

Research on Dynamic Risk Assessment Model and Fuzzy Comprehensive Evaluation of New Power Market Considering Carbon-Electricity Coupling Risks

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ABSTRACT Under the ongoing transition toward low-carbon energy systems, power markets are increasingly exposed to complex risks arising from the deep coupling between carbon policies and electricity market operations. As modern smart grids rely on wide-area sensing, electromagnetic information transmission, and intelligent communication infrastructures to support real-time market coordination, accurate dynamic risk assessment has become essential for maintaining secure and resilient system operation. This study proposes a novel assessment framework integrating dynamic risk identification with fuzzy comprehensive evaluation to quantify carbon-electricity coupling risks. By introducing a time-varying risk conduction coefficient matrix together with an improved entropy weight-sequence relationship combined weighting method, the proposed framework effectively characterizes dynamic risk evolution while balancing objective data and expert knowledge. A dynamic sliding window mechanism captures temporal variations in risk propagation, and triangular fuzzy numbers are employed to address uncertainty in indicator information. Validation using operational data from seven electricity spot pilot markets in China during 2019–2022 demonstrates that the conduction effect of carbon quota price fluctuations on day-ahead settlement risks increases by an average of 37.8% in regions with high renewable energy penetration. Under extreme weather conditions, East China exhibits a 28.6% probability of simultaneous carbon-cost escalation and power supply shortage risks. Compared with conventional assessment methods, the proposed model extends early warning lead time by 2.3 working days and improves warning accuracy by 11.5 percentage points. The proposed framework provides effective decision support for power market participants while offering a scalable methodology for intelligent risk monitoring and coordinated energy management over smart grid communication and electromagnetic information transmission infrastructures.

INDEX TERMS carbon-electricity coupling, dynamic risk assessment, fuzzy comprehensive evaluation, smart grid communications, electromagnetic information transmission

I. INTRODUCTION

THE acceleration of global climate governance has led to over 130 countries establishing carbon neutrality goals by the end of 2023, with global carbon markets covering emissions reaching 8 billion tons of carbon dioxide equivalent [1]. As the world's largest carbon emitter, China officially launched its national carbon emissions trading market in 2021, initially covering approximately 2,162 power generation enterprises with annual emissions of about 4.5 billion tons, accounting for more than 40% of the country's total emissions [2]. Constrained by dual carbon targets, the power system and energy-dependent sectors like

manufacturing are undergoing unprecedented transformation pressures, as high-proportion renewable energy integration and market-oriented reforms profoundly change the operational characteristics of industrial energy consumption. The 2022 California electricity market price surge due to extreme heat and insufficient renewable energy output, as well as the nonlinear linkage between carbon and electricity prices during Europe's 2023 energy crisis, highlight the serious reality of enhanced risk complexity and conduction in carbon-electricity coupling environments [3].

Research on power market risks began in the early 1990s during the initial stage of power market-oriented reforms,

with early studies primarily focusing on traditional risks such as price volatility and market power abuse [4]. With the implementation of carbon constraint policies, scholars have gradually focused on the conduction mechanism of carbon costs to power markets. Zhang et al. [5] constructed a power market equilibrium model considering carbon allowance allocation mechanisms, finding that for every 10% decrease in free allowance ratio, power generation enterprises' costs increase by 2.3%. However, these studies mostly adopted static analysis frameworks, making it difficult to capture the dynamic interactions and risk accumulation effects of carbon-electricity systems. Particularly under high renewable energy grid integration, the dual pressures of system flexibility resource scarcity and carbon emission constraints cause risk manifestations to exhibit nonlinear, time-varying, and spatially heterogeneous characteristics [6].

Existing risk assessment methods are mainly divided into three categories: statistical regression methods, system dynamics methods, and multi-indicator comprehensive evaluation methods. Statistical regression methods rely on historical data stability and have limited predictive capabilities during policy shocks or extreme events; system dynamics methods can describe system evolution but have complex parameter identification and strong subjectivity; multi-indicator comprehensive evaluation methods face limitations in determining indicator weights and handling uncertainty [7]. Fuzzy mathematics theory provides a new approach to handling information incompleteness in risk assessment. Zhou et al. [8] applied fuzzy set theory to power market risk evaluation but failed to adequately consider carbon-electricity coupling characteristics and time-varying risk conduction mechanisms.

