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Cooperative trading mechanism and supply guarantee efficiency optimization in inter-regional power mutual market

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SUMMARY: *Aiming at the shortcomings of traditional clearing methods in multi-agent strategy interaction, channel blockage and disturbance risk response, this paper proposes a method for collaborative trading and supply protection efficiency optimization in cross-regional power mutual assistance market. Based on 6 regional power grid nodes, 15 cross-regional contact channels and 8640 groups of trading time samples, the research uses multi-source data collection, graph structure state representation, multi-agent game and reinforcement learning strategy network to realize mutual transaction clearing, and correcates the guarantee strategy through risk scoring, hierarchical early warning and online calibration mechanism. The experimental results show that the average clearing time of the proposed method is 1.84 s, and the transaction rate reaches 96.8%. In the compound disturbance scenario, the guaranteed supply satisfaction rate remains 90.8%, which is 10.3 percentage points higher than that of rule clearing. The multi-agent bidding strategy gradually converged after 20 rounds, and the price volatility decreased to 4.8%. The research shows that the proposed method can improve the intelligent clearing ability, risk response ability and supply protection resilience of the cross-regional power mutual market, and provide technical support for the collaborative allocation of regional power resources under the new power system.*

KEYWORDS: *Inter-regional power mutualization; Collaborative trading mechanism; Multi-agent game; Guarantee supply efficiency optimization*

1 Introduction

Cross-regional power mutual cooperation is an important marketization means to improve the safety margin of the power system, alleviate the mismatch between regional supply and demand and promote the absorption of new energy [1]. With the large-scale access of fluctuating power sources such as wind power and photovoltaic, the power supply and demand state of each region shows stronger timing uncertainty and spatial difference [2]. Some areas face power supply pressure during peak load, extreme weather or lack of new energy output, while others may experience periods of surplus power. The traditional operation mode relying on administrative scheduling or single regional balance is difficult to timely reflect the dynamic coupling relationship between the capacity of cross-regional transmission channels, the quotation strategy of market players, the response ability of load side and the supply guarantee constraints. Therefore, the cross-regional mutual market needs to be supported by a more refined and intelligent collaborative trading mechanism [3]. Existing research on cross-regional power trading mainly focuses on the design of trading

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rules, transmission capacity allocation, price mechanism optimization and power dispatch model construction, which has provided a theoretical basis for market-oriented mutual cooperation [4]. However, in actual operation, there are some problems between regional power grids, such as heterogeneous supply and demand information, inconsistent objectives of transaction subjects, real-time changes in transmission constraints, and complex risk transmission paths. Simply relying on static optimization or empirical rules for transaction clearing will easily lead to the lag of mutual aid resource allocation, and it is difficult to give consideration to transaction efficiency, market fairness and supply guarantee stability [5, 6]. Especially in the scenario of high proportion of new energy access, power-side fluctuations, load-side disturbances and cross-zone channel blocking will simultaneously affect the trading results, which makes the collaborative trading mechanism face higher computational complexity and real-time decision-making requirements.

Computer intelligence technology provides a new realization path for cross-regional power mutual market optimization. Through multi-source data acquisition and simulation modeling, the data such as regional load forecasting, new energy output, unit available capacity, cross-regional transmission constraints, market quotes and risk events can be uniformly mapped into the transaction state space. Through the multi-agent game model, it can describe the strategic interaction between different regions, power generation enterprises, power sales agents and dispatchers. Through reinforcement learning algorithm, the transaction clearing and scheduling strategy can be learned in the continuously changing supply and demand environment, so that the model has dynamic adaptability [7-9]. The introduction of the above method into the cross-regional power mutual assistance market will help to improve the response speed and supply guarantee efficiency of the trading mechanism for complex scenarios [10].

Based on this, this paper focuses on the two core issues of "collaborative trading mechanism" and "supply guarantee efficiency optimization", constructs a multi-source data-driven simulation scenario of cross-regional power mutual market, establishes the feature representation of power supply and demand state and cross-regional transmission constraint model, and designs a collaborative trading mechanism based on multi-agent game. The reinforcement learning algorithm is further integrated to realize mutual trade clearing and scheduling optimization. On this basis, a risk early warning and dynamic calibration mechanism for supply and guarantee efficiency is constructed, and the clearing efficiency, supply and guarantee ability and transaction stability under different supply and demand disturbance scenarios are experimentally verified. The research of this paper can provide technical reference for the intelligent operation of cross-regional power mutual market, the cooperative allocation of regional power resources and the security of power system.

2 Related Research

The research of cross-regional power mutual market mainly focuses on resource abundance, market mechanism, cross-regional transaction profit, risk control and intelligent optimization method. Wolak analyzed the capacity guarantee pressure brought by the high proportion of intermittent renewable energy entering the wholesale electricity market from the perspective of long-term resource abundance, and pointed out that the electricity market needs to give consideration to long-term supply capacity and system reliability in addition to energy trading [11]. Kozlova et al. further discussed the connection between renewable energy support mechanism and power supply security, and believed that there was institutional coupling between capacity mechanism, subsidy policy and guarantee responsibility, which provided reference for the design of guarantee constraint in cross-regional mutual aid market [12]. Starting from the price mechanism, Varawala et al. incorporated the market power suppression and environmental externality control into the pricing framework of the electricity market, indicating that the collaborative trading mechanism should not only pursue the transaction size, but also reflect the fairness, low-carbon and constraint consistency [13]. Lopez Prol et al. studied the potential benefits of long-distance electricity trade and proved that cross-regional trade can alleviate the local imbalance between supply and demand and improve the efficiency of resource allocation, but its effect is significantly affected by transmission capacity, price difference and regional complementality [14].

In terms of market clearing and network constraint modeling, Bichler and Knorr emphasized that the advanced power flow model has an important impact on the price formation in the electricity spot market, indicating that ignoring transmission constraints and node power flow relationships in cross-regional transactions is easy to cause distortion of price signals [15]. Mobius et al. integrated risk aversion and flexible resources into the analysis of electricity market, and showed that flexibility options such as energy storage, demand response and reserve capacity can reduce the trading risk under extreme supply and demand fluctuations [16]. Fabra discussed the electricity market reform in light of the European energy crisis, and proposed that the market design needs to enhance the ability to resist shocks and price stability [17]. Lebeau et al. started from the design defects of the energy single market under the background of deep decarbonization, and pointed out that it is difficult to support long-term investment and system security only by relying on short-term energy prices [18]. Pollitt et al. put forward more resilient institutional proposals for future electricity market design, emphasizing the importance of cross-regional coordination, risk sharing and long-term incentive mechanisms [19].

In recent years, demand reduction, tail risk, futures price formation and market upgrading in interconnected electricity markets have also received attention. Fraunholz et al. studied the demand reduction allocation problem in the interconnected market, which provided a basis for the priority division of supply protection in the tight supply and demand scenario [20]. Billimoria et al. focused on hedging and tail risk in the electricity market, indicating that traders needed more elaborate risk measurement methods in the high-volatility environment [21]. Olmstead and Yatchew analyzed the price formation of electricity futures market through empirical method, reflecting that forward price signals have a regulating effect on market expectations and trading decisions [22]. Lo Prete et al. reviewed the design of the wholesale power market for the future, and proposed that the traditional market rules need to be upgraded under the background of increasing the proportion of new energy, increasing the participation of load side and deepening the market interconnection [23]. Di Persio et al. applied reinforcement learning to optimize the bidding strategy in the day-ahead energy market and proved that the intelligent algorithm could learn a better trading strategy in a dynamic price environment [24]. Sanchez Jimenez et al. discussed the capacity compensation mechanism in the decarbonized power system, which provided institutional support for the evaluation of supply guarantee capacity in the mutual assistance market [25]. Petitet et al. compared the hour-level market coupling and bilateral agreement mode in cross-border power transaction, and showed that the transaction organization mode would directly affect the efficiency of cross-regional mutual assistance [26]. The meta-study of De Blauwe et al. on the impact of cross-border spot prices further shows that inter-regional electricity price linkage has a significant transmission effect, and it is necessary to consider price, network and subject behaviors synchronously in the model [27]. In general, the existing research provides a solid foundation for the cross-regional power mutual market, but there is still room for further development in multi-source data-driven state modeling, multi-agent collaborative transaction inference, reinforcement learning clearing optimization, and dynamic calibration of guaranteed supply risk.

