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Research on the safety of oil and gas loading and unloading operations in enterprises based on data mining and correlation analysis algorithms

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ABSTRACTS

With the acceleration of economic globalization and industrialization process, the processing technology of natural gas and oil is being more and more challenged and influenced. This elevates the likelihood of oil and gas leakage impacting the surrounding environment during the loading and unloading processes. To enhance the safety of oil and gas handling, an index system has been developed which is based on an improved correlation analysis algorithm and a hierarchical analysis method, as well as a correlation analysis network model of risk source. The results proved that in the night experiment, the accuracy of the correlation rule of the improved algorithm increased from 90% to 95%, and the error value was even close to 0, while the traditional algorithm fluctuated between-1 and 1. In general, the proposed evaluation system and model effectively improve the prediction and identification probability of operation safety in the oil and gas processing process.

Keywords: Hierarchical analysis, Data mining, Association analysis, Oil and gas handling, Equipment risk sources

1. Introduction

In recent years, the workload of crude oil loading and unloading in oil, gas and chemical terminals has continued to rise, bringing more safety risks and increasing the possibility of accidents. The characteristics of crude oil make the loading and unloading process subject to many safety hazards, such as leakage and fire, etc. At the same time, the increased pressure of personnel operation can easily lead to negligence and errors, which further exacerbate the safety risks [1-3]. The use of digital technology for risk identification and assessment, combined with existing safety management measures, can effectively prevent and respond to various safety risks, ensure the smooth progress of

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loading and unloading operations, and maximize personnel and environmental safety [4-7].

Oil and gas chemical terminals are key locations for crude oil loading and unloading, and their safety issues are directly related to personnel life safety and environmental protection [8]. The crude oil loading and unloading operation process involves many steps and a wide range of specialties, and requires the crew, pilot, marine management personnel, terminal loading and unloading operators, depot operators and other parties to work together in order to successfully complete [9-11]. If there is improper coordination or personnel operating errors in the operation process, it can cause oil, gas and chemical leakage, ship collision with the pier, machine damage, cargo damage and other accidents, and in serious cases, it can cause extensive sea pollution, fire and explosion and other malicious accidents, which not only cause huge economic losses, but also cause adverse social impacts [12-15]. Crude oil generated by explosion or leakage may also bring great influence and danger to the neighboring communities and ecological environment [16]. Therefore, it is of great practical significance and urgency to utilize digital technology to deeply analyze the safety risks of crude oil loading and unloading operations in chemical terminals, carry out safety risk identification and assessment, and formulate effective preventive countermeasures [17-19].

For the risk of leakage in crude oil loading and unloading operations at chemical terminals, a large number of scholars have studied the relevant analytical tools to avoid accidents during transportation and loading and unloading. Linlin, L. U. et al. established a fuzzy probabilistic risk level assessment method by identifying the staff loading and unloading operation behaviors in order to calculate the probability of human error in the whole process, and comparing the results of this risk level and quantitative assessment method with the enterprise accident data, which can provide scientific safety warnings for managers [20]. Bariha, N. et al. analyzed the risk of transfer operations in oil and gas companies and used modeling tools such as ALOHA and PHAST to model the probability of accidents due to transportation and handling of oil and gas and to further predict the extent of the accident that will be affected [21]. Aliabadi, M. M. et al. emphasized the importance of implementing control measures on oil and gas loading and unloading behaviors to reduce the frequency of accidents, and by identifying and analyzing the behavioral patterns of workers in the loading and unloading process, the critical steps of human error can be assessed to provide certain recommendations to reduce the risk of oil and gas loading and unloading accidents [22]. Chen, C. et al. used an index-based approach to extract the special characteristics of the chemical handling accidents that have occurred and analyzed the main reasons for this domino accident phenomenon from the perspective of risk management to provide good data support for the development of risk contingency strategies [23].

Fuentes-Bargues, J. L. et al. used chemical and petroleum loading and unloading terminals to investigate hazardous areas and factors in the loading and unloading process using a hazard-based and operability analysis methodology, which was combined with a fault tree analysis methodology to develop preventive and corrective measures for possible accidents [24]. Liu, Z. et al. proposed a risk assessment method based on randomly colored Petri nets for loading and unloading of refined oil products, which strengthened the safety of the process of transporting and loading and unloading of refined oil products in enterprises by identifying the key risk factors and the evolution process in the enterprise's logistic operations, and realizing the overall assessment of the risks and formulation of the safety measures [25]. Alzbutas, R. et al. analyzed and evaluated the probability of hazardous accidents in oil and gas terminals and the possible consequences through quantitative assessment methods, and based on this, they developed measures to check and limit hazardous situations to create a safe and acceptable workplace for oil and gas handling [26]. The risk assessment methodology described above has been effective in avoiding accidents, as well as negative impacts related to the economy, the environment and human health resulting from accidents, and a comprehensive impact assessment is therefore essential.

The study is divided into four sections to analyze the content of the improved algorithm. The first section is a discussion on data mining and safety situation of oil and gas handling at home and abroad.

The second section is the data mining and processing in oil and gas handling process based on AHP and improved correlation analysis algorithm. The third section is the performance test of the algorithm proposed in the study and the analysis of the application effect. The fourth section is the discussion and analysis of the application effect of the algorithm and the shortcomings of the algorithm.

2. Safety of oil and gas handling operation based on data mining and correlation analysis algorithm

Risk data mining and analysis for oil and gas handling operation

The continuous expansion of loading and unloading scale and the rapid development of industrial construction make the method of loading and unloading treatment more difficult. In addition, in the real loading and unloading process, the damage and impact will change over time. Consequently, the safety data obtained through traditional data mining lacks the requisite rigor. To address this shortcoming, an enhanced association analysis algorithm has been developed to process data. Meanwhile, the basic analysis of the oil and gas processing data is conducted through hierarchical analysis. The computational procedure of the hierarchical analysis is shown in Figure 1.

