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Multi-market joint optimization bidding model considering risk preference under limit price constraint

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SUMMARY: *In order to support intelligent bidding in multi-market, this paper proposes a joint bidding model of risk preference modeling under price limit constraint. The electric energy market is divided into day-ahead and real-time sub-markets, and the auxiliary services are divided into standby and frequency regulation sub-markets. The framework integrates temporal state encoding, preference utility estimation, feasible region modification and iterative policy search to generate quotes based on historical prices, renewable forecasts, load trajectories and settlement signals. The experimental results on 17,520 hours of samples collected from 4 trading zones show that compared with the three benchmark strategies, the expected operating cost of the proposed method is reduced by 11.8%, the average bidding profit is increased by 9.6%, the downside risk based on CVaR is reduced by 13.4%, the average absolute bidding deviation is 2.7%, and the average computation time per round is 0.41 s. The results show that the proposed model maintains the stability of revenue under the limit price constraint, and improves the bidding feasibility from 91.2% to 97.8%, which can provide decision support for the computer-driven bidding system in the actual operation scenario of the electricity market.*

KEYWORDS: *Multi-market joint bidding; Risk appetite; Price limit constraint; Temporal feature encoding*

1 Introduction

Under the background of the evolution of the new power system and the refinement of the market mechanism, the trading behavior of the generation side, the load side and the aggregate subject has changed from the single market declaration to the joint decision-making across time periods, categories and rules. There are price transmission, clearing coupling and income linkage relationships among the day-ahead market, real-time market, auxiliary service market and related energy trading links. The bidding results are not only affected by resource boundaries and price fluctuations, but also restricted by limit price rules, risk tolerance degree and calculation time. In this high-dimensional dynamic trading environment, it is difficult to support stable decision-making by only relying on experience reporting or static optimization. Using computer methods to construct a joint optimization bidding model that can be iterated, coded and verified has become an important path for market players to carry out intelligent trading analysis.

Various computational frameworks have been developed for electricity market bidding modeling. Liu studied the bidding strategy of virtual power plant under the coupled market

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mechanism of electricity and carbon, and incorporated carbon cost and electric energy trading profit into a unified framework to provide coupling modeling basis for multi-market joint declaration [1]. Guo studied the bounded rational bidding behavior of power generation companies under the condition of renewable energy, and revealed the influence of random output disturbance on bidding decision and game equilibrium [2]. Sun proposed a multi-agent energy management optimization method for energy-carbon collaborative trading market, and introduced the distributed decision-making mechanism into the comprehensive energy scenario [3]. Chang studied the two-stage collaborative operation framework of multi-stakeholder microgrid aggregation in the deregulated electricity market to provide structural reference for joint transaction convergence [4]. Ji proposed a two-tier electricity market bidding model based on deep reinforcement learning, and introduced the strategy learning method into the solution process of renewable energy participation transaction [5]. Mei studied the optimal bidding strategy for virtual power plants to participate in the joint market of electric energy and auxiliary services, which strengthened the analysis of multi-market revenue coordination [6]. Wang studied the random bidding mechanism of auxiliary services in virtual power plants and showed the dynamic response mode of declaration decision under uncertainty [7]. Zheng proposed a risk-averting bidding strategy for EV aggregators considering price fluctuations, which promoted the risk preference parameters into the market decision calculation process [8]. Liu studied the bidding strategy of integrated energy system considering subjective risk aversion, and showed that risk attitude would directly change the revenue distribution and bidding boundary [9]. Ren proposed a two-tier strategic bidding model for electric-natural gas integrated market based on reinforcement learning, which provided technical support for the integration of multi-market, two-tier and intelligent solution [10].

The above studies lay the foundation for the modeling of joint bidding, but for the multi-market collaborative bidding under the limit price constraint, the existing methods still need to be tightened in the computational expression. One kind of method focuses on revenue maximization or cost minimization, and the expression of risk preference is not detailed enough, so it is difficult to describe the different choice of tail loss and return stability of different subjects. One kind of methods emphasize game or bilayer optimization, but rarely put the price limit boundary, market coupling rules and temporal state codes into the same computing link. Although some methods introduce reinforcement learning or stochastic optimization, the connection between feasible region correction, declaration safety verification and multi-market linkage generation is not close enough.

Based on this, this paper constructs a joint optimization bidding model and its calculation mechanism around the three factors of limit price constraint, risk preference and multi-market coupling. At the model level, the income term, risk term and price boundary constraint were written into the objective function and linkage constraint system. At the method level, the process of time series data coding, risk preference parameter embedding, joint search and bid generation are introduced, and the steps of feasible region correction and safety check are set up, so that the bidding results meet the requirements of market rules and computational stability at the same time. This study transforms the multi-market transaction scenario into a trainable, searchable and evaluable computational task, which provides a modeling basis for the implementation of an intelligent bidding system in the power market.

2 Related work

At present, the research on multi-market joint optimal bidding under limit price constraint is mainly carried out along two paths: one is model-driven method, the other is learning-driven method. Model-driven methods usually take revenue function, risk term and market constraint as the core, and describe the reporting behavior of market entities in multi-transaction scenarios through bileveval-level optimization, robust optimization, stochastic programming or game modeling. The learning-driven method relies more on state perception, strategy update and data feedback to complete the bidding decision generation, which is suitable for the trading environment with strong price fluctuations, deep market coupling and high computational efficiency requirements.

In learning-driven research, Rokhforoz et al. studied the optimal bidding strategy of power generation units in the electricity market, and proposed a method combining graph convolutional network and multi-agent reinforcement learning to enable the interactive relationship between market players to enter the state representation process, thereby enhancing the dynamic strategy search ability [11]. Wang et al. studied the day-ahead bidding strategy of regional integrated energy system considering multiple uncertainties, and unified the scene disturbance, price change and market declaration process into the same optimization framework to enhance the bidding adaptability under multi-scenario conditions [12]. Wang et al. also studied the optimal energy management method for the integrated energy system to participate in the competitive power market, which unified the operation scheduling and market bidding decision, so that the market participation behavior had stronger computational consistency [13]. Chang et al. studied the day-ahead bidding strategy of cloud energy storage serving multiple heterogeneous microgrids, emphasizing the coordinated allocation and price response of shared energy storage resources in aggregated transactions, which provided resource organization ideas for multi-agent joint declaration [14]. Wang J et al. studied the self-scheduling method of multi-energy virtual power plant under the overall market framework, and incorporated electric energy and standby services into the unified declaration interface to enhance the consistency of multi-category market participation [15].

Based on the existing literature, it can be found that different methods have obvious differences in state expression ability, risk handling method, market coupling depth and offer generation path. In order to summarize the main technical routes of related research on multi-market joint bidding and further illustrate the connection between the modeling position of this paper and existing work, the technical characteristics of representative literature are summarized in Table 1.

