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Dynamic Identification Path of Performance Risks and Financial Prevention and Control Strategies for Energy Storage Capacity Insurance Base Contracts

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SUMMARY: *This paper clarifies the participating subjects in the energy storage capacity insurance service and proposes a service model that considers balance regulation. A case study is carried out with 109 power sales companies in a province as the research object, and a performance risk network model is established. Analyze the performance risk characteristics and relationships, and identify the performance risk based on the improved COPOD. Relying on the ideas of system dynamics and evolutionary game, the guarantee mechanism for the performance of the basic contract of energy storage capacity insurance is revealed. It is found that revenue capacity, cash flow ratio, and contract performance deviation rate have the highest point out degree and influence, and revenue capacity has an influence strength of 0.312 on contract performance deviation rate, which is the core conduction chain. The improved COPOD algorithm improves the identification accuracy by 7.34%, and correctly identifies the risk level of 108 power sales companies. The evolutionary game shows that the system is stabilized in the state of low risk preference of the power selling companies and strong control of the trading center. Combined with the results of the study, the financial defense and control strategy for the performance of the basic contract of energy storage capacity insurance is proposed.*

KEYWORDS: *energy storage capacity insurance; performance risk; social network analysis; COPOD; evolutionary game*

1 Introduction

Energy storage refers to the conversion process of storing energy through a specific medium and releasing it when needed, which can be categorized into mechanical energy storage (e.g., pumped storage), electrochemical energy storage (e.g., lithium-ion battery), and electrical energy storage [1-3]. Energy storage can provide various services for grid operation such as peak shifting, frequency regulation, standby, black start, demand response support, etc., which is an important means to enhance the flexibility, economy and security of traditional power systems [4, 5]. While energy storage capacity is the total value of energy storage, the dynamic identification of its insurance-based contract performance risk is crucial to ensure the smooth execution of energy storage projects and maintain the interests of all parties [6, 7].

One of the performance risks of the insurance-based contract for energy storage capacity is financial risk, which mainly arises from the fluctuation of energy storage prices, project cost overruns, and payment delays [8, 9]. To mitigate this risk, parties should conduct a comprehensive financial analysis, set clear payment terms, and incorporate cost adjustment and

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dispute resolution mechanisms in the contract [10, 11]. Another significant risk is technology risk, which is related to the adoption of new technologies and the uncertainty of their performance [12]. To cope with this, parties should conduct rigorous technology assessments to ensure system compatibility and establish an ongoing framework for technology updates and maintenance [13, 14]. In addition, legal and regulatory risks should not be ignored. Changes in laws and regulations may have a significant impact on the feasibility of new energy projects. To mitigate this risk, parties should pay close attention to legal and regulatory developments, incorporate compliance requirements into contracts, and establish mechanisms to respond to regulatory changes [15-17]. Given the dynamic nature of the new energy industry and the complexity of the project implementation process, it is imperative to utilize effective methods, paths, and strategies for identifying, assessing, and preventing and controlling potential risks.

In this paper, the theory of insurance economics is applied to the electricity market, and the modeling idea of shared energy storage providing deviation mutual insurance service for multiple market players is clarified. The relevant theories of social network analysis, including point degree centrality and traditional cohesive subgroup classification, are systematically sorted out. The mutation point anomaly detection method is introduced to improve the COPOD anomaly detection model. For the empirical cumulative distribution of input data, the empirical Copula function is estimated by a nonparametric method. Realize the anomaly detection of mutation cases in the base contract of energy storage capacity insurance based on the generated outlier scores. Identify the key risks and potential risk diffusion paths of the study case through four types of indicators of social network analysis. The COPOD before and after the improvement is used to calculate the outlier scores of different categories of indicators of performance risk to assess the effectiveness of the improvement scheme in this paper. A research model of guarantee mechanism based on system dynamics and evolutionary game is established to explore the impact of changes in system parameters on returns. Aiming at the demand for balanced development of multiple subjects in energy storage capacity insurance, corresponding financial defense and control strategies are proposed.

2 Study on the methodology for identifying performance risks in the underlying contracts for storage capacity insurance

2.1 Modeling Ideas for Optimizing Decision Making for Storage Capacity Insurance Services

With the continuous improvement of China's electric power market, the assessment of electric energy deviation has gradually formed a market mechanism of medium- and long-term and spot “double deviation” settlement. There are medium- and long-term deviations and spot deviations between uncontrollable new energy enterprises and non-adjustable industrial and commercial users in the process of trading in the electric energy market. Medium and long term deviation is the deviation between the medium and long term contract power and the power declared in the spot before the day, and the deviation power is settled in accordance with the clearing price of the spot before the day. Spot deviation is the deviation between the declared power and the actual power consumption of the previous day's spot, and the deviated power is settled according to the real-time price.

The way of avoiding deviation by multiple market players is shown in Figure 1. Uncontrollable new energy enterprises and unregulated industrial and commercial users due to their own randomness and uncontrollability, will inevitably produce power deviation, in order to avoid deviation of the two can take the means to improve their own power or load forecasting accuracy, self-built energy storage power plant to regulate the deviation of the new energy and regulated power bundling and industrial and commercial users to the sale of electricity company agents and other inter-subjective alliance form to participate in the market.