3 Cooperative trading and supply guarantee efficiency optimization method in cross-regional power mutual assistance market

3.1 Multi-source data collection and simulation scenario construction of cross-regional power mutual supply market

The data of cross-regional power mutual market has the characteristics of dispersed sources, inconsistent time scales and complex constraint relationships. In this paper, six regional power grid nodes are set up in the simulation environment with a sampling interval of 15 min to construct a multi-scenario dataset covering normal supply and demand, peak load, new energy fluctuations, transmission blockage and extreme disturbances. At the data acquisition end, the scheduling operation data, transaction quotation data, meteorological prediction data and risk event data are written into the same data cache queue by using a unified timestamp index. Then, the ETL process is used to complete the elimination of outliers, missing point interpolation, unit conversion and interval normalization. The processed data are organized as region-time-variable three-dimensional tensors, which provide input for subsequent supply and demand state identification, collaborative transaction modeling and supply guarantee efficiency evaluation. Table 1 shows the main data types and variable Settings in the cross-regional power mutual market simulation.

Table 1: Main data types and variable Settings of cross-regional power mutual market simulation

Data Type	Collected Content	Sampling Frequency or Scale	Preprocessing Method	Simulation Variable Setting
Regional Load Data	Industrial load, residential load, commercial load	15 min, 210,240 records	Abnormal peak removal, moving average imputation, normalization	Regional load demand, peak-valley difference, load ramping rate
Renewable Output Data	Wind power output, photovoltaic output, available generation capacity	15 min, 210,240 records	Meteorological matching, short-term fluctuation smoothing, capacity conversion	Renewable output proportion, fluctuation amplitude, forecast deviation
Inter-Regional Channel Data	Tie-line capacity, power flow direction, available transmission margin	15 interconnected channels formed by 6 regions	Over-limit point marking, capacity boundary verification	Maximum transmission capacity, congestion rate, channel utilization rate
Market Bidding Data	Buyer bids, seller bids, intended transaction volume	8,640 trading-period samples	Outlier bid identification, price interval mapping	Bidding curve, transaction willingness, price difference
Reserve and Supply Guarantee Data	Spinning reserve, emergency capacity, demand response resources	Reserve resource pools in 6 regions	Capacity unit conversion, callable-level coding	Reserve rate, response delay, interruptible load
Risk Event Data	Extreme weather, unit failures, line maintenance	5 disturbance scenarios, 1,200 event samples	Event labeling, disturbance intensity grading	Risk level, duration, impact range

In order to eliminate the influence of different data dimensions on model training, this paper performs interval normalization on the original observations:

$$z_{r,\tau,k} = \frac{x_{r,\tau,k} - \min(x_{\cdot,\cdot,k})}{\max(x_{\cdot,\cdot,k}) - \min(x_{\cdot,\cdot,k}) + \varepsilon_k} \tag{1}$$

where, $x_{r,\tau,k}$ represents the KTH original variable of region r under time period τ, $z_{r,\tau,k}$ represents the normalized eigenvalues, and ε_k is a tiny smoothing term to prevent the denominator from being zero. This process can make load, price, capacity and risk indicators enter a unified feature space, and reduce the dominance of large-scale variables on model training.

In the simulation scenario construction, this paper further sets the regional mutual aid pressure index, which is used to determine whether cross-regional mutual aid transactions need to be triggered in a certain period of time:

$$\mu_{r,\tau} = \eta_1 q^L_{r,\tau} + \eta_2 q^R_{r,\tau} + \eta_3 q^C_{r,\tau} - \eta_4 q^B_{r,\tau} \tag{2}$$

where, $\mu_{r,\tau}$ represents the mutual pressure index of region r at time period τ, $q^L_{r,\tau}$ is the peak load intensity, $q^R_{r,\tau}$ is the new energy output fluctuation intensity, $q^C_{r,\tau}$ is the cross-zone channel blocking degree, $q^B_{r,\tau}$ is the reserve capacity adequacy, η_1, η_2, η_3, η_4 are the corresponding weights. This metric can integrate "load pressure, output uncertainty, channel constraints, and backup support" into a unified scene label.

In order to avoid the simulation samples concentrated in the conventional operating state, this paper extracts the samples weighted according to the scene difficulty:

$$\omega_m = \frac{\exp(\gamma\bar{\mu}_m + \delta\phi_m)}{\sum_{u=1}^{M} \exp(\gamma\bar{\mu}_u + \delta\phi_u)} \tag{3}$$

where, ω_m represents the sampling weight of the MTH simulation scene, $\bar{\mu}_m$ represents the average mutual pressure of the scene, ϕ_m represents the joint fluctuation degree of new energy prediction error and load disturbance in the scene, γ and δ are the scene sensitivity coefficients, and m is the total number of scenes. Through this method, the key samples such as peak load, limited channel and sudden decline of new energy obtain higher occurrence probability in the training set, which can improve the learning ability of the subsequent collaborative trading algorithm for guaranteed supply risk scenarios.

3.2 Feature representation of power supply and demand states and modeling of cross-regional transmission constraints

In the cross-regional power mutual assistance market, the collaborative trading decision should not only be based on the load gap of a certain region, but also take into account the output fluctuation of new energy sources, the adjustable capacity of conventional units, the reserve support level, the trading quotation signal and the state of cross-regional transmission channels. In order to enhance the model's ability to express multi-region, multi-time period and multi-constraint information, the power supply and demand state is constructed as a computational structure of "regional node-time slice-state characteristics", and the graph structure encoding method is introduced to describe the interconnection relationship between regions. Each region is regarded as a power trading node, and the tie line is regarded as an edge with capacity boundary. The node state reflects the balance pressure of supply and demand, and the edge state reflects the transmissible capacity and the blockage risk. After this process, the cross-regional mutual assistance problem can be transformed into the transaction clearing and scheduling optimization problem in the constrained graph state.

Let the embedded vector of supply and demand state of regional node a at time period b be ha,b, whose input is composed of load demand, renewable energy output, available output of conventional units, reserve capacity, offer level and risk disturbance intensity. The state encoding process is expressed as follows:

$$h_{a,b} = \sigma\left(W_s\left[d_{a,b}, g_{a,b}^{ren}, u_{a,b}^{conv}, v_{a,b}^{res}, c_{a,b}^{bid}, e_{a,b}^{risk}\right]^T + b_s\right) \tag{4}$$

where, $d_{a,b}$ represent regional load demand, $g_{a,b}^{ren}$ represent available renewable energy output, $u_{a,b}^{conv}$ represent adjustable output of conventional units, $v_{a,b}^{res}$ represent reserve capacity, $c_{a,b}^{bid}$ represent market quote characteristics, $e_{a,b}^{risk}$ represent risk disturbance intensity. W_s and b_s are the state-encoding weight matrix and bias term, respectively, and $\sigma(\cdot)$ is the nonlinear activation function. The embedding vector can compress the power operation information and market transaction information into a unified computing space, which is convenient for subsequent game deduction and reinforcement learning strategy network call.

In the judgment of supply and demand state, this paper further defines the regional net supply margin, which is used to describe whether a region has outbound capacity or has incoming demand in the current period:

$$\Delta_{a,b} = g_{a,b}^{ren} + u_{a,b}^{conv} + v_{a,b}^{res} + \sum\nolimits_{p\in\mathcal{I}_a} f_{p,b}^{in} - d_{a,b} - \sum\nolimits_{q\in\mathcal{O}_a} f_{q,b}^{out} \tag{5}$$

where, $\Delta_{a,b}$ represents the net supply margin of regional node a in time period b. Ia is the set of channels flowing into region a, O_a is the set of channels flowing out of region a. $f_{p,b}^{in}$denotes the incoming power of the p-th inflow channel in time period b, and $f_{q,b}^{out}$ denotes the outgoing power of the q-th outflow channel in time period b. If $\Delta_{a,b}$ is positive, it means that the region has a certain outbound or spare release capacity; If the value is negative, it means that there is mutual access demand in the region. This index provides a direct basis for the identification of sender and receiver in transaction matching.

Cross-region transmission constraint is a key factor affecting the feasibility of mutual aid transactions. Considering that the actual transmission channel has upper capacity limit, safety margin and blocking state, this paper constructs the channel feasibility mask, which is used to shield the unexecutable transaction actions at the algorithm level:

$$m_{a,c,b} = \mathbb{I}\left(0 \le f_{a,c,b}^{req} \le \bar{F}_{a,c,b}^{ava} - s_{a,c,b}^{safe}, \lambda_{a,c,b} \le \lambda_{a,c}^{max}\right) \tag{6}$$

where, $m_{a,c,b}$ represent the transmission feasibility mask from region a to region c in time period b. When the value is 1, it means that the transaction path is available; when the value is 0, it means that the path is excluded by the constraint. $ff_{a,c,b}^{req}$ represent the proposed mutual trade power, $\bar{F}_{a,c,b}^{ava}$ represent the available transmission capacity of the channel, $s_{a,c,b}^{safe}$ represent the security reservation margin, $\lambda_{a,c,b}$ represent the channel blocking rate, $\lambda_{a,c}^{max}$ represent the maximum allowed blocking threshold. By embedding the mask into the subsequent transaction clearing algorithm, the model can synchronously consider the physical constraints of power when generating the transaction scheme, and avoid the problem that the transaction result can be calculated but the scheduling execution is not feasible.