Table 1: Comparison of technical characteristics of related studies on multi-market joint bidding

Reference	Research Object	Method Type	Technical Characteristics	Application Focus
[11]	Optimal bidding of generation units	Graph learning and multi-agent reinforcement learning	Combines graph convolutional networks with multi-agent reinforcement learning to strengthen market interaction state representation and dynamic strategy search	Complex interactive markets
[12]	Day-ahead bidding of regional integrated energy systems	Stochastic optimization	Incorporates multiple uncertainties into the day-ahead bidding process and emphasizes joint bidding computation under scenario disturbances	Multi-scenario bidding decisions
[13]	Participation of integrated energy systems in competitive electricity markets	Coordinated dispatch optimization	Unifies operational scheduling and market bidding within the same computational chain	Integrated scheduling–bidding
[14]	Bidding of cloud energy storage serving heterogeneous microgrids	Aggregated trading optimization	Focuses on coordinated allocation and price response of shared energy storage resources in multi-agent trading	Aggregated resource bidding
[15]	Bidding of multi-energy virtual power plants in energy and reserve service markets	Self-scheduling optimization	Constructs a unified bidding interface to improve consistency in participation across multiple market categories	Participation in joint markets
[16]	Bidding equilibrium in imperfect electricity markets	Reinforcement learning and distributed algorithms	Uses reinforcement learning to solve Nash equilibrium and realizes linked computation of bidding and market clearing	Game-based bidding scenarios
[17]	Robust bidding of data center operators	Bi-level robust optimization	Integrates revenue, energy consumption, and robust boundaries into a unified framework to improve constraint computability	Boundary-constrained bidding
[18]	Day-ahead trading of distributed energy resource aggregators	Risk preference modeling	Directly embeds risk preference behavior into day-ahead trading decisions	Preference-driven bidding
[19]	Bidding of virtual power plants in green certificate and carbon trading markets	Multi-market coordinated optimization	Introduces green certificate and carbon trading factors into the electricity market bidding process	Extended market transactions
[20]	Electricity–heat–carbon coordinated trading of multiple virtual power plants	Stackelberg game optimization	Achieves multi-agent and multi-market coordinated computation through hierarchical game modeling	Multi-market coupled decision-making

It can be seen from Table 1 that the existing research has formed multiple technical routes such as graph learning, reinforcement learning, stochastic optimization, bi-level optimization, co-scheduling and hierarchical game. Different methods strengthen the ability of market state modeling, risk control, resource aggregation or trading collaboration respectively, but there is still room for further refinement in the explicit expression of limit price boundary, dynamic embedding of risk preferences and integrated calculation of multi-market linkage generation.

In model-driven research, Yu et al. studied the bidding equilibrium calculation in incomplete electricity market, and proposed a Nash equilibrium search method based on reinforcement learning and a distributed algorithm oriented to ISO, which formed a closer linkage relationship between bidding strategy and market clearing process [16]. Chen et al. studied the multi-objective robust bidding strategy of data center operators and proposed a modeling method based on bilevel optimization, which unified revenue, energy consumption and robust boundary into the same computational framework, reflecting strong constraint computability [17]. Dong et al. studied the day-ahead trading strategy of distributed energy aggregators considering the risk preference behavior, so that the degree of risk aversion can directly enter the trading decision-making process, which enhances the connection between revenue control and preference expression [18]. Wang et al. studied the bidding strategy of virtual power plants considering green certificate and carbon trading, and introduced the green certificate cost and carbon market factors into the electric energy trading process, expanding the market application scope of traditional bidding model [19]. Cao et al. studied the collaborative optimization mechanism of multiple virtual power plants in the power-heat-carbon trading scenario, and proposed a multi-agent collaborative strategy based on Stackelberg game to make the multi-market coupled trading have a clearer hierarchical structure and decision logic [20].

In general, the existing research has provided a good method foundation for multi-market bidding calculation, but from the perspective of computer modeling, there is still a need to further tighten. Some methods are more interested in revenue maximization or operation scheduling, and the explicit expression of price limit constraint is insufficient. There is no uniform interface between price ceiling, application modification and transaction feasible region. Although some methods consider risk preferences, most of them enter the objective function in the form of static parameters, and have not formed synchronous linkage with the process of temporal state coding, strategy iterative update and bid generation. There are also some methods to achieve dual-market or multi-agent coordination, but the coverage of joint search, boundary correction and safety check under multi-market coupling is not complete. Based on this, this paper integrates the limit price boundary, risk preference and multi-market linkage into the same computational framework, and constructs a joint optimization bidding method for practical trading systems through time series state representation, parameterized strategy iteration, joint search and feasible region verification.

3 Method Introduction

3.1 Intelligent decision-making architecture for multi-market joint bidding

In this paper, an intelligent decision-making architecture for multi-market joint bidding is constructed for the collaborative processing of limit price constraints and risk preferences. The architecture takes price sequence, load forecast, renewable output, reserve demand and market settlement signals as inputs, completes multi-source transaction information access through the unified data interface, and then forms the computable market state vector by the state coding module. The decision center adopts a hierarchical linkage structure: the bottom layer is responsible for local bid generation in day-ahead, real-time and auxiliary service sub-markets, the middle layer is responsible for risk preference mapping, limit price boundary constraint and income correction, and the upper layer is responsible for joint search, strategy screening and result write-back, so that the application results of different markets are consistent. As shown in Fig. 1, the overall architecture is composed of data access layer, state representation layer, policy generation layer and security verification layer, and closed-loop computing links are formed between each layer through parameter transmission and constraint feedback.

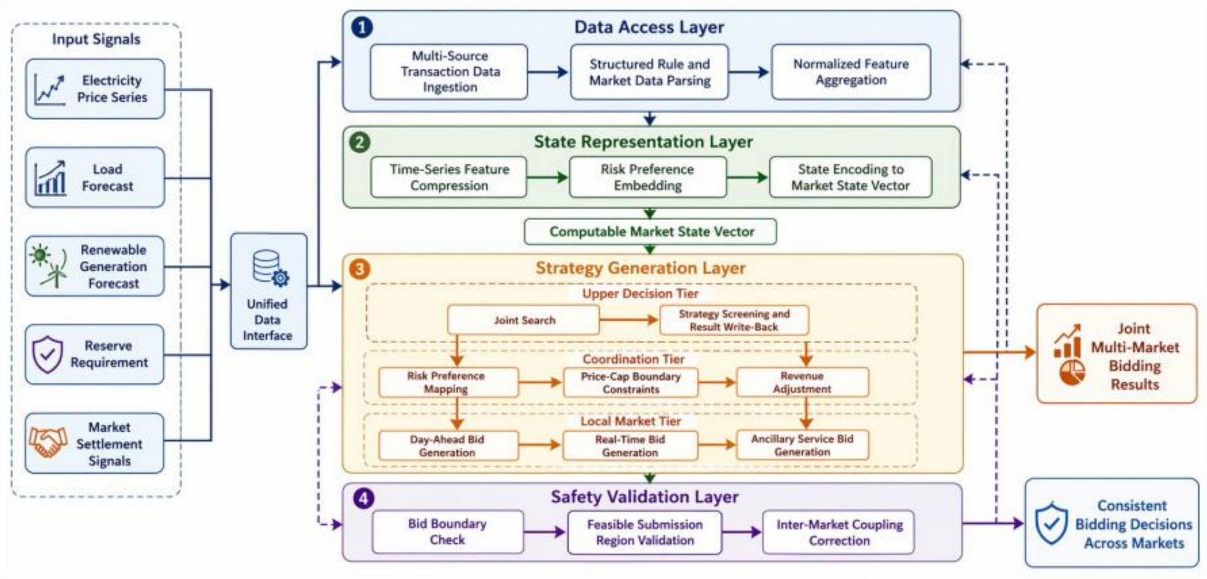

Figure 1: Multi-market joint bidding intelligent decision architecture

The data access layer is responsible for the structured arrangement of price, load and transaction rules. The state representation layer completed time series feature compression and risk preference embedding. The strategy generation layer outputs the multi-market joint bidding results. The security checking layer modifies the quotation boundary, the application feasible region and the market linkage relationship. The architecture transforms the multi-market trading process into a coding, iterative and verifiable calculation process, which can provide unified support for subsequent model construction and algorithm solution, and enhance the stability and consistency of system online response.

