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REGULAR ARTICLE

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Multi-dimensional early warning of the entire supply chain of power materials based on RFID technology

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Abstract. Early warning system needs to process a large amount of real-time data, and carry out in-depth analysis and mining of these data to identify potential risks and hidden dangers. However, existing data processing and analysis capabilities may not be able to meet this demand. To this end, a multi-dimensional early warning of the entire supply chain of power materials based on radio frequency identification (RFID) technology is designed. According to the real-time failure probability of power materials, the probability of early warning accidents is calculated and classified, and the risk is graded based on these probabilities. Through the methods of bonus points, deduction points, and grade evaluation, the risk early warning indicators of different stages in the whole supply chain of power materials were quantified. The objective and rationality of risk assessment can be ensured by means of comprehensive weight. A multi-dimensional early warning system based on RFID technology is established, combining multiple linear regression models and particle swarm optimization algorithms to determine the time window of multi-dimensional early warning, and carry out dynamic monitoring and early warning of the supply chain. The experimental results show that the early warning effect of the design method can reach 95% and the highest early warning effect can reach 98% at 10 s. The average warning error is only 2.91%, and the average warning time is only 1.34 s, which is more accurate in identifying the number of first-level risks, second-level risks, and third-level risks.

Keywords: RFID technology, Electric power materials, Full supply chain, Multi-dimensional early warning, Time window.

1 Introduction

The whole supply chain of power materials refers to the whole process management from the purchase, production, transportation, and inventory to sales of power materials. In the power industry, the management of materials is very important to ensure the stability and security of the power supply. The reason is that efficient material management can accurately predict demand, optimize inventory allocation, reduce resource waste, and ensure that the materials used meet safety standards and regulatory requirements, thereby comprehensively ensuring the stability, safety, and sustainability of power supply, laying a solid foundation for the healthy development of the power industry. However, there are many drawbacks to traditional material management, such as opaque information, low efficiency, and high management costs. Therefore, the efficient management of the entire supply chain of power materials has become an urgent problem for the power industry [1, 2].

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Aljohani *et al.* [3] proposed an innovative strategy that utilizes machine learning and early warning analysis methods to promote real-time risk prevention and improve agility. Based on context and historical data, machine learning models can be trained to discover patterns and correlations, as well as anomalies pointing to imminent danger. Organizations can identify risks when they arise and take preventive measures by integrating these models into real-time monitoring systems. Setiawan *et al.* [4] collected data from respondents through a survey questionnaire

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distributed using Google spreadsheets. Digitization has an impact on supply chain integration, green supply chain, and resilience. Digitization can create strong integration, energy efficiency, and survival benefits in the supply chain. Supply chain integration affects green supply chains and supply chain resilience. Integrating supply chain systems can overcome environmental issues and optimize resources. A green supply chain affects supply chain resilience. Supply chain integration, green supply chain, and supply chain resilience affect a company's competitive advantage. Based on the theory of group information processing, van den Adel *et al.* [5] explored when and how cross-functional teams can fully unleash the potential of information reconnaissance to ensure organizational resilience. In real-world supply chain management simulations, data from multiple sources and information was collected from 80 cross-functional teams exposed to supply chain disruptions. The results indicate that the ability of cross-functional teams to effectively utilize information search to ensure their organizational resilience depends on the degree to which team members share information and make consistent decisions internally (*i.e.*, internal integration). The research findings further indicate that when cross-functional teams face an unstable environment where multiple supply chain disruptions (*i.e.*, higher supply chain fragility) may occur, the moderating effect of internal integration is strengthened. Wang *et al.* [6] established a dynamic adaptive agent-based supply chain model to assess risks and establish more targeted and reliable electricity security policies, simulating the direct and cascading indirect economic loss risks of multiple small-scale power outages. Apply this model to the economic loss risk assessment of power outages in China in 2018 as a case study. Through daily simulations throughout the year, the results show that the total economic loss risk caused by power outages in 2018 accounted for 0.49% of the national GDP (ranging from 0.32% to 0.63%), and the indirect economic loss risk was 2.35 times that of direct losses (ranging from 1.18 to 3.28). From the perspectives of logistics and information flow, the research results show that power outages have different impacts on upstream and downstream supply chains. Overall, the model can evaluate the economic loss risk caused by any historical power outage event using available data, and achieve early warning of financial risks by proposing power intervention policies.

RFID technology, that is, radio frequency identification technology, is a non-contact automatic identification technology, it automatically identifies the target object through the radio frequency signal and obtains the relevant data, without manual intervention, fast and convenient operation. RFID technology has the advantages of being waterproof, anti-magnetic, high-temperature resistance, large reading distance, data can be encrypted, etc., so it has been widely used in many fields. In recent years, with the rapid development of Internet of Things technology, RFID technology has been widely used and applied. RFID technology has the advantages of non-contact identification, fast reading, data encryption, etc., so it has a wide application prospect in the whole supply chain management of power materials. Through the application of RFID technology, the real-time monitoring and tracking of power materials can be realized, and the efficiency and accuracy of material management can be improved. At the same time, RFID technology can also be combined with the Internet of Things technology to achieve the intelligent management of the entire supply chain of power materials. In response to the above issues, research on multi-dimensional warning of the entire power supply chain based on RFID technology is proposed, aiming to achieve efficient management and multi-dimensional warning of the entire power supply chain through the application of RFID technology and improve the stability and security of power supply. In 10 s, the warning effect of the design method reaches 95%, and the maximum warning effect can reach 98%. The average warning error is only 2.91%, and the average warning time is only 1.34 s. It is relatively accurate in identifying the number of primary, secondary, and tertiary risks. The main contents of this article are as follows:

1. Calculate and classify the occurrence probability of early warning accidents according to the real-time failure probability of power materials, and grade the risks based on these probabilities.
2. Quantify the risk early warning indicators at different stages in the whole supply chain of power materials through the methods of bonus points, deduction points, and grade evaluation.
3. To ensure the objectivity and rationality of risk assessment by means of comprehensive weight.
4. Establish a multi-dimensional early warning system based on RFID technology, combine multiple linear regression models and particle swarm optimization algorithm, determine the time window of multi-dimensional early warning, and dynamically monitor and warn the supply chain.