The above state representation method encodes regional supply and demand states, market quotation information and cross-region transmission constraints into computable features, so that the collaborative trading mechanism no longer stops at the static rule matching level, but has the ability of dynamic identification and constraint perception for complex supply and demand disturbances. Based on the modeling results, the subsequent multi-agent game model can further characterize the strategic interaction between different regions and market players.

3.3 Design of cooperative trading mechanism based on multi-agent game

The transaction behavior in the cross-regional power mutual market has a significant multi-agent interaction feature. The sending region focuses on the delivery profit and reserve safety, the receiving region focuses on the power purchase cost and power supply reliability, the trading platform focuses on the transaction efficiency, and the dispatching agency focuses on the network feasibility and system stability. Aiming at the problem that the traditional centralized clearing is difficult to fully reflect the heterogeneous preferences of agents and real-time strategy response, this paper constructs a collaborative trading mechanism based on multi-agent game, which brings the sending agent, the receiving agent, the market coordination agent and the scheduling verification agent into the unified decision-making framework. Relying on the regional state embedding vector and channel constraint information, each agent uses an event-driven asynchronous negotiation method to complete the bidding, power matching, constraint verification and profit feedback. At the same time, the transaction intention of adjacent regions is extracted by using graph message passing technology to realize adaptive collaborative trading for complex scenarios.

Let the strategy vector of the NTH market player in round ℓ of negotiation be as follows:

$$\mathbf{a}_{n,\ell} = [\pi_{n,\ell}, \kappa_{n,\ell}, \upsilon_{n,\ell}, \iota_{n,\ell}]^{\mathrm{T}} \tag{7}$$

where, $\pi_{n,\ell}$ denotes the offer level, $\kappa_{n,\ell}$ denotes the declared transaction electricity quantity, $\upsilon_{n,\ell}$ denotes the reserve committed capacity, and $\iota_{n,\ell}$ denotes the risk tolerance parameter. The vector describes the economic goals and security preferences of market players at the same time, and can provide structured action input for subsequent game solutions.

For a sender principal p, its utility function is defined as follows:

$$\mathrm{U}_{\mathrm{p},\ell}^{\mathrm{out}} = \pi_{\mathrm{p},\ell}\kappa_{\mathrm{p},\ell} - \mathrm{c}_{\mathrm{p}}^{\mathrm{gen}}\kappa_{\mathrm{p},\ell} - \alpha_{\mathrm{p}} \max\left(0, \bar{\mathrm{v}}_{\mathrm{p}} - \mathrm{v}_{\mathrm{p},\ell}\right) - \beta_{\mathrm{p}}\varsigma_{\mathrm{p},\ell} \tag{8}$$

where, $\mathrm{c}_{\mathrm{p}}^{\mathrm{gen}}$ is the unit generation marginal cost, $\bar{\mathrm{v}}_{\mathrm{p}}$ is the minimum reserve requirement, $\varsigma_{\mathrm{p},\ell}$ is the additional cost caused by channel occupancy and strategy adjustment, α_{p} and β_{p} are the insufficient reserve penalty coefficient and the transaction friction penalty coefficient, respectively. The utility function makes the sender retain the necessary adjustment ability while pursuing profit, and avoids excessive outbound crowding out local guaranteed resources.

For a recipient subject q, its utility function is expressed as follows:

$$U_{q,\ell}^{\mathrm{in}} = \phi_q\left(\kappa_{q,\ell}, \hat{\kappa}_{q,\ell}\right) - \pi_{q,\ell}\kappa_{q,\ell} - \gamma_q\psi_{q,\ell} \tag{9}$$

where, $\kappa_{q,\ell}$ represents the target incoming power of the receiver region in this round of negotiation, ϕ_q is the unit guaranteed supply profit coefficient, $\psi_{q,\ell}$ represents the load loss risk caused by the residual supply gap, and γ_q is the risk penalty coefficient. Through this design, the strategy of the receiver does not only depend on the price level, but also considers the risk of power shortage and the income of guaranteed supply.

In order to make decentralized decision-making converge to a stable result that takes into account both efficiency and security, this paper introduces a market-level collaborative potential function to uniformly evaluate the global trading state:

$$\mathcal{J}_\ell = \sum_{p\in\mathcal{S}} U_{p,\ell}^{\mathrm{out}} + \sum_{q\in\mathcal{D}} U_{q,\ell}^{\mathrm{in}} - \mathfrak{c}\mathcal{E}_\ell - \mathfrak{d}\mathcal{V}_\ell \tag{10}$$

where, S is the set of sender agents, D is the set of receiver agents, $\mathcal{E}_\ell$ represents the system power loss measure after this round of negotiation, $\mathcal{V}_\ell$ represents the price dispersion volatility, c and d are the corresponding penalty weights. Aiming at maximizing $\mathcal{J}_\ell$, the market coordination agent matches and sorts the declaration strategies of each subject, and submits the candidate results to the scheduling verification agent for feasibility screening. If the trigger channel of a group of trading schemes is over limited or the reserve is insufficient, the local strategies of the participants are modified by the constraint back transmission mechanism, so as to form a closed loop of "game negotiation - constraint test - profit feedback - strategy update".

The overall operation relationship of the multi-agent collaborative trading mechanism is shown in Figure 1. Based on the input of regional load, renewable energy output, transmission state, market quotation and risk events, the mechanism forms the strategy interaction among the sending end area, the receiving end area, the power generation subject and the power selling subject in the multi-agent negotiation layer, and completes the bidding matching, price coordination, transaction negotiation and clearing decision through the market coordination module. The dispatching feedback module further carries out feasibility check, safety assessment and supply guarantee warning on the transaction results, so that the market transaction results can be consistent with the cross-regional power system operation constraints.

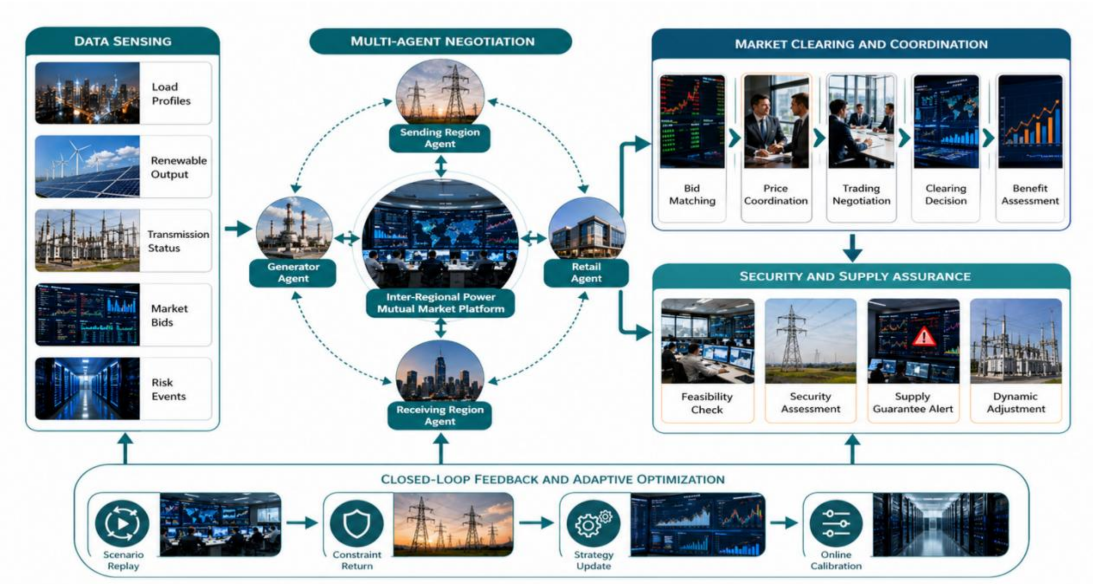

Figure 1: Framework diagram of multi-agent cooperative trading mechanism in cross-regional power mutual assistance market

It can be seen from Figure 1 that the collaborative trading of cross-regional power mutual market is a dynamic deduction system composed of data perception, subject negotiation, market coordination, dispatching feedback and closed-loop calibration. The framework can incorporate the behavior of market players, cross-regional transmission constraints and supply security requirements into the same decision-making chain, and provide structured support for subsequent reinforcement learning clearing optimization and risk dynamic calibration.

