Renewable Energy and Power Quality Journal
https://repqj.com/index.php/repqj/index
RE&PQJ, Vol. 23, No. 4, 2025

Optimizing the Capacity Cost Recovery Mechanism of Shanxi Power Market through Improved Double-layer Stackelberg Game Model

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Abstract. Aiming at the problem of insufficient capacity cost recovery caused by the fluctuation of renewable energy and information asymmetry in Shanxi power market, this paper constructs an improved two-layer Stackelberg game model. The model constructs a sequential decision-making framework of leaders and followers. The backward induction method is used to solve the equilibrium, and the information entropy is innovatively introduced to quantify the uncertainty of enterprise data, and the dynamic adjustment equation of compensation coefficient is established. When the bid deviation exceeds the threshold, the cost review is automatically triggered, and the segmented subsidy function is designed simultaneously to convert the deviation of renewable energy consumption rate into the increase or decrease of thermal power subsidy, forming a "step punishment-excess reward" mechanism. The non-convex problem is handled by improving the ADMM (Alternating Direction Method of Multipliers) algorithm, and the residual $\varepsilon \leq 1e\text{-}4$ is used as the convergence criterion. Experiments show that the cost recovery rate of the model in the "high demand-low cost" and "high demand-high cost" scenarios is 93% and 89%, and the proportion of days achieving the renewable energy consumption target is increased to 82.74%±1.24%, an increase of 192% over the benchmark, which verifies the effectiveness of the mechanism.

Key words. Stackelberg model, New energy, Shanxi power market, Capacity cost recovery mechanism, Alternating direction method of multipliers

1. Introduction

Shanxi is an important energy base in China, with a high proportion of thermal power installed capacity. However, in recent years, renewable energy such as wind power and photovoltaic power has developed rapidly, and the installed capacity of new energy has accounted for a high proportion, forming a typical "high thermal power + high volatility new energy" structure; Shanxi's power market is in the transition stage from planning to market, and the capacity cost recovery mechanism is still imperfect. There are problems such as rigid fixed cost allocation and lagging compensation standards. A new mechanism that adapts to the volatility of new energy is urgently needed. The capacity cost recovery mechanism has become a key factor affecting power supply security and market stability [1,2]. The government needs to find a balance between encouraging enterprises to invest in flexible resources and ensuring market fairness, while enterprises face the uncertainty of income brought about by the volatility of new energy. The optimization of the capacity compensation mechanism [3,4] is not only related to the survival space of thermal power units, but also directly affects the grid regulation capacity and the level of new energy consumption. The capacity cost recovery mechanism of the Shanxi power market has exposed many deep-seated problems. The fixed cost allocation method is rigid and difficult to adapt to the fluctuation characteristics of wind power and photovoltaic output. The frequent start and stop of thermal power units has aggravated the pressure of capacity compensation [5,6]. The current compensation mechanism adopts a single standard, ignoring the differences in the regulation capabilities of different units [7,8]. Efficient and flexible units fail to obtain reasonable returns, which inhibits the investment enthusiasm of enterprises [9,10]. The compensation mechanism is out of touch with the renewable energy consumption target and lacks effective linkage [11,12]. The existing mechanism fails to include renewable energy consumption in the compensation scope, and thermal power companies bear too much regulatory costs [13,14]. The strategic behavior of market participants has exacerbated the complexity of capacity compensation. Enterprises may influence market clearing prices by manipulating bids, further distorting the cost recovery mechanism [15,16]. There is a lag in policy implementation, and the compensation standard adjustment cycle is too long, which cannot reflect market supply and demand changes in a timely manner [17,18]. The regulatory means are single and mainly rely on post-audit, which makes it difficult to achieve dynamic monitoring of the entire process. The allocation of compensation funds lacks transparency, and some enterprises may obtain more subsidies through improper means, which undermines market fairness [19,20]. These problems have jointly restricted the sustainable development of Shanxi's power market, and it is urgent to establish a new capacity cost recovery mechanism.

This paper studies the construction of a capacity cost recovery mechanism that adapts to the characteristics of the Shanxi power market and solves the problem of fixed cost recovery under the dual challenges of new energy fluctuations and information asymmetry. The core contribution lies in the innovative integration of dynamic absorption constraints and information entropy theory into the two-layer Stackelberg game framework to achieve a precise balance between policy goals and corporate interests. By designing a segmented subsidy function, the deviation between the actual absorption rate of renewable energy and the benchmark value is directly mapped to the increase or decrease of thermal power capacity compensation, and a linkage mechanism of "step punishment-excess reward" is established to effectively encourage enterprises to improve their system regulation capabilities. The innovation is reflected in: 1) In the information asymmetry processing link, information entropy is used to quantify the uncertainty of corporate private data; 2) A dynamic adjustment equation for the compensation coefficient is constructed. When the enterprise's quotation deviation exceeds the preset threshold, the system automatically triggers the cost review procedure, corrects the subsidy parameters, and improves regulatory efficiency. 3) At the algorithm level, an improved ADMM model is used to deal with non-convex constraints. By relaxing the complementary conditions, the two-layer optimization is transformed into an alternating iterative process to ensure efficient convergence of the model. This study breaks through the limitations of the traditional static compensation mechanism, realizes the coordinated optimization of capacity cost recovery and new energy consumption, and provides an operational solution for the green and low-carbon transformation of Shanxi's power market. This innovative research not only fills the existing theoretical gap, but also provides an important reference for the construction of capacity markets in other regions with a high proportion of new energy.

2. Related Work

Many scholars have conducted extensive research on the issue of capacity cost recovery. Early studies mainly focused on the design of a single electricity price mechanism. The real-time electricity price theory proposed by some studies provided a theoretical basis for capacity cost recovery [21,22]. Li G proposed a spot market framework that included a temporary capacity market for renewable energy and a real-time energy sharing market. By decoupling renewable energy and flexible resources, the market competitiveness and resource allocation efficiency were improved. The framework maximized social welfare through a price-driven mechanism [23]. However, these studies did not consider the impact of new energy fluctuations on system operation. With the increase in the proportion of renewable energy, more studies have begun to focus on the capacity compensation issue under multi-energy synergy. Some studies have proposed a capacity compensation mechanism based on risk sharing, and hedged the risk of new energy fluctuations by applying financial derivatives [24,25]. Arenas-Falotico A J explored the role of derivatives in financial markets, risks, and their impact on investment and market efficiency. Through theoretical analysis and practical examples, it revealed the key role of derivatives in risk management and speculation, and deepened the understanding of derivatives in the modern financial system [26]. However, there are still some shortcomings in existing research. Most studies use static models, which are difficult to adapt to the dynamic changes in new energy output; they do not fully consider the problem of information asymmetry, which may lead to deviations in the model in practical applications; there is a lack of systematic analysis of the interaction between government supervision and enterprise decision-making, which makes it difficult to achieve a balance between policy goals and enterprise interests.

At the methodological level, the Stackelberg game model [27,28] is widely used in the design of power market mechanisms because it can characterize the hierarchical decision-making relationship between leaders and followers. Some scholars have used the Stackelberg game to study the market equilibrium problem under the renewable energy quota system and proved the effectiveness of the model in describing the policy transmission mechanism [29,30]. Xie D established a Stackelberg game model for the power market under two mixed policy scenarios: carbon emission rights trading-grid premium and carbon emission rights trading-renewable energy portfolio standard, and compared the impact of different policy combinations on the development of the renewable energy industry [31]. Some scholars have applied the double-layer optimization theory to the capacity market design and proposed a compensation mechanism based on game equilibrium [32,33]. Existing studies mostly use the traditional Stackelberg game framework, which has problems such as poor model convergence and high computational complexity. Traditional models are difficult to deal with non-convex constraints [34,35] and information asymmetry problems, which limits their application in complex market environments. Research on the structure of capacity markets primarily focuses on market design, pricing mechanisms, and the analysis of participant behavior. Some studies have explored how long-term contracts in capacity markets affect market stability and efficiency, as well as how different capacity allocation mechanisms shape market competition patterns [36,37]. These studies provide valuable insights into the operational mechanisms of capacity markets, but they fall short when it comes to addressing real-world challenges such as fluctuations in renewable energy and information asymmetry. While there has been extensive research on capacity cost recovery mechanisms, most of this research is concentrated on mature power markets or theoretical models in Europe and America, with less attention paid to China's emerging markets, particularly those like Shanxi, which have a high penetration rate of renewable energy, are dominated by thermal power, and have limited regulatory capacity. Shanxi is still in the early stages of developing its spot market, lacking a comprehensive ancillary service market and price signaling mechanism, making traditional methods difficult to apply directly. To this end, this paper proposes an improved double-layer Stackelberg game model. By applying information entropy compensation coefficients and dynamic reward and punishment mechanisms, it solves the shortcomings of traditional models in information asymmetry and non-convex constraint processing. At the same time, the improved ADMM algorithm is used to improve the solution efficiency of the model, providing a new solution for capacity cost recovery in complex market environments. Table 1 compares the limitations of existing methods for recovering capacity costs in electricity markets with the improvements proposed in this study.