3.2 Multi-market joint optimization bidding model under limit price constraint

3.2.1 Risk appetite-driven return-risk coupling objective function

In multi-market joint bidding under limit price constraint, the objective function needs to simultaneously reflect the revenue level, tail loss, bid continuity and state-driven difference. To this end, in this paper, the risk preference parameter is embedded into the return calculation main chain, and it is made to act on the bidding decision together with the market state coding results.

In order to achieve the collaborative expression of multi-market returns, price volatility and risk tolerance in the unified computing link, this paper constructs the overall coupled objective function as follows:

$$\max F=\sum_{t=1}^{T}\sum_{m=1}^{M}\omega_{m,t}\Pi_{m,t}-\alpha CVaR_{\beta}(L)-\mu\sum_{t=2}^{T}\| u_t-u_{t-1}\|_2^2 \quad (1)$$

Here, F represents the joint optimization objective value, $\Pi_{m,t}$ represents the net income of period t in market m, $\omega_{m,t}$ represents the corresponding market weight, α represents the tail risk penalty coefficient, μ represents the bid smoothing coefficient, and u_t represents the comprehensive declaration vector in this period. The formula puts the return term, risk term and strategy continuous term into the same target surface, so that the search process no longer only pursues a single return peak, but retains the ability to suppress extreme loss and price jump, which is more suitable for iterative solution in computer environment.

In order to make the clearing income, deviation cost and limit edge impact of each trading market enter the calculation process synchronously, the net income of a single market is as follows:

$$\Pi_{m,t}=x_{m,t}(p_{m,t}^{clr}-c_t)-\kappa_m|x_{m,t}-\hat{x}_{m,t}|-\phi_m\delta_{m,t} \quad (2)$$

Here, $x_{m,t}$ represents the amount of electricity traded, $p_{m,t}^{clr}$ represents the clearing price, c_t represents the marginal declaration cost, $\hat{x}_{m,t}$ represents the predicted volume, κ_m represents the deviation penalty coefficient, ϕ_m represents the limit price edge penalty coefficient, $\delta_{m,t}$ represents the boundary trigger mark. The formula expanded the transaction revenue, prediction error and boundary cost in layers, which not only ensured that different markets had comparable revenue descriptions, but also reserved a clear interface for subsequent multi-market coupling search.

In order to make risk preference no longer stop at static coefficient setting, this paper uses conditional value at risk to describe tail loss, as follows:

$$CVaR_{\beta}(L)=\zeta+\frac{1}{(1-\beta)S}\sum_{s=1}^{S}[L_s-\zeta]^{+} \quad (3)$$

Here, β represents the confidence level, S represents the total number of scenarios,L_s represents the loss value under scenario s, ζ represents the risk quantile benchmark, and $[\cdot]^{+}$ represents the positive part operator. This formula can concentrate on identifying the pulling effect of high-loss samples on the objective function, so that risk-averse-type agents still retain the profit stability bias when the profit space is compressed by the limit price, which is more suitable for multi-scenario data-driven bidding calculation.

In order to make the state encoding results directly participate in the payoff distribution and strategy selection process, the market weight function is as follows:

$$\omega_{m,t}=\frac{\exp(z_t^{T}q_m-\rho r_t)}{\sum_{k=1}^{M}\exp(z_t^{T}q_k-\rho r_t)} \quad (4)$$

Here, z_t represents the market state vector output by the timing encoder, q_m represents the preference prototype vector of market m, r_t represents the risk preference intensity, and ρ represents the risk mapping coefficient. This formula uses the normalized weight to couple the state identification results and risk preference parameters into the revenue allocation process, so that the high volatility market and the robust market get different attention under different risk orientations, so as to provide a learnable target basis for joint bidding generation.

In summary, the above objective function integrates revenue acquisition, tail risk suppression, continuous bid control and state-aware weight allocation into the same calculation framework, so that risk preference is no longer attached to the revenue term as an isolated parameter, but embedded in the main calculation link of multi-market joint bidding. In this way, the revenue contribution, risk exposure and boundary trigger effect between different markets can be measured at the same time on the unified target surface, which also provides a clear target basis for the subsequent limit price boundary constraint, multi-market linkage constraint and joint search solution process.

3.2.2 Limit price boundary and multi-market linkage constraints

In the process of multi-market joint bidding, constraints are not only used to limit the filing boundaries, but also to connect different market rules, trading rhythms and risk control logics. In this paper, a uniform set of constraints is established among day-ahead market, real-time market, reserve market and frequency modulation market, so that price, declared quantity, reserve capacity and clearing deviation can be updated in the same computing space.

In order to ensure that the quotation of each sub-market is always within the limit price range, and to suppress the cross-border and invalid edge contact in the joint declaration, the following boundary constraint formula is constructed in this paper, as shown below:

$$\underline{p}_{m,t} - g_t \le p_{m,t} \le \overline{p}_{m,t} + g_t, \quad g_t = \eta_m \tanh(h_t) \tag{5}$$

Where $p_{m,t}$ represents the declared price of market m in time period t, $\overline{p}_{m,t}$ and $\underline{p}_{m,t}$ represent the upper and lower price bounds of the corresponding market respectively, g_t represents the dynamic buffer term activated by the limit price rule, η_m represents the market sensitivity coefficient, and h_t represents the volatility intensity of the state encoder output. The formula combines the fixed limit price and the state disturbance buffer, which can keep the boundary constraint continuous when the price fluctuates and avoid the shock caused by discrete truncation.

In order to ensure that the power, reserve and frequency declaration meet the resource consistency in capacity allocation, and prevent the local optimum from crowding out the cross-market adjustable capacity, the linkage constraint is set as follows:

$$x_t^E + \lambda_1 x_t^R + \lambda_2 x_t^F \le \xi_t P_t^{av} - \Delta_t \tag{6}$$

Here, x_t^E, x_t^R and x_t^F represent the declared power in the electric energy market, standby market and frequency modulation market respectively; P_t^{av} represents the available capacity in time period t; ξ_t represents the reduction factor obtained by equipment state coding; Δ_t represents the reserved climbing margin; λ_1 and λ_2 represent the conversion weights of standby and frequency modulation on available capacity. This equation maps multi-market filings uniformly into the same capacity pool, so that the joint search synchronously identifies the equilibrium relationship between trading revenue and physical occupancy.

In order to make the bidding trajectory and real-time correction process of adjacent periods meet the timing executability, and weaken the impact of sudden price change on the stability of online solution, this paper further gives the following dynamic constraints, as shown below:

$$u_t = Au_{t-1} + Bs_t + \varepsilon_t, \quad \|u_t - u_{t-1}\|_\infty \le r^{max} \tag{7}$$

Here, u_t represents the integrated bid vector, A and B represent the state transition matrix and control mapping matrix respectively, s_t represents the market state coding result, ε_t represents the allowed correction band, and r^{max} represents the maximum variation range. The formula directly relates the decision sequence to the state update process, so that the bid generation in consecutive periods conforms to the temporal evolution logic, and also provides a stable search boundary for the subsequent iterative algorithm.

In order to keep the risk of the joint declaration result controllable after the market is cleared, and the tail deviation control is embedded in the feasible region correction process, this paper constructs the following safety check constraint, as shown below:

$$\mathrm{CVaR}_{\beta}(L_t) + \chi \sum_{m=1}^{M} |\, x_{m,t} - \tilde{x}_{m,t}| \leq \Gamma B_t \tag{8}$$

Here, L_t represents the combined loss after clearing, B_t represents the budget boundary, CVaR_{β} represents the conditional value at risk with confidence level β, $\tilde{x}_{m,t}$ represents the corrected volume of market m, χ represents the deviation penalty coefficient, and Γ represents the acceptable risk threshold. This formula takes clearing deviation, budget limit and tail risk into the checking link at the same time, so that the bidding results meet the limit price requirements while retaining the robustness.