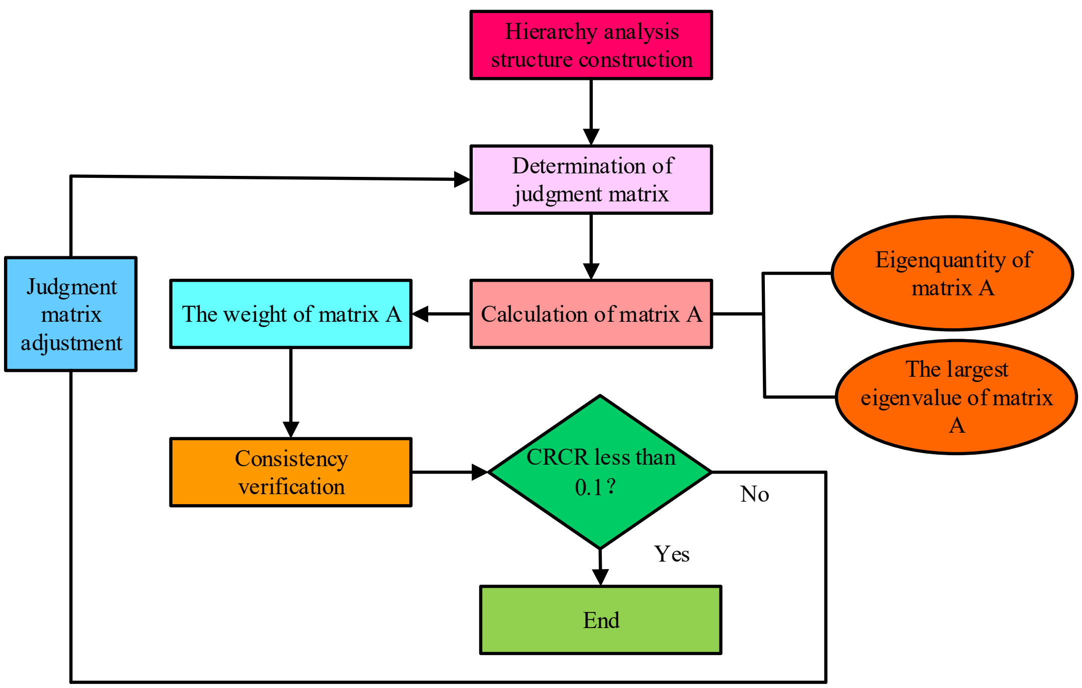


Fig. 1. The calculation process of analytic hierarchy process

The AHP in Figure 1 is a commonly used qualitative and quantitative analysis method in decision reaching techniques. AHP begins with an understanding and definition of the decision-making problem, followed by the specification of the corresponding indicator system, determination of the corresponding matrix type, and finally, the derivation of the weight values of specific factors through specified calculations. According to the identification of oil spill risk factors existing in port oil handling operations, the oil spill hierarchy analysis structure of port oil handling operations is constructed. The normalization of the weight vector of the judgment matrix in the weight analysis method can be expressed as Equation (1).

$$W = \frac{A_1^{\frac{1}{n}}}{\sum_{i=1}^{n} A_i^{\frac{1}{n}}} \tag{1}$$

In Equation (1), A denotes the matrix form. n denotes the number of square roots. i denotes factor coefficients and W denotes weight vector. The combination of weights in the multilevel structure can be expressed as Equation (2).

$$W_g = W_c \times W_s \tag{2}$$

In Equation (2), W_g denotes the global weight, W_c denotes the weight of the previous layer, and W_s denotes the current weight. Finally, the calculated weights can be used to assess the importance of the risk factors. The risk priority number can be expressed as Equation (3).

$$R_i = W_g \times S_i \tag{3}$$

In Equation (3), S_i represents the one severity score for the ith risk factor. If it is necessary to consider the combined impact of multiple risk factors, a composite risk index can be calculated and expressed in Equation (4).

$$RI = \sum_{i=1}^{n} R_i \times P_i \tag{4}$$

In Equation (4), P_i denotes the probability of occurrence of the ith risk factor and R denotes the risk index. Among them, the one about the eigenvectors in the process of oil and gas handling can be expressed in Equation (5).

$$AW = \lambda \max W \tag{5}$$

In Equation (5), A denotes the judgment matrix, W denotes the weight vector, and $\lambda \max$ denotes the maximum eigenvalue. The consistency metric in the algorithm can be expressed as Equation (6).

$$CI = \frac{\lambda \max - n}{n-1} \tag{6}$$

In Equation (6), n denotes the order of the judgment matrix.

The relationship between the various factors in the loading and unloading process obtained according to AHP is shown in Figure 2.

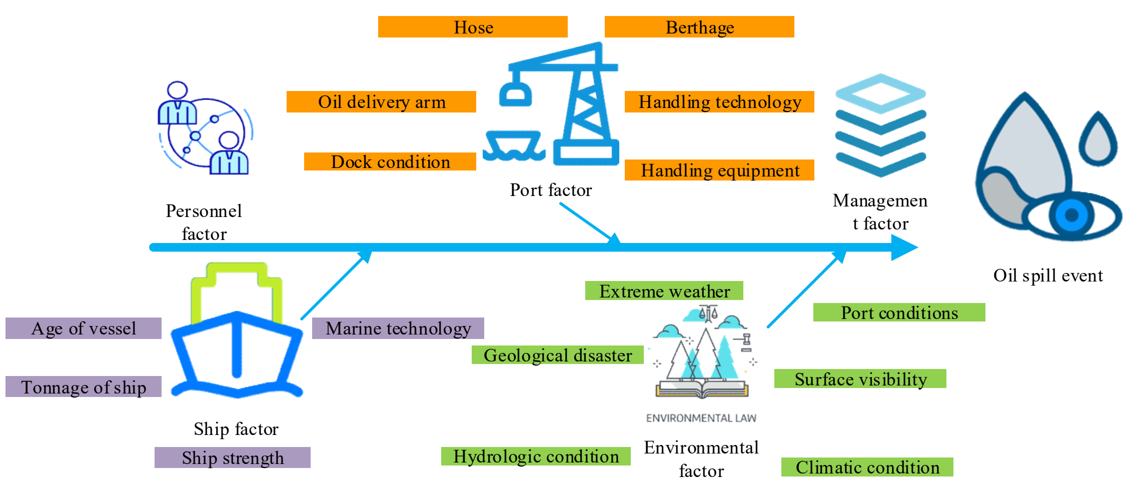


Fig. 2. The relationship between the factors causing the oil spill

The main factors in the relationship between the different factors in Figure 2 are dominated by five factors: personnel, port, ship, management, and environment. The terminal is the location where oil loading and unloading operations are conducted within the harbor, and the environment and facilities of the terminal are highly complex. To analyze and identify the factors contributing to oil spills during the loading and unloading process, it is essential to consider the potential risks associated with the various components and systems involved. These include mechanical equipment, piping devices, berths, and other pertinent elements. The risk factors of oil spill in the transportation tools include the strength structure, tonnage size and operation status of the tools. The primary risk sources within the environmental factors category pertain to the fluency and cleanliness of the loading and unloading environment. The climatic aspects are primarily concerned with hydrology, geology, and certain climatic hazards associated with temperature fluctuations. Factors in management mainly include the development of indicators and systems, as well as the promulgation and setting of relevant hazard notices. Through the identification of oil spill risk factors during oil loading and unloading operations in the port, the risk early-warning index system is shown in Figure 3.

