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Study on Constructing a Risk Monitoring and Early Warning Model for Transactions in Southern Regional Electricity Market under New Power System Based on Time Series Bayesian Networks

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ABSTRACT
Aiming at the potential risks existing in the power market transaction under the new power system, and considering the temporal attributes of the information, this paper proposes to use dynamic Bayesian network to construct the risk monitoring and early warning model of the power market transaction. The dynamic Bayesian network is utilized to calculate the correlation between different risk factors, estimate the risk value of power market transactions, and classify the warning level. Taking the southern regional electricity market as the research object, the relationship between electricity price and transaction volume is explored based on the experimental dataset. A credit grading system is introduced to carry out transaction prediction simulation experiments, relying on the prediction data to determine the link between electricity price and transaction volume. The results show that overall power price and transaction volume show a negative correlation, but in June, when the power price is 0.4370 yuan per kWh, the transaction volume still reaches 19.65 million kWh, and the inverse relationship between the transaction volume and the price is not obvious. The use of dynamic Bayesian network to construct the power market transaction risk monitoring and early warning model can dynamically update and adjust the risk monitoring with the passage of time, making the power market transaction early warning more flexible and real-time.

Keywords: power market transactions, Bayesian network, time series information, risk monitoring

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1. Introduction

Under the traditional integrated monopoly operation, electric power from planning, construction, production until the use of electricity has a strong planning, electric power enterprise operation has the integration of generation, transmission, distribution and supply characteristics, the resistance to risk is relatively strong [1-2]. After the introduction of the power market mechanism, the various aspects of power production were split [3].

With the formation of the unified power market in the southern region, the market members on the power purchase side (power supply companies and power users) will participate in competition as independent market players, and each transaction link between coal enterprises, power generation enterprises, power grid enterprises and users will bring more risks to power enterprises [4-6]. At the same time, electric energy, because of the difficulty of large-scale long-term storage and the lack of short-term price elasticity, its price fluctuations are much larger than ordinary commodities, so risk management is very important, whether for power generators, power suppliers or large users [7-9].

Electricity trading, as an important force to promote the efficient use of energy and economic development, has brought unprecedented challenges to market participants due to its own complexity and uncertainty in practical application [10-11]. Power market transaction risks originate from many aspects, including price fluctuations, supply and demand imbalance, policy adjustments, natural disasters, etc. [12-14]. These risks not only affect the stable operation of the power market, but also directly relate to the economic benefits and social responsibility of power enterprises. Existing risk warning methods are difficult to deal with the uncertainty of complex systems, resulting in the accuracy and timeliness of risk warning is limited, and the warning results lack of scientific and objective [15-18].

The future unified power market mechanism in the southern region will be able to effectively promote enterprise competition, improve operational efficiency, reduce operating costs and optimize resource allocation [19]. Market participants should actively create conditions to adapt to the new situation [20]. However, the market-oriented power system is full of many uncertainties, including the volatility of wind and hydropower output, the uncertainty of the demand side affected by the economic crisis and other factors [21-22]. The existence of these uncertainties leads to the emergence of risks, and the concentration of these risks is the frequent fluctuation of electricity prices [23].

Improvement and optimization of the power market trading system is a key direction for scholars in this field. Literature [24] combines the current situation and characteristics of Yunnan's power market practice, focusing on the optimal control of clean energy generation capacity and market-based consumption incentives, as well as the market deviation processing system, aiming to improve and optimize Yunnan's clean energy trading system. Literature [25] focuses on the operation and practice of local power markets and systems in order to improve the local power derivation such as laws, market fragmentation, and challenges of demand response integration. Literature [26] builds a nonlinear mathematical model with stochastic programming as the underlying logic, and solves the market price and customer charge usage solution with mixed-integer linear programming, pointing out that customer composite and market price fluctuation under different confidence coefficients significantly affects the profit of power sales companies.