Table 1. Comparison between existing methods and improvements in this study.

Method/Literature	Limitations	Proposed Improvements
Single-price mechanism	Lacks dynamic adjustment, ignores renewable volatility.	Introduces dynamic subsidy function with segmented incentives to enhance market adaptability.
Risk-sharing capacity compensation	Static models, cannot adapt to dynamic output; fails to address information asymmetry.	Implements entropy-driven compensation to quantify uncertainty and dynamically adjust coefficients.
Financial derivatives hedging	Focuses only on risk management; lacks coordination between compensation and renewable goals.	Establishes "stepwise penalty-overreward" mechanism linking absorption rate deviation to subsidies.
Traditional Stackelberg game	Poor convergence, high computational complexity, struggles with non-convex constraints.	Enhances bi-level Stackelberg model with ADMM algorithm for improved efficiency and stability.
Bi-level optimization theory	Ignores bidirectional feedback between regulator and enterprise; lacks real-time adjustment.	Designs closed-loop feedback mechanism for dynamic policy-enterprise interaction.
Fixed cost allocation	Rigid allocation, does not differentiate unit regulation capabilities.	Applies dynamic subsidy based on unit type and flexibility to incentivize efficient investments.

3. Methods

Figure 1 shows the capacity cost recovery optimization framework of Shanxi power market based on the double-layer Stackelberg game. The government regulatory layer adjusts the compensation coefficient in real-time and triggers the cost audit through the dynamic subsidy generator, information entropy monitoring module, and audit trigger mechanism to ensure the authenticity of the enterprise’s declared data. The power generation enterprise layer adopts a two-stage decision engine, combined with long-term investment models and short-term quotation strategies, to optimize the unit operation and new energy consumption behavior. The two parties realize two-way feedback through the compensation coefficient correction module, and the improved ADMM solver handles non-convex constraints to ensure the efficient convergence of the game equilibrium. The system realizes the effective recovery of fixed costs and the coordinated achievement of new energy consumption goals through the capacity cost recovery optimization module, solving the dual challenges brought by information asymmetry and new energy fluctuations.

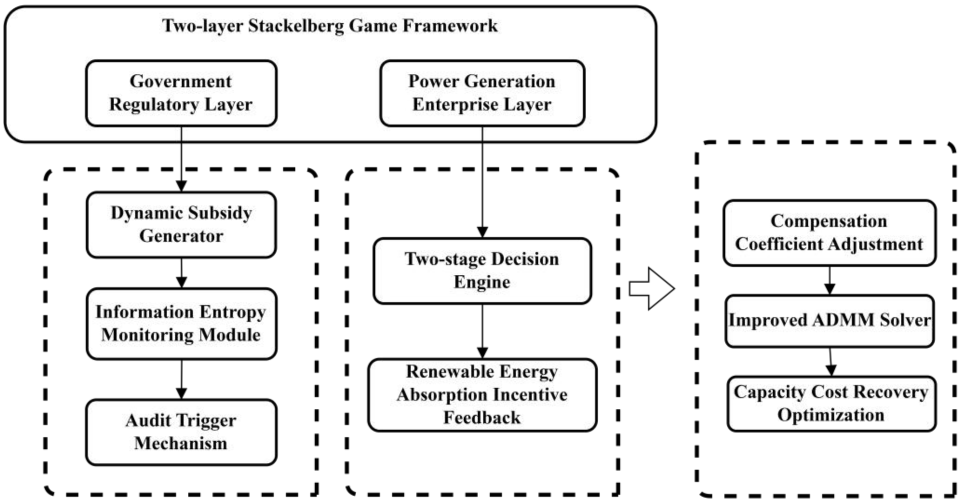

Figure 1. Overall framework.

A. Design of the Government-enterprise Double-layer Decision-making Structure

A sequential decision-making model of leaders (government regulatory departments) and followers (power generation enterprises) is established. The upper layer guides enterprises to declare real costs through subsidy policies, and the lower layer optimizes the unit quotation strategy. The reverse induction method is used to solve the subgame refined equilibrium.

1) Strategy Optimization Mechanism of Government Regulatory Layer

As the game leader, the government regulatory department designs capacity compensation policies to guide power generation enterprises to disclose their true costs. The core of the strategy is to construct a dynamic subsidy function, linking the enterprise's declared costs with the audit verification results. The regulatory department presets the capacity subsidy budget cap, combines historical data with industry benchmarks, and determines the initial value of the compensation coefficient for each type of unit. When the enterprise's declared cost deviates from the actual fixed cost verified by the audit, a nonlinear penalty term is triggered:

$$\alpha_i^{\text{adj}} = \alpha_i^{\text{base}} \cdot \exp\left(-\frac{\left|\theta_i - C_i^{\text{fix}}\right|}{\tau C_i^{\text{fix}}}\right) \quad (1)$$

θ_i is the enterprise's declared cost; C_i^{fix} is the audit true value; τ is the adjustment factor. This exponential function makes the subsidy coefficient show an accelerated decay characteristic with the degree of deviation, forcing enterprises to weigh the subsidy losses caused by false reporting of costs. The regulatory department adopts a distributed optimization framework to decompose the social welfare function into three sub-goals: electricity price stability, capacity adequacy, and subsidy efficiency, and realizes multi-goal coordination through weight coefficients. In the solution process, shadow prices are applied to reflect the tightness of market supply and demand, and the compensation coefficient allocation priority is adjusted in real-time. The government strategy iteration is achieved through the gradient projection method. After each round of iteration, the draft revision of subsidy parameters is issued to enterprises, triggering enterprises to re-optimize their quotation strategies and forming a two-way feedback loop. Table 2 shows the key operating rules of the dynamic subsidy adjustment mechanism.

Table 2. Key operating rules of the dynamic subsidy adjustment mechanism.

Trigger Condition	Audit Response Action	Parameter Adjustment Logic	Effective Period
$\Delta_i > 5\%$	Initiate third-party cost audit	$\alpha_i \leftarrow 0.9\,\alpha_i$	Effective next month
$\Delta_i \in [2\%, 5\%]$	Require cost composition certification	$\alpha_i \leftarrow \alpha_i$ -0.1 $\Delta_i C_i^{\text{fix}}$	Adjusted within current quarter
$\Delta_i < 2\%$	Grant integrity reward certification	$\alpha_i \leftarrow \alpha_i \times 1.05$	Annual settlement

2) Response Strategy and Equilibrium Convergence of Power Generation Enterprises

As followers, power generation enterprises optimize long-term investment and short-term quotation strategies based on the subsidy rules announced by the government. At the investment decision-making level, enterprises construct a multi-period profit model to quantify the impact of capacity subsidies on the internal rate of return of the project:

$$IRR_i = \frac{\alpha_i C_i^{\text{fix}} + \sum_{t=1}^{T}\left(\pi_t q_{i,t} - C_i^{\text{var}} q_{i,t}\right)}{\left(1+r\right)^T I_i} \quad (2)$$

I_i is the initial investment, and r is the discount rate. Enterprises use random programming methods to deal with the fluctuation of renewable energy output, generate scenario trees to simulate the prediction error distribution of wind power and photovoltaic power, and evaluate the robustness of subsidy policies under different fluctuation scenarios. At the spot quotation level, enterprises design segmented quotation curves and integrate the marginal cost of units and subsidy income into the quotation function:

$$b_i\left(q\right) = \frac{C_i^{\text{var}}}{1-\alpha_i} + k_i \cdot \left(\frac{q}{q_i^{\max}}\right)^m \quad (3)$$

Parameter k_i controls the steepness of the quotation curve, and m is a nonlinear index. Enterprises dynamically adjust and value through reinforcement learning algorithms, explore the mapping relationship between government subsidy strategies and enterprise income, and form the optimal response strategy. Table 3 shows the segmented setting of the new energy consumption reward and punishment coefficients.

