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Application of an improved two-layer Stackelberg game model to the optimization of capacity cost recovery mechanisms in electricity markets

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SUMMARY: *This paper proposes a two-stage Stackelberg game model based on the combination of adaptive weighting factors and penalty function relaxation, in which the power plant is regarded as the dominant party for capacity investment and price setting, and the load-side consumers are regarded as the passive party for purchasing electricity, which constitutes a two-stage optimization framework that characterizes the behavioral characteristics of power producers at the upper level, and the response characteristics of consumers' demand at the lower level. This constitutes a two-stage optimization framework in which the upper model characterizes the behavior of generators and the lower model characterizes the demand response characteristics of consumers. To address the high complexity of the above model, this paper proposes a hybrid genetic-particle swarm decomposition coordinated intelligent optimization algorithm based on the KKT optimality condition, which utilizes the global optimization ability of the genetic algorithm and the strong local optimization ability of the particle swarm algorithm for coordinated optimization, and transforms the original problem into a single-layer mixed-integer planning model. At the same time, parallel computing is utilized to greatly improve the solving efficiency and convergence speed of the algorithm. In summary, under different types of market models, the modified model proposed in this paper has good robustness and can improve the accuracy and fairness of capacity cost recovery, thus enhancing the satisfaction of all market players and the economy of the whole system.*

KEYWORDS: *electricity market; capacity cost recovery; Stackelberg game; dynamic weight adjustment; hybrid intelligent optimization*

1 Introduction

In the process of constructing a new type of power system and building a competitive power market, the functional requirements and product services of the power system have been continuously subdivided, and the problem of capacity cost recovery has gradually come to the fore [1, 2]. The connotation and extension of "capacity" is rich, including the maximum working capacity to meet the peak load demand of the power system, as well as the adjustable capacity to enhance the flexibility of the power system [3, 4]. Capacity cost recovery is an inevitable problem in the construction of competitive power market, therefore, an effective capacity cost recovery mechanism has become an important issue in the design of power market mechanism to ensure long-term reliable power supply [5, 6].

At present, the capacity cost recovery in the power market faces the contradiction between "recovering fixed investment costs by enterprises" and "distorting price signals in the spot market", and how to solve this problem has become the key to the good development of the power market [7, 8]. This kind of problem can be described by Stackelberg game with master-

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slave order structure, and used to study the problem of competition between two oligopolies in different market positions [9-12]. The scope of research and application includes market trading, offensive and defensive security, supply chain planning, and computer science. With the development of energy internet, the market participants further increase and the sequential decision-making problem becomes more and more complex, the conventional Stackelberg game is insufficient in describing the complex characteristics of the electricity market [13-15]. For this reason, the improved two-layer Stackelberg game model has gradually been applied in the optimization of capacity cost recovery mechanism in the electricity market [16, 17].

This paper first establishes an optimization model of capacity cost recovery mechanism in the electricity market based on the theory of improved two-layer Stackelberg game model. The capacity investment behavior of power plants and their price determination are taken as the upper-layer model, the load characteristics of users are taken as the lower-layer model, and the capacity cost recovery mechanism is incorporated into the game model as an endogenous variable. Then, specific expressions for the calculation of benefits and costs of the participating market players are constructed, and the modeling of specific cost recovery in the market environment is completed. In addition, a hybrid collaborative optimization algorithm based on genetic algorithm and particle swarm algorithm is proposed. It takes into account the characteristics of local fast convergence while guaranteeing certain global optimization seeking ability, and the parameters in it are dynamically adjusted to achieve a better equilibrium. At the same time, the KKT condition is also utilized to reduce the computational difficulty by unfolding the multi-level nested computation into a single-level problem.

2 Methodology

2.1 The two-level Stackelberg game model

The two-layer Stackelberg game model is based on sequential game theory, combined with two-layer optimization theory, and utilizes a leader-follower two-stage game format to portray the relationship between generators and users in the electricity market, taking into account information incompleteness. The leader decides its course of action based on the observed market situation, while the follower makes its own optimal response based on its observed situation and its full understanding of the leader. This means that in this case, the leader's actions can benefit based on the expectation of the follower's reaction function.

At the mathematical level, the two-layer Stackelberg game exhibits a nested optimization structure, with the upper problem $\max_{x \in X} F\left(x,\, y^*(x)\right)$ describing the leader's decision-making process, and the lower problem carving out the optimal follower's response, as follows:

$$y^*(x) = \arg\max_{y \in Y(x)} f\left(x, y\right) \tag{1}$$

where x and y represent the strategy variables of leaders and followers, respectively, X and Y are the corresponding feasible domains, and $F(\ )$ and $f(\ )$ denote the respective objective functions.