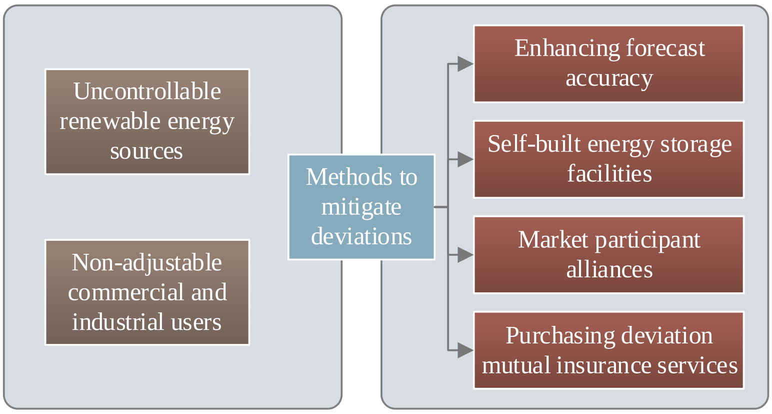

Figure 1: Ways for multiple market entities to avoid bias

The process of shared energy storage deviation mutual insurance service is shown in Figure 2. In the business model of deviation mutual insurance service based on shared energy storage, the uncontrollable new energy enterprises and unadjustable industrial and commercial users purchase deviation mutual insurance service from shared energy storage operators and pay mutual insurance fees to shared energy storage operators, who bear the deviation risk instead of new energy enterprises and industrial and commercial users.

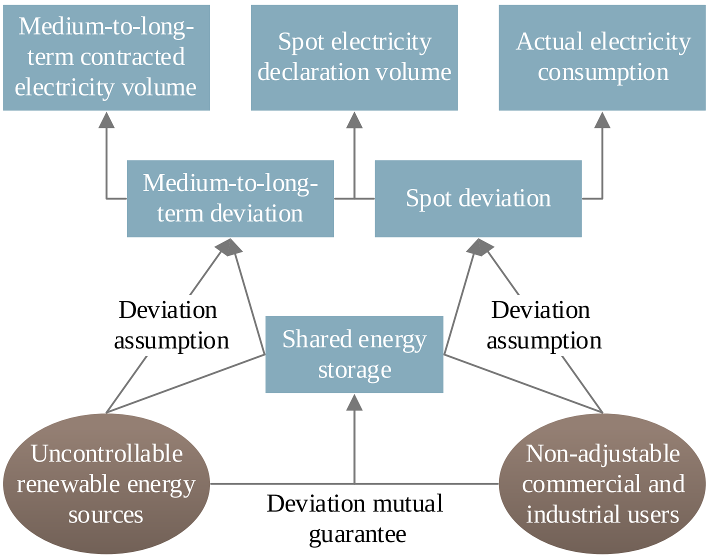

Figure 2: Shared energy storage deviation mutual protection service process

The deviation mutual insurance business model based on shared energy storage draws on the service model of the traditional insurance industry, and the core element of the deviation mutual insurance business model designed by shared energy storage as an insurer is to apply risk management theory and insurance theory to the pricing of services in the electricity market to avoid the risk of balancing account capital loss. However, the difference between deviation mutual insurance services for electricity and traditional insurance services lies in the specificity of electricity, with certain differences in terms of the insurer, policyholder, insured, subject matter of the insurance and possible insured risks.

Shared energy storage operators act as insurers to establish balancing accounts, which not only need to have the ability to underwrite capital losses, but also have the ability to regulate and meet the regulatory requirements of grid operation.

Uncontrollable new energy enterprises and unregulatable industrial and commercial users as the target public, so that they have sufficient willingness to insure is the basis for the sustainability of the business model.

Insured new energy enterprises and industrial and commercial users as the insured need to support the deviation liability transfer when the deviation liability is recognized in the power market, and the responsible body of the deviation assessment after the insured pays the premium should be changed to a shared energy storage operator.

As the subject of insurance, the deviation of electric energy cannot be simply offset by positive and negative deviation, and should adhere to the basic principle of "enhancing the system regulation capability", and restrict the siting of shared energy storage power stations, service scope, market entry conditions, underwriting scale and scheduling and operation control requirements, etc., so as to prevent speculation and arbitrage.

The probability of power deviation of uncontrollable new energy enterprises and unregulated industrial and commercial users is a possible insurance risk, and the size of power deviation determines the revenue and service pricing of shared energy storage operators.

2.2 Social Network Analysis Theory

2.2.1 Introduction to Social Network Analysis

A social network refers to a collection of social actors and the relationships between them. It can also be said that a social network is a collection of multiple points (social actors) and lines connecting the points (relationships between actors). Expressing a network in terms of points and lines is a formalized definition of a social network.

Social actors take many forms: individuals, families, organizations, villages, schools, communities, cities, nations, etc.

Social network analysis is used to describe and measure the relationships between social actors and the various tangible or intangible things that flow through these relationships, such as information, resources, etc.

Social network analysis is a unique perspective in the social sciences that is based on an important assumption: that there are very important relationships between interacting individual social objects. Social network theories, models, and applications are based on relational data, and relationships are the foundation of social network analysis theory.

2.2.2 Introduction to pointwise centrality

Point centrality is an indicator of "power" based on degrees (out and in).

(1) Point centrality

"Point centrality" is used to describe the degree to which a node is located in the "core" of the graph.

There are two types of point centrality: absolute point centrality and relative point centrality. A node i absolute point degree centrality (expressed as $C_{AD}(i)$) is the value of the degree of the point, expressed as in equation (1):

$$C_{AD}(i) = d(i) \tag{1}$$

Relative point centrality is a standardized form of absolute point centrality. The relative point degree centrality $(C_{RD}(i))$ of a node i is the ratio of the degree of i to its maximum possible degree, expressed as in equation (2):

$$C_{RD}(i) = \frac{d(i)}{n-1} \tag{2}$$

where n is the number of nodes in the graph where point i is located.

(2) Point Center Potential

“Point degree center potential” this indicator is to describe the graph whether there is a core node trend.

The calculation method of the point degree central potential indicator: find out the maximum value of the center degree of the node in the graph $C_{\max}$; then calculate the difference between $C_{\max}$ and the center degree of all other nodes; sum these differences; and finally use this sum to remove the maximum possible value by the sum of the above differences. As formula (3):

$$C = \frac{\sum_{i=1}^{n}\left(C_{\max} - C_i\right)}{\max\left[\sum_{i=1}^{n}\left(C_{\max} - C_i\right)\right]} \tag{3}$$

We can describe the centrality potential indicator in terms of absolute dot degree centrality and relative dot degree centrality.