2 Risk assessment and weight determination of the entire supply chain of power materials

2.1 Extract the characteristics of emergency risk events in the entire supply chain of power materials

The causes of sudden risk events in the whole supply chain of power materials are complex and diverse, with both internal and external factors. Internal factors may include mistakes or failures in the production, storage, transportation, and distribution of power materials, such as equipment failure, improper operation, and management negligence. External factors include natural environmental factors and social environmental factors. These internal and external factors work together, leading to the occurrence of sudden risk events in the supply chain. The sudden risk events in the whole supply chain of power materials have a wide range of influences, which may not only directly affect the normal operation of power enterprises, but also affect the whole power industry and even the social and economic system. The sudden risk events in the whole supply chain of power materials have the characteristics of complex causes, wide

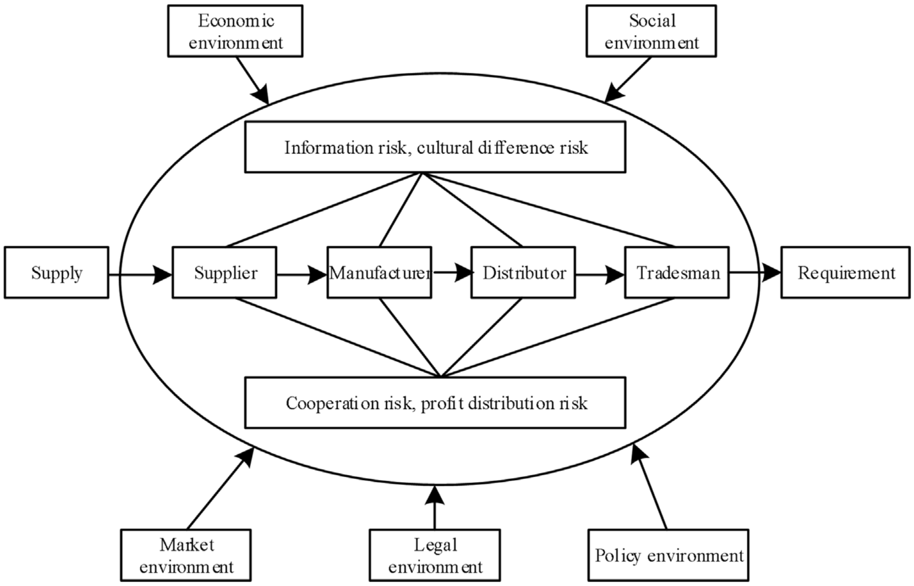

Fig. 1. Multi-factor disturbance risk types of supply chain.

influence, high urgency, strong complexity, and obvious derivation. In order to effectively deal with these risk events, power enterprises need to establish a sound emergency management system and risk management mechanism, strengthen the coordination and communication of all links in the supply chain, improve the flexibility and toughness of the supply chain, and ensure the safe and stable supply of power materials. In this analysis process, the entire supply chain of electric power materials is regarded as a whole, and the classification results of possible risks in the supply chain are obtained, as shown in Figure 1.

Taking the analysis results of Figure 1 as the guiding content of this study, according to the multi-disturbance factors and the types and characteristics of risks in the supply chain, appropriate technologies are applied to complete the risk assessment of the whole supply chain of power materials.

After analyzing the risk types of the whole supply chain of power materials, it is determined to use association rules to analyze the relationship between sudden risk events and supply chain links [7], grasp the law between them, and determine the possibility of sudden risks when some risk factors appear. Set $A = a_1, a_2, \ldots, a_n$ is a full supply chain of power supplies comprising n supply links, where $a_1, a_2, \ldots, a_n$ represents the joints in the supply chain, given a supply chain transaction database $S = \{Q_1, Q_2, \ldots, Q_n\}$, each transaction Q_i is a part of the full supply chain of power supplies, and each transaction has a specific identifier A_{id} if the condition $S \subseteq A$ is satisfied. At the same time, B is set as A child of A, if $B \subseteq A_{id}$, then A contains the components of B, then B can be regarded as a set of sub-transactions. Therefore, the association rules between the whole supply chain of power materials can be obtained. The prerequisite of this rule is B, and the result of the association rule is A. In short, because B has A risk problem, there is a chain reaction in A. If there is A probability of $v\%$ that the link containing B also contains A, then there is a probability of B ∪ A that contains $j\%$ in the power supply chain, then the support of B → A can be expressed as $j\%$. Then the support degree and confidence degree of related events in the supply chain can be expressed as:

$$\text{support}(\mathrm{B} \Rightarrow \mathrm{A}) = \mathrm{P}(\mathrm{B} \cup \mathrm{A}) \tag{1}$$

$$\text{confidence}(\mathrm{B} \subseteq \mathrm{A}) = \mathrm{P}(\mathrm{B}|\mathrm{A}). \tag{2}$$

According to previous research results, the larger the support value, the greater the confidence in the correlation calculation results. In this study, in order to comprehensively analyze the correlation between supply chain sudden risk transactions, the minimum support and minimum confidence of each transaction were calculated to obtain the strong association rules of the supply chain. The specific formula is as follows:

$$\text{support}(\mathrm{B} \Rightarrow \mathrm{A}) \geq \min\sup \tag{3}$$

$$\text{confidence}(\mathrm{B} \subseteq \mathrm{A}) \geq \min\text{conf} \tag{4}$$

Based on this formula, the risk events of the whole supply chain of electric power materials are obtained, and their correlation is calculated to determine the possibility of sudden risk occurrence in the supply chain and provide a basis for the subsequent risk assessment of the whole supply chain of electric power materials.

The characteristics of sudden risk events in the whole supply chain of power materials not only reveal the essential attributes of risk events but also provide an important basis and reference for subsequent risk assessment. These characteristics together constitute the complex background of power material supply chain risk management, which requires enterprises to quickly identify, accurately evaluate, and effectively deal with risks when facing them.

2.2 Risk assessment of the entire supply chain of power materials

After extracting the characteristics of sudden risk events in the whole supply chain of power materials, these risks are scientifically evaluated. Risk assessment is a process of identifying, analyzing, and quantifying potential risks. Its purpose is to help enterprises understand the possibility, influence, and possible consequences of risks, and to provide decision support for enterprises to formulate effective risk management strategies. The risk assessment of the whole supply chain of power materials is a systematic work, which involves the comprehensive consideration of all links, participants, and external environmental factors in the supply chain. The whole supply chain risk assessment of power materials is divided into three steps.

