

Article

Analysis and Research on Directed Weighted Network Model of Coal Mine Gas Explosion Accident Based on Genetic Algorithm Optimization

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Abstract

A coal mine gas explosion is a systematic failure caused by the interaction of multiple factors. In previous studies, most research determined the key causes based on practical experience or a single static indicator. This study puts forward a comprehensive method that integrates complex network theory and a genetic algorithm. By analyzing the explosion mechanism, a network model with 43 causal factors as nodes and their relationships as edges was established, thus capturing the overall structure of the accident system. Subsequently, the genetic algorithm was employed to optimize the identification of key nodes in the network. At present, most of the research on accident risk assessment relies on static topological analysis, failing to take into account the synergistic effects resulting from the simultaneous removal of multiple nodes, and is prone to getting stuck in local optimal solutions. The purpose of this study is to be able to search for the most influential node set and reduce the reliance on static indicators. The results show that both random attacks and deliberate attacks can reduce network efficiency. Meanwhile, when attacking the key cause combinations identified through searching, the network efficiency drops most rapidly. This indicates that the network is more vulnerable in more targeted attacks. This method encourages us to transition from a single-dimensional risk assessment to a comprehensive and multi-dimensional analysis framework.

Keywords: complex network theory; genetic algorithm; gas explosion; network attack efficiency; node optimization; accident causation



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1. Introduction

At present, coal is still the main body of energy in China. Since the beginning of the new century, the rapid development of the national economy has led to an increase in the demand for coal energy [1]. Coal mines are complex safety-critical systems where accidents occur [2] frequently. In recent years, with the continuous improvement of laws and regulations and the improvement of mechanization and intelligence in coal mines, the safety situation of China's coal mines has gradually improved, but coal mine accidents occur [3,4] frequently. For gas explosion accidents in Chinese coal mines, many studies have carried out statistical analysis. These studies have carried out a detailed discussion about the severity of accidents, the time of occurrence, and the geographical distribution.

The results show that large and serious accidents occupy a major position in coal mine gas explosion events, especially particularly serious accidents, which lead to a high death toll, and the scope of accidents is also relatively wide [5]. The safety management of gas explosions at home and abroad mainly includes safety risk identification and safety risk early warning.

In order to study the cause factors of coal mine gas explosion accidents and enhance their control, many domestic scholars have studied these accidents. Zhu Qihu et al. [6] constructed an evidence-based safety management system for gas explosion accidents by using the evidence-based safety management method, selecting the time data of a gas explosion accident as the research angle, and proposed a coal mine gas control mode optimized by the best safety evidence. Xue Haideng et al. [7] conducted a qualitative and quantitative analysis of gas explosion accidents in coal mines from four aspects: human, material, environment and pipe. The structural importance of basic events affecting gas explosion accidents was obtained by the accident tree analysis method. According to the structural importance, an improved analytic hierarchy process model of gas explosion accidents in coal mines was constructed to provide reference for their prevention. Fu Jing et al. [8] constructed a research framework for the classification characteristics of unsafe actions in coal mine gas accidents based on the 2–4 model theory, which provides a reference for enterprises to carry out specific safety countermeasures and training. Zhao Ziqi [9] used the 2–4 model to study 63 typical accidents, identified 76 types of unsafe actions, and used Pearson and Spearman correlation coefficient methods to analyze the correlation and influence relationship between unsafe actions. Wang Wanqing et al. [10] used the Improved Analytic Hierarchy Process (IAHP) to establish an analysis model, and carried out qualitative identification and quantitative analysis of gas explosion accidents in coal mines, which provided a basis for daily gas explosion risk prevention and control and safety management in coal mines. Zhang Ning [11] used a Bayesian network as a research method to construct a risk identification model of a coal mine gas explosion Bayesian network, which provided support for the timely and accurate identification of accident risk sources. Liu Zengliang [12] constructed the behavior cause model of a coal mine gas explosion accident by using the “2–4” model of behavior safety. Wu Joli [13] used the quantitative analysis method of minimum cut set and minimum path set in the accident tree analysis method to quantitatively analyze the risk factors of coal mine gas explosions. Zhang Yong et al. [14] systematically identified the hidden dangers of gas explosion accidents based on evidence, analyzed the coupling relationship between hidden dangers and the risk evolution path by using a logic diagram, and proposed a three-dimensional risk matrix to classify and evaluate accident risk, which provided reference for the identification and risk evaluation of gas explosion accident hidden dangers. Liu Qi [15] selected typical gas explosion accident reports and used the text extraction method to sort the causes of accidents. Based on the correlations among the causes derived from quantitative social network analysis, a map of gas explosion accidents was established, and a Bayesian network for such accidents was further constructed. Then, the parameters of the Bayesian network were determined according to the data and parameter learning method, the cross-validation method was used to prove the authenticity and effectiveness of the model, and finally, the key causes of gas explosion accidents were determined. Zuo Minhao [16] studied the evolution process of coal mine gas explosion risk based on the cumulative effect, and constructed a gas explosion risk evolution model combined with system dynamics. Combined with specific example analysis, he used Vensim PLE(7.3.5) software to simulate and propose corresponding control measures for coal mine gas explosion risk. Guo Yajuan [17] used Hierarchical Holographic Modeling (HHM) to extract the risk factors of a coal mine gas explosion, and then constructed a gas explosion risk evolution model based on accident

chain theory. Finally, the improved risk integrated propagation method was proposed by introducing the topological network algorithm. The software is used to construct the gas explosion risk topological network measurement model, which provides support for gas explosion accident prevention. Aiming at the mining industry with a large number of casualties in China, Hou Wei et al. [18] analyzed the gas explosion accident with the largest number of casualties and proposed an improved Bow-tie model.

Similarly, there are also many achievements in the research of gas explosion accidents abroad. Divad et al. [19] analyzed the occurrence characteristics of major gas explosion accidents from the aspects of gas accumulation, ignition source, explosion site, working area, accident time and coal mine ownership. Ajrash et al. [20] studied the influence characteristics of different gas concentrations, different obstacles and other factors on gas explosions. In terms of the construction of a risk index system, Diaz, J et al. [21] assessed the predictive performance via cross-validation and finally identified the optimal risk prediction model. Cioca et al. [22] established a gas explosion accident evaluation index system from two aspects: methane-air mixture and ignition source. Lenné et al. [23] analyzed the cause factors of coal mine accidents through human factors and a classification system. Sundermeyer et al. [24] used deep learning technology to automatically mine the potential associations between data to improve the accuracy of gas change prediction.

The research on complex networks first originated abroad. In 1736, in order to solve the Königsberg Seven Bridges problem, Euler first abstracted Bridges as nodes and edges in geometric graphics, thus laying the foundation of graph theory in the process of solving the problem. With the deepening of research, more and more scientists have solved complex mathematical problems such as the four-color conjecture and the Hamiltonian circuit through the abstraction of graph models. In the 1960s, the introduction of the random graph model made the study of complex networks gradually become an important research field. The study of complex networks has roughly progressed through three stages: regular networks, random networks and complex networks. Among them, the regular network is the simplest one, which usually shows a ring or tree structure. Albert et al. [25] first proposed the concept of scale-free network and proposed a BA scale-free network model in their paper published in *Science*. Strogatz et al. [26] published a related paper in *Nature* in 1998. Since then, research on small-world networks has gradually emerged. These two properties are the two main characteristics of complex networks.

The research on complex networks started relatively late in China. Wang Xiaofan's [27] paper published in 2002 is one of the earliest research results on the theory of complex networks in China. He discussed the characteristics and models of complex networks abroad in detail. Since then, research on the models and theories of complex networks has gradually increased in China. Deng Hao et al. [28] used a genetic algorithm to analyze the characteristics of attack sequences, as well as attack sequences obtained by other methods, for randomly generated complex networks under different average degrees. In theory, Wang et al. [29] proposed introducing a "network robustness index" into the fitness function to analyze the feasibility of reconstructing topological connections by an edge rewiring strategy. At present, research on complex networks and accident analysis is at a leading position in China. Chen Liao yuan [30] improved the HFACS framework in order to deeply analyze accidents that caused significant losses in the construction industry. Through the analysis of 156 accident reports, the accident cause chain was extracted, the complex network of collapse accidents was constructed and analyzed in detail, and then targeted accident prevention and control suggestions were put forward. Based on complex network theory, Wu Ying [31] collected accident data from China's power industry in the past ten years, used Gephi (v0.9.2) and PyCharm (v2025.1) to construct and analyze the cause network of power accidents, and clarified the characteristics of the entire network and the

role of key causative factors. In view of these key factors, he proposed targeted prevention and control measures to prevent the occurrence of accidents by cutting off connection and transmission in the accident-causing network. Based on a large number of chemical explosion accident reports, Guo Zhonghua et al. [32] established a network evolution model of chemical explosion accident risk factors, and evaluated the risk factors in a particularly serious explosion accident. Based on complex network theory, Ni et al. [33] constructed the cause network model of bridge construction accidents, revealed the relationship between bridge construction accidents and key causes, clarified the evolution law of the accident, evaluated the influence of each cause, and put forward relevant suggestions to strengthen the safety management of bridge construction. Through the analysis of accidents, Yao Hao et al. [34] proposed a coupling assessment method of the major safety risks of super-high-rise building construction based on a complex network.

Extensive research on coal mine gas explosion accidents has yielded substantial progress in areas such as statistical analysis, causation theory, risk evolution, and early-warning systems. This established body of work offers a strong foundation for further investigation. Notably, the incorporation of complex network theory into accident causation analysis has established a systematic framework. By constructing accident causation networks, the intricate relationships among contributing factors can be visually represented, thereby offering a novel perspective for identifying key risks.

However, most of the current research on accident risk assessment relies on static topological analysis, using indicators such as degree or betweenness centrality to identify key nodes. This approach merely captures the snapshot of the network's structure and often leads to unsatisfactory results due to the tendency to get stuck in local optima. To overcome these limitations, this study integrates the modeling capability of complex networks with the global optimization capability of genetic algorithms. A customized model is developed that incorporates a reward mechanism into the fitness function, enabling the simultaneous optimization of both degree and betweenness centrality. This method can identify the most influential factors that affect the stability of the network, overcoming the limitations of static analysis, and identifying the major cause groups that have a significant impact. It reduces subjective bias and provides scientific and reliable decision support for preventing and mitigating the risk of gas explosions.