The absolute point degree centrality is used to describe the point degree centrality potential as in equation (4):

$$C_{AD} = \frac{\sum_{i=1}^{n}\left(C_{AD\max} - C_{ADi}\right)}{n^2 - 3n + 2} \tag{4}$$

The pointwise centroid potential is described in terms of relative pointwise centroid degrees as in Equation (5):

$$C_{RD} = \frac{\sum_{i=1}^{n}\left(C_{RD\max} - C_{RDi}\right)}{n-2} \tag{5}$$

Here $C_{AD} = C_{RD}$, which is C_D (point degree centered potential).

2.2.3 Classification of cohesive subgroups

A cohesive subgroup is a subgroup of a network whose members are more closely related to each other, e.g., neighboring, high accessibility, higher frequency of comings and goings between members, or higher density of relationships between members.

From the above simple definition of cohesive subgroups, we can see that cohesive subgroups are examined from four aspects:

(1) The members are neighborly, this we call reciprocity;

(2) The members are reachable to each other, this we call reachability;

(3) Degree relationships between members, which can be referred to as relationship frequency;

(4) The strength of the relationship between members relative to the relationship between internal and external members.

Based on the aspects examined in the above four categories, traditional cohesive subgroups are categorized as follows:

(1) Factions

A faction is defined as a maximal complete subgraph containing at least three nodes in a graph.

From the definition, it can be seen that every two points inside a faction are adjacent, greater than three nodes, and are not contained by other factions. That is, every node is adjacent, so factions are cohesive subgroups based on reciprocity.

(2) $n-$ factions

An $n-$ faction is any subgraph in the total graph that satisfies the maximum distance between any members in the total graph not exceeding n. So n-factions are cohesive subgroups based on reachability.

(3) $n-$ sects

$n-$ sect is a subgraph in which the maximum distance between any two points in the subgraph does not exceed n. It is also a cohesive subgroup based on reachability.

(4) $k-$ clumps

A $k-$ clump is a subgraph that satisfies the condition that any point in the subgraph is directly connected to at least all but k points in the subgraph. That is, if a cohesive subgroup is of size n, then the cohesive subgroup is a $k-$ clump only if all of its points have degrees not less than $n-k$. Thus the $k-$ clump is a cohesive subgroup based on the basis.

(5) $k-$ kernel

The $k-$ kernel is also a cohesive subgroup based on the frequency of relations (degrees of points), which is a subgraph that satisfies the condition that any point in that subgraph is directly connected to at least k points in the subgraph. That is, the degree of any point in the $k-$ kernel is not less than k.

(6) Lambda sets

A lambda set is a set of nodes based on the strength of the relationships between the inner and outer members of a subgroup.The notion of lambda set is derived from the idea that a cohesive subgroup should be relatively stable, i.e., a cohesive subgroup should not become disassociated by removing a few lines from it.

In order to formally describe lambda sets, a notion of edge associativity is first introduced. The edge associativity between a point n_i and a point n_j is denoted as $\lambda(i, j)$, which is equal to the minimum number of lines that must be removed from the graph in order for there to be no pathway between these two points. Then, the larger the value of $\lambda(i, j)$, the more robust the relationship between n_i and n_j; the smaller the value of $\lambda(i, j)$, the more sensitive the relationship between n_i and n_j.

For a set of nodes N_S of a subgraph G_S, we say that the set is a lambda set if the following condition is satisfied, i.e., the edge correlation of any pair of nodes inside N_S is greater than the edge correlation of the pair of nodes formed by a point from the inside of N_S and a point from the outside of N_S.

The formal description of a lambda set is as follows:

Let the set of nodes $N_S \subseteq N$ of a subgraph G_S be $\lambda(i, j) > \lambda(k,l)$ if for any nodes $n_i, n_j, n_k \in N_S$ and $n_l \in N - N_S$, then we call the set of nodes N_S a lambda set.

2.3 Anomaly detection model based on improved COPOD

2.3.1 Principles of mutation point anomaly detection methods

The mutation point anomaly detection method determines whether there is a sudden increase or decrease by comparing it with the proximity point. This is done by comparing each time series value with the historical value, traversing the historical data using a sliding window, subtracting the statistical value of the traversed data from the statistical value of the window, which in turn leads to the new time series data, and then utilizing the new time series data to calculate the normal range as in Eq. (6).

$$f(x)=\begin{cases}1, & x<Q_3+c\times IQR\\ 0, & x\geq Q_3+c\times IQR\end{cases} \tag{6}$$

where c is the interquartile distance multiplier, which is used to determine the upper range, IQR denotes the interquartile distance of s, and Q_3 denotes the third quartile of the new time series data. If the difference between the current value and the window score statistic is not in the normal range, it is considered an anomaly, otherwise it is considered normal.

2.3.2 Copula functions

The Copula function, from Sklar's theorem, is a function that connects the joint distribution function to their respective marginal distribution functions. Suppose $x_1, x_2, ..., x_n$ are n random variables, $F_1(x_1), F_2(x_2), ..., F_n(x_n)$ are their respective marginal distribution functions, then there exists a Copula function $H(x_1, x_2, ..., x_n)$ is satisfied:

$$H(x_1,x_2,...,x_n)=C(F_1(x_1),F_2(x_2),...,F_n(x_n)) \tag{7}$$

The function C represents the “connection” of multiple marginal distribution functions to the joint distribution function. And according to the marginal distribution of the CDF inverse transformation, i.e., $x_i = F_i^{-1}(u_i)(i=1,2,...,n)$, the Copula function is expressed as:

$$C(u_1,u_2,...,u_n)=H(F_1^{-1}(u_1),F_2^{-1}(u_2),...,F_n^{-1}(u_n)) \tag{8}$$

where $F^{-1}(u)$ represents the inverse function of $F(u)$, the inverse cumulative distribution function.