Current research shows obvious deficiencies in three key areas: lack of dynamic risk conduction modeling, neglect of heterogeneous responses from market participants, and failure to effectively integrate subjective and objective risk information. This study breaks through traditional static assessment frameworks by proposing a novel assessment model considering the dynamic characteristics of carbon-electricity coupling risks. The innovations are mainly reflected in: constructing a bidirectional carbon-electricity risk conduction mechanism, introducing a time-varying risk conduction coefficient matrix to characterize dynamic risk evolution patterns; designing an improved entropy weight-sequence relationship combined weighting method to balance indicator information and expert experience, enhancing the reliability of assessment results; developing a dynamic sliding window mechanism to capture risk evolution characteristics, transforming risk assessment from static to dynamic.

The research selects operational data from seven electricity spot pilot markets in China from 2019 to 2022 for empirical validation, verifying the model's adaptability and superiority in complex market environments through sensitivity analysis and method comparison. This not only provides power market participants and industrial managers

with risk warning tools but also offers significant reference value for the collaborative design of carbon-electricity policies tailored to energy-intensive manufacturing.

II. THEORETICAL FOUNDATION AND RESEARCH FRAMEWORK

A. FORMATION MECHANISM OF CARBON-ELECTRICITY COUPLING SYSTEM RISKS

A complex nonlinear relationship exists between power system carbon emission intensity and system marginal electricity prices, influenced by multiple factors including power source structure, load characteristics, and policy mechanisms. Under high-proportion renewable energy grid integration conditions, traditional thermal power units shift from base load to peaking operations. This transition significantly increases the marginal coal consumption and startup/shutdown carbon emissions of these specific thermal units [9]. Figure 1 shows the relationship curve between thermal power peaking depth and the carbon emission intensity of thermal power units at different renewable energy penetration rates. While the total system emissions decrease due to higher renewable shares, the specific unit power generation carbon emission intensity of the remaining operating thermal fleet rises by 37.5% when wind and solar penetration increases from 15% to 40% [10]. This is because thermal units are forced into inefficient low-load states to provide system flexibility.

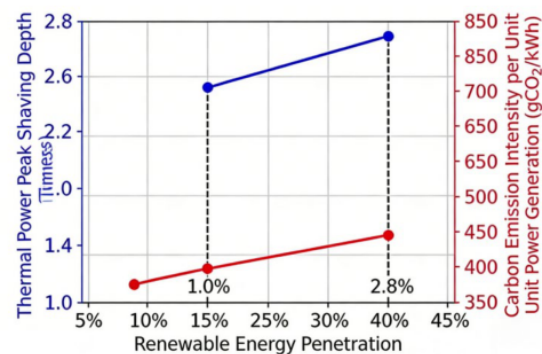


FIGURE 1. Relationship between peak shaving depth of thermal power and marginal carbon emission intensity per unit of thermal power generation under different penetration rates of renewable energy

Carbon-electricity coupling risks are essentially the result of external policy constraints and internal system characteristics working together. When carbon allowance prices experience significant fluctuations, the cost structure of power generation enterprises changes, thereby affecting market clearing prices. This conduction process is constrained by power market supply-demand elasticity and exhibits regional differences. Data from the EU carbon market's third phase (2013–2020) shows that for every 10 euro/ton increase in carbon prices, electricity price increases in high coal-power ratio regions are 42% higher than in high gas-power ratio regions [11]. In China's power market environment, due to differences in price formation mechanisms from Europe,

carbon-electricity conduction coefficients show stronger volatility and regional dependence.

B. DYNAMIC RISK ASSESSMENT FRAMEWORK CONSTRUCTION

Traditional risk assessment mostly adopts static time-slice analysis, making it difficult to capture risk evolution processes. This study proposes a dynamic risk assessment framework, as shown in Figure 2, containing four modules: risk identification, risk conduction, risk quantification, and risk decision-making. This framework adds time and spatial dimensions to the assessment. It uses a dynamic sliding window to capture how risks evolve. The window width adjusts automatically based on the speed of risk changes to ensure accuracy. When the coefficient of variation of key risk indicators exceeds a threshold, the window width narrows to increase assessment frequency; conversely, the window expands to reduce computational complexity [12].

