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Evolutionary Game Theory-Based Analysis of Power Producers' Carbon Emission Reduction Strategies and Multi-Group Bidding Dynamics in the Low-Carbon Electricity Market

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Abstract: China's power generation system has undergone reforms, leading to a competitive electricity market where independent producers participate through competitive bidding. With the rise of low-carbon policies, producers must optimize bidding strategies while reducing carbon emissions, creating complex interactions with local governments. Evolutionary game theory (EGT) is well-suited to analyze these dynamics. This study begins by summarizing the fundamental concepts of electricity trading markets, including transaction models, bidding mechanisms, and carbon reduction strategies. Existing research on the application of evolutionary game theory in power markets is reviewed, with a focus on theoretical constructs such as evolutionary stable strategies and replicator dynamics. Based on this foundation, the study conducts a detailed mathematical analysis of symmetric and asymmetric two-group evolutionary game models in general market scenarios. Building upon these models, a three-group evolutionary game framework is developed to analyze interactions within power producer groups and between producers and regulators under low-carbon mechanisms. A core innovation of this study is the incorporation of a case study based on China's electricity market, which examines the evolutionary dynamics between local governments and power producers regarding carbon reduction strategies. This includes analyzing how regulatory incentives, market-clearing prices, and demand-side factors influence producers' bidding and emission reduction behaviors. The study also provides a detailed analysis of the bidding strategies for small, medium, and large power producers, revealing the significant impact of carbon pricing and market-clearing prices on strategic decision-making. Specifically, the study finds that small producers tend to adopt more conservative bidding strategies, aligning closely with market-clearing prices, while large producers take advantage of economies of scale, adjusting their strategies at higher capacities. The study explores the conditions under which carbon emission reduction strategies achieve stable equilibrium, as well as the implications of these equilibria for both market efficiency and environmental sustainability. The study reveals that integrating carbon reduction strategies into power market dynamics significantly impacts bidding behaviors and long-term market stability, especially under the influence of governmental penalties and incentives. The findings provide actionable insights for both power producers and policymakers, contributing to the advancement of low-carbon market theories and supporting the global transition to sustainable energy systems.

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1. Introduction

The reform of China's power generation market system is still in its developmental stages. In an effort to invigorate the electricity industry, the original planned generation system has gradually transitioned into a market-based bidding mechanism, characterized by the establishment of centralized electricity trading platforms and numerous independent power generation enterprises [1]. Under this new market-oriented mechanism, power generation companies have become more competitive than under the previous planned economy system. The maximum electricity output awarded through competitive bidding and the minimum electricity price offered in these bids are critical factors that determine the profitability of power producers. Consequently, power producers must rely on various strategies, such as predicting competitors' bidding behaviors and simulating future market demand fluctuations, to analyze market trends and devise bidding strategies that align with their financial interests [2].

For power producers, the optimal strategy typically involves setting bidding prices marginally below the future market-clearing price. This approach maximizes profitability by ensuring bids are competitive yet sufficiently rewarding. On the other hand, from the perspective of the government, the ideal market bidding scenario is one where power producers bid according to their marginal costs. Such bidding behavior enables optimal resource allocation and improves the overall operational efficiency of the electricity market. Whether it is power producers aiming to maximize profits or regulators seeking to design policies that promote sustainable market development, understanding and analyzing the evolutionary dynamics of multi-group bidding strategies in power markets is of paramount importance.

One effective method for predicting bidding behaviors and market dynamics involves developing practical models of power market interactions based on evolutionary game theory. Although the application of evolutionary game theory to power market competition is still in the exploratory phase, significant progress has been made. For example, Cheng et al. (2020) [3] focused on the general N-population multi-strategy evolutionary games, and used them to investigate the generation-side long-term bidding issues in electricity markets. Based on this, Ref. [4] adopted evolutionary game theory to analyze the bidding equilibrium in electricity markets under the marginal cost pricing (MCP) and pay-as-bid (PAB) mechanisms. They further compared the bidding behaviors of power producers under different mechanisms. Building on this, some researchers have conducted detailed investigations into multi-group strategic interactions in power markets operating under the MCP mechanism, including the long-term evolutionary stability of bidding equilibria.

In the renewable energy sector, the application of evolutionary game theory (EGT) in renewable electricity markets has become a pivotal approach to understanding stakeholder interactions and promoting sustainable energy transitions. Jamali et al. (2022) [5] used EGT to analyze the technological transformation of industries toward renewable electricity procurement, focusing on both technological-based (TB) and non-technological-based (NTB) strategies. They demonstrated how subsidies and regulatory incentives significantly influence industries' adoption of renewable energy and identified equilibrium conditions that favor renewable electricity. In a subsequent study, Jamali et al. (2023) [6] extended this analysis to the long-term behavior of industries purchasing renewable and non-renewable energy in Iran. This research highlighted the importance of dynamic regulatory mecha-

nisms, such as subsidies and carbon taxes, in driving tipping points where industries shift to renewable energy. Both studies emphasize that aligning industry strategies with regulatory frameworks is critical to achieving low-carbon objectives. Building on this foundation, Sun et al. (2024) [7] explored the coordination between renewable energy suppliers and grid operators using EGT. Their study constructed a game model to analyze strategies for renewable energy integration and peak shaving, revealing that cooperation between these stakeholders is vital for improving grid stability and efficiency. Key factors, such as grid capacity, market-clearing prices, and renewable penetration rates, significantly affect strategy outcomes, underscoring the need for dynamic pricing models and infrastructure investments. Huang et al. (2024) [8] introduced a tripartite evolutionary game model to examine interactions among renewable energy suppliers, coal-fired power plants, and market users. Their findings demonstrated that market equilibrium could be achieved through optimized trading strategies, leading to increased renewable energy consumption. They further emphasized the role of green electricity demand and pricing behaviors in shaping market dynamics. These studies collectively highlight EGT's capability to model the complex interactions among stakeholders in renewable energy markets. By identifying evolutionary stable strategy (ESS) and equilibrium conditions, they provide actionable insights for policymakers, market participants, and regulators. Key takeaways include the importance of subsidies, penalties, and carbon pricing in accelerating renewable energy adoption, the necessity of cooperation among stakeholders to achieve stable market operations, and the critical role of investment in renewable technologies and grid infrastructure. Future research should integrate EGT with other modeling approaches, such as system dynamics, to capture the multi-dimensional complexities of renewable energy systems. Together, these findings contribute to the global understanding of renewable energy markets and offer practical strategies for fostering sustainable energy transitions. These studies highlight the utility of evolutionary game theory in uncovering critical developmental patterns within diverse power market scenarios. The ongoing exploration of evolutionary game theory in power markets continues to focus on the strategic behaviors of generation groups, with particular attention to identifying bidding strategies that maximize profitability. As this research domain matures, it is anticipated that more researchers will explore the dynamics of group bidding evolution in power markets.

For power producers, evolutionary game theory offers a novel approach to forecasting bidding behaviors and market trends. Meanwhile, for market regulators, evolutionary game studies in power bidding can provide valuable recommendations for improving relevant laws and regulations governing electricity markets. The integration of this approach not only enhances the theoretical understanding of electricity market dynamics but also offers practical tools for both market participants and policymakers, contributing to the efficient and sustainable operation of modern power systems. For power producers, EGT has emerged as a crucial tool for modeling dynamic interactions in competitive electricity markets. Unlike traditional models, EGT accommodates the continuous adaptation of strategies by market participants, capturing the iterative decision-making processes required in markets influenced by factors such as renewable energy integration, market-clearing prices, and regulatory policies. This adaptability makes EGT particularly effective in addressing uncertainties, including those arising from demand fluctuations and the variability of renewable energy sources.

Recent studies have validated the utility of EGT in electricity markets. Under this background, the integration of renewable energy into electricity markets has become a key area of research, particularly as countries aim to balance economic growth with carbon emission reduction targets. The following studies explore innovative frameworks and methodologies for addressing this challenge through game-theoretic approaches.

Zhang et al. (2023) [9] developed a hybrid game model to study the evolutionary dynamics of renewable energy bidding strategies in China's electricity-carbon integrated market. The paper incorporates a multi-agent framework that combines cooperative and non-cooperative game elements to analyze interactions between renewable energy producers, traditional power plants, and regulatory authorities. The study reveals that carbon pricing mechanisms and green certificate incentives significantly influence bidding strategies and market equilibrium. Importantly, the hybrid model provides insights into how renewable energy producers can optimize their bids under varying carbon pricing policies. However, the model assumes that all market participants possess complete information, which may limit its applicability in real-world scenarios where uncertainties and asymmetric information often exist. A key contribution of the paper lies in its ability to combine multiple market elements (electricity, carbon, and green certificates) into a single analytical framework, offering regulators a comprehensive tool for policy evaluation.

Perera (2018) [10] explored a two-population evolutionary game to examine carbon emission reduction strategies in electricity markets. The study contrasts the strategic behaviors of power producers using fossil fuels and those adopting cleaner renewable energy sources. The results indicate that stricter carbon penalties and subsidies for renewables drive the market toward a sustainable equilibrium. However, the study emphasizes that the evolutionary process is highly sensitive to the initial conditions of the market, such as the relative costs of renewable versus fossil fuel energy. A notable limitation is the study's lack of focus on policy mechanisms that could mitigate these sensitivities, leaving room for future research on adaptive regulatory frameworks. Despite these shortcomings, the research provides a foundational understanding of how carbon pricing and subsidies influence producer behaviors over time.

Wang et al. (2023) [11] proposed an evolutionary game model to optimize the joint operation of green certificates, carbon emission rights, and electricity markets in a system comprising thermal, wind, and photovoltaic power producers. The study highlights the interplay between carbon prices, renewable energy subsidies, and green certificate trading in shaping market dynamics. Results from numerical simulations suggest that higher carbon prices and stricter emission controls create favorable conditions for renewable energy consumption, leading to increased market penetration of wind and solar power. A strength of the paper is its incorporation of multi-dimensional market mechanisms, which reflects the complexity of real-world systems. However, the study assumes static carbon prices, which may not fully capture the dynamic nature of carbon markets. Additionally, while the model provides valuable insights into market optimization, its reliance on theoretical assumptions could benefit from validation through real-world case studies.

A common limitation across these studies is the lack of empirical validation. While their theoretical contributions are substantial, future research should focus on applying these models to real-world scenarios to enhance their reliability and policy relevance. Additionally, incorporating uncertainties, such as fluctuating carbon prices and renewable energy intermittency, would improve the robustness of these models. Despite these limitations, the studies collectively provide valuable tools for optimizing renewable energy integration into electricity markets and offer actionable insights for policymakers aiming to balance economic efficiency with environmental sustainability.

In competitive electricity markets, power producers and generation groups commonly adopt bidding prediction measures prior to submitting their bids. These measures are designed to help producers formulate optimal bidding strategies that maximize their profitability in dynamic market environments. Various researchers and power producers have proposed mathematical models to address the challenges of designing optimal bidding strategies from different perspectives. For example, one approach involves forecasting the

unified market-clearing price and then submitting bids slightly lower but still close to this forecasted price. Researchers have employed different models to predict market-clearing prices. For instance, Peng et al. (2005) [12] constructed an optimization model for power generation strategies based on generation costs and market price variations. Zhao et al. [13] proposed a single-bid period profit model using genetic algorithms, while Conejos et al. [14] developed a profit model based on the probability density distribution of electricity trading.

A second approach focuses on predicting the bidding strategies of competing producers, allowing individual producers to adjust their own strategies accordingly. This approach has led to numerous mathematical models for power producer bidding, each based on distinct principles. For example, Wang et al. [15] utilized fuzzy algorithms to establish a bidding model for power producers, while Ma et al. [16] proposed a bidding strategy model tailored to specific market conditions. Similarly, Liu et al. [17] developed a model that incorporates the probability distribution of electricity market loads to predict bidding outcomes.

Despite the diversity of these methodologies, they share a critical limitation: both approaches rely heavily on extensive historical data about market changes and competitors' bidding behaviors. For instance, forecasting market-clearing prices necessitates a comprehensive understanding of market conditions, including transmission constraints and the historical bidding decisions of all producers. Similarly, predicting competitors' bidding strategies requires access to sensitive data such as cost functions and profit curves, which are typically confidential and not shared among competitors. Moreover, these methods often fail to account for the interdependence of multiple participants in the market. For instance, predicting market-clearing prices assumes a perfectly competitive market where prices remain constant and unaffected by individual bidding strategies—an assumption that rarely holds in real-world electricity markets characterized by complex and interdependent bidding behaviors.

Additionally, some power producers and researchers have opted to establish cost models based solely on their own historical data, using a cost-plus-margin approach to formulate bids. For example, Gountis et al. [18] developed a mathematical model based on self-reported generation costs and historical data. Zhang et al. [19] extended this approach by forecasting thermal power companies' bidding strategies using cost functions and historical profit data. However, these self-focused models overlook the competitive dynamics of the market, making them inadequate for today's complex and rapidly evolving electricity markets. Such models fail to consider the influence of competitors' bidding strategies, thereby limiting producers' ability to maximize profits in a highly competitive environment.

A more promising approach involves integrating EGT with the dynamics of modern electricity markets. By treating bidding groups as distinct game participants, EGT allows researchers to model interactions between multiple groups within a competitive bidding framework. Unlike traditional models, EGT accounts for the interdependence and iterative interactions of participants, making it well suited for analyzing multi-group evolutionary dynamics in electricity markets. The previously mentioned methods are primarily designed for studying competitive and non-cooperative bidding scenarios. In contrast, EGT enables the examination of bidding situations where participants influence and balance one another. For instance, Zhang et al. [20] applied EGT to develop an optimization strategy model for deregulated electricity markets, while Wen et al. [21] constructed an EGT model to analyze asymmetric information and bidding strategies among power producers. Similarly, Guo et al. [22] investigated power company bidding decisions using EGT, and Wang et al. [23] incorporated networked group behaviors into an evolutionary game model.

The key strength of EGT lies in its ability to model interconnected game participants, where some groups exert influence over the entire market. This framework is particularly advantageous for analyzing multi-group asymmetric cooperative games under incomplete information. For example, Wang et al. [24] introduced a networked EGT model under partial information constraints, where each group has limited knowledge of the market but can refine their strategies through repeated interactions. In such models, game participants iteratively adapt based on historical data and evolving strategies, leading to more realistic representations of market dynamics.

While EGT addresses many limitations of traditional bidding models, its practical application faces several challenges. First, the computational complexity of EGT-based models increases significantly with the number of participants and the intricacy of market interactions. Second, while EGT accommodates partial information, the quality of predictions still depends on the availability and accuracy of historical data. Finally, validating EGT-based models in real-world electricity markets remains an ongoing area of research. Future studies should focus on integrating real-time data, incorporating stochastic elements to capture market uncertainties, and testing these models in live market environments.

Therefore, EGT offers a dynamic framework for understanding the decision-making processes of power producers in competitive markets [25,26]. Unlike traditional optimization or forecasting models, EGT does not depend on fixed, deterministic inputs or extensive historical data. Instead, it focuses on how strategies evolve over time based on interactions between participants and the payoffs they receive. For instance, producers in emerging electricity markets can iteratively adjust their bidding strategies based on observed market outcomes, which allows them to gradually identify stable and profitable bidding behaviors.

Additionally, EGT's flexibility in incorporating external factors, such as regulatory changes, renewable energy integration, and demand fluctuations, makes it uniquely suited for markets that are still developing [27–31]. This flexibility addresses a key limitation of conventional bidding strategies, which often fail to account for the dynamic and uncertain nature of early-stage electricity markets. Studies have demonstrated that EGT provides robust insights into equilibrium conditions and can guide both market participants and regulators in designing strategies that promote market efficiency and sustainability [32–34].

The integration of EGT with electricity market dynamics represents a significant advancement over traditional bidding models [35]. By addressing the limitations of historical data reliance and incorporating multi-group interactions, EGT provides a robust framework for analyzing and optimizing bidding strategies [36–38]. However, further research is required to overcome practical challenges and fully realize the potential of EGT in modern electricity markets.

The bidding strategies discussed rely on extensive historical data, making them ideal for established markets with stable structures. However, EGT is particularly valuable for emerging electricity markets with limited data and evolving mechanisms. EGT provides a flexible framework to model and analyze strategic interactions in dynamic, uncertain environments.

In this paper, we propose that, for the power producers, employing appropriate evolutionary game models is one of the most effective tools for formulating optimal bidding strategies. In bidding models constructed based on evolutionary game theory, different groups possess varying levels of information, engage in sequential bidding, and influence one another. These characteristics align the models with the current development patterns of the domestic power bidding market. By establishing a game model through the initial market profit matrix, we can calculate the system's final stable equilibrium points under various influencing factors. This enables us to determine the stable market states that emerge when power groups adopt different bidding strategies. Power producers can

use these insights to identify strategies that maximize their returns while ensuring stability. This study has conducted dynamic simulations of two-group and three-group two-strategy bidding models within the power market and elucidated the practical significance of the equilibrium points. Based on these findings, power producers can incorporate additional influencing factors to develop more complex market game models.

For regulatory authorities, the continuous transformation of the power market necessitates the refinement of bidding systems in China's power sector. Utilizing multi-group evolutionary game models allows for the analysis of how various factors—such as regulations, clearing prices, and the intensity of rewards and penalties—affect the equilibrium points in power market bidding. This understanding helps in discerning the current developmental trends of the power market and forecasting future market dynamics. Furthermore, by implementing measures such as fines and subsidies, malicious competitive behaviors like market monopolization and manipulation can be mitigated, thereby fostering healthy competition within the power market. This paper investigates the impact of governmental oversight, market-clearing prices, and varying market demands on the long-term stability of the market. These insights provide regulatory bodies with valuable recommendations for enhancing bidding systems.

Additionally, this study integrates a critical research focus: evolutionary game analysis between local governments and power companies under low-carbon mechanisms. This aspect examines how local governments and power producers interact and evolve their strategies in response to low-carbon policies. Understanding this dynamic is essential for both policymakers and power companies to collaboratively achieve low-carbon objectives. By analyzing the strategic adaptations of local governments and power companies, this research contributes to the formulation of more effective low-carbon policies and the optimization of corporate strategies to align with sustainability goals.

The paper is organized as follows: Section 1 reviews forecasting and bidding behaviors in domestic and international power markets, alongside a discussion of evolutionary game theory applications. Section 2 focuses on the core components of evolutionary game theory and develops a three-group evolutionary game model. Section 3 uses real data from the East China Power Market to analyze bidding strategies under varying load demands and market-clearing prices. Sections 4–6 discuss the role of local governments in low-carbon mechanisms, present further discussions and prospects, and summarize the conclusions.

2. Evolutionary Game Theory and Its Application in Power Generation Bidding

2.1. EGT and Its Main Conceptions

EGT combines the analysis of static game theory with dynamic processes, providing a theoretical framework to study the evolution of strategies over time. In contrast to traditional game theory, where equilibrium concepts such as Nash equilibrium assume rational players with complete knowledge, EGT emphasizes the process of strategic adaptation through repeated interactions among players within a population. The core elements of EGT models include the population size, the set of available strategies, and the payoff functions that define the fitness or success of each strategy. These factors govern how strategies evolve based on interactions among players.

In power generation bidding, EGT is particularly useful for modeling the behavior of multiple power producers (agents) as they participate in the market. It allows us to simulate the competitive dynamics of strategy selection, where agents aim to optimize their bids to maximize their profits. The evolutionary process, which takes into account how strategies spread or disappear over time, can lead to either stable equilibria or ongoing instability

depending on the market conditions. Understanding the reasons for instability—such as misaligned incentives or external perturbations—becomes critical for system design.

2.1.1. Replicator Dynamics

Replicator dynamics (RD) form the cornerstone of evolutionary game theory. They describe how the proportion of a strategy within a population changes over time, based on its relative payoff compared to other strategies. The replicator equation is given as follows:

$$\frac{\mathrm{d}x(p_i)}{\mathrm{d}t} = p_i[u(p_i, p) - u(p, p)] \tag{1}$$

where p_i represents the proportion of the population adopting strategy i, $u(p_i, p)$ is the payoff for strategy i, and $u(p, p)$ is the average payoff across all strategies. This equation indicates that strategies yielding above-average payoffs will increase in prevalence, while less successful strategies will diminish.

In power generation bidding scenarios, RD are used to model how bidding strategies evolve over time among different producers. For instance, if a certain bidding strategy consistently yields higher profits, more participants are likely to adopt it, leading to a shift in the overall strategy distribution. Conversely, less profitable strategies will fade out as producers shift toward the more successful ones. While this framework is powerful for modeling adaptive behavior in competitive settings, it may oversimplify the dynamics of real-world markets, which are often influenced by stochastic factors like demand fluctuations or regulatory changes. Future research could consider incorporating stochastic elements into the RD or adopting agent-based modeling to capture these complexities more effectively.

