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A Risk Monitoring and Early Warning Model for Transactions in the Southern Regional Electricity Market Based on a Novel Power System

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Abstract The smooth and healthy development of the power market is an important goal of power market management. During the operation of the power market, the operation risk plays a crucial role in the safe, reliable and stable development of the power market. The article starts from the deviation probability that exists in the new energy access to the southern regional power market, combines with the southern regional power market clearing model, and constructs the power market transaction risk evaluation index system. It also utilizes the cloud entropy method to solve the index weights, and then combines the cloud model with the material element topology model to construct the material element topology cloud model for evaluating the transaction risk level of the southern regional power market. Based on Stacking integrated learning, a variety of machine learning algorithms are introduced to construct an early warning model for power trading risks. The study shows that the comprehensive score of the power market transaction risk in the southern region is 1.52, and the overall risk rating is "low", with a low leakage rate of the power market transaction risk warning, the average value of which is only 2.05%. Relying on the access of new energy in the new power system, combined with the power market transaction risk assessment and early warning model, the accurate early warning of power market transaction risk can be realized, laying a foundation for ensuring the stability of power market transactions.

Index Terms southern regional electricity market, cloud entropy method, object-element topologizable cloud model, Stacking integrated learning, risk early warning models

I. Introduction

The power industry is a cornerstone of modern societal development, and the stable operation of the power market is critical to the growth of the socio-economic sector. Currently, the renewable energy penetration rate in China's southern region (Guangdong, Guangxi, Yunnan, Guizhou, and Hainan) is approaching 60%, with emerging market entities such as virtual power plants and new energy sources gaining prominence. Market-based electricity transactions account for over 70% of total electricity transactions, featuring a variety of market types including long-term, spot, and ancillary services markets, and establishing a multi-product, high-frequency transaction mechanism that facilitates the optimal allocation of power resources across provinces and regions [1]-[4].

The new power system is driving the power market toward a clean, low-carbon, safe, reliable, intelligent, flexible, efficient, and open interactive structure, promoting the development of power market transactions. However, it also brings some risks, such as physical constraints on the network, green certificate risks, and algorithm similarity risks [5]-[8]. Power trading serves as a vital link between power supply and demand, playing a significant role in promoting efficient energy utilization, economic development, and reducing greenhouse gas emissions. However, due to its inherent complexity and uncertainty, it presents unprecedented challenges to market participants in practical applications [9]-[11].

Power market transaction risks stem from multiple sources, including price fluctuations, supply-demand imbalances, policy adjustments, and natural disasters. These risks not only impact the stable operation of the power market but also directly affect the economic benefits and social responsibilities of power companies [12]-[15]. To ensure the normal operation of the power market, comprehensive and accurate market monitoring and risk warning analysis are required. Through monitoring and warning of power transactions, unfair competitive behaviors can be promptly identified and corrected, maintaining the order of fair competition in the market. Additionally, market supply and demand conditions and price fluctuations can be analyzed, warnings issued, and corresponding response measures formulated to promote the healthy and stable development of the market [16].

Existing risk monitoring and early warning methods struggle to address uncertainty issues in complex systems, leading to limitations in the accuracy and timeliness of risk warnings, as well as a lack of scientific rigor and objectivity in warning outcomes. As a result, many researchers have conducted studies on this topic and put forward their own perspectives. Reference [17] uses power transaction data as input to conduct anomaly monitoring and early warning design for power market transactions under the Local Outlier Factor algorithm and its improved algorithm (Local Accessible Density of k-Nearest Neighbors) and the Nearest Distance to Center algorithm. Reference [18] introduces an internal control compliance risk monitoring mechanism for power transaction institutions, which is primarily realized through the developed internal control compliance risk monitoring system, which is now operational. Literature [19] established a power transaction risk warning model oriented toward market price fluctuation risks and proposed corresponding warning mechanisms. Literature [20] uses principal component analysis to extract key risk features from power sales data and performs adaptive classification on related historical data. Under the adaptive sparrow optimization density peak clustering algorithm, risks are processed in a graded manner, and dynamic risk early warning is achieved in the stacked identification model. The effectiveness of this early warning method was explored through verification using data from the provincial power trading management platform. Literature [21] investigates the application of ARIMA and SARIMAX models in power price fluctuation risk prediction modeling and early warning, and establishes a new early warning mechanism based on power price distribution characteristics and power fluctuation risk indicators.

The risk of power market operation is a problem that involves various subjects in the power market, government regulators, trading centers and other aspects that need attention, so it is necessary to synthesize multiple subjects in order to realize the risk monitoring and early warning of power market transactions. In this paper, on the basis of considering the access to new energy grids in the new power system, we constructed the southern regional power market clearing model, and based on this, we designed the power market transaction risk evaluation index system. The cloud model and entropy weight method are used to solve the weights of the indicators, and the cloud model is combined with the material element topology model to construct an improved material element topology cloud model to evaluate the risk level of power market transactions. Support vector machine, random forest, K-nearest neighbor algorithm, extreme gradient boosting tree and other machine algorithms are introduced and combined with the Stacking integrated learning algorithm to construct an early warning model for the risk of electricity addition. For the above methods, the article carries out a validation analysis through simulation experiments, aiming to provide reliable early warning results for the stability of power market transactions in the southern region.

II. Risk Evaluation Model for Electricity Market Transactions Based on Keto Cloud

Power spot market is the symbol of modern power market, without power spot market can not be called modern power market. Relying on the trading scene of the power spot market, combined with the power market trading risk operation scene, in order to realize the risk warning of the power market operation, so as to better protect the stable operation of the power trading market, and enhance the optimization of the scheduling level of power resources.

II. A.Methodology for constructing operational scenarios for trading risk

It is inevitable that there will be deviation between the predicted value and the actual value of the power transaction operation risk early warning, which leads to the discrepancy between the actual value and the declared value. This paper assumes that the prediction error of new energy output and load demand a few days ago satisfies the normal distribution with mean value 0. A large number of scenarios are generated by sampling through the Latin supraliminal method and combined with the integrated learning to control the uncertain power trading operation risk.

(1) PV power output deviation probability distribution model

The PV power output uncertainty model is:

$$P_t^{PV,a} = P_t^{PV,pre} + \Delta P_t^{PV} \tag{1}$$

where $P_t^{PV,a}$ is the actual output of the PV unit in time period t, $P_t^{PV,pre}$ is the predicted output of the PV unit in time period t, and ΔP_t^{PV} is the power deviation of the PV output.

The probability distribution of the power deviation ΔP_t^{PV} caused by the uncertainty of PV power output is:

$$f(\Delta P_t^{PV}) = \frac{1}{\sqrt{2\pi}\sigma_t^{PV}} \exp\left(-\frac{(\Delta P_t^{PV})^2}{2\sigma_t^{PV}}\right) \tag{2}$$

where σ_t^{PV} is the maximum uncertainty value of power that may occur in the process of PV power generation, this paper takes it as 10% of the predicted output value of PV power plant in time period t.