Academic research in the field of electricity market transaction risk mainly focuses on transaction credit, risk assessment, risk hedging and risk analysis. Literature [27] puts forward the necessity and significance of the establishment of the power market transaction credit system, and combined with the existing market credit management guidelines, puts forward the specific power market transaction credit management theory. Literature [28] constructed a power trading portfolio assessment model with the goal of maximizing profit based on the scenario method to simulate random risk variables, and evaluated and demonstrated it in combination with four power trading models. Literature [29] conceptualized a transaction risk assessment methodology based on the multiple fractal theory as the basic structure, and was informed of the sources of electricity transaction risk and the characteristics of electricity price fluctuations. Literature [30] conceived a power trading risk hedging methodology that predicts the power market alone, effectively limits the losses of power trading, and optimizes the risk metrics. Literature [31] conducted a risk analysis for the transaction cost of P2P trading smart contracts in the power market, and at the same time put forward specific suggestions to reduce the transaction risk, looking forward to the future development direction and potential of this field. Literature [32] envisioned a data-driven approach to analyze the risk appetite of power plants combined with historical data theory and inverse reinforcement learning strategy, and in simulation experiments, it was confirmed that the thermal power plants were of risk appetite type, and the rest of the power plants were of moderate risk. Literature [33] refers to the electricity spot market trading mechanism in order to assess the risk of customer day-ahead market transactions and builds a relevant customer purchase model, and conducts a performance evaluation test through simulation and numerical testing.

This paper identifies and analyzes the power market transaction risk by combining the power transaction situation of power supply companies under the new power system in China. The relevant theories of Bayesian network are sorted out and elaborated, and it is proposed to use dynamic Bayesian network to construct the power market transaction risk monitoring and warning model. Based on the dynamic Bayesian network, the power market transaction risk value is estimated, and different warning levels are divided. The transaction data of the southern regional power market under the new type of power system in the past five years is selected as the experimental data set, and the relationship between power price and transaction volume is explored by taking the data of a certain month as an example. Based on the Delphi method, the credit evaluation of the users on both sides of the generation and consumption sides of the electricity market is carried out to predict their virtual transaction results. Determine the random variables, analyze the relationship between the target variables and the decision variables relying on the prediction result data, and discuss the advantages of introducing the dynamic Bayesian network.

2. Electricity market transaction risk identification and analysis

In the power market, trading activities not only involve complex market rules and operational processes, but also face a variety of potential risks. With the gradual opening up of the market and the continuous improvement of the power trading mechanism, the management of trading risks in the power market is particularly important. Therefore, this chapter applies the power market theory, combined with the actual situation of power supply companies in China's power market reform process, firstly, identifies and analyzes the risks faced by power supply companies in the power market, summarizes the risks of power supply companies as price risk, load forecast error risk and grid reliability risk, and discusses and analyzes them respectively.

2.1. Price risk

Under the traditional management system for the electricity industry, the State exercises strict control over electricity prices, and the Government unifies the management of electricity prices and conducts strict audits of electricity prices. Under such rigid control, the fluctuation of electricity price is rare, and there are almost no independent power generation, transmission and distribution enterprises, so they do not face the risk caused by the fluctuation of electricity price. However, with the reform of the power system in the direction of marketization, the feed-in tariffs, wholesale tariffs and retail tariffs on the generation side of the power market will be gradually liberalized, and the tariffs will be determined through market bidding, which will inevitably lead to fluctuations in market prices. In addition, due to the special characteristics of electricity commodities, its demand elasticity is very small, so that the price of electricity is susceptible to the impact of supply and demand for electricity, so that the price of electricity fluctuations, for example, within a day of the peak and valley prices can be several times the difference, and even the price of the valley can be a negative, and the price of electricity on different days and in different months is even more different. This will expose participants in the electricity market to huge price risks.

Therefore, the price of electricity in the power market is different from other general commodities, its daily prices are in a large fluctuation. This high volatility of electricity market price is the main factor of financial risk in the electricity market, especially in the case of power shortage, it will lead to the soaring of electricity price, which will make the relevant electricity market participants suffer from huge economic losses, thus triggering a serious financial crisis.

