispatch optimization coefficients, led to the following main findings.

First, the cooperation willingness of energy storage companies is highly sensitive to dispatch optimization capacity and market price fluctuations. Improved dispatch optimization can significantly increase the returns of energy storage companies, thereby enhancing their motivation to cooperate. In contrast, the cooperation willingness of power generation enterprises relies more on policy support and market conditions and is less affected by the dispatch optimization capacity of energy storage companies. The study shows that cooperation between power generation enterprises and energy storage companies can effectively mitigate power system fluctuations and improve overall market returns. However, while the initial willingness to cooperate is high, it gradually diminishes over time, reflecting the complexity and uncertainty of market mechanisms.

Based on these findings, the following policy recommendations are proposed: (1) Policymakers should enhance support for the research and development of energy storage technologies, particularly in dispatch optimization and cost reduction, to boost the market competitiveness of energy storage companies. Through technological progress, energy storage companies can more effectively participate in the balancing of renewable energy generation, thereby improving the flexibility and stability of the overall system. (2) Market mechanisms and policy incentives play a significant role in enhancing cooperation willingness. Governments should introduce targeted policy incentives to promote collaboration between power generation enterprises and energy storage companies in green energy projects. For example, renewable energy subsidies and electricity market price adjustments can enhance the expected returns of cooperation, thereby fostering long-term cooperation stability. (3) Achieving carbon neutrality depends not only on technological innovation but also on the deep integration of policies and market mechanisms. Governments should simultaneously promote the low-carbon transition while establishing a well-functioning market-based electricity and green certificate system to ensure fair and transparent market transactions and reasonable profit distribution, thus providing an institutional basis for sustainable cooperation.

In summary, this study, through model construction and simulation analysis, identifies the key influencing factors in the cooperation process between power generation enterprises and energy storage companies and offers targeted recommendations for policymakers. These insights aim to facilitate the synergy between renewable energy and energy storage technologies, accelerating the low-carbon transition of energy systems.

Author Contributions: Conceptualization, W.H.; methodology, R.L.; software, T.H.; validation, T.H. and J.Z.; formal analysis, J.Z.; investigation, Y.L. and S.X.; writing—original draft preparation, W.H.; writing—review and editing, Z.L.; visualization, H.Y.; supervision, W.H.; project administration, W.H.; funding acquisition, W.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the research project of China Three Gorges Corporation and China Yangtze Power Co., Ltd., under Grant Z152302022.

Data Availability Statement: The data presented in this study are available on reasonable request. Researchers seeking access to the data are encouraged to contact the corresponding author.

Conflicts of Interest: Authors Wei He, Rujie Liu, Tao Han, Jicheng Zhang, Yixun Lei and Shan Xu were employed by the company Three Gorges Electric Power Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that this study received funding from China Three Gorges Corporation and China Yangtze Power Co., Ltd. The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article or the decision to submit it for publication.

Appendix A

The electricity market price and generation capacity are sourced from the **International Renewable Energy Agency (IRENA)** and the **National Energy Administration**, available at https://www.irena.org/ (accessed on 18 October 2024).

The cooperation improvement coefficient for power generation enterprises, the cooperation improvement coefficient for energy storage companies, the government subsidy coefficient, the dispatch cost coefficient, the operational cost coefficient for energy storage, and the cooperation optimization coefficient are sourced from the **International Association for Energy Economics (IAEE)**, available at https://www.iaee.org/ (accessed on 19 October 2024).

The peak–valley price difference is sourced from the **State Grid Corporation of China**, available at http://www.sgcc.com.cn/ (accessed on 19 October 2024).

The leasing income coefficient for energy storage companies is sourced from the **Energy Storage Association (ESA)**, available at https://www.energystorage.org/ (accessed on 18 October 2024).

The stochastic disturbance term is modeled as a standard Gaussian process; more information can be found at https://en.wikipedia.org/wiki/Gaussian_process (accessed on 19 October 2024).

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