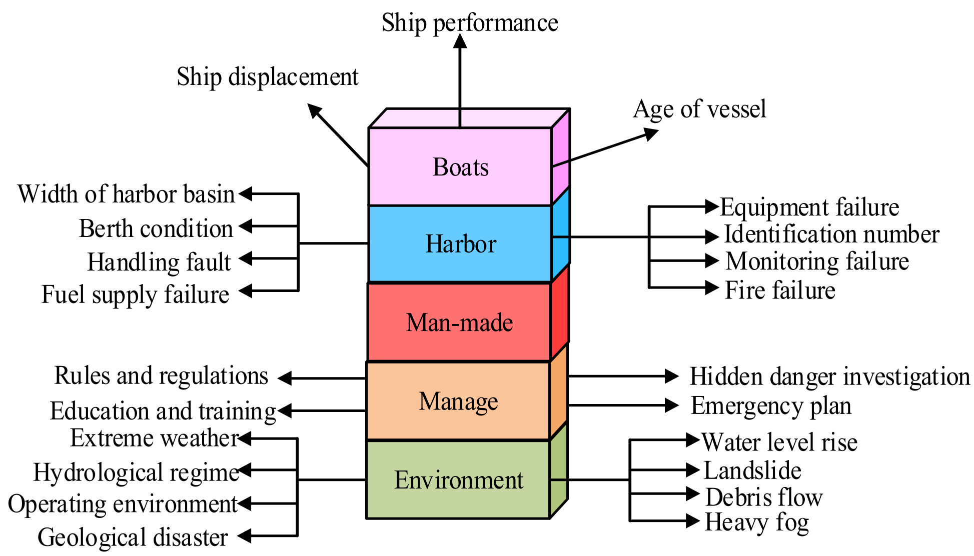


Fig. 3. Risk early-warning index system

Figure 3 shows the key factors of safety issues in loading and unloading works. The size of the word is indicative of its primary role in the loading and unloading process. The primary factors influencing the safety of hydrocarbons during the loading and unloading process are personnel, system management, ports, ships, and the environment. These factors represent the five major risk sources in the loading and unloading process. The lesser risk sources than the five major risk sources are the loading and unloading process, the quality of the equipment, the safety of the grounding devices, the hoses, and the delivery arms. It is equally important to consider the role of safety warning signs and malfunctioning monitoring systems in this context. Additional sources of wind energy include personnel, specifically the number of personnel responsible for safety protocols, the number of certified construction professionals, and the number of violations committed by personnel engaged in construction activities. The factors pertaining to the ship include its age, tonnage, structural composition, and operational status.

Network modeling of oil and gas handling risk with improved correlation analysis algorithm

The data sources of possible risks in the oil and gas handling project are obtained through AHP, and simple data processing is carried out to serve as the data basis for the correlation analysis algorithm. In the context of the loading and unloading process, the correlation analysis algorithm is specifically concerned with the utilization of the laws and connections between the variables in the obtained data, with the objective of identifying the hidden correlations within the data set and subsequently deriving the correlation rules, which are then employed in the analysis and resolution of the underlying issues. The association rules reflect the interdependence or correlation between things. The flow of the improved algorithm is shown in Figure 4