Obviously, the high volatility of electricity prices is the most important feature of the electricity market, which poses a major threat to the financial security and safe and stable operation of the electricity market. It is widely recognized that the severity of the financial risks arising from electricity price volatility in the electricity market may even exceed the financial risks of bank failures, to which the financial community attaches great importance.

2.2. Risk of Load Forecast Error

Power supply companies usually enter into power purchase contracts with generators based on load forecast data, with the difference compensated through the real-time market. Therefore, the risk of short- and medium-term load forecasting errors affects the power supply company's contracted power. When the actual load is very different from the forecast value, it is necessary for the power supply company to adjust the power purchase plan in real time and re-determine the amount of power purchased. If the load forecast value is too high compared to the actual value, the power supply company will reduce the amount of power purchased from the grid, in which case the power supply company may need to pay liquidated damages to the power generating company, resulting in an increase in the cost of power purchases; if the load forecast value is too low, the amount of power purchased from the real-time market will need to be increased, and due to the sharp fluctuations in the real-time market price of electricity, if it is much higher than the contracted price of electricity, the cost of purchasing power for the grid enterprise will skyrocket. If the price of electricity in the real-time market fluctuates drastically, if it is much higher than the contracted price, it will lead to a sharp rise in the cost of electricity purchased by the grid enterprises, which will make the power supply companies suffer losses.

The traded electricity can be categorized into contracted and bidding electricity. Consider firstly time period t, let P_c be the contracted electricity price, $Q_{c,t}$ be the contracted electricity in t period, $P_{b,t}$ be the bidding electricity price in t time period, $Q_{b,t}$ be the bidding electricity in time period, Q_g be the predicted traded electricity in the whole time period, and ΔQ_g be the error of the predicted traded electricity in the whole time period. Then the settlement average price $P_{avg,t}$ for the t time period can be expressed by equation (1)

$$P_{a,t} = P_c \frac{Q_{c.t}}{Q_g + \Delta Q_g} + P_{b,t} \frac{Q_{b,t}}{Q_g + \Delta Q_g} \tag{1}$$

The factor K of the impact of the contracted tariff on the average settlement tariff in time period t can be found using equation (2)

$$K_t = \frac{\partial P_{a,t}}{\partial P_c} = \frac{Q_{c,t}}{Q_g + \Delta Q_g} \tag{2}$$

From equation (2), we can conclude that the larger the error ΔQ_R in forecasting electricity, the smaller the impact of the contracted electricity price on the settlement average price, and the closer the settlement average price is to the spot price, the more risky the market will be.

For the yearly time period, we can divide the year into n hourly segments t and the contracted electricity Q_c for the whole year needs to be allocated within each hourly segment. For the average price P_a^v of the traded electricity after allocation can be expressed by equation (3)

$$P_e^y = \frac{\sum_{i=1}^{n} P_c \times Q_{c,t} + \sum_{p=1}^{n} P_{b,t} \times Q_{b,t}}{Q_g + \Delta Q_g} = P_c \frac{\sum_{i=1}^{n} Q_{c,t}}{Q_g + \Delta Q_g} + \frac{\sum_{i=1}^{n} P_{b,t} \times Q_{b,t}}{Q_g + \Delta Q_g} \tag{3}$$

The impact factor K_{year} of the contract tariff on the average annual tariff can be obtained from equation (4)

$$K_{year} = \frac{\partial P_a^y}{\partial P_c} = \frac{\sum_{r=1}^{n} Q_{e,r}}{Q_g + \Delta Q_g} \tag{4}$$

Obviously, the larger the error ΔQ_g of the forecasted power, the smaller the impact of the contracted tariff on the annual settlement average price, and the closer the annual settlement average price is to the spot tariff, the more risky the market will be.

2.3. Grid reliability risk

Under the traditional monopoly system, the power company does not have to compensate for the supply of electricity when it takes to pull the switch on the load to disconnect the power supply due to the failure of the original system. However, in the power market environment, power supply reliability should be used as a commodity quality assessment standards, interruptible contracts as a means of demand-side management, can improve the operational reliability of the system, and can optimize the load curve by cutting peaks and filling valleys. In order to comprehensively analyze the risks of the power supply company, it is necessary to consider not only the risks incurred by the power supply company during the transaction process, but also that the power supply company, as an operator, has a financial responsibility for the delivery of electricity, and that the power supply company may face financial compensation if it fails to provide power supply to its customers.