Copula adopts a concise way to realize the establishment of multi-volume data interdependent structure, which makes the univariate marginal distributions correlate with each other to form a multi-dimensional joint distribution function that may take values between 0 and 1. If multiple random variables with marginal distributions are known and there is correlation between the random variables, modeling the joint distribution using the Copula function can be a good tool.

2.3.3 Principles of COPOD

Copula-based anomaly detection method uses a nonparametric approach to estimate the empirical Copula function against the empirical cumulative distribution of the input data, whereby the joint distribution of the multidimensional data is estimated, after which the obtained empirical Copula function is used to estimate the tail probabilities of the joint distribution on all dimensions, and finally the generated outlier scores are used for the assessment of the anomalies.

Assuming that X is a d-dimensional dataset with n observations, and that X_{ij} represents the j-dimension of the i-observation, the empirical probability measure can be derived in the case where the i-observation and j-dimension are independent of each other (in this paper, we use only one of the subscripts to denote either the observation or the dimension):

$$P(A)=\frac{1}{n}\sum_{i=1}^{n}\Pi\left(X_i \le A\right) \tag{9}$$

where Π denotes the indicator function. The cumulative distribution function $F(x)$ can be derived from Eq. (9) as:

$$F(x)=P\left(\left(-\infty,x\right]\right)=\frac{1}{n}\sum_{i=1}^{n}\Pi\left(X_i \le x\right) \tag{10}$$

Ideally one should consider both the possibility of the sample falling in the left and right tails of the joint distribution, but in practice the situation may be more complicated. It is possible for outliers to appear on the left side of the joint distribution, on the right side of the joint distribution, and of course on both sides of the joint distribution. If all outliers appear on the left side of the joint distribution, then estimation using the tail probabilities of the left tail is better, but estimation using the tail probabilities of the right tail will be poor. Similarly, if all the anomalies appear on the right side of the joint distribution, estimation using the right-tailed tail probabilities is superior, but estimation using the left-tailed tail probabilities will be poor. The results obtained by using different tail probabilities for different situations are different, so the skewness of the distribution needs to be calculated, and based on the skewness of the distribution, a decision is made on which tail probabilities to use to generate the outliers.

2.3.4 Algorithmic flow of COPOD

First, the COPOD algorithm fits a left-tailed cumulative distribution function for each dimension according to Eq. (7), denoted as $F_d(x)$. The right-tailed cumulative distribution function for each dimension, denoted as $\overline{F_d}(x)$, is obtained by transforming x into $-x$. b_i denotes the skewness of each dimension. The b_i can be computed by the following equation:

$$b_i=\frac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\overline{x_i}\right)^3}{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i-\overline{x_i}\right)^{2}}^{3}} \tag{11}$$

where n denotes n observations.

Next, the observations of the empirical Copula function corrected for skewness are computed, denoted as $W_{d,i}$, then:

$$W_{d,i} = \begin{cases} F_d(x_i) & b_d < 0 \\ \overline{F_d}(x_i) & b_d \geq 0 \end{cases} \tag{12}$$

where b_d denotes the skewness of dimension d.

Finally, the probability that this observation is an outlier is calculated based on the X_i distribution of each dimension by means of the left-tailed empirical Copula function, the right-tailed empirical Copula function, and the bias-corrected empirical Copula function, respectively, and the negative logarithm is taken of the result. The probability that this observation is an outlier is then defined by taking the maximum of the three. It can be assumed that the smaller the tail probability, the more outlier the point behaves.

$$p_l = -\sum_{j=1}^{d} \log\left(F_j(x_i)\right) \tag{13}$$

$$p_r = -\sum_{j=1}^{d} \log\left(\overline{F_j}(x_i)\right) \tag{14}$$

$$p_{tr} = -\sum_{j=1}^{d} \log\left(W_{j,i}\right) \tag{15}$$

$$O\left(x_i\right) = \max\left(p_l, p_r, p_{tr}\right) \tag{16}$$

where p_l denotes the left-tailed empirical Copula function, p_r denotes the right-tailed empirical Copula function, and p_{tr} denotes the bias-corrected empirical Copula function. d denotes the dimension and $O(x_i)$ denotes the final tail probability, which is the anomaly score.

From Eq. (15), it is also possible to represent the anomaly score of dimension d, whereby the degree of anomaly of each dimension can be calculated, thus providing some explanation for the method's determination of outliers.

3 Empirical analysis of the dynamic identification of performance risk in the underlying contract for storage capacity insurance

In this paper, 109 electricity sales companies in a provincial electricity market in 2024 are selected as research objects, among which 12 companies have performance problems. Nine indicators (numbered X1~X9, respectively), namely quick ratio, cash flow ratio, gearing ratio, power sales price deviation, revenue capacity, historical credit evaluation rating, guarantee coverage ratio, settlement delay rate, and contract performance deviation rate, are selected for the case study of performance risk identification.

3.1 Characterization of the performance risk network of the underlying contract for storage capacity insurance

Utilizing Ucinet 6.0 software to construct a performance risk network for the underlying contract of energy storage capacity insurance and sort out the association of different risk types.

3.1.1 Analysis of the centrality of compliance risk

Calculated performance risk network degree center degree results are shown in Table 1.

(1) Degree of centrality. It indicates the closeness of the direct connection between risks, and is divided into point out degree and point in degree. For the point out degree, revenue capacity, cash flow ratio and contract performance deviation rate have larger values, which can have an impact on other performance risks but are not easily controlled by other risks, and play a major role in influencing the performance risk network, which is the power core of the network. Historical credit evaluation rating and power sales price deviation have larger point entry and are risk takers, i.e. they are susceptible to other risks and are the direct cause of project suspension. Therefore they should be strictly controlled.

(2) Proximity to the center degree. Reflects the independence of performance risk. Smaller values of historical credit rating and settlement delay rate indicate that these risks play a dominant role in the performance risk network and are independent risks when risks spread.