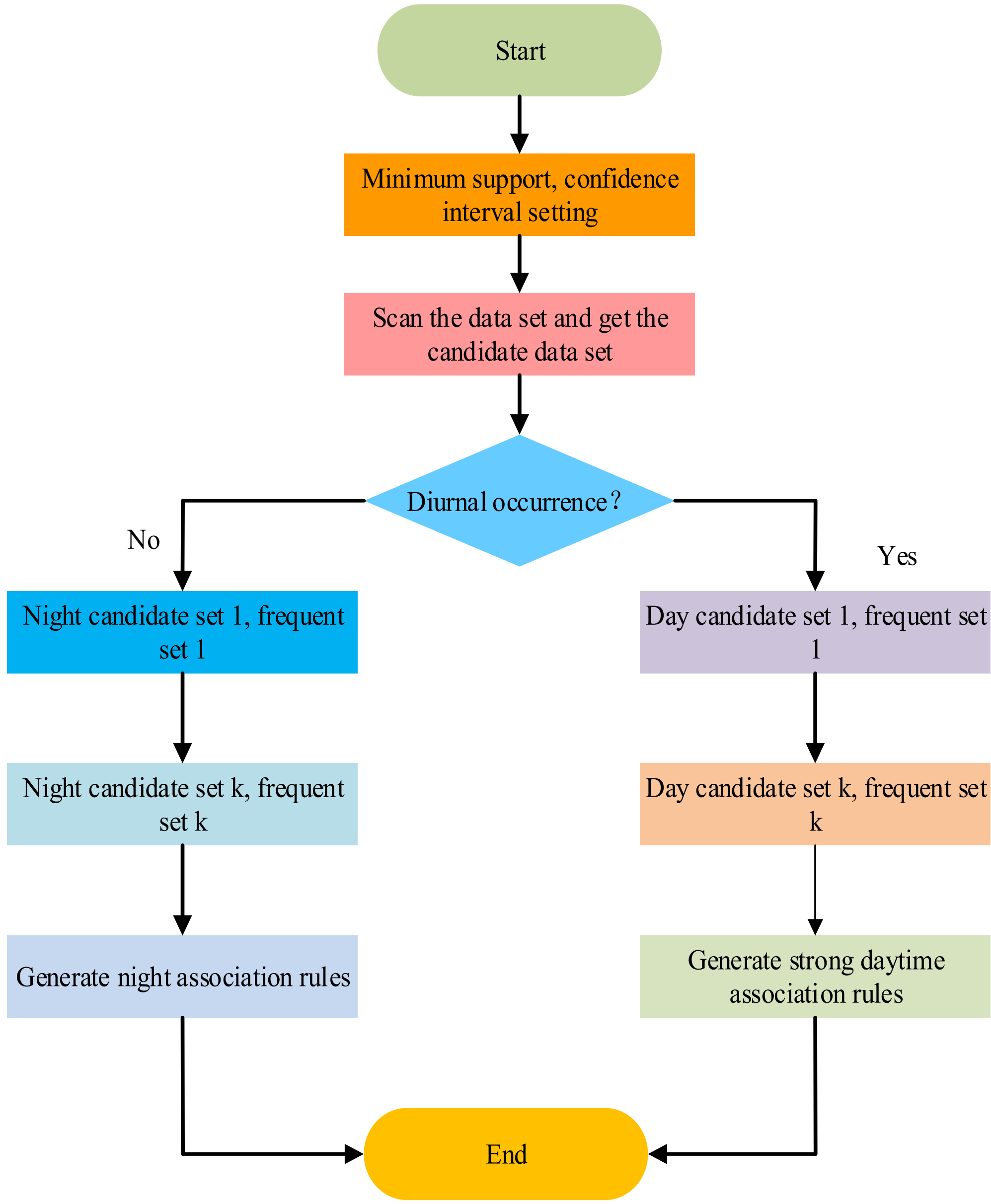


Fig. 4. Process flow for improving the algorithm

In the main process of the improved algorithm in Figure 4, the minimum confidence and support metrics are set first, where the metrics are set as an example to facilitate the subsequent mining of data and association of rules. The way to study the improvement algorithm is by improving the support and confidence interval in the correlation analysis algorithm. The improved support is expressed as Equation (7).

$$\mathrm{Im}\,p-Sup(A\rightarrow B) = \begin{cases} \dfrac{w(A,B)\times number}{number(Allsamples)}, Acci\in A(B) \\ \dfrac{number(A,B)}{number(Allsamples)}, Acci\notin A(B) \end{cases} \tag{7}$$

In Equation (7), A and B denote the datasets of accidents in the oil and gas handling process.

$number(Allsamles)$ denotes the set of all data in the oil and gas handling process. $number(A,B)$ denotes the number of datasets in which the accident A and the risk source B occur simultaneously in the loading and unloading process. P denotes the probability of accidents. The metrics of confidence can be expressed as Equation (8).

$$\begin{aligned} &\mathrm{Im}\ p - Conf\ (A \rightarrow B) \\ &= \begin{cases} \dfrac{w(A,B) \times number}{w(A) \times number\ (A)} \\ \dfrac{number\ (A,B)}{number\ (A)} \end{cases} \end{aligned} \tag{8}$$

In Equation (8), the confidence metric represents the probability of the presence of an oil and gas handling risk data item after the presence of a data item with a loading and unloading risk, and the presence of another oil and gas handling risk data item. Among them, the lifting degree can be expressed in Equation (9).

$$\begin{aligned} &lift = (A \rightarrow B) \\ &= \frac{number\ (A,B)}{number\ (A) \times number\ (B)} \end{aligned} \tag{9}$$

The improved algorithm provides a method to assess the confidence of B event occurrence in case of A event occurrence and considers the weights of the events in the dataset. The flow of risk source association analysis network model for oil and gas handling transportation process is shown in Figure 5.

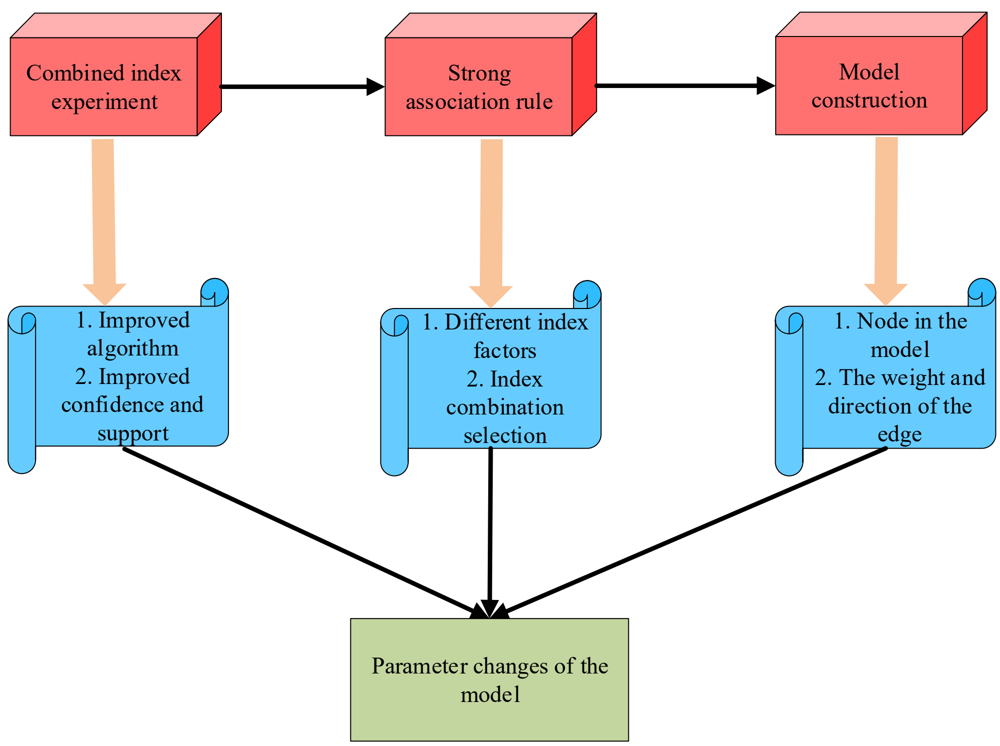


Fig. 5. Network model of risk source association analysis

In the process of constructing a complex network model for the risk source correlation analysis network model in Figure 5, a combination of indicators needs to be selected first. These indicators represent possible risk factors in the oil and gas handling process. After that, the algorithm identifies strong association rules which reveal the interactions and dependencies between risk factors. The improved algorithm enables the appropriate combination of support and confidence parameters to be selected for the purpose of collecting strong association rules at different time points. A complex network model for risk source association analysis is constructed using defined network nodes and edges in combination with time factors. The definition of network nodes in the network model can be expressed as Equation (10).

$$V = \{v_1, v_2, \ldots, v_k \tag{10}$$

In Equation (10), V denotes the number of network nodes, v denotes the risk source node, and k denotes the risk source coefficient. The weight of each edge can be calculated by improving the support in the correlation analysis algorithm, as expressed in Equation (11).

$$\begin{aligned} w(e_{ij}) &= lift(f_i \rightarrow f_j) \\ &= \frac{\sup(f_i \cup f_j)}{\sup(f_i) \times \sup(f_j)} \end{aligned} \tag{11}$$

In Equation (11), e_{ij} denotes directed edges and f denotes association rules. The model is generally trained using historical data to train the network model and adjust the parameters of nodes and edges. If the time factor is considered, the dynamic risk analysis of the network model at different points in time can be expressed as time (12).

$$RI_t = R(G_t(V_t, E_t)) \tag{12}$$

In Equation (12), V denotes the set of nodes and E denotes the set of edges. G denotes complex network model and t denotes different time. The set of metrics of risk factors in the complex network model in feature selection can be expressed as Equation (13).

$$F = (f_1, f_2, \ldots, f_n) \tag{13}$$

The collection of risk factors in Equation (13) can be derived from historical OIL and GAS handling data, including accident records, operation logs, environmental monitoring data, and so on. The comprehensive risk index based on the complex network model can be expressed as Equation (14).

$$RI = \sum\nolimits_{e_{ij} \in E} w(e_{ij}) \times P(f_i) \times P(f_j | f_i) \tag{14}$$

In Equation (14), $P(f_j | f_i)$ denotes the conditional probability of f_i occurring when f_j occurs. The study constructs a comprehensive risk source association analysis network model. The model is able to consider the risk factors and their interrelationships in the oil and gas handling process and perform dynamic risk assessment. The oil and gas handling risk prevention strategy set according to the model is shown in Figure 6.