3. Bayesian network theory foundation

3.1. Bayesian network concepts

The Bayesian network approach is a model for uncertainty knowledge representation and inference based on probabilistic analysis, graph theory, a framework for representing information that combines causal and probabilistic knowledge. A Bayesian network is a directed acyclic graph in which nodes represent variables in the domain, directed arcs represent relationships between variables, and the strength of relationships between variables is represented by the conditional probabilities between nodes and their parents. In network graphs, although the relationship between parent and child nodes is not required to be causally linked, this representation in fault diagnosis accurately reflects the dependencies between them. In Bayesian networks, qualitative information is mainly expressed through the topology of the network, while quantitative information is mainly expressed through the joint probability density of the nodes.

The topology of a typical Bayesian network is shown in Fig. 1.

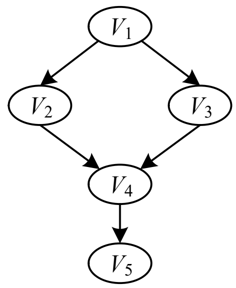

Fig. 1. Topology of Bayesian network

A Bayesian network represented by the symbol $B(G,P)$ has two components:

1) a directed acyclic graph $B(G,P)$ with individual nodes, where N nodes represent random variables G and directed edges between nodes represent node interrelationships. The node variables can be an abstraction of any problem, such as fault information, equipment state, observed phenomena, etc.

Directed graphs imply the assumption of conditional independence, which is manifested by the absence of directed arc connections between two variables if they are conditionally independent of each other, and by directed arc connections between two variables if they are dependent on each other. The network prescribes that each node V_t in the graph is conditionally independent of any subset of nodes consisting of non V_t children given by the V_t parent node, i.e., if $\overline{child}(V_t)$ is used to denote any subset of nodes nodes consisting of non V_t children, and $parents(V_i)$ is used to denote the immediate parent node of V_i, then $I\left(V_i,\overline{child}(V_i)\,|\,parents(V_t)\right)$, which has the meaning:

$$p\left(V_t\,|\,\overline{child}(V_t),\ parents(V_i)\right)=p\left(V_t\,|\,parents(V_t)\right) \tag{5}$$

2) A conditional probability table P associated with each node, the conditional probability table can be described by $p\left(V_i\,|\,parents(V_i)\right)$, which expresses the strength one conditional probability of a node's correlation with its parent node. Nodes without any parent have a priori probabilities.

With the nodes and their interrelationships (directed edges), the conditional probability table, the Bayesian network can express the joint probability of all nodes (variables) in the network and can compute the probability information of any other node based on the a priori probability information or on the values of certain nodes.

Applying conditional independence to the chain rule yields:

$$p(V_1,V_2,\cdots,V_k)=\prod_{i=1}^{k}p\left(V_i\,|\,parents(V_t)\right) \tag{6}$$

According to the probability chain rule, there are joint probabilities for the Bayesian network shown in Figure 1:

$$\begin{aligned}&p(V_1,V_2,\cdots,V_5)=p(V_5\,|\,V_1,V_2,V_3,V_4)\\&p(V_4\,|\,V_1,V_2,V_3)\,p(V_3\,|\,V_1)\,p(V_2\,|\,V_1)\,p(V_1)\end{aligned} \tag{7}$$

Considering the conditional independence of Bayesian networks, then the above equation can be rewritten as:

$$\begin{aligned}p(V_1,V_2,\cdots,V_5)&=\prod_{t=1}^{5}p\left(V_1\,|\,parents(V_t)\right)\\&=p(V_5\,|\,V_4)\,p(V_4\,|\,V_2,V_3)\,p(V_3\,|\,V_1)\,p(V_2\,|\,V_1)\,p(V_1)\end{aligned} \tag{8}$$

It can be seen that Bayesian networks can express the joint probability distribution of variables and make the joint probability solution of variables much simpler. Assuming that all variables are binary (e.g., normal and faulty power system components, inoperative and operative protections, taken as 0 or 1), for the K-variable case, finding the joint probability by the chain rule requires pointing 2^K independent joint probabilities. For the $K=5$ shown in Fig. 1, this value is $2^5=32$ and according to Eq. (8), only 10 $(2+4+2+2+2)$ probabilities need to be specified.