This study assumes a competitive market with heterogeneous power producers, each operating under different cost structures and capacities. These differences lead to varied strategic interactions. The evolutionary dynamics ensure that strategies with higher benefits gradually dominate the market, while the system remains resistant to sudden, abrupt changes in strategy profiles. Instead, the evolution of strategies is typically incremental and adaptive.

2.1.2. Evolutionarily Stable Strategy (ESS)

An ESS is a key concept in evolutionary game theory. It represents a strategy that, once established within a population, cannot be invaded by alternative strategies. Mathematically, a strategy s is ESS if, for any alternative strategy $s' \neq s$, the following condition holds:

$$f(s, s_{\mathrm{ms}}) > f(s', s_{\mathrm{ms}}) \tag{2}$$

where $f(s, s_{\mathrm{ms}})$ denotes the payoff for strategy s when mixed with the population adopting strategy $s_{\mathrm{ms}} = es + (1 - e)s'$, for all $e \in (0, 1)$.

In the context of power generation group bidding, an ESS corresponds to a bidding strategy that remains optimal even when a small proportion of participants deviate from it. If the system dynamics governed by the RD equation converge to an ESS, the market achieves evolutionary stability. At this point, all participants settle on a stable bidding strategy, maximizing collective and individual benefits.

The identification of ESS in power markets is crucial for designing policies that ensure market stability. For example, regulatory mechanisms can encourage convergence toward socially optimal strategies, such as bidding strategies that balance profitability with grid reliability and sustainability. However, achieving ESS in practical markets may be challenging due to external shocks, incomplete information, and heterogeneity among participants.

2.1.3. Lyapunov-Based Stability Analysis

Lyapunov's method offers a systematic approach to assess the stability of equilibria in dynamic systems. For evolutionary game systems governed by RD equations, Lyapunov stability analysis involves computing the Jacobian matrix at equilibrium points and evaluating its eigenvalues. The stability conditions are summarized as follows:

- If all eigenvalues of the Jacobian matrix at an equilibrium point have negative real parts, the equilibrium is locally stable and corresponds to an ESS.
- If any eigenvalue has a positive real part, the equilibrium is unstable, leading to oscillations or divergence in strategy distributions.
- If eigenvalues have zero real parts, further analysis is required to determine stability.

In power generation bidding markets, Lyapunov stability analysis can help predict whether market rules or pricing schemes will lead to stable equilibria or cause volatility. By identifying stable equilibria, regulators can design mechanisms that minimize price fluctuations and strategic uncertainty. While this approach is robust, it relies on linear approximations near equilibrium points, which may not fully capture the nonlinear dynamics present in complex real-world markets. To overcome this limitation, advanced methods such as bifurcation analysis or machine learning-based stability prediction could be applied.

Stability of Equilibrium Points: To analyze the stability of equilibrium points, we derive the Jacobian matrix from the RD equations. The equilibrium points are stable if the eigenvalues of the Jacobian matrix are negative, indicating that the population will converge to these points over time. It is described as $\boldsymbol{J} = \frac{\partial \dot{x}_i}{\partial x_j}$, where $\boldsymbol{J}$ is the Jacobian matrix of the system and describes how the change in one strategy affects the dynamics of others. The stability condition is derived by analyzing the eigenvalues of this matrix at equilibrium points.

Overall, Section 2.1. highlights the theoretical foundations and practical applications of evolutionary game theory in modeling power generation group bidding strategies. By integrating concepts such as RD, ESS, and Lyapunov stability analysis, researchers can systematically analyze the evolution of strategies in competitive markets. The insights gained from these models are invaluable for designing market mechanisms that promote stability, efficiency, and fairness. These concepts are crucial for understanding the strategic behavior of power producers in a competitive electricity market. In our research, we apply these principles to model the bidding behavior of small, medium, and large power producers. Specifically, we build a three-group evolutionary game model to analyze the dynamics of bidding strategies under various market conditions, such as fluctuating market-clearing prices and load demands. The resulting equilibrium strategies provide insights into how power producers adapt their bids in response to market forces and regulatory policies.

2.2. Evolutionary Game Models Applied in Power Generation Bidding

The application of EGT to power generation bidding has garnered significant attention in recent years, primarily due to its ability to bridge the gap between theoretical equilibrium analysis and the practical complexities of market dynamics. Unlike traditional static game theory models that assume perfect rationality and instantaneous equilibrium, EGT captures the adaptive and iterative nature of strategy selection among competing power producers. This is particularly valuable in deregulated electricity markets, where numerous generators dynamically adjust their bidding strategies in response to market signals, policy interventions, and competition.

2.2.1. Current Developments in EGT for Power Generation Bidding

The development of EGT in power generation bidding has focused on modeling the evolutionary dynamics of competing strategies within the context of deregulated energy markets. Key advancements include the following:

(1) Dynamic modeling frameworks: Evolutionary models extend static Nash equilibrium concepts by incorporating time-dependent strategy adjustments, often represented through systems of differential equations such as RD. These models capture the gradual evolution of strategies as agents learn and adapt based on observed payoffs.
(2) Multi-agent systems and heterogeneity: Electricity markets consist of diverse participants, including fossil fuel plants, renewable energy sources, and storage systems. Recent research incorporates heterogeneous agent characteristics, such as generation costs, capacity constraints, and emissions penalties, into evolutionary models. This ensures that the models accurately reflect real-world complexities.
(3) Algorithmic advancements: Computational algorithms, such as agent-based simulations and reinforcement learning, have been integrated into EGT frameworks. These methods enable researchers to explore high-dimensional strategy spaces, simulate complex market dynamics, and identify stable bidding strategies under varying market conditions.
(4) Policy-oriented applications: Evolutionary models have been employed to study the impact of policy measures, such as carbon pricing, renewable energy subsidies, and capacity auctions, on bidding strategies and market outcomes. These applications provide valuable insights into the design of market mechanisms that promote stability, efficiency, and sustainability.

2.2.2. A Key Model: RD in Power Markets

One of the foundational models in EGT is the RD model, which describes the evolution of strategy proportions within a population over time. This model is particularly well-suited for analyzing power generation bidding, where generators iteratively adjust their strategies based on relative payoffs. The RD equation is given as follows:

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = x_i[u_i(x) - \overline{u}(x)] \tag{3}$$

where x_i is the proportion of the population adopting strategy i and $u_i(x)$ is the payoff associated with strategy iii in the current population distribution x. $\overline{u}(x) = \sum_j x_j u_j(x)$ is the average payoff of the population, weighted by strategy proportions. This equation highlights two key principles: Strategies with payoffs above the population average ($u_i(x) > \overline{u}(x)$) increase in prevalence over time. Conversely, strategies yielding below-average payoffs ($u_i(x) < \overline{u}(x)$) gradually decline.

2.2.3. Application to Power Generation Bidding

In the context of a deregulated electricity market, let us define x_i as the proportion of generators adopting bidding strategy i, and $u_i(x)$ as the profit associated with that strategy. The RD equation can be extended to incorporate specific market features, such as price caps, demand elasticity, and capacity constraints. A generalized form of the RD in power markets is the following:

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = x_i[\pi_i(p, q, c) - \overline{\pi}(p, q, c)] \tag{4}$$

where $\pi_i(p, q, c)$ is the profit function for generators using strategy i, dependent on market price (p), quantity sold (q), and generation cost (c). $\overline{\pi}(p, q, c)$ is the average profit across all strategies. In this formula, some key mathematical components are elaborated as follows.

(1) Profit function ($\pi_i(p, q, c)$): The profit function for a generator is typically expressed as $\pi_i = p \cdot q_i - c_i(q_i)$, where p: Market-clearing price; q_i: Quantity of electricity generated by strategy i; and $c_i(q_i)$: Cost of generating q_i, which may be linear ($c_i = c \cdot q_i$) or nonlinear (e.g., including startup or ramping costs).

(2) Market-clearing condition: The market-clearing price p is determined by balancing supply and demand:

$$\sum_i q_i = D(p) \tag{5}$$

where (p) represents the electricity demand as a function of price p. This condition ensures that the price dynamically adjusts to match supply with demand in each market iteration.

(3) Evolutionary stability criterion: An equilibrium strategy x^* is considered evolutionarily stable if it satisfies the following:

$$\forall i \neq j, u_i(x^*) > u_j(x^*) \tag{6}$$

This implies that no alternative strategy can achieve a higher payoff in the presence of x^*.

2.2.4. Explanation of the Mathematical Framework and Future Directions

The above introduced mathematical framework includes four main features:

(1) Dynamic adjustment of strategies: The RD equation models how generators adjust their bidding strategies based on profit differentials. If a specific strategy i consistently yields higher profits, it will attract more participants, leading to an increase in x_i. Over time, this mechanism drives the population toward an equilibrium distribution of strategies.

(2) Role of payoff functions: The payoff functions (x) capture the economic incentives for generators to adopt specific strategies. In power markets, these payoffs depend not only on direct profits but also on external factors, such as regulatory penalties for emissions or rewards for renewable generation.

(3) Market equilibrium and stability: The market-clearing condition ensures that prices dynamically adjust to reflect the interplay between supply and demand. By coupling this condition with the RD equation, the model captures both short-term pricing dynamics and long-term strategic evolution.

(4) Stability analysis: Stability is assessed by examining whether the RD system converges to an equilibrium distribution x^*. Evolutionary stability ensures that once an equilibrium is reached, no participant has an incentive to unilaterally deviate from the prevailing strategy.

Based on the above, while RD provide a robust framework for modeling power generation bidding, several challenges remain:

Stochastic factors: Real-world electricity markets are subject to uncertainty, such as fluctuating renewable output and demand variability. Integrating stochastic dynamics into EGT models would enhance their realism.

Incorporating grid constraints: Future models should account for transmission constraints, grid reliability, and reserve requirements, which significantly impact bidding behavior.

Algorithmic innovations: Machine learning techniques, such as reinforcement learning, could complement evolutionary models by enabling agents to learn optimal strategies in complex, dynamic environments.

In conclusion, the application of evolutionary game theory to power generation bidding offers a powerful toolset for understanding and predicting market behavior. By leveraging models like RD and integrating advanced computational methods, researchers can design mechanisms that ensure market stability, efficiency, and sustainability.

2.3. Evolutionary Game Model Simulation for Two-Strategy Groups in Power Markets

2.3.1. Typical Two-Group Two-Strategy Symmetric Evolutionary Game Model

(1) Basic assumptions: We consider two homogeneous groups A and B participating in the electricity market. The strategies available to group A are $S_{A1} = x$ and $S_{A2} = 1 - x$, where $x \in [0, 1]$, while the strategies for group B are $S_{B1} = y$ and $S_{B2} = 1 - y$, with $y \in [0, 1]$. Both groups operate under the assumption of incomplete information regarding the payoff matrix in the competitive market. This two-group evolutionary game is represented by the payoff matrix shown below:

$$\begin{array}{ccc} & S_{B1}(y) & S_{B2}(1-y) \\ S_{A1}(x) & (a,a) & (c,d) \\ S_{A2}(1-x) & (d,c) & (g,g) \end{array} \tag{7}$$

Here, a, c, d, g represent the payoff parameters for the combination of strategies adopted by the two groups. These parameters are flexible and depend on the specific market conditions and empirical data. Using Equation (7), the system's RD equations can be derived as follows:

$$\begin{cases} \dfrac{dx}{dt} = x(1-x)[(a-c-d+g)y + c - g] \\ \dfrac{dy}{dt} = y(1-y)[(a-c-d+g)x + c - g] \end{cases} \tag{8}$$

The system's equilibrium points are determined by setting $\dfrac{dx}{dt} = 0$ and $\dfrac{dy}{dt} = 0$. Solving this yields the following:

$$\begin{cases} x(1-x)[(a-c-d+g)y + c - g] = 0 \\ y(1-y)[(a-c-d+g)x + c - g] = 0 \end{cases} \tag{9}$$

The equilibrium points are as follows:

$$\varphi_{ESS} = \{(0,0), (0,1), (1,0), (1,1)\} \tag{10}$$

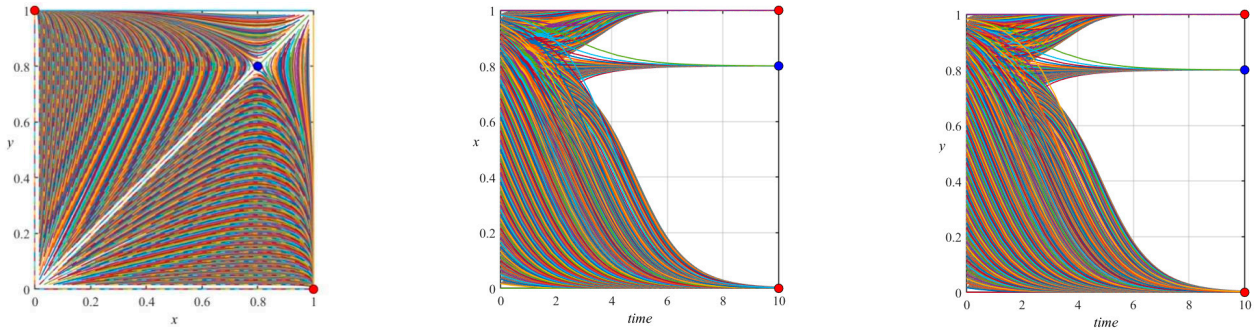
(2) Evolutionary stability analysis: To determine the stability of these equilibrium points, the Jacobian matrix for the evolutionary game model is constructed as follows:

$$J_1 = \begin{bmatrix} (1-2x)[(a-c-d+g)y + c - g] & x(1-x)(a-c-d+g) \\ y(1-y)(a-c-d+g) & (1-2y)[(a-c-d+g)x + c - g] \end{bmatrix} \tag{11}$$

The determinant and trace of the Jacobian matrix are computed as follows:

$$\begin{cases} \det(J_1) = (1-2x)(1-2y)[(a-c-d+g)x + c - g][(a-c-d+g)y + c - g] - \\ \qquad [x(1-x)(a-c-d+g)][y(1-y)(a-c-d+g)] \\ \mathrm{tr}(J_1) = (1-2x)[(a-c-d+g)y + c - g] + (1-2y)[(a-c-d+g)x + c - g] \end{cases} \tag{12}$$

In our study, we utilized MATLAB software, version 2019b, for the simulation research. The software was provided by MathWorks, located in Natick, Massachusetts, USA. Based on this, the payoff parameters (a, c, d, g) are set as (3, 6, 4, 2), and the dynamics of x and y over time are simulated with a time step of 1/60 s for 50 iterations using MATLAB 2019b (MathWorks, Natick, MA, USA). The resulting trajectories in the $x - y$, $x - t$, and $y - t$ spaces are depicted in Figure 1. The observations are summarized below:



(**a**) (**b**) (**c**)

Figure 1. The phase trajectory simulation results for a typical symmetric two-group two-strategy evolutionary game when considering a = 3, b = 6, c = 4, and d = 2. (**a**) The phase trajectory of (x, y). (**b**) The phase trajectory of (x, t). (**c**) The phase trajectory of (y, t).

(1) **Stable equilibria:**

The system stabilizes at equilibrium points (0, 1) and (1, 0), where one group fully adopts a single strategy. These equilibria are evolutionarily stable and indicate that, under specific payoff conditions, the market will converge to a state where groups settle on distinct, stable strategies.

(2) **Intermediate states:** A saddle-point equilibrium exists at $\left(\frac{a-d}{a-c-d+g}, \frac{a-d}{a-c-d+g}\right)$, representing a transient state of partial strategy adoption. This equilibrium is unstable, meaning that the market will not remain in this intermediate state under normal dynamics.

(3) **Payoff impacts:** The analysis reveals that the stability of equilibria depends heavily on the relative magnitudes of the payoff parameters. Consider the following, for instance:

- When $c > g$, equilibria (0, 0) and (1, 1) are unstable.
- When $a > d$, the system stabilizes at (0, 1) or (1, 0).

(4) **Impact of incentives:** If market regulators introduce penalties or subsidies, the parameters a, c, d, g can be adjusted to guide the system toward desired equilibria. For example, the increasing g could make renewable energy strategies more competitive, encouraging their widespread adoption. This two-group two-strategy evolutionary model provides a valuable framework for analyzing the dynamics of bidding strategies in power generation markets. By incorporating payoff parameters that reflect real-world incentives, the model can simulate the impact of regulatory interventions, such as carbon pricing or renewable subsidies, on market stability.

2.3.2. Typical Two-Group Two-Strategy Asymmetric Evolutionary Game Model

(1) Basic assumptions: Consider a heterogeneous market involving two groups, A and B, each with their own distinct strategies and payoffs. The strategy set for group A is defined as $S_{A1} = x$ and $S_{A2} = 1 - x$, where $x \in [0, 1]$. Similarly, the strategies for group B are $S_{B1} = y$ and $S_{B2} = 1 - y$, with $y \in [0, 1]$. Both groups operate under incomplete

information about the competitive environment, and their payoffs are governed by a non-symmetric payoff matrix:

$$\begin{array}{ccc} & S_{B1}(y) & S_{B2}(1-y) \\ S_{A1}(x) & (a,b) & (c,d) \\ S_{A2}(1-x) & (e,f) & (g,h) \end{array} \tag{13}$$

Here: a, b, c, d, e, f, g, h are the payoff parameters associated with the strategic interactions between groups A and B. These values depend on empirical data and market-specific characteristics, such as pricing mechanisms and regulatory constraints. Using Equation (13), the RD equations for the system are derived as follows:

$$\begin{cases} \dfrac{dx}{dt} = x(1-x)[(a-c-e+d)y+c-g] \\ \dfrac{dy}{dt} = y(1-y)[(b-d-f+h)x+f-h] \end{cases} \tag{14}$$

To find the system's equilibrium points, we set $\dfrac{dx}{dt} = 0$ and $\dfrac{dy}{dt} = 0$, resulting in the following:

$$\begin{cases} x(1-x)[(a-c-e+d)y+c-g] = 0 \\ y(1-y)[(b-d-f+h)x+f-h] = 0 \end{cases} \tag{15}$$

The equilibrium points are denoted as $\varphi_{ESS} = \{(0,0),(0,1),(1,0),(1,1)\}$.

(2) Evolutionary stability analysis: To analyze the stability of these equilibrium points, we construct the Jacobian matrix for the evolutionary game model as:

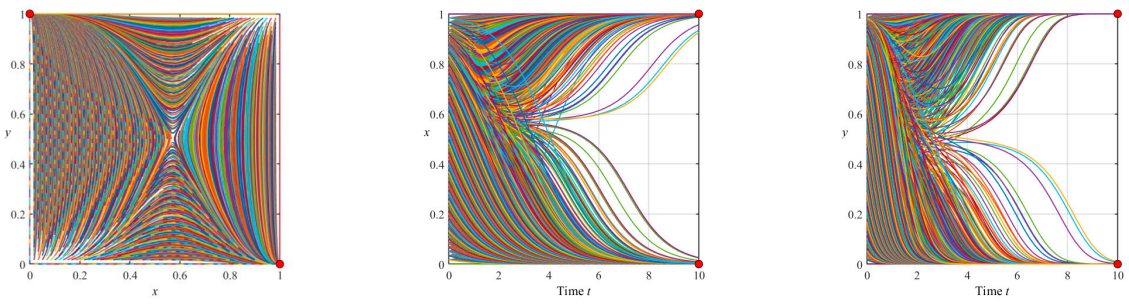
$$J_2 = \begin{bmatrix} (1-2x)[(a-c-e+d)y+c-g] & x(1-x)(a-c-e+d) \\ y(1-y)(b-d-f+h) & (1-2y)[(b-d-f+h)x+f-h] \end{bmatrix} \tag{16}$$

The determinant and trace of the Jacobian matrix $\boldsymbol{J}_2$ are computed as follows:

$$\begin{cases} \det(J_2) = (1-2x)(1-2y)[(a-c-e+d)y+c-g][(b-d-f+h)x+f-h] - \\ \qquad xy(1-x)(1-y)(a-c-e+d)(b-d-f+h) \\ \mathrm{tr}(J_2) = (1-2x)[(a-c-e+d)y+c-g] + (1-2y)[(b-d-f+h)x+f-h] \end{cases} \tag{17}$$

The stability of the system is determined by evaluating $\det(\boldsymbol{J}_2)$ and $\mathrm{tr}(\boldsymbol{J}_2)$. The equilibrium points are classified as stable if $\det(\boldsymbol{J}_2) > 0$ and $\mathrm{tr}(\boldsymbol{J}_2) < 0$.