2. Theory and Method

This study proposes a research methodology that integrates complex network theory with a genetic algorithm. First, a complex network model of gas explosion accidents is constructed. Subsequently, to address the core challenge of identifying key nodes in complex networks, a genetic algorithm is employed to optimize the model. By designing an appropriate fitness function and systematically configuring the processes of selection, crossover, and mutation, the genetic algorithm enables efficient and global identification of the most influential set of key nodes within the network topology, thereby minimizing subjective bias inherent in manual analysis. The main research ideas are shown in Figure 1.

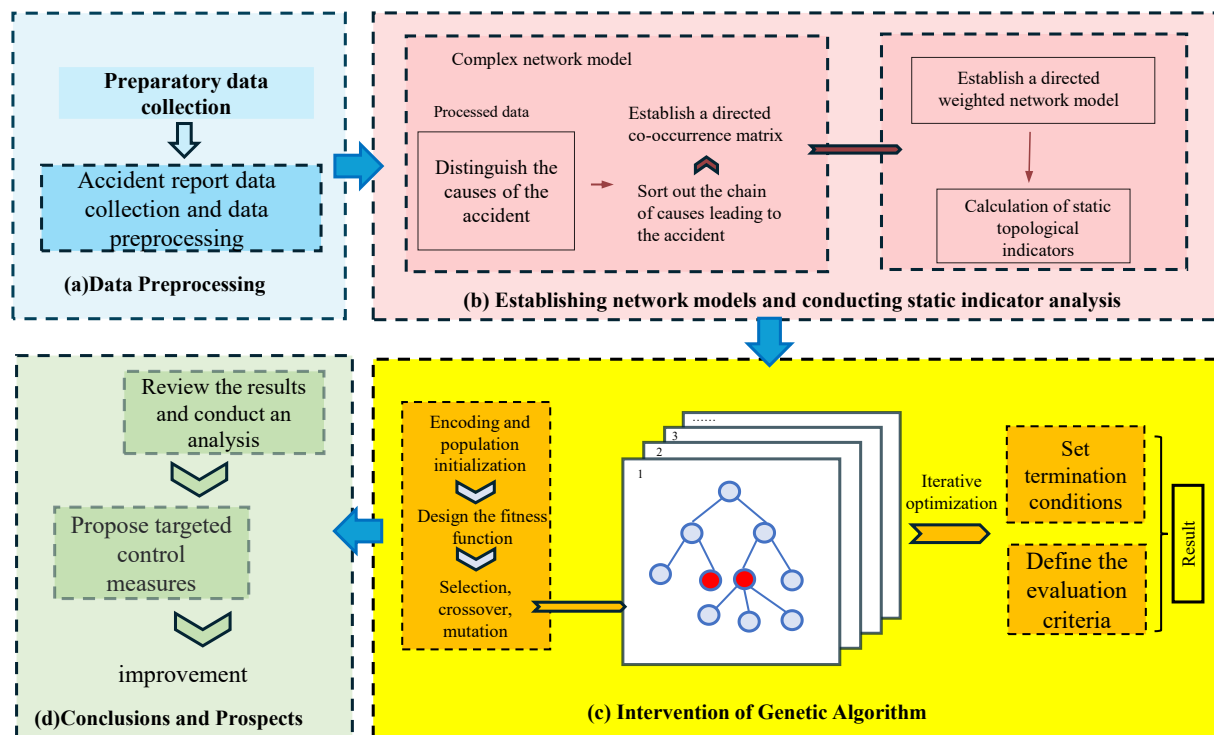


Figure 1. Technology road map.

2.1. Chain of Causes of Accidents

In the field of coal mine safety management, an accident cause chain is a core tool to analyze the process and root causes of coal mine accidents. The factors involved in the causal chain of coal mine accidents are highly complex, encompassing multiple dimensions such as geological conditions, mining techniques, equipment operational status, personnel operational behavior, and safety management mechanisms. In order to dig deeper into the causes of accidents, according to the specific characteristics of the mining system in the mining area, combined with existing accident cause theories such as the trajectory intersection theory, human factor classification analysis system, and comprehensive accident model, various influencing factors of accidents can be efficiently classified and deeply analyzed. Among them, the influencing factors of accidents can be first divided into four system categories: human factors, physical factors, environmental factors and regulatory factors. These four system factors interact and restrict each other in the occurrence process of coal mine accidents, and together constitute the basic framework of accidents. Furthermore, human factor theory, failure mode and impact analysis methods can be used to connect the above factors one by one in series, and a complete accident cause chain can be constructed. In this process, through the detailed disassembly and summary of each link of the cause chain, potential weak links can be accurately identified, and then scientific support can be provided for the development of targeted safety management measures. In addition, relying on the in-depth research and analysis of the accident cause chain, the potential systemic risk points can also be mined, which provides a decision-making basis for the early prevention of and effective response to coal mine accidents that may occur in the future. Among the common accidents in coal mines, gas explosion accidents are often caused by specific trigger factors, which are defined as the end nodes of each accident cause chain in the research framework of this paper.

2.2. Complex Network Theory and Applicability Analysis

Complex networks refer to those systems that exhibit self-organization, self-similarity, attractors, small-world effects, and scale-free properties. The exploration of complex network theory can be traced back to the end of the 18th century, when the German mathematician Euler solved the Königsberg Seven Bridges problem using graph theory, which is regarded as the beginning of the field. In the 1950s, Hungarian mathematicians Erdős and Renyi proposed the theory of random graphs, which marked the beginning of the systematic study of complex networks [35]. Complex networks are usually divided into two extreme types: regular networks and random networks. Regular networks have a fixed topology, and the distribution of nodes and edges is very regular. In contrast, the connections of nodes in random networks are determined based on probability, so there is no obvious rule. Two important models in the study of complex networks are the small-world network model and the scale-free network model. The small-world network model reveals that the distance between any two nodes in the network is very short, which reflects the phenomenon of “six degrees of separation” [36]. The scale-free network model describes the phenomenon that the degree distribution of nodes follows a power-law distribution; that is, a small number of nodes have a large number of connected edges, while the majority of nodes have relatively few connected edges [37]. Complex networks lie between regular networks and random networks. The relationship between events can be represented by directed edges, and the weights represent the degree of connection. Based on this, this study quantifies the occurrence frequency of the accident cause factors as the edge weight in the directed network, and intuitively reveals the influence relationship between the factors by constructing the directed weighted network model. The construction and analysis of the complex network model proposed in this paper includes three core steps: first, the causes of roof accidents and their causal chains are identified based on accident reports, and a directed and weighted causal network is constructed accordingly. Secondly, static topology analysis is carried out to evaluate the importance of each causative node by calculating a series of indicators such as degree, betweenness, and eigenvector centrality. Finally, genetic algorithm optimization was carried out to explore the internal relationship between network nodes and the overall robustness of the network by simulating random and deliberate node attack modes.

The topological index in complex network theory is a key tool to quantify the importance of nodes and reveal the intrinsic properties of accident systems. Choosing the appropriate index is very important for analyzing the network structure comprehensively and reasonably [38]. Based on this, this paper selects a series of topological indicators for analysis. Firstly, the concept of degree is introduced: degree represents the total number of connections between a node and other nodes in the network, which is the basic indicator to measure the connectivity of a node. Specifically, it is divided into out-degree and in-degree. Out-degree refers to the number of edges from node i to other nodes, and in-degree refers to the number of edges from other nodes to node i . The formula for the degree k_i , out-degree, and in-degree of a node i is as follows.

$$K_i = \sum_{i \neq j} a_{ij} \quad (1)$$

$$K_i^{in} = \sum_j a_{ji} \quad (2)$$

$$K_i^{out} = \sum_j a_{ij} \quad (3)$$

Degree distribution: The degree distribution is an important macroscopic statistical property of the network. It describes the probability that an arbitrary node has a degree of

exactly k . Specifically, this probability can be estimated by the ratio of the number of nodes with degree k to the total number of nodes in the network. The formula is as follows:

$$P_K = \frac{N_K}{N} \quad (4)$$

where N is the total number of nodes in the network, and N_k is the number of nodes with node degree k .

Network density: it reflects the degree of interconnection between the nodes of the network. The density of the network is equal to the ratio of the actual number of edges in the network to the maximum possible number of edges in the network. The value ranges from 0 to 1. The higher the density, the more connected the nodes are.

Clustering coefficient: it expresses the degree of clustering of a node. The ratio of the actual number of edges (E_i) between all its neighboring nodes and the maximum number of edges that these neighboring nodes can theoretically form is the degree of node i . The formula is as follows:

$$C_i = \frac{2E_i}{K_i(K_i - 1)} \quad (5)$$

Betweenness: Node betweenness centrality reflects the ability of nodes to control network information flow or connectivity. Computationally, it counts the proportion of all shortest paths between all pairs of nodes in the network that pass through node i . The larger its betweenness centrality is, the more important the node is in the network. The formula is as follows:

$$B_i = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (6)$$

where σ_{st} is the total number of shortest paths from node s to node t , and $\sigma_{st}(i)$ is the number of those paths that pass through node i .