Table 1: Results of degree centrality

Node	Out-degree	In-degree	Closeness centrality
X1	18	12	72.89
X2	21	15	78.34
X3	15	18	75.01
X4	12	21	70.37
X5	24	18	84.46
X6	9	24	61.91
X7	15	15	73.44
X8	18	12	67.35
X9	21	15	80.09

3.1.2 Performance risk impact analysis

The influence analysis index is different from the direct influence relationship described by the degree center degree, but considers the indirect influence of nodes and the influence size between nodes, and gives the influence size ranking. By calculating the Huber influence index and the influence relationship matrix to obtain the influence ranking and influence relationship matrix are shown in Table 2 and Table 3, respectively. Among them, the influence index of revenue capacity, cash flow ratio, and contract performance deviation rate is large, and the total influence intensity on other variables is more than 2. The influence relationship matrix shows that revenue capacity, as a core node, has an influence intensity of 0.312 on the contract performance deviation rate, and it can significantly drive the key indexes of settlement delay rate, cash flow ratio, and other key indexes. Those with strong influence relationships include revenue capacity on contract performance deviation rate and settlement delay rate; cash flow ratio on revenue capacity and contract performance deviation rate; gearing ratio on contract performance deviation rate; and contract performance deviation rate on revenue capacity.

Table 2: Ranking of influence

Node	Row sums	Col sums
X5	2.284	2.360
X2	2.179	1.678
X9	2.067	2.462
X3	1.983	1.773
X7	1.777	1.726
X1	1.687	1.400
X8	1.495	2.073
X4	1.321	1.230
X6	1.294	1.385

Table 3: Influence relationship matrix

	X1	X2	X3	X4	X5	X6	X7	X8	X9
X1	1.000	0.111	0.072	0.000	0.204	0.000	0.091	0.064	0.145
X2	0.103	1.000	0.198	0.000	0.307	0.000	0.184	0.152	0.235
X3	0.065	0.162	1.000	0.000	0.204	0.088	0.104	0.122	0.238
X4	0.000	0.000	0.000	1.000	0.054	0.022	0.000	0.143	0.102
X5	0.098	0.187	0.122	0.056	1.000	0.115	0.158	0.236	0.312
X6	0.000	0.000	0.016	0.035	0.052	1.000	0.022	0.063	0.106
X7	0.042	0.066	0.109	0.000	0.151	0.088	1.000	0.135	0.186
X8	0.026	0.054	0.035	0.067	0.112	0.021	0.042	1.000	0.138
X9	0.066	0.098	0.221	0.072	0.276	0.051	0.125	0.158	1.000

3.2 Results of performance risk identification for the underlying contract for storage capacity insurance

The raw data of each indicator of 109 market operators are collected, and their empirical cumulative distribution functions are studied separately. The empirical distribution function obtained by standardizing the nine indicators is shown in Fig. 3, which indicates the empirical cumulative distributions of different indicators, and the cumulative distributions can be used to judge to what type of indicator the indicator belongs. It can be seen that quick ratio, cash flow ratio, revenue capacity, historical credit rating, and guarantee coverage ratio belong to benefit-type indicators, while gearing ratio, power sales price deviation, settlement delay rate, and contract performance deviation rate belong to cost-type indicators.

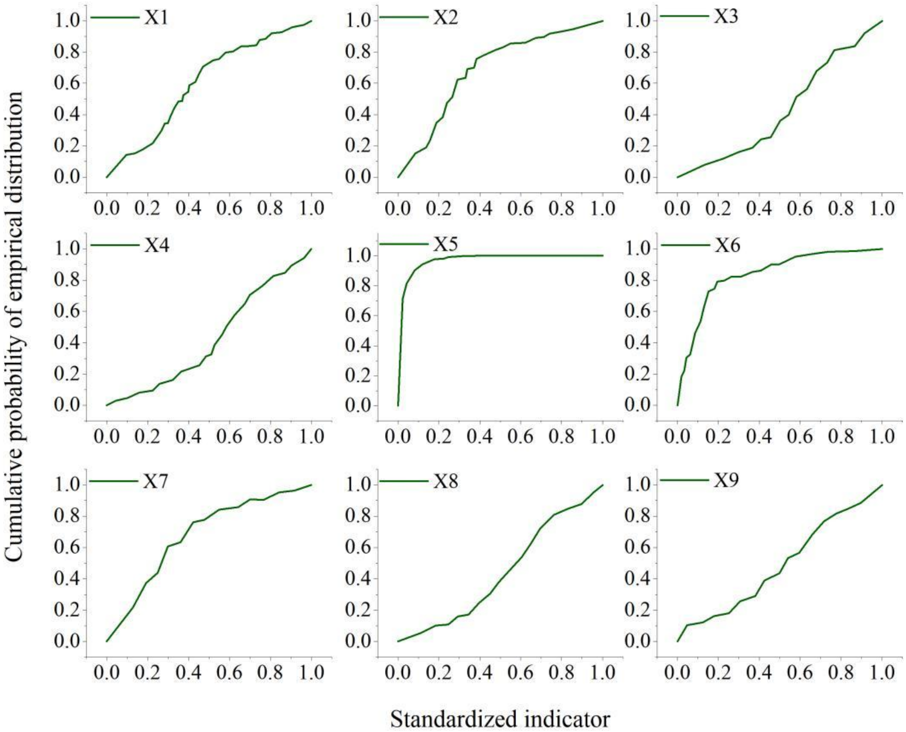

Figure 3: Empirical cumulative distribution functions for each indicator

Taking the benefit-based indicators X1 and X2 as an example, the COPOD algorithm before and after the improvement is used to identify the performance risk, and the comparison of the identification results is shown in Figure 4. The performance risk identification accuracy of the COPOD algorithm before and after improvement reaches 91.74% and 99.08% respectively, and the accuracy of the improved COPOD algorithm is significantly higher than that of the initial COPOD algorithm. The closer to the lower left corner of the market operating subject is more likely to be a suspicious performance anomaly subject. The initial COPOD algorithm incorrectly identifies the market operating subjects in the upper right corner as abnormal subjects, while the improved COPOD algorithm correctly identifies the market operating subjects in the upper right corner as normal subjects, which shows the effectiveness of the improved COPOD algorithm.