In summary, the above constraints complete the unified modeling from four levels: price boundary, capacity linkage, timing execution and security verification, which provides the basis for subsequent joint search and bid generation, and enhances cross-market collaboration performance.

3.3 Joint optimization bid solving mechanism

3.3.1 Market state representation method based on time series data coding

In the process of solving joint optimal bidding, the market state representation assumes the role of compressing the original trading sequence, extracting the key volatility structure and providing a unified input to the subsequent strategy module. In this paper, the day-ahead price, real-time deviation, power demand, reserve request, renewable output and limit price trigger tags are reconstituted according to the sliding window, and the deep timing coding link is used to complete the multi-market state compression, so that the discrete transaction information is transformed into a continuous computable vector.

In view of the obvious temporal coupling characteristics of multi-market price, load, clearance and boundary signal, this paper constructs a unified state coding link as follows:

$$h_t = \mathrm{GRU}(W_x x_t + W_h h_{t-1} + b_h) \tag{9}$$

where x_t represents the original market input in time period t, h_t represents the hidden state, and W_x, W_h, and b_h represent the input weight, recursive weight, and bias term, respectively. The formula is used to extract the local timing dependencies, so that the price, load and boundary trigger information before the declaration are encoded in the unified recursive link, and the basic representation is reserved for the subsequent cross-market association calculation.

In order to complete association propagation, strength identification and dynamic screening of time series segments in different markets in a unified representation space, this paper defines the cross-market attention matrix as follows

$$A_{m,n,t} = \frac{\exp\left((Q_{m,t}K_{n,t}^{T})/\sqrt{d}\right)}{\sum_{j=1}^{M}\exp\left((Q_{m,t}K_{j,t}^{T})/\sqrt{d}\right)} \tag{10}$$

Here, $A_{m,n,t}$ represents the attention weight of market m to market n in time period t, $Q_{m,t}$ and $K_{n,t}$ represent the query vector and key vector, respectively, and d represents the feature dimension. This equation is used to measure the correlation strength of different submarkets in the same time period, so that the price disturbance and capacity coupling between the electric energy, reserve and frequency modulation markets can be identified synchronously.

In order to preserve local volatility information, global trading semantics and boundary trigger features at the same time, this paper further gives the state fusion expression as follows:

$$z_t = \gamma_1 h_t + \gamma_2 \sum_{m=1}^{M} A_{m,:,t} V_{m,t} + \gamma_3 e_t \tag{11}$$

Here, z_t represents the final state vector, $V_{m,t}$ represents the market value vector, e_t represents the boundary triggered embedding, and γ_1, γ_2, and γ_3 represent the fusion coefficients. This formula jointly compresates local timing features, cross-market interaction information and boundary states, so that the state representation results can be directly entered into the strategy generation module. In general, this method transforms the scattered trading signals into trainable, propagable and callable computational objects, which provides a unified state base for subsequent risk preference embedding and joint search.

3.3.2 Risk preference parameter embedding and bidding strategy iteration mechanism

In the multi-market joint bidding scenario, risk preferences cannot only be quantitatively attached to the objective function as an external hypothesis, but need to enter the strategy update link, and act synchronously with payoff feedback, boundary correction and state change. In this paper, the combination of parameter embedding and iterative updating is used to make the risk orientation maintain continuous and stable transmission in the process of strategy generation.

In order to clearly show the mapping process of risk preference from external input into internal strategy space, and illustrate its connection relationship with return feedback and boundary correction, Fig. 2 shows. In the figure, state input, preference vector mapping, policy network update, boundary backtransmission and candidate bid output are given in turn from left to right, and a closed loop is formed between each module through a feedback arrow.

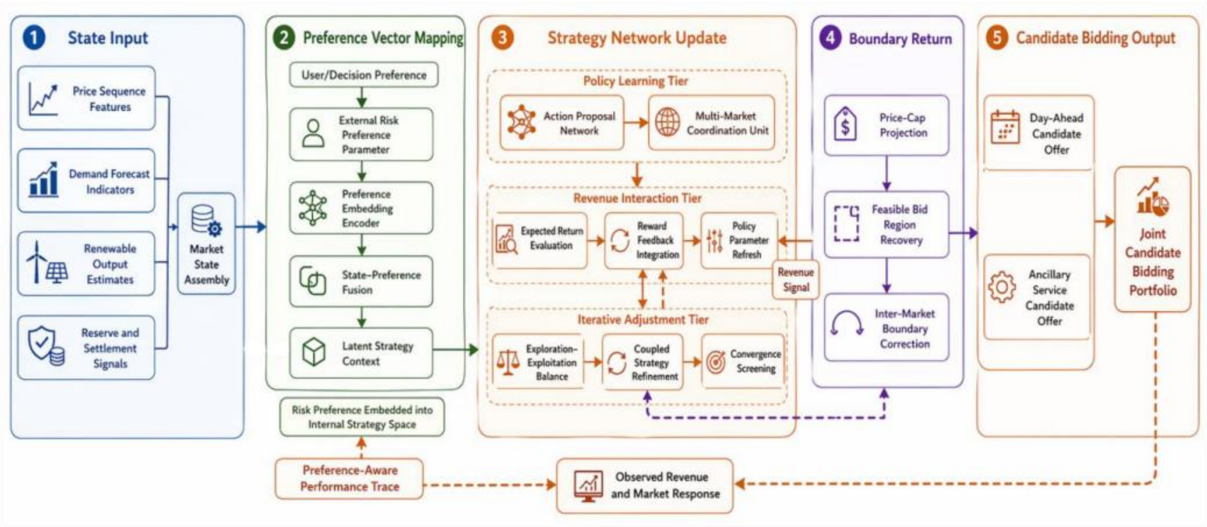

Figure 2: Risk preference parameter embedding and bidding strategy iteration flow chart

In order to quantitatively transform the risk preference parameters into trainable, propagable and updatable internal vectors from external Settings, the risk preference embedding function is defined as follows:

$$r_t = \sigma(W_r[\theta, z_t, c_t] + b_r) \tag{12}$$

Here, r_t represents the risk preference embedding vector of time period t, θ represents the given risk preference coefficient, z_t represents the state encoding result, c_t represents the boundary triggering context, W_r and b_r represent the mapping matrix and bias term respectively, and $\sigma(\cdot)$ represents the nonlinear activation function. This formula transforms the subjective risk orientation into an internal representation that can participate in the calculation, so that risk preferences can be adjusted synchronously with state changes and boundary corrections.

In order to make the strategy update reflect the results of revenue feedback, risk feedback, boundary correction and state evolution at the same time, the joint bidding iteration rule is constructed as follows:

$$u_t^{(k+1)} = u_t^{(k)} + \lambda_1 \nabla_u \widehat{R}_t - \lambda_2 \nabla_u \widehat{L}_t - \lambda_3 \nabla_u \widehat{B}_t \tag{13}$$

Here, $u_t^{(k)}$ represents the bidding vector under the k iteration, $\widehat{R}_t$ represents the estimated revenue, $\widehat{L}_t$ represents the risk loss, $\widehat{B}_t$ represents the boundary penalty term, and λ_1 to λ_3 represents the corresponding update step. This formula makes the revenue promotion, risk suppression and boundary contraction complete the trade-off in the same update link, so as to avoid the strategy only moving to the direction of a single profit extreme value. The iterative mechanism can embed risk preference into the multi-market quotation generation process stably, and provide a more differentiated set of candidate strategies for the next joint search.

3.3.3 Joint search and bid generation process for multi-market coupling

When the state representation and risk preference vector are updated, the solution process needs to put the candidate applications of multiple sub-markets into the same search space to identify the optimal combination of returns, risks and boundaries. In this paper, a joint search process oriented to multi-market coupling is used to score, sort and generate the offer vectors of the electric energy, standby and frequency modulation markets synchronously to avoid local offset caused by the independent solution of the sub-markets.