Network diameter: The maximum distance between all pairs of nodes in the network, with the following formula:

$$D = \max(d_{ij}) \quad (7)$$

Average path length: The average distance between any two nodes i and j in the network, and the formula is as follows.

$$L = \frac{1}{\frac{1}{2}N(N+1)} \sum_{i \geq j} d_{ij} \quad (8)$$

Eigenvector centrality: The importance of a node depends not only on the number of connections, but also on the importance of its neighbor nodes themselves. In other words, being connected to a node with high importance significantly increases the importance of the node itself. This recursive concept is mathematically defined by the adjacency matrix $A = (a_{ij})$, where the basic idea is that the importance score of a node should be proportional to the sum of the importance scores of all its neighbors. The formula for the eigenvector centrality of node i is as follows:

$$EC_i = \lambda^{-1} \sum_{j=1}^i a_{ij} x_j \quad (9)$$

2.3. Basic Principle of Genetic Algorithm

A genetic algorithm is a global optimization search algorithm that simulates the mechanism of “natural selection and survival of the fittest” in the process of biological evolution in nature [39–41]. Professor J.H Holland proposed this algorithm in the 1970s. Its core idea is to propose potential solutions to solve the problem of coding into a “chromosome” in the form of a string, which constitutes a population. By simulating genetic operations such as

natural selection, crossover and mutation, the algorithm iteratively evolves the individuals in the population to gradually approach the optimal solution of the problem [42–45]. The algorithm mainly includes the following core steps: The first step is encoding and population initialization. Encoding is a key step to transform the solution of the problem from the solution space to the search space that the genetic algorithm can handle. During the configuration of the initial node groups, each group is generated according to a predetermined ratio. Notably, this generation process does not rely solely on random selection; rather, it employs sampling without replacement, thereby preventing the same node from being repeatedly selected into different node groups. The second is the selection of the fitness function, which is the only basis for the natural selection of the genetic algorithm, and is used to evaluate the quality of each individual (solution). The higher the value of the function, the stronger the survival ability of the individual, and the greater the possibility of being selected to inherit to the next generation [46]. In this study, the design of the fitness function is crucial, which must be able to effectively quantify the network optimization objective. In the expression, S represents the set of nodes in the attack sequence. $E\left(\frac{G}{S}\right)$ represents the efficiency of the network after removing the node. $R(S)$ represents the reward item. α is the weight coefficient.

$$F(S) = \left(1 - E\left(\frac{G}{S}\right)\right) + \alpha R(S) \quad (10)$$

The fitness function can be defined as the attenuation degree of the maximum connected subgraph size or global efficiency of the network under a specific attack strategy. This is followed by the selection operation, which simulates the natural selection. The purpose of selection is to screen out excellent individuals with high fitness from the current population and use them as parents to reproduce the next generation. The commonly used selection operators include the roulette wheel selection method, tournament selection method and so on. The basic principle is as follows: the higher the fitness of the individual, the greater the probability of being selected, so as to ensure that good genes can be inherited and spread [47–49]. In genetic algorithms, crossing and mutation are key operations, with crossing serving as the primary method for generating new individuals. It simulates the process of sexual reproduction in biological evolution. During the crossing operation, selected parent individuals are randomly paired, and based on a certain crossover probability, parts of their chromosome structures are exchanged, thereby producing new offspring individuals. In this article, an individual is defined as a group of accident causes consisting of individual accident causes. Accordingly, the crossing operation involves exchanging some accident causes between two such groups. The mutation operation, on the other hand, randomly alters certain gene values in an individual's encoded string with a small mutation probability. In this context, mutation manifests as changes to the accident causes within an accident cause group. After the selection, crossing, and mutation operations, a new-generation population is generated. Through this process, the genetic algorithm evolves from one generation to the next. When the preset termination condition is satisfied, the algorithm terminates, and the individual with the highest fitness in the previous generation is output as the optimal (or nearly optimal) solution of the problem [50].

The genetic algorithm is applied to the optimization problem of the complex network caused by coal mine gas explosions, with the aim of objectively identifying the key causal factors that affect the occurrence of accidents. At the same time, this method has the following advantages: it can conduct parallel and efficient searches in the solution space composed of causal factor nodes, find the optimal or approximately optimal risk control nodes, and provide scientific decision support for formulating accurate and efficient prevention strategies for gas explosion accidents. In the study of complex networks of coal

mine gas explosion accidents, the introduction of genetic algorithms aims to address the network optimization problem—namely, how to scientifically identify the most critical set of risk factors and how to optimize the network structure within the causal network.

3. Results and Analysis

3.1. Extracting Causal Chains to Construct Causal Networks

In the field of coal mine safety management, the accident cause chain is an important tool for revealing the causes and processes of coal mine accidents. By analyzing 101 complete accident reports collected, based on the characteristics of the overall mining system in the mining area and in combination with some classic theories of accident causes, various factors leading to the accidents can be more clearly identified and understood. This study employs the selected accident data for investigation primarily because the publicly available accident investigation reports comprehensively encompass the critical contributing factors governing the occurrence and progression of accidents, featuring well-documented information and strong representativeness. Through systematic collation, induction, and in-depth analysis of multiple accident cases, the core causative factors leading to accidents can be effectively identified. Furthermore, by reconstructing the entire sequence of accident initiation and evolution, the dominant accident causation chains can be established. Concurrently, during the extraction and definition of accident causes, rigorous screening and deduplication have been implemented to eliminate redundant information to the greatest extent. This mitigates potential computational redundancy in modeling and search procedures caused by repetitive content, thereby ensuring favorable convergence speed and stability throughout subsequent analytical processes. The specific process is shown in Figure 2.

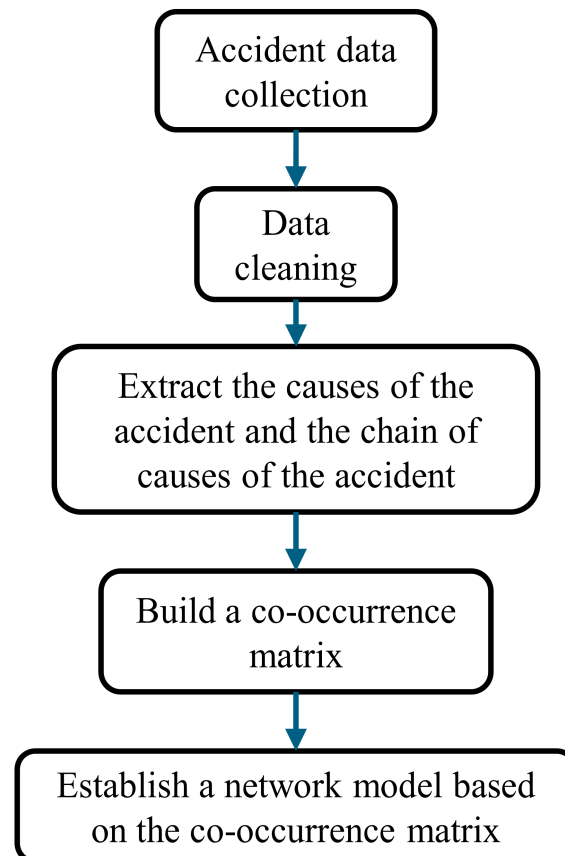


Figure 2. Detailed flowchart.

Firstly, in the construction of the accident cause chain, all kinds of accident factors are classified and divided into four system factors, including human factors, physical factors, environmental factors and management factors, as shown in Table 1.

Table 1. Accident cause set.

Types of Causes	Key Causative Factor
Human factors	Poor security awareness E1; Violation of order E2; Illegal production E3; Irregular operation E4; Escrow violation E5; Illegal command E6; Illegal shelter hidden danger E7; Intentionally concealing hidden dangers E8; Illegal cross-border mining E9; Illegal purchase of pyrotechnical products E10; Hidden trouble investigation is not in place E11; Forcing workers to take risks E12; Deliberately evading supervision E13; Illegal rescue E14; Illegal power supply E15
Factor of matter	Monitoring system missing W1; Poor job design W2; Poor support facilities W3; Inadequate safety facilities W4
Environmental factors	Sealing wall crack H1; Gas accumulation H2; Geological environment evolution H3
Management factors	Safety management confusion M1; Insufficient safety education M2; Ventilation management confusion M3; Poor superior supervision M4; Failure to investigate hidden dangers M5; Mechanical and electrical equipment management confusion M6; Disorder of labor organization relations M7; Insufficient qualifications of workers M8; Inadequate staffing M9; Insufficient safety investment M10; Inadequate implementation of safety system M11
Final cause	Spark caused by material friction Y1; Gas enters the fire area Y2; Illegal blasting Y3; Spontaneous combustion of coal Y4; Motor explosion Y5; Short circuit produces spark Y6; Workers smoking Y7; Improper operation produces sparks Y8; Open flame Y9; Violation of unsealed fire area Y10

Then, the occurrence of an accident chain is caused by the mutual influence and interaction between a certain event and the surrounding disaster-causing environment and other causes. Similarly, the occurrence of an accident will also have an impact on the environment, creating conditions for the occurrence of other accidents. This chain reaction between the event, the disaster-causing environment, and the causes forms the accident chain. Through manual reading, the accident cause chains in each accident report are extracted in order to explain as much as possible why this accident occurred, as shown in Table 2. Since a gas explosion accident is ultimately caused by a specific factor, this final cause is taken as the endpoint of each accident causation chain in this paper. For each accident causation chain, the analysis is conducted based on the accident occurrence process and its causal factors. The length of a causation chain is determined by the accident itself, so the lengths may vary slightly across chains. Statistical analysis shows that the maximum chain length is 9, the minimum is 4, and the average length is approximately 6.

After comprehensively combing and systematically sorting the cause chains of various accidents mentioned above, further in-depth analysis of the data was carried out, and finally the cause–cause directed co-word matrix was successfully constructed. As shown in Table 3, the key to the construction of this matrix is to quantify the relationship between each cause, which helps to reveal the role of different causes in the process of accidents and their interaction patterns. By counting the co-occurrence frequency of each cause with other factors in the accident chain, the interaction and influence between each cause and other factors can be more clearly identified. Further analysis showed that the co-occurrence frequency of some causes was higher, indicating that they might be more closely related in the accident, while some causes might have relatively weak links with other factors. In order to visualize these associations, Gephi software was used to visualize the above data, and an accident cause association network diagram was drawn, as shown in Figure 3.

Table 2. Sets of cause chains of the accident.