(2) Probability distribution model of wind turbine power deviation

The wind turbine output power uncertainty model is:

$$P_t^{w,a} = P_t^{w,pre} + \Delta P_t^w \tag{3}$$

where $P_t^{w,a}$ is the actual output of WTGs in time period t, $P_t^{w,pre}$ is the predicted output of WTGs in time period t, and ΔP_t^w is the power deviation of WTG output.

The probability distribution of the power deviation ΔP_t^w caused by the uncertainty of WT output is:

$$f(\Delta P_t^w) = \frac{1}{\sqrt{2\pi}\sigma_t^w}\exp\left(-\frac{(\Delta P_t^w)^2}{2\sigma_t^w}\right) \tag{4}$$

where σ_t^w is the maximum uncertainty value of power that may occur in the process of wind power generation, and this paper takes it as 10% of the predicted output value of WTGs in time period t.

(3) Load demand deviation probability distribution model

The load demand uncertainty model is:

$$P_t^{load,a} = P_t^{load,pre} + \Delta P_t^{load} \tag{5}$$

where $P_t^{load,a}$ is the actual load demand for time period t, $P_t^{load,pre}$ is the load demand forecast for time period t, and ΔP_t^{load} is the load demand power deviation.

The probability distribution of power deviation ΔP_t^{load} due to load demand uncertainty is:

$$f(\Delta P_t^{load}) = \frac{1}{\sqrt{2\pi}\sigma_t^{load}}\exp\left(-\frac{(\Delta P_t^{load})^2}{2\sigma_t^{load}}\right) \tag{6}$$

where σ_t^{load} is the maximum possible power uncertainty value of the load demand, which in this paper is taken to be 5% of the predicted value of the load demand in time period t.

After modeling the probability distribution of price deviations at each moment in the day-ahead and real-time markets, data sampling is required to derive different sample sets of random prices for model solving. In this paper, the Latin Hypercube Sampling (LHS) method is used to extract the random sample groups of electricity prices, which is a superior method to the traditional Monte Carlo sampling method [22]. The LHS method has a great improvement in the one-dimensional projection and the uniform stratified distribution, which greatly improves the distribution of the sample points in the low dimension, and it can evenly cover the whole probability distribution, which greatly improves the sampling efficiency. The specific process of the method is as follows:

Assuming that the sampling object is N-dimensional and the number of samples is L, then the problem is described as needing to take L samples in the N-dimensional vector space. For high-dimensional samples, it is necessary to first perform (0,1) uniformly distributed sampling in each dimension. Set an N*L matrix P, which will be used to hold the intermediate computational process, and set an N*L matrix Q, which will be used to hold the sampling results.

The first step is to divide the intervals equally. Divide each dimension of the object to be sampled into L interval, each of equal size, i.e., each interval is of length $1/L$.

Step 2: Start sampling. In the first sub-interval $(0,1/L)$, N values are randomly selected, $X_{11}, X_{21}, \cdots, X_{n1}$, and the first column of matrix P is the set of N values, $(X_{11}, X_{21}, \cdots, X_{n1})$. After that, the same procedure is repeated for the second sub-interval, where N values are obtained, $X_{12}, X_{22}, \cdots, X_{n2}$, and the second column of the matrix is the set of N values, $(X_{12}, X_{22}, \cdots, X_{n2})$. Repeat the above steps until the sampling is completed in each interval, and the matrix P takes the following form

$$P = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1m} \\ X_{21} & X_{22} & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{nm} \end{bmatrix} \tag{7}$$

Step 3, reordering. Reorder each row of values in matrix P by disrupting them to form matrix Q, where the elements are noted as Y, i.e:

$$Q = \begin{bmatrix} Y_{11} & Y_{12} & \cdots & Y_{1m} \\ Y_{21} & Y_{22} & \cdots & Y_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ Y_{n1} & Y_{n2} & \cdots & Y_{nm} \end{bmatrix} \tag{8}$$

Since each of the N values in each column vector of the matrix Q represents the coordinates of that sample point in each dimension, the final L extracted sample points are obtained. By using the Latin hypercubic sampling method for the sampling simulation of electricity prices in the electricity spot market, it is possible to effectively simulate the uncertainty of electricity spot market prices without sea sampling.

II. B.Modeling of electricity market clearing in the southern region

(1) Objective function of the electricity trading market model

Under the unilateral market environment, the total social value is maximized, which is reflected by the minimum power purchase cost [23]. In this paper, the objective function is to minimize the total power purchase cost in the market, because the market needs to consider the unit start-up situation in the past day, the objective function takes into account the start-stop cost of the unit, and the unit with a low offer should be given priority to win the bid. The specific mathematical model is as follows:

$$\min\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{s=1}^{M}C_{i,s}P_{i,s,t}+\sum_{i=1}^{N}\sum_{t=1}^{T}(1-I_{i,t-1})I_{i,t}\lambda_{i,t}^{th}\right) \tag{9}$$

where N is the number of generating units participating in the spot market, M is the total number of segments offered by the unit, T is the total number of time slots, $P_{i,s,t}$ is the winning power bid of unit i in segment s in time slot t, $C_{i,s}$ is the price corresponding to segment s declared by unit i, $\lambda_{i,t}^{th}$ is the startup and shutdown cost of thermal unit i, and $I_{i,t}$ is the operating status of thermal unit i in time slot t (0-1 variable).

With the objective function of minimizing the total power purchase cost in the market, the unit with the lower offer price should be preferred to win the bid, and the specific mathematical model is as follows:

$$\min\sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{s=1}^{M}C_{i,s}P_{i,s,t} \tag{10}$$

(2) Power trading market model constraints

For each trading session, the system load supply and demand should be guaranteed to be in balance, i.e:

$$\sum_{i=1}^{N}\sum_{s=1}^{M}P_{i,s,t}=D_t \tag{11}$$

where D_t is the system load demand for time period t.

The generating unit output meets its maximum and minimum technical output, i.e:

$$I_{i,t}P_{i,\min}\le\sum_{s=1}^{M}P_{i,s,t}\le I_{i,t}P_{i,\max} \tag{12}$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum technical output of unit i, respectively.

The thermal power unit's output increment or decrement in a time period needs to satisfy the technical constraints of the unit's technical creep rate, respectively:

$$P_{i,t}-P_{i,t-1}\le R_i^U I_{i,t-1}+P_{i,\min}(I_{i,t}-I_{i,t-1})+P_{i,\max}(1-I_{i,t}) \tag{13}$$

$$P_{i,t-1}-P_{i,t}\le R_i^D I_{i,t}-P_{\min,i}(I_{i,t}-I_{i,t-1})+P_{\max,i}(1-I_{i,t-1}) \tag{14}$$

where $P_{i,t}$ is the winning power of thermal unit i in time period t, and R_i^U and R_i^D are the upward and downward creep rates of thermal unit i, respectively.