To illustrate how the joint search module receives the state vector, preference embedding and constraint feedback and further generates the multi-market unified bidding results, Fig. 3 shows.

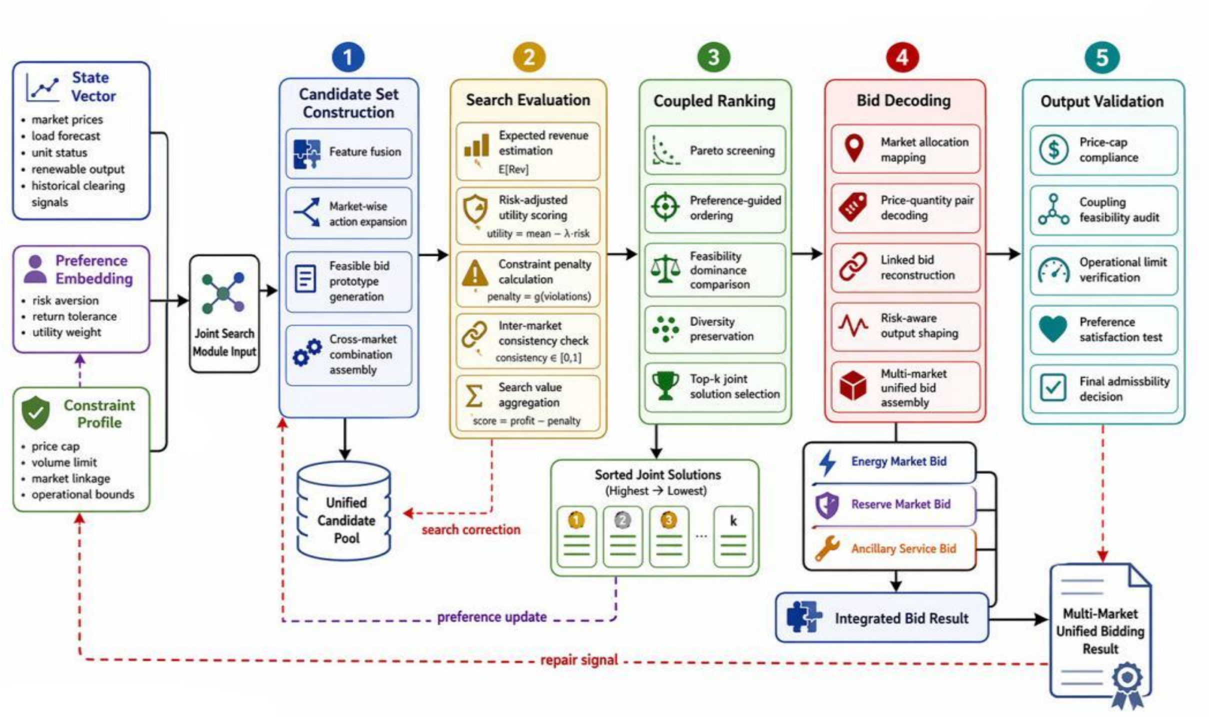

Figure 3: Flow chart of joint search and bid generation for multi-market coupling

In order to make the joint search process consider multi-market revenue contribution, risk load, boundary occupation and coupling revenue simultaneously, this paper defines the search evaluation function as follows:

$$S(\mathcal{U}_t) = \sum_{m=1}^{M} \psi_{m,t} \widehat{\Pi}_{m,t} - \tau_1 \widehat{\Omega}_t - \tau_2 \widehat{\Lambda}_t \tag{14}$$

Here, $S(\mathcal{U}_t)$ represents the comprehensive score of the candidate strategy set $\mathcal{U}_t$ in time period t, $\psi_{m,t}$ represents the market weight, $\widehat{\Pi}_{m,t}$ represents the predicted revenue, $\widehat{\Omega}_t$ represents the risk load, $\widehat{\Lambda}_t$ represents the boundary occupancy penalty, and τ_1 and τ_2 represent the penalty coefficients. This formula projects the revenue and constraint cost into the same scoring surface, so that the search process can stably screen out the candidate strategies with high risk and high boundary crossing tendency.

In order to make the candidate strategies output the multi-market offer vector with consistent structure and controllable boundary after joint search, this paper gives the bid generation mapping as follows:

$$\hat{b}_{m,t} = \mathrm{SoftClip}\left(W_b[z_t, r_t, \mathcal{U}_t^*] + b_b; \underline{p}_{m,t}, \overline{p}_{m,t}\right) \tag{15}$$

where $\hat{b}_{m,t}$ represents the final declared price of market m in time period t, $\mathcal{U}_t^*$ represents the optimal candidate strategy set retained by search, W_b and b_b represent the decoding matrix and bias term, respectively, and $\mathrm{SoftClip}(\cdot)$ represents the soft truncation function. This formula uses soft boundary projection to generate the final offer, which not only retains the revenue information obtained by the search, but also avoids the damage to the multi-market coupling structure caused by hard truncation. The joint search and bid generation process thus formed can transform the multi-market coupling solution into a stable, continuous and traceable calculation process.

3.3.4 Feasible region correction and safety verification method under price limit constraint

After the joint bid is generated, it is necessary to modify the feasible region and check the security of the bid result to ensure that it not only meets the linkage requirements of price boundary and capacity, but also keeps the risk stable and the execution controllable before the clearance. In this paper, projection correction, linkage check and tail safety discrimination are set at the end of the solution, so that the final quotation can be directly used for market declaration.

In order to keep the initial offer continuously solvable when it touches the price boundary, capacity boundary and linkage threshold, this paper uses the projection feasible region correction as follows:

$$\bar{u}_t = \Pi_{\mathcal{C}}(\hat{u}_t - \eta \nabla_{\hat{u}} \Phi_t) \tag{16}$$

where $\bar{u}_t$ denotes the initial offer vector, $\hat{u}_t$ denotes the modified offer vector, $\Pi_{\mathcal{C}}(\cdot)$ denotes the projection operator to the feasible region $\mathcal{C}$, Φ_t denotes the integrated boundary penalty term, and η denotes the modified step size. This formula changes the boundary constraint from discrete clipping to continuous projection, so that the quotation correction process remains derivable and iterable, and is more suitable for online solution in computer programs.

In order to make the modified result meet the relationship of multi-market transaction consistency, capacity balance and revenue coordination, this paper constructs the unified linkage check constraint as follows:

$$\sum_{m=1}^{M} \rho_m \bar{x}_{m,t} \leq P_t^{av}, \quad \left| \sum_{m=1}^{M} \bar{x}_{m,t} - \bar{x}_t^{clr} \right| \leq \epsilon_t \tag{17}$$

Here, $\bar{x}_{m,t}$ represents the volume after correction, ρ_m represents the market capacity conversion factor, P_t^{av} represents the available capacity during the period, $\bar{x}_t^{clr}$ represents the estimated total clearing volume, and ϵ_t represents the allowable deviation. This formula controls the capacity occupation and transaction consistency at the same time, and avoids the destruction of the overall revenue structure after the amplification of a market price.

In order to keep the risk stable, the strategy safe and the execution controllable before the final offer is cleared, this paper further sets the tail safety discriminant function as follows:

$$\Upsilon_t = 1\left(\mathrm{CVaR}_\beta(\bar{L}_t) \leq \varrho_t \ \wedge \ \max_m \kappa_{m,t} \leq 1\right) \tag{18}$$

Here, Υ_t represents the safety discrimination result, $\bar{L}_t$ represents the modified loss distribution, ϱ_t represents the risk threshold, $\kappa_{m,t}$ represents the boundary occupancy rate of market m in time period t, and $1(\cdot)$ represents the indicator function. This formula puts the tail risk and boundary occupation into the same discriminant condition, so that the final offer not only meets the formal constraints, but also has an executable safety margin.