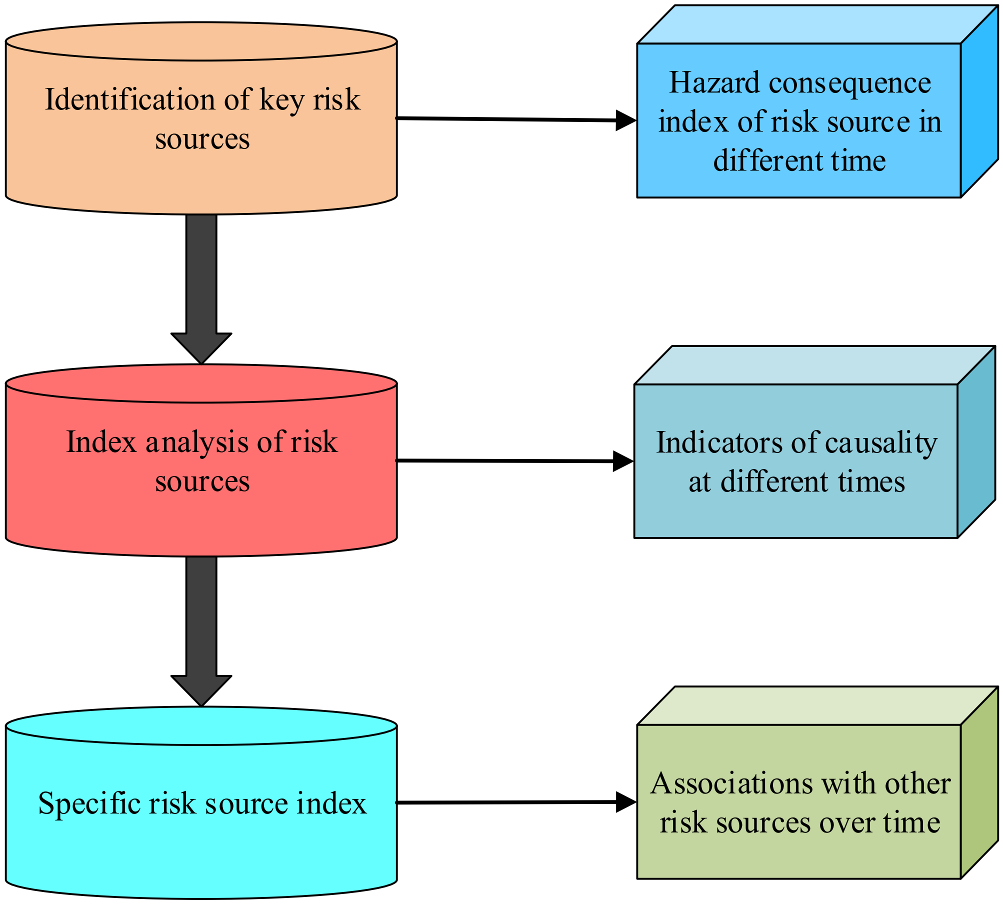


Fig. 6. Oil and gas handling risk prevention strategy

3. Performance testing of the improved algorithm and application effect analysis

The historical data and actual operation logs utilized in the study will serve as the foundation for testing the algorithms. The study will evaluate the algorithm's ability to predict and identify potential risk factors using the constructed risk early-warning index system and risk source association analysis network model. After an in-depth discussion of the data mining and correlation analysis algorithm based oil and gas handling operation safety study, the next step is to test the performance of the improved algorithm and analyze its effectiveness in real-world applications. The changes in the correlation before and after the algorithm improvement are shown in Figure 7.