The output of the starting unit in each time period must satisfy the positive and negative standby constraints of the system according to a certain standby ratio, respectively:

$$\sum_{i\in N_G}I_{i,t}P_{i,\max}\ge D_t\left(1+R_t^U\right) \tag{15}$$

$$\sum_{i\in N_G}I_{i,t}P_{i,\min}\le D_t\left(1-R_t^D\right) \tag{16}$$

where N_G is the set of all generating units in the system, and R_t^U and R_t^D are the system reserved upper and lower standby factors, respectively.

For time period t, the active tidal current flowing through section f should be no greater than the upper limit of the stability limit for that section and no less than the lower limit of the stability limit for that section is:

$$p_{f,\min}\le\sum_{d=1}^{D}G_{d-f}P_{Load,d,t}-\sum_{i=1}^{N}\sum_{s=1}^{M}G_{i-f}P_{i,s,t}+P_f^{Sc}\le p_{f,\max} \tag{17}$$

where $P_{Load,d,t}$ is the load of user d in time period t, G_{i-f} and G_{d-f} are the power transfer factors of the thermal unit and the node where the load is located for section f, respectively, P_f^{Sc} is the planned tidal current for section f, and $p_{f,\max}$ and $p_{f,\min}$ are the maximum and minimum stability limits for section f, respectively.

Due to the physical properties of the thermal power units and the actual operational needs, the thermal power units are required to fulfill the minimum continuous start/stop time constraints, respectively:

$$T_{i,t}^{D}-\left(I_{i,t}-I_{i,t-1}\right)T^{D}\geq 0 \tag{18}$$

$$T_{i,t}^{U}-\left(I_{i,t-1}-I_{i,t}\right)T^{U}\geq 0 \tag{19}$$

where T^D and T^U are the minimum continuous startup and shutdown times of the unit, and $T_{i,t}^D$ and $T_{i,t}^U$ are the times that unit i has been continuously started and shutdown during time period t, respectively.

II. C. Construction of trading risk evaluation index system

Influenced by market system, market structure, market members' behavior and market efficiency and other factors, the electricity market shows many kinds of risks, wide range of influence and great difficulty in supervision, and faces power shortages due to unclear perception of risks, and disorders in market operation caused by imperfect price mechanism.

According to the current stage of the construction of the southern regional power market status quo and trends, combined with the current pilot market in the behavior of the members, rule-making, operational mechanisms and market efficiency and other aspects, the formation of a set of comprehensive reflection of the power market risk of the multi-dimensional evaluation index system, the specific content of which is shown in Table 1. The indicator system mainly includes four types of market structure risk, market member behavior risk, market efficiency risk and market operation risk, aiming to provide data support for the assessment and early warning of power market risk [24].

Table 1: Risk assessment index system of power market

Primary indicator	Secondary indicator	Symbol
Market structure risk	Electricity supply and demand ratio	MS1
	The capacity proportion of thermal power units	MS2
	The proportion of renewable energy unit capacity	MS3
	Load peak-to-valley ratio	MS4
	Load fluctuation percentage	MS5
Risk of behavior of market members	Market concentration on the power generation side	RM1
	Market concentration on the power sales side	RM2
	User market engagement	RM3
	High quotation winning rate	RM4
	The max quoted price difference is	RM5
	Quotation Consistency	RM6
	Retention ratio	RM7
Market efficiency risk	The proportion of competitive electricity generated by thermal power units	ME1
	The proportion of competitive electricity generated by renewable units	ME2
	Market contracted electricity rate	ME3
	Revenue-cost index per kilowatt-hour	ME4
	Marginal electricity price limit rate	ME5
Market operating risk	Demand elasticity coefficient	MO1
	Lerner index	MO2
	Electricity price change rate/coal price change rate	MO3
	Standby capacity rate	MO4
	Equivalent availability factor	MO5

With regard to the structural risk of the electricity market, the relationship between supply and demand of electricity and the contrast between the supply and demand situations are the key factors influencing the behavior of market members and thus determining the market price. In terms of market members' behavioral risk, the market concentration of quotation members, joint quotation, etc. is an important indicator reflecting the existence of irregular trading behavior in the market. The operational efficiency of the electricity market is mainly affected by macro policies, the market's own mechanism and physical factors in three aspects. The current power market pilot units are developing or trial operation of various medium- and long-term or spot market trading rules, the need to consider in advance the operation of the power market may exist in a variety of risk factors.

II. D.Improved topological cloud modeling of physical elements

The cloud model is a model that can convert qualitative information with quantitative information in an uncertain way, which better reflects the ambiguity and randomness of the assessment object. The overall characteristics of the cloud model can be reflected by the numerical characteristics of the cloud, expecting the three numerical characteristics of Ex, entropy En, and hyperentropy He to characterize a concept as a whole. Combining the cloud model with the method of determining weights using the comprehensive assessment formula, the calculated weights are used to correct the characteristic parameters of the cloud model, resulting in a comprehensive assessment value with the characteristic parameters of the cloud model, which in turn leads to the risk assessment level.

The weights are calculated using the characteristic parameters of the cloud model itself (Ex, En, He) and then the risk assessment is performed using the forward cloud algorithm. Since in the actual situation the expert scoring is oscillating around a certain central value of a certain magnitude, the introduction of a fixed weight calculation method does not take into account the randomness of the expert scoring, and therefore a random number with a stable trend is needed to replace this value. This study combines the two and determines the assignment method of cloud entropy method with the following calculation formula:

$$w_i = \frac{\dfrac{Ex_i}{\ln\left(1+En_i\right)+1}}{\sum_{i=1}^{n}\dfrac{Ex_i}{\ln\left(1+En_i\right)+1}} \tag{20}$$

Based on the existing research, this paper utilizes the theory of topologizable object element and cloud model theory to construct an improved topologizable object element cloud model. The model utilizes the cloud entropy-based method to calculate the weights of the indicators in the evaluation system. At the same time, combining the topable object element theory with the cloud model theory, the topable object element cloud model evaluation model of power trading market risk is proposed. The advantage of this model is that it overcomes the randomness of subjective assignment and the absoluteness of objective assignment, and the weights of indicators are more reasonable, which can better solve the ambiguity and uncertainty in the evaluation process.