In general, this paper realizes the continuous correction and layer-by-layer verification from the initial offer to the final declaration result, which makes the multi-market joint bidding under the limit price constraint more robust in calculation and more controllable in execution.

4 Experiment and analysis

4.1 Data Source and experimental setup

In terms of the experimental platform construction, this paper completed the multi-market joint bidding simulation based on the mixed environment of Python and MATLAB, in which the timing coding, strategy update and risk preference embedding modules were implemented under Python 3.10, and the market clearing calculation, limit price verification and revenue statistics were completed in MATLAB R2023b. The sample consists of 17,520 hourly market records from 2022 to 2024 in four trading zones. The fields include day-ahead electricity price, real-time electricity price, reserve demand, auxiliary service compensation coefficient, load forecast, scenery output forecast and limit price boundary. In order to ensure that different market states can enter the unified computing link, this paper normalizes the continuous variables, adopts one-hot coding for the boundary trigger variables, and constructs the time series samples with a 24-hour sliding window. The core experimental setup is shown in Table 2.

Table 2: Experimental data and parameter Settings

Item	Setting
Sample size	17,520 hourly records
Data period	2022–2024
Trading scenarios	Day-ahead, real-time, reserve, and ancillary services
Data split	7:1:2
Window length	24 hours
Batch size	32
Learning rate	0.001
Training epochs	80
Optimizer	Adam
Hardware environment	RTX A5000, 128 GB memory

On the basis of the Settings listed in Table 2, this paper further sets up three groups of comparison schemes: risk-free preference embedding, no boundary correction and single market independent bidding, and uses the same data source, the same clearing mechanism and the same constraint process to complete the training and testing. The experimental setup can support multi-market state coding, joint search and security verification, and also provide a consistent data basis for subsequent revenue response analysis and comparison of limit price constraint effects.

4.2 Results of joint bidding and multi-market revenue response

In order to verify the response ability of the proposed model in multi-market collaborative filing, this paper statistics the hourly return distribution, quote deviation and clearing consistency of four types of trading markets on the test set. The joint optimization bidding model undertakes the main revenue acquisition in the day-ahead market, completes the deviation correction in the real-time market, and undertakes the marginal compensation in the standby and auxiliary service market, so as to form a clear hierarchical revenue structure. The test results show that compared with the baseline strategy, the average bidding profit of the proposed method is increased by 9.6%, the expected operating cost is decreased by 11.8%, and the average absolute bidding deviation is controlled within 2.7%, which indicates that the revenue increment and the price stability can be maintained at the same time after the multi-market coupling solution.

In order to show the difference of return absorption path and peak and valley response of different markets over 24 time periods, this paper draws the joint return heat map, as shown in Fig. 4. In the figure, the horizontal axis is the period, the vertical axis is the market type, and the color depth indicates the net return per unit period. The results show that the day-ahead market forms a continuous high return area from 7 to 10 o 'clock and 18 to 21 o 'clock, the real-time market presents a partial compensation peak in the load correction stage, and the standby and auxiliary service market provides stable compensation in the high fluctuation range, so that the total revenue no longer depends on a single market.

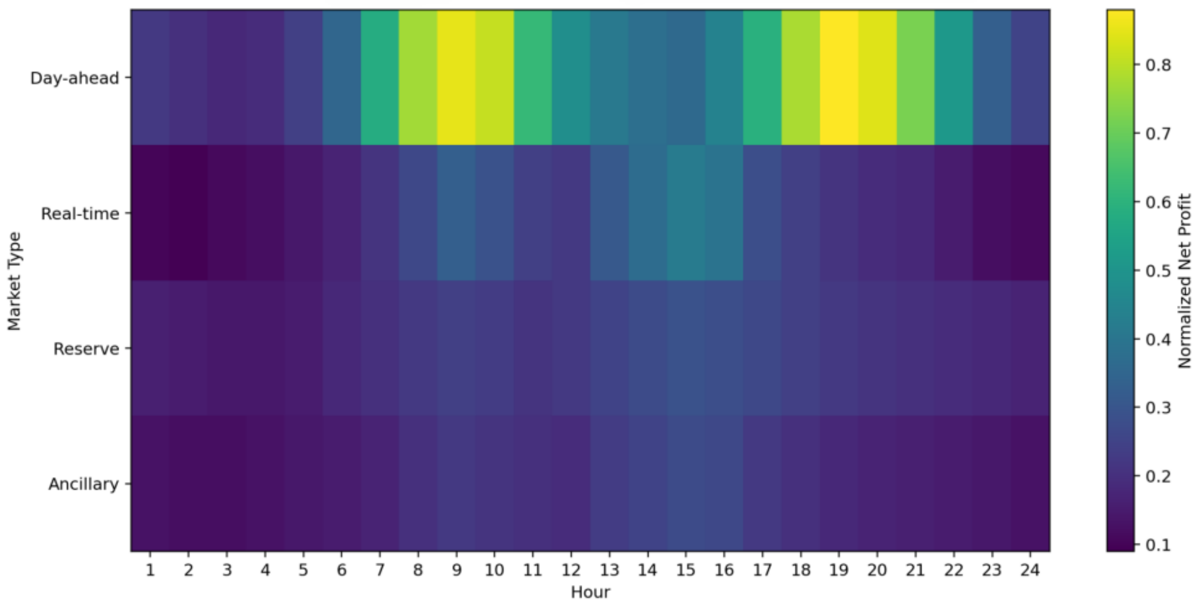

Figure 4: Heat map of hourly joint returns for the four categories of markets

As shown in Fig. 4, the proposed model does not show revenue collapse in the superposition period of high load and high volatility, but maintains the continuity of the revenue surface by relying on the co-allocation between markets. Compared with the single market independent bidding, the real-time deviation cost is reduced by 8.9%, and the spare revenue proportion is increased from 11.4% to 15.7%, indicating that the joint search mechanism can identify more effective market switching opportunities.

In order to investigate the degree of stability and the discrete distribution of deviation of the bidding results in each trading zone, this paper further draws the box plot of the quotation deviation, as shown in Fig. 5. The figure compares the distribution of the declared price deviation, the interquartile range, and the number of outliers in the test phase for the four trading partitions. The median deviation of the proposed method is maintained near 2.5%, the interquartile range is significantly reduced, and the number of extreme deviation points is less than that of the comparison model, indicating that state coding and boundary correction can jointly compress high deviation samples.