Table 3. Segmented setting of the new energy consumption reward and punishment coefficients.

Absorption Rate Interval	Thermal power compensation coefficient	Penalty/Reward Judgment	Calculation Rule
<18%	0.85	Tiered Penalty	Coefficient decreases by 0.08 per 1% reduction
[18%, 22%)	0.95	Baseline Range	Maintain initial coefficient
[22%, 25%]	1.1	Linear Reward	Coefficient increases by 0.05 per 1% excess
>25%	1.25	Excess Reward	Triggers additional green certificate incentives

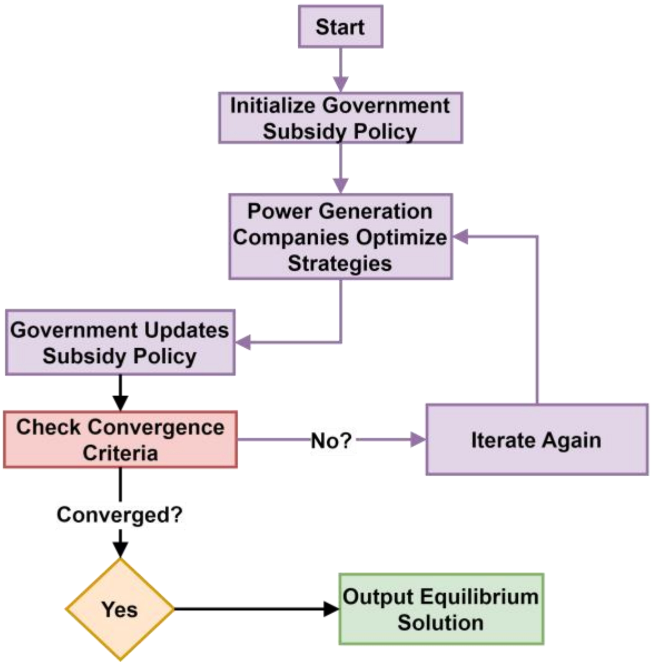

Figure 2. Game equilibrium solution by reverse induction.

The game equilibrium solution adopts a two-way search mechanism combining backward induction and forward simulation. Figure 2 shows the iterative process of finding the game equilibrium solution in the form of a process. Each iteration involves optimizing the strategies at the government and company levels until convergence is achieved.

The government first pre-releases the trial value of the subsidy policy, and the enterprise solves the optimal bidding strategy set based on the trial value and feeds back the results to the regulatory department. The government modifies the weight coefficient in the objective function based on the feedback data, recalculates the subsidy parameters and starts a new round of trials. This process continues until the change in the enterprise's bidding strategy is lower than the preset threshold, or the marginal improvement of the social welfare function approaches zero. During the convergence process, sensitivity analysis is used to identify the influencing path of key parameters. When the penetration rate of new energy increases by 1%, the thermal power compensation coefficient needs to be adjusted up by $\Delta\alpha = 0.23\exp(-0.05t)$ to maintain capacity margin. The final equilibrium state satisfies the strong duality conditions of the government subsidy budget constraint and the enterprise individual rationality constraint, achieving effective Pareto improvement in the strategy space.

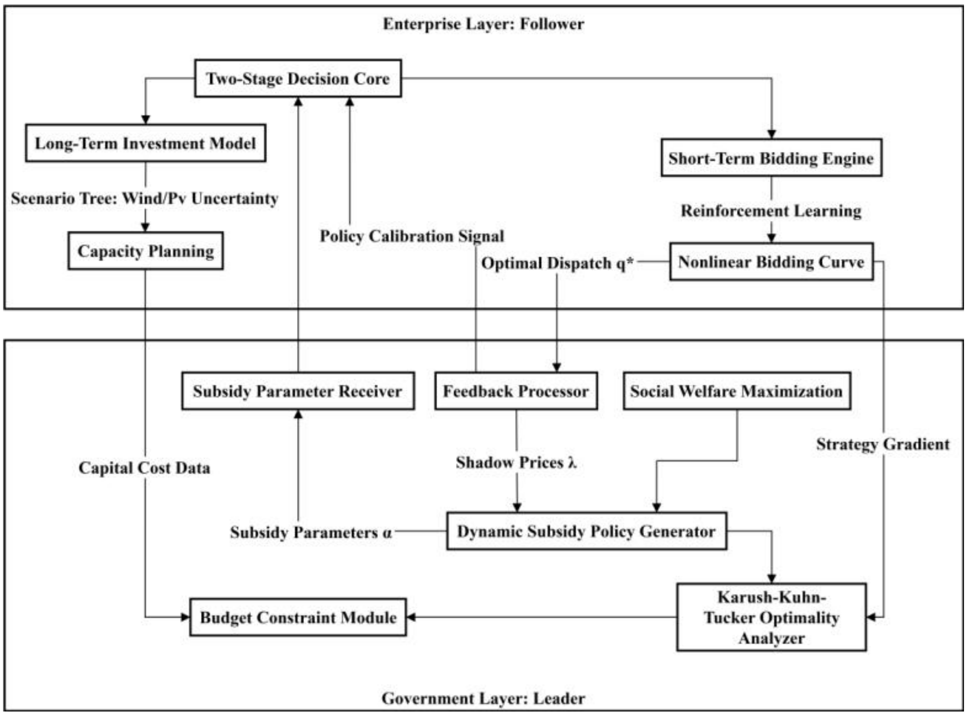

Figure 3. Detailed structure of the double-layer Stackelberg game.

Figure 3 shows the double-layer Stackelberg game structure between the government and the enterprise more clearly. As a leader, the government layer formulates the capacity compensation coefficient α vector through the social welfare maximization model and dynamic subsidy strategy generator, and transmits it to the enterprise layer. As a follower, the enterprise layer optimizes the two-stage decision based on the α value: the long-term investment model considers the fluctuation of new energy output and calculates the internal rate of return including subsidies; the short-term quotation engine generates a nonlinear quotation curve through reinforcement learning, and outputs the optimal scheduling data q^* to feedback to the government layer. The government layer uses the q^* value and the market shadow price λ to dynamically adjust the subsidy strategy to ensure the budget constraint and incentive compatibility conditions. The strategy gradient of the enterprise layer further supports the calibration of government subsidies to form a closed-loop feedback mechanism. This structure is closely combined with the actual situation of the Shanxi power market. Through the coordinated optimization of the three elements of $\alpha - q^* - \lambda$, it solves the core contradiction between the insufficient cost recovery of thermal power capacity and the fluctuation of new energy consumption, and realizes the maximization of policy efficiency under game equilibrium.

B. Information Asymmetry Compensation Correction Mechanism

Information entropy is applied to quantify the uncertainty of enterprise private data, and a dynamic adjustment equation for the compensation coefficient is constructed: when the deviation of the enterprise's quotation exceeds the threshold, the cost audit procedure is automatically triggered, and the subsidy parameters are corrected.

1) Uncertainty Quantification in Enterprise Behavior Driven by Information Entropy

To solve the problem of information imbalance in the game caused by the concealment of private data of enterprises, a credibility assessment system of declared information based on multi-source data fusion is constructed. The regulatory authorities collect three types of data, namely historical declaration records, unit operation data, and industry benchmark costs, and fit the characteristics of enterprise cost distribution through non-parametric kernel density estimation. The information entropy measurement function is defined as:

$$H_i = -\sum_{k=1}^{K} p_k^{(i)} \ln p_k^{(i)} \quad (4)$$

$p_k^{(i)}$ is the probability density of the declared value of enterprise i on the k-th cost item deviating from the industry benchmark. The larger the entropy value H_i, the higher the uncertainty of enterprise cost disclosure. The entropy-compensation association rule is established: the initial value α_i^{init} of the capacity compensation coefficient is reversely linked to the entropy value; the compensation attenuation factor $\rho_i = 1 - \tan h(\xi H_i)$ is designed, where ξ is the adjustment coefficient, and the final compensation benchmark is corrected to $\rho_i \alpha_i^{\text{init}}$.