The topological object element theory adopts the unit object element to characterize the risk evaluation index of the power trading market. The comprehensive evaluation problem in the risk evaluation system of the power trading market is described as the object-element relationship in the object-element model, and the object-element is the logical unit of risk evaluation, $R=(N,C_i,v_i)$ is called the object-element of risk evaluation of the power trading market, N,N_i,N_i' is the object to be evaluated in the system, C_i is the evaluation index directly related to the object to be evaluated, and v_i is the description of the risk status of the i th evaluation index. Through the evaluation level of multiple indicators, the risk level of the southern regional electricity market is determined. The object-element relationship expression is.

$$\begin{aligned} R=[\bar{N},C,v] \Rightarrow R_i &= \begin{bmatrix} N_1 & C_1 & v_1 \\ N_2 & C_2 & v_2 \\ \vdots & \vdots & \vdots \\ N_n & C_n & v_n \end{bmatrix} = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{bmatrix} \\ \Rightarrow R_i' &= \begin{bmatrix} N_1' & C_1' & v_1' \\ N_2' & C_2' & v_2' \\ \vdots & \vdots & \vdots \\ N_n' & C_n' & v_n' \end{bmatrix} = \begin{bmatrix} R_1' \\ R_2' \\ \vdots \\ R_i' \end{bmatrix} \end{aligned} \tag{21}$$

A cloud model is defined as $U=\{x\}$ denotes a value of the thesis quantified by a precise number, e.g., an indicator x of an electricity trading market, C denotes a certain qualitative concept on $U=\{x\}$, x a one-time stochastic realization of a qualitative concept U, and x a deterministic degree of certainty $\mu(x)$ with a stabilizing tendency to U, which is then $\mu(x)$ a cloud droplet, and $\mu(x)$ between $\{0,1\}$, i.e.,:

$$\mu : U \to [0,1], \forall x \in U, x \in \mu(x) \tag{22}$$

In this paper, normal cloud model is adopted to realize the mutual transformation between quantitative numerical values and qualitative concepts, and the eigenvalue V in the topologizable object element model is expressed by the cloud model, and the expectation Ex in the cloud numerical feature $\left(Ex, En, He\right)$ indicates the mean value of the cloud droplet, the entropy En indicates the degree of dispersion of the cloud droplet, and the superentropy He indicates the uncertainty of the entropy. The theory of topologizable object element is combined with the cloud model, the theory of topologizable object element can recursively realize the risk evaluation of power market transaction from bottom to top, and the cloud model can deal with the indicator ambiguity and the randomness of the result. The topable object element cloud model can be expressed as:

$$R=\begin{bmatrix} N & C_1 & (Ex_1, En_1, He_1) \\ & C_2 & (Ex_2, En_2, He_2) \\ & \vdots & \vdots \\ & C_n & (Ex_n, En_n, He_n) \end{bmatrix} \tag{23}$$

where R is the research object, C_i is the evaluation index, and V is the description of the safety state of the research object, which is described by using cloud digital features $\left(Ex, En, He\right)$.

The correlation function indicates the degree of correlation between the warned unit and each warning level, and its formula is:

$$\rho(x, X)=\left|x-\frac{a+b}{2}\right|-\frac{b-a}{2} \tag{24}$$

where X represents the standard threshold $\left[a, b\right]$ used to determine the risk warning level, and $\rho(x, X)$ represents the “distance” between x and X within the standard fluctuation range of the power market risk warning.

Next, the correlation function of each element to be evaluated under each warning level is calculated. Symbol $K_{tk}(x)$ represents the correlation between the range of market risk warning indicator x and the standard interval $\left[a, b\right]$, then:

$$K(x)=\begin{cases} -\dfrac{\rho(x, X)}{b-a}, & x \in X \\ \dfrac{\rho(x, X)}{\rho(x, Y)-\rho(x, X)}, & x \notin X \text{ And } x \in Y \end{cases} \tag{25}$$

$K_{tk}(x)$ represents the set of correlations between the actual value of the k nd electricity market risk warning indicator and each warning level, then:

$$K_{tk}(x)=\left\{K_{1k}(x), K_{2k}(x), \ldots, K_{nk}(x)\right\} \tag{26}$$

Determine the combined correlation between the object to be warned and the warning level. The combined correlation of the object to be evaluated N_t to each risk level j is:

$$K_j(N_t)=\sum_{i=1}^{n}\omega_i K_j(v_i) \tag{27}$$

According to the principle of maximum affiliation of correlation, the level of the object element N_t to be warned is determined, and if $K_j=\max\{K_j(N_t)\}$, $j=1,2,\ldots,m$, then it represents the risk level of the object element N_t to be warned is j. That is:

$$\overline{K}_j(N_t)=\frac{K_j(N_t)-\min_j K_j(N_t)}{\max_j K_j(N_t)-\min_j K_j(N_t)} \tag{28}$$

$$j^*=\frac{\sum_{j=1}^{m} jK_j(N_t)}{\sum_{j=1}^{m} K_j(N_t)} \tag{29}$$

where j^* is the value of the characteristic of the object element N_t to be evaluated, and its tendency level to neighboring grades is judged.

III. Integrated learning-based early warning model for power trading risks

In the context of the new round of power system reform, the spot market, as a key link connecting the medium- and long-term transactions and real-time operation, can fully restore the commodity attributes of electricity, and truly play the role of price discovery and optimal allocation of resources. With the comprehensive deepening of the current power system reform, the spot market has become the core and focus of the next stage of power market construction.

III. A. Stacking Integration Learning

Stacking integrated learning refers to training a model for combining all individual learners, i.e., first training several different individual learners and then training a model with the outputs of these individual learners as inputs to get a final output. Figure 1 shows the Stacking algorithm flow. Multiple training subsets are first obtained by resampling method on the entire training dataset, and then a series of classification models, called Tier1, are trained using these newly generated training sets.Then, the outputs of Tier1 are combined and used to train the meta-classifiers of Tier2. In addition to resampling methods, cross-validation is also often used in training Tier1 classifiers, i.e., the training set is first divided into N equal parts, and then each individual learner in Tier1 is trained based on the first N-1 copies of the training set, and finally tested on the Nth training set [25].