Bayesian networks are useful for probabilistic inference as they use a graphical network structure to visually represent the joint probability distributions of the variables and their conditional independence, which can result in substantial savings in probabilistic inference computations.

3.2. *Dynamic Bayesian Networks*

Dynamic Bayesian networks are probabilistic graphical models used to represent and reason about time processes to model the evolution of a system over time and can be used to predict the future state of a system. Dynamic Bayesian networks consist of two components, a Bayesian network that models the static structure of the system and a temporal model that models the dynamic evolution of the system over time. The Bayesian network component is used to represent the static structure of the system, while the temporal model is used to represent the dynamic evolution of the system over time. In other words, a dynamic Bayesian network is formed by taking a static Bayesian network and forming a probability distribution model with the ability to process temporal information by adding a temporal dimension, and multiple time slices (static Bayesian network) can be extended to obtain a dynamic Bayesian network. A dynamic Bayesian network can be defined as $(B_0, B_\rightarrow)$, and its specific state transfer is shown in Figure 2.

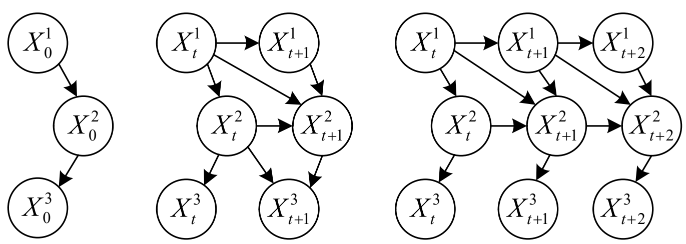

Fig. 2. Dynamic Bayesian network state transfer

The initial network B_0 represents the prior probability distribution $P(X_i=0)$ of X, and $B_\rightarrow$ represents the transfer network between two neighboring time slices. The state transfer probability between two time slices in a dynamic Bayesian network can be expressed as:

$$P(X_i \mid X_{t-1}) = \prod_{i=1}^{N} P\left(X_i^i \mid P_a\left(X_t^i\right)\right) \tag{9}$$

Dynamic Bayesian networks usually have the following assumptions:

1) Markov's assumption: i.e., the conditional probability of each node depends only on its parent node and the state of the previous moment, and not on the states of other nodes or earlier moments. This means that in a dynamic Bayesian network, if we know the state of each node at the previous moment and the parent node of each node, then we can accurately compute the distribution of node states at any moment. This assumption simplifies the dynamic Bayesian network model and reduces the complexity of the model.

$$P(X_{t+1} \mid X_1, X_2, \cdots, X_t) = P(X_{t+1} \mid X_t) \tag{10}$$

2) Time-aligned assumption: in Bayesian networks, the conditional probability between two time-slice transfers is always consistent i.e., the state transfer law of the system is the same within different time slices, which further simplifies the computation of the model.

$$P\left(X_{t+1} \mid X_t\right) = P\left(X_{t,2} \mid X_t\right) \tag{11}$$

According to the consistent smoothness property of the dynamic Bayesian network, the joint distribution probability of the nodes in the system can be computed from the initial node conditional probability and the state transfer probability between time slices.

$$\begin{aligned} &P(X[1], X[2], \cdots, X[t]) = P_{B_0}(X[1]) \prod_{t=1}^{T} P_{B_{\rightarrow}}(X[t+1] \mid X[t]) \\ &= \prod_{t=1}^{N} P_{B_0}\left(X_1^i \mid P_o\left(X_1^i\right)\right) \times \prod_{t=2}^{T} \prod_{i=1}^{N} P_{B_{\rightarrow}}\left(X_i^i \mid P_a\left(X_i^i\right)\right) \end{aligned} \tag{12}$$

where X_i^i denotes the i rd node on the t nd time slice, N denotes the number of dynamic Bayesian network nodes, $P_a\left(X_i^i\right)$ denotes the parent node of the node, and T denotes the task time.