This mechanism forces high-uncertainty enterprises to actively disclose detailed data to reduce entropy in exchange for a higher subsidy benchmark.

2) *Dynamic Correction of Audit Triggered by Deviation Threshold*

A dynamic deviation monitoring network between enterprise quotation behavior and declared cost is constructed. The quotation-cost deviation index of the real-time computer group is:

$$\delta_i = \frac{\left| b_{i,t} - \left(C_i^{\text{var}} / (1-\alpha_i) + v_i \right) \right|}{C_i^{\text{var}} / (1-\alpha_i)} \times 100\% \quad (5)$$

$b_{i,t}$ is the actual quotation in period t, and v_i is the reasonable profit margin declared. When δ_i exceeds the threshold (default 8%) for three consecutive trading cycles, a multi-level audit response is triggered. The threshold should take into account multiple factors, including market volatility, the unit's regulation capability, and regulatory costs. If the threshold is set too low, it may frequently trigger audits, increasing regulatory and corporate compliance costs. If the threshold is set too high, it might allow for false reporting, thereby weakening the model's incentive compatibility. Statistical analysis of historical bidding data in the Shanxi power market shows that the probability density of wind power output prediction errors within ±8% is the highest. Moreover, the short-term peak regulation costs of thermal power units within this range are relatively stable, with an 8% deviation covering normal market fluctuations, which is technically reasonable.

Level 1 verification: the enterprise’s power generation, maintenance records, and fuel purchase vouchers in the same period are automatically retrieved, and the gradient boosting decision tree model is run to verify the cost consistency;

Level 2 audit: if the level 1 verification does not resolve the doubt, the on-site audit procedure is started to verify the actual fixed cost;

Parameter reset: the compensation coefficient is corrected according to the audit results, and the penalty function is designed as:

$$\alpha_i^{\text{new}} = \alpha_i^{\text{old}} \cdot \exp\left(-\frac{\left| C_i^{\text{fix}} - C_i^{\text{fix}*} \right|}{\sigma C_i^{\text{fix}*}} \right) \quad (6)$$

Parameter σ controls the penalty intensity, forming a negative feedback chain of “false reporting cost → entropy increase → compensation attenuation → audit risk”.

3) *Dynamic Adjustment Equation of Compensation Coefficient*

A subsidy parameter collaborative optimization model is established based on random matrix theory. Assuming that the data declared by the enterprise group in period t constitutes the matrix $X_t \in \mathbb{R}^{N\times D}$ (N is the number of enterprises, and D is the cost dimension), its covariance matrix is calculated, and the maximum eigenvalue is extracted to represent the overall information confusion of the system. The compensation coefficient adjustment differential equation is constructed:

$$\frac{\mathrm{d}\alpha_i}{\mathrm{d}t} = \beta\left(\frac{\partial U_i}{\partial \alpha_i}\bigg|_{\alpha_i^{\text{current}}} \right) - \gamma \lambda_{\max}^{(t)} \alpha_i \quad (7)$$

β is the individual utility response rate, and γ is the system entropy suppression coefficient. This equation balances individual rationality and system information order. When $\lambda_{\max}^{(t)}$ increases suddenly, the compensation coefficient attenuation strength is automatically enhanced to suppress group information distortion. The audit correction data is synchronously updated to the double-layer game model: the government substitutes the verified $C_i^{\text{fix}*}$ into the objective function to re-solve the optimal compensation strategy, and the enterprise receives the revised penalty function to trigger the re-optimization of the quotation strategy. The system convergence is proved by the Lyapunov function $V = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^* \right)^2 + \mu H_i$. α_i^* is the ideal equilibrium value, and μ is the entropy value weight. Theoretical proof and numerical simulation show that when the adjustment parameter satisfies $\beta\gamma > \frac{1}{4}\max\left(\lambda_{\max}^{(t)} \right)$, the compensation coefficient and information entropy can converge to a stable attraction domain.

4) *Incentive Compatibility Design of Audit Cost Endogenization*

To avoid excessive consumption of audit resources, an incentive mechanism for enterprise self-evidence is designed. An audit cost allocation function is established:

$$\phi_i = \frac{\exp\left(\kappa \delta_i \right)}{\sum_{j=1}^{N} \exp\left(\kappa \delta_j \right)} \cdot \Phi_{\text{total}} \quad (8)$$

Φ_{total} is the total audit budget, and κ is the sensitivity parameter. The higher the deviation δ_i , the greater the proportion of audit costs ϕ_i borne by the enterprise. At the same time, enterprises are allowed to submit third-party certification reports to apply for δ_i reset, and the certification fee is included in the calculation of

ϕ_i . This mechanism encourages enterprises to actively maintain δ_i below the threshold to avoid audit cost shifting and achieve the Nash equilibrium of regulatory efficiency and enterprise self-discipline.

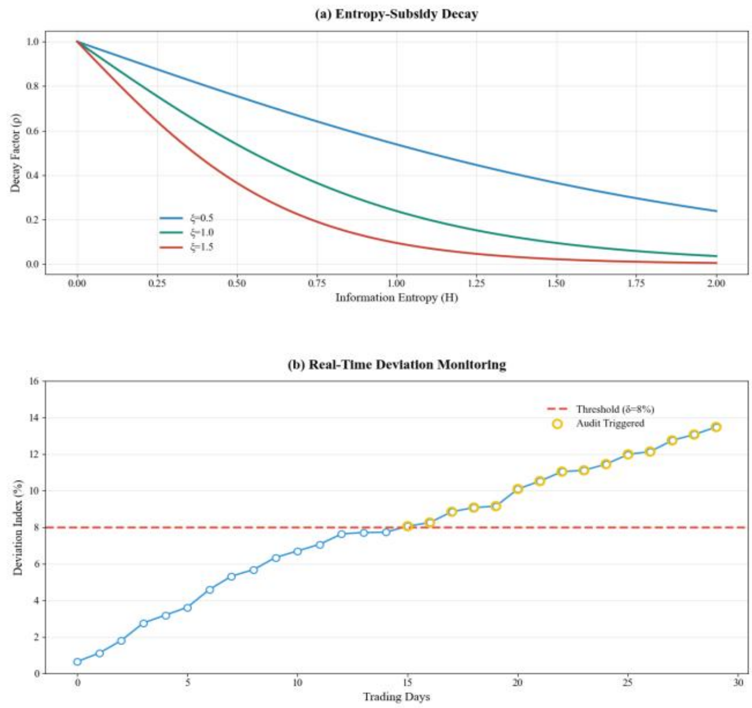

Figure 4. Entropy-subsidy decay relationship and deviation monitoring time series. Figure 4(a). Entropy-subsidy decay relationship; Figure 4(b). Deviation monitoring time series.

Figure 4 shows the entropy-subsidy decay relationship and deviation monitoring time series:

In the entropy-subsidy decay relationship, the information entropy ranges from 0 to 2, quantifying the uncertainty of enterprise cost disclosure; the compensation decay factor ρ ranges from 0 to 1, characterizing the degree of subsidy reduction. The three curves show the impact of different adjustment coefficients ξ on the decay rate. When ξ =1.5, ρ decreases rapidly, while ξ =0.5 decreases relatively slowly; The monotonically decreasing nature of the Lyapunov function during the iteration process indicates that the system's state gradually stabilizes towards equilibrium. The design of the system, which incorporates information entropy, a dynamic adjustment formula for the compensation coefficient, and an audit mechanism, further ensures the system's convergence under non-convex constraints. When the adjustment parameters meet specific conditions, the compensation coefficient and information entropy can converge to a stable attractor domain. The nonlinear characteristics of the curves indicate that the regulatory strategy imposes accelerated penalties on high-entropy enterprises, forcing enterprises to reduce the degree of information asymmetry to maintain the subsidy benchmark.