The payoff parameters (a, b, c, d, e, f, g, h) are set as (6, 2, 4, 5, 7, 6, 3, 2), and dynamic simulations of x and y are conducted using MATLAB with a time step of 1/60 s for 50 iterations. The trajectories in the $x-y$, $x-t$, and $y-t$ spaces are shown in Figure 2. The simulation results provide the following observations:



(**a**) (**b**) (**c**)

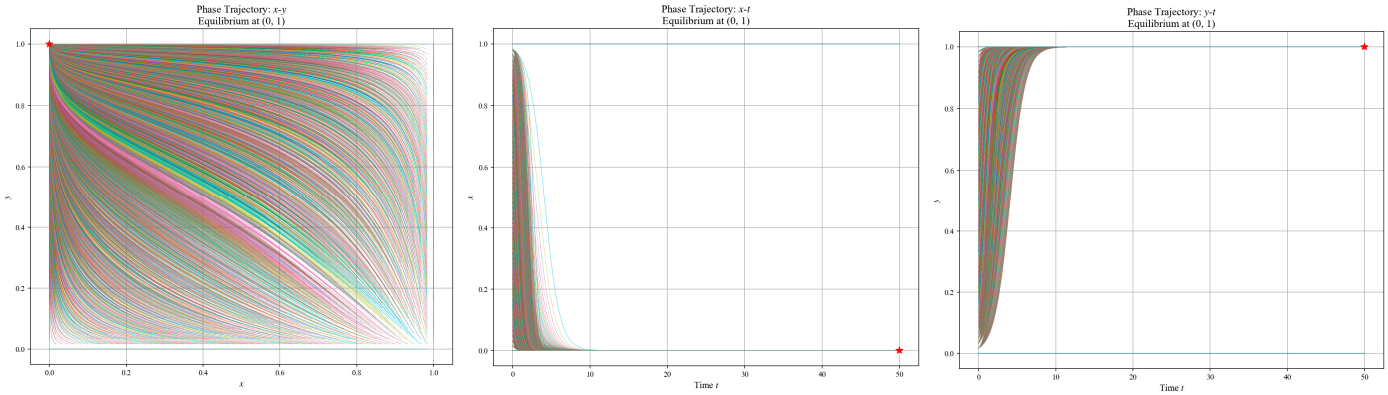
Figure 2. The phase trajectory simulation results for a typical asymmetric two-group two-strategy evolutionary game when considering a = 6, b = 2, c = 4, d = 5, e = 7, f = 6, g = 3, h = 2. (**a**) The phase trajectory of (x, y). (**b**) The phase trajectory of (x, t). (**c**) The phase trajectory of (y, t).

(1) **Stable equilibria:** The system converges to two stable equilibria: (0, 1) and (1, 0). These represent scenarios where one group fully adopts a dominant strategy while the other group selects an alternative strategy. This aligns with practical market dynamics, where different groups settle on distinct bidding behaviors over time.
(2) **Absence of saddle points:** The simulation reveals that no saddle points exist in the phase trajectories. This is due to the condition $a - c - e + d = 0$, which eliminates the possibility of intermediate equilibrium states.
(3) **Regulatory impacts:** If S_{A1}, S_{A2} represent low-cost and high-cost bidding strategies, regulators aiming to achieve balanced competition can introduce penalty mechanisms. For instance, ensuring $c \geq g, f \geq h, a > e, b > d$ restricts the system to the equilibrium (1, 1), encouraging both groups to adopt low-cost strategies.
(4) **Impact of parameter variations:** Stability is influenced by the signs of $(a - e)$, $(b - d)$, $(c - g)$, $(f - h)$. By systematically analyzing 16 different cases, it is evident that stability outcomes vary based on the relative magnitudes of these parameters. This highlights the importance of fine-tuning regulatory policies to guide market dynamics effectively.
(5) **Critical evaluation and expansion:** The non-symmetric evolutionary game model presented here extends the classical symmetric model by incorporating heterogeneity between groups. This framework is particularly relevant to power generation markets, where different participants—such as renewable energy producers, fossil fuel plants, and storage providers—operate under distinct cost structures and strategic priorities.

To this end, we give a summary and analysis of the four scenarios for unique evolutionary stable equilibria.

Scenario 1: Unique Equilibrium at (0, 0). The parameter settings are as follows: $a = 1$, $b = 1$, $c = 2$, $d = 1$, $e = 2$, $f = 2$, $g = 3$, $h = 2$. Purpose and Motivation: In this scenario, the system is designed such that (0, 0) becomes the only evolutionary stable equilibrium (ESE). This equilibrium implies that both groups, A and B, predominantly select their respective S_{A2} and S_{B2} strategies. The primary purpose of this setup is to investigate conditions under which both groups avoid adopting aggressive or high-cost strategies. Conditions to Ensure Stability: The payoff parameters c and g dominate, ensuring that deviations from $x = 0$ or $y = 0$ incur greater penalties compared to maintaining $x = 0$ and $y = 0$. The interactions between groups (represented by $a - c - e + d$ and $b - d - f + h$) are balanced to disincentivize any deviation. Analysis: By ensuring that $c > g$ and $f > h$, the payoff matrix penalizes any attempt to increase x or y. As a result, the system's trajectories converge to (0, 0). This setting reflects a scenario where cooperation or conservative strategies dominate, leading to stability at low strategic engagement levels.

Scenario 2: Unique Equilibrium at (0, 1), as illustrated in Figure 3. Parameter Settings: $a = 1$, $b = 3$, $c = 2$, $d = 1$, $e = 2$, $f = 2$, $g = 3$, $h = 1$. Purpose and Motivation: In this scenario, the system converges to (0, 1), where group A predominantly selects S_{A2}, and group B predominantly selects S_{B1}. This configuration simulates conditions where one group prefers a conservative strategy ($x = 0$), while the other adopts a more aggressive strategy ($y = 1$). Conditions to Ensure Stability: $b > d > f$ ensures that $y = 1$ is the dominant strategy for group B, while $a < c$ and $g > e$ ensure that $x = 0$ is the preferred strategy for group A. The interaction terms between the two groups reinforce the asymmetry, with b heavily incentivizing $y = 1$ while ccc discourages $x > 0$. Analysis: This scenario reflects an asymmetric market dynamic where group B gains a competitive advantage by adopting an aggressive strategy (S_{B1}), while group A settles into a supporting or complementary role by avoiding S_{A1}. Such a setup can model situations where one group leverages a cost advantage or market power to dominate.



(**a**) (**b**) (**c**)

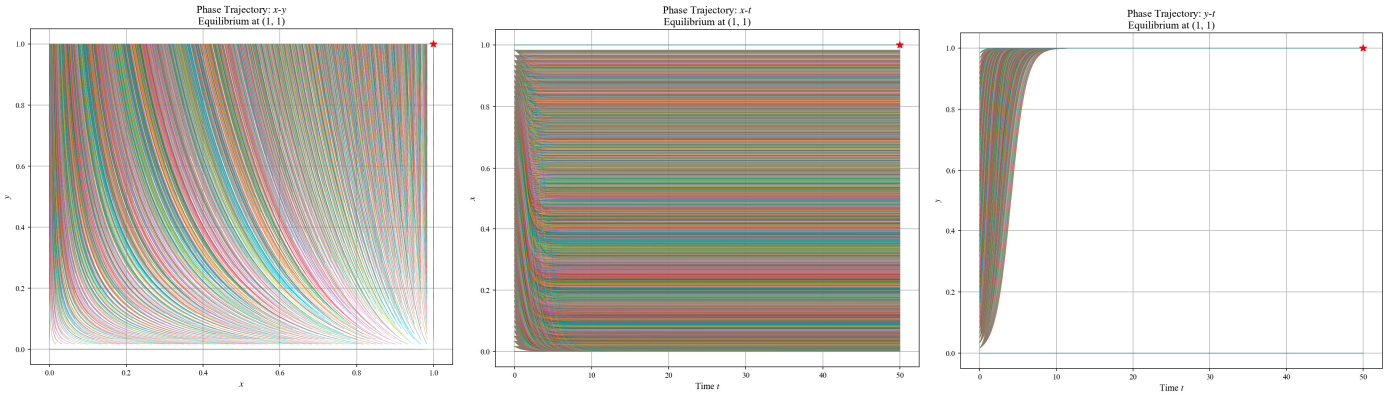
Figure 3. The phase trajectory simulation results for a typical asymmetric two-group two-strategy evolutionary game achieving a unique ESE at (0, 1) when considering $a = 1$, $b = 3$, $c = 2$, $d = 1$, $e = 2$, $f = 2$, $g = 3$, $h = 1$. (**a**) The phase trajectory of (x, y). (**b**) The phase trajectory of (x, t). (**c**) The phase trajectory of (y, t).

Scenario 3: Unique Equilibrium at (1, 0). Parameter Settings: $a = 3$, $b = 1$, $c = 2$, $d = 1$, $e = 1$, $f = 2$, $g = 3$, $h = 2$. Purpose and Motivation: Here, the system converges to (1, 0), where group A predominantly selects S_{A1}, and group B predominantly selects S_{B2}. This scenario represents a reversed asymmetry compared to Scenario 2, with group A now adopting an aggressive strategy ($x = 1$) while group B adopts a conservative strategy ($y = 0$). Conditions to Ensure Stability: $a > e > c$ ensures that $x = 1$ is the dominant strategy for group A, while $b < f$ and $h > d$ disincentivize any deviation from $y = 0$. The interaction terms balance the stability, with $a - c - e + d$ and $b - d - f + h$ adjusted to reinforce the dominance of the respective strategies. Analysis: This configuration models a situation where group A drives market dynamics by adopting an aggressive strategy, while group B acts more passively or defensively. Such a scenario could represent a market with a dominant player and a supporting or regulated competitor.

Scenario 4: Unique Equilibrium at (1, 1), as demonstrated in Figure 4. Parameter Settings: $a = 3$, $b = 3$, $c = 2$, $d = 1$, $e = 1$, $f = 2$, $g = 3$, $h = 1$. Purpose and Motivation: This scenario forces the system to converge to (1, 1), where both groups A and B predominantly select their respective aggressive strategies (S_{A1} and S_{B1}). The purpose is to study conditions under which mutual aggression or competition leads to stable outcomes. Conditions to Ensure Stability: $a > c > e$ and $b > d > f$ ensure that $x = 1$ and $y = 1$ are the dominant strategies for groups A and B, respectively. The interaction terms $a - c - e + d$ and $b - d - f + h$ are balanced to disincentivize deviations from (1, 1). Analysis: This setting models a highly competitive market where both groups adopt aggressive strategies to maximize their payoffs. The stability at (1, 1) suggests that aggressive competition is sustainable under these specific conditions, which may reflect markets with high stakes or significant rewards for dominating strategies.

Overall, the parameters a, b, c, d, e, f, g, h play a critical role in determining the system's dynamics and equilibria. By carefully adjusting these parameters, we can control the stability and location of the evolutionary stable equilibria (ESS). Increasing Payoff for Specific Strategies: To ensure stability at a specific equilibrium, increase the payoff for the desired strategies (e.g., A and B for (1, 1)) while reducing the payoffs for competing strategies. Balancing Interaction Terms: The terms $a - c - e + d$ and $b - d - f + h$ determine the interaction dynamics between the groups. Adjusting these terms ensures that the system strongly favors one equilibrium over others. Eliminating Saddle Points: To avoid unstable intermediate equilibria, ensure that the payoff differences $a - c - e + d$ and $b - d - f + h$ do not cancel out, which could create transient states. By fine-tuning the parameters,

the system's behavior is modeled through evolutionary dynamics, allowing for detailed analysis of strategic interactions, market outcomes, and carbon reduction strategies under different regulatory environments.



(**a**) (**b**) (**c**)

Figure 4. The phase trajectory simulation results for a typical asymmetric two-group two-strategy evolutionary game achieving a unique ESE at (1, 1) when considering $a = 3$, $b = 3$, $c = 2$, $d = 1$, $e = 1$, $f = 2$, $g = 3$, $h = 1$. (**a**) The phase trajectory of (x, y). (**b**) The phase trajectory of (x, t). (**c**) The phase trajectory of (y, t).

2.3.3. Typical Three-Group Two-Strategy Asymmetric Evolutionary Game Model

Basic Assumptions: This section considers a market region comprising three categories of power generation groups with distinct capacities: small capacity (SP), medium capacity (MP), and large capacity (LP). Here, the producers are classified based on their installed capacity (i.e., the total capacity of their power generation units) and market share within the relevant electricity market. In the real-world electricity market, these factors are significant because they affect producers' ability to influence market-clearing prices and their bidding behavior. Larger producers, with more capacity, have a greater ability to affect market outcomes, while smaller producers often have less influence on price formation.

- Large producers (LP): Typically, these are the dominant players in the market with a significant share of total market capacity (e.g., large utility companies or multinational power generation firms). These companies tend to have greater financial resources and can employ more sophisticated bidding strategies, such as strategic bidding to influence market prices. In our model, we define large producers as those with a capacity that constitutes over 30% of the total market capacity.
- Medium producers (MP): These producers have a moderate market share, generally between 10-30% of the total market capacity. They may have some ability to influence prices but are not as dominant as large producers. Their bidding strategies often focus on optimizing profits while responding to the strategies of larger producers and market conditions.
- Small producers (SP): These are usually independent producers or renewable energy producers (e.g., wind farms or solar power plants) with smaller market shares (typically less than 10%). These producers are price takers, and their bidding strategies are often more passive compared to larger producers.

To better reflect the practical dynamics of the electricity market, it is assumed that these three groups operate with incomplete information regarding each other's strategies, and each group has only two bidding strategies, S_H (high-price bidding) and S_L (low-price bidding). The evolutionary game model prioritizes the allocation of capacity, with larger-capacity groups bidding first, followed by smaller-capacity groups. Assuming that each

group SP, MP, and LP consists of N_A, N_B, and N_C power producers, respectively, each producer's generation capacity is determined by its individual strategy S_L or S_H. The cost of production, $C(P_j)$, is defined by $C(P_j) = a_j + b_j P_j + c_j P_j^2, j \in \{1, 2, \cdots, N_i\}$, where P_j is the actual power generation output of producer j, and a_j, b_j, c_j are cost coefficients specific to the producer within each group.

The expected market-clearing price is denoted as P_{MCP}, and the revenue for each producer, $f(P_j)$, is expressed as follows:

$$f(P_j) = P_{MCP} P_j - C(P_j) \tag{18}$$

Under the market-clearing price (MCP) mechanism, the optimal strategy for maximizing profit $f(P_j)$ is determined by the following optimization problem:

$$\begin{cases} \max f(P_j) \\ s.t. \sum P_j = Q_{Ma}, B_j(S_j, P_j) = B_{MCP} \end{cases} \tag{19}$$

where S_j is strategy set for the power producer, Q_{Ma} is market demand during trading, and $B_j(S_j, P_j)$ is the cost–benefit equation for bidding in the MCP market. The payoffs for the SP, MP, and LP groups are summarized in Table 1.

Table 1. The payoffs for the SP, MP, and LP groups.

Group SP and Group MP				Group LP	
				S_H	S_L
SP	S_H	MP	S_H	(a_1, a_2, a_3)	(b_1, b_2, b_3)
			S_L	(c_1, c_2, c_3)	(d_1, d_2, d_3)
	S_L		S_H	(e_1, e_2, e_3)	(f_1, f_2, f_3)
			S_L	(g_1, g_2, g_3)	(h_1, h_2, h_3)

Based on Table 1, each payoff reflects the profit parameters for power producers bidding within each group, derived from actual operational data. The expected payoffs for executing strategies S_H and S_L for each group are given by E_{SP1}, E_{SP2}, E_{MP1}, E_{MP2}, E_{LP1}, and E_{LP2}, while the average payoffs for these groups are denoted as E_{Spav}, E_{Mpav}, and E_{Lpav}. These are expressed by the following equations:

$$\begin{cases} E_{SP1} = y[za_1 + (1-z)b_1] + (1-y)[zc_1 + (1-z)d_1] \\ E_{SP2} = y[ze_1 + (1-z)f_1] + (1-y)[zg_1 + (1-z)h_1] \\ E_{MP1} = z[xa_2 + (1-x)e_2] + (1-z)[xb_2 + (1-x)f_2] \\ E_{MP2} = z[xc_2 + (1-x)g_2] + (1-z)[xd_2 + (1-x)h_2] \\ E_{LP1} = x[ya_3 + (1-y)c_3] + (1-x)[ye_3 + (1-y)g_3] \\ E_{LP2} = x[yb_3 + (1-y)d_3] + (1-x)[yf_3 + (1-y)h_3] \end{cases} \tag{20}$$

$$\begin{cases} E_{SPav} = xE_{SP1} + (1-x)E_{SP2} \\ E_{MPav} = yE_{MP1} + (1-y)E_{MP2} \\ E_{LPav} = zE_{LP1} + (1-z)E_{LP2} \end{cases} \tag{21}$$

These equations capture the interaction dynamics between groups, where the variables x, y, and z denote the probabilities of selecting low-price bidding strategies for SP, MP, and LP groups, respectively. Critical expansion and discussion are shown as follows.

Economic rationale: The three-group $2 \times 2 \times 2$ evolutionary game model reflects the real-world dynamics of electricity markets, where generators of varying capacities adopt different strategies based on cost structures and market-clearing prices. Larger-capacity producers often dominate the bidding process, influencing the strategic choices of smaller-

capacity producers. By incorporating two strategy options (S_H and S_L) for each group, this model captures the competitive interplay among heterogeneous participants.

Policy implications: The payoffs in Table 1 suggest that strategic adjustments to the parameters a, b, c, d, e, f, g, h can be used to influence market outcomes. For instance, regulators can incentivize low-cost bidding by providing subsidies (reducing c_j) or imposing penalties on high-cost strategies (increasing a_j). The MCP-based optimization ensures that the market operates efficiently by aligning power generation output with demand while maximizing individual profits.

Model limitations: While the model accounts for the heterogeneity in generation capacities, it assumes uniform behavior within each group (SP, MP, LP). This may oversimplify the complexities of real-world markets, where individual producers often have unique constraints and objectives.

Future directions include incorporating stochastic elements into the MCP mechanism to account for demand variability and renewable energy intermittency, as well as extending the model to include additional strategy options (S_H, S_L, S_M) or dynamic capacity adjustments, reflecting real-time grid conditions. The three-group $2 \times 2 \times 2$ evolutionary game model provides a robust theoretical framework for understanding the strategic bidding behaviors of heterogeneous power producers. By linking individual profit maximization to market-clearing mechanisms, this model offers valuable insights into the dynamics of competitive electricity markets. Further research should focus on enhancing the model's realism and exploring its applicability to scenarios involving renewable energy integration, grid constraints, and long-term market stability.

Formulation of the RD: The RD equations for the three-group $2 \times 2 \times 2$ evolutionary game model are formulated as follows:

$$\begin{cases} h_{SP}(x) = \dfrac{dx}{dt} = x(E_{SP1} - E_{SPav}) \\ h_{MP}(y) = \dfrac{dy}{dt} = y(E_{MP1} - E_{MPav}) \\ h_{LP}(z) = \dfrac{dz}{dt} = z(E_{LP1} - E_{LPav}) \end{cases} \tag{22}$$

By substituting the payoff expressions, the RD can be expanded into the following form:

$$\begin{cases} h_{SP}(x) = x(1-x)g_{SP}(y,z) \\ h_{MP}(y) = y(1-y)g_{MP}(x,z) \\ h_{LP}(z) = z(1-z)g_{LP}(x,y) \end{cases} \tag{23}$$

$$\begin{cases} g_{SP}(y,z) = (a_1 - b_1 - c_1 + d_1 - e_1 + f_1 + g_1 - h_1)yz + (b_1 - d_1 - f_1 + h_1)y + \\ \qquad (c_1 - d_1 - g_1 + h_1)z + d_1 - h_1 \\ g_{MP}(x,z) = (a_2 - b_2 - c_2 + d_2 - e_2 + f_2 + g_2 - h_2)zx + (e_2 - f_2 - g_2 + h_2)z + \\ \qquad (b_2 - d_2 - f_2 + h_2)x + f_2 - h_2 \\ g_{LP}(y,x) = (a_3 - b_3 - c_3 + d_3 - e_3 + f_3 + g_3 - h_3)xy + (c_3 - d_3 - g_3 + h_3)y + \\ \qquad (e_3 - f_3 - g_3 + h3)x + g_3 - h_3 \end{cases} \tag{24}$$

The RD can be expressed in matrix form for clarity:

$$\begin{bmatrix} \dfrac{dx}{dt} \\ \dfrac{dy}{dt} \\ \dfrac{dz}{dt} \end{bmatrix} = \begin{bmatrix} x(1-x)g_{SP}(y,z) \\ y(1-y)g_{MP}(x,z) \\ z(1-z)g_{LP}(x,y) \end{bmatrix} \tag{25}$$

At equilibrium ($dx/dt = 0$, $dy/dt = 0$, $dz/dt = 0$), the system satisfies the following:

$$\begin{cases} x(1-x)g_{SP}(y,z) = 0 \\ y(1-y)g_{MP}(x,z) = 0 \\ z(1-z)g_{LP}(x,y) = 0 \end{cases} \tag{26}$$

Stability Analysis: The Jacobian matrix ($\boldsymbol{J}$) of the system corresponding to the RD Equation (25) derived earlier can be used to analyze the stability of the internal equilibrium points in the system by examining the positivity or negativity of the eigenvalues. The focus of this section is on the three groups SP, MP, and LP. Let $\boldsymbol{J}$ represent the associated three-by-three matrix, which has three eigenvalues denoted by λ_k ($k = 1, 2, 3$).