4. Bayesian network-based risk monitoring and early warning model for power market transactions

Based on the above identified power market transaction risks, dynamic Bayesian networks are utilized to calculate the correlation between different power market transaction risk factors, from which the power market transaction risk value is estimated. Dynamic Bayesian network, as a probability distribution model dealing with time-series information, is applied to this paper to better analyze the dynamic dependencies between different risk factors.

4.1. Risk Early Warning Classification

Based on the dynamic Bayesian network to estimate the value of risk of power market transactions, divided into different warning levels, its specific risk warning level division is shown in Table 1.

Table 1. Electricity market trading risk warning levels

Serial number	Value at risk	Level of warning	Electricity market transaction status	
			Market price	Supply and demand
1	(0,0.1)	Without warning	Trading status is normal	
2	[0.1,0.2)	Light warning	Less volatility	Fundamental balance
3	[0.2,0.5)	Moderate warning	Some volatility	Slight imbalance
4	[0.5,0.8)	High warning	High volatility	Short term imbalances
5	[0.8,1.0)	Severe warning	Abnormal volatility	Serious imbalance

4.2. Risk Monitoring and Early Warning Modeling for Electricity Market Transactions

4.2.1. Experimental data. In the experiment, the hardware environment of this experiment is set first, with Intel Core i7 as the processor equipped with 32GB DDR4 RAM, and a high-speed SSD is used as the memory to provide at least 1TB of storage space. Then set the corresponding software environment, using Ubuntu as the operating system, using Python libraries such as Pandas and NumPy as the data processing tools to process and analyze the experimental data. Machine learning libraries such as pomegranate or pgmpy were used as machine learning libraries for ensuring the stable operation of the Bayesian network. Python libraries such as Matplotlib and Seaborn were used as data visualization tools to show the experimental results more intuitively. Its specific experimental parameters are shown in Table 2.

Table 2. Experimental parameters

Serial number	Experimental parameter	Parameter setting
1	Number of iterations	2000
2	Number of cross-validated folds	10
3	Bayesian network number of input nodes	10
4	Bayesian network number of hidden nodes	15
5	Bayesian network output number of nodes	1
6	Sampling interval	5

Based on the parameters in Table 2, the experimental test is conducted. In this experiment, the experimental dataset selected is the transaction data of the southern regional electricity market under the new type of power system in the last five years, which has a variety of transaction data types, including electricity price data, transaction volume, supply-demand ratio and other data. This experimental dataset is divided into two parts, of which, 20% is the training dataset and 80% is the test dataset. In the experiment, the power market transaction data are analyzed, and the power price data and the corresponding transaction volume data of hydroelectric power generation in September 2024 are taken as an example, and its experimental data are shown in Figure 3. As can be seen from Figure 3, the higher the price of electricity, the lower the trading volume, and when the price of electricity decreases, the trading volume rises. It can be seen that the power price and trading volume show a negative correlation.