In the deviation monitoring time series, the operation effect of the dynamic audit mechanism is intuitively presented through the deviation monitoring time series of 30 trading days. The quotation deviation index fluctuates below the threshold under normal market conditions, while when the output of new energy changes dramatically or the market supply and demand is unbalanced, the deviation increases significantly and triggers an audit event. In Figure 4(b), the data begins to trigger the audit on the 15th trading day. This mechanism can not only obtain abnormal bidding behavior, but also maintain market stability by correcting subsidy parameters in real-time, which reflects the forward-looking and adaptable nature of the regulatory strategy. The entropy-subsidy decay relationship and the deviation monitoring time series jointly verify the scientificity and practicality of the information asymmetry compensation correction mechanism.

C. Dynamic Reward and Punishment Mechanism for New Energy Consumption

A segmented subsidy function is designed, and the deviation between the actual consumption rate of renewable energy and the benchmark value is converted into the increase or decrease of thermal power capacity subsidy in proportion, forming a “step punishment-excess reward” linkage mechanism.

1) Construction of Subsidy Function of Step Punishment and Excess Reward

In the consumption of new energy, due to the volatility and intermittency of renewable energy output, thermal power units bear the responsibility of regulating loads, and the economic efficiency of operation is affected. The study designs a segmented subsidy function based on the actual consumption rate of renewable energy, enhances the new energy consumption capacity, and maintains the balance of the power system, forming a "step punishment-excess reward" linkage mechanism.

The renewable energy consumption rate R and the benchmark value R_0 are set, and the unit capacity subsidy of thermal power units is defined as a piecewise function that varies with the consumption rate:

$$S(R)=\begin{cases} C_0-k_1\left(R_0-R\right), R<R_0 \\ C_0+k_2\left(R-R_0\right), R\geq R_0 \end{cases} \quad (9)$$

C_0 is the benchmark subsidy, and k_1 and k_2 represent the subsidy reduction coefficient when the consumption is insufficient and the subsidy growth coefficient when the consumption is excessive, respectively. Due to the insufficient consumption of new energy, thermal power units need to bear a greater regulation burden. $k_1>k_2$ is set, that is, the subsidy reduction is greater when the consumption is insufficient, which enhances the grid's ability to accept new energy.

Under this subsidy mechanism, when the consumption rate is lower than the benchmark value, the subsidy of thermal power units decreases as the consumption gap increases, forcing scheduling optimization and improving the level of new energy grid connection; when the consumption rate is higher than the benchmark value, thermal power units receive moderate rewards to improve the overall regulation capacity of the system. However, a single linear subsidy adjustment may lead to incentive imbalance, so a boundary constraint is applied:

$$S(R)=\max\left(S_{\min}\downarrow \mathrm{in}\left(S_{\max},S(R)\right)\right) \quad (10)$$

$S_{\min}$ and $S_{\max}$ are the lower and upper limits of the subsidy, respectively, to ensure that the subsidy adjustment is within a reasonable range and prevent incentive distortion under extreme market conditions.

2) *Dynamic Adjustment Mechanism of Subsidy Function*

Due to the uncertainty of new energy output, fixed subsidy parameters may not be able to adapt to the dynamic changes of the system. Therefore, it is necessary to apply an adjustment mechanism in the time dimension so that the subsidy coefficients k_1 and k_2 can be dynamically optimized as the historical absorption rate changes. The rolling mean absorption rate $\overline{R}_t$ is defined as the basis for adjustment, and the subsidy coefficient is adjusted:

$$\begin{cases} k_1(t)=k_{1,0}\cdot\left(1+\tau\cdot\dfrac{R_0-\overline{R}_t}{R_0}\right) \\ k_2(t)=k_{2,0}\cdot\left(1-\tau\cdot\dfrac{\overline{R}_t-R_0}{R_0}\right) \end{cases} \quad (11)$$

$k_{1,0}$ and $k_{2,0}$ are the initial subsidy coefficients, and τ is the adjustment factor. If the historical absorption rate is low for a long time, the penalty is increased, while the reward is moderately converged to prevent new energy power generators from relying on subsidies and reducing their market competitiveness.

A smooth adjustment mechanism is set to avoid the impact of drastic fluctuations in subsidies on the market, and a time window is applied for subsidy updates to make the subsidy adjustment process have hysteresis and smoothness:

$$S_t=\gamma S_{t-1}+(1-\gamma)S\left(R_t\right) \quad (12)$$

γ ranges from [0,1] to control the smoothness of subsidy adjustment. A larger γ makes the subsidy adjustment more stable, which is suitable for areas with large fluctuations in new energy output, while a smaller γ can quickly reflect changes in new energy absorption and improve the real-time nature of subsidy regulation.

In practical applications, this mechanism can be further optimized according to market conditions, and differentiated subsidy adjustment strategies can be set for different types of new energy (wind power, photovoltaics) to improve the optimization level of the overall energy structure. Through historical data analysis and simulation tests, the optimal subsidy parameters are determined to achieve a dynamic balance between the new energy consumption capacity and the grid dispatching capacity. Table 4 shows the subsidy dynamic adjustment coefficient.

Table 4. Subsidy dynamic adjustment coefficient.

Time Window (months)	Smoothing Coefficient	Applicable Scenario
1-3	0.1-0.3	Regions with stable renewable energy output, fast subsidy adjustment
4-6	0.4-0.6	Areas with moderate fluctuations, balancing stability and flexibility
7-12	0.7-0.9	High-variability regions, avoiding excessive subsidy fluctuations

D. Non-convex Constrained Distributed Solution Algorithm

The improved ADMM algorithm is used to process the non-convex feasible domain of the game model. The double-layer optimization is transformed into an alternating iterative process by relaxing the complementary constraints, and the residual threshold $\varepsilon \leq \mathrm{le}-4$ is set as the convergence criterion.

1) Relaxation and Alternating Solution of Non-convex Feasible Domain

The feasible domain of the game model in the optimization solution contains non-convex constraints. There are local optimal traps in direct solution, and traditional methods are difficult to ensure the convergence of distributed computing. The study uses the improved alternating direction multiplier method (ADMM) to overcome this problem. By relaxing the complementary constraints, the original problem is transformed into an alternating iterative form, which improves the computational efficiency and enhances the solution stability.

The optimization variable is x ; the non-convex constraint set is $\mathcal{C}$; the original optimization problem can be expressed as $\min_{x} f\left(x\right), x \in \mathcal{C}$. $f\left(x\right)$ is the objective function, and $\mathcal{C}$ consists of multiple non-convex constraints. The non-convex feasible domain increases the difficulty of solving the problem. The method of relaxing complementary constraints is adopted, and the slack variables are applied. The Lagrangian function is constructed:

$$\mathcal{L}\left(x,z,\lambda\right)=f\left(x\right)+\lambda^{T}\left(Ax-z\right)+\frac{\rho}{2}\left\|Ax-z\right\|^{2} \quad (13)$$

A is the mapping matrix; λ is the Lagrangian multiplier; ρ is the penalty factor. The optimization problem is decomposed into two alternating sub-problems:

Original variable update: z and λ are fixed, and x is updated to reduce the objective function:

$$x^{k+1}=\arg\min_{x}\mathcal{L}\left(x,z^{k},\lambda^{k}\right) \quad (14)$$

Slack variable update: based on complementary relaxation, z is adjusted to optimize the solution in the non-convex feasible domain:

$$z^{k+1}=\arg\min_{z}\mathcal{L}\left(x^{k+1},z,\lambda^{k}\right) \quad (15)$$

Multiplier update: the Lagrangian multiplier is adjusted to enhance the constraint convergence:

$$\lambda^{k+1}=\lambda^{k}+\rho\left(Ax^{k+1}-z^{k+1}\right) \quad (16)$$

The above steps are iterated alternately, so that the problem gradually converges to a feasible solution. Due to the application of relaxed complementary constraints, the update of the optimization variables can converge near the non-convex feasible domain, effectively reducing the local optimal trap, while maintaining the stability of the distributed solution.