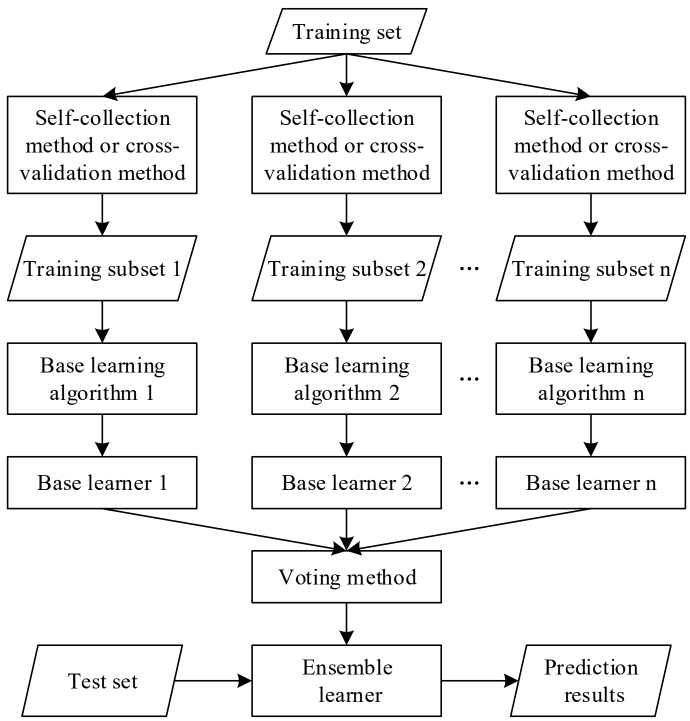

Figure 1: Stacking algorithm process

Stacking uses the primary learner to generate a new training set to train the secondary learner, but there is a high risk of overfitting if the training set of the primary learner is used directly to generate the secondary training set, so a cross-validation method is usually used to generate the secondary training set. In this algorithm, the type of data in the secondary training set and the choice of secondary learners are two key factors. Using multiple powerful and different primary learners and using class label probabilities instead of predictive class labels as attributes of the secondary learners produces better results, and the choice of simple models for the secondary learners reduces the risk of overfitting.

III. B. Early warning model for power trading risks

(1) Support Vector Machine Model. The classification idea of Support Vector Machine (SVM) model is to find the optimal classification hyperplane to maximize the interval between two classes of samples. Let $f(x_j)$ be the decision function of the support vector machine, α_k^* be the Lagrange multiplier, $K(x_k, x_j)$ be the kernel function, and b^* be the intercept term. Then $f(x_j)$ is the:

$$f(x_j)=\sum_{k=1}^{n} y_k\alpha_k^* K(x_k,x_j)+b^* \tag{30}$$

Let $p_{svm}(j)$ be the probability of risk in the electricity trading market predicted by the support vector machine. Converting the above equation by Sigmoid function gives $p_{svm}(j)$ as:

$$p_{svm}(j)=(1+\exp(Af(x_j)+B))^{-1} \tag{31}$$

where A and B are unknown parameters that can be estimated by the great likelihood method.

(2) Random forest model. Random forest (RF) model is a classification model composed of multiple decision trees, determining the optimal division index of decision tree nodes with the minimum Gini index as the standard, constructing multiple decision trees, and using the voting method to obtain the prediction results of random forest. The Gini index $Gini\left(D_q,x^{(i)}\right)$ of indicator i is:

$$Gini(D_q,x^{(i)})=\frac{N_q^l}{N_q}Gini(D_q^l)+\frac{N_q^r}{N_q}Gini(D_q^r) \tag{32}$$

where $Gini(D_q)$, $Gini(D_q^l)$ and $Gini(D_q^r)$ are the Gini values of D_q, D_q^l and D_q^r respectively.

Let $p_{rf}(j)$ be the risk probability of the electricity trading market predicted by the random forest. K -Number of decision trees. $p^k(j)$ - Risk probability of electricity trading market predicted by the k th decision tree. Then $p_{rf}(j)$ is:

$$p_{rf}(j)=\frac{1}{K}\sum_{k=1}^{K} p^k(j) \tag{33}$$

(3) XGBoost model: XGBoost model is an integrated model with regression tree as the base classifier, using the gradient statistic of the loss function as the information gain criterion, determining the node branches of the regression tree, establishing multiple regression trees, and integrating the predictions of multiple regression trees as the prediction results of the XGBoost model.

Let $\hat{y}_j^{(K)}$ be the predicted value of the XGBoost model, K be the number of regression trees, F be the set of all regression trees, f_k be the k th regression tree, x_j be the indicator data of the j th enterprise, and $f_k(x_j)$ be the prediction result of the k th regression tree. Then $\hat{y}_j^{(K)}$ is the:

$$\hat{y}_j^{(K)}=\sum_{k=1}^{K} f_k(x_j), f_k\in F \tag{34}$$

Let $p_{xgb}(j)$-XGBoost predicted probability of risk in the electricity trading market. Transforming the predicted value $\hat{y}_j^{(K)}$ by Sigmoid function gives $p_{xgb}(j)$ as:

$$p_{xgb}(j)=(1+\exp(-\hat{y}_j^{(K)}))^{-1} \tag{35}$$

In order to realize the accurate early warning of power market transaction risk, this paper constructs a power market transaction risk early warning model based on Support Vector Machine (SVM), Random Forest (RF), K Nearest Neighbor Algorithm (KNN) and Extreme Gradient Boosting Tree (XGBoost) as the base classification model combined with the Stacking algorithm as shown in Fig. 2. It mainly includes the processing of raw data, then feature association analysis, selecting features with strong correlation, and hyper-parameter optimization of the model through grid search, model performance comparison and visualization analysis [26].

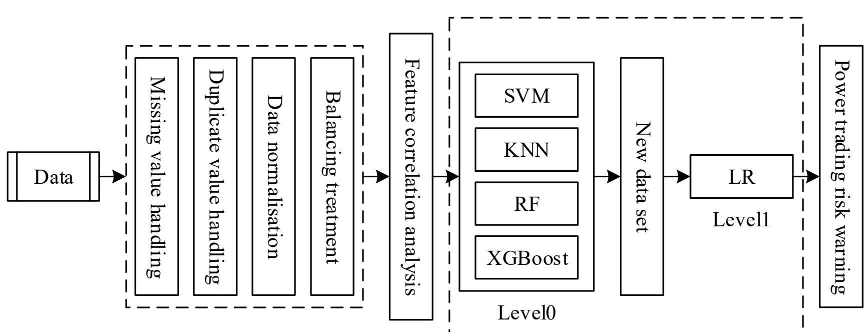

Figure 2: Electric power Trading Risk early warning model

The specific steps of the model are as follows:

Step1 Preprocess the original data and then perform feature selection by Pearson correlation coefficient ranking to generate a new dataset.

Step2 Divide the dataset into training set and test set according to the ratio of 7:3.

Step3 In the first layer of the architecture, four base classifiers, namely, support vector machine, random forest, K-nearest neighbor and gradient boosting tree, are selected for individual modeling, and the optimal parameters are selected by grid search method to evaluate the model performance.