Step 1: Definition of risk assessment for the entire supply chain of power materials

The risk assessment methods mentioned in this paper are defined as follows:

$$R_{\text{Risk}}\left(X_{t,f}\right) = \sum_i \Pr(E_i)\left(\sum_j \Pr\left(X_{t,j}|X_{t,f}\right) \cdot M_{\text{sev}}(E_i, X_{t,j})\right) \tag{5}$$

where $X_{t,f}$ is the expected operating state at time t, $X_{t,j}$ is the load state occurring at time t, $\Pr(X_{t,j}|X_{t,f})$ is the probability of $X_{t,j}$ occurring at time t, E_i is the i warning accident, $\Pr(E_i)$ is the probability of the i warning accident occurring under the j operating condition, and $M_{\text{sev}}(E_i, X_{t,j})$ is the severity of the i warning accident occurring under the j operating condition. The risk assessment and grading system regards the risk generated by the early warning accident in the process of risk assessment as a single individual, that is, R_{Risk}.

The definition of the whole supply chain risk of power materials:

$$\begin{cases} R_{Risk} = \{L, K, P, S, N_{\text{REASON}}, Q_{\text{CONSEQ}}\} \\ N_{\text{REASON}} = \{R_1, R_2, \ldots, R_n\} \\ Q_{\text{CONSEQ}} = \{C_1, C_2, \ldots, C_n\} \end{cases} \tag{6}$$

where L represents the risk level of R_{Risk}; K represents the type of R_{Risk}, P represents the probability of R_{Risk} occurring, S represents the severity of R_{Risk} occurring, N_{REASON} represents the cause set of R_{Risk} occurring, Q_{CONSEQ} represents the consequence set of R_{Risk} occurring, R represents the cause of the risk occurring, and C represents the consequence of the risk occurring.

$$R = \{K_r,\ D_r, P_r\} \tag{7}$$

where K_r represents the type of R, D_r represents the description of R and P_r represents the occurrence probability of R

$$C = \{K_c,\ D_c, S_c\} \tag{8}$$

where K_c represents the type of C, D_c represents the description of C, and S_c represents the severity of C.

Step 2: Risk classification of the entire supply chain of power materials

According to the real-time failure probability of power materials, the accident probability of early warning can be calculated. Assuming that the state set of power materials outage in the early warning accident is $\mathbf{\Omega}$, there are N power materials in total, and the probability of the supply chain of power materials stopping operation is P_1, P_2, …, P_n, then the probability of the early warning accident is

$$P_f = \prod_{i\in\mathbf{\Omega}} P_i \prod_{j\notin\mathbf{\Omega}} (1 - P_j). \tag{9}$$

Since the calculated early-warning probability will vary in order of magnitude according to the length of power materials, the standard limit for its classification and grading will also change accordingly, because the probability of stopping the operation of power materials is generally small, so the probability of calculating early-warning accidents can be written as follows:

$$P_f = \prod_{i\in\mathbf{\Omega}} P_i. \tag{10}$$

Before determining the grade of risk probability, the risk assessment of each early-warning power material failure operation state is carried out. If there is a risk, the probability of risk occurrence should be graded first to facilitate the subsequent risk rating. In this study, risk levels are divided into three categories: first-level risk, second-level risk, and third-level risk [8]. This classification method is divided according to the probability of risk occurrence, the probability of risk occurrence is more than 1×10^{-4} as a first-level risk, the probability of 1×10^{-5} ~ 1×10^{-4} as a second-level risk, the probability of 1×10^{-6} ~ 1×10^{-5} as a third-level risk, of which the first-level risk is the most serious.

In the process of index evaluation, the risk early warning indicators in different stages are quantified through the methods of bonus points, deduction points, and grade evaluation. Through a large number of basic data analyses, according to the business characteristics, management requirements, and implementation of electric power enterprises, reference to the index value, relevant management regulations, industry indicators, etc., to determine the risk level of each risk early warning index, as shown in Table 1.

Step 3: Power materials occurrence risk rating

The severity of the risk of power materials can be classified into the risk severity of reduced supply load, the risk severity of heavy load or overload, the risk severity of voltage deviation, the risk severity of power grid disconnection, the risk severity of plant and station shutdown, and the risk severity of important users.

According to the probability level of risk occurrence and the severity of risk, the risk level can be obtained:

$$L = \text{round}((1-\mu)L_p + \mu L_s) \tag{11}$$

Table 1. Risk classification of each risk index.

Risk level	Risk-free	Low risk	Medium risk	High risk
Bad behavior handling records	No record	General misbehavior	Gross misconduct	Particularly serious misconduct
Delivery timeliness	Supplier on time delivery	Due to the supplier's delayed delivery, no more than 1 project unit will be affected within 12 months	The supplier delayed delivery due to the cumulative impact on 2 project units within 12 months	Due to delayed delivery by the supplier, the cumulative impact on 3 or more project units within 12 months
Service satisfaction	100 points	[70, 100]	[50, 70]	Below 50 points
Quality inspection before delivery	Sampling pass rate ≥90%; Reinspection and multiple owner unit testing are qualified	Random inspection pass rate (80–90%), but reinspection and multiple owner units test qualified	Random inspection pass rate (70–80%), but reinspection and multiple owners of the unit test qualified	The pass rate of sampling inspection is less than 70% or the reinspection fails or multiple owner units fail to pass the test
Arrival acceptance	Up to standard	–	–	Below standard
Handover test acceptance	Up to standard	–	–	Below standard
Product operation	100	–	[40, 100)	[0, 40)

where L_p represents the grade of risk occurrence probability, L_s represents the grade of risk severity, μ represents the weight coefficient with the value interval of (0, 1), and round(·)represents rounding. In formula (11), when μ is 1, it represents the traditional deterministic security assessment method. However, risk assessment should have the possibility of risk occurrence and the consequences after risk occurrence, so the value range of μ is set within the interval (0, 1). When μ approaches 1, the risk level approaches the outcome after the risk occurs, and when μ approaches 0, the risk level focuses on the likelihood of the risk occurring.

The risk assessment of the whole supply chain of power materials is the key link to ensure the stability and reliability of the supply chain, which not only helps enterprises understand the current risk situation of the supply chain, but also provides important data support and decision-making basis for the subsequent risk management strategy formulation.

2.3 Determine the risk assessment weight of the entire supply chain of power materials

After completing the risk assessment of the whole supply chain of power materials, the next step is to determine the relative importance of these risks, that is, the risk assessment weight. This is because, in practice, different risk factors may have different effects on the overall stability of the supply chain. Some risks may have a low probability, but once they occur, they will have serious consequences; Some risks may occur frequently, but each time the impact is relatively small. Therefore, by determining the weight of risk assessment, enterprises can more accurately identify those risk factors that have the greatest impact on the stability of the supply chain, to formulate risk management measures in a targeted manner.