For simplification, let us assume the following:

$$\begin{cases} s_1 = a_1 - b_1 - c_1 + d_1 - e_1 + f_1 + g_1 - h_1 \\ s_2 = b_1 - d_1 - f_1 + h_1 \\ s_3 = c_1 - d_1 - g_1 + h_1 \\ s_4 = d_1 - h_1 \\ m_1 = a_2 - b_2 - c_2 + d_2 - e_2 + f_2 + g_2 - h_2 \\ m_2 = e_2 - f_2 - g_2 + h_2 \\ m_3 = b_2 - d_2 - f_2 + h_2 \\ m_4 = f_2 - h_2 \\ l_1 = a_3 - b_3 - c_3 + d_3 - e_3 + f_3 + g_3 - h_3 \\ l_2 = c_3 - d_3 - g_3 + h_3 \\ l_3 = e_3 - f_3 - g_3 + h_3 \\ l_4 = g_3 - h_3 \end{cases} \tag{27}$$

Then, Equation (24) can be simplified as follows:

$$\begin{cases} g_{SP}(y,z) = s_1yz + s_2y + s_3z + s_4 \\ g_{MP}(x,z) = m_1zx + m_2z + m_3x + m_4 \\ g_{LP}(y,x) = l_1xy + l_2y + l_3x + l_4 \end{cases} \tag{28}$$

The corresponding Jacobian matrix ($\boldsymbol{J}$) of the system is expressed as

$$\begin{aligned} \boldsymbol{J} &= \begin{bmatrix} (1-2x)g_{SP}(y,z) & x(1-x)\dfrac{\partial g_{SP}(y,z)}{\partial y} & x(1-x)\dfrac{\partial g_{SP}(y,z)}{\partial z} \\ y(1-y)\dfrac{\partial g_{MP}(x,z)}{\partial x} & (1-2y)g_{MP}(x,z) & y(1-y)\dfrac{\partial g_{MP}(x,z)}{\partial z} \\ z(1-z)\dfrac{\partial g_{LP}(x,y)}{\partial x} & z(1-z)\dfrac{\partial g_{LP}(x,y)}{\partial y} & (1-2z)g_{LP}(x,y) \end{bmatrix} \\ &= \begin{bmatrix} (1-2x)(s_1yz + s_2y + s_3z + s_4) & x(1-x)(s_1z + s_2) & x(1-x)(s_1z + s_3) \\ y(1-y)(m_1x + m_3) & (1-2y)(m_1zx + m_2z + m_3x + m_4) & y(1-y)(m_1x + m_2) \\ z(1-z)(l_1y + l_3) & z(1-z)(l_1x + l_2) & (1-2z)(l_1xy + l_2y + l_3x + l_4) \end{bmatrix} \end{aligned} \tag{29}$$

The set of all solutions formed by the internal equilibrium equations of the system is denoted as Ψ_{ESS}. These solutions can be categorized into four scenarios, as shown in Table 2.

Based on Table 2, we set the payoff distribution parameters as follows:

$$\begin{cases} a_1 = 24, b_1 = 24, c_1 = 24, d_1 = 2, e_1 = 24, f_1 = 24, g_1 = 24, h_1 = 5 \\ a_2 = 78, b_2 = 78, c_2 = 78, d_2 = 78, e_2 = 78, f_2 = 6, g_2 = 78, h_2 = 13 \\ a_3 = 120, b_3 = 120, c_3 = 120, d_3 = 120, e_3 = 120, f_3 = 120, g_3 = 4, h_3 = 8 \end{cases} \tag{30}$$

$$\begin{cases} s_1 = -3, s_2 = 3, s_3 = 3, s_4 = -3 \\ m_1 = -7, m_2 = 7, m_3 = 7, m_4 = -7 \\ l_1 = -4, l_2 = 4, l_3 = 4, l_4 = -4 \end{cases} \tag{31}$$

Table 2. Distribution of all the equilibrium points in Ψ_{ESS}.

Case 1	**Case 2**
$\begin{cases} x(1-x)=0 \\ y(1-y)=0 \\ z(1-z)=0 \end{cases}$	$\begin{cases} g_{SP}(y,z)=0 \\ g_{MP}(z,x)=0 \\ g_{LP}(y,x)=0 \end{cases}$
Case 3	
$\begin{cases} g_{SP}(y,z)=0 \\ y(1-y)=0 \\ z(1-z)=0 \end{cases}$ or $\begin{cases} x(1-x)=0 \\ g_{MP}(z,x)=0 \\ z(1-z)=0 \end{cases}$ or $\begin{cases} x(1-x)=0 \\ y(1-y)=0 \\ g_{LP}(y,x)=0 \end{cases}$	
Case 4	
$\begin{cases} x(1-x)=0 \\ g_{MP}(z,x)=0 \\ g_{LP}(y,x)=0 \end{cases}$ or $\begin{cases} g_{SP}(y,z)=0 \\ y(1-y)=0 \\ g_{LP}(y,x)=0 \end{cases}$ or $\begin{cases} g_{SP}(y,z)=0 \\ g_{MP}(z,x)=0 \\ z(1-z)=0 \end{cases}$	

Then, based on the parameter settings above, the evolutionary stability of each equilibrium point can be obtained, as summarized in Table 3.

Table 3. The evolutionary stability of each equilibrium point.

Ψ_{ESS}	Evolutionary Stability	Ψ_{ESS}	Evolutionary Stability
(0, 0, 0)	ESS	(1, 0, 1)	Unstable
(1, 0, 0)	Unstable	(1, 1, 0)	Unstable
(0, 1, 0)	Unstable	(0, 1, 1)	Unstable
(0, 0, 1)	Unstable	(1, 1, 1)	Unstable

Simulation results: The RD equations were implemented in MATLAB 2019b, with simulations performed at 0.2 s intervals over 50 iterations to analyze the evolutionary dynamics of a three-group system (SP, MP, LP). The results of the (x, y, z) phase trajectory are shown in Figure 5. The summary of results from Figure 5 is elaborated as follows.

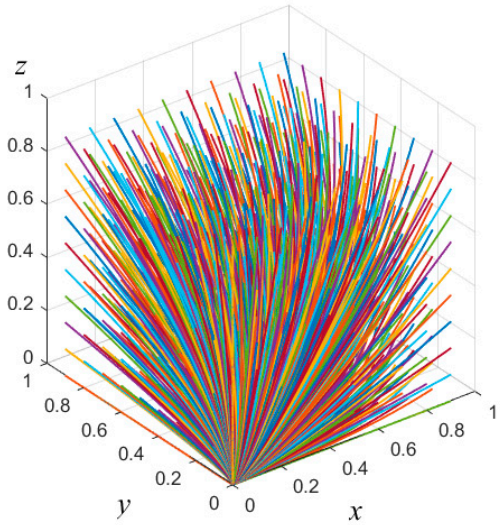


Figure 5. The phase trajectory simulation results of (x, y, z) for a typical asymmetric three-group two-strategy evolutionary game with a time step of 0.2 s.

(a) The system's phase trajectories converge only at (0, 0, 0): The simulation demonstrates that under the given parameter settings, the phase trajectories of the three groups converge exclusively at the equilibrium point (0, 0, 0). This equilibrium satisfies the conditions for an evolutionarily stable strategy (ESS), indicating that it is the only stable state in this specific scenario.

At (0, 0, 0), all three groups (SP, MP, LP) exclusively adopt the low-cost bidding strategy, leading to a uniform strategy profile. From a market perspective, this implies that all power producers opt for cost-efficient energy generation. However, this outcome may not be advantageous for producers who seek higher profits through aggressive bidding strategies.

As elaborated above, when high-price bidding strategies dominate (S_H), power producers achieve higher revenues at the expense of increased market prices. This scenario is suboptimal for consumers and policymakers, as it leads to higher electricity prices. Policymakers generally aim to align power generation costs with marginal prices to maintain market efficiency.

(b) Policy interventions to shift strategy adoption toward low-cost bidding: To encourage the adoption of low-cost strategies, regulators could implement penalty mechanisms for high-cost bidding strategies. For instance, modifying the payoff parameters to ensure $e_1<a_1$, $c_2<a_2$, $b_3<a_3$ would diminish the profits associated with high-cost strategies (S_H) while incentivizing low-cost bidding (S_L).

Specifically, penalty mechanisms can reduce the perceived benefits of aggressive bidding. This adjustment ensures that the system converges to the equilibrium point (0, 0, 0), where all groups consistently choose S_L.

Additionally, setting the coefficients s_4, m_4, l_4 to values below zero guarantees that the system stabilizes at (0, 0, 0). These parameters can be used as forecasting variables to assess whether the market is likely to exhibit aggressive competition among producers.

From a policy standpoint, regulators must pay close attention to the positivity of these penalty coefficients, as they directly influence the likelihood of achieving low-cost, cooperative equilibria. Monitoring these coefficients allows for more precise predictions of the market's evolution and potential strategic misalignments.

(c) The system exhibits 28 evolutionary scenarios across different parameters: The analysis reveals that the evolutionary stability of the system depends on the interplay between parameter settings and the eigenvalues associated with the Jacobian matrix ($\boldsymbol{J}$). Across the 28 evolutionary scenarios considered, the eigenvalues' positivity or negativity determines whether a given equilibrium is evolutionarily stable.

Notably, the final stability of the system varies significantly with changes in payoff parameters. This variation underscores the importance of initial conditions and group-specific payoffs in determining the system's trajectory.

For example, an initial configuration favoring high-cost bidding may trap the system in suboptimal equilibria, necessitating targeted interventions to reorient the groups toward more cooperative outcomes. By carefully adjusting the initial payoff structure, it is possible to enhance the system's long-term stability while minimizing inefficiencies.

Overall, from the aspect of market dynamics and equilibria, the simulation highlights the sensitivity of equilibrium outcomes to changes in payoff parameters. By tuning these parameters, policymakers can effectively influence the strategic behaviors of power producers, ensuring that the system converges to desirable equilibria. For instance, the equilibrium at (0, 0, 0) corresponds to a highly cooperative market environment where all groups adopt low-cost strategies, minimizing overall electricity costs. From the aspect of policy design and implementation, introducing penalties for aggressive bidding strategies (S_H) can shift the equilibrium toward cooperative outcomes. However, such policies must be

carefully calibrated to avoid excessive penalties that may disincentivize participation in the market altogether. Additionally, subsidies for low-cost strategies (S_L) could complement penalty mechanisms, further encouraging cost-efficient behavior among power producers. The simulation results from Figure 5 offer valuable insights into the dynamics of power generation bidding strategies within a three-group evolutionary game framework. By analyzing the conditions for evolutionary stability, this study provides a theoretical basis for designing market interventions that promote cooperative, cost-efficient equilibria. The findings underscore the importance of careful parameter calibration in achieving long-term market stability and efficiency, paving the way for future research on adaptive strategies and policy design in competitive electricity markets.

Future research directions: The findings suggest several avenues for future research. Incorporating stochastic elements into the RD could provide a more realistic representation of market volatility and uncertainty. Moreover, extending the model to include additional strategy options or heterogeneous player behaviors would enhance its applicability to complex electricity markets. Further analysis could also explore the long-term implications of different policy interventions on market stability, efficiency, and producer–consumer welfare.

3. Bidding Strategies for Power Generation Groups Based on Evolutionary Game Theory

3.1. Model Parameter Settings

This section utilizes the electricity market rules in East China as a case study to analyze the three-group evolutionary game model, particularly focusing on bidding mechanisms, transaction models, and carbon reduction strategies. The three groups—small producers (SP), medium producers (MP), and large producers (LP)—represent key players in the market, with generation capacities of 100 MW, 300 MW, and 500 MW, respectively. The model provides insights into how transaction models and bidding strategies play out among these groups. The parameters P_{SP}, P_{MP}, P_{LP} represent the bidding prices for each group, and the unit is measured in yuan per megawatt-hour (MWh).

The cost function for each group, along with bidding parameters, is illustrated in Table 4, showcasing the different strategies adopted by each group under varied market conditions. The unit costs are expressed as quadratic functions of the bidding volume. The generation groups submit bids across five capacity segments, with the minimum stable generation capacity for each group set as 50% of the rated capacity. The forecasted market-clearing price for electricity is assumed to be 480 yuan/MWh. Based on these assumptions and settings, Table 5 presents the calculated bidding strategies for small producers, medium producers, and large producers, which are influenced by transaction costs, market-clearing prices, and carbon reduction incentives.

Table 4. Bidding parameters for power generation groups.

Parameters	Group SP	Group MP	Group LP
Generation cost function (yuan/MWh)	$4800 + 170P_{SP} + 0.18{P_{SP}}^2$	$9600 + 136.8P_{MP} + 0.17{P_{MP}}^2$	$18760 + 118.6P_{LP} + 0.164{P_{LP}}^2$
Rated capacity (MW)	100	300	500
Minimum load capacity (MW)	50	150	250
Maximum controllable price (yuan/MWh)	480	480	480
Minimum controllable price (yuan/MWh)	275	244.9	234.6

The bidding strategies of the three groups—small producers (SP), medium producers (MP), and large producers (LP)—are influenced by several key factors such as market-clearing prices, generation costs, and capacity constraints. These strategies, both theoretical and practical, are outlined in Table 5 and analyzed in depth below:

1. Small Producers (SP)

Theoretical aspect: Small producers often face higher unit costs due to lower economies of scale, which directly influences their bidding strategy and their capacity to compete in carbon reduction efforts. Their bidding strategies focus on maintaining competitiveness at lower capacity levels by adopting more conservative pricing, which impacts both their market position and carbon reduction potential. The bidding strategy is influenced not only by the market-clearing price and production costs but also by the transaction models that account for carbon costs and environmental impact.

Practical aspect: In practice, small producers tend to align their bids with the market-clearing price, ensuring participation and minimizing risks associated with price volatility. This strategy also influences carbon reduction incentives as it ensures ongoing market participation, as seen in the price range for high-price bidding (SH) between 313 to 431 yuan/MWh and low-price bidding (SL) between 275 to 313 yuan/MWh. This strategy allows them to remain competitive while mitigating risks associated with price volatility.

Practical insight: As the market becomes more competitive, small producers may benefit from forming alliances with larger entities or adopting niche strategies focused on specific market segments or regional markets.

Table 5. Bidding strategies at 480 Yuan/MWh.

Group SP	**Capacity Segment**				
	(50 60]	**(60 70]**	**(70 80]**	**(80 90]**	**(90 100]**
High-price bidding strategy S_H	313	352	391	431	480
Low-price bidding strategy S_L	275	313	352	391	431
Group MP	**Capacity Segment**				
	(150 180]	**(180 210]**	**(210 240]**	**(240 270]**	**(270 300]**
High-price bidding strategy S_H	277	324	367	412	480
Low-price bidding strategy S_L	245	277	324	367	412
Group LP	**Capacity Segment**				
	(250 300]	**(300 350]**	**(350 400]**	**(400 450]**	**(450 500]**
High-price bidding strategy S_H	276	321	370	421	480
Low-price bidding strategy S_L	235	276	321	370	421

2. Medium Producers (MP)

Theoretical aspect: Medium producers strike a balance between cost efficiency, market positioning, and carbon reduction strategies, adapting their pricing in response to market shifts and regulatory frameworks. Their bidding strategy typically involves a wider range of pricing flexibility, allowing them to capture higher margins during favorable market conditions while remaining competitive in times of lower prices.

Practical aspect: The medium producers (MP) group exhibits versatility in their strategy, with high-price bids ranging from 277 to 480 yuan/MWh, reflecting a dynamic adjustment to both market conditions and carbon regulation incentives. The low-price bids from 244.9 to 367 yuan/MWh. Their ability to shift between these price ranges offers a strategic advantage, particularly when market conditions fluctuate.

Practical insight: Medium producers may adopt a dual strategy approach, utilizing both aggressive low-price bidding to gain market share and high-price bidding to optimize profit margins. Moreover, understanding demand fluctuations is crucial for adapting these strategies.

3. Large Producers (LP)

Theoretical aspect: Large producers (LP), benefiting from economies of scale, can offer lower prices at higher production capacities, ensuring they remain competitive in carbon-efficient bidding strategies. This strategic advantage is reflected in their ability to maintain competitive pricing even with large generation volumes. Their bidding strategy encompasses not only pricing but also market share maximization, with carbon reduction strategies often integrated into their long-term goals for profitability and market stability.

Practical aspect: Large producers exhibit a clear preference for lower-price bidding at higher capacities, with high-price bidding ranging from 292 to 528 yuan/MWh and low-price bidding from 210 to 292 yuan/MWh. Their ability to offer low prices at large capacities ensures they capture a larger share of the market.

Practical insight: Large producers are likely to dominate the market, but their strategic decisions, especially at high capacity levels, require careful balancing between maintaining competitiveness and optimizing revenue. As competition increases, LPs may be compelled to adopt more dynamic pricing models, especially with fluctuating market-clearing prices.

Analysis of Table 4: bidding parameters for power generation groups. Table 4 presents the cost functions, capacity constraints, and bidding limits for the three groups:

Small Producers (SP):

- Cost function: $4800 + 170P_{SP} + 0.18P_{SP}^2$;
- Rated capacity: 100 MW;
- Bidding price range: 275–431 yuan/MWh;
- Notably, small producers exhibit lower cost coefficients, making them more competitive at lower capacity levels.

Medium Producers (MP):

- Cost function: $9600 + 1136.8P_{MP} + 0.17P_{MP}^2$;
- Rated capacity: 300 MW;
- Bidding price range: 244.9–492 yuan/MWh;
- Medium producers balance between cost efficiency and scalability, providing flexible pricing strategies.

Large Producers (LP):

- Cost function: $18760 + 118.6P_{LP} + 0.164P_{LP}^2$;
- Rated capacity: 500 MW;
- Bidding price range: 210–528 yuan/MWh;
- Large producers demonstrate higher fixed costs but achieve economies of scale at higher capacities.

This setup highlights the heterogeneity of the groups, considering differences in generation scale, cost structure, and their respective bidding flexibility and carbon mitigation approaches.

Table 5 provides the detailed bidding strategies for the three groups when the market-clearing price is set at 480 yuan/MWh. Each group submits bids across five capacity segments, representing a range of potential production levels as follows.

Small Producers (SP):

- Capacity Segments: 50–60 MW, 60–70 MW, 70–80 MW, 80–90 MW, 90–100 MW.
- High-price bidding (S_H) ranges from 313 to 431 yuan/MWh, while low-price bidding (S_L) ranges from 275 to 313 yuan/MWh.
- Observations: Small producers tend to adopt conservative bidding strategies, aligning closely with the forecasted clearing price. Their bidding behavior indicates sensitivity to marginal cost increases at higher capacity levels.

Medium Producers (MP):

- Capacity Segments: 210–240 MW, 240–270 MW, 270–300 MW.
- High-price bidding (S_H) ranges from 367 to 492 yuan/MWh, while low-price bidding (S_L) ranges from 244.9 to 367 yuan/MWh.
- Observations: Medium producers exhibit a wider range of bidding prices compared to small producers. Their bidding strategies suggest flexibility in adapting to market conditions, balancing between competitiveness and profitability.