3.4 Mutual trade clearing and Scheduling optimization algorithm with reinforcement learning

In the cross-regional power mutual market, the transaction clearing results need to simultaneously meet multiple objectives such as market transaction efficiency, electricity purchase and sale cost, cross-regional channel security and supply protection priority. Traditional optimization algorithms usually rely on fixed objective functions and static constraints, which are prone to the problem of clearance scheme adjustment lag or local optimization when sudden drops in new energy output, load spikes and tie line blockage occur at the same time. In this paper, the mutual transaction clearing process is modeled as a sequential decision task with security constraints, and the transaction clearing and scheduling optimization algorithm combined with reinforcement learning is constructed. The algorithm takes multi-region supply and demand status, quotation curve, channel availability margin, reserve resources and risk level as input, extracts cross-region coupling features by graph encoder, and then generates mutual electricity, trading path, reserve call and scheduling correction actions by policy network, realizing the closed-loop optimization of "clearing-verify-feedback-updating".

Figure 2 shows the network structure of mutual aid trading clearing strategy integrated with reinforcement learning. The network took the market state input as the starting point, and sent the regional load demand, new energy output, transmission status, market quotation, reserve resources and risk early warning information into the feature coding layer. The unified state representation was formed through timing aggregation, graph structure coupling, multi-source fusion and state embedding. The policy network is further divided into the policy branch and the value branch, which complete the distribution generation of transaction actions and the state value evaluation respectively. The policy output is transformed into executable clearing and scheduling actions through the security filtering module.

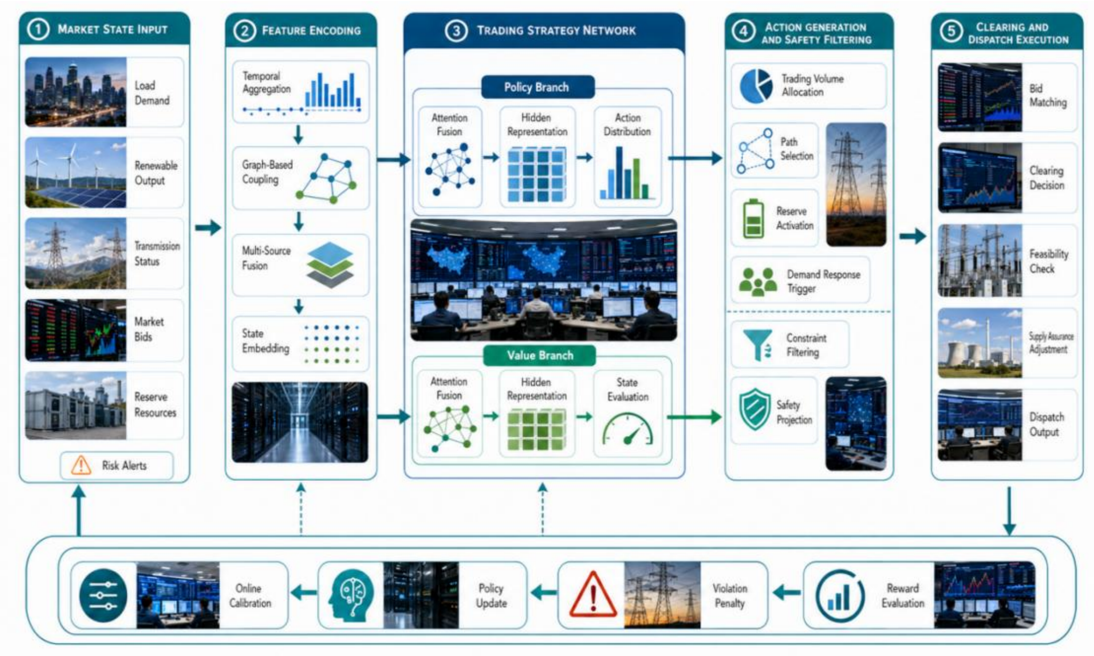

Figure 2: Network structure diagram of mutual aid clearing strategy driven by reinforcement learning

In each round of decision step ρ, the system first concatenates the multi-regional operating state and the market state into a global observation representation:

$$\Xi_\rho = \mathrm{Concat}\left(\mathbf{H}_\rho^{node}, \mathbf{G}_\rho^{link}, \mathbf{P}_\rho^{quote}, \mathbf{B}_\rho^{reserve}, \mathbf{A}_\rho^{risk}\right) \tag{11}$$

where, Ξ_ρ denotes the global observation vector of transaction clearing in round ρ. $\mathrm{H}_\rho^{\mathrm{node}}$ represents the regional node supply and demand state coding, $\mathrm{G}_\rho^{\mathrm{link}}$ represents the cross-zone channel state coding, $\mathrm{P}_\rho^{\mathrm{quote}}$ represents the market quote feature, $\mathrm{B}_\rho^{\mathrm{reserve}}$ represents the standby resource callable state, and $\mathrm{A}_\rho^{\mathrm{risk}}$ represents the risk level feature. The representation inputs physical grid constraints and market transaction information into the reinforcement learning environment in a unified way, which ensures that the policy network can sense economic signals and safety boundaries at the same time.

In order to avoid the model generating unexecutable trading paths, this paper introduces a constraint mask mechanism in the action output stage. The policy network generates a distribution of candidate actions based on global observations, and filters the action space using channel feasibility, alternate constraints, and guaranteed priority:

$$\Theta_\rho = Softmax\left(\Gamma_\rho \odot F_\vartheta(\Xi_\rho)\right) \tag{12}$$

where, $\Theta_\rho$represents the transaction and scheduling action vectors output by the reinforcement learning strategy, including the mutual transaction proportion, cross-zone transmission path, reserve call intensity and demand response trigger level. Γ_ρ represents the feasible action mask, whose value is jointly determined by the transmission capacity, the channel security margin and the regional guarantee threshold. $F_\vartheta(\cdot)$ denotes the policy network with parameter ϑ; $\odot$ indicates element-by-element filtering. This mechanism can directly exclude the over-limited path in the generation stage of the algorithm, and reduce the correction cost of subsequent scheduling verification.

The design of reward function is the key to whether the reinforcement learning clearing algorithm can take into account both market efficiency and supply security. In this paper, multi-objective rewards are constructed, and transaction efficiency, power supply security, transaction cost, network overrestriction and price fluctuation are included in the unified evaluation:

$$\mathfrak{M}_\rho = \omega_\rho^{clr} tanh(\mathrm{CE}_\rho) + \omega_\rho^{sup} tanh(\mathrm{SG}_\rho) - \omega_\rho^{eco} \ln(1 + \mathrm{TC}_\rho) - \omega_\rho^{net} \mathrm{NV}_\rho - \omega_\rho^{pri} \mathrm{PV}_\rho \tag{13}$$

where, $\mathfrak{M}_\rho$ represents the risk-adaptive comprehensive reward obtained by the clearing action in round ρ. CE_ρ represents the efficiency of collaborative transaction, SG_ρ represents the level of guarantee and supply satisfaction, TC_ρ represents the comprehensive cost of cross-regional mutual transaction, $\mathrm{NV}\rho$ represents the degree of violation of network security constraints, and PV_ρ represents the intensity of market price fluctuation. $\omega_\rho^{\mathrm{clr}}, \omega_\rho^{\mathrm{sup}}, \omega_\rho^{\mathrm{eco}}, \omega_\rho^{\mathrm{net}}, \omega_\rho^{\mathrm{pri}}$ are the reward weights that change dynamically with the risk state of supply and demand, respectively. The design uses the $\tanh(\cdot)$ function to limit the excessive amplification of the benefits of efficiency class and supply protection class, and reduces the impact of extreme cost values on the training process through $\ln(1 + \mathrm{TC}_\rho)$, so that the reinforcement learning strategy can give priority to the security of power supply in high-risk scenarios, while taking into account the transaction economy and price stability.

The strategy update adopts the proximal strategy optimization idea to limit the update range of the old and new strategies, so as to avoid violent oscillations of the clearing strategy under high disturbance samples. The policy update goal is expressed as follows:

$$\mathcal{L}_{\text{clip}}(\boldsymbol{\vartheta}) = \mathbb{E}_{\rho}\left[\min\left(\zeta_{\rho}(\boldsymbol{\vartheta})\widehat{\mathfrak{A}}_{\rho}, \text{clip}\left(\zeta_{\rho}(\boldsymbol{\vartheta}), 1-\varpi, 1+\varpi\right)\widehat{\mathfrak{A}}_{\rho}\right)\right] \tag{14}$$

where, $L_{clip}(\vartheta)$ represents the clipping optimization objective of the policy network, $\zeta_{\rho}(\vartheta)$ represents the probability ratio of the old and new policies, A_{ρ} represents the advantage estimate, and ϖ represents the clipping boundary of the policy update. This objective can improve the stability of strategy training, and make the model maintain better convergence performance under different load disturbances and new energy fluctuations.