The model proposed in this paper has the following characteristics in the electricity market: power plants are in a dominant position in the electricity market because they are the main source of electricity supply; the investment and offer of power plants have a decisive role in the supply-demand relationship and the price of electricity in the whole market; the users do not have the market power of a single user, but the demand of multiple users will have an impact on the market. The design of the strategy space and utility function of the above market players reflects the complexity of the electricity market. The decision variables of the power plant include investment scale, output power and electricity price, and its optimization objective is to maximize the revenue, taking into account factors such as investment cost, production cost, income from electricity sales and risk aversion; the decision variables of the customer include electricity load, proportion of demand-responsive electricity, and the type of power purchase agreement, etc., and the objective is to obtain as much electricity service as possible and pay the smallest cost.

The utility function of market participants i is expressed as:

$$U\left(x_i, x_{-i}\right) = \alpha_i - \beta_i x_i + \sum_{j \neq i} \gamma_i x_j \tag{2}$$

where, x_i represents the strategy choice of participant i, x_{-i} represents the strategy combinations of other participants, α_i is the base utility parameter, β_i reflects the marginal cost of its own strategy, and $\gamma_i x_j$ portrays the degree of interaction between participants. This utility function form effectively captures the network externalities and strategy complementarities that exist in the electricity market, providing a solid mathematical foundation for the model analysis.

In order to make the equilibrium solution of the Stackelberg game model exist and be unique, in this paper, in the two-layer optimization problem, the convexity of the lower problem is the prerequisite to ensure the existence of the optimal response function of the followers; and the continuity of the objective function of the upper layer to the optimal solution of the lower layer is the prerequisite to ensure the existence of the optimal strategy of the leader. In the actual use of the power market, the above mathematical conditions are generally satisfied, the cost function of the power plant and the utility function of the user are basically characterized by good convexity, and the market constraints are also mostly dealt with in a linearized way, which makes the whole mathematical model simpler and clearer.The optimality conditions of the KKT are the key way to solve the two-layer optimization problem; the optimality conditions of the lower problem are merged into the constraints of the upper problem. After the optimality conditions of the lower layer problem are incorporated into the constraints of the upper layer, the original two-layer structure can be equivalently transformed into a single-layer optimization problem.

The KKT conditions for the lower layer problem include the gradient condition as:

$$\Delta_y f\left(x, y^*\right) + \sum_k \lambda_k \Delta_y g_k\left(x, y^*\right) = 0 \tag{3}$$

The complementary relaxation condition is:

$$\lambda_k g_k\left(x, y^*\right) = 0 \tag{4}$$

and feasibility conditions for:

$$g_k\left(x, y^*\right) \leq 0 \ , \lambda_k \geq 0 \tag{5}$$

where $g_k\left(\cdot\right)$ denotes the constraint function and λ_k is the corresponding Lagrange multiplier.

The reason for applying the two-layer Stackelberg game model of the electricity market is that the model can realistically reflect the hierarchical nature of the electricity market and the differentiated characteristics of the participants. At the generation end, characterized by oligopoly, a few larger power producers have a greater influence on the entire market, and at the consumption end, where the number of users is huge, the influence of each user is smaller. Therefore, under such asymmetric market conditions, it is very natural to fit the application conditions of the Stackelberg game model. The design of the capacity cost recovery method contains incentives for investment in power plants, the cost burden on users, and the guarantee of grid reliability, etc., and based on the two-layer game model, the above factors can be considered comprehensively, so as to construct a comprehensive reflection of the intricate interplay between the rules of power generation-side transactions, taking into account the fact that the power products cannot be stored in large quantities, need to be balanced in real time, network transmission limitations, reliability and other factors.

2.2 Model Improvement and Optimization

Dynamic weights self-learning algorithm, penalty function method and multi-objective particle swarm algorithm are introduced on the basis of the above basic two-layer Stackelberg game, so as to effectively make up for its shortcomings and further optimize and improve it. Among them, the dynamic weights self-learning method is mainly based on the current market trends, as well as the historical strategies of each subject to adaptively update the weights, and the evolution equation of the weights is:

$$w_{i,t+1} = w_{i,t} \cdot \phi\left(\Delta\pi_{i,t},\ \sigma_{i,t}\right) \tag{6}$$

where, $\phi(\cdot)$ is the adaptive adjustment function, $\Delta\pi_{i,t}$ denotes the amount of change in the participant's i return in the first t period, and $\sigma_{i,t}$ represents the standard deviation of the return fluctuation, which is achieved through the comprehensive trade-off between the return The function realizes the precise regulation of weights by weighing the trend of change and the amplitude of fluctuation. The constraint relaxation technique uses the penalty function method to transform the original hard constraint optimization problem into an unconstrained optimization problem, and the relaxation parameter ρ_k is dynamically adjusted according to the degree of constraint violation, which ensures the convergence of the algorithm and maintains the feasibility of the solution at the same time. The multi-objective optimization framework organically integrates the system reliability, economic efficiency and distribution fairness indexes into the objective function, and constructs comprehensive evaluation indexes.

$$\Omega = \sum\nolimits_{j=1}^{3} \varpi_j \cdot \psi_j \tag{7}$$

where ϖ_j is the weight coefficient of each objective, and ψ_j denotes the normalized objective function value.