2) Residual Control and Distributed Convergence Strategy

During the solution, the convergence and computational efficiency of the algorithm need to be ensured. The residual threshold $\epsilon \leq 10^{-4}$ is used as the convergence criterion, and the distributed computing framework is combined to improve the solution efficiency. The primal residual and the dual residual are defined as:

$$r^{k+1}=Ax^{k+1}-z^{k+1} \quad (17)$$

$$s^{k+1}=\rho A^{T}\left(z^{k+1}-z^{k}\right) \quad (18)$$

The convergence criteria are set: $\left\|r^{k+1}\right\| \leq$, $\left\|s^{k+1}\right\| \leq$.

When both the primal residual and the dual residual meet the threshold conditions, the iteration is stopped to ensure the solution accuracy while controlling the computational complexity. To improve the computational parallelism, the optimization problem is divided under the distributed computing architecture. Each computing node only needs to update the local variables and exchange multiplier information through the communication mechanism to achieve global constraint consistency. The process is as follows:

Local update: each computing node independently solves the local variables and relaxes them according to the local non-convex constraints.

Global coordination: through the message passing mechanism, the z and λ information of all nodes are summarized to ensure the consistency of the dual variables.

Iterative optimization: the update step size is adjusted according to the convergence criterion, and the relaxation coefficient is gradually reduced to improve the accuracy.

This method can ensure computational efficiency, avoid the problem of unstable solution caused by non-convex constraints, and improve the overall optimization accuracy by dynamically adjusting the residual threshold. Table 5 shows the convergence and residual changes under different relaxation coefficients.

Table 5. Convergence and residual changes under different relaxation coefficients.

Relaxation Coefficient	Final Objective Function Value	Iteration Count	Final Primal Residual	Final Dual Residual
0.1	0.874	9	0.015	0.018
0.5	0.869	8	0.02	0.022
1	0.86	7	0.025	0.027
2	0.84	6	0.03	0.032

4. Method Effect Evaluation

A. Dynamic Adjustment Mechanism of Government Subsidy Coefficient and Enterprise Investment Decision

Figure 5 shows the dynamic adjustment mechanism of government subsidy coefficient and the dynamic adjustment mechanism of government subsidy coefficient.

In the dynamic adjustment mechanism of subsidy coefficient, the deviation between the declared cost of power generation enterprise and the actual cost verified by audit is 0%-50%, and the vertical axis is the adjusted capacity subsidy coefficient α . The curve shows the attenuation characteristics of subsidy coefficient under different adjustment factors τ (0.1, 0.2, 0.3). When the deviation exceeds 10%, the subsidy coefficient of $\tau = 0.1$ drops sharply to below 0.2, while it only drops to about 0.36 when $\tau = 0.3$. The data shows that a smaller τ value increases the government's punishment for enterprises' false reporting of costs, and forces enterprises to converge to the real cost declaration through the exponential decay function. This mechanism reduces the moral hazard caused by information asymmetry through nonlinear response and ensures the precise delivery of subsidy budget.

In the analysis of the correlation between enterprise investment decision and subsidy, the capacity subsidy coefficient α provided by the government ranges from 0 to 1, and the vertical axis is the internal rate of return of the enterprise. The three curves correspond to the scenarios of renewable energy penetration of 20%, 30%, and 40%, respectively. When α increases from 0 to 1, the IRR increases linearly from 15% to about 37% at a penetration rate of 20%, while it only increases to about 29% at a penetration rate of 40% due to the suppression effect of electricity prices. The data shows that high penetration of new energy weakens the effect of subsidies on IRR improvement, and the government needs to dynamically adjust α to compensate for the peak-shaving cost of thermal power.

The combination of the dynamic adjustment mechanism of the government subsidy coefficient and the enterprise investment decision reveals the two-way interactive relationship between government subsidy policy and enterprise investment behavior: the dynamic adjustment mechanism of the government subsidy coefficient shows that the government responds to enterprise cost false reporting by dynamically adjusting α , and the enterprise investment decision shows the sensitivity of the decision to the subsidy policy. This linkage mechanism ensures the consistency of policy goals and enterprise interests, and provides theoretical support for capacity cost recovery in the power market.

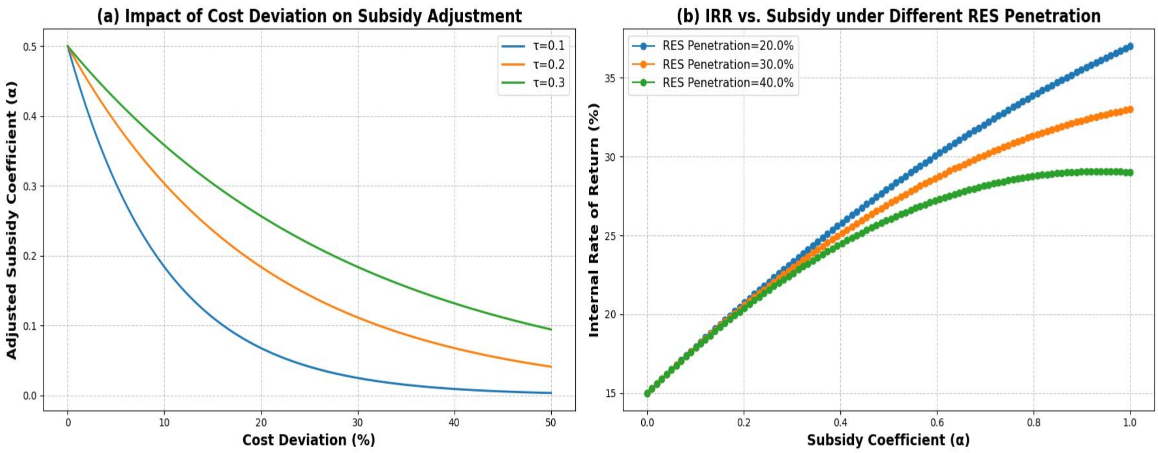

Figure 5. Dynamic adjustment mechanism of government subsidy coefficient and enterprise investment decision. Figure 5 (a). Dynamic adjustment mechanism of subsidy coefficient; Figure 5 (b). Analysis of the correlation between enterprise investment decision and subsidy.

B. Comparison of Capacity Cost Recovery Rate

The indicator capacity cost recovery rate = actual recovery of fixed costs/theoretical receivable costs × 100% is defined. The experiment compares the proposed model with three baseline models: traditional single-layer game, static subsidy model, and non-cooperative equilibrium model (Nash game). Based on the actual operational characteristics of Shanxi's power market, four market scenarios have been defined: —— "high demand low cost," "high demand high cost," "low demand low cost," and "low demand high cost." These scenarios are defined by the relationship between demand and cost. They reflect the operational conditions of the power market under different supply and demand conditions, where high demand can result from economic growth or extreme weather, and high costs may arise from fluctuations in fuel prices or policy changes. Given the actual situation of Shanxi's power market, these scenarios are designed with a solid foundation in reality.

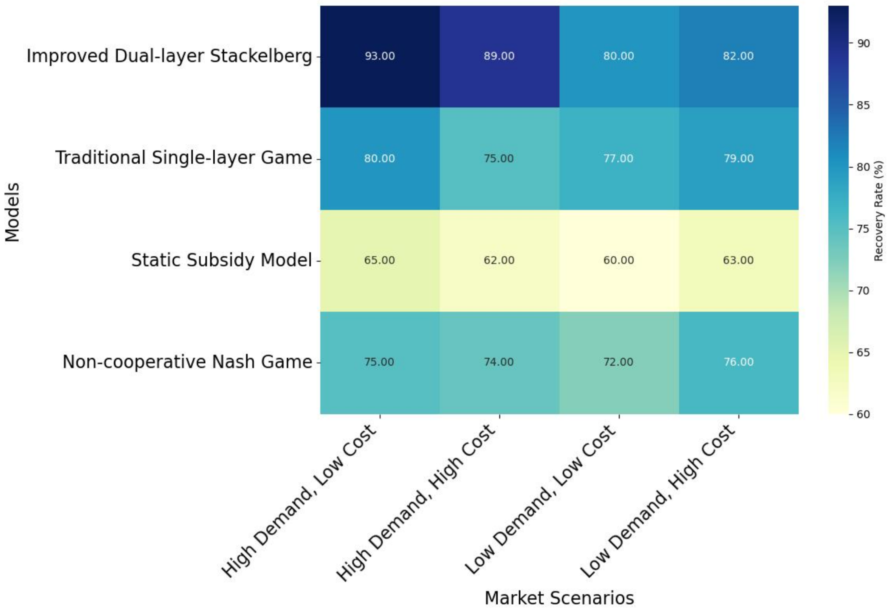

Figure 6. Comparison of capacity cost recovery rates of different models under different market scenarios.