Serial Number	Accident-Causing Chain
1	M4-M9-M5-M3-W3-Y1
2	M4-M1-E3-H1-Y2
3	M9-E11-E3-M1-Y3
4	E3-M2-M1-W1-Y6
5	M4-M2-M1-E4-Y6
6	M4-E8-M2-E1-W1-Y3
7	M4-E2-E3-E5-M1-Y9
8	M4-E8-M1-W1-H2-Y3
9	M4-E3-E1-M1-Y3
10	M4-E1-W3-Y1
11	M4-W2-E1-M1-M6-Y5
12	M4-E8-M1-E12-Y8
...	...
94	M4-E1-E3-W2-M1-M11-H1-H2-Y6
95	M4-W1-E13-E3-E9-M1-M3-H2-Y6
96	E8-M4-M2-M1-E14-M3-H2-Y3
97	M4-M1-H1-H2-Y6
98	E2-E9-E8-M3-H2-Y6
99	E2-E3-M10-M8-W1-M3-H2-Y8
100	E1-E3-E9-W2-M3-H2-Y3
101	E3-E9-E8-E13-M1-W1-Y3

In this figure, the causes are marked with different colors according to the categories, which facilitates the intuitive identification of the relationship and influence between different categories. The color coding makes it easy to distinguish the causes of similar categories and helps to understand their role in the accident. This visualization method not only shows the location and connection of each cause, but also highlights their integrity and dependence in the whole network. Through the network diagram, the interaction between each causative factor and other factors and their importance in the causal chain can be clearly seen. At the same time, the diagram reveals the relationship between different categories of factors, which helps to understand the mechanism of the accident and provides theoretical support for subsequent preventive measures.

Table 3. Co-word matrix.

	E1	E2	E3	E4	E5	...	Y6	Y7	Y8	Y9	Y10
E1	0	0	11	3	0	...	5	0	7	2	0
E2	1	0	19	0	1	...	2	1	5	4	2
E3	2	0	0	0	1	...	8	3	8	7	2
E4	0	0	0	0	0	...	1	0	1	1	0
E5	0	0	0	0	0	...	0	0	0	1	0
E6	0	0	0	0	0	...	1	0	1	1	0
E7	0	0	2	0	0	...	1	0	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...
Y9	0	0	0	0	0	...	0	0	0	0	0
Y10	0	0	0	0	0	...	0	0	0	0	0

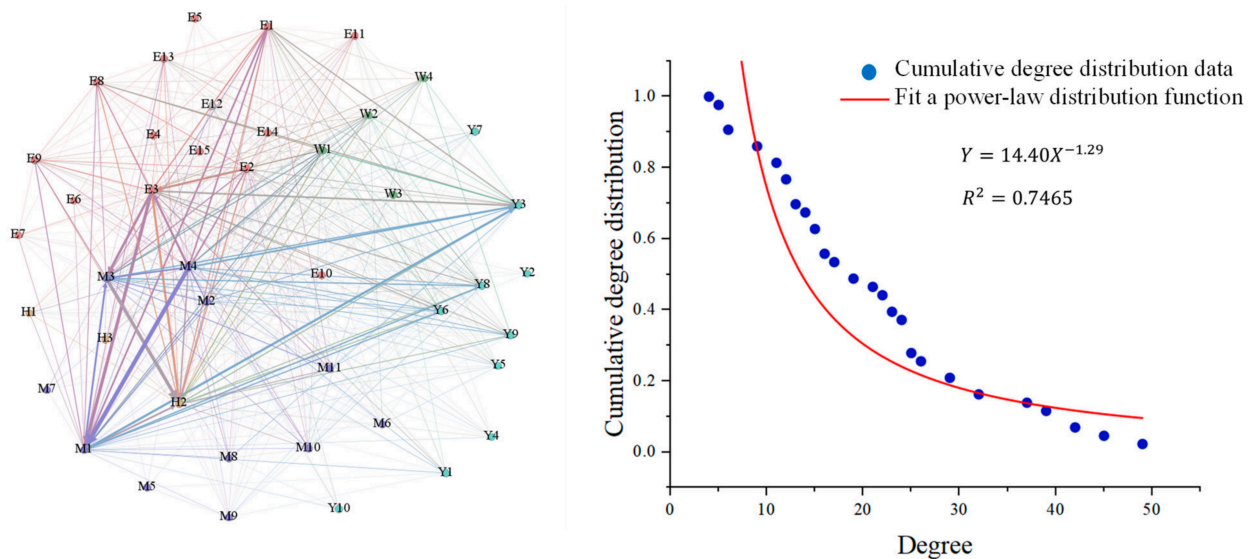


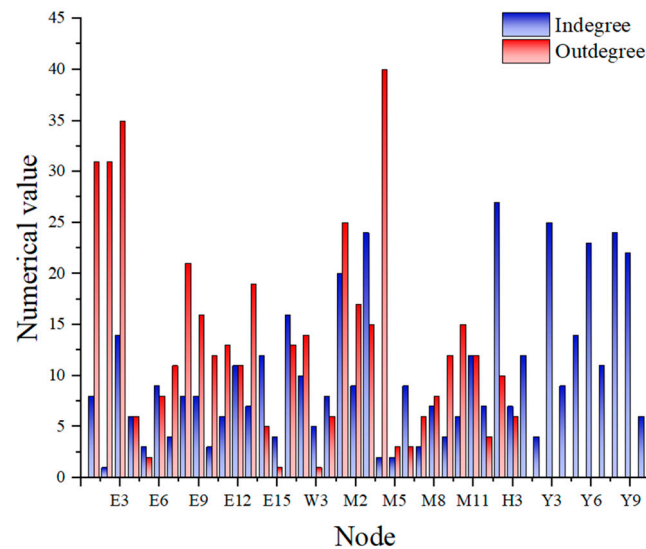
Figure 3. Complex network models and verification of scale-free networks.

3.2. Analysis of Node Indicators

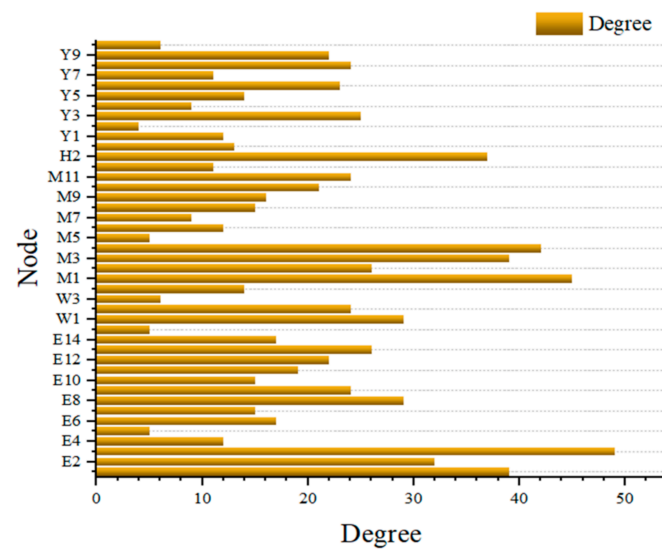
In the study of complex networks, research on static topological indices is of great significance. Among them, the degree value is a fundamental indicator for measuring the degree of node connectivity. Specifically, the degree value of a given node is defined as the total number of edges directly connected to it. When the considered network is directed, the concept of degree is further refined into two different components: out-degree and in-degree, as shown in Figure 4. The out-degree refers to the number of directed edges originating from this node, thereby representing the connection situation between this node and other nodes in the network. Conversely, the in-degree refers to the number of directed edges pointing to this node, reflecting the degree of connection of other nodes to it. This distinction between out-degree and in-degree is particularly important in the analysis of directed networks, as it enables a more detailed understanding of the influence, functional role, and position of the node within the overall topological structure of the network.

The total degree value of the causal network shows the distribution of connections and influences among each node in the network, as shown in Figure 4. By analyzing the total degree value, the importance of each node in the network can be revealed, which is helpful for identifying key nodes and their roles in the overall network structure. Nodes with higher total degree values usually play more crucial roles.

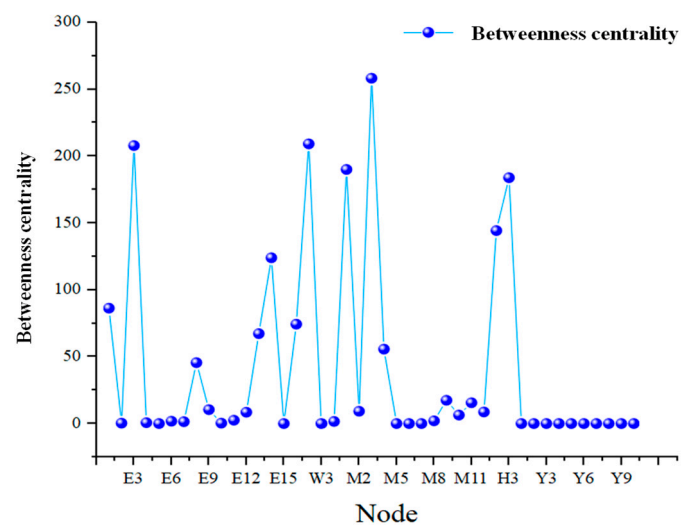
Figure 4 presents the static topological index analysis of the network. This figure illustrates the four key indicators for each node. From the above chart, it can be seen that, apart from the ultimate factor at the end of the accident chain, nodes such as M4, E3, E7 and M1 have a higher out-degree, while nodes such as M1, H2 and W1 have a larger in-degree. Specific analysis indicates that the out-degree of E7 is 21, while the in-degree is only 8, which means it may affect 21 causes, thus requiring attention. The highest in-degree of H2 is 27, indicating that there are 27 causes that may lead to H2, and the transmission path also needs to be noted. Nodes with a high total degree involve aspects such as personnel, objects, environment and management, suggesting that the gas explosion accident is caused by the combination of multiple factors and paths. Therefore, prevention and control should adopt a comprehensive approach.



(I) The in-degree and out-degree of the node



(II) The total degree value of the node



(III) Node betweenness centrality

Figure 4. Cont.