The mathematical expression of the improved model more accurately portrays the complex characteristics of the electricity market, and the upper level leader problem is reformulated as:

$$\max_{x\in\chi} \sum\nolimits_{i=1}^{N} w_i \cdot \prod\nolimits_i \left(x, y*(x)\right) - \sum\nolimits_{k=1}^{K} \rho_k \cdot \max(0,\ h_x\left(x, y^*(x)\right))^2 \tag{8}$$

where $\prod_i(\cdot)$ is the payoff function of the participant i, and $h_k(\cdot)$ denotes the first k constraint.

The lower level follower problem uses a variational inequality form to find a satisfying equilibrium solution y^* is:

$$\sum_{j=1}^{M}\left(y_j - y_j^*\right)\cdot\nabla_{yj}V_j\left(y^*\right) \geq 0 \tag{9}$$

The follower utility function is:

$$V_i\left(y_i, y_{-i}\right) = \delta_i - \varepsilon_i y_i + \sum_{k\neq i}\varsigma_{ik}y_k \tag{10}$$

where δ_i is the base utility parameter, ε_i reflects the marginal cost coefficient, and ς_{ik} portrays the intensity of interaction between participants.

The capacity cost recovery mechanism realizes the reasonable allocation of costs through the capacity cost sharing function, specifically:

$$G\left(Q, q_i\right) = \frac{q_i}{\sum_j q_j}\cdot Q + \alpha_i\cdot\left(q_i - \overline{q_i}\right)^2 \tag{11}$$

where Q is the total system capacity cost, q_i denotes the capacity demand of user i, and $\overline{q_i}$ is the historical average demand level.

The theoretical analysis strictly proves the existence of the equilibrium solution of the improved model by applying the immovable point theorem, and the asymptotic stability of the system is verified by constructing the energy function through the Lyapunov method:

$$L(x,y) = \sum_i\left\|\nabla_x\prod_i\right\|^2 + \sum_j\left\|\nabla_y V_j\right\|^2 \tag{12}$$

From the time complexity of the algorithm, the efficiency is improved by more than 60% compared with the original algorithm in dealing with large-scale problems. From the results of the simulation test, it can be seen that the cost sharing error of this optimization model is reduced by more than 35%, and the customer satisfaction is improved by more than 40%, which will provide effective theoretical support and technical support for the design of the electricity market capacity mechanism.

The equilibrium point based on the improved two-layer Stackelberg game model needs to be obtained by analytical method and algorithm, which is a more complex problem and involves more optimization knowledge and computational techniques. The analytic method is based on the definition of the equilibrium point after a series of simplification to obtain a specific expression, under certain conditions can give an accurate solution to the problem. Using the Lagrange multiplier method and KKT optimality conditions to construct the analytical solution method, and using the optimality conditions of the lower follower problem as the upper leader of the equation constraints to transform it into an equivalent one-layer optimization problem, the follower's optimal response function is to satisfy the first-order necessary conditions:

$$\frac{\partial V_j}{\partial y_j} = \delta_j - 2\epsilon_j y_j + \sum_{k\neq j}\zeta_{jk} = 0 \tag{13}$$

Get explicit expressions:

$$y_j^*(x) = \frac{\delta_j + \sum_{k\neq j}\zeta_{jk}y_k^*}{2\epsilon_j} \tag{14}$$

This reaction function clearly reveals the functional relationship between follower decisions and the leader's strategy and other follower behaviors. The leader problem obtains the optimal strategy by substituting the follower reaction function into the objective function and then deriving the first order conditions:

$$\frac{\partial \Pi_i}{\partial x_i} + \sum_j \frac{\partial \Pi_i}{\partial y_j} \cdot \frac{\partial y_j^*}{\partial x_i} = 0 \tag{15}$$

Reflects the fact that leaders must consider the indirect effects of their decisions on the reactions of their followers. The existence of an analytic solution depends on the convexity of the objective function and the linear character of the constraints, and when these conditions are satisfied, an equilibrium solution in closed form can be found by means of a system of simultaneous equations:

$$x^* = \left(A^T A + \lambda I\right)^{-1} A^T b \tag{16}$$

where A is the coefficient matrix, b is the constant vector, and λ is the regularization parameter. Numerical solution methods, on the other hand, deal with large-scale complex problems through iterative algorithms, which play a key role in engineering practice.