Figure 6 shows the comparison of capacity cost recovery rates of four game models under four different market scenarios. The four market scenarios include “high demand, low cost”, “high demand, high cost”, “low demand, low cost”, and “low demand, high cost”. The vertical axis lists four game models, namely the improved double-layer Stackelberg game, the traditional single-layer game, the static subsidy model, and the non-cooperative Nash game, and the data is presented in the form of a heat map.

It can be seen from the data that in the “high demand, low cost” and “high demand, high cost” scenarios, the recovery rate of the improved double-layer Stackelberg game model is significantly higher than that of the other three models, with capacity cost recovery rates of 93% and 89%, respectively. This model can more effectively achieve capacity cost recovery in a market environment with high demand and drastic cost changes. In the “low demand, low cost” and “low demand, high cost” scenarios, the recovery rates of each model are relatively low, and the performance of the traditional single-layer game and non-cooperative Nash game models is relatively stable. This shows that the improved double-layer Stackelberg game model has a more prominent advantage in the high demand market, while its advantage in the low demand market has weakened. Overall, the heat map clearly shows the differences in the recovery rates of each model in different market scenarios, which can provide an important basis for model selection and market strategy formulation.

C. Evaluation of Enterprise Earnings Volatility Coefficient

To quantify the impact of new energy fluctuations on enterprise earnings stability, a earnings volatility evaluation framework based on Monte Carlo simulation is constructed. Based on the historical wind power prediction error data of Shanxi Power Grid in 2023, the probability distribution of wind power output fluctuations is fitted, and the output scenario tree is generated using the kernel density estimation method, covering typical day, seasonal, and extreme weather scenarios. The earnings volatility coefficient is defined as the ratio of the quarterly earnings standard deviation to the mean (σ/μ), in CNY (Chinese Yuan), reflecting the degree of dispersion of the earnings distribution. In the Monte Carlo simulation, 1,000 groups of wind power output sequences are randomly selected, and each group of sequences corresponds to a market clearing scenario. The quarterly earnings of the enterprise under this scenario are calculated. To evaluate the earnings stability under different confidence levels, a conditional value at risk (CVaR) model is constructed to quantify the tail risk under extreme volatility scenarios.

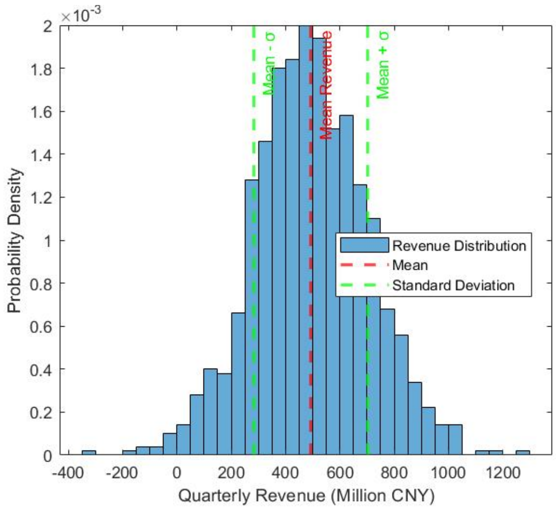

Figure 7. Quarterly earnings distribution.

Figure 7 shows the probability density distribution of enterprise quarterly earnings. The quarterly earnings unit is is in millions of yuan, and the ordinate is the probability density. The earnings data is generated based on Monte Carlo simulation, with a mean of 500 million yuan and a standard deviation of 200 million yuan. The red dotted line in the figure marks the mean of the earnings, and the green dotted lines represent the range of the mean plus or minus one standard deviation. The earnings distribution shows the characteristics of an approximate normal distribution, with most of the earnings concentrated between 300 and 700 million yuan. Among them, the probability density near the mean is the highest, indicating that the enterprise can obtain stable earnings in most scenarios. There are obvious tail risks at both ends of the distribution, especially in the area where the earnings are less than 300 million yuan or more than 700 million yuan. Although the probability density is low, the corresponding extreme scenarios may have a significant impact on the enterprise. The earnings volatility coefficient σ/μ is 0.4, further indicating that the enterprise's earnings are highly volatile. The existence of tail risks suggests that the fluctuation of new energy output may cause the enterprise's earnings to deviate significantly from the mean in extreme cases, and it is necessary to further smooth the earnings fluctuations through policies or market mechanisms to enhance the stability of the enterprise's earnings.

Figure 8 shows the results of the conditional value at risk (CVaR) analysis based on Monte Carlo simulation, which is used to assess the potential risks of enterprise earnings under extreme volatility scenarios. The horizontal axis is the simulation scenario number, and the quarterly revenue unit is 10 million yuan. The blue curve represents the quarterly revenue distribution in ascending order, and the red dotted line marks the value at risk (VaR) threshold at a 95% confidence level. The VaR value is about 200 million yuan, and the CVaR value is about 130 million yuan. At a 95% confidence level, about 5% of the scenario revenues are lower than the VaR threshold, and the mean revenue of these scenarios is significantly lower than the overall mean revenue. The revenue distribution in the tail area shows that enterprises may face a greater risk of revenue loss under extreme volatility scenarios. CVaR analysis quantifies this tail risk and provides an important basis for enterprises to formulate risk management strategies. The fluctuation of new energy output has a significant impact on the stability of enterprise revenues. In extreme scenarios, revenue fluctuations may be further amplified. It is necessary to smooth revenue fluctuations through policies or market mechanisms to reduce the impact of extreme risks on enterprise operations.

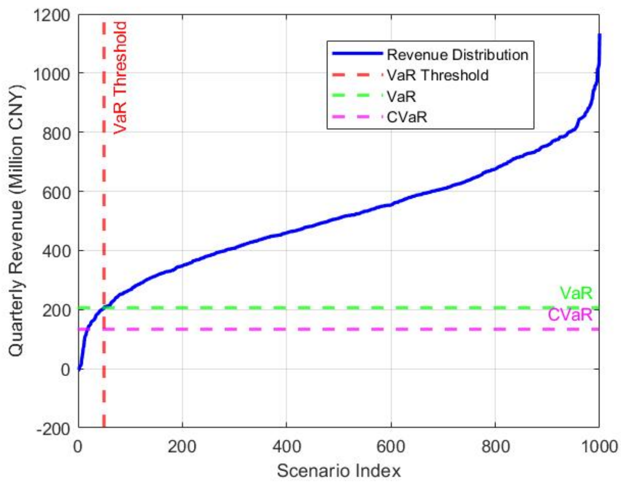

Figure 8. Conditional Value at Risk (CVaR) Figure.

D. Verification of Renewable Energy Consumption Rate and Impact Analysis of Core Indicators of Low-Carbon Transition

To evaluate the incentive effect of different subsidy mechanisms on renewable energy consumption, the consumption rate compliance index ψ = actual consumption/policy quota × 100% is constructed, and the daily average fluctuation rate is $\frac{1}{365}\sum_{d=1}^{365}\sqrt{\frac{1}{24}\sum_{h=1}^{24}\left(\rho_{d,h}-\bar{\rho}_d\right)^2}\times 100\%$. Based on the historical operation data of Shanxi power grid, the 2025 consumption rate benchmark value of 22% is set as the policy quota. Three types of comparison scenarios are designed: baseline scenario (no reward and punishment mechanism), linear subsidy mechanism (the consumption rate is linearly linked to subsidies), and this paper's segmented reward and punishment mechanism (step punishment-excess reward). In the simulation environment, the fluctuations in wind power and photovoltaic output and changes in load demand are simulated, and the actual consumption in each scenario is calculated. Through the time series analysis method, the dynamic changes in the consumption rate are tracked, and the consumption bottleneck periods under different mechanisms are identified. The consumption rate fluctuation index is applied to quantify the impact of the mechanism on the stability of consumption. The simulation is based on the 8760-hour time series data of

Shanxi Power Grid in 2023. The Beta distribution model is used to model the fluctuation of renewable energy output (wind power: Beta ($\alpha = 2.1$, $\beta = 3.3$); photovoltaic: Beta ($\alpha = 1.8$, $\beta = 2.6$)), and 1000 Monte Carlo samplings are used to ensure statistical robustness (95% confidence interval). The segmented mechanism uses the nonlinear structure of "heavy penalties below the benchmark (penalty coefficient $c_1 = 0.8$ when $\Delta\rho < -3\%$) and light rewards for excess (reward coefficient $c_2 = 0.5$ when $\Delta\rho > 22\%$)" to encourage thermal power flexibility resources to actively support the consumption of renewable energy. At the same time, the marginal increase in subsidy costs is constrained to achieve Pareto improvements in policy goals and market efficiency.