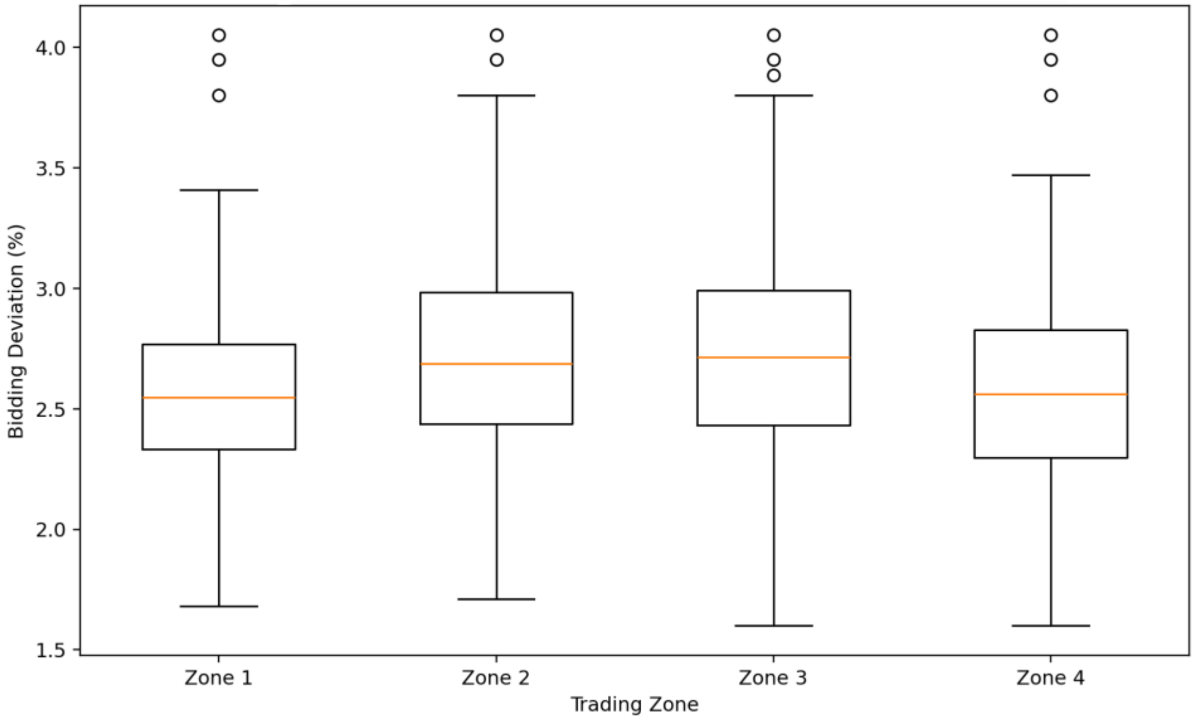

Figure 5: Box plots of quotation deviations for the four trade zones

In general, the proposed model can achieve the unity of revenue improvement, cost compression and deviation convergence in the multi-market collaborative filing scenario. Its advantage is not only reflected in the improvement of average results, but also reflected in the high load and high fluctuation period can still maintain good clearance consistency and declaration stability. After the complementary division of labor is formed among the markets, the dependence of the system on the return fluctuation of the single market is significantly weakened, and the robustness of the bidding strategy is enhanced. It can be seen that this method has strong practical application value, and can also provide reference for the subsequent research on collaborative bidding under multiple time scales and multiple constraints.

4.3 Comparative Experiments

In order to evaluate the comprehensive performance of the proposed model, three sets of comparison schemes are set up under the same data source, the same clearing mechanism and the same limit price rule: single market independent bidding, risk-free preference embedding and no boundary correction. The comparison indicators are selected as expected cost, average profit, CVaR, bid deviation and feasible rate, and the results are shown in Table 3.

Table 3: Comprehensive performance comparison under different methods

Method	Cost Reduction / %	Profit Increase / %	CVaR Reduction / %	Deviation / %	Feasibility / %
Single-market independent bidding	0.0	0.0	0.0	6.8	91.2
Without risk preference embedding	6.4	4.7	5.1	4.9	94.6
Without boundary correction	8.1	6.3	7.8	4.1	93.5
Proposed method	11.8	9.6	13.4	2.7	97.8

It can be seen from Table 3 that the proposed method is superior to the comparison schemes in the three core indicators of revenue, risk and feasible rate, indicating that joint search, preference embedding and boundary checking jointly improve the stability of multi-market bidding. Although the full model adds a small amount of computation, it embodies higher computational value in terms of revenue quality and tail loss control.

To further identify the contribution of each module to the results, ablation experiments were carried out and the results are listed in Table 4. In this experiment, only internal key structures are removed, and no external baselines are introduced to observe the change of model capability with module reduction.

Table 4: Comparison of the results of ablation experiments

Model Setting	Profit Increase / %	CVaR Reduction / %	Deviation / %	Feasibility / %
Without temporal state encoding	5.8	6.2	4.8	93.9
Without risk preference embedding	6.9	4.7	4.2	95.1
Without feasible-region correction	7.4	8.1	3.9	92.8
Full model	9.6	13.4	2.7	97.8

Table 4 shows that the timing state coding directly affects the efficiency of market switching identification and revenue capture, risk preference embedding mainly acts on tail loss compression, and feasible region correction determines the feasible rate of quotation and the convergence level of deviation.

The comprehensive results show that the proposed model can give consideration to revenue acquisition, tail risk suppression and quotation feasibility control under the joint action of price limit constraint and risk preference, and reflect a better joint decision-making ability. The joint search improves the cross-market portfolio identification accuracy, the preference embedding enhances the risk adaptation of bidding behavior, and the feasible region correction ensures that the output results are consistent with the boundary conditions. On the whole, this method is more in line with the actual operation requirements of multi-market collaborative bidding, and also provides a further technical basis for the subsequent model expansion for complex transaction scenarios.

4.4 Analysis of risk appetite and effect of limit price constraint

In order to show the cooperative variation characteristics of each performance index under different risk preference intensities, this paper draws the multi-index radar chart, as shown in Fig. 6. In the figure, the normalized average profit, CVaR reduction, feasible rate, offer stability and boundary utilization are used as five dimensions to compare the difference of strategy shape under different risk preference Settings. The results show that when the risk appetite coefficient increases from 0.1 to 0.7, the CVaR decreases from 17.9% to 13.4%, the feasible rate increases from 94.1% to 97.8%, and the average profit remains above 9.0%, indicating that the medium-high intensity risk appetite can better reduce the tail loss.

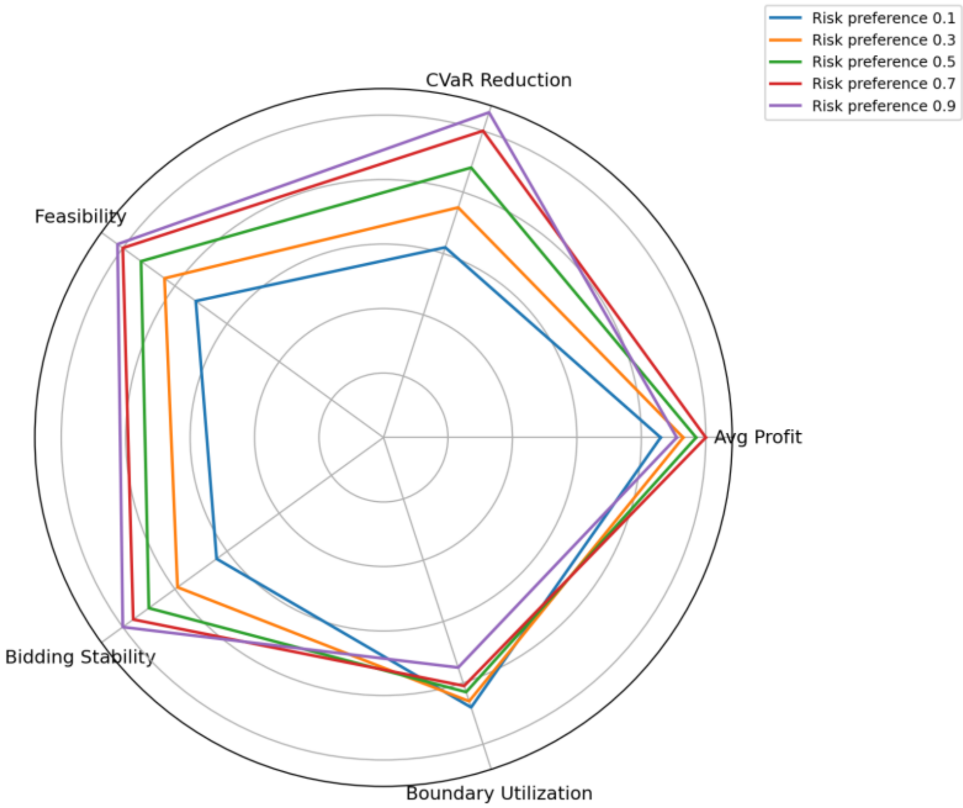

Figure 6: Multi-indicator radar plots for different risk preference coefficients

As shown in Fig. 6, when the risk appetite continues to increase to 0.9, although the quotation deviation further converges to 2.5%, the average profit falls back to 8.4%, indicating that too strong risk suppression will compress the tradable space. In contrast, the parameter interval around 0.7 forms a more balanced structure between profit, risk and feasible rate.