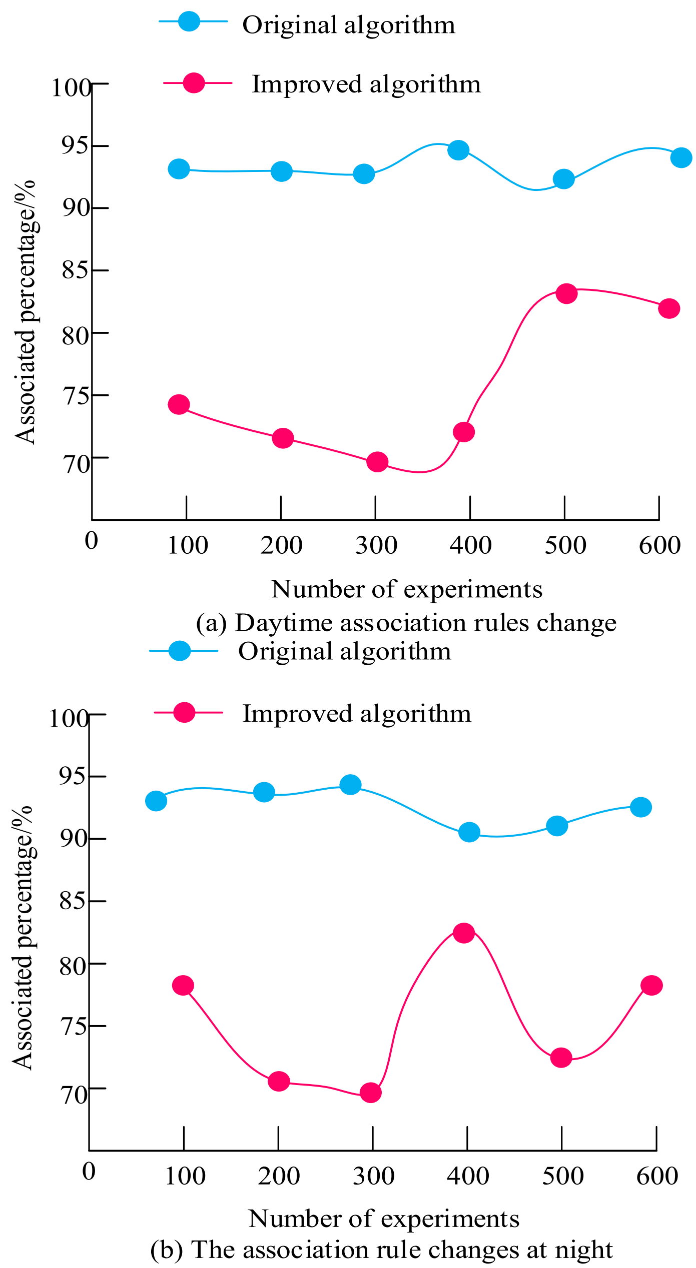


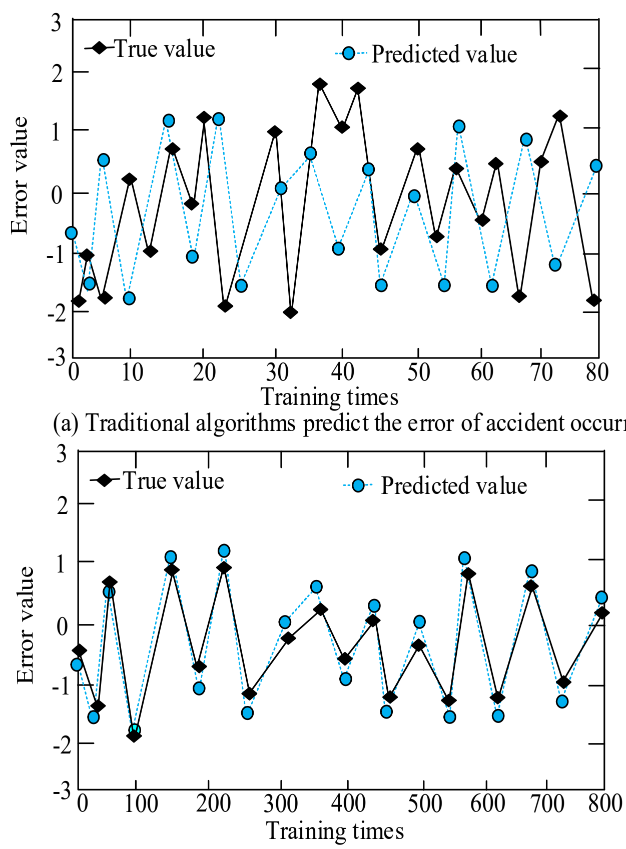
Fig. 7. The correlation changes before and after algorithm improvement

A comparison of the association rule changes between the original algorithm and the improved algorithm during daytime and nighttime is shown in Figure 7. During the daytime Figure 7(a) day experiment, the association rules of the original algorithm exhibits minimal fluctuations, with an average association percentage of approximately 90%. In contrast, the association rule of the improved algorithm demonstrates greater volatility, yet gradually rises and ultimately exceeds that of the original algorithm in the latter portion of the experiment, reaching a maximum of approximately 95%. In Figure 7(b), the association rule of the improved algorithm gradually exceeds that of the original algorithm as the number of experiments increases. It maintains a high level up to 95% in the late stage of the experiment, while the original algorithm stabilizes at about 90%. It shows that the improved algorithm has better learning ability and adaptability, and is able to continuously improve the accuracy of association rules in the changing environment. Taking the equipment risk sources as an example, the equipment risk types are specifically shown in Table 1

Table 1. Risk source type and description of the device

Source of risk	Risk source number	Description of risk sources
Facility	F10	Equipment brake system
Facility	F11	Circuit fault
Facility	F12	Filter clogging
Facility	F13	The fastening connector is faulty
Facility	F14	Signaling failure
Facility	F15	Compressor failure
Facility	F16	Refrigeration pressure anomaly
Facility	F17	Electrostatic device problem

The types of risk sources and their descriptions for the oil and gas handling equipment are presented in Table 1. The data indicates that the greatest number of risk sources within the category of "Facility" is comprised of six items: equipment braking system, circuit failure, filter clogging, fastening connector failure, signaling failure, and compressor failure. There are also abnormal refrigeration pressures (and electrostatic device problems, with collective equipment risk failures of F10-F17, respectively. This may indicate that equipment failures and abnormalities represent significant risk factors in oil and gas handling operations. For example, a failure of the compressor (F15) may directly affect the efficiency and safety of oil and gas handling operations. Similarly, a signaling failure (F14) may result in operators being unable to obtain timely information about the status of the equipment, thus increasing the risk of accidents. The variation of error values of the improved algorithm is shown in Figure 8.



(a) Traditional algorithms predict the error of accident occurrence

(b) Improved algorithm to predict the error of accident occurrence

Fig. 8. The correlation changes before and after algorithm improvement

A comparison of the performance of the traditional algorithm and the improved algorithm in terms of error in predicting the occurrence of accidents is shown in Figure 8. In Figure (a), the prediction error value of the traditional algorithm reaches its maximum at 10 times of training with an error value of -2. When the number of training is 80 times, the error value is around -1. The error value decreases when the number of training times is increasing. In Figure (b), the error value of the improved algorithm is close to 0 when the number of training times reaches 600 times. The prediction error of the traditional algorithm fluctuates between -1 and 1 when the number of training times is 400. Moreover, the improved algorithm basically maintains between -0.5 and 0.5, indicating that the improved algorithm is less affected by the training samples and more robust. The correlation between different risk factors and accidents after applying the algorithm is shown in Figure 9.