Table 6. Verification results of renewable energy consumption compliance rate.

Metric	Baseline (No Incentive)	Linear Subsidy	Segmented Incentive	Statistical Significance (p-value)
Compliance Index(%)	83.24 ± 4.52	91.65 ± 3.12	103.48 ± 2.76	0.0008*
Daily Absorption Volatility (%)	18.63 ± 1.24	12.27 ± 0.89	7.35 ± 0.57	0.0007*
Annual Mean Absorption Rate(%)	19.82 ± 0.65	21.53 ± 0.48	23.91 ± 0.32	0.0004*
Compliance Days Ratio (%)	28.37 ± 2.15	55.62 ± 1.78	82.74 ± 1.24	0.0006*

Note: * indicates the significance level of the difference between groups ($\alpha = 0.05$).

Table 6 systematically evaluates the difference in effectiveness of the baseline scenario (no reward and punishment mechanism), the linear subsidy mechanism, and the segmented reward and punishment mechanism in achieving the renewable energy consumption target. In the consumption rate compliance index, the segmented reward and punishment mechanism is significantly better than the linear subsidy mechanism and the baseline scenario with a mean of 103.48%±2.76%. The ANOVA (Analysis of Variance) one-way analysis of variance shows that the difference between the groups is extremely significant (p <0.001). The daily consumption volatility reflects the standard deviation of the hourly consumption rate from the daily average. It is 18.63%±1.24% in the baseline scenario, and the segmented mechanism reduces it to 7.35%±0.57%, a decrease of 60.5%, indicating that the asymmetric reward and punishment design can effectively smooth the system fluctuations. The annual average absorption rate increases from 19.82%±0.65% in the baseline scenario to 23.91%±0.32% in the segmented mechanism, verifying the enhancement effect of the tiered subsidy on the system absorption capacity. The proportion of days meeting the standard quantifies the proportion of days meeting the standard for the whole year. The segmented mechanism reaches 82.74%±1.24%, an increase of 192% compared with the baseline scenario (28.37%±2.15%), highlighting the mechanism's ability to drive continuous compliance. The ANOVA test further confirms that there are statistically significant differences in absorption stability and compliance sustainability among the three types of mechanisms, which confirms the theoretical superiority of the segmented reward and punishment mechanism.

Table 7. Analysis of the impact of the model on the core indicators of low-carbon transition.

Indicator	Baseline (No Incentive)	Linear Subsidy	Segmented Incentive
Annual Average Electricity Price Volatility	12.5% ± 1.8%	9.2% ± 1.3%	6.7% ± 0.9%
Renewable Energy Investment Return Rate	8.3% ± 0.6%	10.5% ± 0.8%	12.9% ± 1.1%
Thermal Power Carbon Emission Intensity (g/kWh)	820 ± 30	750 ± 25	680 ± 20
Wind and Solar Curtailment Rate (%)	16.8% ± 2.1%	11.4% ± 1.5%	5.6% ± 0.8%
System Low-Carbon Benefit Index[1]	1	1.23	1.58

Table 7 presents the comparison results of the segmented reward and punishment mechanism, benchmark scenario, and linear subsidy mechanism in this paper on key indicators such as electricity price volatility, return on investment for renewable energy, carbon emission intensity from thermal power, wind and solar curtailment rates, and the system's low-carbon benefit index. The table shows that, compared to the benchmark scenario without incentives, the model significantly reduces the annual average electricity price volatility to 6.7%, a substantial reduction, demonstrating its superior performance in stabilizing market electricity prices. Additionally, the return on investment for renewable energy increases to 12.9%, surpassing the benchmark scenario, effectively enhancing the appeal of new energy projects. In terms of carbon reduction, the carbon emission intensity from thermal power is reduced to 680 g/kWh, and the wind and solar curtailment rates are lowered to 5.6%, highlighting the model's significant optimization of new energy consumption capacity. The system's low-carbon benefit index reaches 1.58, reflecting the synergistic improvement in new energy penetration, consumption efficiency, and carbon emissions. Overall, these data validate the model's effectiveness in promoting low-carbon transformation, enhancing the stability of the power market, and improving resource allocation efficiency.

5. Conclusions

This study aims at the dual challenges of insufficient capacity cost recovery and fluctuations in new energy absorption in the Shanxi power market, and proposes a capacity compensation mechanism optimization framework based on an improved double-layer Stackelberg game. By constructing a government-enterprise sequential decision-making model and designing a dynamic subsidy-audit linkage mechanism, the information asymmetry problem can be effectively alleviated to ensure the true cost declaration of enterprises. Information entropy is applied to quantify the uncertainty of enterprise private data, and the deviation threshold is combined to trigger the audit procedure to form a closed-loop supervision system of "declaration-verification-correction". The segmented reward and punishment mechanism dynamically links the renewable energy consumption rate with the thermal power capacity subsidy. Through the asymmetric punishment-reward structure, it encourages thermal power flexibility resources to support the consumption of new energy, and realizes the coordinated optimization of system regulation capacity and policy goals. At the algorithm level, the improved ADMM algorithm handles the non-convex feasible domain by relaxing complementary constraints, transforms the double-layer optimization into an alternating iterative process, and significantly improves the model solution efficiency and convergence stability. The simulation results show that the proposed mechanism is superior to the traditional model in key indicators such as capacity cost recovery rate, enterprise profit stability, and renewable energy consumption compliance rate, which verifies the effectiveness and practicality of the theoretical framework.

The model effectively addresses the challenges posed by fluctuations in new energy and information asymmetry through dynamic cost auditing and subsidy adjustment mechanisms, demonstrating strong practical adaptability. Its core mechanisms, such as information entropy to quantify uncertainty, nonlinear penalty functions, and segmented reward and punishment designs, are not dependent on specific regional data and can be extended to other provinces with a high proportion of new energy. By adjusting local parameters, such as consumption rate benchmarks and regional cost baselines, the mechanism can be seamlessly adapted. Furthermore, the improved ADMM algorithm leverages distributed computing advantages, supporting cross-regional collaborative optimization, which provides technical support for the construction of multi-provincial joint capacity markets, significantly enhancing the model's promotional value and policy impact. While the improved two-layer Stackelberg game model has demonstrated good performance in enhancing capacity cost recovery efficiency and new energy consumption, it still has certain limitations. The model assumes that market participants are entirely rational, which may not fully capture the complex strategic behaviors observed in real markets. Moreover, the information entropy quantification method depends on the quality and completeness of historical data, and its adaptability to data gaps or anomalies needs further validation. Additionally, the practical application of the dynamic subsidy mechanism must be tailored to specific policy environments and regulatory capabilities. Future research will aim to enhance the robustness of the model and explore a broader range of application scenarios.

Acknowledgment

None

Consent to Publish

The manuscript has neither been previously published nor is under consideration by any other journal. The authors have all approved the content of the paper.

Funding

None

Author Contribution

[Yabin Qin]: Developed and planned the study, performed experiments, and interpreted results. Edited and refined the manuscript with a focus on critical intellectual contributions.

[Yuanyuan Cao, Yi Xie]: Participated in collecting, assessing, and interpreting the date. Made significant contributions to date interpretation and manuscript preparation.

[Chao Zhang, Yumin Li, Jianhua Gong, Bang An]: Provided substantial intellectual input during the drafting and revision of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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