Step4 In the first layer model architecture, take the SVM model as an example, divide the training set O into 10 copies, 7 copies as the training of the base classifier model, and 3 copies as the validation of the base classifier model, and get the prediction dataset $u_i(i \in \{1 \sim 10\})$ of the validation set, which will be combined into U_1. Then, the base classifier model trained based on the 7 copies of the dataset will be predicted on the test set P, and the prediction dataset $v_i(i \in \{1 \sim 10\})$ will be obtained. 10 prediction results $v_i(i \in \{1 \sim 10\})$ are averaged by rowwise summing to obtain dataset V_1. The above steps are repeated to train and predict the remaining base models separately, obtaining the corresponding prediction results U_2, U_3, and U_4, as well as V_2, V_3, and V_4. All the cross-validated results are stacked vertically to form a new feature matrix, in which U_1 to U_4 form a new training set U, and V_1 to V_4 form a new test set V.

Step5 In the second layer model architecture, the logistic regression model is selected, which is less computationally expensive and easy to implement compared to other complex models, and in the second layer model logistic regression can better deal with the linear differentiability of the classifier outputs, further controlling the complexity of the model, reducing the risk of overfitting the model, and providing the ability to interpret and predict the classification of risk.

In the second layer architecture the predictions of the base model on the original training set are used as the training set, the predictions of the base model on the original dataset are used as the test set, the test data are used as the input features of the meta-model, training is performed, and then final predictions are performed on the test set to obtain the final predictions and visualize and analyze the results.

IV. Example results

With the gradual completion of the approval of transmission and distribution tariffs in all provinces and the continuous improvement of the medium- and long-term bidding model of the pilot power sales side reform, the market structure and operation model of the spot market are already in the pipeline. The spot market is an important part of the power market system, which plays a fundamental supporting role for the open, competitive and orderly operation of the power market, and is also the key to coordinating market transactions and system security.

IV. A. Introduction to the test system

In this paper, the improved IEEE30 node system is used to verify the effectiveness of the power market operation scenarios and models designed in this paper, and the structure of this system is shown in Fig. 3. In order to better reflect the model effect, the arithmetic example simulates a high proportion of renewable energy systems, with a total of two thermal power units, three wind power plants, three photovoltaic power plants, two watershed terraced hydropower plants, and one run-of-river hydropower plant. The total installed capacity is 5000 MW, of which the installed capacities of thermal power, wind power, photovoltaic and hydropower are 2200 MW, 800 MW, 600 MW and 1400 MW, respectively.

In order to simulate the typical load distribution, the load curves on Wednesdays and Fridays in the four seasons are selected as the typical load curves in this paper. Further, based on the abundance of wind resources in each season, the new energy access resources are categorized into three scenarios of abundant and less abundant, which correspond to one typical new energy output curve respectively. Therefore, each season contains four typical operation scenarios, and a total of 16 typical operation scenarios of the electricity spot market are constructed for the whole year.

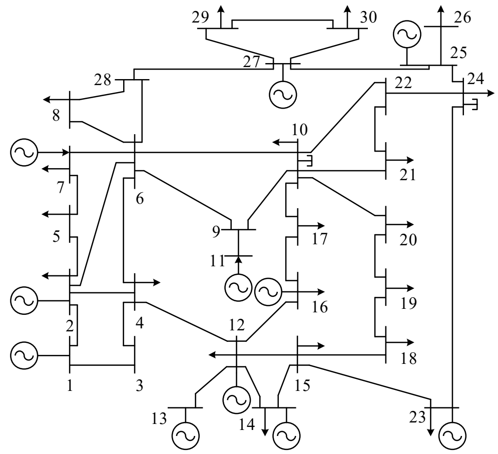

Figure 3: Improved IEEE 30-node system

IV. B. Transaction risk ratings

(1) Analysis of indicator weights

For the risk assessment indicators of power market transactions proposed in this paper, the data of each indicator as a sample input, the use of the cloud entropy method given in the previous section to solve the steps of indicator weights, for the samples of each indicator to find the expectation, super entropy and other data, and then get the evaluation of the distribution of indicator weights as shown in Table 2.

Based on the weight distribution data of the indicators in the table, it can be seen that in the assessment of the risk of power market transactions, the weights of market structure risk, market member behavior risk and market efficiency risk are relatively small, with weight values of 0.2416, 0.2358 and 0.2294, respectively, while the weight of market operation risk is relatively high, with a weight proportion of 29.32%. This indicates that during the operation of power market transactions, relying on the changes in the elasticity of market demand and the rate of change of electricity prices, combined with the Lerner index and standby capacity rate to fully reflect the effect of power market operation, quantifying the indicators can provide reliable data support for the assessment of the risk of power market transaction operation. In addition, among the secondary indicators, the weights of the demand elasticity coefficient (OM1), the rate of change of electricity/coal price (OM3) and the Lerner index (OM2) rank in the top three, with weights of 0.06295, 0.05934 and 0.05726, respectively, which are consistent with the trend of the weights under the primary indicators. Therefore, when carrying out the risk assessment of power market transactions in the power system, more consideration can be given to the impact of this part of the data on the power trading market, so as to accurately assess the risk situation of power market transactions in the southern region.

(2) Risk assessment analysis

The parameters of market structure risk, market member behavior risk, market efficiency risk and market operation risk in the improved material element topological cloud model are designed, and the Latin hypercube sampling method is adopted, and the 16 typical scenarios constructed in the previous section are sampled 1,000 times respectively, and a total of 16,000 electric power spot market risk operation scenarios are generated, and each scenario contains 24 time periods, and each time period involves multiple variables. . Subsequently, spot market clearing calculations are performed for each risk scenario to obtain the four risk indicator values for a single time period, and the remaining scenarios have a total of 241,726 single time period clearing results after eliminating the scenarios with clearing failures, and all the results are subjected to risk evaluation according to the following steps.

The trading risks in the electricity spot market are categorized into five classes {very low, low, average, high, and very high} according to their severity. The first step in risk rating using the object-element topable cloud model is to establish typical domains for each risk indicator under these five classes.

First, delineate the range of values for each metric under different risk levels, and subsequently calculate the cloud expectation value for each level. 1/5 of the size of the risk delineation interval is used as the reference value of cloud superentropy and fine-tuned. Through the cloud entropy optimization algorithm, the cloud entropy value of each single time period risk indicator is calculated. Taking the sample of a time period as an example, the actual values of its four indicators and the corresponding typical domain parameters are shown in Table 3.