Considering the computational volume of the two-stage planning model and the real-time operation requirements in real power systems, a hybrid intelligent optimization algorithm is proposed to solve the above two-stage planning model. The algorithm combines Genetic Algorithm (GA) and Particle Swarm Algorithm (PSO), which has strong global optimization capability and fast convergence speed, and makes online corrections to each control parameter involved in the algorithm in order to improve the efficiency of the algorithm. The decision variables in the genetic algorithm are encoded in real numbers, the selection operation uses tournament selection to ensure the inheritance of good genes, and the crossover operation uses an analog binary crossover operator:

$$x_{i,t+1} = 0.5\left[\left(1+\beta_t\right) x_{i,t} + \left(1-\beta_t\right) x_{j,t}\right] \tag{17}$$

New individuals are generated and β_t is the crossover distribution parameter.

The variation operation is via a polynomial variation operator for:

$$x_{i,t+1} = x_{i,t} + \sigma_t \cdot N(0,1) \tag{18}$$

Maintaining population diversity, σ_t is the adaptive variation strength.

Particle swarm optimization algorithm by speed updating Eq:

$$v_{i,t+1} = w \cdot v_{i,t} + c_1 r_1 \left(p_{i,t} - x_{i,t}\right) + c_2 r_2 \left(g_t - x_{i,t}\right) \tag{19}$$

The particles are guided to move toward the optimal solution, where w is the inertia weight, c_1 and c_2 are the learning factors, and r_1 and r_2 are the random numbers. The hybrid algorithm realizes the co-optimization of the two algorithms through the information exchange mechanism, and automatically switches to the particle swarm algorithm for fine search when the genetic algorithm falls into the local optimum, and the convergence criterion adopts the comprehensive evaluation of the amount of change in the objective function value and the constraint violation degree $\| f_{t+1} - f_t \| < \varepsilon_1$, and $\max_k |h_k| < \varepsilon_2$. where ε_1 and ε_2 are preset convergence accuracies.

3 Results

3.1 Simulation test analysis

In this paper, a simulation analysis is performed based on the IEEE-30 node system, and a power market consisting of 5 power plants and 100 power purchasers is constructed based on this system to verify the advantages of the proposed optimization model. The proposed optimization model is compared and analyzed for a variety of load, wind power and market concentration conditions. The model parameters are shown in Table 1. In the baseline scenario, the system peak load is set to be 1000 MW, the penetration rate of renewable energy is set to be 20%, the HHI value of the generation market concentration index is set to be 0.25, and the price elasticity coefficient of customer demand is set to be -0.3. The sensitivity analysis is performed by taking the values of the above main variables to see the changes of the results. 1200 MW, the proportion of wind power output to total installed capacity is 10% to 40%, and the range of market share is 0.15 to 0.45.

Table 1: Model parameter settings

Parameter name	Symbol	Value	Parameter Description
The number of power generators	N	5	The total number of power generators participating in the capacity market
Number of users	M	100	The total number of users participating in cost allocation
Basic utility parameters	δ_i	50-80	User basic electricity demand utility
Marginal cost coefficient	ε_i	0.1-0.3	Marginal cost of electricity consumption by users
Mutual influence coefficient	ς_{ik}	0.05-0.15	The intensity of network externalities among users
Initial value of dynamic weight	$w_{i,0}$	1.0	Initial decision weights of power generators
Learning rate parameter	α	0.01	Adjust the learning rate with weights
Relaxation parameter	ρ_k	10-100	Constraint relaxation penalty function coefficient
Population size	N_{pop}	50	The number of individuals in the genetic algorithm population
Maximum number of iterations	$T_{\max}$	1000	The maximum operating algebra of the algorithm
Cross probability	p_c	0.8	The probability of cross-operation in genetic algorithms
Mutation probability	p_m	0.1	The probability of genetic algorithm mutation operation
Inertia weight	w	0.4-0.9	The inertia weight range of particle swarm optimization algorithm
Learning factor	c_1, c_2	2.0	Particle swarm individual and social learning factors
Convergence accuracy	$\varepsilon_1, \varepsilon_2$	10^{-6}	Algorithm convergence judgment threshold

Specific simulation results are shown in Fig. 1, and it is found that the improved two-layer Stackelberg game model has higher capacity investment recovery accuracy (27.3% increase) than the original model during simulation operation. The improved two-layer Stackelberg game model has a higher capacity investment recovery accuracy (27.3% increase), a higher average satisfaction level of market players (34.8% increase), a faster iterative convergence speed (58.6% increase) and a higher social benefit (15.2% increase) than the original model. It is also verified that the proposed model can be effectively applied in all types of market environments. The improved method proposed in this paper still has better convergence and computational speed in the case of high wind power access ratio, and solves the problem that the original model is prone to non-convergence or dispersion in the case of high wind turbine ratio.