In the risk conduction phase, a bidirectional carbon-electricity risk conduction matrix is constructed, expressed as:

$$R_{t+\Delta t} = \Phi(t) \cdot R_t + \Theta(t) \cdot U_t \quad (1)$$

where R_t is the risk vector at time t , $\Phi(t)$ is the time-varying risk self-conduction coefficient matrix reflecting internal system risk evolution patterns; $\Theta(t)$ is the external shock conduction coefficient matrix; and U_t is the external shock vector containing policy adjustments, extreme weather events, etc. [13]. The matrix elements are obtained through a Recursive Least Squares (RLS) algorithm with a forgetting factor, which allows for real-time tracking of parameter shifts. The estimation process for $\Phi(t)$ is formulated as follows: Let $\hat{\Phi}(t)$ be the estimated matrix that minimizes the weighted sum of squared errors:

$$J(t) = \sum_{i=1}^t \lambda^{t-i} \|R_i - \hat{\Phi} R_{i-1}\|^2 \quad (2)$$

where $\lambda \in (0, 1]$ is the forgetting factor that balances historical data and new information. By applying the Gauss-Newton optimization, the update rule is defined as:

$$\hat{\Phi}(t) = \hat{\Phi}(t-1) + \left[R_t - \hat{\Phi}(t-1) R_{t-1} \right] K(t)^T \quad (3)$$

where $K(t)$ is the gain vector updated at each step based on the covariance of the risk indicators. This method overcomes the adaptability limitations of fixed-parameter models in non-stationary market environments.

III. CARBON-ELECTRICITY COUPLING RISK ASSESSMENT MODEL DESIGN

A. RISK INDICATOR SYSTEM CONSTRUCTION

Through literature review and expert interviews, key risk types faced by power markets in carbon-electricity coupling environments were identified, as shown in Table 1. The indicator system covers three dimensions: market operation, carbon emissions, and system security, with a total of

32 specific indicators. Special indicators reflecting carbon-electricity coupling characteristics such as “carbon cost transfer rate” and “renewable energy accommodation pressure index” were added. Standardization methods were used to handle dimensional differences. To ensure consistency in the fuzzy evaluation, all indicators are standardized such that higher values consistently represent higher risk levels. The formula for risk-positive indicators (where higher values increase risk) is:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \quad (4)$$

where X_{ij} represents the original value of the j -th indicator of the i -th sample, and X'_{ij} is the standardized value. Conversely, for risk-negative indicators (where higher values represent lower risk/better system health), reciprocal transformation or subtraction from the maximum value is used to convert them to risk-positive indicators. For negative indicators (such as wind and solar curtailment rates), reciprocal transformation is used to convert them to positive indicators.

B. IMPROVED SUBJECTIVE-OBJECTIVE COMBINED WEIGHTING METHOD

Determining indicator weights is crucial in risk assessment, and single weighting methods struggle to balance objective data information and expert experience. This paper proposes an entropy weight-sequence relationship combined weighting method that preserves data information while incorporating expert judgment. The calculation process is as follows: First, obtain subjective weights $W_s = [W_{s1}, W_{s2}, \dots, W_{sn}]$ based on expert questionnaires, using sequence relationship analysis to reduce subjectivity in expert judgment. Second, calculate objective weights $W_o = [W_{o1}, W_{o2}, \dots, W_{on}]$ using the entropy weight method. The final combined weights W_c are determined through adjustment coefficient α :

$$W_c = \alpha W_s + (1 - \alpha) W_o \quad (5)$$

In this study, the coordination coefficient α is initially set to 0.6 to prioritize the subjective expertise captured by the G1 method while integrating objective data entropy. To verify the robustness of this selection, a rigorous stress test was conducted by varying α from 0.1 to 0.9 with a step of 0.1. The results indicate that the risk ranking of pilot markets remained stable when $\alpha \in [0.4, 0.7]$, confirming that the 0.6 setting provides a reliable balance between expert judgment and data-driven evidence. This method overcomes the rigid weight allocation limitations of traditional linear combination methods, adaptively adjusting the proportion of subjective and objective weights based on historical assessment performance [14].