Large Producers (LP):

- Capacity Segments: 250–300 MW, 300–350 MW, 350–400 MW, 400–450 MW, 450–500 MW.
- High-price bidding (S_H) ranges from 292 to 528 yuan/MWh, while low-price bidding (S_L) ranges from 210 to 292 yuan/MWh.
- Observations: Large producers consistently offer lower prices at higher capacity levels due to economies of scale. Their strategic focus is on maintaining competitiveness while achieving high capacity utilization.

Based on the above, some critical insights and strategic implications are elaborated as follows.

Market dynamics: The bidding strategies reflect the interplay between cost structures, market positioning, and transaction models, which integrate carbon costs and regulatory factors that influence bidding behavior. Small producers focus on niche segments, medium producers leverage their flexibility in adapting bidding strategies, and large producers dominate due to economies of scale, with implications for carbon reduction and market fairness.

Policy implications: This analysis stresses the need for regulatory oversight, particularly to ensure fair competition and to foster bidding strategies that are both market-efficient and aligned with carbon reduction goals.

Future research directions: Incorporating stochastic elements, such as demand uncertainty and renewable energy variability, can enhance the model's realism, while also providing insights into carbon mitigation and evolving market dynamics. Analyzing the impact of policy mechanisms (e.g., carbon pricing, subsidies) on bidding strategies would provide valuable insights for sustainable market design.

Overall, the parameter settings and bidding strategies outlined in Tables 4 and 5 provide a comprehensive framework for understanding the strategic behaviors of heterogeneous power generation groups in a competitive electricity market. By linking cost structures to bidding strategies, this study demonstrates the importance of aligning market rules with the objectives of efficiency, fairness, and sustainability. Future research should focus on integrating real-world complexities to further refine the model's predictive accuracy and policy relevance.

3.2. Bidding Strategies for Power Generation Groups

3.2.1. Market Oversupply

1. **Parameter settings**

When the market demand is no less than the total rated generation capacity of the three groups, totaling 900 MW, each group is capable of selling its entire generation output. Under conditions without government regulation, the profit matrices of the generation groups are presented in Table 6.

Table 6. Benefit matrix for unregulated market conditions when the clearing price is set at 480 yuan/MWh.

Group SP and MP				LP	
				S_H	S_L
SP	S_H	MP	S_H	(24400, 78060, 120940)	(24400, 78060, 120940)
			S_L	(24400, 78060, 120940)	(24400, 78060, 120940)
	S_L		S_H	(24400, 78060, 120940)	(24400, 78060, 120940)
			S_L	(24400, 78060, 120940)	(5900, 13530, 8200)

Table 6 provides the bidding benefit matrix when the clearing price is set at 480 yuan/MWh under conditions of no government regulation, which is shown as follows.

Small producers (SP): Whether adopting high-cost bidding (S_H) or low-cost bidding (S_L), their payoffs are equal, demonstrating that all generation output is sold regardless of the bidding strategy.

Medium producers (MP): Similar to SP, the payoff for MP remains unchanged regardless of the bidding strategy. Their benefit is equally distributed across S_H and S_L, as demand is sufficient to absorb the total capacity of the market.

Large producers (LP): While high-cost bidding yields uniform benefits across scenarios, low-cost bidding (S_L) generates slightly reduced payoffs for LP due to its large-scale generation and cost inefficiencies at lower prices.

2. **RD equations**

These results highlight that, under unregulated conditions, there is no incentive for any group to alter their bidding behavior as the oversupply guarantees full dispatch of their capacities. Thus, the corresponding payment parameters under oversupply conditions are detailed as follows:

$$\begin{cases} a_1 = 24400, b_1 = 24400, c_1 = 24400, d_1 = 24400, \\ e_1 = 24400, f_1 = 24400, g_1 = 24400, h_1 = 5900, \\ a_2 = 78060, b_2 = 78060, c_2 = 78060, d_2 = 78060, \\ e_2 = 78060, f_2 = 78060, g_2 = 78060, h_2 = 13530, \\ a_3 = 120940, b_3 = 120940, c_3 = 120940, d_3 = 120940, \\ e_3 = 120940, f_3 = 120940, g_3 = 120940, h_3 = 8200, \end{cases} \tag{32}$$

By substituting these payment parameters into the RD equation, we derive the following:

$$\begin{cases} h_{SP}(x) = x(1-x)g_{SP}(y,z) \\ h_{MP}(y) = y(1-y)g_{MP}(x,z) \\ h_{LP}(z) = z(1-z)g_{LP}(x,y) \end{cases} \tag{33}$$

$$\begin{cases} g_{SP}(y,z) = 18500yz + (-18500)y + (-18500)z + 18500 \\ g_{MP}(x,z) = 64530zx + (-64530)z + (-64530)x + 64530 \\ g_{LP}(y,x) = 112740xy + (-112740)y + (-112740)x + 112740 \end{cases} \tag{34}$$

3. **Equilibrium stability analysis**

Using the parameters from Table 6, the stability of equilibrium points is analyzed based on evolutionary stability conditions. The results are summarized in Table 7, which shows the stability of all internal equilibrium points (Ψ_{ESS}): None of the eight equilibrium points, including (0, 0, 0), (1, 0, 0), (0, 1, 0), (1, 1, 0), etc., are evolutionarily stable under unregulated conditions. This indicates that the system lacks a stable evolutionary trajectory and is unable to reach a state of balance.

Table 7. Evolutionary stability analysis of each internal equilibrium point for unregulated market conditions when the clearing price is set at 480 yuan/MWh.

Ψ_{ESS}	Evolutionary Stability	Ψ_{ESS}	Evolutionary Stability
(0, 0, 0)	Unstable	(1, 0, 1)	Unstable
(1, 0, 0)	Unstable	(1, 1, 0)	Unstable
(0, 1, 0)	Unstable	(0, 1, 1)	Unstable
(0, 0, 1)	Unstable	(1, 1, 1)	Unstable

4. Simulation study

Figure 6 presents the results of the RD simulation conducted in MATLAB 2019b, with a time step of 0.1 s and 50 iterations. The *x*-*y*-*z* phase trajectories are visualized under the unregulated condition where the market-clearing price is set at 480 yuan/MWh. The results are analyzed as follows.

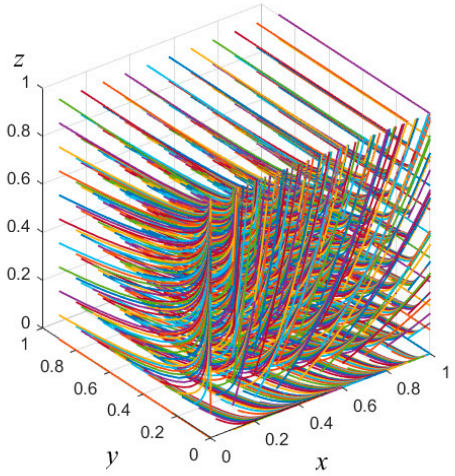


Figure 6. The RD simulation of the bidding evolution game under unregulated market conditions when the clearing price is set at 480 yuan/MWh.

Absence of stable equilibrium: The simulation demonstrates that in the absence of government regulation, the system fails to converge to any equilibrium. Instead, phase trajectories exhibit chaotic or divergent behavior.

Profit maximization through high-cost bidding: All power producers, regardless of group size, tend to pursue high-cost bidding (S_H) to maximize their individual payoffs. This is driven by the market-clearing price mechanism, which incentivizes aggressive bidding strategies.

Implications for arket dynamics: The lack of equilibrium reflects the inefficiencies of an unregulated market, where producers prioritize individual profits over collective market stability. This behavior leads to inflated electricity prices, reducing consumer welfare and undermining the efficiency of the electricity market.

Aiming at Figure 6, critical insights and policy recommendations are elaborated from several aspects as follows.

Market oversight is crucial: Figure 6 underscores the necessity of government regulation in electricity markets. Without oversight, aggressive bidding behavior dominates, leading to price distortion and market inefficiencies.

Role of penalty mechanisms: Introducing penalties for high-cost bidding or incentivizing low-cost bidding strategies could guide the system toward more stable equilibria. For example, adjusting payoff parameters such that $g_{SP}(y, z)$, $g_{MP}(x,z)$, $g_{LP}(x, y) \leq 0$ could shift the system dynamics toward cooperative outcomes.

Future research directions: The integration of renewable energy sources or stochastic demand variations can further enrich the model and provide deeper insights into how these dynamics affect carbon strategies and market performance. Additionally, analyzing the long-term effects of various regulatory policies would enhance the model's applicability to diverse market scenarios.

The findings from Figure 6 and the corresponding RD analysis highlight the limitations of unregulated electricity markets. Without intervention, the market fails to achieve equilibrium, and aggressive bidding strategies prevail, leading to higher electricity costs. To address these challenges, policymakers must design mechanisms that balance individual incentives with collective welfare, ensuring a stable and efficient electricity market.

As analyzed above, Figure 6 provides a dynamic simulation of the evolutionary game under government regulation in a power market with a clearing price of 480 Yuan/MWh. It clearly demonstrates that the introduction of government oversight fundamentally shifts the system's behavior. Unlike the unregulated scenario (Figure 6), which lacked equilibrium points and promoted bidding strategies aimed solely at maximizing profit by exploiting high-price strategies, government intervention leads to a stable evolutionary equilibrium. Under government regulation, the system converges to evolutionary stable equilibria (ESE) at (1, 1, 1), where all groups adopt low-price strategies, ensuring market fairness and efficiency while promoting carbon reduction. This result is significant because it indicates that all three market participants—SP (small producers), MP (medium producers), and LP (large producers)—eventually adopt the low-price strategy, achieving an optimal and stable outcome. The intervention ensures that the participants refrain from consistently engaging in high-price bidding, as the penalties and costs associated with such actions outweigh the potential benefits. This outcome aligns with the regulatory aim of ensuring market efficiency and discouraging manipulative bidding practices. It illustrates that when penalties are carefully calibrated, the inherent game-theoretic dynamics can steer market participants toward socially optimal strategies. Specifically, the penalties encourage producers to prioritize market stability and fairness over short-term profit maximization.

From Figure 6, it can be observed that in the absence of government supervision, there is no equilibrium point in the market. Each power generation company can sell all of its electricity at high prices. In practice, such a situation leads to power generation groups deliberately inflating electricity prices. Under the market-clearing price (MCP) mechanism, all companies intentionally bid high prices to raise the market-clearing price and maximize their profits. This outcome is a direct result of supply shortages and the lack of necessary oversight.

Obviously, based on the elaborations above, the absence of government regulation, as illustrated in Figure 6, is a critical issue that underscores a key flaw in the unregulated power market. The lack of a stable equilibrium when firms are free to manipulate their bidding strategies leads to a situation where all power generation groups push for higher prices, resulting in market inefficiency. This scenario exemplifies a classic problem in economic theory known as "market failure", where the absence of appropriate oversight allows companies to exploit the system for maximum profit, exacerbating the effects of supply shortages. Under these conditions, the MCP becomes excessively high, which, although benefiting large corporations in the short term, ultimately destabilizes the entire market.

Therefore, the introduction of government supervision alters the system's behavior, ensuring that market dynamics and bidding strategies are aligned with long-term sustainability and carbon reduction goals. The proposed penalty mechanism acts as a deterrent to excessive pricing behavior. By incorporating the costs of violations into the power generation companies' decision-making processes, the government forces companies to reassess the long-term profitability of their pricing strategies. When the financial gains

from charging higher prices become outweighed by the penalties imposed for such actions, the companies are incentivized to lower their bids, thereby fostering more equitable market conditions.

Furthermore, the introduction of such regulatory measures ensures that the system tends toward a stable equilibrium, specifically at (1, 1, 1), where all participants are operating under reasonable pricing strategies. This stands in contrast to the unregulated market's tendency to spiral towards (0, 0, 0), an equilibrium point where no sustainable strategy exists, thus destabilizing the system in the long run.

The mathematical representation $e_1 = 0.5a_1$, $c_2 = 0.5a_2$, $b_3 = 0.5a_3$ simplifies the calculation of these equilibria, providing a convenient approximation to study the effects of regulatory oversight on the market. This adjustment also facilitates the understanding of how different payment parameters influence the dynamic interactions between firms under government supervision. The model suggests that with proper regulatory mechanisms, such as penalties for non-compliance, the market can stabilize and move toward a more efficient and sustainable equilibrium.

Based on the above, the practical implications and policy recommendations are summarized from several aspects as follows. This analysis highlights the importance of government intervention in preventing market manipulation and fostering a more competitive and fair energy market. From a policy perspective, the findings suggest several critical insights:

- Regulation and oversight: Government involvement is essential to curb the detrimental effects of unregulated high-price bidding strategies. Without oversight, power generation firms are likely to engage in price manipulation, harming consumers and destabilizing the market.
- Penalty mechanisms: Implementing a penalty system is a robust approach to discourage excessive pricing. When the cost of violating market norms is factored into decision-making, companies will naturally tend to adopt more reasonable, competitive pricing strategies.
- Stability through low-price strategies: The introduction of government regulation enables a shift toward low-price strategies, which benefits consumers and ensures market stability. This approach can help balance the interests of both large and small power generation firms, mitigating the risk of monopolistic behavior.
- Dynamic market adjustments: The mathematical modeling of this system, particularly through the payment parameters, provides a quantitative understanding of how regulatory measures affect market equilibrium. It also offers a foundation for further exploration into how specific parameters can be adjusted to optimize market performance.

In summary, the research in Section 3.2.1 underscores the need for proactive government regulation in energy markets, especially in scenarios where supply constraints lead to price inflation. By implementing well-designed penalty mechanisms and fostering a competitive bidding environment, the government can steer the market towards a stable and sustainable equilibrium, benefiting both producers and consumers in the long term. However, if government supervision is introduced, and a penalty mechanism is applied when malicious high pricing trends emerge, it forces the power generation groups to account for the costs of violations in their profit considerations. When the profit from high pricing is less than the profit from low pricing, power generation companies tend to adopt a low-price strategy. This government regulation ensures that the payment parameters meet the conditions $e_1 < a_1$, $c_2 < a_2$, and $b_3 < a_3$, and it is necessary to avoid situations where the warning parameters s_4, m_4, l_4 are negative. The system will ultimately converge to the stable equilibrium point (1, 1, 1), while it will be impossible to achieve long-term evolutionary stability at the equilibrium point (0, 0, 0). For the convenience of calculation, the model

assumes the following relations for the payment parameters: $e_1 = 0.5a_1$, $c_2 = 0.5a_2$, and $b_3 = 0.5a_3$.

Therefore, based on the conditions above, new payoff parameters are calculated as follows:

$$\begin{cases} a_1 = 24400, b_1 = 24400, c_1 = 24400, d_1 = 24400, \\ e_1 = 12200, f_1 = 24400, g_1 = 24400, h_1 = 5900, \\ a_2 = 78060, b_2 = 78060, c_2 = 39030, d_2 = 78060, \\ e_2 = 78060, f_2 = 78060, g_2 = 78060, h_2 = 13530, \\ a_3 = 120940, b_3 = 60470, c_3 = 120940, d_3 = 120940, \\ e_3 = 120940, f_3 = 120940, g_3 = 120940, h_3 = 8200, \end{cases} \tag{35}$$

Based on Equation (35), the new RD equations are shown as

$$\begin{cases} h_{\mathrm{SP}}(x) = x(1-x)g_{\mathrm{SP}}(y,z) \\ h_{\mathrm{MP}}(y) = y(1-y)g_{\mathrm{MP}}(x,z) \\ h_{\mathrm{LP}}(z) = z(1-z)g_{\mathrm{LP}}(x,y) \end{cases} \tag{36}$$

$$\begin{cases} g_{\mathrm{SP}}(y,z) = 30700yz + (-18500)y + (-18500)z + 18500 \\ g_{\mathrm{MP}}(x,z) = 103560zx + (-64530)z + (-64530)x + 64530 \\ g_{\mathrm{LP}}(y,x) = 173210xy + (-112740)y + (-112740)x + 112740 \end{cases} \tag{37}$$

Then, we can obtain the stability of equilibrium points with government supervision and market-clearing price of 480 RMB/MWh, as shown in Table 8.

Table 8. The stability of equilibrium points with government supervision and market-clearing price of 480 RMB/MWh.

Ψ_{ESS}	Evolutionary Equilibrium Stability	Ψ_{ESS}	Evolutionary Equilibrium Stability
(0, 0, 0)	Unstable	(1, 0, 1)	Unstable
(1, 0, 0)	Unstable	(1, 1, 0)	Unstable
(0, 1, 0)	Unstable	(0, 1, 1)	Unstable
(0, 0, 1)	Unstable	(1, 1, 1)	ESS

Table 8 presents the stability of equilibrium points under the conditions where the market-clearing price (MCP) is set to 480 RMB/MWh, with the assumption that government supervision is in place. The equilibrium points (denoted as ESS) reflect the tendency of the system toward stability when the evolutionary game dynamics are in play. Notably, the table shows that, without government intervention, the system remains unstable in most scenarios, suggesting that power generation groups are likely to engage in aggressive pricing strategies that lead to competition that doesn't reach a stable equilibrium.

However, with the implementation of government supervision, an ESS at (1, 1, 1) emerges, which is an indicator that the system tends toward a balanced state. The ESS reflects a scenario where power generation companies would converge towards a mutually beneficial low-price strategy due to the enforcement of penalties for overpricing. The government's role here is pivotal in steering the system toward stability. Based on Table 8, we conduct a simulation study to verify this scenario, as illustrated in Figure 7. This figure demonstrates the evolutionary simulation results under government supervision with market-clearing price of 480 RMB/MWh. In this figure, we visualize the evolutionary simulation results under the condition where government supervision is introduced. The simulation results are based on a time interval of 0.1 s and are run for 50 iterations using MATLAB 2019b.

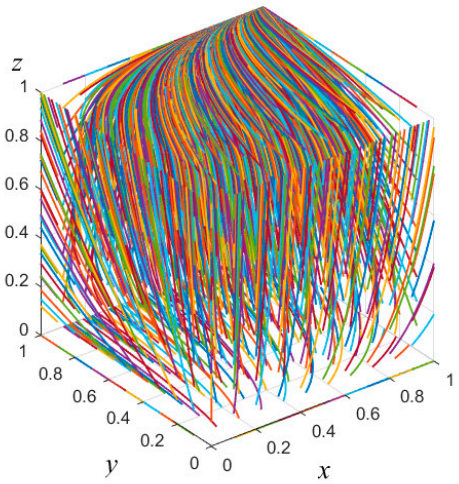


Figure 7. Evolutionary simulation results under government supervision with market-clearing price of 480 RMB/MWh.

From Figure 7, we also observe that the system, which was unstable under market-clearing conditions without government intervention, stabilizes once penalties are introduced for excessive pricing behavior. In particular, all three groups (Group SP, Group MP, and Group LP) tend toward the low-price strategy, reaching the ESS. This suggests that government regulation plays a critical role in ensuring fair competition in the electricity market. In the absence of such regulation, companies would likely engage in price manipulation, driving up the market-clearing price. The introduction of penalties for excessive pricing ensures that companies are incentivized to adopt strategies that benefit the market as a whole, rather than focusing on individual profits.

Based on Figure 7, we can further summarize some important findings, as discussed from three aspects as follows.

First, with respect to the evolutionary stability in power generation bidding, the concept of evolutionary stability is crucial when applying game theory to power generation bidding strategies. Under the assumption of competitive electricity markets, companies (or power generation groups) must continually adjust their strategies based on the actions of others, with the goal of maximizing profits. The evolutionary game framework used in this study accounts for the dynamic interactions between these players. In a deregulated electricity market, without supervision, companies have an incentive to bid aggressively, inflating prices and maximizing their revenue. However, this often leads to inefficiency, where the market price exceeds the marginal cost of electricity generation, leading to a socially suboptimal outcome. Figure 7 illustrate how, under government supervision, the system evolves towards a stable equilibrium where companies adopt lower bidding prices. This ensures a more competitive and fair pricing mechanism, ultimately benefiting consumers and promoting overall market efficiency.

Second, with respect to the impact of government supervision on market stability, from a broader perspective, the analysis demonstrates the importance of government supervision in maintaining market stability. In real-world electricity markets, when players (power generation companies) are left unchecked, they can collectively influence the market in ways that reduce overall welfare. The concept of the ESS in this context shows that the system can be stabilized through interventions such as penalties for overbidding or price manipulation. The critical finding here is that the implementation of government supervision not only ensures market efficiency but also facilitates a self-regulating mechanism among the firms. By penalizing firms that engage in excessive pricing strategies, the government forces them to internalize the costs of their actions. This leads to the adoption of lower price

strategies, where firms realize that the long-term benefits of competitive pricing outweigh the short-term gains from overpricing.