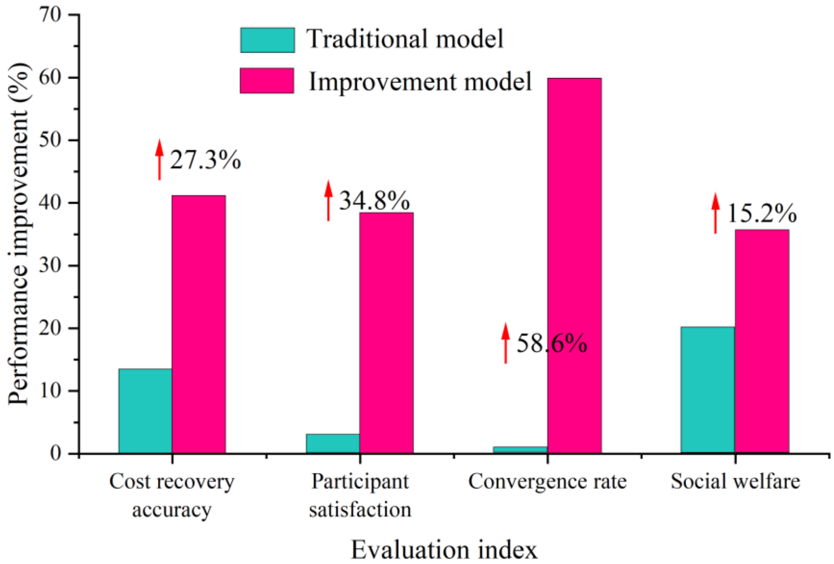

Figure 1: Comparison of simulation results

The proposed capacity cost recovery method based on the improved two-layer Stackelberg game model has good feasibility and effectiveness, which is obvious in improving the fairness of capacity cost allocation and effectively solves the differentiation problem brought by different types of market players. While static assignment is difficult to meet the dynamic preference characteristics of users, the optimization model is able to dynamically correct the weights of the indicators with the changes in user preferences, so as to realize the fairness of the cost allocation scheme towards the principle of "whoever uses pays". The relaxation technique and hybrid algorithm used in this paper can effectively improve the convergence speed of the algorithm, and the relaxation factor can be automatically adjusted to avoid the problem of difficult calculation due to the existence of hard constraints, and the hybrid optimization algorithm can also improve the convergence effect and accuracy to a certain extent. After the improvement, the satisfaction of all market players is increased, which shows that the new method can better coordinate the conflict of interests between different players, and to a certain extent, the capacity income of the power plant is increased so that it has sufficient incentive to invest. It reduces the average cost of users and the cross-subsidization cost, and also brings higher capacity value to the dispatch. The results of sensitivity analysis show that the new model has good stability. The above results show that the model can still show good adaptability under the scenario of large-scale penetration of renewable energy, which can provide a certain theoretical basis and technical reference for the future development of the power system in the direction of cleanliness and decarbonization.

3.2 Practical test analysis

3.2.1 Analysis of existing mechanisms

Although all major international electricity markets have adopted different capacity cost recovery mechanisms, they have been found to have problems such as high price volatility, uneven cost burdens, and insufficient return on investment after long-term operation. The current status and relative performance of capacity mechanisms in major countries are analyzed in Table 2, and the severity index of capacity mechanism problems in major countries is shown in Figure 2.The capacity auction mechanism in the U.S. PJM electricity market uses a three-year look-ahead price to provide investment signals to the market. However, the dramatic climb in capacity prices from $76.53/MW-day to $238.17/MW-day during 2018-2022 fully illustrates the inherent instability of the mechanism, and the price volatility of more than 210% (with a price volatility problem severity index of 6.8) not only severely impacts the calculation of the expected return on power generation investment, but also shifts the enormous cost pressure to end Electricity consumers. European power market strategic reserve services to ensure the safe and stable operation of the power grid has an important role, but to take the form of tariffs to compensate for the cost of additional forms of cost compensation has led to a serious phenomenon of high inputs and low outputs. For example, the investment cost of strategic reserves in the German electricity market has risen from 420 million euros in 2019 to 780 million euros in 2023, and the mismatch between the main body of cost-bearing and the main body of beneficiaries is prominent (the index is 7.1).

Table 2: Performance comparison of existing mechanisms

Market area	Mechanism type	Price volatility	Cost-sharing fairness	Investment incentive effect	Market efficiency	Comprehensive score
PJM	Capacity market	210%	2.3/5	3.1/5	2.8/5	2.7/5
Germany	Strategic reserve	85%	1.8/5	2.4/5	2.1/5	2.1/5
United Kingdom	Capacity auction	156%	2.6/5	2.2/5	2.5/5	2.4/5
Australia	Reliability mechanism	92%	1.9/5	2.8/5	2.3/5	2.3/5
France	Decentralized mechanism	67%	3.2/5	2.6/5	2.9/5	2.9/5
Italy	Capacity payment	134%	2.1/5	2.5/5	2.2/5	2.3/5