In order to characterize the joint impact of limit price contraction on the feasible region and revenue response surface of multi-market bidding, a 2D contour plot is further drawn, as shown in Fig. 7. In the figure, the horizontal axis is the shrinkage ratio of the upper bound of the price, the vertical axis is the coefficient of risk appetite, and the color represents the comprehensive return score. As the upper bound of price shrinks from 1.00 to 0.85, the return surface gradually moves down. However, when the risk appetite is in the range of 0.5-0.7, the decrease of the score is significantly smaller than that of the low preference region, indicating that the risk embedding mechanism can buffer the profit loss caused by the tightening of the boundary.

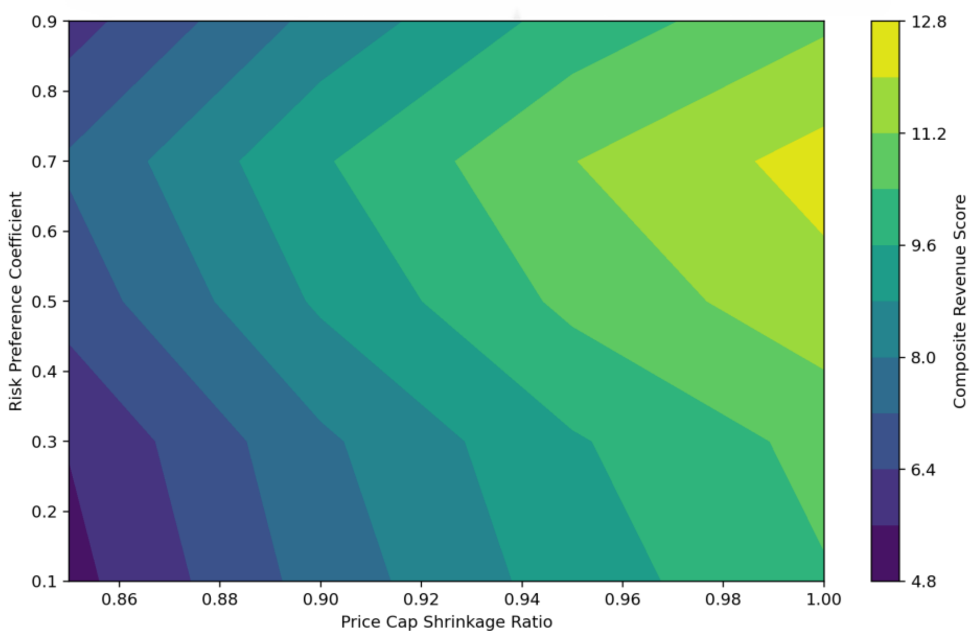

Figure 7: The integrated return contour plot of the ratio of limit price contraction and the coefficient of risk appetite

Based on the above, risk preference and limit price constraint are not independent adjustment items, but jointly shape the quotation boundary, risk exposure level and profit release space in the joint bidding process. When the limit price boundary remains moderately elastic, medium-high risk appetite is easier to maintain the stability of returns. When the boundary is continuously tightened, either too low or too high preference setting will weaken bid adaptability. Therefore, the risk coefficient and the limit price parameter need to be matched and set in the linkage framework to ensure that the multi-market joint bidding results have good robustness and enforceability.

5 Discussion

The experimental results show that the multi-market joint optimization bidding model considering risk preference under the limit price constraint forms a more balanced calculation structure among revenue acquisition, tail risk suppression, bidding feasibility and online solution stability. This advantage does not come from single module reinforcement, but is supported by time series state coding, risk preference embedding, joint search and feasible region correction. After the state encoding module compressed the day-ahead price, real-time deviation, reserve demand and boundary trigger information into a unified vector, the original scattered volatility relationship between the markets was transformed into a trainable correlation structure, so that the model could maintain a relatively stable revenue response in the periods of high load and high volatility. After embedding the risk preference parameter, the strategy update no longer only pursues the short-term profit peak, but synchronously integrates the tail loss under the CVaR constraint into the trade-off process, which is the main reason why the profit increase reaches 9.6% while the downside risk still decreases 13.4%.

From the perspective of the effect of the limit price boundary, the boundary contraction does not simply compress the revenue space, but redistributes the capacity occupation and switching rhythm of different markets. When the price upper bound decreases, the compensation effect of the real-time market and the auxiliary service market increases, and the revenue share of the day-ahead market converges. The proposed method keeps the quotation continuous through soft projection correction, so that the boundary control and the market switch are in the same update link. Therefore, when the upper bound of the price shrinks to 0.90, the quotation feasible rate of 96.9% and the profit increase of 9.1% can still be maintained. The comparison results also show that the recognition of cross-market linkage signals by the model is significantly weakened after removing the temporal state coding. After removing the risk preference embedding, although the strategy can still maintain a certain income, the tail loss control ability decreases more obviously. After removing the feasible region correction, the quotation deviation and the cross-border probability rise simultaneously. This demonstrates that the value of the complete framework lies in bringing benefit, risk, and margin treatment into the same computational surface, rather than patching them separately.

From the perspective of calculation and implementation, the model takes an average of 0.41 s to make a single round of decision, which can adapt to the multi-market hourly bidding update. Although the joint search and safety check increase part of the calculation, the overall efficiency still has good engineering adaptability. This method is suitable for power trading scenarios with strong rule constraints and emphasizing stable revenue, and also has the basis for transferring to other intelligent decision-making tasks.

6 Conclusions

Focusing on the multi-market joint optimization bidding task considering risk preferences under the limit price constraint, this paper constructs a computational framework consisting of time series state representation, risk preference embedding, joint search generation and feasible region verification. The experimental results show that the proposed method can maintain revenue growth, tail risk contraction and quotation feasibility improvement at the same time in the multi-market linkage environment. The expected cost decreases by 11.8%, the average profit increases by 9.6%, the CVaR decreases by 13.4%, and the quotation feasibility rate reaches 97.8%. It shows that the model can better adapt to the trading scenario with strong rule constraints and obvious price fluctuations. The limitations of this paper are mainly reflected in two aspects. First, the current experiment is based on the historical samples of four trading zones, and the market size and transaction categories are still limited, so the description of higher-dimensional cross-zone coupling scenarios still needs to be extended. Second, the risk preference parameter is set in a piecewise manner, which has not yet realized the adaptive update with the feedback and environmental changes. Future research can introduce more complex market topology, dynamic preference learning mechanism and online migration update method under the collaborative framework of graph neural network and reinforcement learning, and combine more fine-grained clearing rules and real-time data flow to further enhance the generalization ability, response efficiency and deployment stability of the model in large-scale intelligent trading systems. In addition, the uncertainty calibration module can be further introduced to jointly model the scenery prediction error, load mutation and price jump, so as to maintain a higher consistency of state input, boundary constraints and revenue evaluation, so as to improve the ability of cross-regional deployment and project landing adaptation.

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