The determination of risk assessment weight is mainly divided into three aspects: subjective, objective, and comprehensive weight [9]. Based on the comparison matrix, the subjective weight is sorted for all risk factors in each layer that are relatively the same as those in the upper layer. The sum method in analytic hierarchy process is used to solve the weight vector, the column vector of A is normalized, and the arithmetic average of the matrix row sum is calculated. The subjective weight expression is obtained as follows:

$$\omega_j^p = \frac{1}{n}\sum_{j=1}^{n} n\left(a_{ij}/\sum_{p=1}^{n} a_{pj}\right), \quad j = 1, 2, \ldots, n \tag{12}$$

where p represents the matrix features and a_{pj} represents the degree of importance of the matrix with features p. The eigenvalue of the matrix is approximated to the maximum value, and the corresponding eigenvector is normalized and approximated to the weight vector of the comparison matrix. The objective weight is determined using the entropy weight method, which is an objective weighting method that constructs a judgment matrix based on risk assessment indicators and determines indicator weights through indicator variation values. The entropy weight method can avoid subjective influence caused by human factors in the calculation process, thus obtaining more accurate risk assessment results for the entire supply chain of power materials. Set m as the number of given index schemes, and construct the judgment matrix expression of risk assessment index as follows:

$$A' = \left(a_{ij}\right)'_{mn} \quad i = 1, 2, \ldots, m \tag{13}$$

The normalization process a'_{ij} obtains the processing result $y_{ij} = a'_{ij} / \sum_{i=1} a'_{ij} (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$, and the normalization matrix $Y = (y_{ij})_{mn}$ is obtained based on the processing result. According to the definition of information entropy, the information entropy of the j risk factor indicator is determined, namely $h_j = -m \sum_{i=1}^{m} y_{ij} (\ln y_{ij})$, of which $h_j \geq 0$. The modified processing result y_{ij} makes the natural logarithm ln y_{ij} meaningful, and the expression of the modified processing result is:

$$y'_{ij} = a'_{ij} m \sum_{i=1}^{m} a'_{ij}. \tag{14}$$

The objective weight of the indicator is determined by the variation value of the indicator, and ω_j^s is set as the entropy weight of the j risk factor indicator, whose expression is as follows:

$$\omega_j^s = \frac{h}{m - \sum_{i=1}^{m} h_j} \left(0 \leq \omega_j^s \leq 1, \sum_{i=1}^{m} \omega_j^s = 1 \right). \tag{15}$$

Combined with subjective weight ω_j^p and objective weight ω_j^s, the comprehensive risk assessment weight ω'_j is determined to ensure the objectivity and rationality of the risk assessment of the entire supply chain of power materials. The expression of risk assessment comprehensive weight ω'_j is as follows:

$$\omega'_j = \frac{\omega_j^p \omega_j^s}{n \sum_{j=1}^{n} \omega_j^p \omega_j^s} \left(0 \leq \omega'_j \leq 1, \sum_{j=1}^{n} \omega'_j = 1 \right). \tag{16}$$

After obtaining the comprehensive weight of the whole supply chain risk assessment of power materials, the data are processed without dimension. The dimensionless processing is one of the steps of the comprehensive evaluation to simplify the calculation. A complete risk assessment index system should include three types of positive indicators, negative indicators, and moderate indicators. The dimensionless processing method is used to process the above indicators. The processing expression of positive indicators is as follows:

$$A'_{+}\left(a'_j\right) = \left\{ \frac{1}{2} \sin \left(\frac{\pi a'_j}{a'_{j\max} - a'_{j\min}} \frac{a'_{j\max} + a'_{j\min}}{2} \right) \right\} \tag{17}$$

where $A'_{+}\left(a'_j\right)$ represents the evaluation value after processing the j risk factor evaluation indicator; a'_j is the initial evaluation value; $a'_{j\max}$ is the maximum evaluation value; $a'_{j\min}$ is the minimum value. The value correlation of the positive indicator is $a'_{j\min} \leq a'_j \leq a'_{j\max}$, $a'_j \leq a'_{j\min}$, or $a'_j \leq a'_{j\max}$. The inverse indicator processing expression is:

$$A'_{-}\left(a'_j\right) = \left\{ -\frac{1}{2} \sin \left(\frac{\pi a'_j}{a'_{j\max} - a'_{j\min}} \left(-\frac{a'_{j\max} + a'_{j\min}}{2} \right) \right) \right\} \tag{18}$$

Table 2. Expert scores of the entire supply chain risk of power materials.

Expert rating scale	Numerical value	Degree of risk
z_1	0–25	Very low risk
z_2	25–40	Low risk
z_3	40–60	Medium risk
z_4	60–75	High risk
z_5	75–100	Extremely high risk

where the value correlation of the inverse index is the same as that of the positive index. The processing expression of the moderate index is as follows:

$$\mathrm{A}'_{\mathrm{mod}}\left(a'_j\right) \begin{cases} A'_{+}\left(a'_j\right), a'_{j\min} < a'_j \leq a'_{j\mathrm{mod}} \\ A'_{-}\left(a'_j\right), a'_{j\mathrm{mod}} < a'_j \leq a'_{j\max} \\ 0, a'_j \leq a'_{j\min} \text{ or } a'_j \leq a'_{j\max} \end{cases} \tag{19}$$

where $a'_{j\mathrm{mod}}$ is a moderate evaluation value. According to the processing formula of the three types of indicators, the evaluation value of risk assessment indicators with intervals of 0–1 is solved, and the weighted average value is directly compared. Set $Z = z_1, z_2, \ldots, z_n$ as the expert score set, and the expert score set after dimensionless processing is $Z = z'_1, z'_1, \ldots, z'_1$. The expert rating level of the entire supply chain risk of electric power materials is set to 5, as shown in Table 2.

After determining the risk assessment weight, the actual evaluation index data of the risk factors of the entire supply chain of electric power materials, the expert score Z'_n after non-dimensional processing and the comprehensive weight ω'_n of each risk assessment index are combined to obtain the final evaluation score $T = Z'_n \times \omega'^{T}_n$ of the risk factors of the entire supply chain of electric power materials. Finally, the optimal decision of the whole supply chain risk assessment of power materials is obtained by comparing the scores of each link.

3 Multi-dimensional early warning of the entire supply chain of power materials based on RFID technology

3.1 RFID technology

RFID is a non-contact automatic identification technology. The target object can be automatically identified by radio frequency signals and relevant data can be obtained. The identification work can be done in various harsh environments without manual intervention. RFID technology is helpful to improve the whole supply chain management ability of power materials, so successful RFID technology and other mobile services can significantly affect the ability of enterprises to provide products and services to consumers.