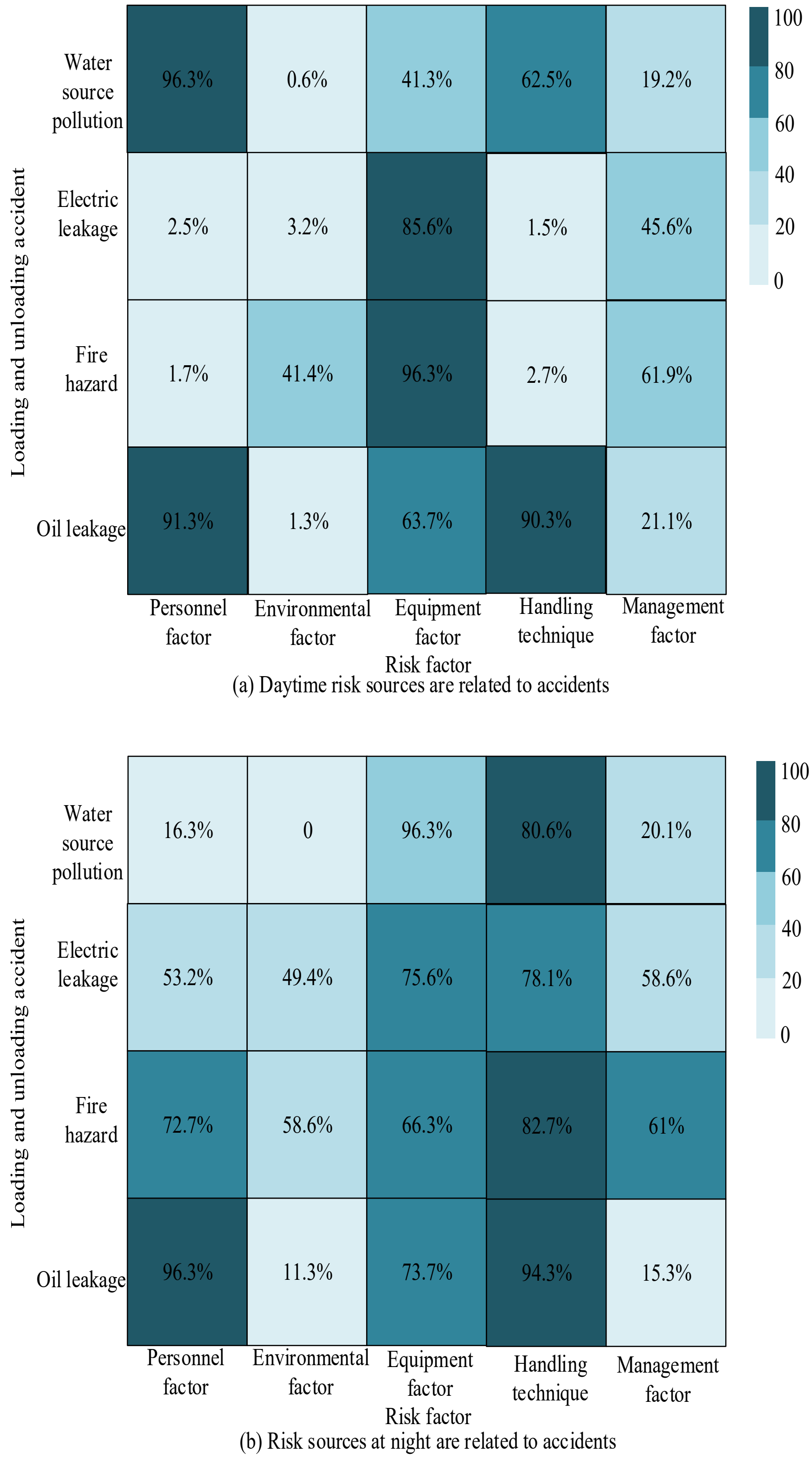


Fig. 9. The correlation changes before and after algorithm improvement

Figure 9 demonstrates the correlation between risk sources and accidents before and after the improvement. In Figure 9(a), during daytime, the risk sources of water contamination are mainly focused on operational techniques with 96.3%, followed by management factors with 19.2%. The risk sources of electrical leakage are mainly environmental factors with 85.6%, followed by operational techniques with 45.6%. In Figure 9(b), during night time, the risk sources of water contamination are mainly concentrated on operational techniques with a high percentage of 96.3%, followed by management factors with 80.6%. The risk sources of electrical leakage are mainly environmental factors with 75.6%, followed by operational techniques with 78.1%. This is due to the fact that the enhanced algorithm is capable of more accurately discerning the interrelationship between discrete risk factors and incidents, which results in a more rational apportionment of correlations. The improved algorithm takes into account more details and variables, allowing it to more accurately assess the extent to which various factors influence accidents. The percentage of equipment at risk during day and night is shown in Figure 10.