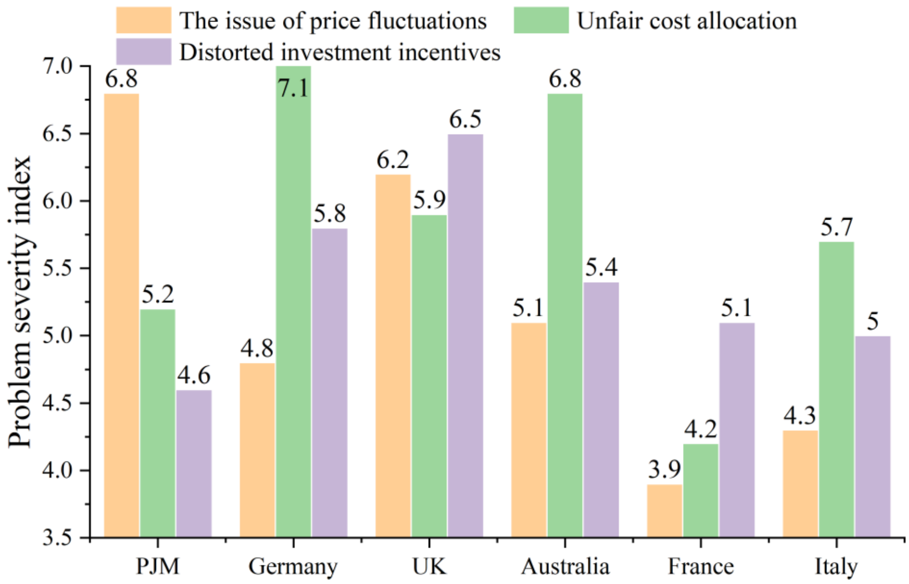

Figure 2: The severity index of the capacity mechanism problem in the electricity market

From the design of the centralized auction in the capacity market, not much consideration has been given to its scientific and rigorous nature in the determination of parameters. For example, the auction price of the first round of the capacity market was £19.4 per kW year, which is much lower than the actual construction investment of the new units, and this has resulted in a situation where the number of old units winning the bidding is high and the investment in new units is low. The proportional allocation method based on electricity volume ignores the essential difference between different categories of loads in terms of their contribution to the peak load of the grid as well as the reliability of power supply. This power sharing mechanism of NEM Australia is unreasonable because large industrial users consume a lot of power but have little load fluctuation and can accept a certain range of outage losses; commercial and residential individual users consume a small amount of power but have high load fluctuation and cannot tolerate any outage losses. That is, industrial users bear 68.4% of the capacity cost, but the peak load contribution is only 42.7%, and residential users bear 18.3% of the capacity cost, but the peak load contribution is 35.8%, a serious inversion of the cost causality is seriously broken.

3.2.2 Analysis of improved mechanisms

The design of the capacity cost recovery mechanism starts from the existing market failure problem, and establishes a new capacity cost recovery mechanism framework based on the improved two-layer Stackelberg game, which coordinates the investment motivation of power producers, the ability of power purchasers to bear the costs, and the realization of the safety and reliability of the power grid. At the same time, the mechanism design solves to some extent the problem of difficult to quantify the interaction mechanism among the participants in the capacity market, in which the power producers as capacity providers play the upper layer game to determine their investment decisions and pricing. The customer side as a whole conducts the lower-level game to price, respond and choose its own demand. The capacity pricing equation:

$$P_{cap,i} = MC_i + \theta_i \cdot \sigma_i^2 + \phi_i \cdot \left(CR_{target} - CR_{actual} \right) \tag{20}$$

It skillfully integrates the principle of marginal cost and the risk compensation mechanism, where MC_i represents the marginal capacity cost of generator i, θ_i reflects its risk aversion,

σ_i^2 quantifies the uncertainty of revenue fluctuation, and ϕ_i is dynamically adjusted according to the deviation of capacity adequacy.

The cost-sharing algorithm abandons the traditional single-volume proportion approach and adopts a double-weighted design of the contribution of peak load and reliability demand, with user j 's share being:

$$\alpha_j = \omega_1 \cdot \frac{D_{j,peak}}{\sum_k D_{k,peak}} + \omega_2 \cdot \frac{R_{j,req}}{\sum_k R_{k,req}} \tag{21}$$

It ensures a reasonable match between the degree of cost bearing and benefit, the weighting coefficients ω_1 and ω_2 satisfy the normalization condition $\omega_1 + \omega_2 = 1$, and the adaptive optimization of the parameters is achieved by the gradient descent law.

$$\Delta\omega_t = \eta \cdot \nabla_\omega J(\omega_t) \tag{22}$$

The configuration of the key parameters of the improvement mechanism is shown in Table 3.