Table 2: Evaluation index weight distribution

Primary indicator	Secondary indicator	Weight
Market structure risk (MS-0.2416)	Electricity supply and demand ratio	0.04528
	The capacity proportion of thermal power units	0.04714
	The proportion of renewable energy unit capacity	0.04924
	Load peak-to-valley ratio	0.04467
	Load fluctuation percentage	0.05529
Risk of behavior of market members (RM-0.2358)	Market concentration on the power generation side	0.03384
	Market concentration on the power sales side	0.03780
	User market engagement	0.03287
	High quotation winning rate	0.03603
	The max quoted price difference is	0.03473
	Quotation Consistency	0.03044
	Retention ratio	0.03009
Market efficiency risk (ME-0.2294)	The proportion of competitive electricity generated by thermal power units	0.04928
	The proportion of competitive electricity generated by renewable units	0.04632
	Market contracted electricity rate	0.04304
	Revenue-cost index per kilowatt-hour	0.04246
	Marginal electricity price limit rate	0.04831
Market operating risk (MO-0.2932)	Demand elasticity coefficient	0.06295
	Lerner index	0.05726
	Electricity price change rate/coal price change rate	0.05934
	Standby capacity rate	0.05720
	Equivalent availability factor	0.05644

Table 3: Typical domain parameters for a specific time period sample

Level	MS	RM	ME	MO
Very low	(2.41,6.35,1.24)	(0.05,0.01,0.00)	(0.02,0.02,0.00)	(2.51,2.17,1.54)
Low	(15.03,1.87,0.69)	(0.25,0.07,0.00)	(0.05,0.03,0.01)	(32.14,23.48,7.16)
General	(35.14,12.79,2.18)	(0.43,0.05,0.00)	(0.19,0.05,0.00)	(28.93,58.51,13.21)
High	(70.48,11.24,2.06)	(0.67,0.09,0.00)	(0.34,0.05,0.00)	(32.69,10.47,12.38)
Very high	(145.39,46.38,4.26)	(0.92,0.08,0.00)	(0.76,0.26,0.00)	(27.51,23.15,20.49)
Evaluation value	13.19	0.00	0.27	0.00

In the second step, the cloud affiliation matrix is calculated. The affiliation of each indicator of the object element to be evaluated with each of the five risk levels is calculated separately. For example, to calculate the affiliation of the “market operation risk” indicator with the “high” risk rating, the calculated affiliation is 0.318. The cloud model of the indicator to be evaluated is expressed as (32.69,10.47,12.38), which is the same as that of a typical domain cloud diagram, and it can be seen that the indicator is related to the ‘average’ and “high” risk ratings. It can be seen that the indicator is closer to the grades “average” and “high”, which is confirmed by the affiliation matrix.

Finally, the weight of each indicator is determined and the comprehensive score is calculated. Based on the weights of the indicators derived in the previous section, the scores of the five risk levels from low to high are set as [1,2,3,4,5], and the risk score of the electricity spot market trading in this time period is calculated to be 1.52, which corresponds to the overall risk rating of “low”. From the affiliation matrix, it can be seen that according to the principle of maximum affiliation, the first three indicators are rated as “very low”, the second indicator is rated between “low” and “average”, the fourth indicator is rated between “low” and “average”, and the fourth indicator is rated between ‘low’ and “average”. The second indicator was rated between “low” and ‘average’, and the fourth indicator was rated between “very low” and “low”, so the overall evaluation results were reasonable.

Risk evaluations were performed for all 241726 single-session scenarios, with sample sizes of [23285, 165896, 73159, 14672, 9714] in descending order for each class. Compared to the results of the unimproved Latin sampling, the number of samples in the “high” risk class doubled, resulting in a more balanced sample distribution. To further balance the sample size, the data were resampled, cleared, and evaluated by increasing the probability of a risk event occurring. The newly generated data were combined with the original 241726 data, and 286498 data were randomly selected, at which time the number of samples from low to high risk level was [34571, 100756, 75872, 62175, 13124].

IV. C. Early warning of risk dynamics

(1) Power market transaction risk prediction error

In this paper, EVIEWS software is used to verify the prediction effect of electricity market transaction risk under different operational scenarios. This paper is based on the 16 scenarios constructed in the previous section, mainly from the consideration of market position indicators for the prediction of different scenarios. In the electricity market, it is necessary to forecast the electricity price trend and its risk for 24 periods throughout the day on the 2nd day 7 days in advance, in which case a dynamic forecasting method is required. In addition, MSE, MAE and MAPE are used as evaluation indicators to obtain the results of the comparison of the forecasting errors of the two models as shown in Table 4. Figure 4 shows the results of the comparison between the static forecast values and the true values considering the market position indicator. Figure 5 shows the results of comparison of dynamic forecasts considering market position indicators.

When using the static prediction method, the electricity market transaction risk prediction model established by the two methods of considering the market status indicator and not considering the market status indicator have better prediction effect on the market price fluctuation. Figure 4 shows that the prediction curve obtained by the power market transaction risk prediction model established by considering market status indicators has a small error between the prediction curve and the real price fluctuation curve. From Figure 5, it can be seen that in the dynamic prediction, the power market transaction risk prediction model that does not consider the market status indicators has a larger error, and although it can describe the price fluctuation trend, it is obviously not strong enough to support the price spike. While the power market transaction risk prediction model considering the market status indicators can make a more accurate description of the future price trend with a smaller error. As can be seen from Table 4, regardless of static or dynamic forecasting methods, the forecasting accuracy of the model considering market status indicators is better than that of the model not considering market status indicators, especially under dynamic forecasting conditions the model not considering market status indicators may produce larger errors, while the model considering market status indicators can still maintain a high forecasting accuracy due to the consideration of the overall market supply and demand situation and the effect of the market status of individual power producers on the price. can maintain a high forecasting accuracy.

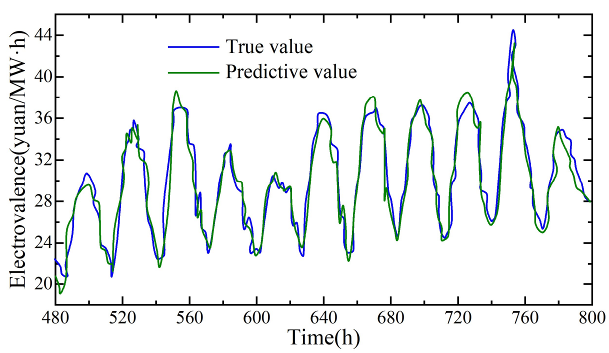

Figure 4: The comparison result between the static predicted and true value

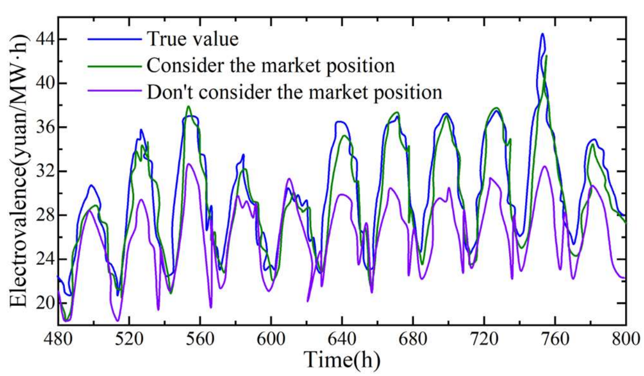

Figure 5: Comparison of dynamic prediction results

Table 4: Error comparison between two models

Error index		Not considering the market position	Consider the market position
Static Prediction	RMSE	0.963	0.834
	MAP	0.775	0.672
	MAPE	2.637	2.351
Dynamic Prediction	RMSE	5.005	1.728
	MAP	4.617	1.429
	MAPE	15.529	4.907