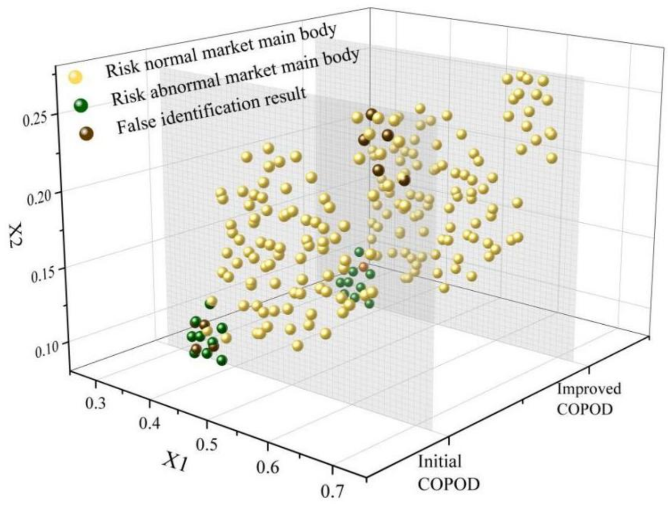

Figure 4: Comparison of performance risk identification results

Another advantage of the improved COPOD algorithm in this paper is the strong interpretability of the performance risk identification results. The algorithm helps to make it clear to the regulator in which aspects of the performance anomaly subject is anomalous as well as the characteristics of the overall environment of the market, providing an effective basis for regulation. The identification results for a typical performance anomaly subject A are shown in Figure 5. Figure 5 shows the location of abnormal subject A's Copula anomaly score in the 85% and 99% market segmentation intervals, and the Copula anomaly score of each index of this abnormal subject A is higher, especially the quick ratio is the most abnormal, and the Copula anomaly score is close to the critical line. For subjects with normal performance, most of the Copula anomaly scores for each indicator are low.

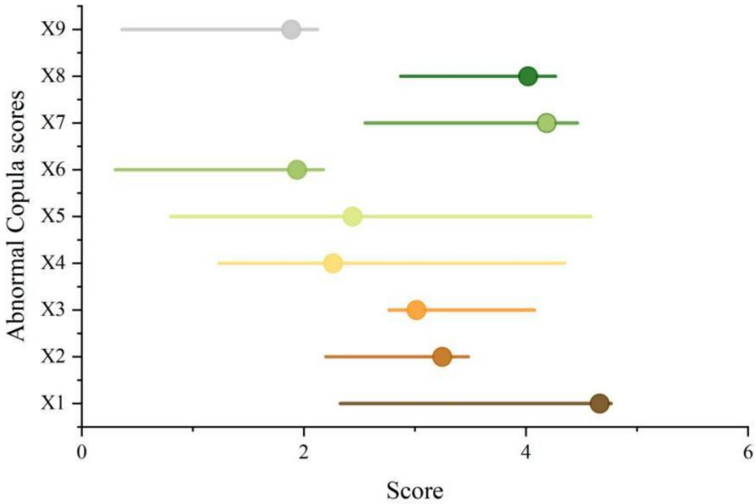

Figure 5: Identification results of A typical performance anomaly subject A

4 Analysis of the evolution of the performance guarantee mechanism for the underlying contracts for storage capacity insurance

4.1 Modeling of performance guarantee mechanisms

(1) Revenue Module.

The revenue function of a power sales company can generally be fitted by a quadratic function as:

$$P_i = -\frac{1}{2}aE_i^2 + bE_i + c \tag{17}$$

where P_i and E_i are the revenue and electricity sales of the electricity sales company under strategy combination i, a,b,c are the revenue coefficients of electricity sales; the quadratic coefficients of the revenue function are generally negative, reflecting the characteristics of diminishing marginal returns.

This paper takes CFDs in the spot market as the background, and the power purchase cost of the power sales company can be expressed as follows:

$$C_{buy}=\begin{cases}\sum_{t}^{T}\left(\rho_{ml,t}e_{ml,t}+\rho_{prc,t}(e_{prc,t}-e_{ml,t})\right) & e_{prc,t}\ge e_{ml,t}\\ \sum_{t}^{T}\rho_{ml,t}e_{prc,t} & e_{prc,t}<e_{ml,t}\end{cases}\tag{18}$$

where C_{buy} is the power purchase cost of the power selling company under strategy combination i; t and T denote the single cycle time period and the total time period, respectively; $e_{ml,t}$, $e_{prc,t}$ denote the medium- and long-term contracted day-ahead electricity and the market electricity demand of the power selling company, respectively; and $\rho_{ml,t}$, $\rho_{prc,t}$ denote the medium- and long-term contract electricity price and spot market electricity price, respectively.

The operating costs of the electricity selling company are:

$$C_{ope}=\lambda E_i\tag{19}$$

where C_{ope} is the operating cost of the electricity selling company under strategy combination i; λ denotes the operating cost required per unit of electricity.

(2) Market trading module.

Electricity sales is a state quantity, and the electricity sales of the electricity selling company in a cycle is denoted as:

$$E_i=\int_0^T E_t dt\tag{20}$$

$$E_t=h_i e_{pre,t}\tag{21}$$

where E_t is the electricity sales of the electricity selling company in time period t; h_i is the power purchase correction coefficient of the electricity selling company under strategy combination i.