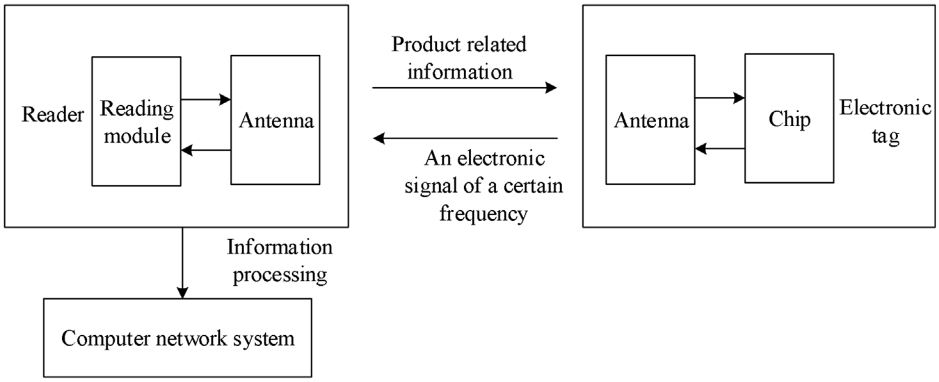

Fig. 2. Basic working principle of RFID technology.

By using RFID technology in the whole process of supply chain, the distribution of goods in the whole supply chain and the information of goods themselves can be completely reflected in the information system of enterprises in real time and accurately, which greatly increases the visibility of enterprise supply chain and makes the whole supply chain and logistics management process of enterprises become a completely transparent system. Fast, real-time and accurate information enables enterprises and even the whole supply chain to respond quickly to complex and changeable markets in the shortest time, and improve the adaptability of the supply chain to market changes.

The basic working principle of RFID technology is shown in Figure 2.

Based on basic working principles, design RFID tags that conform to the characteristics of electric power materials. These labels need to have characteristics such as high-temperature resistance and resistance to electromagnetic interference to ensure stable operation in complex power environments. Deploy RFID tags in appropriate locations for power supplies, such as equipment, packaging boxes, etc. Ensure that the position of the label can easily read data without affecting the normal use of electrical materials. Deploy RFID readers at key nodes in the power supply chain (such as warehouses, transportation vehicles, production lines, etc.) and build a reader network. Ensure that the coverage range of the reader network is wide enough to cover all power supplies deployed with RFID tags. When power supplies with RFID tags enter the coverage range of the reader network, the reader will automatically read the information in the tag and transmit the data to the central processing system. The central processing system will process and analyze the received data, extracting useful information such as the location, status, quantity, etc. of power supplies.

3.2 Multi-dimensional early warning method for the whole supply chain of electric power materials

The main steps of multi-dimensional early warning of the whole supply chain of electric power materials are as follows: Firstly, experimental data, including dynamic data such as material inventory, quantity in transit, and demand, are obtained, and the above data is preprocessed by principal component analysis to achieve feature dimension reduction; Then a fitting model is established according to the multiple regression coefficients of the characteristic factors and supply chain changes to obtain the early warning characteristics. Finally, the support vector machine (SVM) was used to establish the early warning classifier, and the multi-dimensional early warning was completed after learning the regression coefficient. The early warning of power material supply chain involves multiple dimensions and a large number of data, which are nonlinear and high-dimensional. As a powerful machine learning algorithm, SVM is especially good at dealing with classification and regression problems, and can effectively extract key features from complex data for the construction of early warning models. SVM maximizes the interval between different types of data by finding an optimal hyperplane, thus improving the accuracy of classification. In the early warning of power material supply chain, accurate classification and prediction are very important for responding to potential risks in time.

After the pre-processing of multidimensional early warning data, it is necessary to further clarify the time period from the change of the supply chain to the possible failure, that is, to determine the time window of multidimensional early warning. Combine the test data and training data in this time window. The early warning threshold is set at 300. When it is lower than the threshold, the optimal time window when the early warning value reaches 300 is obtained by using a multiple linear regression model and particle swarm optimization algorithm. When the threshold is exceeded, considering that the supply chain will change more rapidly, the optimal time window value is obtained by using the statistical analysis of historical supply chain changes.

Let time window 1 reach 300 after m sample supply chain changes, and n feature samples of the corresponding m groups are x_{1i}, x_{2i}, …, x_{ni}. After fitting this sample with T_{ci} multiple linear regression of the supply chain, the regression model generated is as follows:

$$T_{ci} = b_0 + b_1 x_{1i} + b_2 x_{2i} + \ldots + b_n x_{ni}, \ldots$$
$$bi = 1, 2, \ldots, m \tag{20}$$

where m is the number of samples; n is the characteristic quantity; b_0, b_1, …, b_n is the linear regression determination coefficient, and its value ranges from 0 to 1. The larger the value, the higher the fit degree and the better the effect. Affected by the number of samples, there is a certain degree of error, so the linear regression determination coefficient is used to correct the determination coefficient, which is calculated as follows:

$$R^2_{\text{adjusted}} = 1 - \frac{(1 - R^2)(m-1)}{m-n-1} \tag{21}$$

where R is the correction coefficient; R_{adjusted} is the correction determination coefficient. According to the relationship between the regression coefficient selected in this paper and the subsequent multidimensional early warning, the best sample with a time interval of 1 is selected as the best window time. In the selection of the best window, this paper adopts the particle swarm optimization algorithm, which uses its excellent global optimization ability to obtain the optimal window time and ensure the best multi-dimensional early warning effect. When the supply chain changes reach more than 300 and the time window value of multi-dimensional early warning reaches $t_{\max}$, descriptive statistical analysis is adopted. The maximum time between the continuous operation of the whole supply chain of power materials and the occurrence of failure after more than 300 is set as $t_{\max}$, and the time window value of the supply chain rapidly rises from 300 to the occurrence of failure within the range of 0 ~ $t_{\max}$. After repeated experimental tests, the adjustment parameter is increased by 5%, and the time window value is T. The specific calculation formula is as follows:

$$T = t_{\max} \cdot (1 + 5\%). \tag{22}$$

Based on the changes in the supply chain within the time window, fault warning is carried out using an improved SVM model for classification warning. Due to the susceptibility of SVM model classification results to parameter influences [10], the golden sine algorithm is adopted to enhance the global search ability of the SVM model. The golden sine algorithm is a new type of metaheuristic optimization algorithm. The inspiration for this algorithm comes from the scanning method of the sine function within the unit circle, and its design concept is similar to searching in the solution space of the problem to be optimized. The golden sine algorithm reduces the search space by introducing the golden ratio, thereby approaching the optimal solution of the algorithm. Compared with traditional metaheuristic optimization algorithms, the golden sine algorithm has the characteristics of simple principle, fewer parameter settings, and strong optimization ability. This algorithm can improve global search capability, and as a metaheuristic optimization algorithm, it has strong global search capability. By applying it to the parameter optimization of SVM, it is possible to effectively search the entire parameter space and find the parameter combination that maximizes SVM classification performance.