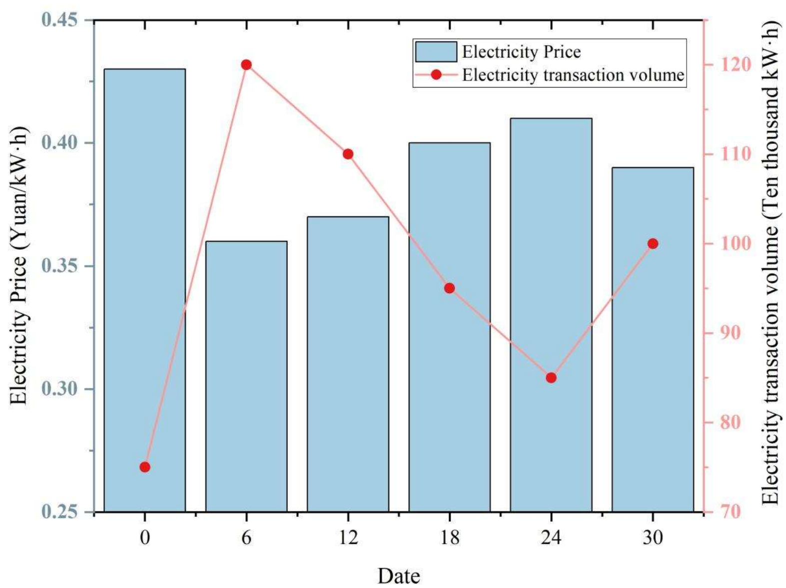

Fig. 3. Partial experimental data

4.2.2. Modeling. Credit level indicators are introduced to process and analyze the above experimental data to identify the risk factors of this electricity market transaction.

This paper adopts the expert assessment method based on the Delphi method to rate the credit of power generation enterprises and power supply enterprises, and categorizes both supply and demand side users into three levels of excellent credit (level A), good credit (level B) and normal credit (level C). The credit levels of power generation and supply companies participating in the market are evaluated as shown in Table 3.

Table 3. Credit level of power generation enterprises and power supply enterprises

Serial number	Power generation enterprise		Power supply enterprise	
	Quotation(Yuan/kW·h)	Credit	Quotation(Yuan/kW·h)	Credit
1	0.4318	A	0.4293	A
2	0.4225	B	0.4211	C
3	0.3992	B	0.4287	A
4	0.4211	C	0.4255	B
5	0.4305	B	0.4246	C
6	0.4257	B	0.4228	B
7	0.4295	A	0.4286	B
8	0.4028	C	0.4245	B
9	0.4255	C	0.4278	A
10	0.4267	B	0.4066	C
...	...	...	...	...

According to the credit level, the transaction between the power generating company and the power supply company is predicted, and the results of the virtual offer transaction are shown in Table 4.

Table 4. Transaction prediction results

Serial number	Power generation enterprise		Power supply enterprise		Transaction price (Yuan/kW·h)	Transaction quantity (Ten thousand kW·h)
	Quotation (Yuan/kW·h)	Serial number	Quotation (Yuan/kW·h)	Serial number		
1	0.4225	2	0.4228	6	0.4226	20188
2	0.4028	8	0.4066	10	0.4046	31000
3	0.4318	1	0.4287	3	0.4295	15340
4	0.4257	6	0.4246	5	0.4252	19885
5	0.3992	3	0.4246	5	0.4088	27999
6	0.4211	4	0.4286	7	0.4281	20740
7	0.4295	7	0.4293	1	0.4293	16068
8	0.4255	9	0.4255	4	0.4255	19999
9	0.4267	10	0.4211	2	0.4247	18035
10	0.4295	7	0.4278	9	0.4285	15370
...	...	...	...	...	...	...

The offer simulation trading method that incorporates the credit rating system can not only meet the requirement of maximizing social welfare, but also guarantee the right of the generation and consumption dual-side users with high credit ratings to trade first, which is closer to the real situation of the power market trading and the prediction results have rationality.

The power trading volume is set as the target variable, the power price is the decision variable, and the load forecast error and grid reliability are set as the state variables. Based on the Delphi method, load forecast error and grid reliability are assigned 5, 4, 3, 2, 1 from good to bad, and the dynamic Bayesian network variables are set as shown in Table 5.

Table 5. Bayesian network variables for example

Type	Description	Variable	Status
Target variable	A variable that describes the management objectives that the system is to achieve	Transaction quantity (Ten thousand kW·h)	<1250
			1250~1650
			1650~2050
			2050~2450
			>2450
Decision variable	A variable that directly implements the target variable	Electricity price (Yuan/kW·h)	<0.38
			0.38~0.40
			0.40~0.42
			>0.42
State variable	Link the variables between the target variable and the decision variable	Load forecasting error	1
			2
			3
			4
			5
		Grid reliability	1
			2
			3
			4
			5

During the modeling process, 3000 sets of data were collected and these data were organized. Thirty sets of data for four variables were put into a matrix with four rows and 30 columns. Using MATLAB, a self-programmed parameter learning program from the BNT toolkit was invoked, and parameter estimation used maximum likelihood estimation with complete data.