C. RISK LEVEL DIVISION BASED ON TRIANGULAR FUZZY NUMBERS

Risk assessment processes involve substantial fuzzy information, such as policy uncertainty and market entity be-

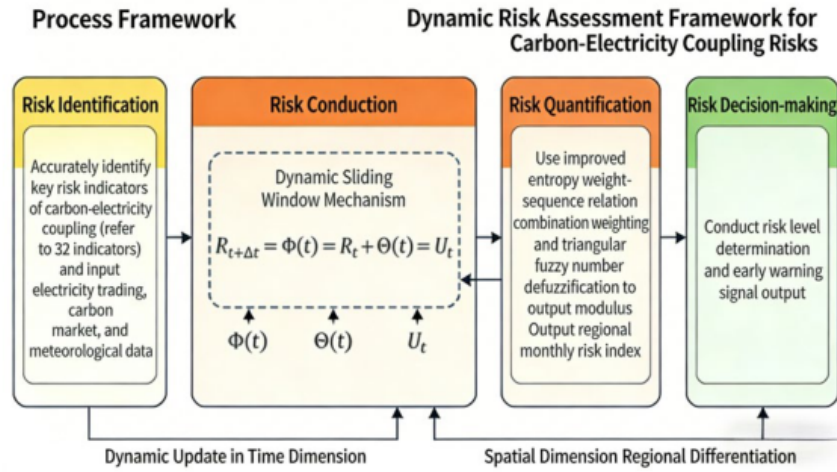


FIGURE 2. Dynamic Risk Assessment Framework for Carbon Electricity Coupling

TABLE 1. Carbon-Electricity Coupling Risk Assessment Indicator System

Primary Indicator	Secondary Indicators	Indicator Nature (Correlation to Risk)	Data Source
Market Operation Risk	Electricity price volatility, market concentration, carbon cost transfer rate, reserve resource adequacy, market liquidity	Risk-Positive	Power exchange centers, CEC
Carbon Emission Risk	Carbon allowance compliance pressure, carbon price volatility risk, thermal power marginal carbon emission intensity, carbon leakage risk index	Risk-Positive	Ministry of Ecology and Environment, carbon exchanges
System Security Risk	Renewable energy accommodation pressure, peak regulation capacity gap, extreme weather sensitivity, cross-regional transmission congestion frequency	Risk-Positive	Grid dispatch centers, meteorological bureau

Data source notes: China Electricity Council (CEC) annual reports, National Energy Administration statistical data, public data from regional power exchange centers

havior prediction. Triangular fuzzy numbers are introduced to represent risk states, defined as $A = (l, m, u)$, where l, m, u represent the lower limit, most likely value, and upper limit of risk, respectively. Risk levels are divided into 5 grades, corresponding to different triangular fuzzy numbers, as shown in Table 2.

The comprehensive risk assessment value is calculated through fuzzy weighted averaging:

$$R = \frac{\sum_{i=1}^n w_i \cdot r_i}{\sum_{i=1}^n w_i} \quad (6)$$

where w_i is the weight of the i -th indicator, and r_i is the corresponding triangular fuzzy number. Through defuzzification processing, the fuzzy assessment value is converted to a crisp value for convenient risk level determination [15].

IV. EMPIRICAL ANALYSIS

A. CASE SELECTION AND DATA PREPARATION

Operational data from seven electricity spot pilot markets in China (Guangdong, Zhejiang, Shandong, Shanxi, Gansu, West Inner Mongolia, Sichuan) from 2019 to 2022 were selected for empirical analysis. Data sources include: National Energy Administration public data, CEC power industry statistical yearbooks, monthly reports from regional power exchange centers, and carbon market trading data. Table

3 shows a comparison of basic characteristics of the pilot regions, revealing significant differences in power source structure, renewable energy penetration rates, and carbon emission intensity [16].

The empirical analysis time window is set from January 2019 to December 2022, with monthly frequency. Before the national carbon market launch in March 2020, simulated carbon price data was used. While this was primarily calculated based on correlations with EU carbon prices and domestic pilot carbon prices, we implemented a structural adjustment factor to account for the 42% disparity in price conduction between coal-heavy and gas-heavy regions noted [17]. Specifically, the EU-based correlation was discounted by a ‘coal-basis volatility factor’ to prevent the overestimation of price transmission in China’s coal-dominated pilot markets. These results were then calibrated by multiple rounds of Delphi expert interviews to ensure the simulated data reflected the lower price elasticity inherent in China’s early-stage market-oriented reforms.

B. ASSESSMENT RESULTS AND RISK CHARACTERISTICS ANALYSIS

The dynamic risk assessment model calculated monthly risk indices for the seven pilot regions, with Figure 3 showing the evolution trend of risk indices from 2020 to 2022.