The change in the electricity sales of the electricity selling company is represented by the power purchase modification factor, which is expressed as follows:

$$h_i=\begin{cases}\eta\dfrac{I_i}{I_{ave}} & I_i\ge I_{ave}\\ \varepsilon\dfrac{I_i}{I_{ave}} & I_i<I_{ave}\end{cases}\tag{22}$$

$$I_i=\frac{P_i-C_{buy,i}}{E_i}\tag{23}$$

where I_i is the kWh return of the electricity selling company under strategy portfolio i in the previous cycle; I_{ave} is the average value of kWh return of the whole market.

The default amount, willingness to perform, and credit level of the electricity selling company are respectively:

$$C_{break,i} = (I - k_i) \times (C_{buy,i} - P_i) \tag{24}$$

$$k_i = g\left(k_i' + u^{\frac{Q_i' - \theta}{\theta}}\right) \tag{25}$$

$$Q_i = \theta\left(1 - \frac{C_{break,i}}{C_{buy,i}}\right)^v \frac{C_{buy,i} - C_{break,i-1}}{C_{buy,i}} \tag{26}$$

where $C_{break,i}, k_i, g_i$ and Q_i are the default amount, willingness to perform, willingness to perform factor, and credit level of the power selling company under strategy combination i, respectively; k_i', Q_i' are the willingness to perform and the credit level of the power selling company in the previous cycle, respectively; u is the factor to adjust the willingness to perform under different risk preferences of the power selling company; v is the factor to control the credit level of the power selling company under different control strengths of the trading center. By adjusting the size of the factor, the willingness to perform or credit level can be increased or decreased; θ is the credit level score, which is set to 100.

(3) Guarantee module.

The guarantee module is divided into the guarantee amount to be paid by the power sales company and the guarantee benefit available to the trading center, which is often linked to the traded electricity volume in the current provincial electricity markets.

The guarantee amount for the power sales company is:

$$F_{cen,i} = \int_0^T L \frac{\gamma_{cen,i} E_t}{\omega E_{\max}} dt \tag{27}$$

$$F_{mt,i} = \int_0^T \gamma_{mt,i} E_i dt \tag{28}$$

where $F_{cen,i}, F_{mt,i}$ are the guarantee amount of the centralized guarantee mechanism and the guarantee amount of the mutual guarantee mechanism to be paid by the selling company under strategy combination i, respectively; $\gamma_{cen,i}$ is the guarantee coefficient of the centralized guarantee, which is actually the bottom area of the guarantee cube of the selling company; $\gamma_{mt,i}$ is the guarantee coefficient of the mutual guarantee mechanism; ω is the maximum bottom area of the guarantee cube graph of the centralized guarantee mechanism; $E_{\max}$ and L are the maximum trading power and the maximum guarantee amount to be paid by the centralized guarantee mechanism setting, respectively.

The guarantee benefit of the trading center is:

$$M_{cen,i} = \sigma_{cen,i} F_{cen,i} \tag{29}$$

$$M_{mt,i} = \sigma_{mt,i} F_{mt,i} \tag{30}$$

where $M_{cen,i}, M_{mt,i}$ are the guarantee benefits of the centralized guarantee mechanism and the guarantee benefits of the mutual guarantee mechanism of the trading centers under strategy combination i ; $\delta_{cen,i}, \delta_{mt,i}$ are the coefficients of guarantee benefits of the centralized guarantee and the mutual guarantee mechanism respectively.

4.2 Analysis of compliance evolution game results

From the social network analysis, it can be seen that the historical credit evaluation level occupies a dominant role in the performance risk network. In order to explore the influence of credit level on the willingness to perform, the initial willingness to perform is set to 0.8, and the initial credit level is set to 90. The probabilities of the power sales company and the trading center choosing two strategies are x, y and 1-x, 1-y, respectively, and there are a total of four strategy choices. Substitute the above parameters for the first cycle of system dynamics evolution, and calculate the return parameter combinations under different parameter combinations. Secondly, the evolutionary game results of the electricity selling company and the trading center under different initial states are analyzed, i.e., the analysis of the evolutionary process of the probabilities (x0,y0) of the two sides of the game choosing a specific strategy at the end of the first cycle of trading. The initial probability x0 is now set to vary from 0 to 1 in steps of 0.2 (without 0 or 1), and its evolutionary result is shown in Fig. 6. It can be seen that after the end of the first cycle of the resulting revenue parameter combinations, after further evolution of the game analysis, the strategies selected by the power sales company and the trading center are gradually converging to stability, and their stable equilibrium points are (0,1), that is, the power sales company selects a low-risk appetite strategy, and the trading center selects a strong control strategy. At the end of the first cycle, both the power sales company and the trading center converge to the stable point no matter what strategy they choose. Analysis shows that in the first cycle, due to certain fluctuations in the CFDs in the spot market, the power sales company incurred certain losses, although the credit level was high at the beginning of the market, which did not pull down the willingness to perform, but eventually the losses made the willingness to perform decline, resulting in a certain percentage of the amount of defaults, and the company chose the low-risk appetite strategy in order to maximize its own revenue. And the trading center to ensure that the guarantee benefits can fully cover the default risk under the premise of the market default situation, so choose a strong control strategy.