The specific process is shown as follows:

Step 1: Data initialization, dividing the training set and the test set by a ratio of 7:3.

Step 2: Initialize the Golde-SA algorithm and SVM model parameters, including the initial value of the golden ratio and the population individual, the number of iterations, and the population size of the Golde-SA algorithm. The initialization formula of the population individual is as follows:

$$V_i = ib_i + \text{rand}(0,1) \times (ub_i - lb_i) \tag{23}$$

where ub_i is the upper limit of individual search; lb_i is the lower limit of individual search. V_i is the initial value. The penalty coefficient and kernel width of the SVM model for each population's individual position were (C, g). The initial value of the golden ratio is x_1, x_2 obtained by equations (24) and (25).

$$x_1 = a(1-\tau) + b\tau \tag{24}$$

$$x_2 = a\tau + b(1-\tau) \tag{25}$$

where τ is the golden ratio, $\tau = (\sqrt{5} - 1/2)$; $a = -\pi$, $b = -\pi$.

Step 3: Use the classical SVM model to calculate the individual fitness in the population, update the individual position synchronously, and select the best individual position in the process of group search. The golden section ratio is integrated into the process of population individual location updating, the golden ratio has been proven to guide the search process to converge to the optimal solution faster in many optimization problems. When updating the position of individuals in the population, adjusting the step size or direction through the golden ratio can help the algorithm explore the solution space more efficiently, reduce unnecessary searches, and improve the overall performance of the algorithm. In the early warning system of the power supply chain, optimization algorithms based on the golden ratio can provide more scientific decision support. The position update formula is as follows:

$$V_i^{t+1} = V_i^t \times |\sin(r_1)| - r_2 \times \sin(r_1) \times |x_1 \times D_i^t - x_2 \times V_i^t| \tag{26}$$

where V_i^{t+1}, V_i^t is the position corresponding to individual i in $(t+1)$, t iterations; D_i^t is the best position in t iterations. r_1, r_2 are random constants, $r_1, r_2 \in ([0, \pi], [0, 2\pi])$.

Step 4: Complete the optimal fitness comparison, obtain the optimal fitness, and iterate and replace. When the iteration condition is satisfied or the termination condition is reached, the optimal parameter solution of the SVM model is obtained, and the final early warning diagnosis model is determined. So far, the multi-dimensional early warning design of the entire supply chain of power materials based on RFID technology has been completed.

4 Experimental results and analysis

4.1 Preparation for experiment

To verify the effectiveness of the multi-dimensional early warning method for the whole supply chain of power materials based on RFID technology proposed in this paper, the design method was compared with the methods given in references [3–6]. This experiment collected operational data from 20 related enterprises and used a deep priority algorithm to identify 15 enterprises belonging to the entire supply chain of power materials. Obtain the operation, credit, and transaction data of this part of the enterprise, obtain 1 million pieces of data, and store them in the experimental database. Process this part to obtain the corresponding data feature vectors and filter out key attributes. According to attributes, the data is divided into multiple components such as enterprise operation status, credit status, interest rates, contracts, etc., and is divided into normal, relatively normal, secondary, relatively abnormal, and abnormal data. The last three groups are considered as non-performing data by default. Based on the above results, complete the experimental data processing work and make it the main content of the experiment. For the processed data, according to relevant regulations, perform statistical analysis on the positive and negative samples in the experimental data. In order to enhance the accuracy of the results obtained in this experiment, approximately 300 000 normal samples were selected from the sample data to avoid inaccurate indicator testing caused by poor data.

Combined with a diesel generator set, battery, and photovoltaic power generation system. The diesel generator set provides a stable power supply and charges the rechargeable battery pack when needed. Photovoltaic power generation systems can capture solar energy and convert it into electricity while storing excess energy in battery packs. When building a multi-dimension early warning system for the entire supply chain of power materials, it is necessary to select suppliers and manufacturers that meet the requirements of the green supply chain and ensure that the purchased diesel generator sets, battery packs, and photovoltaic power generation systems meet the environmental management system standards and have environmental protection certification. It is necessary to control and optimize energy consumption during the operation of the multi-dimensional early warning system of the whole supply chain of power materials. Through the reasonable management of the running time of the diesel generator set, the charge and discharge control of the battery, and the maximum utilization of the photovoltaic power generation system, the efficient use of energy is realized and the carbon emission is reduced. In this process, the basic parameters of power operation are analyzed according to the experimental requirements, and the relevant contents are shown in Table 3.

Based on mastering the basic parameters of power operation, based on the needs of power operation enterprises and their upstream and downstream power enterprises, the construction of a green supply chain for power materials is carried out. In the green supply chain for power materials, the power parameters in the power grid of each enterprise

Table 3. Basic parameters of power operation.

Argument	Parameter value
Initial battery charge/(A.h)	0.4
Battery minimum charge/(A.h)	0.2
Maximum battery charge/(A.h)	0.8
Maximum diesel engine climb rate/(kW.h)	10
Minimum diesel engine climb rate/(kW.h)	−10

are analyzed, and they are used as power materials in the supply chain. Referring to the above content, the analysis and statistics of the operational parameters of power enterprises in the green supply chain of power materials were completed before the experiment. Based on this, the method proposed in this article was used to coordinate and optimize the green supply chain of power materials. In the optimization process, a three-level green supply chain model for power materials is first established. At the same time, the sparrow search algorithm is introduced to search and update local demand in the green supply chain. Finally, through coordinated decision-making of the centralized green supply chain, the application in the testing environment is completed.

The time window is determined, and the regression coefficient and particle swarm optimization algorithm adopted in this paper are demonstrated experimentally. Combined with practical application, the value range of the time window is set to be 1200–3600 s. The initial parameters of PSO were set as population size 500, iteration 100, and acceleration 1.5. The number of convolutional layers and pooling layers in the CNN-PSO network is set to 2, and the number of convolutional nuclei and the sampling size of pooling layers are set to 1×2.

The interface of the early warning system is shown in Figure 3.

The experimental environment parameters in the experiment are shown in Table 4.