Third, with respect to the implications and practical applications, the results of the evolutionary game analysis can be directly applied to the design of electricity market regulations. Specifically, regulators can implement policies that ensure firms adopt pricing strategies that align with the social welfare maximization objectives. This could include the following:

- Penalties for price manipulation: Ensuring that firms are not able to manipulate prices upwards without consequences.
- Incentives for low-price bidding: Encouraging firms to adopt low-price strategies that foster competition and consumer welfare.
- Market monitoring systems: Implementing systems that track and analyze the pricing behavior of firms to detect and prevent anti-competitive behavior.

The findings of this research also highlight the need for balancing market competition with support for smaller players in the market. As shown in the simulations, large-capacity firms (such as Group LP in this study) have a significant advantage due to their lower costs and larger market share. Without government intervention, smaller firms may struggle to compete effectively, leading to market monopolization. Therefore, policymakers should ensure that smaller firms receive the necessary support, possibly through subsidies or preferential treatment, to foster a more diverse and competitive market landscape.

Overall, the EGT approach to modeling the bidding strategies of power generation groups has provided valuable insights into the dynamics of electricity market competition. The findings from the simulations, especially the role of government supervision in stabilizing the market, emphasize the necessity of regulatory interventions to ensure that market behavior remains competitive and efficient. This research has practical implications for energy market regulators, who can use these insights to refine pricing mechanisms and competitive strategies. By leveraging evolutionary game theory, regulators can anticipate and mitigate market inefficiencies, fostering a fairer and more sustainable energy market for all stakeholders. Moreover, the findings underscore the importance of adaptive and flexible regulatory frameworks that can respond to the ever-changing dynamics of the power generation industry. Future research should continue to explore multi-strategy evolutionary models that can account for the complexities of real-world energy markets, including the role of renewable energy sources, technological innovations, and global energy trends.

3.2.2. Market Oversupply (Market Demand Decreases by 20%)

When market demand reduces to 720 MW, and there is no governmental oversight, the bid volumes and revenue volumes for each group are shown in Tables 9 and 10. From Table 10, the payment parameters when market demand is reduced to 720 MW are derived as follows:

$$\begin{cases} a_1 = 18448, b_1 = 10606, c1 = 15031, d_1 = 0, \\ e_1 = 23900, f_1 = 24400, g_1 = 22900, h_1 = 0, \\ a_2 = 61776, b_2 = 39100, c_2 = 73560, d_2 = 8154, \\ e_2 = 59712, f_2 = 26136, g_2 = 73560, h_2 = 8154, \\ a_3 = 97560, b_3 = 110940, c_3 = 82390, d_3 = 8390, \\ e_3 = 94834, f_3 = 110940, g_3 = 75294, h_3 = 8390, \end{cases} \tag{38}$$

Table 9. Cleared market price at 480 CNY/MWh - bid volumes.

Ψ_{ESS}	Bid Volume	Ψ_{ESS}	Bid Volume
(0, 0, 0)	(80, 240, 400)	(1, 0, 1)	(100, 120, 500)
(1, 0, 0)	(100, 232, 388)	(1, 1, 0)	(100, 300, 320)
(0, 1, 0)	(70, 300, 350)	(0, 1, 1)	(0, 220, 500)
(0, 0, 1)	(55, 165, 500)	(1, 1, 1)	(0, 220, 500)

Table 10. Revenue matrix for each group at a market-clearing price of 480 CNY/MWh.

Group SP and MP				LP	
				S_H	S_L
SP	S_H	MP	S_H	(18448, 61776, 97560)	(10606, 39100, 110940)
			S_L	(15031, 73560, 82390)	(0, 8154, 8390)
	S_L		S_H	(23900, 59712, 94834)	(22400, 26136, 110940)
			S_L	(22900, 73560, 75294)	(0, 8154, 8390)

By substituting these parameters into the RD equation, which is obtained as follows:

$$\begin{cases} h_{SP}(x) = x(1-x)g_{SP}(y,z) \\ h_{MP}(y) = y(1-y)g_{MP}(x,z) \\ h_{LP}(z) = z(1-z)g_{LP}(x,y) \end{cases} \tag{39}$$

$$\begin{cases} g_{SP}(y,z) = 16211yz + (-13794)y + (-7869)z \\ g_{MP}(x,z) = (-10900)zx + (-31830)z + 12964x + 17982 \\ g_{LP}(y,x) = (-4370)xy + 7096y + (-83010)x + 66904 \end{cases} \tag{40}$$

By incorporating these payment parameters into the evolutionary stability conditions, the stability of each equilibrium point is determined, as shown in Table 11.

Table 11. Stability of equilibrium points at a market-clearing price of 480 CNY/MWh.

Ψ_{ESS}	Evolutionary Stability	Ψ_{ESS}	Evolutionary Stability
(0, 0, 0)	Unstable	(1, 0, 1)	Unstable
(1, 0, 0)	Unstable	(1, 1, 0)	Unstable
(0, 1, 0)	ESS	(0, 1, 1)	Unstable
(0, 0, 1)	ESS	(1, 1, 1)	Unstable

By inputting the RD equation into MATLAB 2019b, and running 50 dynamic simulations with an interval of 0.1 s, the results are plotted in Figure 8. This figure demonstrates that the system reaches an ESS under two specific conditions: when the medium-capacity group adopts a low-price strategy while the other two groups adopt high-price strategies; and when the large-capacity group adopts a low-price strategy while the other groups adopt high-price strategies.

The equilibrium outcome is largely determined by the strategic choices of the large-capacity group. This is attributed to its advantages in capacity, lower operational costs, and significant market share. Without governmental regulation, such a dominant position can manipulate the bidding market, potentially leading to monopolistic practices and other forms of destructive competition. Based on this, from the simulation results presented in Figure 8, the following observations can be made:

(a) Influence of Large-Capacity and Medium-Capacity Groups on Market Stability

The findings highlight the critical role of the large-capacity (LP) group in determining market dynamics. As the primary market leader, the LP group possesses inherent advantages in volume, cost efficiency, and market share. These factors enable it to exert significant influence over the bidding outcomes. The MCP mechanism amplifies this advantage, as the

LP group can dictate price levels based on its strategic choices. Without external oversight, such dominance poses serious risks, including the potential for monopolistic behavior or aggressive predatory pricing strategies. This not only destabilizes the bidding environment but can also lead to long-term consequences, such as a reduction in market diversity and the marginalization of smaller participants. The study underscores the importance of designing regulatory frameworks to mitigate these risks, ensuring a more balanced and competitive market environment. Implications are as follows:

- Policy need: Regulatory bodies must monitor large-capacity groups to prevent exploitative behaviors. This may involve implementing price caps, market share limits, or stricter anti-monopoly measures.
- Strategic flexibility: The LP group's ability to switch between high-price and low-price strategies provides a significant edge. Encouraging transparency in strategy selection could reduce market manipulation risks.

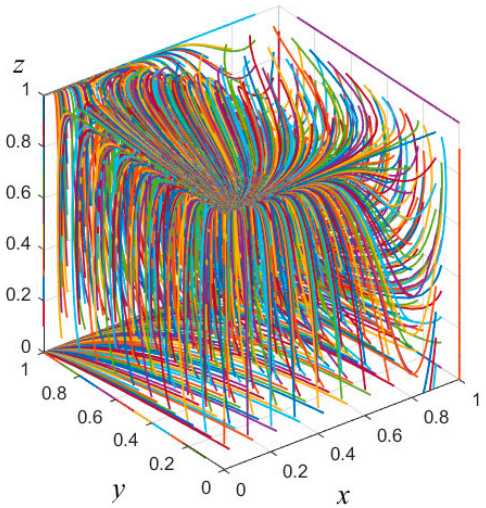


Figure 8. Evolutionary simulation results for three groups (Interval: 0.1s).

(b) Challenges Faced by Small-Capacity Groups in Competitive Markets

When the two larger-capacity groups simultaneously adopt low-price strategies, the small-capacity group faces insurmountable challenges. The fierce competition at lower price levels leaves the small-capacity group unable to secure contracts, primarily due to its higher generation costs. This dynamic illustrates the inherent structural disadvantage of smaller players in a deregulated electricity market.

The small-capacity group's exclusion from market participation has broader implications for market efficiency and equity. Over time, the lack of governmental support could lead to the elimination of smaller players, resulting in market consolidation. Such outcomes not only harm competition but may also reduce market resilience against supply disruptions. Recommendations for governmental intervention are elaborated as follows:

Support for small-capacity groups: Provide subsidies or tax incentives to reduce their operational costs and improve competitiveness. Establish quota mechanisms to ensure smaller participants secure a minimum share of contracts.

Balancing low-price competition: While promoting low-price strategies enhances consumer welfare and market efficiency, it is essential to implement safeguards that prevent the complete marginalization of smaller players. Introduce adaptive policies that adjust group revenue parameters dynamically based on market conditions, guiding the system toward more equitable outcomes.

Dynamic policy frameworks: Ensure that market adjustments are data-driven, using warning parameters such as s_4, m_4, l_4 as benchmarks to prevent imbalances. Allow for

policy flexibility to address specific challenges faced by different groups while maintaining overall market stability.

Broader insights: Supporting smaller-capacity groups fosters market diversity and innovation, as they often bring unique approaches to energy generation. The absence of smaller players could reduce competition, leading to higher prices and less incentive for innovation in the long term.

(c) Critical Stability of the (1, 1, 1) Equilibrium

The (1, 1, 1) equilibrium is identified as a critically stable point, where the eigenvalues of the corresponding equilibrium are all zero. This critical stability highlights a key limitation of the current model: it does not achieve strict evolutionary stability. Consequently, the system is highly sensitive to external disturbances or perturbations, which could drive the market away from this equilibrium. This finding raises important questions about the robustness of the model and its applicability in real-world scenarios. In practice, market dynamics are often influenced by stochastic factors such as demand fluctuations, policy changes, and technological advancements. The absence of strict stability Implies that the market may oscillate or diverge from equilibrium in response to these factors. To this end, suggested model enhancements are elaborated as follows.

Incorporation of stochastic dynamics: Introduce random perturbations into the RD equation to simulate real-world uncertainties. Analyze how external shocks (e.g., sudden demand changes or policy shifts) impact the stability of the system.

Refinement of stability criteria: Use alternative stability concepts, such as asymptotic stability or Lyapunov functions, to provide a more comprehensive assessment of equilibrium behavior. Explore the use of non-linear dynamics to capture complex interactions between groups.

Simulation of real-world scenarios: Conduct simulations under varying market conditions (e.g., changes in demand, entry of new players) to evaluate the robustness of the (1, 1, 1) equilibrium. Assess the long-term behavior of the system under different policy interventions.

The analysis provides valuable insights into the dynamics of deregulated electricity markets. Key takeaways include the following:

Dominance of large-capacity groups: The LP group's strategic choices significantly influence market outcomes, necessitating robust regulatory oversight to prevent market distortions.

Vulnerability of small-capacity groups: Without targeted support, small-capacity groups are at risk of being excluded from the market, which could reduce competition and innovation.

Limitations of stability assumptions: The critical stability of the (1, 1, 1) equilibrium highlights the need for more sophisticated modeling approaches to capture real-world complexities.

Furthermore, when both the large-capacity and medium-capacity groups opt for low-price strategies, the small-capacity group faces severe disadvantages. Regardless of its strategy, the small group cannot secure contracts due to its higher production costs and inability to compete in an aggressive low-price environment. This dynamic highlights the vulnerability of smaller entities in deregulated markets.

(1) Role of Governmental Intervention

In such market conditions, governmental intervention becomes crucial. Specifically, Ppolicies should be enacted to support smaller-capacity generators, ensuring their survival in highly competitive low-price markets. Simultaneously, policies must encourage all groups to adopt low-price strategies to promote market efficiency. However, these

interventions should be tailored to preserve diversity among generators and avoid excessive market dominance by any single group. One potential approach involves adjusting revenue parameters such that smaller-capacity groups can compete on a more equitable basis. For instance, subsidy mechanisms or preferential access to market opportunities could be explored.

(2) Stability of the Equilibria

The simulation identifies some equilibria as "critically stable" rather than strictly stable, due to the fact that the characteristic roots of the corresponding equilibrium points are zero. This does not satisfy the strict criteria for evolutionary stability as defined in game theory. As a result, the system is vulnerable to external perturbations and may oscillate rather than settle into a robust equilibrium. Enhancements to the model, such as incorporating stochastic dynamics or refining payoff structures, could provide a more realistic representation of market behavior.

(3) Research Implications and Practical Applications

This study yields several significant insights:

- Strategic behavior and market stability: The strategic choices of dominant players significantly influence market stability. In particular, large-capacity groups possess the leverage to dictate market outcomes, underscoring the importance of designing mechanisms to limit their undue influence.
- Policy recommendations: Policymakers should aim to: Support smaller-capacity generators to prevent market concentration. Use dynamic pricing regulations or incentives to discourage monopolistic behaviors. Adjust market parameters (e.g., subsidies, quotas) to guide the market toward more equitable and sustainable equilibria.
- Model refinements: The findings indicate the need for enhanced modeling approaches to capture real-world complexities. For example: Introducing stochastic elements into the RD equation can account for random fluctuations in market conditions. Analyzing the impact of external shocks, such as sudden demand surges or regulatory changes, could provide deeper insights into market dynamics.
- Broader applications: While this study focuses on electricity markets, its implications extend to other sectors characterized by competitive bidding dynamics, such as telecommunications or resource allocation in decentralized networks.

(4) Suggestions for Further Improvement

To advance the research further, the following avenues can be explored:

- Incorporating real-world data: Validate the model using empirical data from electricity markets to ensure its practical applicability and robustness.
- Expanding group dynamics: Extend the analysis to include more diverse groups with varying cost structures and market shares, enabling a more comprehensive understanding of market dynamics.
- Policy simulation: Conduct scenario-based simulations to evaluate the effectiveness of different regulatory interventions. For instance: Assess how subsidies for small-capacity groups impact overall market efficiency; and analyze the long-term implications of imposing price caps or quotas.
- Addressing critical stability: Refine the model to address the limitations of critically stable equilibria. Introducing non-linear dynamics or alternative stability criteria could yield more actionable insights.
- Environmental considerations: Incorporate environmental metrics, such as carbon emissions, into the payoff structure. This would align the study with broader sustainability objectives.

(5) Broader Implications and Recommendations

Policy implications: Design incentive mechanisms to level the playing field for small-capacity groups while maintaining overall market efficiency. Implement regulatory frameworks that discourage monopolistic practices and promote healthy competition.

Research directions: Extend the model to incorporate multi-period analysis, capturing the dynamic evolution of strategies over time. Explore the role of technological innovations (e.g., renewable energy sources) in reshaping market dynamics.

Practical applications: The findings can inform the design of bidding strategies for market participants, helping them optimize their outcomes under different market conditions. Policymakers can use the insights to develop targeted interventions that promote sustainability, equity, and efficiency in electricity markets.

By addressing the identified limitations and expanding the scope of analysis, future research can provide deeper insights into the interplay between strategic behavior, market stability, and policy interventions. These advancements will be instrumental in guiding the development of more resilient and sustainable energy markets. Overall, this study provides a rigorous analysis of the evolutionary dynamics in a deregulated electricity market with oversupply conditions. It underscores the need for targeted governmental interventions to balance market efficiency with equity. By refining the model and incorporating real-world data, future research can further enhance our understanding of competitive bidding strategies and their implications for market stability and sustainability.

3.3. A Summary

Based on Section 3.1, Section 3.2 employs the Chinese electricity market as a case study to examine the impact of governmental supervision, market-clearing prices, market demand, and generation group capacity sizes on their bidding strategies. The findings from simulations conducted under different conditions can be summarized as follows.

Firstly, our analysis shows that lowering the market-clearing price reduces the profitability of high-price strategies for enterprises, which incentivizes generation groups to adopt low-price strategies. However, a reduction in the market-clearing price narrows the competitive space for smaller-capacity groups, thereby intensifying the pressure to adopt low-price strategies.

Second, as market electricity demand decreases, the strategic choices of large-capacity generation groups increasingly influence the market. When the supply–demand balance reaches a critical point, large-capacity groups must adopt low-price strategies to remain competitive and sustain long-term market development. However, if large-capacity groups persist in aggressively adopting low-price strategies, smaller players are marginalized, diminishing their chances of securing contracts.

Third, effective government supervision of market competition is essential. When generation groups simultaneously adopt high-price strategies, government interventions, such as penalties or adjustments to subsidies, can encourage smaller-capacity groups to actively participate in the market through low-price strategies. This enables smaller-capacity groups to remain viable competitors in the market. Although the equilibrium point (1, 1, 1) represents a scenario where all groups adopt high-price strategies, it is neither optimal nor sustainable in the long term. Regulators should focus on developing policies that promote fair competition and encourage the majority of generation groups to adopt cost-aligned strategies, balancing both market efficiency and fairness.

In summary, Section 3.2 highlights the crucial balance between economic efficiency, fairness, and sustainability in competitive electricity markets. By tackling the challenges faced by smaller-capacity groups and fostering responsible behavior among large-capacity players, policymakers and market participants can contribute to a more resilient and

equitable market. Future research should refine the models, explore new strategies, and integrate sustainability metrics to align market dynamics with broader policy objectives. These efforts will enhance market stability and also aid in transitioning toward a more sustainable and inclusive energy system.

4. The Evolutionary Game Between Local Governments and Power Producers Under Low-Carbon Mechanisms

4.1. Evolutionary Game Model Construction

4.1.1. Payoff Matrix Construction

Building upon the basic evolutionary game model and simulation study in Section 2, and compared with the scenario study in Ref. [39], we extend the analysis by focusing on the evolutionary game dynamics between local governments and power producers under low-carbon mechanisms, with an emphasis on bidding strategies and carbon reduction incentives. We first present the payoff matrix for both government and enterprise strategies in Table 12, integrating both transaction models and carbon trading mechanisms to evaluate the impact of regulatory interventions.

Table 12. The payoff matrix for government and power enterprise strategies.

Game Players		Power Producer Enterprise	
		Honest Strategy (S_{P1})	**Dishonest Strategy (S_{P2})**
Government	Supervision strategy (S_{G1})	$R + J - C_1 - P - S_E$ $H + B - J - C_2 - S_G$	$R' - C_1' - P' - F - S_E$ $H' + F - C_2 - L - S_P$
	Non-Supervision strategy (S_{G2})	Honest strategy (S_{P1}) $R - C_1 - P - M_E$ $H - M_G$	Dishonest strategy (S_{P2}) $R' - C_1' - P' - M_E$ $H' - L - M_G$

Table 12 outlines the potential payoffs for both the government and enterprises, showcasing different strategic combinations and their implications for carbon reduction and market stability. Below, we provide a detailed analysis of the payoff outcomes for each player when specific strategies are selected, considering the probabilities of each strategy. The strategy combinations and payoffs are described as follows.

Case 1: When the government supervises and the enterprise acts honestly, their payoffs reflect the direct financial incentives and penalties related to carbon compliance and transaction costs. In this case, the payoffs are as follows.

Government's payoff: The government's payoff in this scenario (where supervision is chosen) is a combination of environmental benefits (H), societal benefits (B), and penalties for dishonesty, weighed against the costs of supervision (C_2) and reputational damage (S_G). The government chooses supervision strategy (denoted by strategy S_{G1}, with selection probability of x in each round of evolution game), and the power enterprise chooses honesty (denoted by strategy S_{P1}, with choosing probability of y in each round of evolution game), so that the government's payoff is shown as: $H + B - J - C_2 - S_G$.

Enterprise's payoff: The enterprise's payoff (under honest strategy) consists of market benefits I from carbon trading, plus rewards (J), minus compliance costs (C_1), carbon purchase costs (P), and reputational penalties (S_E). The enterprise's payoff in this scenario is $R + J - C_1 - P - S_E$.

Case 2: Government adopts the supervision strategy, and the enterprise adopts the dishonest strategy. In this case, the payoffs are as follows.

Government's payoff: When the government chooses supervision (S_{G1}, probability x) and the enterprise chooses dishonesty (probability $1 - y$), the government's payoff is as follows: $H' + F - C_2 - L - S_P$. Enterprise's payoff: The enterprise's payoff in this scenario is: $R' - C_1' - P' - F - S_E$.

Case 3: Government adopts the non-supervision strategy, and the enterprise adopts the honest strategy. In this case, the payoffs are as follows.

Government's payoff: When the government chooses non-supervision (probability $1 - x$) and the enterprise chooses honesty (probability y), the government's payoff is: $H - M_G$. Enterprise's payoff: The enterprise's payoff in this scenario is $R - C_1 - P - M_E$.