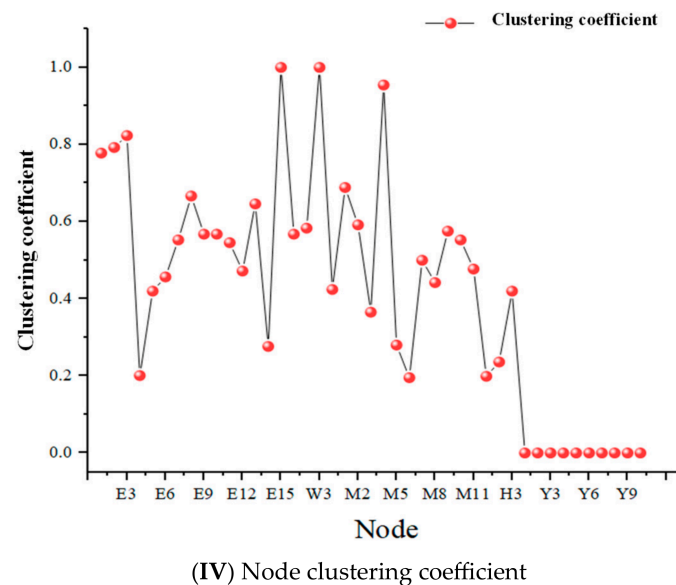


Figure 4. Static indicator chart.

The figure also includes the betweenness centrality index, which is used to assess the relative importance of nodes or edges in the network, reflecting the critical role of nodes in information transmission. It reveals the role that nodes play in influencing the efficiency of the network. Nodes with high betweenness centrality are usually the core of the network, have strong influence, and are indispensable parts. Figure 4 shows the distribution of betweenness centrality for each node.

Through in-depth analysis of the network structure, it can be concluded that the betweenness centrality of M3 and E3 nodes is higher than that of other nodes, indicating that their influence in the whole network is more prominent. This means that M3 and E3 not only play a key role in connecting other nodes in the network, but also may be the main hub of information flow, and any path or information transmission related to these two nodes may have a significant impact on the whole network. At the same time, M1 and W2 are also key connecting points. These nodes have a significant impact on information flow and network connectivity, so they must be prioritized for risk management and control.

It can be seen from the clustering coefficient graph of the factor network nodes in Figure 4 that the clustering coefficient of some nodes, such as E1, E15, and W3, is high, close to 0.8, indicating that the neighboring nodes of these nodes are closely related to each other, and the network aggregation degree is high, reflecting the close network relationship around them. Meanwhile, for nodes such as the H3 and M11, the clustering coefficient is low, meaning fewer of the other nodes are connected, and the connection with the factor of the node in the network is more dispersed, suggesting that the impact of these nodes is relatively independent. A node with a low clustering coefficient also indicates that the relationships among the other causes connected to it are loose, and the influence of such nodes is relatively weak.

Through calculation, the average clustering coefficient of this network is 0.428, which indicates that there is a certain degree of freedom or dispersion between each node. However, although the nodes maintain a certain degree of independence, they are still associated with each other. Specifically, although each node and other nodes around the connection relationship are not too dense, and instead are spread over the whole network, they still maintained certain interactions and relationships between themselves. The average clustering coefficient indicates that the nodes in the causal network are not completely isolated; rather, they are interconnected to a certain extent, thereby forming a specific network

structure and interactions. Consequently, the nodes of the network not only maintain a certain degree of flexibility but also exhibit their intrinsic connections.

3.3. Overall Index Analysis of the Network

(1) Average path length

According to the calculation results of Gephi, the average path length of the network model is 2.329, which reflects that there is a short connection distance between nodes, indicating that the propagation efficiency of the cause in the whole network is very significant. On average, any two nodes only need 2 or 3 connections to achieve the transmission of information or influence, which means that the cause can quickly spread from the source to the key factors that eventually lead to the accident. Due to the short path, the obstruction and attenuation in the propagation process are greatly weakened, which significantly enhances the overall connectivity and propagation ability of the network. Therefore, the network exhibits the structural characteristics of high transmission rate and strong connectivity. In such a highly connected topology, the disturbance of any local node or link may trigger cascading reactions of non-adjacent nodes within a very short path, which will cause systemic chain effects and eventually lead to disasters or accidents.

(2) Network density

According to the Gephi platform, the overall density of the network is 0.239, which belongs to the medium level. This result shows that the network has a certain connectivity efficiency as a whole, and there are direct connections between some of the accident cause nodes, so that the causal influence can be rapidly transmitted in the local scope. At the same time, the connection between the relationships does not reach a high concentration level; some nodes still lack a tight connection between cause and result in the network, which in a global perspective, shows the characteristics of a relatively sparse structure. Such structural characteristics indicate that the evolution process of accidents does not rely on extensive and random connections, but tends to advance in a local subnetwork composed of key nodes along a number of relatively fixed paths.

Due to the limitation of the overall connection of the network and the obvious directness of the path, it is a structurally feasible and operatively targeted prevention and control strategy to effectively cut off the evolution chain of the accident by accurately identifying and removing the specific causes on the critical path in the practice of risk governance.

3.4. Model Validation

In complex network analysis, the verification of small-world and scale-free properties is very important. They provide the theoretical basis for risk and robustness analysis. Small-world networks have a high clustering coefficient and short average path length, which indicates that the causal nodes are closely connected and the risk diffusion path is short, which may cause major accidents through several key nodes. Therefore, verifying the small-world property is helpful to analyze the degree of clustering between nodes.

The scale-free network is naturally robust due to the uneven distribution of node connectivity, but it will be vulnerable when subjected to attacks targeting critical nodes. Therefore, verifying the scale-free property provides the basis for the subsequent robustness analysis.

3.4.1. Verification of Small-World Networks

For a criterion based on a small-world network, if a network at the same time has a shorter average path length, usually less than 10, and a high clustering coefficient, generally greater than 0.1, it can be considered a small-world network.

According to the analysis of the above indicators, the average path length of the network model is only 2.329, and its clustering coefficient reaches 0.428. These two indicators are significantly better than the benchmark threshold of small-world networks, which fully confirms its small-world network characteristics. In order to evaluate the network characteristics of the model, it was compared with three random networks of the same size. As shown in Table 4, the comparison of key topological indicators is as follows: the average path length (2.329) is smaller than the average of the random network (2.849), while its clustering coefficient (0.428) is much higher than the average level of the random network (0.057). This result clearly reveals the small-world effect of the model and verifies its small-world network property. The average path length of this article is 2.329, which is comparable to the values reported in similar coal mine accident networks, indicating consistent structural characteristics among different data sets.

Table 4. Indicators of random networks.

Metrics	Random Network 1	Random Network 2	Random Network 3	Average
Average clustering coefficient	0.03	0.077	0.063	0.057
Average path length	2.732	2.936	2.88	2.849

3.4.2. Scale-Free Network Verification

The scale-free property was verified through node analysis. Linear regression was performed on the logarithmically transformed data, followed by curve fitting. Using the total degree of nodes as the independent variable and the cumulative probability of nodes as the dependent variable, the scale-free property was confirmed via the cumulative degree distribution, as shown in Figure 3. The distribution fitting of the model is $P(K) \sim 14.40x - 1.29$, $R^2 = 0.7465$. This result conforms to the power-law distribution characteristics, which confirms the scale-free property of the network and lays a foundation for the subsequent robustness research. This property is also clarified from the perspective of network structure: by appropriately increasing the network diameter and average path length, the resilience of the network can be effectively improved, so as to suppress the evolution and propagation of the cause.

The “preferred connection” property of scale-free networks makes hub nodes (M1, E3, etc.) become the core structure of the network. These nodes are robust to random failures, but have a decisive impact on the overall connectivity of the network. Therefore, targeted preventive control of hub nodes can effectively evacuate the network structure, cut off the critical path of cause transmission, significantly reduce the overall connectivity of the network, and fundamentally restrain the probability of accidents.

3.5. Model Robustness Analysis

In the research framework of robustness analysis, an important application is to identify and analyze the complex association between various causes of gas explosion accidents. By introducing network seepage theory, a propagation model of the causes of gas explosions can be constructed, and then the changes in network structure under different attack strategies can be simulated. Specifically, there are two typical types of attacks on nodes in a network. One is a random attack, which removes nodes or edges indiscriminately. The other is a deliberate attack, which selectively removes critical nodes or links based on their importance. Through these two attack methods, it can effectively evaluate whether the remaining nodes can still maintain the basic functions of the network and whether the overall connectivity of the network can be maintained after the failure of some cause nodes.

In order to systematically evaluate the robustness and vulnerability of the network, this section designs two types of simulation experiments: random attack and deliberate attack. The specific experimental scheme is as follows: First, the random attack simulates a random failure in the network, and all the nodes in the model are randomly sampled many times to realize the attack. Secondly, in the deliberate attack, according to the topological structure characteristics of the network, two strategies are used. One is a degree-based attack, which preferentially removes the nodes with the highest degree values in the network. The other is a betweenness-based attack, which preferentially removes the nodes with the highest betweenness centrality. The specific indicators and their core characteristics based on these two deliberate attack strategies are shown in Table 5.

Table 5. Indicators and characteristics of deliberate attack.

Indicators	Characteristics
Degree	At its core, the strategy of targeting highly valued nodes in a deliberate attack is to break the connectivity of the network. This is mapped to production practice, guiding enterprises to focus on those high-frequency factors as “common causes” or “hub nodes” for key prevention and control, so as to realize effective intervention for the entire risk network.
Betweenness centrality	In a network, the betweenness centrality of a node quantifies the frequency of being crossed by the global shortest path, and is a key indicator to measure the role and influence of hubs. This is mapped to enterprise safety management, which means that those factors that act as key factors in the cause chain of the accident should be accurately identified and controlled, so as to effectively block the transmission path of the risk in the whole system.

By comparing the degradation patterns of network performance under random and deliberate attacks, this study aims to accurately reveal the potential risks of the network. Based on the identified attack methods, a dynamic simulation model is constructed based on the PyCharm (v2025.1) platform. The specific steps and logical relationships of the entire workflow are shown in Figure 5. The ultimate goal of this process is to identify and determine the key node groups that meet specific requirements through a series of operations. Regarding the complexity issues involved in the methods adopted in this paper, it should be noted that the number of nodes in the network model constructed in this paper is relatively small and does not reach the scale of large-scale network models. Under this premise, the overall computational complexity of this algorithm is within a controllable and reasonable range, and will not cause excessive consumption of computing resources or excessively long running time. Therefore, the current method and its complexity level are suitable for the small-scale network model established in this paper and can meet the requirements for conducting relevant analyses.