4.2 Experimental result

First, the system was built on the Microsoft Visual Studio platform. After the system was built, training was carried out to verify the normal operation of the system. The data used in this paper was the power material supplier database, with a total of 572 data. Among them, there were 35 first-level risks, 48 second-level risks, 56 third-level risks, and the rest were normal. 200 data were randomly selected for system training, and after the system could run normally, comparative experiments were carried out. The comparison of the warning effects of the five methods is shown in Figure 4.

As can be seen from Figure 4, the early warning effect of the design method has reached 95% at 10 s, and the maximum early warning effect can reach 98%. However, the multi-dimensional early warning effect of the whole supply chain of electric power materials in the reference [3] method

Fig. 3. Interface diagram of early warning system.

Table 4. Experimental environmental parameters.

Build a platform	Microsoft Visual Studio
CPU	Core i5-9100
Internal memory	8 GB
System	Windows 10
Experimental data type	.txt

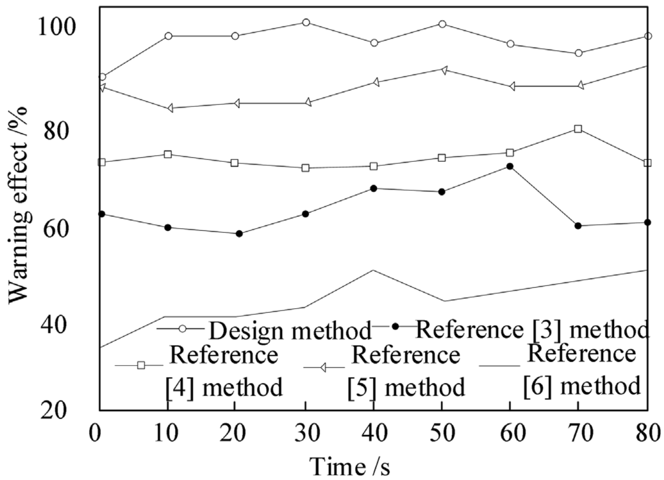

Fig. 4. Comparative analysis of early warning effect.

only reaches 62% and the highest warning effect reaches 70% when it is 10 s, and the multi-dimensional early warning effect of the reference [4] method only reaches 77% and the highest warning effect reaches 79% when it is 10 s. The multi-dimensional early warning effect of the whole supply chain of electric power materials in the reference [5] method only reaches 82% and the highest warning effect reaches 86% in 10 s. The multi-dimensional early warning effect of the reference [6] method only reaches 42% and the highest warning effect reaches 51% in 10 s. The design method has excellent performance in the multi-dimensional early warning of the whole supply chain of electric power materials, which can not only achieve a high early warning effect in a short time, but also a high early warning accuracy. The reason is that after analyzing the risk types of the whole supply chain of power materials, the design method determines to use association rules to analyze the relationship between supply chain sudden risk events and supply chain links, grasp the law between them, and determine the possibility of sudden risks when certain risk factors appear, thus improving the early warning effect. It can be seen that the multi-dimensional early warning effect of the whole supply chain of electric power materials studied in this paper is better than the other four.

In order to verify the reliability of the research system, this paper also designed an experiment on the accuracy of early warning, using all the data in the database to conduct graded early warning of risks. The comparison of experimental results is shown in Figure 5.

Based on RFID technology, the number of primary risk, secondary risk, and tertiary risk warnings measured in this paper are 45, 58 and 66, respectively. However, the risk warning data of the reference [3] method is 39 first-level risks, 44 second-level risks, and 54 third-level risks. The measured risk early warning data of the reference [4] method are 37 first-level risks, 42 second-level risks, and 49 third-level risks. The measured risk early warning data of the reference [5] method are 31 first-level risks, 44 second-level risks, and 48 third-level risks. The measured risk early warning data of the reference [6] method are 31 first-level risks, 38 second-level risks and 57 third-level risks. In summary, RFID technology shows good performance in the multidimensional early warning of the entire supply chain of power materials, and can more accurately identify different levels of risk. The reason is that before determining the level of risk probability, this method first evaluates the risk of each early warning power material fault operation state. If there is a risk, the probability of the risk is graded first, which is convenient for the subsequent risk grading. In the process of index evaluation, the risk early warning indicators at different stages are quantified by adding points, deducting points, and evaluating grades. Through a large number of basic data analyses, according to the business characteristics, management requirements, and implementation of electric power enterprises, referring to index values, relevant management regulations, industry indicators,

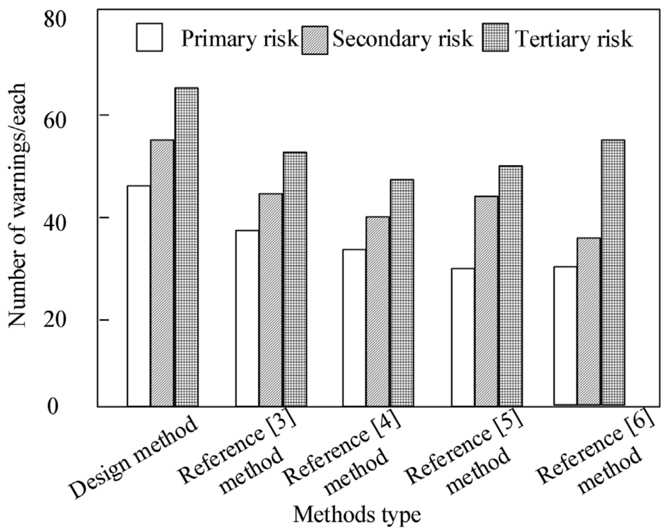

Fig. 5. Comparison of the number of risk warnings.

etc., the risk levels of various risk early warning indicators are determined.

In order to further verify the effectiveness of the multi-dimensional early warning method for the whole supply chain of power materials based on RFID technology proposed in this paper, the comprehensive test results are analyzed and studied. The comparison of early warning errors of each method under different indicators is shown in Table 5.