Case 4: Government adopts the non-supervision strategy, and the enterprise adopts the dishonest strategy. In this case, the payoffs are as follows.

Government's payoff: When the government chooses non-supervision (probability $1-x$) and the enterprise chooses dishonesty (probability $1 - y$), the government's payoff is: $H' - L - M_G$. Enterprise's payoff: The enterprise's payoff in this scenario is $R' - C_1' - P' - M_E$.

The variables related to both government and enterprise strategies are defined to capture the impact of transaction models, penalties, and carbon trading incentives on bidding behaviors and market outcomes.

- H: The environmental benefits from compliance (unit: yuan or equivalent environmental impact metric), including reductions in greenhouse gas emissions, mitigation of climate change, pollution alleviation, and societal energy savings, forming part of the carbon reduction strategy for enterprises.
- H': Reduced environmental benefits when enterprises act dishonestly (unit: yuan or equivalent environmental impact metric), reflecting the diminished environmental and societal gains due to non-compliance.
- B: Additional societal benefits from compliance (unit: yuan), representing co-benefits, such as health improvements from reduced pollution, enhanced renewable energy adoption, and long-term economic sustainability.
- J: Compliance rewards provided to enterprises (unit: yuan). Here, the financial incentives or subsidies granted by the government to promote honest carbon reduction behavior.
- F: Penalty for enterprise dishonesty (unit: yuan). Here, the monetary fines or punitive measures imposed on enterprises that fail to comply with carbon reduction targets.
- C_2: Supervision cost for the government (unit: yuan). Resources required for monitoring, auditing, and verifying enterprise carbon reduction activities.
- L: Environmental damage caused by dishonesty (unit: yuan or equivalent environmental impact metric). Quantifies the economic cost of environmental degradation, including loss of biodiversity, increased health burdens, and climate-related risks.
- S_G: Government reputational costs (unit: yuan). Reputational damage to the government resulting from perceived ineffectiveness or inability to enforce carbon reduction measures.
- M_G: Missed government environmental gains due to non-supervision (unit: yuan). Lost benefits resulting from a lack of monitoring, such as reduced emissions reductions and public dissatisfaction.

The variables related to enterprises are explained as follows:

- R: Market benefits from carbon trading under compliance (unit: yuan). The revenue gained by enterprises through carbon trading markets and improved market competitiveness.
- R': Reduced market benefits due to dishonesty (unit: yuan), reflecting reduced consumer willingness to pay, reputational losses, and diminished trading opportunities.
- C_1: Compliance costs for emissions reduction (unit: yuan). Direct investment costs for implementing carbon reduction technologies and meeting reduction targets.

- C_1': Reduced compliance costs from dishonest behavior (unit: yuan). The cost savings achieved by enterprises through non-compliance or avoiding emissions reduction investments.
- P: Cost of purchasing carbon quotas for compliance (unit: yuan). The expense incurred by enterprises in acquiring carbon credits to meet their reduction targets.
- P': Reduced trading costs from dishonesty (unit: yuan), reflecting reduced expenses when enterprises report lower-than-actual emissions or avoid purchasing quotas.
- S_E: Reputational penalties for enterprises (unit: yuan). The losses incurred by enterprises due to reputational damage caused by dishonesty, including reduced market share and public backlash.
- M_E: Missed enterprise market gains due to non-compliance (unit: yuan), representing forgone revenue and growth opportunities caused by a lack of regulatory alignment.
- S_P: Penalty-related social costs for enterprises (unit: yuan), which capture indirect penalties, such as strained relations with stakeholders, lawsuits, or exclusion from government incentives.

The discussion and practical implications for these payoff parameters are elaborated as follows.

1. Impacts of Supervision

When the government supervises, the payoff matrix reflects higher direct costs (C_2) but ensures better compliance, higher environmental benefits (H), and stronger societal gains (B). Enterprises acting dishonestly under supervision face substantial penalties (F), reputational costs (S_E), and additional social penalties (S_P), discouraging non-compliance.

2. Role of Rewards and Penalties

The inclusion of J (rewards) and F (penalties) creates a dynamic system that aligns financial incentives with carbon compliance goals, encouraging enterprises to adopt low-carbon strategies. The penalties (F) are dynamic and should scale with the severity of non-compliance to maximize their effectiveness.

3. Long-Term Implications

Honest enterprises benefit from increased market competitiveness and access to government incentives (J), which support sustainable carbon reduction strategies. This creates a virtuous cycle, aligning profitability with environmental responsibility. Dishonest enterprises might see short-term cost savings (C_1'), but long-term risks arise from penalties (F), reduced market benefits (R'), and reputational damage (S_E), which undermine sustainable carbon reduction strategies.

4. Strategic Choices for Non-Supervision

Non-supervision avoids immediate supervision costs (C_2) but leads to long-term environmental damage (L) and missed economic opportunities (M_G, M_E), while undermining the long-term sustainability of the low-carbon transition.

Design adaptive reward (J) and penalty (F) mechanisms that respond to enterprise performance, particularly emphasizing carbon reduction efforts and compliance behavior in the evolutionary game dynamics. For the enhanced monitoring technology, implement digital solutions (e.g., blockchain and IoT sensors) to reduce supervision costs (C_2) and enhance accuracy in monitoring carbon compliance, ensuring greater market stability and transactional transparency. For stakeholder engagement, promote consumer-driven incentives (R) by encouraging green branding and sustainability certifications, which support market competitiveness and carbon reduction behaviors. For integrated long-term planning, align enterprise compliance with broader sustainability goals, ensuring that emissions reduction integrates seamlessly with economic growth and energy transition strategies.

This payoff matrix in Table 12 provides a robust framework for analyzing government and enterprise interactions under carbon reduction policies. It integrates real-world complexities and offers actionable insights to guide policymakers and enterprises in achieving sustainable and equitable outcomes.

4.1.2. RD and Jacobian Matrix for the Enhanced Payoff Matrix

The RD framework models the evolutionary strategy dynamics between government and enterprise players, capturing how strategies evolve over time based on payoff outcomes and carbon incentives [40,41]. This mathematical framework is based on the principle that strategies with higher payoffs will increase in prevalence over time.

Step 1: Definitions and Setup

Let us define the following:

(1) Strategy probabilities:

- The probability that the government adopts the supervision strategy is x, and the probability of adopting non-supervision is $1-x$.
- The probability that the enterprise adopts the honest strategy is y, and the probability of adopting dishonesty is $1-y$.

(2) Payoffs from Table 12:

For the government, the payoffs for each strategy combination are:

$$\begin{cases} \pi_G^{S,H} = H + B - J - C_2 - S_G \text{ (Supervision, Honest)} \\ \pi_G^{S,D} = H' + F - C_2 - L - S_P \text{ (Supervision, Dishonest)} \\ \pi_G^{NS,H} = H - M_G \text{ (Non-Supervision, Honest)} \\ \pi_G^{NS,D} = H' - L - M_G \text{ (Non-Supervision, Dishonest)} \end{cases} \tag{41}$$

For the enterprise, the payoffs are as follows:

$$\begin{cases} \pi_E^{S,H} = R + J - C_1 - P - S_E \text{ (Supervision, Honest)} \\ \pi_E^{S,D} = R' - C'_1 - P' - F - S_E \text{ (Supervision, Dishonest)} \\ \pi_E^{NS,H} = R - C_1 - P - M_E \text{ (Non-Supervision, Honest)} \\ \pi_E^{NS,D} = R' - C'_1 - P' - M_E \text{ (Non-Supervision, Dishonest)} \end{cases} \tag{42}$$

(3) Average payoffs: The average payoff for each player is the weighted average based on the strategy probabilities.

For the government, average payoff is calculated as follows:

$$\begin{aligned} \overline{\pi}_G &= x\left[y\pi_G^{S,H} + (1-y)\pi_G^{S,D}\right] + (1-x)\left[y\pi_G^{NS,H} + (1-y)\pi_G^{NS,D}\right] \\ &= xy(H + B - J - C_2 - S_G) + x(1-y)(H' + F - C_2 - L - S_P) + (1-x)y(H - M_G) + (1-x)(1-y)(H' - L - M_G) \end{aligned} \tag{43}$$

For the enterprise, average payoff is calculated as follows:

$$\begin{aligned} \overline{\pi}_E &= y\left[x\pi_E^{S,H} + (1-x)\pi_E^{NS,H}\right] + (1-y)\left[x\pi_E^{S,D} + (1-x)\pi_E^{NS,D}\right] \\ &= yx(R + J - C_1 - P - S_E) + y(1-x)(R - C_1 - P - M_E) + (1-y)x(R' - C'_1 - P' - F - S_E) + (1-y)(1-x)(R' - C'_1 - P' - M_E) \end{aligned} \tag{44}$$

Step 2: RD Equations

The RD describe how the probabilities x and y evolve over time. They are given as follows:

$$\begin{cases} \dot{x} = x\left(\pi_G^X - \overline{\pi}_G\right) \\ \dot{y} = y\left(\pi_E^Y - \overline{\pi}_E\right) \end{cases} \tag{45}$$

Step 3: Jacobian Matrix of the System

The Jacobian matrix is used to evaluate the stability of equilibrium points, providing insights into how government and enterprise strategies evolve in response to policy changes and carbon compliance incentives. The Jacobian matrix, $\boldsymbol{J}_{\mathrm{GP}}$, is derived from the partial derivatives of the replicator equations with respect to x and y.

$$\boldsymbol{J}_{\mathrm{GP}} = \begin{bmatrix} \dfrac{\partial \dot{x}}{\partial x} & \dfrac{\partial \dot{x}}{\partial y} \\ \dfrac{\partial \dot{y}}{\partial x} & \dfrac{\partial \dot{y}}{\partial y} \end{bmatrix} \tag{46}$$

where

$$\begin{cases} \dfrac{\partial \dot{x}}{\partial x} = \pi_{\mathrm{G}}^{\mathrm{S}} - \overline{\pi}_{\mathrm{G}} + x\dfrac{\partial(\pi_{\mathrm{G}}^{\mathrm{S}} - \overline{\pi}_{\mathrm{G}})}{\partial x} \\ \dfrac{\partial \dot{x}}{\partial y} = x\dfrac{\partial(\pi_{\mathrm{G}}^{\mathrm{S}} - \overline{\pi}_{\mathrm{G}})}{\partial y} \\ \dfrac{\partial \dot{y}}{\partial x} = y\dfrac{\partial(\pi_{\mathrm{E}}^{\mathrm{H}} - \overline{\pi}_{\mathrm{E}})}{\partial x} \\ \dfrac{\partial \dot{y}}{\partial y} = \pi_{\mathrm{E}}^{\mathrm{H}} - \overline{\pi}_{\mathrm{E}} + y\dfrac{\partial(\pi_{\mathrm{E}}^{\mathrm{H}} - \overline{\pi}_{\mathrm{E}})}{\partial y} \end{cases} \tag{47}$$

By substituting the payoff equations (π_{G}, π_{E}) into these expressions, the Jacobian matrix can be explicitly calculated. The stability of equilibrium points is determined by analyzing the eigenvalues of $\boldsymbol{J}_{\mathrm{GP}}$. The RD and Jacobian matrix derived from the enhanced payoff matrix provide a mathematical framework for understanding the evolution of government and enterprise strategies. The stability of equilibrium points hinges on payoff parameters (H, R, C_1, J, F, etc.), illustrating the interactions between government policies, enterprise behaviors, and carbon reduction strategies.

4.1.3. Evolutionary Stability Conditions

The evolutionary stability conditions for specific equilibria are summarized as follows:

1. Equilibrium $(x, y) = (0, 0)$:

   $x = 0$: Government always adopts non-supervision.

   $y = 0$: Enterprise always adopts dishonesty.

   Stability Condition: The government and enterprise payoffs under these strategies must make deviations $\pi_{\mathrm{G}}^{\mathrm{S,D}} < \pi_{\mathrm{G}}^{\mathrm{NS,D}}$ and $\pi_{\mathrm{E}}^{\mathrm{S,D}} < \pi_{\mathrm{E}}^{\mathrm{NS,D}}$.

2. Equilibrium $(x, y) = (0, 1)$:

   $x = 0$: Government always adopts non-supervision.

   $y = 1$: Enterprise always adopts honesty.

   Stability Condition: Deviations $\pi_{\mathrm{G}}^{\mathrm{S,H}} > \pi_{\mathrm{G}}^{\mathrm{NS,H}}$ and $\pi_{\mathrm{E}}^{\mathrm{S,H}} > \pi_{\mathrm{E}}^{\mathrm{NS,H}}$ must be unfavorable.

3. Equilibrium $(x, y) = (1, 0)$:

   $x = 1$: Government always adopts supervision.

   $y = 0$: Enterprise always adopts dishonesty.

   Stability Condition: $\pi_{\mathrm{G}}^{\mathrm{S,D}} > \pi_{\mathrm{G}}^{\mathrm{NS,D}}$ and $\pi_{\mathrm{E}}^{\mathrm{S,D}} > \pi_{\mathrm{E}}^{\mathrm{NS,D}}$ must be favorable for these strategies.

4. Equilibrium $(x, y) = (1, 1)$:

   $x = 1$: Government always adopts supervision.

   $y = 1$: Enterprise always adopts honesty.

   Stability Condition: $\pi_{\mathrm{G}}^{\mathrm{S,H}} > \pi_{\mathrm{G}}^{\mathrm{NS,H}}$ and $\pi_{\mathrm{E}}^{\mathrm{S,H}} > \pi_{\mathrm{E}}^{\mathrm{NS,H}}$.

5. Mixed Strategy Equilibrium

The mixed strategy equilibrium occurs when x and y lie strictly between 0 and 1 ($0 < x < 1, 0 < y < 1$).

Mixed strategy probabilities are described as follows.

At the mixed strategy equilibrium:

(1) $\dot{x} = 0$: The government is indifferent between supervision and non-supervision, i.e., $\pi_G^S = \pi_G^{NS}$. Substituting payoffs:

$$y(H + B - J - C_2 - S_G) + (1 - y)(H' + F - C_2 - L - S_P) = y(H - M_G) + (1 - y)(H' - L - M_G) \quad (48)$$

(2) $\dot{y} = 0$: The enterprise is indifferent between honesty and dishonesty, i.e., $\pi_E^H = \pi_G^D$. Substituting payoffs:

$$x(R + J - C_1 - P - S_E) + (1 - x)(R - C_1 - P - M_E) = x(R' - C'_1 - P' - F - S_E) + (1 - x)(R' - C'_1 - P' - M_E) \quad (49)$$

Solving for x^* and y^*:

The solutions to the above equations provide the equilibrium probabilities x^* (probability of government supervision) and y^* (probability of enterprise honesty).

In conclusion, the equilibrium points are outlined as follows.

- 5 strategy equilibria as $(x, y) = (0, 0)$, $(0, 1)$, $(1, 0)$, $(1, 1)$, and (x^*, y^*).
- Stability Conditions: Stability depends on payoff comparisons between strategies and eigenvalues of the Jacobian $\boldsymbol{J}_{GP}$.
- Mixed Strategy Equilibrium: x^* and y^* are determined by the indifference conditions $\pi_G^S = \pi_G^{NS}$ and $\pi_E^H = \pi_E^D$, leading to probabilistic mixes of strategies.

4.2. Simulation Study and Analysis

Based on Section 4.1, we conduct a simulation study to verify the theoretical model constructed in Section 4.1. The simulation results are illustrated in Figure 9. Concretely, this simulation study investigates the evolutionary game between local governments and power producers under low-carbon mechanisms, emphasizing the impact of compliance costs (C_1) on bidding strategies and carbon reduction behaviors. The motivation for this research lies in understanding how regulatory strategies and compliance incentives interact dynamically to encourage power producers' honesty and governments' active supervision in carbon reduction efforts. The model uses RD to simulate the evolutionary process between these two players, with "government" (x) representing the probability of active supervision and "enterprise" (y) denoting the probability of honest compliance.

As shown in Figure 9, the key model features are summarized as follows:

- Payoff structure: The payoff matrix is derived from the enhanced Table 2, which includes compliance rewards, penalties, supervision costs, and market benefits for both players. This matrix captures the nuanced interactions of both sides under different strategies.
- Dynamic equations: The RD equations model how the strategy fractions evolve over time based on the relative payoffs of each strategy.
- Core innovation: The incorporation of realistic cost and benefit structures into the model highlights the interplay between government supervision probability and enterprise honesty probability under varying compliance costs.

Based on the above, the simulation parameters for Figure 9 are set as follows.

- Compliance costs for emissions reduction (C1): 500, 1000, and 2000 yuan.
- Simulation time: 50 time units, with 20 evaluation points.
- Initial conditions: Strategy fractions uniformly sampled in [0, 1].

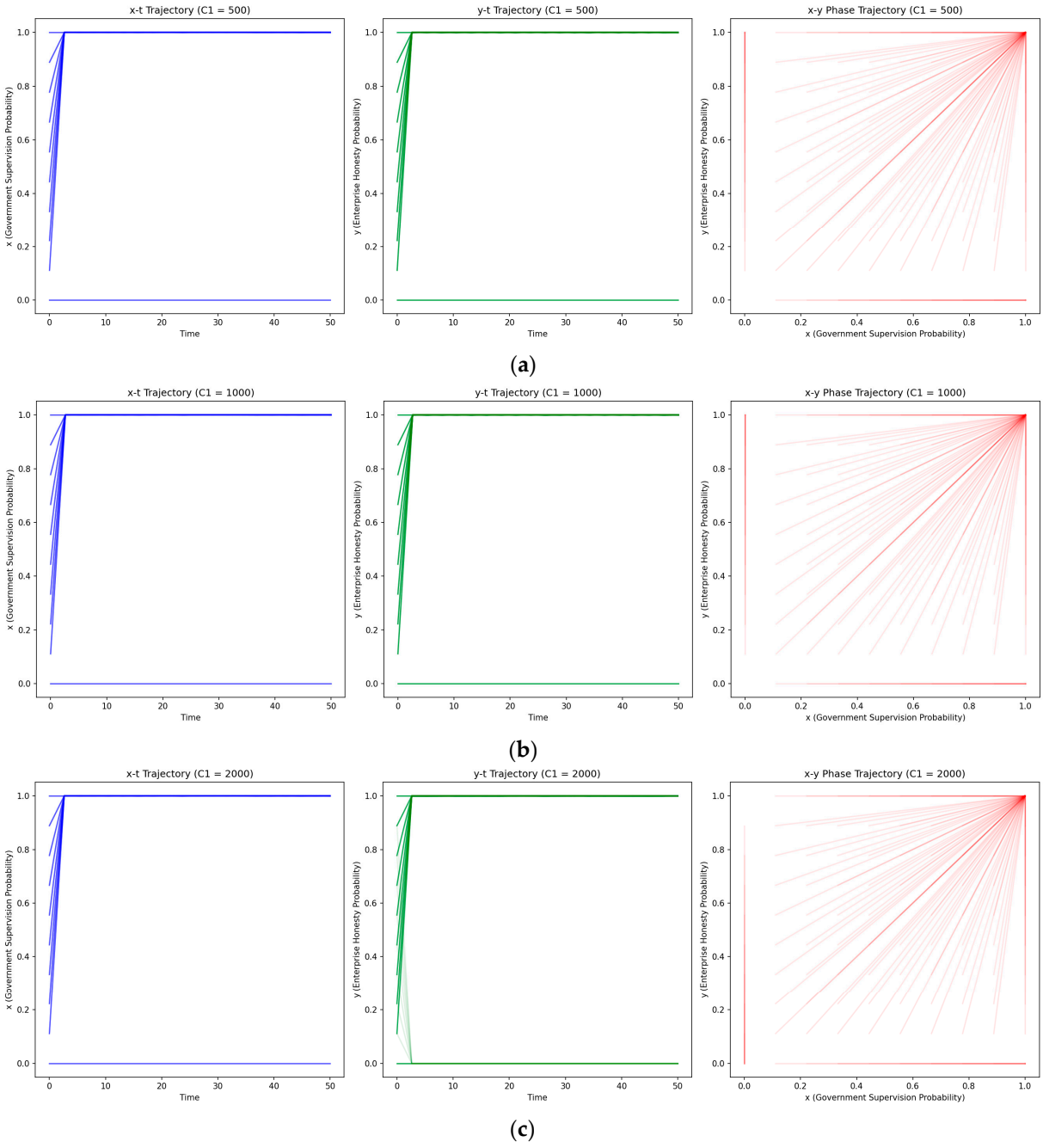


Figure 9. Simulation results for evolutionary game-theoretic analysis of government supervision and enterprise compliance strategies under low-carbon mechanisms. (**a**) The first subfigure shows the temporal evolution of the government's supervision probability (x) under compliance cost $C_1 = 500$. (**b**) The second subfigure demonstrates the temporal evolution of the enterprise's honesty probability (y) under compliance cost $C_1 = 1000$. (**c**) The third subfigure displays the phase trajectories of government supervision (x) and enterprise honesty (y) under compliance cost $C_1 = 2000$.