Considering that the reinforcement learning output may still be affected by approximate calculation errors, we add a safe projection correction layer before the action execution to map the candidate trading actions back to the feasible scheduling space:

$$\boldsymbol{\Theta}_{\rho}^{adj} = \boldsymbol{\Theta}_{\rho} - \mathbf{K}_{grid}^{\dagger}\left[\left(0, \mathbf{K}_{grid}\boldsymbol{\Theta}_{\rho} - \boldsymbol{\Omega}_{grid}\right)\right] \tag{15}$$

where, Θ_{ρ}^{adj} represents the modified secure trading action, K_{grid} represents the grid constraint matrix consisting of transmission channel capacity, reserve boundary and power balance condition, $\mathbf{K}_{grid}^{\dagger}$ represents the pseudo-inverse of the constraint matrix, and Ω_{grid} represents the scheduling security boundary. The security projection layer can quickly backoff the mutual power and path selection that exceeds the boundary, and ensure that the output of the algorithm has the feasibility of scheduling execution.

Through the above design, the mutual transaction clearing algorithm integrated with reinforcement learning can establish an adaptive mapping relationship between the strategy changes of multi-regional market players and the changes of power grid operation constraints. Compared with static rule clearing, this method is more suitable for dealing with random disturbance scenarios with a high proportion of new energy access, and can provide a sustainable update strategy basis for risk early warning and dynamic calibration of later renewal.

3.5 Risk early warning and dynamic calibration mechanism for guaranteed supply efficiency

Under the conditions of high proportion of new energy access, rapid load fluctuation and dynamic change of tie line constraints, the cross-regional power mutual market is prone to risks such as imbalance between supply and demand, channel congestion and insufficient reserve. If we only rely on the fixed threshold alarm or offline parameter tuning, it is often difficult to identify the risk diffusion path in time, and it is also difficult to modify the trading and scheduling strategy according to the real-time operation deviation. To this end, this paper constructs a risk early warning and dynamic calibration mechanism oriented to guarantee supply efficiency, which integrates streaming monitoring, anomaly detection, risk classification and online calibration into a unified closed loop. In the data layer, the system continuously collects the regional load gap, tie line over-limit rate, reserve attenuation level, new energy prediction error and market price deviation. In the calculation layer, the risk scoring model is used to generate the early warning level.

Figure 3 shows the closed-loop mechanism of risk warning and dynamic calibration of guaranteed supply efficiency. The mechanism operates according to the process of "real-time perception, risk assessment, level warning, strategy calibration, and execution feedback", and connects the market transaction results with the grid security constraints as a sustainable update feedback loop.

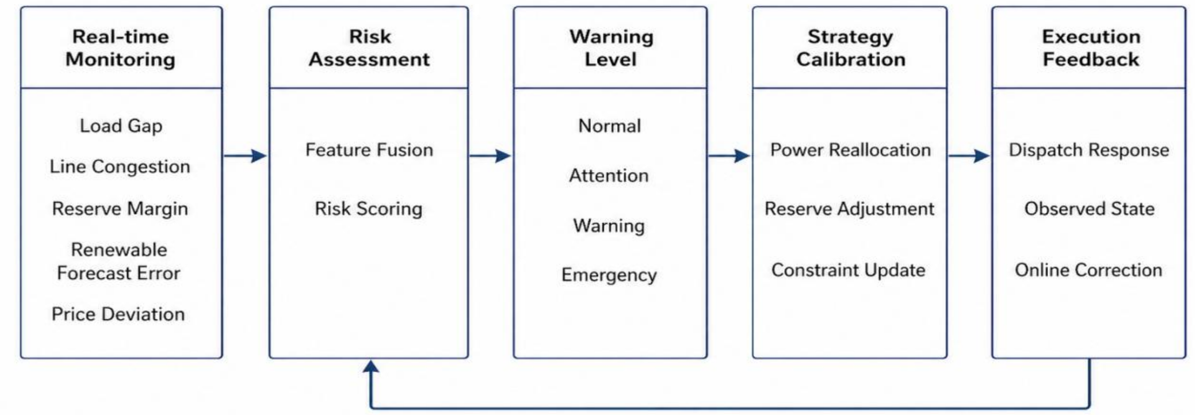

Figure 3: Closed-loop mechanism diagram of risk warning and dynamic calibration of guaranteed supply efficiency

In the stage of risk identification, this paper constructs a comprehensive early warning score function to uniformly quantify multiple types of disturbances:

$$\chi_\tau = \sigma\left(\xi_1\delta_\tau^{gap} + \xi_2\delta_\tau^{line} + \xi_3\delta_\tau^{res} + \xi_4\delta_\tau^{err} + \xi_5\delta_\tau^{pri}\right) \tag{16}$$

where, χ_τ represents the comprehensive risk score of time period τ, δ_τ^{gap} represents the intensity of supply and demand gap, δ_τ^{line} represents the degree of channel over-limit, δ_τ^{res} represents the level of reserve shortage, δ_τ^{err} represents the deviation of new energy forecast, δ_τ^{pri} represents the intensity of abnormal market price fluctuation, ξ_1 to ξ_5 are the corresponding weights. $\sigma(\cdot)$ is the Sigmoid mapping function. This formula can compress the heterogeneous risk signals into a unified scoring interval, which is convenient for online discrimination.

In order to improve the interpretability of early warning results, this paper maps the comprehensive risk score into a graded early warning state:

$$g_\tau = \begin{cases} 0, \chi_\tau < \Theta_1 \\ 1, \Theta_1 \le \chi_\tau < \Theta_2 \\ 2, \Theta_2 \le \chi_\tau < \Theta_3 \\ 3, \chi_\tau \ge \Theta_3 \end{cases} \tag{17}$$

where, g_τ represents the warning level, 0, 1, 2 and 3 correspond to normal, concern, warning and emergency states respectively, Θ_1, Θ_2 and Θ_3 are the classification thresholds. This grading result is not only used for interface alarm, but also directly drives the trigger strength of the subsequent calibration strategy.

Considering the continuous deviation between the simulation model and the real operation, this paper introduces an online calibration matrix to correct the parameters of the guarantee policy on a rolling basis:

$$\mathbf{K}_{\tau+1}^{cal} = (1-\nu_\tau)\mathbf{K}_\tau^{cal} + \nu_\tau\mathbf{R}\left(\mathbf{y}_\tau^{obs} - \mathbf{y}_\tau^{sim}\right) \tag{18}$$

where, K_τ^{cal} represents the calibration matrix of time period τ, ν_τ is the adaptive update step, y_τ^{obs} represents the actual running observation vector, y_τ^{sim} represents the simulation prediction vector, and R is the error mapping matrix. Through this update method, the system can continuously modify the parameters according to the real-time deviation, so that the risk warning and the guarantee scheduling are consistent.

In the policy execution phase, the risk level and the calibration matrix are embedded into the clearing result correction process to generate the guaranteed action satisfying the security constraints:

$$d_\tau^{sup} = \Pi_{S_\tau}\left(d_\tau^{clr} + g_\tau K_\tau^{cal}\right) \quad (19)$$

where, d_τ^{sup} denotes the calibrated guaranteed execution action, d_τ^{clr} denotes the original transaction scheduling scheme output by the reinforcement learning clearing algorithm, and $\Pi_{S_\tau}(\cdot)$ denotes the operation projected to the safe feasible region S_τ. The higher the risk level is, the larger the correction range of the original clearing scheme is, so as to give priority to protecting the power supply security of the critical receiver area and the high-risk period.

It can be seen from the above mechanism that the risk warning and dynamic calibration method constructed in this paper is not a simple post-warning, but integrates risk perception, level judgment, parameter update and strategy correction into a computational framework that can be closed loop iteration. The mechanism can continuously correct the model deviation, restrain the accumulation and diffusion of risks, improve the adaptability of trading results to the guarantee and supply target, and also provide methodological support for the analysis of the guarantee and supply efficiency in the subsequent experiments.

4 Results

4.1 Experimental environment and parameter setting

In order to verify the effectiveness of the collaborative trading mechanism and the supply guarantee efficiency optimization method in the cross-regional power mutual aid market, this paper constructs a simulation environment including six regional grid nodes, 15 cross-regional contact channels and multiple types of market players. The experimental data were organized according to the time interval of 15 min, covering regional load, new energy output, adjustable capacity of conventional units, availability margin of cross-zone channels, market quotation, reserve resources and risk events. After cleaning, 210240 operating state records, 8640 groups of trading period samples and 1200 disturbance event samples were formed. The disturbance scenarios include normal supply and demand, peak load, sudden drop of new energy, channel blockage and extreme composite disturbance, which are used to test the clearing ability and supply protection effect of the algorithm under different operating pressures.