(2) Comparison of power market transaction risk prediction model performance

In order to improve the reliability of the comparison between different models, the ten-fold cross-validation method is used to assess the model performance. In order to verify the effectiveness of the model in this paper, it is compared and analyzed with five machine learning models, including KNN, SVM, Logistic, LightGBM, and AdaBoost.Meanwhile, in order to find out that the classification prediction model shows superiority under resampling, this study compares the model prediction performance with SMOTE oversampling, ADASYN sampling, and after resampling. The prediction performance metrics of various classification algorithms are shown in Table 5. In addition, the comparison of ROC curves of various models under resampling is demonstrated as shown in Figure 6.

As can be seen from the table, compared with the SMOTE and ADASYN sampling methods, the classification prediction performance indexes of various classification algorithm models for a few classes are generally improved after resampling. This indicates that the resampling technique is effective in dealing with unbalanced data and can effectively improve the prediction performance of the power trading risk prediction model. Further comparison shows that the prediction model combined with Stacking integrated learning in this paper performs well in power market transaction risk prediction, and the comprehensive indexes show that its accuracy rate is as high as 0.981, and the AUC value also reaches 0.999, which demonstrates excellent prediction ability. From the ROC curve in the figure, it can be clearly seen that after resampling, the AUC value of the power market transaction risk prediction model designed in this paper is significantly improved, and its ROC curve is the steepest, which further verifies the excellent prediction performance of this paper's model for power market transaction risk.

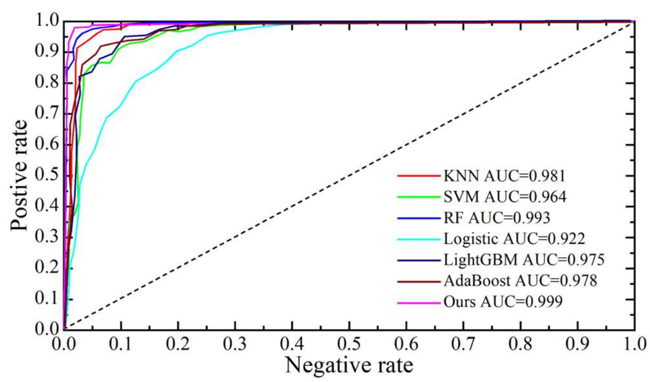

Figure 6: The comparison of ROC curves of various models

Table 5: Performance Evaluation of Classification Algorithm Model

Sampling technique	Model	Precision	Recall	*F*1	Accuracy	AUC
SMOTE	KNN	0.831	0.983	0.901	0.895	0.952
	SVM	0.812	0.932	0.872	0.854	0.934
	Logistic	0.785	0.845	0.814	0.802	0.886
	LightGBM	0.856	0.941	0.898	0.893	0.963
	AdaBoost	0.893	0.942	0.915	0.913	0.972
	Ours	0.932	0.979	0.947	0.945	0.999
ADASYN	KNN	0.841	0.931	0.883	0.901	0.953
	SVM	0.843	0.982	0.912	0.883	0.928
	Logistic	0.816	0.865	0.834	0.842	0.963
	LightGBM	0.845	0.928	0.885	0.885	0.974

	AdaBoost	0.912	0.924	0.927	0.927	0.981
	Ours	0.946	0.989	0.956	0.956	0.999
Resampling	KNN	0.923	0.991	0.951	0.951	0.993
	SVM	0.894	0.943	0.927	0.914	0.972
	Logistic	0.856	0.865	0.863	0.853	0.904
	LightGBM	0.905	0.952	0.928	0.916	0.963
	AdaBoost	0.914	0.943	0.927	0.924	0.975
	Ours	0.967	0.988	0.974	0.981	0.999

On this basis, in order to further illustrate the practical application effect of this paper's method in the southern regional electricity market transaction risk prediction species and early warning accuracy, selecting the underreporting rate as an evaluation index for model comparison experiments. Comparison model is based on data visualization technology (A) and text emotional features (B) risk early warning model, the experiment using three methods of the southern region of the power market transaction risk ten fold cross-validation, statistics of its risk warning results of the underreporting rate. Figure 7 shows the comparison results of the underreporting rate of the three models of the power market transaction risk warning.

As shown in the figure, in the process of multiple warnings for power market transactions, the leakage rate of the risk warning for power market transactions combining Stacking and various machine learning algorithms is lower, with values below 3.5%, and the average value of the overall leakage rate is only 2.05%. The leakage rate of power market transaction risk early warning based on data visualization technology and text sentiment features is higher, with values of 25.21% and 11.02% respectively, which are 23.16 and 8.97 percentage points higher than the model in this paper. It indicates that there are many times of ignoring the power market transaction risk in its early warning process, which brings hidden dangers to the operation of the power market. Therefore, the southern regional power market transaction risk assessment index system and risk early warning model designed in this paper have high early warning accuracy in practical application, which can provide support for preventing the power market transaction risk and ensuring the stability of the power market transaction.

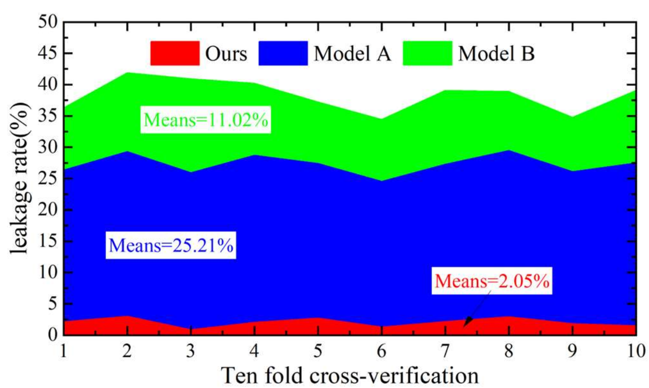

Figure 7: Comparison results of underreporting rates

V. Conclusion

This paper constructs a power market transaction risk evaluation index system based on the southern regional power market clearing model, and designs an improved material element topological cloud model for evaluating the power market transaction risk. Then based on the evaluation index data, a variety of machine learning algorithms are integrated using the Stacking integrated learning algorithm to construct a southern regional power market transaction risk warning model. The simulation results show that the current risk level of power market transactions in the southern region is at a “low” level, and the risk dynamic warning model is effective, which can be used in the accurate warning of power market transactions in the southern region.

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