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Causes Prediction of Coal Mine Gas Explosion Accidents Based on Fault Tree and Bayesian Network

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Abstract. Coal mine gas explosions occur frequently, posing a severe threat to mine safety production and the life and property security of personnel. However, traditional single analytical methods suffer from significant shortcomings, including low accuracy in risk assessment and inadequate connectivity between cause identification and risk prediction. To address these issues, this study constructs an integrated risk assessment and prediction model combining Fault Tree Analysis, Analytic Hierarchy Process, and Bayesian Network, aiming to improve the risk management capacity for coal mine gas explosion accidents. This study uses 64 coal mine gas explosion accidents that occurred in China from 2016 to 2026 as research samples. Firstly, six key causal indicators are identified and their importance coefficients are calculated via FTA; subsequently, a judgment matrix is constructed by integrating AHP with probability importance, and after passing the consistency test, the weight quantification of each indicator is completed. Finally, the comprehensive weights obtained from AHP are incorporated into the BN model to realize quantitative assessment, dynamic prediction, and causal traceability analysis of gas explosion accidents. The research results indicate that ventilation system failure, excessive gas concentration, and unsafe operations by personnel form the core causal system, whereas electrical spark generation, monitoring equipment failure, and safety management deficiencies serve as indirect causes. The importance hierarchy of each causal factor is clearly defined. This integrated model effectively overcomes the limitations of traditional single methods, significantly improving the accuracy, reliability, and dynamic adaptability of risk analysis for gas explosions in complex mining systems. It provides scientific quantitative analysis methods and important technical support for the precise prevention and control of coal mine gas explosions, refined mine safety management, and optimization of the prevention and control system.

1. Introduction

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Coal mining is prone to various accidents. As one of the five major hazards in underground mines, gas explosion features strong suddenness and high destructiveness, posing a severe threat to coal mine safety in China. Over the past decade, the country has experienced frequent major gas explosion accidents. Although coal mine safety management has improved and accident frequency declined in recent years, major and extraordinarily serious accidents still occur occasionally, indicating that the prevention and control system requires further optimization. Therefore, a systematic analysis of the causal mechanism of coal mine gas explosions is of great significance for enriching safety theories, enhancing prevention and control capabilities, identifying key causal factors, and mitigating accident risks.

Currently, scholars worldwide have carried out extensive and in-depth research oncoal mine gas explosion accidents. In terms of safety risk assessment and causal analysis of such accidents, existing studies have demonstrated that risk evaluation and risk control are highly significant for reducing the incidence of coal mine gas explosions. Meanwhile, research on accident causes provides a reliable theoretical basis for accident prevention, risk prediction, and the improvement of emergency management practices. Lu et al [1] established a risk assessment method for coal mine gas explosions based on the three-category hazard source theory, by integrating the grey system theory and the matter-element extension model, and identified the key factors influencing gas explosion accidents. Wen et al [2] put forward a risk identification model and determined 19 high-dimensional discriminant indicators. Wang et al [3] adopted FTA, selected 22 indicators from four aspects (human, management, environment, and equipment), and constructed a gas explosion risk evaluation model using the AHP-SPA method. Li et al [4-5] carried out extensive studies mainly based on safety analysis methods such as fault tree, event tree, and safety checklist, through which hazard sources were identified and a corresponding risk evaluation system was established. Li et al [6-7] mined relevant accident information from a textual perspective to further explore the interaction mechanisms among different accident causes. Ye et al [8] emphasized that human factors play a dominant role in the occurrence of gas explosion accidents. Based on the three elements and six stages of safety information transmission. Li et al [9] built a gas explosion causation model, adopted the combined decision-making trial and evaluation laboratory and interpretive structural modeling method to quantitatively analyze accident causes, and concluded that the failure of safety information transmission is a critical factor leading to accidents. Jing et al [10] analyzed the causes of gas accidents using an improved Human Factors Analysis and Classification System model, chi-square test, and contrast analysis. Shao et al [11] proposed a coal mine gas explosion prediction method based on accident characteristics and case-based reasoning, by combining fault tree analysis with the defensive pessimism theory. In terms of safety information loss in coal mine gas explosions, Li et al [12] extracted 30 gas explosion causation factors from accident cases and determined the association rules among these factors using the Carma algorithm. Most of these studies investigated gas explosion risk factors from the human-machine-environment-management framework, while the emergence of safety information science has provided a new perspective for gas explosion accident research. For the causal analysis of safety information loss at the accident level, Wang et al [13] constructed a MAUAN network for coal mine gas explosions and calculated its topological structure to identify key unsafe behaviors and critical behavior paths. Guo et al [14] classified the causes of gas explosion accidents into a multi-level hierarchical structure and explored the interrelationships and attribute characteristics among these causes. Lin et al [15] combined Bayesian networks with game theory, together with sensitivity analysis and key causal chain analysis, to determine the critical risk factors and paths that affect gas explosions.