The experimental platform is configured as Windows Server 2019 operating system, the processor is Intel Xeon Silver 4214R, the memory is 64 GB, the GPU is NVIDIA RTX 3090, and the algorithm implementation environment is Python 3.10 and PyTorch 2.1. The reinforcement learning clearing model adopts the parallel structure of policy network and value network, and the input dimension is composed of regional state features, channel state features, offer features, reserve features and risk level features. The training rounds are set to 3000 rounds, the batch size is 256, the learning rate is 0.0003, the discount factor is 0.96, the policy pruning threshold is 0.2, and the experience cache capacity is 50000. In order to ensure the fairness of the comparison experiment, the same data partition, disturbance scenario and evaluation index are used for rule clearing, centralized optimization, genetic algorithm, DQN, PPO and the proposed method. The evaluation indicators include the average clearing time, transaction turnover rate, guarantee and supply satisfaction rate, channel over-limit rate, average transaction cost and price volatility. The performance of the model is measured from three dimensions: computational efficiency, market effect and power supply security.

4.2 Analysis on clearing efficiency of cross-regional collaborative transactions

In order to evaluate the clearing efficiency of the proposed method in the cross-regional power mutual market, this paper selects rule clearing, centralized optimization, genetic algorithm, DQN, PPO and the method in this paper for comparison test, and analyzes the performance of the algorithm from two dimensions of average clearing time and transaction turnover rate. Experimental results show that there are obvious differences between different algorithms in transaction efficiency and computational overhead. Although rule clearing is simple to implement, it is difficult to adapt to the dynamic changes of supply and demand in multiple regions. Centralized optimization and genetic algorithm have certain optimization ability, but the calculation time increases rapidly after the expansion of the transaction scale. DQN and PPO can use interaction data to improve the clearing strategy, and the proposed method shows better real-time clearing ability under the synergy of state encoding, action screening and security constraint projection. The bi-axis comparison results of clearing time and turnover rate under different algorithms are shown in Figure 4.

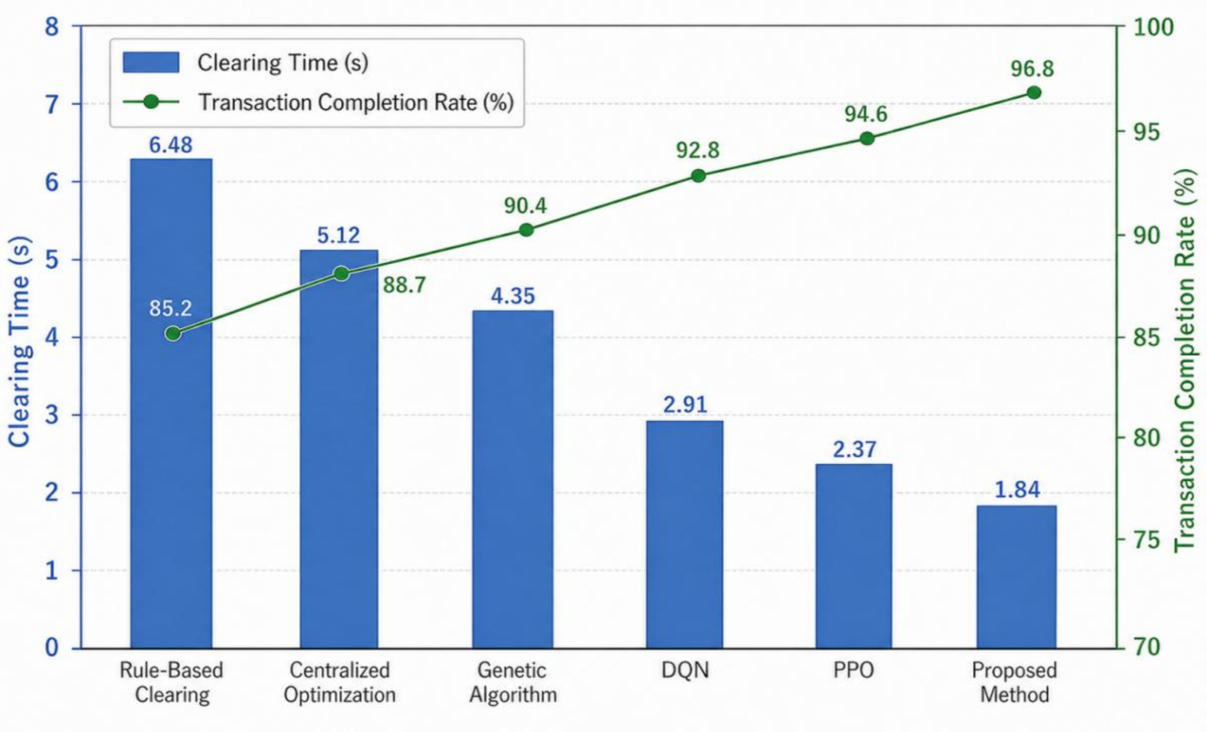

Figure 4: Dual-axis comparison of clearing time and turnover rate under different algorithms

It can be seen from Figure 4 that the average clearing time of the proposed method is 1.84 s, which is significantly lower than 6.48 s of rule clearing, 5.12 s of centralized optimization, 4.35 s of genetic algorithm, 2.91 s of DQN and 2.37 s of PPO. At the same time, the transaction rate of the proposed method reaches 96.8%, which is higher than that of PPO (94.6%) and DQN (92.8%). This shows that the reinforcement learning clearing mechanism constructed in this paper not only reduces the transaction decision time, but also improves the efficiency of cross-regional supply and demand matching, and can still maintain a high transaction level under complex constraints.

In order to further test the adaptability of the algorithm under the condition of transaction scale expansion, this paper sets up transaction scenarios with different scales, gradually increases the number of participants and the number of matching orders, and statistics the changing trend of the clearing time of each algorithm. As the transaction scale expands from small scenarios to large-scale scenarios, the computation time of traditional algorithms shows an increasing trend, but the growth slopes are different. Figure 5 shows the growth trend of the algorithm clearing time under different transaction sizes.

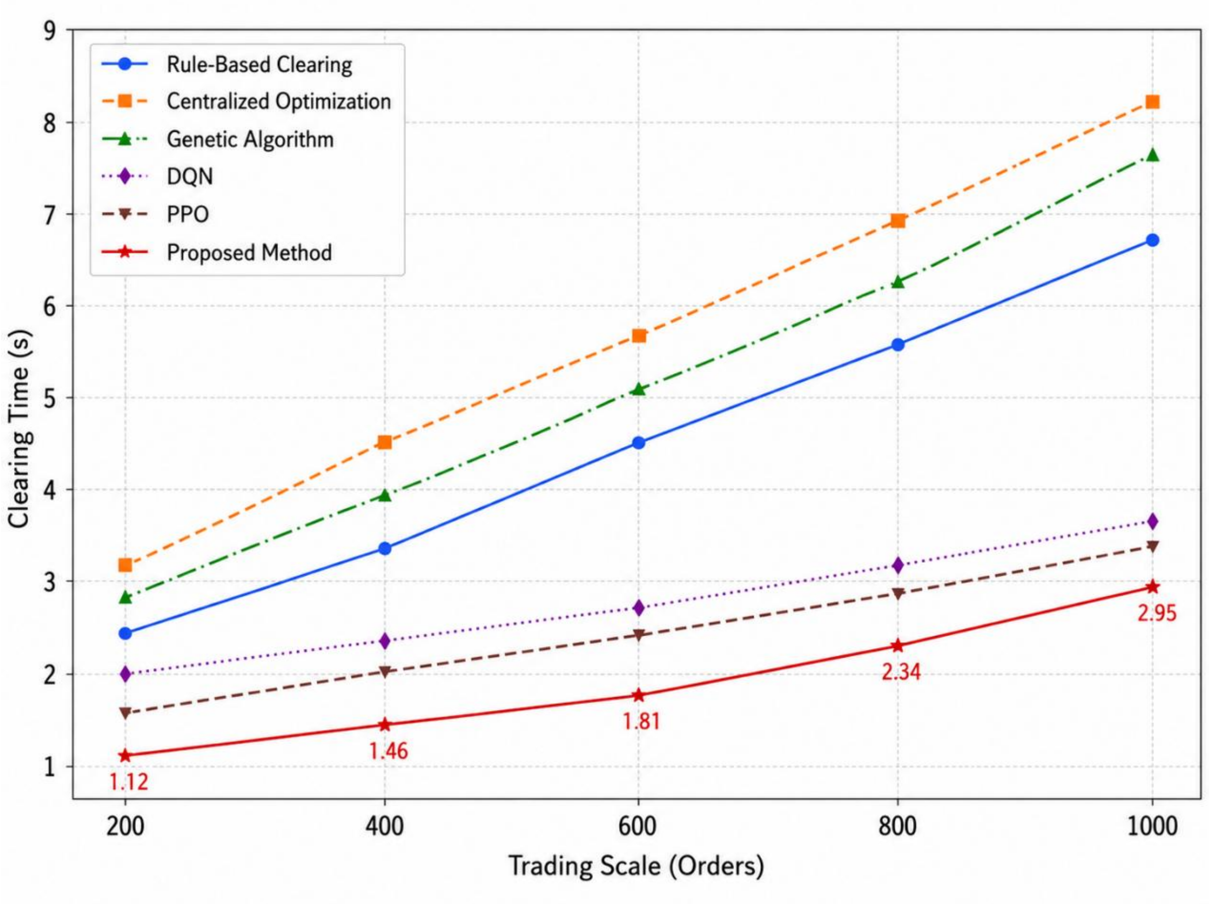

Figure 5: The growth trend of the algorithm clearing time under different transaction sizes