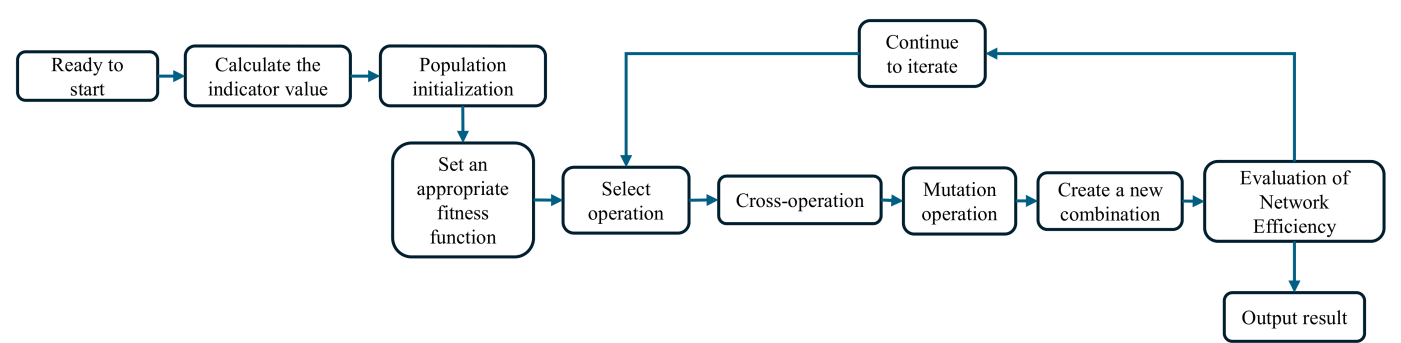


Figure 5. Workflow diagram.

Firstly, the independent network efficiency evolution graph of each attack mode is generated by executing the customized analysis code.

Then, by extracting and integrating the core data in the graph, the comprehensive comparison chart as shown in Figure 6 is finally generated. The chart realizes the horizontal comparison of different attack effects, clearly shows that deliberate attack is the dominant factor leading to the sharp decline in network efficiency, and provides key evidence for the formulation of risk prevention strategies.

Figure 6 presents the simulation results, which clearly show that random attack damage to the network performance is far inferior to the two kinds of deliberate strategy. In the figure, the Y-axis represents network efficiency. Its primary function is to assess whether the remaining nodes can maintain normal operational performance and ensure network connectivity when the causal nodes fail. The actual situation shows that by taking certain measures to control some accident causes—removing specific nodes representing those causes and breaking the accident chain—the probability of accidents can be reduced. This comparison strongly confirms the effectiveness and importance of the attack method based on degree and betweenness in accurately identifying critical nodes in the network. In both of the deliberate attack scenarios, interruptions and gradual failures of 24 to 26 nodes led to a significant reduction in network efficiency. In this case, the network efficiency dropped to $47 \pm 2\%$ of its initial value, indicating a decline in the overall operational performance of the network.

However, under the same conditions, the network efficiency can still maintain at about 70% under random attacks, which shows the inherent robustness of the network to random failures. From the perspective of security management, the above phenomenon has profound implications: if only random or blind control measures are taken, it is difficult to effectively cut off the critical path in the accident-causing chain, and the risk can still circulate in the network, resulting in a high probability of accidents. On the contrary, the simulation results show that the whole risk propagation network can be effectively disintegrated by implementing the key control of the identified key causative factors (that is, the “important nodes” in the network), which provides a solid theoretical basis and quantitative support for the safety management strategy of “grasping the key and ensuring the whole situation” in practice.

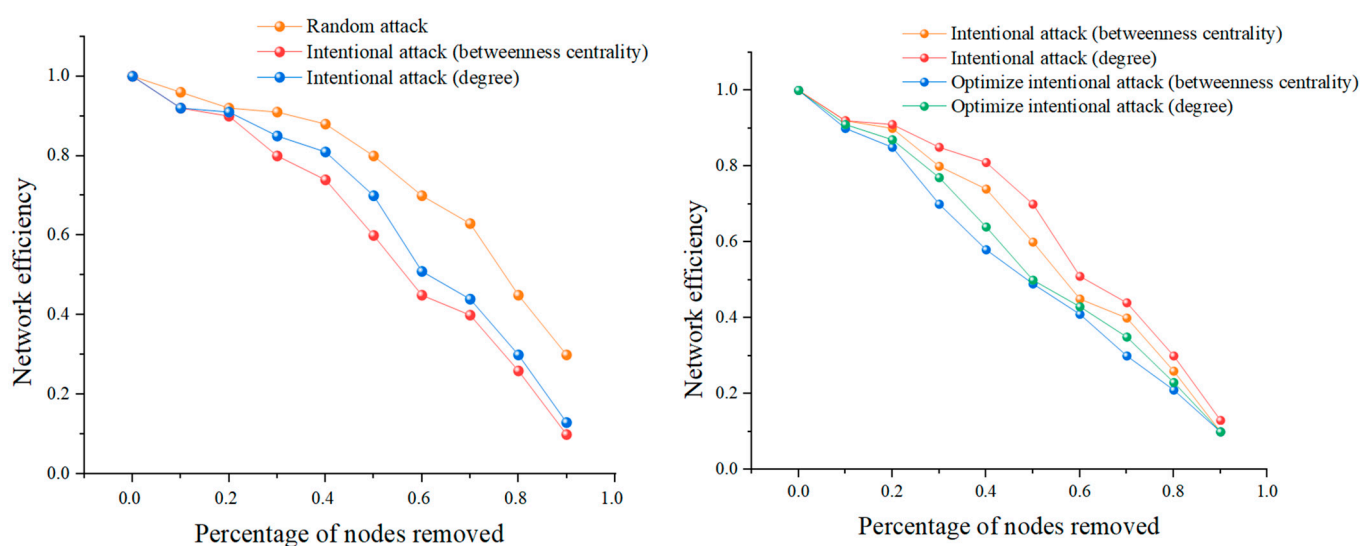


Figure 6. Attack efficiency chart.

Comparing three different attack methods, the effect from best to worst is: deliberate attack based on betweenness centrality > deliberate attack based on degree > random attack.

Further analysis shows that both deliberate attacks are better than random attacks, but it is easy to find that although the effect of deliberate attacks is stronger than random attacks, it still needs to control more nodes to achieve effective control. Therefore, in order to achieve the purpose of accurate control, the genetic algorithm is used to optimize the established complex network model structure to increase the network invulnerability. The specific indicators are shown in Table 6.

Table 6. Summary of node indicators.

Node	Betweenness Centrality	In Degree	Out Degree	Degree
E1	86.25	8	31	39
E2	0.25	1	31	32
E3	207.85	14	35	49
E4	0.63	6	6	12
...	...	...	...	...
Y7	0	11	0	11
Y8	0	24	0	24
Y9	0	22	0	22
Y10	0	6	0	6

At the same time, the key nodes are fully mined in the optimization process to provide a basis for key control and reduce the probability of accidents.

The first step is to optimize for betweenness centrality. The core goal of the genetic algorithm is to optimize the attack sequence of nodes with high betweenness centrality. By simulating the “selection–cross–mutation” process of biological evolution, the node removal sequence (attack sequence) that can make the network efficiency decline the fastest is found. The specific implementation steps are as follows:

The first is the label coding based on the “attack node sequence”. In the genetic algorithm, each “individual” corresponds to an “attack sequence”, and the sequential coding is used, that is, each individual is a list of fixed length, the elements in the list are “node labels to be removed”, and the order of the list represents the “order of node removal”. A single individual is a list of length num (num is the total number of nodes to be removed, calculated by the number of nodes in the network $\times$ removal ratio), and each element in the list is a node label in the network. There are no duplicate nodes in the list, the same node cannot be attacked repeatedly, and all nodes are from the node set of the original network. Then, population initialization is weighted sampling that favors nodes with high betweenness. In the initialization process, nodes with high betweenness centrality are preferentially selected to ensure that the initial population has a good basis for optimization. If the network has betweenness centrality, the relative betweenness of all nodes is calculated first, and the weight difference in high-betweenness nodes is enlarged by the power of three, and the weight lower limit is set to 0.1 to avoid the low-betweenness nodes being completely ignored. If the betweenness centrality is invalid, such as if there are too few nodes in the network, equal weight sampling is used. Then, each individual is generated by weight sampling, and nodes are extracted from the network nodes without replacement to form an attack sequence.

The third step is to design the appropriate fitness function. The fitness function is the core component of the genetic algorithm, which is used to quantify the pros and cons of each attack sequence. The goal of this paper is to find the optimal attack sequence, so the higher the fitness value, the stronger the damage ability of the sequence to the network efficiency, and the more in line with the target expectation. Therefore, the core of the fitness function designed in this paper is a comprehensive score of “efficiency decline + high betweenness node reward”.

In the iterative process of the genetic algorithm, selection operation is the key link to realize the “survival of the fittest” of the population. Its core goal clearly points to “retain excellent individuals with high fitness and eliminate inferior individuals with low fitness”, so as to screen out the high-quality basis for population evolution. In order to balance the necessary randomness in the evolution process (to avoid premature homogenization of the population) and the convergence efficiency (to ensure that the algorithm steadily moves closer to the optimal solution), the two mechanisms of probabilistic selection and deterministic retention are combined in this operation.

Among them, the deterministic retention mechanism is the core defense line to ensure that “high-quality genes do not lose”. It will directly screen out the best individual with the highest fitness in the current population, and directly copy it into the next generation population without any random screening process. The key purpose of this design is to avoid the subsequent crossover, mutation and other random operations to destroy the excellent individual structure formed, and to ensure that the population always retains the optimal evolution results at the current stage. The probabilistic selection mechanism plays an important role in “maintaining the diversity of the population”. It calculates the selection probability according to the fitness value of the individual (usually, the individual with higher fitness is more likely to be selected, such as in the roulette wheel selection method or tournament selection method), and randomly selects two individuals from the screened population as the parent and the mother, respectively. The two parent individuals will be used as the “gene donors” for the subsequent crossover operation, providing the genetic basis for the generation of new individuals, and avoiding the population falling into a single evolutionary path by random selection.