Combined with Table 5, the design method has the lowest early warning error in order response speed, only 0.71%, which is significantly better than the other four methods. This shows that the design method based on RFID technology has high efficiency and accuracy in order processing and response. The early warning error of the design method in the timely delivery of materials is 1.92%, which is lower than that of the methods in references [3–6]. This shows that the design method performs better in material management and delivery, and can predict the time of material delivery more accurately. Under the design method, the early warning error of the actual production capacity is 4.41%, which is slightly higher than the methods in references [5, 6], but significantly lower than those in references [3, 4]. This may mean that the design method still has room for improvement in actual capacity prediction, but generally performs well. The average value of early warning error directly reflects the comprehensive performance of various methods in different indexes. As can be seen from the table, the average early warning error of the design method is 2.91%, which is much lower than the other four methods, which fully verifies the effectiveness of the multi-dimensional early warning method of the entire supply chain of power materials based on RFID technology. The reason is that after the design method obtains the comprehensive weight of the whole supply chain risk assessment of power materials, the data is dimensionless. Dimensionless processing is a link in the comprehensive evaluation step, aiming at simplifying calculation and reducing early warning error to some extent. In summary, the performance of the RFID technology-based multi-dimensional early warning method for the whole supply chain of power materials is better than or close to other comparison methods in various indicators, especially in order response speed, timely delivery of materials, inventory of key materials, on-time delivery of finished products and logistics capabilities. These results show that the design method has high application value in the supply chain management of power materials, and can effectively improve the early warning ability and operation efficiency of the supply chain.

In order to see the warning effect of the five methods on the risk level of the power supply chain more intuitively, the experiment will test the warning time of the five methods, and the test results are shown in Table 6.

As can be seen from the analysis table of warning time comparison results in Table 6, the average warning time of the design method is 1.34 s, which is the lowest among all methods. This indicates that the design method based on RFID technology has high efficiency in the power supply chain risk early warning and can complete the early warning process in a short time. The early warning time of the design method in terms of order response speed was 1.07 s, which was much lower than the other four methods. This means that the design approach can respond quickly and provide timely warning information when dealing with order response speed risks. The warning time of the design method for timely delivery of materials is 1.56 s, which is also lower than other methods. This shows that the design method has high early warning efficiency in material management and timely delivery. The early warning time of the design method in the on-time delivery of finished products is 1.66 s, which is slightly lower than the method in the reference [6] method, but significantly lower than the other three methods. This further demonstrates the early warning efficiency of the design approach in the planning and execution of the finished product delivery. In terms of logistics capacity warning, the time of the design method is 1.42 s, which is the least time of all the methods. This indicates that the design method has high efficiency in evaluating and optimizing logistics capability. The reason is that the design method uses principal component analysis to preprocess the above data to realize feature dimension reduction; Then, according to the characteristic factors and the multiple regression coefficients of supply chain changes, a fitting model is established to obtain the early warning characteristics; Finally, the SVM is used to establish an early warning classifier, and the multi-dimensional early warning is completed after learning the regression coefficient. Based on the above analysis, the design method based on RFID technology shows high efficiency in the early warning of the risk level of the power supply chain and can quickly and accurately complete the early warning process. Compared with other methods, the early warning time of the design method is lower in many indicators, which shows its advantages in the risk management of power supply chain. Therefore, it can be considered that the design method based on RFID technology has high effectiveness and practicability in the power supply chain risk early warning.

Table 5. Comparative analysis of test results.

Index	Design method/%	Reference [3] method/%	Reference [4] method/%	Reference [5] method/%	Reference [6] method/%
Order response speed	0.71	0.95	2.84	3.64	3.78
Timely delivery of materials	1.92	2.88	2.54	3.67	3.49
Actual capacity	4.41	5.37	5.80	4.16	4.15
Finished goods inventory	3.37	5.46	5.15	3.79	4.16
Critical material inventory	2.66	3.48	3.40	3.48	3.19
On-time delivery of finished products	2.53	4.13	3.81	3.79	3.47
Logistics capability	4.77	7.82	9.36	10.25	10.54
Average warning error	2.91	4.29	4.7	4.68	4.68

Table 6. Comparative results of early warning time consumption under five methods/s.

Index	Design method/%	Reference [3] method/%	Reference [4] method/%	Reference [5] method/%	Reference [6] method/%
Order response speed	1.07	2.06	2.84	3.67	3.78
Timely delivery of materials	1.56	2.45	2.54	3.67	3.59
Actual capacity	1.16	2.37	2.40	3.16	3.15
Finished goods inventory	1.21	3.46	3.15	3.39	3.16
Critical material inventory	1.32	3.78	3.50	3.58	3.49
On-time delivery of finished products	1.66	4.53	3.71	3.79	3.27
Logistics capability	1.42	4.67	3.27	3.57	3.59
Average warning time	1.34	3.33	3.06	3.55	3.43

5 Conclusion

The multi-dimensional early warning of the entire supply chain of power materials based on RFID technology is designed, and the association rule technology is applied to analyze the connection between the unexpected risk events in the entire supply chain of power materials and the supply chain links, to master the law of risk transmission. The multi-dimensional early warning of the whole supply chain of power materials based on RFID technology is designed this time, and the association rule technology is applied to analyze the relationship between sudden risk events and supply chain links in the whole supply chain of power materials, to grasp the law of risk propagation. The following conclusions are obtained through experiments:

1. The multi-dimensional early warning effect of the whole supply chain of power materials studied in this paper is good.
2. RFID technology shows good performance in multi-dimensional early warning of the whole supply chain of power materials, and can accurately identify different levels of risks.
3. The performance of the design method in order response speed, timely delivery of materials, inventory of key materials, timely delivery of finished products, and logistics capacity is better than or close to other comparison methods, which shows that the design method can effectively improve the early warning capability and operational efficiency of the supply chain.
4. The design method shows high efficiency in the early warning of power supply chain risk level, which can complete the early warning process quickly and accurately, and has high effectiveness and practicability.

Although RFID technology provides real-time monitoring and tracking capabilities for the entire power supply chain, the reading stability and accuracy of RFID tags may be affected in certain extreme environments, such as high temperatures, high humidity, or areas with strong electromagnetic interference. Future work can be further studied in the following areas:

1. This platform will use advanced analysis algorithms to deeply mine massive data, intelligently analyze from multiple dimensions such as inventory levels, material flow speed, transportation safety, and equipment health status, and automatically identify potential risks and trigger warning mechanisms.
2. When the inventory level is below the safety threshold, the system will automatically generate replenishment

suggestions and notify the supplier; During the transportation of materials, any abnormal deviation from the predetermined route or environmental conditions exceeding the safety range will immediately trigger an alarm to ensure the safe delivery of materials; Meanwhile, through continuous monitoring of equipment usage data, predictive maintenance can be achieved, reducing unplanned downtime and ensuring stable operation of the power grid.

3. The addition of blockchain technology will further enhance the security and immutability of data, ensure the authenticity and reliability of supply chain information, and provide a solid trust foundation for power enterprises and regulatory agencies. Combined with smart contracts, contract terms such as payments and insurance claims can be automatically executed, simplifying processes and improving efficiency.

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Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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