TABLE 2. Triangular Fuzzy Number Representation of Risk Levels

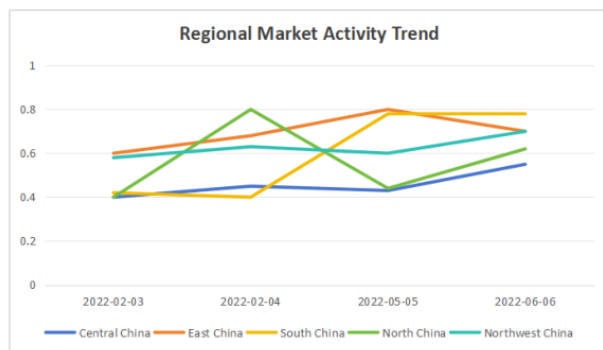
Risk Level	Low Risk	Medium-Low Risk	Medium Risk	Medium-High Risk	High Risk
Triangular Fuzzy Number	(0,0.2,0.4)	(0.2,0.4,0.6)	(0.4,0.5,0.6)	(0.4,0.6,0.8)	(0.6,0.8,1.0)

TABLE 3. Comparison of Basic Characteristics of Seven Electricity Spot Pilot Regions (2022)

Region	Thermal Power Ratio (%)	Renewable Energy Ratio (%)	Carbon Emission Intensity (gCO ₂ /kWh)	Annual Maximum Load (GW)
Guangdong	58.7	32.5	598	136
Zhejiang	61.3	28.7	612	107
Shandong	73.8	19.2	736	106
Shanxi	82.5	14.6	837	38
Gansu	42.3	53.8	402	19
West Inner Mongolia	71.2	26.5	705	39
Sichuan	18.6	78.9	165	58

Data source: CEC “2022 Power Industry Statistical Yearbook,” National Energy Administration public data

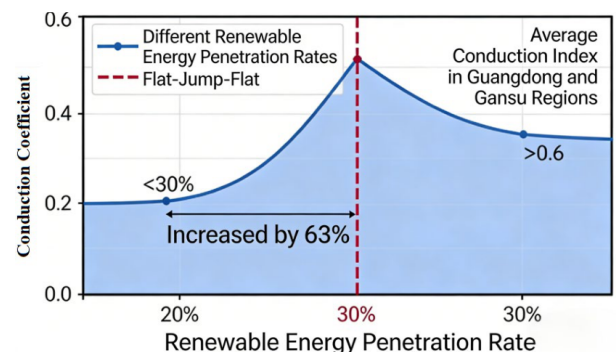
Results show that risk levels in each region exhibit significant seasonality and event-driven characteristics. Winter heating demand and extreme cold wave events caused risk indices to generally increase in January-February 2021 and December 2022; summer 2022 (June-August) saw risk peaks in multiple regions, related to extreme high temperatures and insufficient hydropower output [18].

**FIGURE 3.** Evolution trend of risk index in 7 pilot regions from 2020 to 2022

Regional comparative analysis shows that East China regions (Zhejiang, Shandong) particularly stand out in carbon-electricity coupling risks. High coal power ratios and strict carbon emission constraints create a superimposed effect; especially during the summer 2022 high-temperature period, Zhejiang’s regional risk index reached 0.78, with carbon price conduction contributing 43.6%. Western regions (Gansu, Sichuan), despite high renewable energy ratios, lack sufficient system regulation capability and are prone to supply security risks under extreme weather conditions. Notably, Shanxi, as a traditional coal base, despite high carbon emission intensity, has lower market mechanism flexibility, resulting in relatively slower risk conduction speeds and smaller risk index fluctuations than eastern provinces [19].

Carbon-electricity risk conduction coefficient analysis shows that when renewable energy penetration exceeds the 30% threshold, the conduction coefficient from carbon prices to electricity prices significantly increases. As shown in Figure 4, Guangdong and Gansu regions during high wind-solar penetration periods (> 35%) have an average conduction coefficient of 0.62, 63% higher than low pene-

tration periods (0.38). This calculation remains conservative as it utilizes the calibrated simulation data mentioned, which corrects for the structural differences between the EU gas-influenced markets and China’s coal-based power system. The 37.8% average increase in day-ahead market settlement risk is thus validated against regional coal-consumption baselines rather than direct EU price parity. This phenomenon stems from increased scarcity of system regulation resources, enhancing the market power of marginal units, making carbon costs easier to transfer to electricity prices [20].