The crossover operation, which follows the selection operation, is the core link of “gene recombination”, which aims to fuse the excellent traits (i.e., attack strategies) of the parent and the mother to generate new individuals. This operation consists of two steps: point selection and gene recombination. Subsequently, sequence repair is applied to remove duplicate nodes in the sequence, ensuring the validity of the new individual sequence. After the crossover operation, a mutation operation is performed, which serves as a key step for introducing new genes and preventing the algorithm from becoming trapped in a local optimum. In this paper, the mutation probability for each individual node is set to 25%. Through the two processes of mutation triggering and node replacement, the random mutation operation based on node replacement is completed. At the same time, the mutated sequence must still satisfy the requirement of having no duplicate nodes to guarantee the validity of the attack sequence. Finally, the above process is executed through multiple generations of loops to gradually improve the overall performance of the algorithm. In the stages of initialization, crossover completion and mutation replacement, the GA gives priority to selecting nodes with high betweenness to ensure that the evolution direction is consistent with the importance of nodes. In the fitness function, an additional reward will be given to the effective attacks on the nodes with high betweenness, which can directly improve the fitness of such attack sequences. The elite retention strategy can ensure that the optimal high-damage sequence in each generation is not lost, and finally realize the accelerated convergence of the algorithm to the global optimum. In the process of optimization attack, the network efficiency is used as the termination criterion. When the efficiency drops below the threshold, it is set to 10%. The network is considered to have entered a state of total failure, and the optimization process stops. In other words, the algorithm does not search for a solution indefinitely, but considers it successful and terminates the search when the evaluation function detects that the network functionality has been weakened below about 10%. The same is true for the optimization attack on the degree.

4. Discussion

In summary, the comparison presented in Figure 7 demonstrates that the optimized deliberate attack strategy is substantially more effective than the non-optimized counterpart in degrading overall network performance. Specifically, it can reduce network efficiency to 50% or below by compromising fewer than 50% of the nodes. This indicates that controlling a subset of critical nodes can significantly impair the system's operational efficiency and reliability, thereby increasing the likelihood of system failures. In complex network models, compared with Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), the Genetic Algorithm (GA) is more suitable for handling discrete problems such as network topology structure, node selection, and combinatorial optimization, and has stronger global search capabilities. The ant colony optimization is more suitable for path searching, while the particle swarm optimization is more prone to fall into the local optimal trap. In this paper, in order to obtain a larger range of node combinations, the genetic algorithm is utilized [51]. In parallel, selecting complex network models as the research subject and employing genetic algorithms as the analytical tool enables the systematic evaluation of network resilience, as well as the efficient identification of pivotal communities, or node clusters, inside the network [52–56]. This graphical network model encompasses all the identified factors contributing to accidents. The highlighted elements specifically correspond to the key groups of causes that have a significant impact on the entire model. In conclusion, local intervention may significantly affect the dynamics of the entire network. Centralized management of key nodes is a feasible and effective strategy to reduce risks. By carefully observing Figure 7, it can be found that in the two different intentional attack scenarios, the nodes consistently identified in multiple attack sequences are M1, E3, M4, E2, and H2. They are frequently selected in different attack strategies, indicating a significant impact on the stability and functional integrity of the network. Therefore, these nodes can be classified as the key nodes of the network. For such nodes, priority should be given to strengthening protection measures or implementing redundant designs.

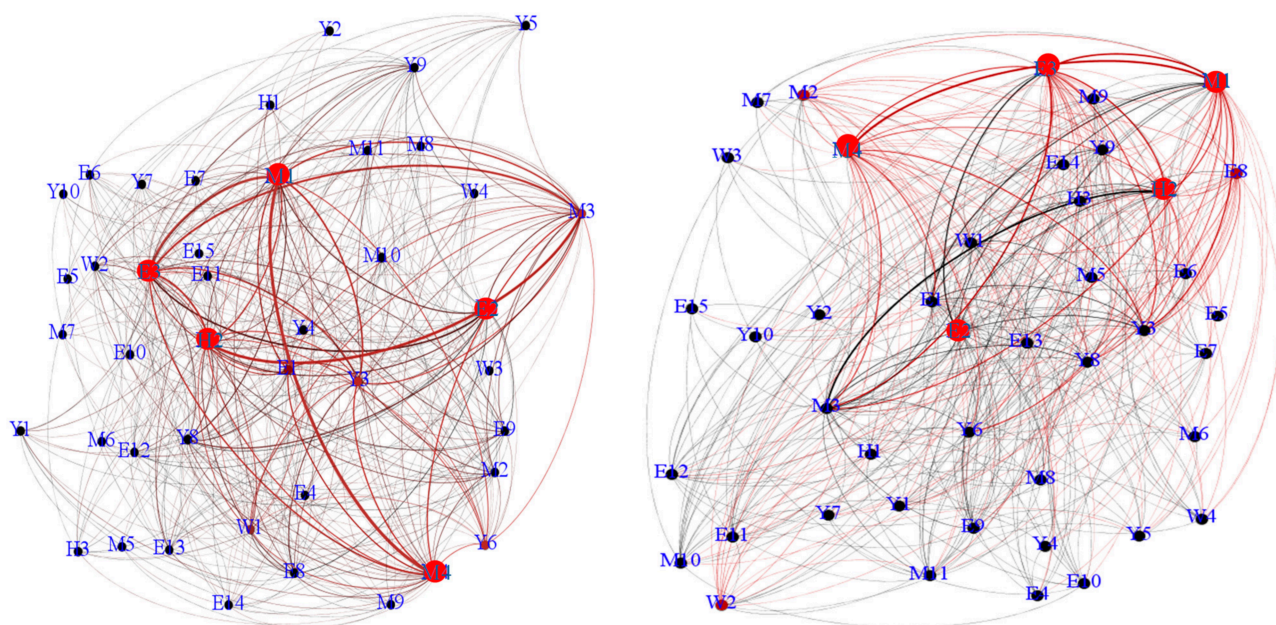


Figure 7. Optimize the attack network diagram.

The analysis shows:

- (1) The impact of random attacks on network efficiency is relatively small, while deliberate attacks are a more effective method. This approach typically ranks network

nodes based on specific topological indicators and removes them in the order of decreasing scores. Although this method is intuitive and easy to implement, it is a typical one-dimensional greedy algorithm. Usually, about 60% of the nodes need to be controlled to effectively reduce network efficiency. Moreover, each deletion decision only relies on the current maximum value of the selected indicator and focuses solely on the immediate topological importance of a single node. Therefore, it cannot take into account potential chain effects or long-term structural consequences resulting from the gradual deletion of nodes.

- (2) The operation mode of the single-node removal strategy is still limited to selecting the locally optimal target node at each step. This method often fails to identify the sets of nodes that, if removed as a whole, would generate a synergy effect and cause damage to the entire system, thus resulting in an overall destructive effect that is not optimal. In contrast, evolutionary algorithms like Genetic Algorithm fundamentally change the presentation of the problem. The attack strategy is no longer a simple sequence of numerical indicators, but a set of nodes to be removed simultaneously. Each set is an individual in the population. Through iterative selection, crossover, and mutation, a parallel and comprehensive search is conducted. This process, while making use of known highly influential nodes, also explores new combinations, thereby being able to discover synergy failure patterns and converge towards the globally optimal attack strategy. By using the actual degree of network damage as the fitness function instead of a single topological indicator like betweenness centrality, the optimization process will directly prioritize the combinations of nodes that cause the greatest damage to the overall function of the network. This approach fundamentally avoids the limitations caused by relying on any single specific structural indicator, thereby avoiding the phenomenon of local optimality in the search process.

To validate the proposed model, we collected an additional set of independent accident statistics from the same type of engineering scenarios, comprising 10 accident reports of similar categories. By analyzing the processes of ten accidents and extracting the causal factors, it was found that all identified causal factors could be covered by the previously established accident causation set. During the analysis, it was observed that some accident causes were not among the five predefined key causes. For example, cause E1 appeared in three accidents, and cause M3 appeared in one accident. However, among the ten accidents, all five key causes were present in eight, while the remaining two accidents each contained four of the five key causes. Furthermore, Table 7 summarizes and compares the performance differences between traditional network analysis methods and the genetic algorithm-based optimization method adopted in this study. The comparative results further demonstrate the advantages of our proposed method in identifying critical nodes. Table 7 presents a comparative analysis of the characteristics of different attack methods. The adoption of the genetic algorithm as the research method in this paper is primarily motivated by two considerations. First, the object of this study is a complex network model of accident causation, characterized by structural complexity, high node coupling, and strong dynamic evolution. Leveraging its global search capability, parallel processing mechanism, and robust adaptability to complex systems, the genetic algorithm achieves an effective alignment and integration with the accident causation complex network model. Second, within the network model space, the genetic algorithm can efficiently search for and identify node combinations that critically influence accident causation, thereby providing an effective computational tool and decision support for revealing accident propagation paths and locating key risk factors. The attack strategy based on genetic algorithms demonstrates two notable advantages. First, its multi-dimensional assessment framework enables the identification of critical nodes with exceptionally high disruption

potential, as such systemic risks only manifest within the overall network structure and cannot be captured by any individual static indicator alone. Second, the inherent robustness of its search mechanism is attained through population diversity and random mutation operations, which effectively sustain the search process, mitigate premature convergence toward suboptimal solutions, and thus substantially reduce the likelihood of becoming trapped in local optima. Therefore, in terms of the search scope and the objectivity of the search results, this comprehensive approach has greater advantages. Analysis shows that traditional attack strategies can affect network efficiency. However, comparative analysis indicates that attack strategies optimized by genetic algorithms have a more significant effect, as shown in Figure 6. This is reflected in the actual process, where controlling only a few key causes of accidents can reduce the probability of their occurrence.