As can be seen from Figure 5, when the transaction size increases from 200 to 1000, the clearing time of the proposed method increases from 1.12 s to 2.95 s, which is significantly smaller than that of the genetic algorithm (2.84 s→7.63 s) and the centralized optimization (3.16 s→8.24 s). Although PPO has good efficiency in medium scale scenarios, it still shows obvious time growth in high scale conditions. In general, the proposed method has better computational stability and scale expansion ability while ensuring high transaction rate, which can provide effective support for real-time clearing of cross-regional power mutual market.

4.3 Optimization analysis of supply guarantee efficiency under different supply-demand disturbance scenarios

In order to test the adaptability of the proposed method under complex operating conditions, this paper sets up five scenarios: normal supply and demand, peak load, sudden drop of new energy, channel blockage and composite disturbance, and selects the guaranteed supply satisfaction rate and power shortage risk index as the core evaluation indicators. Among them, the guaranteed supply satisfaction rate is used to measure the guarantee degree of load demand in critical areas, and the power shortage risk index is used to describe the comprehensive risk level of power gap in the recipient area under disturbance impact. Figure 6 shows the comparison of guaranteed supply satisfaction rate and power shortage risk under different disturbance scenarios.

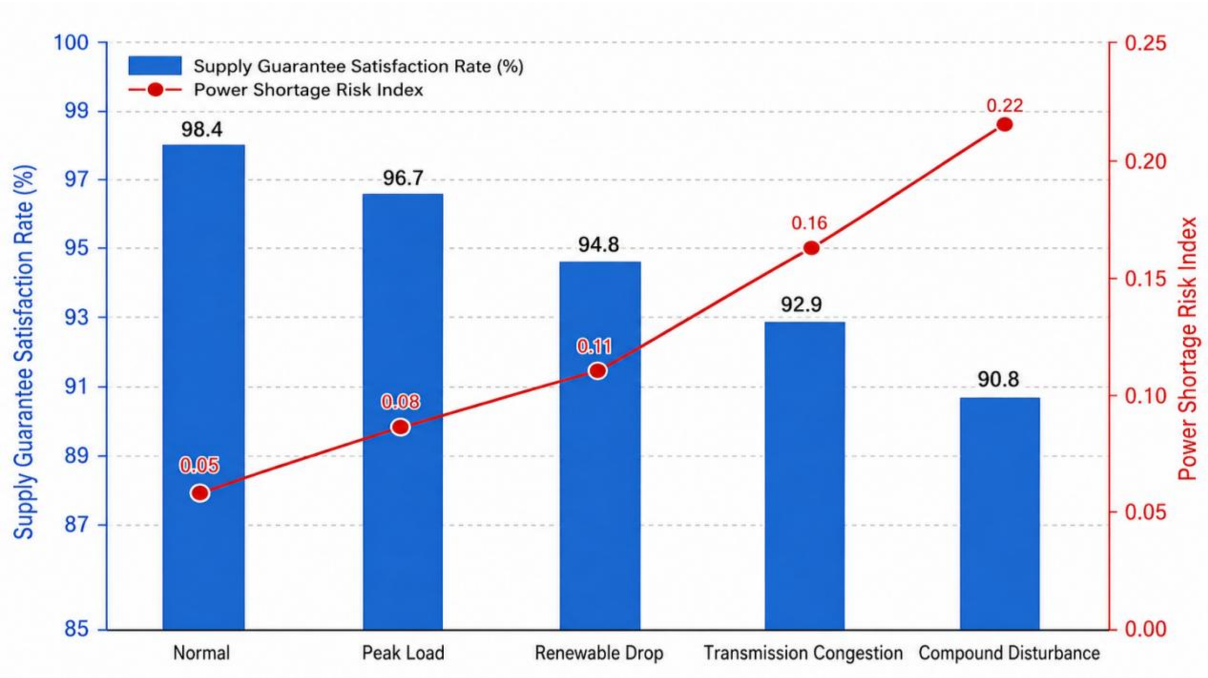

Figure 6: Comparison of guaranteed supply satisfaction rate and power shortage risk under different disturbance scenarios

As can be seen from Figure 6, in the normal scenario, the guaranteed supply satisfaction rate of the proposed method reaches 98.4%, and the power shortage risk index is only 0.05. When the scenario switched to peak load and new energy sudden drop, the guaranteed supply satisfaction rate remained at 96.7% and 94.8%, respectively, which were still significantly higher than 93.9% and 91.6% of the PPO method. In the channel blocking and compound disturbance scenarios, the system is affected by the compression of transmission capacity and the superposition of supply and demand fluctuations, and the overall difficulty of the guaranteed supply is significantly increased. However, the proposed method still maintains the guaranteed supply satisfaction rate at 92.9% and 90.8%, which are 8.6 and 10.3 percentage points higher than that of rule clearing respectively. The power shortage risk index is controlled at 0.16 and 0.22 respectively. This shows that the proposed method can not only improve the efficiency of cross-regional resource allocation, but also effectively suppress the spread of power shortage risk in high pressure scenarios.

In order to further analyze the identification ability of the risk early warning mechanism for complex disturbances, this paper constructed a two-dimensional coupling scenario of new energy prediction error and channel blocking probability, and used a three-dimensional bar chart to show the change law of risk score under different combination conditions. This figure can more intuitively reflect the evolution process of system risk from low to high when the uncertainty of the power side and the limitation of the network side rise synchronously. Figure 7 shows the 3D columnar distribution of risk score under coupling of new energy prediction error and channel blocking rate.

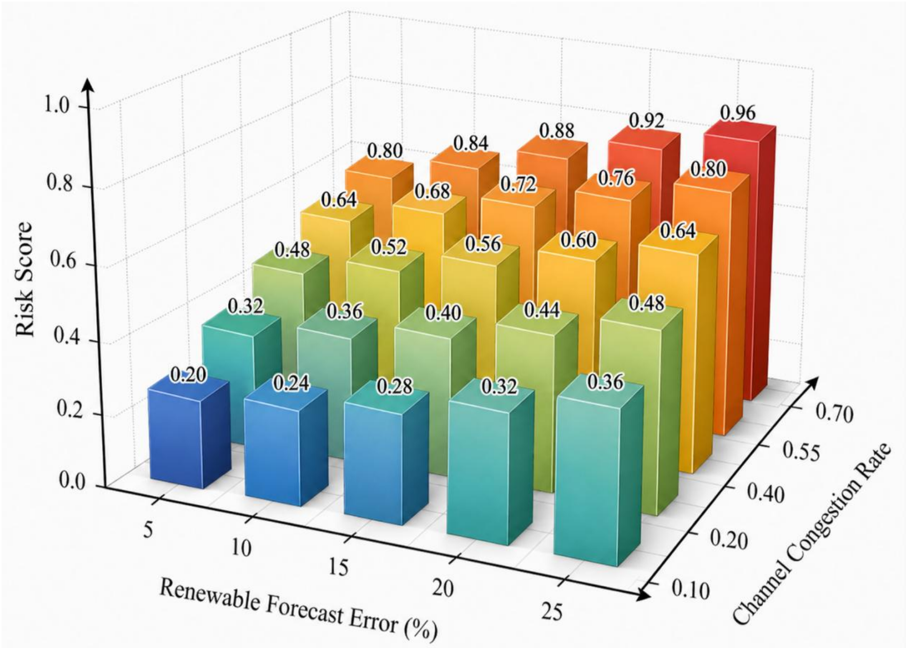

Figure 7: 3D bar chart of risk score under coupling of new energy prediction error and channel blocking rate

It can be seen from Figure 7 that the risk score continues to rise with the increase of new energy prediction error and channel blocking rate, showing an obvious cooperative amplification feature as a whole. When the new energy prediction error is 5% and the channel blocking probability is 0.10, the risk score is only 0.20, and the system is in a low-risk operation state. When the prediction error increases to 10% and the channel blocking probability increases to 0.20, the risk score increases to 0.36, indicating that the local supply and demand fluctuations start to conduct to the safe side of the channel. When the prediction error reaches 15% and the channel blocking probability increases to 0.40, the risk score increases to 0.56. When the prediction error is 20% and the channel blocking probability is 0.40, the risk score further reaches 0.60, which indicates that the system enters a more obvious risk accumulation interval. If the prediction error is extended to 25% and the channel blocking probability is close to 0.70, the risk score can be increased to 0.96, which indicates that there is a strong coupling effect between supply and demand uncertainty and network congestion, which will significantly amplify the supply pressure. Combined with the results in Figure 6, it can be seen that the risk early warning and dynamic calibration mechanism constructed in this paper can identify high-risk combination scenarios at an early stage, and maintain a high level of guarantee supply through mutual electricity quantity adjustment, reserve call enhancement and constraint boundary correction, so as to improve the operation resilience of the cross-regional power mutual assistance market under complex disturbance conditions.