The simulation in Figure 9 is designed to observe how different compliance costs influence the stability and trajectory of strategies for both government and enterprises. Analysis of the simulation results is conducted as follows.

Figure 9a: Temporal Evolution of Government Supervision Probability ($C_1 = 500$)

Under lower compliance costs ($C_1 = 500$), the government supervision probability (x) converges rapidly to 1. This indicates that the government strongly favors active supervision when compliance costs are low, as the enterprises' honest strategies lead to higher payoffs for both players. This figure reveals that low compliance costs create a

favorable environment for government supervision and enterprise cooperation, fostering a stable and effective low-carbon mechanism.

Figure 9b: Temporal Evolution of Enterprise Honesty Probability (C_1 = 1000)

With moderate compliance costs (C_1 = 1000), enterprises' honesty probability (y) also converges quickly to 1. The convergence is slightly slower compared to Figure 9a, indicating that higher compliance costs reduce the immediate benefits of honesty but still promote it over time. This figure indicates that moderate compliance costs strike a balance between affordability for enterprises and incentives for honest behavior, ensuring long-term cooperation.

Figure 9c: Phase Trajectories of Government and Enterprise Strategies (C_1 = 2000)

Under high compliance costs (C_1 = 2000), the phase trajectories still converge to the equilibrium point (x = 1, y = 1). However, the paths are more spread out, reflecting greater variability in the initial adjustments of strategies. This figure shows that even with higher compliance costs, the system converges to full supervision and honesty. However, the increased variability suggests that enterprises face greater challenges in adopting honest strategies when costs are prohibitive.

Overall, the simulations in Figure 9 validate the enhanced payoff matrix from Table 2, demonstrating that the proposed RD effectively capture the evolutionary interactions between local governments and enterprises under low-carbon mechanisms. The results highlight the following:

- Policy design: Lower compliance costs lead to faster convergence to cooperative strategies, emphasizing the importance of cost-effective carbon reduction policies.
- Robustness: The system converges to the equilibrium (x = 1, y = 1) across all tested compliance costs, showcasing the robustness of the model under varying conditions.
- Application: This research provides a quantitative framework for designing policies that balance government incentives with enterprise costs, fostering sustainable low-carbon development and enhancing regulatory compliance.

As demonstrated in Figure 10, the simulation study focuses on modeling the interaction between local governments and power producers under a low-carbon regulatory framework. The primary aim is to investigate the dynamic evolutionary behavior of government supervision strategies and enterprise honesty strategies, specifically under varying compliance cost scenarios. The study is motivated by the need to understand the incentives and trade-offs that shape cooperation between regulators and industry players in achieving low-carbon development goals. By employing evolutionary game theory, this research identifies conditions under which both parties converge to cooperative strategies, thus fostering sustainable carbon reduction.

The simulation results in Figure 10 validate the enhanced payoff matrix and demonstrate that the RD model effectively captures the interplay between government supervision and enterprise compliance under varying cost scenarios. Key conclusions include the following:

- Policy design: Low compliance costs promote rapid and stable cooperation, while moderate costs balance incentives and affordability. High compliance costs, though less effective, can still achieve cooperation with additional policy support.
- Model robustness: The system consistently converges to cooperative equilibria (x = 1, y = 1) across all tested scenarios, demonstrating the model's robustness.

Based on these findings, future improvements are elaborated as follows.

- Dynamic costs: Introduce time-varying compliance costs to simulate real-world scenarios where policies evolve.

- Uncertainty analysis: Incorporate stochastic elements to study the impact of uncertainties in cost and benefits.
- Dynamic policy Adjustments: Introduce adaptive compliance costs to simulate real-world policy evolutions.
- Multi-agent interactions: Expand the model to include multiple governments and enterprises to study regional and sectoral dynamics.
- Multi-agent extension: Expand the model to include multiple governments and enterprises to explore regional and sectoral interactions in low-carbon mechanisms.
- Stochastic extensions: Incorporate uncertainty to reflect variability in costs and benefits, providing deeper insights into real-world applications.

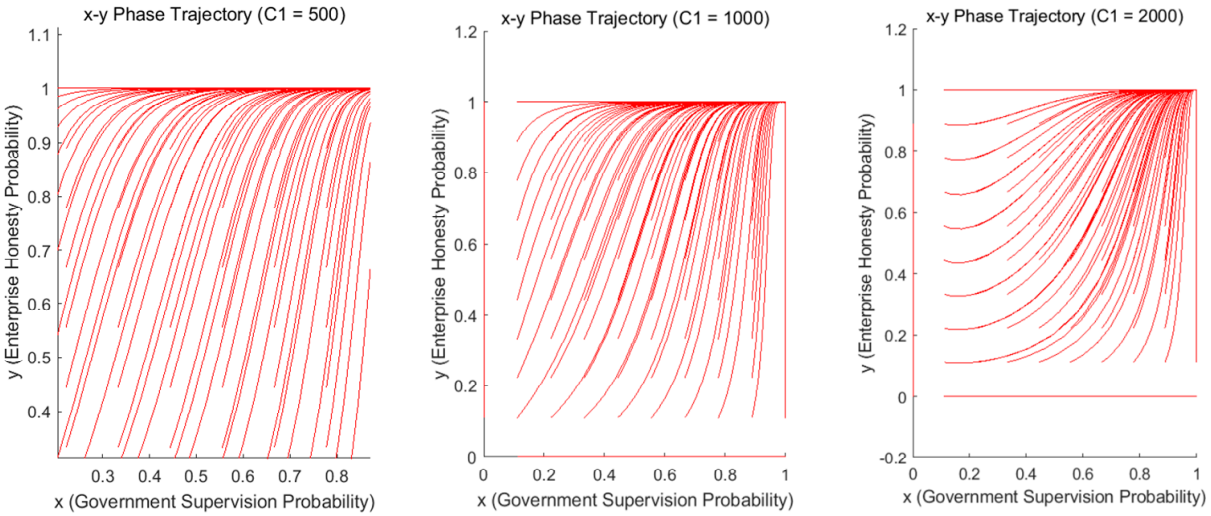


Figure 10. Simulation results for evolutionary game-theoretic analysis of government supervision and enterprise compliance strategies under low-carbon mechanisms. (**a**) The first subfigure shows the phase trajectories of government supervision probability (x) and enterprise honesty probability (y) under compliance cost $C_1 = 500$. (**b**) The first subfigure shows the phase trajectories of government supervision probability (x) and enterprise honesty probability (y) under compliance cost $C_1 = 1000$. (**c**) The first subfigure shows the phase trajectories of government supervision probability (x) and enterprise honesty probability (y) under compliance cost $C_1 = 2000$.

Overall, this study provides a rigorous framework for designing and evaluating low-carbon policies, offering actionable insights for fostering sustainable cooperation in carbon reduction initiatives. The evolutionary game-theoretic approach proves to be a powerful tool for modeling complex interactions and optimizing regulatory strategies. This study demonstrates the practical applicability of evolutionary game theory in low-carbon policy design, providing insights into the dynamic interplay between regulation and compliance. Further improvements can enhance the model's realism and policy relevance.

4.3. A Summary

1. **Findings from Simulation Study**

The simulation results reveal several key insights into evolutionary game dynamics, emphasizing the role of government supervision, penalties, and market incentives in shaping enterprise compliance and carbon reduction outcomes:

(i) Government supervision: As compliance costs decrease, the government is more likely to adopt a supervision strategy, promoting environmental compliance among power producers. This effect is most pronounced when penalties for dishonesty are high.

(ii) Power producer behavior: Power producers are more likely to adopt honest strategies when the costs of non-compliance are high, especially when regulatory supervision is strong. However, higher compliance costs lead to a trade-off where producers may be tempted to adopt dishonest strategies to reduce costs.
(iii) Stable equilibrium: The system converges to a stable equilibrium where both the government adopts supervision and power producers adopt honest strategies when regulatory incentives and penalties are effectively calibrated.

Overall, the findings offer actionable insights into the design of low-carbon policies and market mechanisms, demonstrating how evolutionary game theory can optimize regulatory interventions and bidding strategies to promote sustainability.

2. **Practical Implications**

The results of this study provide several policy implications for both local governments and power producers:

(i) Government regulation: The study underscores the importance of effective regulatory frameworks that incorporate appropriate incentives and penalties to ensure compliance with low-carbon initiatives. Government supervision strategies should be dynamically adjusted based on compliance costs and the level of dishonesty observed in the market.
(ii) Power producers' strategic adjustments: Power producers must carefully balance their strategies between profitability and environmental responsibility. The inclusion of carbon reduction rewards and penalties in market mechanisms can help align their incentives with societal goals.

3. **Recommendations for Future Research**

Future research should focus on the following:

(i) Incorporating stochastic elements: The current model assumes deterministic dynamics, but incorporating stochastic factors such as demand fluctuations and renewable energy variability can enhance the model's realism.
(ii) Exploring multi-agent interactions: Expanding the model to include multiple players, such as third-party intermediaries, can provide a more comprehensive understanding of the complex dynamics in low-carbon electricity markets.
(iii) Real-time policy adaptations: Developing real-time monitoring systems and adaptive policies can help governments respond dynamically to changes in market conditions and power producers' behaviors.

5. Discussions and Prospects

5.1. Discussions

This study explores the strategic dynamics of power producers within low-carbon mechanisms, employing EGT to incorporate carbon reduction strategies in competitive bidding. The findings offer insight into how governmental oversight, carbon pricing, and low-carbon policies shape the bidding behaviors and strategic interactions of power producers with diverse capacities. By incorporating RD equations, this study investigates stable equilibria across various scenarios, a key aspect in crafting practical and sustainable energy policies.

1. Core Contributions and Observations

(i) Model innovation: This study presents a three-group evolutionary game model for power producers, categorized into small, medium, and large producers, each with unique cost functions and capacity limitations. The model integrates regulatory

policies and carbon incentives into the payoff structures, making it more applicable to real-world electricity markets.

(ii) Insights into equilibria: Simulations demonstrate that the system stabilizes at ESS under defined payoff conditions. For example, cooperative equilibria emerge when regulatory incentives are strong, encouraging groups to adopt low-cost bidding strategies. When carbon incentives are weak, competitive equilibria result in aggressive, high-cost bidding.

2. Policy Impacts

Table 13 illustrates the key findings from simulations across varying scenarios. Based on this, the policy impacts are summarized as follows.

(i) Penalties for dishonesty and subsidies for low-carbon compliance directly affect the evolution of strategies. For instance, a higher penalty for non-compliance shifts equilibrium points toward more cooperative and environmentally sustainable outcomes.

(ii) Rising compliance costs (such as carbon taxes) diminish the profitability of non-compliance, prompting shifts toward adopting low-emission technologies.

Table 13. Key findings from simulations across different scenarios.

Scenario	Parameters	Key Observations	Policy Implications
High Compliance Costs	$C_1 = 2000$, $C_2 = 800$	Low compliance probability ($x, y < 0.5$). Both groups adopt competitive, high-cost strategies.	Stronger subsidies or penalties are required to incentivize low-carbon behaviors.
Moderate Compliance Costs	$C_1 = 1000$, $C_2 = 500$	Stable equilibrium at cooperative strategies ($x, y > 0.7$).	Current regulatory policies are effective, but additional incentives can enhance stability further.
Low Compliance Costs	$C_1 = 500$, $C_2 = 300$	Both groups adopt low-cost, cooperative strategies ($x, y \approx 1$).	No additional intervention required; the market self-stabilizes.
Weak Carbon Penalties	$F = 500$, $P = 300$	High dishonesty levels ($x, y < 0.4$). Groups favor high-emission strategies.	Increase penalties for non-compliance to discourage dishonest behavior.
Strong Carbon Penalties	$F = 1500$, $P = 700$	High honesty levels ($x, y > 0.8$). Both groups favor low-emission, compliant strategies.	Carbon penalties are effective; maintain or increase support for low-carbon compliance.

Based on Table 13, the challenges and limitations are summarized as follows.

(i) Model simplification: Though the replicator dynamics equations capture strategic evolution, real-world complexities like stochastic fluctuations and information asymmetry are not fully accounted for.

(ii) Homogeneous groups: The model assumes uniform behavior within each group (small, medium, large producers), but this may not capture the individual heterogeneities seen in real-world markets.

(iii) Market constraints: Transmission and capacity constraints were not explicitly included, which limits the applicability of the findings to grid-constrained markets.

5.2. Prospects

The findings from this study provide a foundation for future research and policy formulation in low-carbon electricity markets. The evolutionary game-theoretic framework proves valuable for capturing multi-group interactions and offers promising avenues for further extension, as shown in Table 14, which summarizes the proposed extensions and

their potential impacts. Based on this table, the future research directions are elaborated as follows:

(i) Integration of Stochastic Dynamics [41–43]:
- Rationale: Real-world electricity markets are subject to demand fluctuations, renewable energy intermittency, and policy uncertainties.
- Proposal: Incorporate stochastic elements into RD equations to account for these uncertainties.
- Expected outcome: Enhanced robustness and applicability of the model in predicting market behaviors under volatile conditions.

(ii) Expanded Strategy Spaces:
- Rationale: Current models restrict producers to binary strategies (compliance or non-compliance). Real markets involve a spectrum of strategies, including hybrid approaches.
- Proposal: Extend the model to include mixed strategies, such as partial compliance or adaptive bidding.
- Expected outcome: More nuanced insights into the interplay of multiple strategies in competitive environments.

(iii) Incorporating Grid Constraints:
- Rationale: Transmission and capacity constraints significantly impact bidding strategies and market outcomes.
- Proposal: Embed grid-related constraints into payoff functions and evolutionary dynamics.
- Expected outcome: Improved applicability of the model to grid-constrained electricity markets.

Table 14. Proposed extensions and their potential impacts.

Extension	Description	Expected Impact
Stochastic RD	Introduce randomness to capture demand volatility and renewable intermittency.	Better alignment with real-world market behaviors; improved predictive accuracy.
Multi-Dimensional Strategy Spaces	Allow mixed strategies (e.g., partial compliance) and adaptive behaviors.	Insights into hybrid strategies; applicability to complex market dynamics.
Inclusion of Transmission Constraints	Model transmission congestion and grid limitations in payoff calculations.	Increased relevance for electricity markets with grid reliability challenges.
Agent-Based Modeling	Replace deterministic equations with agent-based simulations for heterogeneous producers.	Improved representation of individual decision-making processes and market heterogeneity.
Real-Time Data Integration	Incorporate real-time market data, such as load forecasts and renewable generation levels.	Dynamic adaptation of strategies; potential for real-world policy implementation.

Based on Table 14, the policy recommendations are summarized as follows.

(i) Strengthening carbon pricing: Introduce dynamic carbon pricing mechanisms to penalize high-emission strategies while rewarding compliance.

(ii) Subsidy optimization: Design targeted subsidies to encourage low-carbon compliance among small and medium producers, leveling the competitive playing field.

(iii) Real-time monitoring: Establish mechanisms for real-time monitoring of market behaviors to enable adaptive policy interventions.

(iv) Broader implications: The integration of evolutionary game theory into electricity market analysis has implications beyond carbon reduction. It provides a framework

for understanding the dynamics of renewable energy integration, grid stability, and market efficiency. By aligning market incentives with long-term sustainability goals, this approach can support the global transition to low-carbon energy systems.

In conclusion, this study highlights the effectiveness of evolutionary game-theoretic models in analyzing strategic interactions among power producers under low-carbon mechanisms. By addressing current limitations and pursuing the outlined prospects, future research can further enhance the theoretical and practical contributions of this field, paving the way for more sustainable and efficient electricity markets.

6. Conclusions

This study provides a comprehensive analysis of power producers' carbon emission reduction strategies and multi-group bidding dynamics in the low-carbon electricity market using EGT. The core contributions and findings of the study are as follows:

(1) **Development of an Evolutionary Game-Theoretic Framework:**

This research advances the application of EGT to model interactions among heterogeneous power producers. The framework incorporates compliance costs, carbon reduction strategies, and regulatory incentives, capturing the complex interplay between market forces and regulatory interventions.

(2) **Insights into Strategic Dynamics:**

(i) The study highlights how compliance costs influence bidding strategies. Higher compliance costs discourage cooperative behaviors, while lower costs promote stable cooperation and the adoption of low-carbon technologies.
(ii) Penalties for dishonesty and subsidies for compliance significantly affect the evolution of strategies. Strong penalties and subsidies drive the market toward cooperation and low-carbon objectives.
(iii) The model shows that well-calibrated regulatory policies can foster stable equilibria, aiding the transition to low-carbon energy systems.

(3) **Policy Implications:**

The findings highlight the need for targeted policies that balance compliance costs, penalties, and subsidies to facilitate a sustainable and equitable transition to a low-carbon electricity market.

The study identifies areas for future research, such as addressing real-world complexities, incorporating stochastic dynamics, and expanding the model to involve broader stakeholder participation. The transition to low-carbon electricity markets is a crucial aspect of global efforts to combat climate change. As the complexity of these markets grows with renewable energy integration and the implementation of carbon reduction policies, the demand for advanced analytical tools becomes more apparent. This study demonstrates the potential of evolutionary game theory to provide a robust framework for understanding and shaping market dynamics. By addressing the aforementioned limitations and pursuing the suggested research avenues, future work can refine this framework and contribute to the development of sustainable, efficient, and equitable electricity markets. Through these efforts, the insights derived from evolutionary game theory can significantly contribute to achieving global carbon neutrality goals.

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Glossary

Term	Definition/Description
Agent-based Model (ABM)	A computational model for simulating the actions and interactions of autonomous agents to assess their effects on the system as a whole.
Bidding Dynamics	The competitive interactions between power producers in electricity markets as they strategize their bids to balance profitability and regulatory compliance.
Carbon Neutrality	A state where net carbon dioxide emissions are zero, achieved through a combination of emission reductions and offsetting measures such as carbon sequestration or trading.
Carbon Quotas	A limit set by regulatory agencies on the maximum amount of carbon emissions an entity is allowed to produce, often tied to carbon credit trading mechanisms.
Carbon Trading	A market-based mechanism designed to reduce greenhouse gas emissions by allowing entities to buy and sell carbon credits.
Clean Energy Transition	The shift from fossil fuel-based energy systems to renewable and low-carbon energy sources such as solar, wind, and hydropower.
Compliance Costs	The monetary expenditure incurred by firms to adhere to carbon emission regulations, including investments in clean technologies, penalties, and other operational adjustments.
Distributed Energy Resources (DERs)	Small-scale energy generation and storage technologies located close to the point of consumption, such as rooftop solar panels or home batteries.
Dynamic Pricing	A flexible pricing mechanism where energy prices fluctuate based on supply, demand, and time of use, incentivizing energy efficiency.
Enterprise Honesty Probability	The probability that enterprises will truthfully comply with carbon emission reduction regulations without engaging in dishonest behaviors such as falsifying emission data.
Evolutionary Game Theory (EGT)	A mathematical framework that studies the strategic interactions and behavioral evolution of competing groups or agents over time, particularly under changing environmental or regulatory conditions.
Government Supervision Probability	The likelihood that regulatory agencies will actively monitor and enforce compliance with carbon reduction policies among enterprises.

Low-Carbon Electricity Market	A regulated energy market that prioritizes the generation, trading, and consumption of electricity produced from low-carbon and renewable sources, incentivized through carbon pricing mechanisms and policies.
Low-Carbon Strategies	A set of operational, technological, and policy measures adopted by enterprises to minimize carbon emissions in compliance with environmental regulations.
Market Benefits	The economic advantages gained by enterprises from participating in low-carbon electricity markets, including increased market share, financial rewards, and improved reputation.
Penalty for Dishonesty	A financial or reputational penalty imposed on enterprises that fail to meet emission standards or falsify compliance data, designed to deter non-compliance.
Replicator Dynamics	A mathematical model used to describe the evolution of strategy proportions in a population, where strategies with higher-than-average payoffs increase in frequency over time.
Subsidy Allocation	Financial support provided by governments to enterprises to incentivize the adoption of low-carbon technologies and compliance with carbon emission reduction targets.

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