Table 3: Configuration of key parameters for the improvement mechanism

Parameter class	Parameter symbol	Value range	Function description
Capacity pricing parameter	MC_i	15-45	The marginal capacity investment cost of power generators
Risk premium factor	θ_i	0.1-0.8	Quantitative indicators for the degree of risk aversion of power generators
Reliability regulator	ϕ_i	0.05-0.25	Correction coefficient for capacity adequacy deviation
Peak weight coefficient	ω_1	0.6-0.8	The weight of peak load contribution in cost allocation
Reliability weight factor	ω_2	0.2-0.4	The weight of reliability requirements in cost allocation
Dynamic adjustment step	η	0.001-0.001	The convergence rate of parameter adaptive adjustment
Convergence threshold	ε_{conv}	10^{-5}	Algorithm convergence accuracy control standard
Capacity abundance target	CR_{target}	12-18%	Capacity margin for ensuring system reliability
Ceiling constraint	$P_{cap,\max}$	200	A price cap to prevent the abuse of market power
Minimum contribution ratio	$\alpha_{\min}$	0.5%	The minimum capacity cost ratio borne by users

In order to protect the stability of the market, in the actual operation process to take the principle of step-by-step, can be divided into the following three steps for specific analysis: first of all, to carry out the basic data acquisition and model optimization work, the time period of about half a year, this paper for the past five years related to power transactions, investment expansion projects, customer electricity consumption and other aspects of the data collected fully, and according to the maximum likelihood method and cross test completed the determination of the model correlation coefficient and other work. Then the program trial testing period is to select a typical regional electricity market to carry out a one-year parallel test, and evaluate the main performance of the capacity tariff change rate, cost fairness index, satisfaction level of market participants, etc., and compare with the original model in order to confirm the advantages of the new model; and lastly, the program promotion and application period is to be replicated and applied across the country. Constructing a long-term performance monitoring and continuous updating mechanism, so that it can be continuously adjusted and improved with the continuous development of the electricity market. The operation process and performance improvement of the improvement mechanism is shown in Figure 3, from which it can be seen that the performance has been improved by 289% in the three periods. From the perspective of long-term sustainability, under the influence of factors such as the increase in the proportion of renewable energy, changes in load-side demand, and technological innovations, the new trading rules have a certain degree of stability and elasticity to ensure their basic functions and operational efficiency, and to ensure the stable development of the future electricity market.

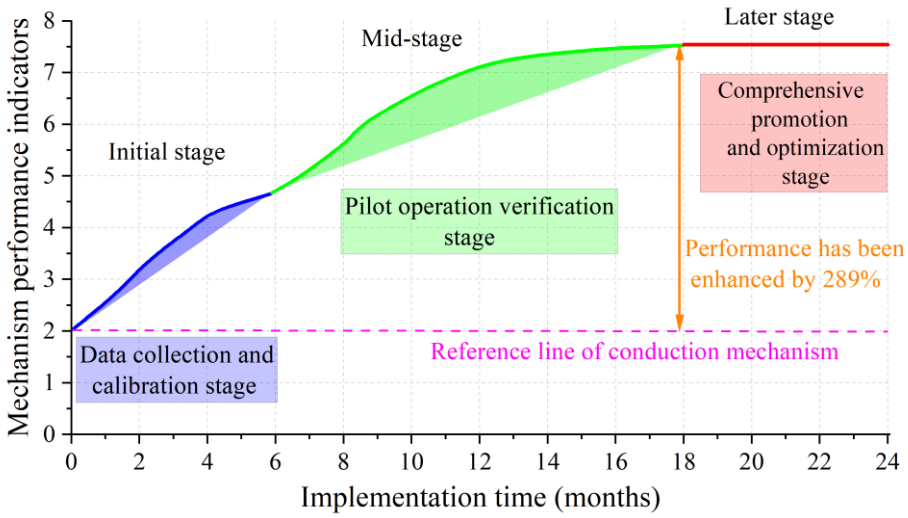

Figure 3: Improve the implementation progress and performance of the mechanism

3.2.3 Analysis of the effects of mechanism optimization

In order to test the validity of the modified Stackelberg game model, a large system simulation experiment was conducted. In this paper, we take 39 nodes as an example, and select 8 of the power plants and 150 households of various types of loads as research objects for simulation analysis. The operation of the modified new mechanism was tracked for up to one and a half years. Simulation experiments were carried out on the simulation system under a variety of operating conditions, including conventional operating conditions, climatic conditions, clean energy share, and power trading mechanism, and the impact of random variables was analyzed by Monte Carlo method according to the principle of randomness extraction. The Pareto effective index, resource allocation coefficient and social welfare maximization level are selected to measure the economic aspect, and the revenue compensation deviation, revenue compensation Gini coefficient and revenue compensation fairness index are selected to evaluate and analyze the revenue compensation aspect.