Table 7. Comparative analysis of characteristics.

Characteristics	Traditional Attack Methods	The Attack Method of This Article
Node collaboration	Without considering node collaboration	Consider node collaboration
Search features	Deterministic sorting	Global random combination
Dependence on a single static indicator	Total reliance	Less reliance
Output result	A single node	Node group
Local optimal risk	Higher	Lower

The selected genetic algorithm parameters are appropriate for the objectives of this study. The population size is set to 15, which not only helps avoid the problem of getting easily trapped in local optima, but also ensures comprehensive coverage of different search spaces. Additionally, it prevents unnecessary computational redundancy caused by an excessively large population size, thereby effectively improving the algorithm's iteration speed and meeting the requirements of the 43-node network used in this research. The crossover probability is set to 0.7, which falls within a reasonable range for genetic algorithms. This value enables efficient gene recombination between individuals, promotes the transmission and integration of superior genes, and facilitates the rapid discovery of the optimal attack sequence. At the same time, it avoids the risk of disrupting superior individuals due to an overly high crossover probability. The mutation probability is set to 0.25. By introducing new gene fragments through moderate mutation, it ensures that the algorithm continues searching for better solutions while preventing slow convergence caused by an excessively high mutation probability. The number of iterations is set to 20, ensuring that the algorithm can converge and obtain the optimal attack sequence. When the network efficiency drops to 0.1, the attack process is terminated. However, certain limitations remain in the parameter selection of this paper. A population size of 15 is suitable for the 43-node network scale used in this experiment. Nevertheless, when the number of network nodes increases significantly (e.g., exceeding 100), this population size struggles to cover a broader search space for attack sequences, which may lead to a decline in optimization performance. The fixed mutation probability of 0.25 cannot be dynamically adjusted according to the fitness distribution of the population. When the population tends to converge, moderately increasing the mutation probability could facilitate further exploration of better solutions; however, the current fixed value makes this optimization difficult to achieve. Moreover, when population diversity is insufficient, it is also challenging to quickly introduce new gene fragments, which may cause the algorithm to become trapped in a local optimum without being able to escape. Therefore, there remains room for optimization in future research. When handling large-scale networks, particularly when the number of nodes exceeds 100, the algorithm requires significantly more time and incurs higher computational costs. When conducting node analysis on large-

scale node networks, it is necessary to adjust the algorithm's parameters to accommodate network models of different scales. This ensures both avoidance of the local optimum trap and consideration of as many results as possible. In future research, application analysis should be carried out based on the established network models of varying sizes.

The identified key nodes can be directly regarded as critical control targets in on-site safety management. Managers can implement risk prevention and control measures at these nodes, thereby achieving targeted risk management. For safety management practices, stricter supervision can be adopted, and the methods of supervision can be further optimized. To address the issue of gas accumulation, real-time monitoring can be strengthened, and isolation facilities can be installed, which effectively reduces the probability of system accidents and improves the overall efficiency of safety management.

However, it must be acknowledged that the risk analysis in this study still has limitations. Firstly, the network model was constructed based on a limited dataset. Although we thoroughly examined the entire dataset and identified the causal factors and causal paths, the comprehensiveness of the model is limited, and some causal paths may not have been fully captured. Secondly, this model assumes that the causal relationships are static and derived from historical data. It has not considered the dynamic changes in risk factors over time or the potential feedback loops that may occur due to changes in the network structure over time. Moreover, although no completely random method was used in the encoding operation, the factors were mixed together for operation during the process, which has certain limitations. Meanwhile, in the verification of scale-free network characteristics in this study, only a single method was used for analysis and testing. No cross-validation or result comparison was conducted by combining multiple different methods. This, to some extent, limited the robustness and persuasiveness of the conclusions, and there are certain limitations.

5. Key Cause Control Measures

Gas explosions in coal mines are caused by various factors (such as human factors and management issues) that lead to loopholes. For instance, in 2024, a gas explosion accident occurred in Anhui Province. The main causes included chaotic safety management, improper command, illegal production, inadequate supervision, and gas accumulation. Regarding core risks such as chaotic safety management, inadequate supervision, onsite illegal operations, and gas accumulation, after rectification, safety management has been strengthened, and the degree of chaos has been reduced. Strictly implementing relevant regulations has eliminated the possibility of illegal production. Strengthening gas detection has reduced the number of alarms, thereby eliminating major safety hazards.

- (1) For safety management confusion (M1) and poor superior supervision (M4), at the enterprise level, efforts should be made to improve the internal self-management ability. The core goal is to establish a professional and efficient full-time safety management team with clear responsibilities to ensure that there is a clear allocation of responsibility for hidden danger detection, rectification tracking and file management. All management work, especially the whole process from hidden danger discovery to rectification completion, should be recorded in detail and traceable, so as to ensure that the safety management can be a successfully closed loop, so as to effectively improve the endogenous safety level of the enterprise. In terms of superior supervision, the supervision mode should be promoted to be more accurate and intelligent. A single traditional inspection method should be avoided, and comprehensive supervision should be carried out by combining various means such as "regular all-round spot inspection, surprise random inspection, and smart platform online supervision", by integrating with monitoring systems to continuously track and analyze key safety data

in real time, such as gas concentration, wind speed, and equipment operation status around the clock. Once a system alarm or abnormal situation occurs, the emergency response is immediately launched, and rectification is required to be completed within the specified time, so as to ensure that the regulatory instructions can be issued in time and effectively implemented, thus forming a strong external supervision pressure.

- (2) For illegal production (E3) and violation of order (E2), coal mining enterprises shall strictly implement safety management measures to ensure that the production environment meets safety standards. Specifically, it should be clearly stipulated that the operation surface with excessive gas concentration must stop production, and any unauthorized adjustment of parameters of gas monitoring equipment should be prohibited. Additionally, operators must strictly comply with the regulations governing the use of personal protective equipment, ensuring adequate safety protection throughout operations to avoid safety incidents resulting from operational negligence. In order to further strengthen safety management, coal mining enterprises need to strengthen on-site supervision to ensure that each safety worker can perform his or her duties. Safety officers should carry law enforcement recorders with them to record all processes on the job site in real time to ensure that every operation complies with safety regulations. If any violation is found, the safety officer should take immediate measures to stop it and report the problem to the safety management department in a timely manner to ensure that the problem can be dealt with quickly. At the same time, enterprises should also strengthen the safety education and training of operators, carry out safety drills regularly, and enhance the safety awareness and emergency handling ability of employees.
- (3) For gas accumulation (H2), high-precision gas sensors should be installed in key areas to monitor gas concentration in real time and provide powerful data transmission functions to ensure that data is accurately transmitted to the safety management platform and the superior supervision system. Through automation technology, sensors can collect and analyze data in real time and trigger alarms, helping to respond quickly to potential risks. When the gas concentration reaches 1.0%, the system automatically triggers the first-level early warning, which is issued through the sound and light alarm equipment. At the same time, the early warning information is pushed to the mobile phone terminals of the operators and safety managers to remind them to stop operation immediately to avoid the escalation of potential risks. If the gas concentration rises to 1.5%, the system triggers a second-level warning, requiring the immediate stopping of operations, cutting-off of power and evacuation personnel, and commencement of emergency disposal procedures. Relevant departments should quickly locate the source of gas leakage, take effective ventilation and exhaust measures, and ensure that the safety risks are completely eliminated.

6. Conclusions and Outlook

6.1. Research Conclusions

Coal mine gas explosion accidents often result in large numbers of casualties and significant economic losses. Therefore, conducting in-depth investigations into such accidents carries both important theoretical implications and substantial practical value. Based on a systematic analysis of 101 coal mine gas explosion accident reports, this study constructs a network model. By integrating the systematic modeling strengths of complex network theory with the optimization capabilities of genetic algorithms, it addresses the limitations of traditional safety analysis approaches in addressing multifactor interactions and multi-objective evaluation. The research results show that a comprehensive understanding of the accident mechanism and the precise identification of key causal factors can enhance the

ability to predict accidents and improve prevention and control measures. The primary research conclusions are as follows:

- (1) The entire accident process was abstracted into a system, with factors being compared to nodes and causal relationships being likened to paths. A complex network model was constructed based on the co-occurrence matrix of accident causes. Subsequently, a systematic analysis was conducted on the static and dynamic topological characteristics of the network. Next, tests were carried out to verify the characteristics of scale-free networks and small-world networks, and the results showed that the network structure was highly consistent with the corresponding theoretical features. Moreover, by introducing topological indicators to simulate targeted attacks, it was found that deliberate attacks caused significantly more damage to the network than random attacks.
- (2) The network attack strategy was optimized through genetic algorithms, and then targeted attack tests were conducted. The results show that after identifying the key node groups, this network is more prone to experiencing paralysis when subjected to such attacks. This method effectively combines complex network theory with genetic algorithms, avoiding excessive reliance on static topological indicators. It can efficiently identify the combinations of key nodes that have the greatest impact on network stability, such as M1, E3, M4, E2, and H2. Moreover, it proposes countermeasures for the key causal factors and can effectively reduce the probability of accidents.
- (3) In determining the stopping threshold, this study primarily adopted network efficiency, a system performance indicator, rather than static topological features. This strategy aligns the optimization process more closely with the ultimate objective. Furthermore, by establishing predefined convergence criteria, the approach effectively eliminates redundant algorithmic iterations, enhances computational efficiency, and ensures the objectivity and reproducibility of the results.

6.2. Outlook

This study has certain limitations. Firstly, the scope of the collected data is limited, which may affect the comprehensiveness of the developed model. Additionally, the operation process is also rather complex. Future work should focus on continuously expanding the data set to enhance the comprehensiveness of the model and simplifying the calculation process to improve computational efficiency.

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Abbreviations

K_i	Fundamental indicator for measuring the connectivity of nodes
P_k	Degree of distribution of the macroscopic statistical characteristics of the network
C_i	Degree of aggregation of expression nodes
B_i	Ability of nodes to control information flow in the network

D	Maximum distance between any pair of nodes
L	Average value of the distance between any two nodes
EC _i	Importance of neighboring nodes

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