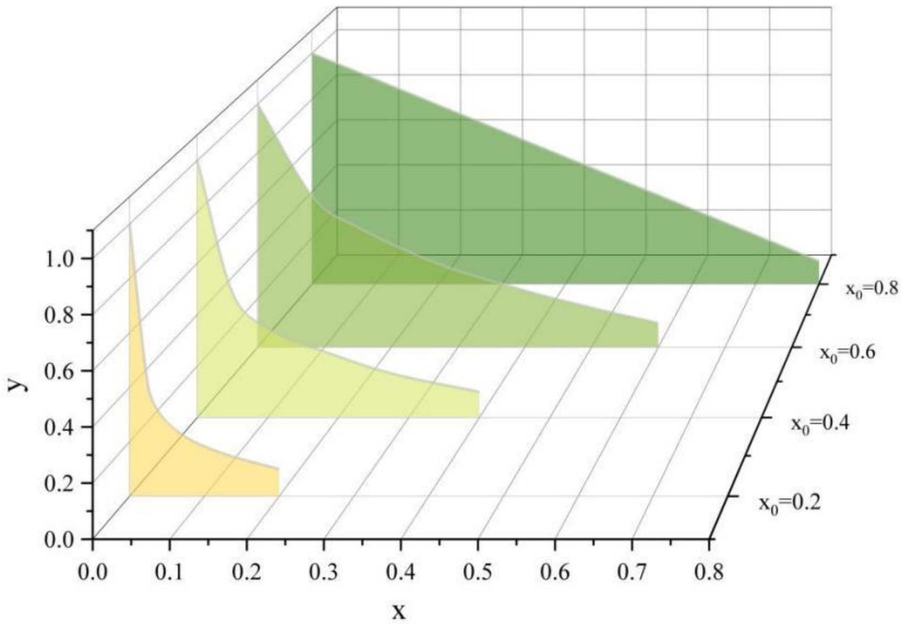

Figure 6: Evolutionary game process in different initial states

Under the four control strategies (numbered S1~S4) of power sales companies with high and low risk preferences and trading centers with strong and weak control, the results of the evolution of credit level and performance willingness of power sales companies over the cycles are shown in Table 4. The credit level of power sales companies with high risk preference is slightly lower than that of those with low risk preference under the same control intensity, with an average credit level of only 64.11 over the five cycles.Under the strong control strategy of the trading center, the credit level of the power sales companies leads to a larger decline due to defaults, and the willingness to perform of the companies is low, which is also reduced by the high risk preference strategy.

Table 4: Credit levels and willingness to perform in different periods

	Credit level			
	S1	S2	S3	S4
Period 1	65.38	81.42	66.07	82.45
Period 2	64.14	78.95	63.58	80.58
Period 3	68.23	84.47	67.92	84.62
Period 4	62.01	80.66	65.63	81.09
Period 5	60.77	77.52	63.51	78.45
	Willingness to perform			
	S1	S2	S3	S4
Period 1	0.736	0.747	0.878	0.879
Period 2	0.628	0.701	0.736	0.805
Period 3	0.745	0.868	0.852	0.941
Period 4	0.633	0.752	0.721	0.833
Period 5	0.579	0.805	0.754	0.784

5 Financial prevention and control strategies for the performance of contracts underlying storage capacity insurance

Based on the risk transmission characteristics of energy storage capacity insurance in the new electric power system and the equilibrium law of multi-body game, this paper proposes systematic financial prevention and control strategies.

(1) Build energy storage capacity insurance product system

Energy storage capacity insurance involves multiple subjects such as uncontrollable new energy enterprises, non-adjustable industrial and commercial users, power sales companies, energy storage operators and trading centers. The risk factors of the energy storage system are complex and diverse, and the corresponding insurance demand and product application scenarios are also very rich, which requires the development of a series of insurance products to meet the insurance demand at different periods and stages. A layered insurance product system should be constructed, and for the original deviation risk on the generation and consumption side, a protection policy covering the price deviation of power sales, settlement delay rate, guarantee deposit coverage and other indicators should be designed. For power sales companies and their agency alliances, a credit linkage mechanism is introduced, and historical credit evaluation ratings are used as the basis for floating rates and guarantee coefficients, so as to realize the precise matching of products with risk sources and conduction paths, and to form constraints and responses to key nodes at the front end.

(2) Improve premium adequacy for sustainable business development

In order to achieve high-quality and sustainable development of energy storage insurance in the power market and give full play to the role of escorting energy storage security, energy storage insurance products must be reasonably priced to truly reflect the level of risk and reduce disorderly competition in rates. Differentiated pricing is implemented for subjects with different risk profiles, with preferential rates for subjects with stable revenue capacity, healthy cash flow and low performance deviation rates, and fee increases for subjects with persistently high abnormal scores, to ensure that premiums adequately cover potential claims. At the same time, core indicator linkage effects are incorporated into actuarial modeling to prevent underpricing from weakening claims-paying ability and to safeguard the long-term sustainable operation of the insurance business in the face of market volatility and the accumulation of deviation risks.

(3) Give full play to the supporting role of reinsurance in business development

From the experience of the international market, during the development of energy storage insurance, reinsurance companies give full play to their data and technology advantages, actively participate in the development of energy storage insurance products, and provide important reinsurance support for direct insurance companies to carry out related business. The development of energy storage insurance business in Chinese market should also give full play to the unique advantages of reinsurance companies, especially since energy storage system is widely used in power supply side, grid side and user side, which is a major national project concerning the stability of the power system and the green transformation of the economy, and involves a lot of sensitive data, so state-owned reinsurance companies should play an even more important role in providing the relevant reinsurance support from the perspective of data security and stability protection. From the perspective of data security and stability, state-owned reinsurance companies should play a more important role in providing reinsurance support.

6 Conclusion

This paper takes the data of 109 power sales companies in a province as a sample to carry out a case study, and the main conclusions are as follows.

Social network analysis is used to construct a performance risk network, and revenue capacity, cash flow ratio, and contract performance deviation rate with outstanding point-out and influence are identified as core risk-driven nodes. Historical credit evaluation rating and power sales price deviation with high point-in degree are risk-sensitive nodes. The improved COPOD algorithm improves the identification accuracy from 91.74% to 99.08% compared with the initial algorithm, and the Copula anomaly score localization of typical anomalous subject A shows the most significant deviation of quick ratio.

The results of the evolutionary game show that under the initial willingness to perform of 0.8 and credit level of 90, the system is stabilized in the (0,1) equilibrium of low risk preference of the power company and strong control of the trading center after the first cycle of evolution, and the credit level and willingness to perform of the different combinations of strategies are gradiently differentiated with the cycle. High risk appetite and strong control accelerate credit depletion and willingness decline.

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