4.4 Analysis of behavior evolution and transaction stability of market entities

In order to verify the effectiveness of the constructed multi-agent game collaborative trading mechanism, this paper further analyzes the evolution characteristics of the bidding strategy of the sending end area, the receiving end area, the power generation subject and the power sale subject in the continuous game process, and evaluates the operation effect of the trading mechanism combined with the market price fluctuation range and the transaction stability index. The experimental results show that in the early stage of the game, due to the lack of cognition of the supply and demand state and competition behavior of each agent, the dispersion of the bidding strategy is large, and the market transaction results have certain fluctuations. With the increase of rounds, each agent gradually adjusted its own price according to the profit feedback, constraint feedback and the change of opponent's strategy, and the overall strategy began to converge to the stable interval. Figure 8 shows the evolution of multi-agent bidding strategies with game rounds.

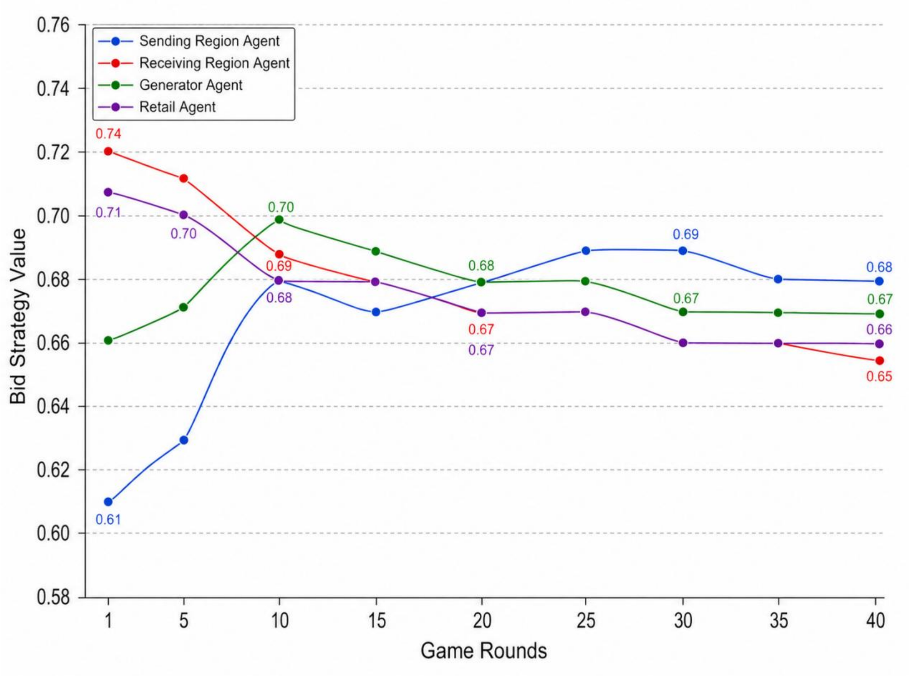

Figure 8: Evolution curve of multi-agent bidding strategies with game rounds

As can be seen from Figure 8, in the first 10 rounds of the game, the bidding level of the main body of the sending end increased from 0.61 to 0.68, and the bidding level of the main body of the receiving end decreased from 0.74 to 0.69. The strategy fluctuation of the power generation subject and the power sale subject was also relatively obvious, indicating that the main body is still in the stage of trial and adjustment. When the game rounds reached 20 rounds, the quotations of various subjects gradually converged, the difference between the quotations of the main subjects of the sending end and the receiving end was reduced to about 0.03, the average turnover rate of the market was stable at more than 95%, and the price volatility dropped to 4.8%. After more than 30 rounds of the game, the strategy curve of each agent tends to be flat, indicating that the method in this paper can effectively guide market agents to form relatively stable trading expectations, reduce the price shock caused by disorderly competition, and improve the trading stability and collaborative operation level of the cross-regional power mutual assistance market.

5 Discussion

The collaborative trading and supply guarantee efficiency optimization method of cross-regional power mutual market constructed in this paper integrates multi-source data collection, supply and demand state representation, multi-agent game, reinforcement learning clearing and risk dynamic calibration into the same technical framework, which can better adapt to the operation characteristics of strong supply and demand fluctuations, large differences in subject objectives, and rapid changes in transmission constraints in cross-regional transactions. Compared with the traditional rule clearing or centralized optimization, the advantages of the proposed method are not only reflected in the transaction matching link, but also reflected in the synchronous processing of the physical constraints of power and the dynamics of market behavior. The multi-source data coding enables the model to identify the input demand, delivery capacity, channel pressure and reserve support level of different regions. The multi-agent game mechanism transforms the strategic interaction between the sending end area, the receiving end area, the power generation subject and the power sale subject into a computable process, making the transaction results closer to the negotiation evolution logic in the real market.

Reinforcement learning algorithm assumes the core function of dynamic clearing and scheduling optimization in the framework of this paper. The clearing strategy in the cross-regional mutual market needs to be continuously adjusted according to load changes, new energy output fluctuations, channel blockage and risk level, and a single static objective function is difficult to cover such complex scenarios. Through state coding, policy network, action mask and security projection layer, this paper combines transaction action generation and scheduling executability to avoid the algorithm only pursuing transaction efficiency but ignoring transmission capacity, reserve requirements and guarantee supply priority. The risk early warning and dynamic calibration mechanism further enhances the adaptability of the model to extreme disturbances, so that the system can correct the mutual power allocation, reserve call intensity and constraint boundary according to real-time deviation, so as to form a closed-loop operation mode of "clearing decision-safety checking-risk feedback-policy update".

There are still some limitations in this paper. Although multiple types of supply and demand disturbances and cross-region constraints are set up, the regulatory rules, auxiliary service mechanisms, cross-region settlement methods and main pricing psychology in the real electricity market are more complex. In the future, the applicability of the model still needs to be further verified by combining actual transaction data and dispatch logs. In addition, the reinforcement learning model has a certain dependence on the sample size and scene coverage, and the policy generalization ability may be affected if the training data is insufficient. In the future, graph neural network, digital twin and federated learning can be introduced into the cross-regional collaborative modeling process to improve the model migration ability while protecting regional data security, and further incorporate energy storage flexibility, demand response incentives and carbon emission constraints, so that the cross-regional power mutual market can better support the low-carbon and efficient operation of the new power system on the basis of ensuring power supply security.

6 Conclusion

In this paper, a comprehensive method combining multi-source data modeling, multi-agent game, reinforcement learning clearing and risk dynamic calibration is proposed to meet the needs of collaborative trading and guarantee supply efficiency optimization in cross-regional power mutual assistance market. Through the unified coding of regional load, new energy output, cross-regional channel, market quotation, reserve resources and risk events, the model can accurately represent the regional supply and demand status and transmission constraints. Through the multi-agent game mechanism, the bidding strategies of the sending end area, the receiving end area, the power generation subject and the power sale subject were incorporated into the iterative negotiation process. Through reinforcement learning policy network, action mask and security projection layer, the transaction clearing results can simultaneously take into account transaction efficiency, scheduling feasibility and supply priority. The experimental results show that the proposed method is superior to the comparison algorithms in terms of clearing time, transaction rate, guarantee and supply satisfaction rate and market stability, and it still shows strong robustness especially in the scenarios of sudden drop of new energy, channel blockage and complex disturbance. Subsequent research can further introduce real transaction data, digital twin grid and federated learning mechanism to improve the generalization ability and deployment value of the model in actual cross-regional markets.

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