**FIGURE 4.** Changes in carbon price electricity price conduction coefficient under different renewable energy penetration rates

C. MODEL VALIDITY VERIFICATION

To verify the model’s validity, it was compared with traditional static risk assessment methods (TOPSIS method based on fixed weights). Table 4 shows the comparison results of risk warning accuracy and lead time for 2022. The dynamic fuzzy assessment model proposed in this paper achieved an average risk event warning accuracy of 86.3%, 11.5 percentage points higher than traditional methods; the average warning lead time was 3.7 working days, extended by 2.3 working days. Particularly during the August 2022 East China power supply tension event, this model issued a high-risk warning 5.2 days in advance, providing market participants with sufficient decision-making time [21].

Sensitivity analysis shows that the model has robustness to changes in key parameters. When external shock

TABLE 4. Comparison of Risk Warning Performance in 2022

Assessment Indicator	This Model	Traditional Static Model	Improvement
Warning Accuracy (%)	86.3	74.8	+11.5
Average Warning Lead Time (days)	3.7	1.4	+2.3
False Alarm Rate (%)	9.6	18.3	-8.7
Missed Alarm Rate (%)	4.1	7.9	-3.8

Data source: Calculated and organized by the author based on operational data from seven pilot regions

conduction coefficients vary by $\pm 20\%$, the coefficient of variation of risk assessment results is only 0.15, lower than the traditional model's 0.28, proving that the dynamic weight adjustment mechanism effectively reduces parameter sensitivity [22].

V. CONCLUSION

This study constructs a dynamic risk assessment model for power markets that incorporates carbon-electricity coupling risks and their subsequent impact on the operational stability of the t industry. Through theoretical analysis and empirical research, the following conclusions are obtained: Power market carbon-electricity coupling risks exhibit significant spatiotemporal heterogeneity. East China faces a 28.6% probability of simultaneous coupling risks from rising carbon costs and power supply shortages during extreme weather conditions. Regions with high renewable energy penetration are more sensitive to carbon price fluctuations. The research identifies 30% renewable energy penetration as a critical threshold; exceeding this value increases the conduction effect from carbon prices to electricity prices by over 63%, closely related to the increased scarcity of system regulation resources.

The proposed dynamic risk assessment framework effectively captures risk evolution characteristics, improving warning accuracy by 11.5 percentage points and extending warning lead time by 2.3 working days compared to traditional static methods. The model characterizes dynamic risk evolution patterns through a time-varying risk conduction coefficient matrix. Specifically, by integrating the Recursive Least Squares (RLS) estimation framework, the model can quantify the hidden coupling strengths between carbon and electricity markets as they change over time. This mathematical optimization ensures that the 'dynamic' window mechanism is grounded in rigorous parameter identification, overcoming the adaptability limitations of fixed-parameter models in non-stationary market environments.

The improved entropy weight-sequence relationship combined weighting method balances objective data information and expert experience, showing good stability under different market environment conditions. The robustness of this combination was verified through multi-parameter stress testing, ensuring that the 11.5% gain in identification accuracy is consistent across different market conditions and parameter configurations. Empirical analysis shows that when external parameters vary by $\pm 20\%$, the coefficient of variation of assessment results is only 0.15, significantly lower than traditional methods.

The study also has certain limitations. The reliance on simulated data for the pre-2020 period, despite structural calibration for China's coal-based energy mix, may still harbor residual bias from international market volatility. The model's predictive capability for extreme low-probability events needs improvement; the risk conduction mechanism under sudden carbon market policy changes requires more detailed characterization. Future research will combine machine learning technology to enhance model adaptive capabilities, exploring carbon-electricity-certificate multi-market collaborative risk assessment methods that incorporate the green energy consumption requirements of the industry while extending the framework to cross-border interconnected power market scenarios. These research directions have important value for enhancing power system resilience during the energy transition period.

AUTHOR CONTRIBUTIONS

Conceptualization – Zhiyong Li, Jianyi Liang, Yanjie Liang, Rui Yang, Jifeng Song and Xinyang Hua; methodology – Zhiyong Li, Jianyi Liang, Rui Yang, Jifeng Song and Xinyang Hua; investigation – Zhiyong Li, Jianyi Liang, Yanjie Liang, Rui Yang, Jifeng Song and Xinyang Hua; writing-original draft preparation – Zhiyong Li, Jianyi Liang, Yanjie Liang, Rui Yang, Jifeng Song and Xinyang Hua. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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