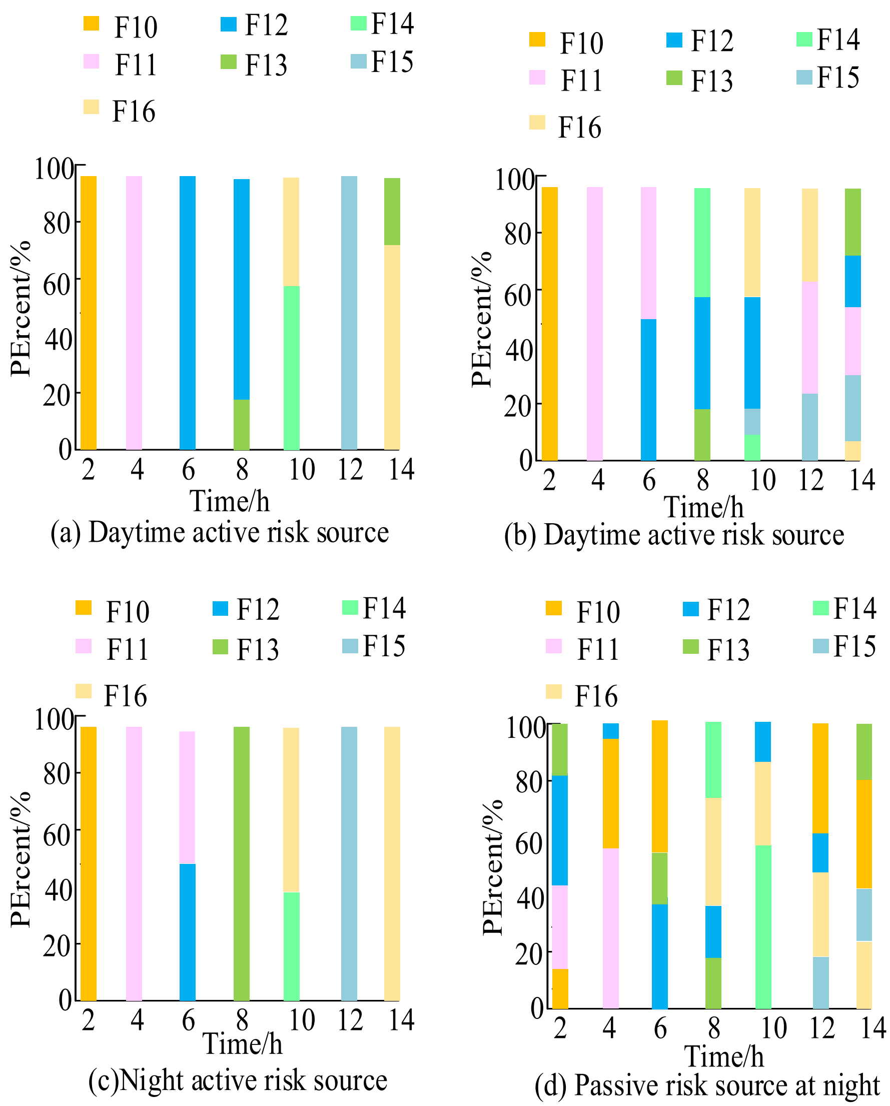


Fig. 10. The correlation changes before and after algorithm improvement

The percentage of different risk sources active during daytime and nighttime is presented in Figure 10. In Figure 10(a), among the risk sources active during the daytime, F16 has the highest risk level of 100%, followed by F14 and F12 with 80% and 60%, respectively. F11 and F13 have the lowest risk degree of 0%. In Figure (b), the risk degree of F16 decreases while the risk degree of F10 and F14 increases with 80% and 60%, respectively. While the riskiness of F11 and F13 remains at 0%. In Figure (c), F10 risk occupies 100% and remains unchanged for all 4 hours, indicating that these risk sources are not active at night. Figure (d) illustrates the temporal distribution of risk sources, revealing gaps in their occupancy at different times of the night. The presence of up to four risk sources concurrently is associated with an elevated probability of accidents at night. This discrepancy can be attributed to the algorithm's heightened sensitivity to the identification of specific risk sources during nocturnal hours. This heightened sensitivity may be attributed to the algorithm's adjustments in weighting, enhanced feature extraction capabilities, or the adoption of a model more aligned with the distinctive characteristics of nighttime data. However, further field validation and algorithmic adjustments may be required to determine the true activity level for risk sources that are consistently 0%. The change in risk source association before and after algorithm use is shown in Figure 11.

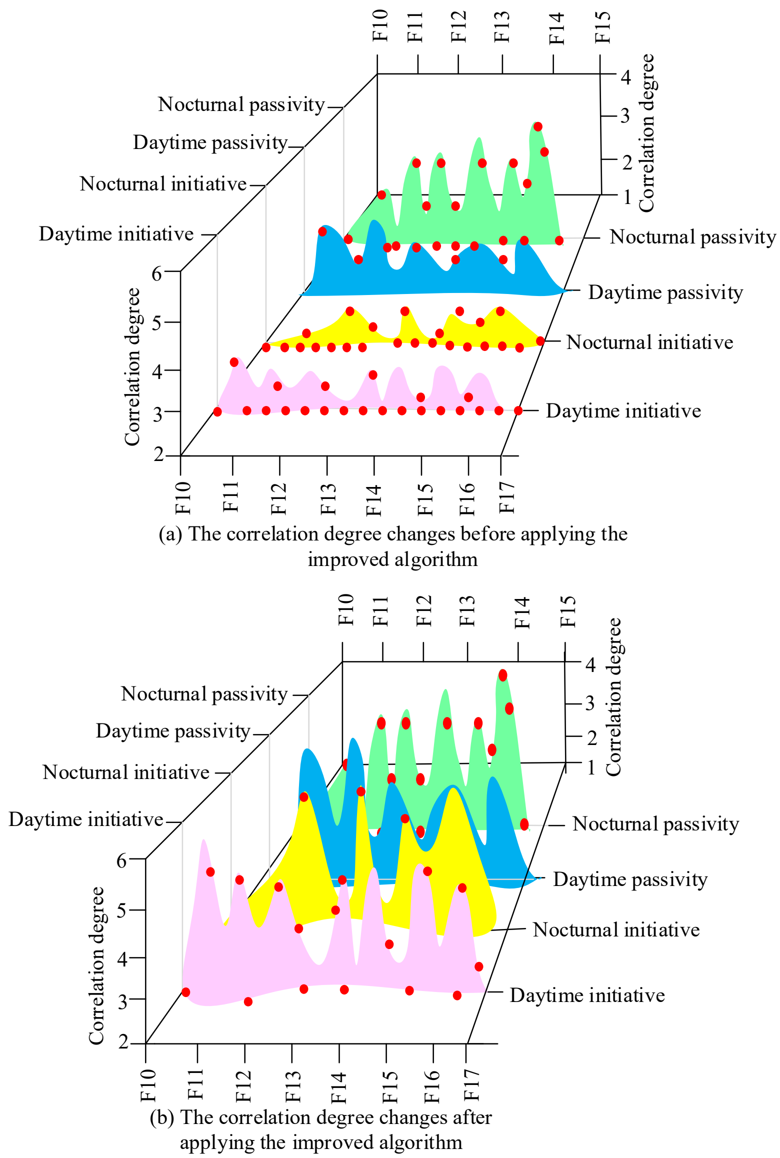


Fig. 11. The correlation changes before and after algorithm improvement

The changes in the correlation of different risk sources in the four states of daytime passive, daytime active, nighttime passive, and nighttime active before and after applying the improved algorithm are shown in Figure 11. In Figure 11(a), the correlation of F10 before improvement is 2 in the nighttime active state and 4 in the daytime active state. The correlation of F11 and F12 in the nighttime active state is also 4. The correlation of F13 and F14 in the daytime passive state is 3.5. The correlation of F15 in the nighttime active state is 4.7. In Figure 11(b), i.e., after the improvement, the change of correlation shows that the correlation of F10 increases in the nighttime active state, while the correlation increases in the daytime active state. F13 and F17 are especially obvious, and the maximum correlation can reach 6. The correlation of the improved algorithm is significantly stronger than that of the traditional because the algorithm reweights the data, which results in an increase in the weight of the data and a rise in the correlation.

4. Conclusions

The growth of the global economy and the expansion of industrialization have resulted in a heightened risk of safety issues in oil and gas handling operations. The study employed the AHP to construct an early-warning index system for risk assessment. Subsequently, enhanced association analysis algorithms were developed to mine association rules among risk factors using the metrics of support, confidence, and enhancement. Finally, a complex network model was constructed for risk source association analysis. The improved algorithm displayed a higher percentage of correlation than the traditional algorithm in both daytime and nighttime experiments, reaching an average of 95%, while the traditional algorithm stabilized at around 90%. The error value stabilized in the range close to 0 when the number of training sessions reached 600. In the correlation analysis of risk sources and accidents, the improved algorithm was able to more accurately identify operational techniques as the main risk source of water contamination with a high percentage of 96.3%. In summary, a dynamic risk assessment model was constructed, which effectively improved the prediction and identification of the safety of oil and gas handling operations. While the study has yielded some findings, there are still some limitations that require further investigation. For instance, the actual activity of certain risk sources that are consistently inactive necessitates additional verification. Additionally, the efficacy of the algorithm under specific circumstances warrants optimization.

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