The output is visualized to analyze the relationship between the target variables and the decision variables, and the visualization results are shown in Figure 4. From Figure 4, it can be seen that in general the power price and trading volume show a negative correlation, but in June, when the power price of 0.4370 yuan per kWh, the trading volume still reaches 19.65 million kWh, and the inverse relationship between trading volume and price is not obvious. This is because in the southern region, affected by typhoons, heavy rains, extreme heat and other weather, the forecast of power load often has a large error. At the same time, due to the hot weather and excessive load, the burden on power grid equipment increased, and the power grid became unstable or failed.

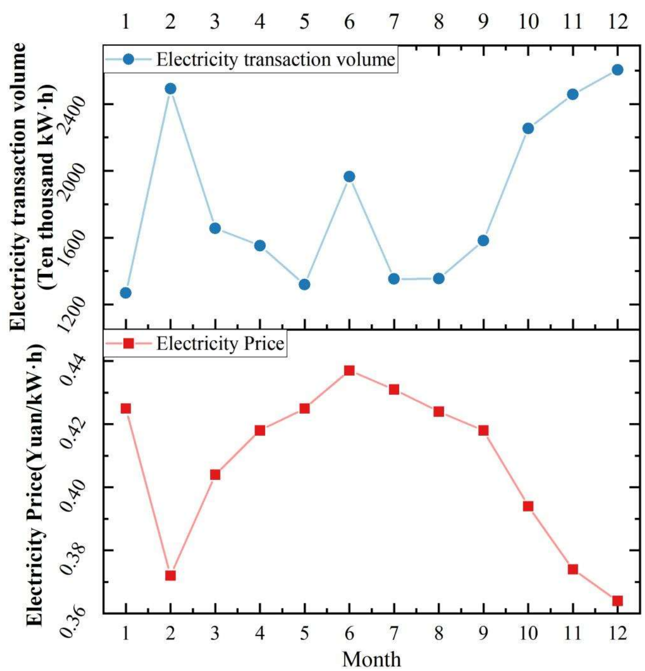

Fig. 4. Relationship between electricity price and trading volume

Finally, according to the early warning level classified in Table 1, early warning is carried out for the power market transaction risk. For different early warning levels, different early warning methods are adopted to ensure the effective management and timely response to power market transaction risks. At the same time, when choosing the early warning method, it can also be analyzed and appropriately adjusted and optimized according to the actual situation of the market at that time. So far, the design of the power market transaction risk early warning model based on dynamic Bayesian network is completed.

Dynamic Bayesian network-based power market transaction risk monitoring and early warning model can comprehensively consider more information to improve the robustness of the risk monitoring model. It can not only capture the immediate risk of the power market, but also warn the potential risk points in advance, so as to help the power market regulator to better manage the market risk and make effective decisions.

5. Conclusion

This paper takes the southern regional power market as the research object, and constructs the power market transaction risk monitoring and warning model based on the dynamic Bayesian network.

Taking the day as the unit, the power price data and the corresponding transaction volume data of a certain month show that the higher the power price is, the lower the transaction volume is, and when the power price decreases, the transaction volume rises. It can be seen that the power price and trading volume show a negative correlation. Taking the month as a unit, the output results show that in general, the power price and the transaction volume show a negative correlation, but in June, when the power price of 0.4370 yuan per kWh, the transaction volume still reaches 19.65 million kWh, and the inverse relationship between the transaction volume and the price is revealed to be inconspicuous.

Based on the dynamic Bayesian network to construct the power market transaction risk monitoring and early warning model can monitor the risk of the power market from multiple dimensions, the model not only focuses on the direct relationship between the power transaction volume and power price, but also more comprehensively evaluates the potential risk of the power market.

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