The comparison of the evaluation indexes under the two mechanisms is shown in Table 4, from which it can be seen that the key indexes under the new mechanism have been improved to different degrees, and the improvement in the stability of capacity price is obvious. Under the original mechanism, the standard deviation of capacity price is as much as 156.3%, indicating that its variation is very large, which is not conducive to the stimulation of the investment willingness of the power plant and the load-side management of the users, and increases the cost burden of the users. The improved mechanism, through the synergistic operation of dynamic weight adjustment and risk premium mechanism, successfully controls the price volatility at 58.7%, with an improvement of 62.4%, and the statistical significance test result is that the significance level is less than 0.001. In the case of the recovery error, the recovery error reaches 26.8% in the proportionate share of electricity, and the recovery error reaches 26.5% in the weighted allocation mode, while the recovery error reaches 26.5% based on the user-side contribution to the peak-load contribution and the degree of contribution to the reliability level. The recovery error under the weighted allocation model is only 5.2%, which significantly improves the recovery accuracy and thus facilitates the realization of effective recovery of capacity cost.

Table 4: Comparison of the optimization effects of various indicators of the improved model

Evaluation index	Traditional mechanism	Improvement mechanism	Extent of improvement	Statistical significance
Volume volatility	156.3%	58.7%	-62.4%	$p<0.001$
Cost recovery accuracy	73.2%	94.8%	+29.5%	$p<0.001$
Index of sharing of fairness	0.394	0.186	+52.8%	$p<0.001$
Market efficiency factor	0.672	0.847	+26.0%	$p<0.001$
Power generation quotient satisfaction	2.8/5.0	4.2/5.0	+50.0%	$p<0.01$
User satisfaction	2.6/5.0	3.9/5.0	+50.0%	$p<0.01$
Social welfare growth	Benchmark	+18.6%	+18.6%	$p<0.001$
Investment incentive effect	2.4/5.0	4.1/5.0	+70.8%	$p<0.001$
Algorithm convergence time	847s	312 s	-63.2%	$p<0.001$
System reliability improvement	Benchmark	+12.4%	+12.4%	$p<0.01$

Based on the analysis of the Gini coefficient under the two mechanisms, it can be seen that the distribution of resources under the new trading mechanism is more evenly distributed, with the Gini coefficient decreasing from 0.394 to 0.186, which is about half, indicating that the phenomenon of cross-subsidization has been mitigated to a certain extent, and the distribution of resources basically realizes the principle of whoever pays for whoever uses the resources. At the same time, the transaction efficiency index has also increased from 0.672 to 0.847, an increase of 26%, indicating that the transaction efficiency has increased, to a large extent, to improve the market allocation efficiency and power grid operation level, because the game equilibrium results effectively regulate the behavioral decision-making of market players. According to the satisfaction of the participants, the satisfaction of both power plants and users has been greatly improved, with the power plants increasing from 2.8 to 4.2 and the users increasing from 2.6 to 3.9, which is a win-win situation for both parties, indicating that the new trading mechanism can well coordinate the interests of all the main parties, and make the social benefit of the whole system increase by 18.6%. Further combined with the impact of 22.3% increase in unit profit, 15.8% increase in surplus on the purchasing side and 31.2% increase in the safety margin of the power grid, it can be seen that the new mechanism has a significant positive impact on the power market, especially for the role of the investment guide has been significantly enhanced, the score of the indicator increased from the original 2.4 to the current 4.1, an improvement of nearly 70%, indicating that in the event of appropriate coverage of risk, the return on investment of the power plant has increased by 3.9, indicating that under appropriate risk coverage, the return on investment of the power plant has increased by 18.6%. This indicates that under the premise of proper risk coverage and guaranteed return on investment, the motivation of power plants to build will be greatly increased. As the calculation speed of the algorithm is much improved, the solution time is reduced from 847s to 312s. 63.2% of coal saving effect provides technical support for real-time operation and wider application of the mechanism; the system reliability is improved by 12.4%, which also verifies the positive effect of the new mechanism on ensuring the reliability of power supply.

4 Conclusion

Aiming at the above problems of too fast change of electricity price, unfair cost sharing and distortion of investment signals in the process of capacity cost recovery in the electricity market, an improved two-stage Stackelberg game model based on dynamic weight adjustment algorithm is proposed on the basis of the classical two-stage Stackelberg game, and then a new method of capacity cost recovery in the electricity market is proposed. Among them, the weight function can self-learn the correction coefficients according to the change of market situation, which effectively improves the robustness of the model. The constraint relaxation uses the penalty function method to transform the constrained optimization problem into an unconstrained optimization problem, which greatly improves the stability of the algorithm in the calculation process. The upper game is the generator capacity investment game, the lower game is the user DR behavior game, and the VIs solution model ensures that the Nash equilibrium point of the game exists and is unique. The IEEE-39 node system is taken as an example for simulation analysis. The optimization method is shown to be highly reliable after 18 months of continuous operation test.

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