On the basis of existing studies on coal mine gas explosion accidents, this paper adopts the systematic analysis framework of Fault Tree Analysis to identify the key causal factors of such accidents. Furthermore, by integrating a self-established network information transmission architecture with the Bayesian network model, this study realizes the quantitative risk assessment and dynamic prediction of coal mine gas explosion accidents.

The main innovations of this study are as follows:

(1) An integrated risk analysis model framework that integrates Fault Tree Analysis, Analytic Hierarchy Process and Bayesian Network is constructed.

(2) This framework adopts FTA for accident causal factor identification and AHP for weight quantification and ranking, which together constitute the input processing module.

(3) The proposed model yields excellent predictive performance and effectively enhances the accuracy and reliability of risk analysis in complex systems.

To clearly elaborate the algorithm proposed in this paper, the entire study is organized into five chapters, as detailed below. Section 1 serves as the introduction, which presents the research background and current research status. Section 2 introduces the relevant fundamental theories, including the systematic theories of Fault Tree Analysis, Analytic Hierarchy Process, and Bayesian Network. Section 3 focuses on the experimental design, illustrating the overall architecture and modular design of the experiment. Section 4 presents the experimental results and analysis, in which the experimental configuration is described and the obtained results are discussed in depth. Chapter 5 provides the conclusion, which comprehensively reviews and summarizes the entire research work of this paper.

2. Theoretical Foundations

2.1 Fault Tree Analysis Theory

Fault Tree Analysis is a deductive reasoning approach, designed to illustrate the logical relationships between potential system accidents and their contributing factors in the form of a tree diagram.

In a fault tree, the minimal set of basic events that can result in the occurrence of the top event is referred to as a minimal cut set. Minimal cut sets are derived using Boolean algebraic operations. First, the top event is expressed via Boolean algebra and expanded in a top-down manner to obtain its Boolean expression. Next, the Boolean expression is simplified. Finally, the minimal cut sets $K_1,K_2,...,K_m$ are obtained, and the occurrence condition of the top event is given by $T=K_1+K_2+\cdots+K_m$.

In a fault tree, the minimal set of basic events that ensures the non-occurrence of the top event is defined as the minimal path set. The minimal path set can be determined by using the duality between minimal path sets and minimal cut sets. First, the dual tree of the fault tree is constructed. The minimal cut sets of this success tree are exactly the minimal path sets of the original fault tree. The success tree is built according to the following rules: replace all AND gates in the fault tree with OR gates, and all OR gates with AND gates; meanwhile, convert each original event into its complementary event to represent non-occurrence instead of occurrence. Assume that the success tree yields m minimal cut sets $P_1, P_2, \dots, P_{\mathrm{m}}$, The condition for the non-occurrence of the top event can then be written as $\overline{T}=P_1 \cdot P_2 \cdot \dots \cdot P_m$.

In a fault tree, structural importance quantifies the influence of each basic event on the occurrence of the top event, evaluated purely from the structural perspective of the fault tree itself. For a fault tree composed of n basic events, the total number of state combinations of these n events is 2^n. When selecting one basic event X_i as the variable (changing from 0 to 1) while keeping all other basic events unchanged, there are 2^{n-1} such control groups. The proportion of cases satisfying $(\phi(1_i,X)-\phi(0_i,X)=1)$ among these groups is defined as the structural importance coefficient of the basic event X_i denoted as $I_{\Phi(\mathrm{i})}$. Its calculation formula is presented as follows:

$$\mathrm{I}_{\Phi(\mathrm{i})}=\frac{1}{2^{\mathrm{n-1}}}\sum[\phi(1_{\mathrm{i}},\mathrm{X})-\phi(0_{\mathrm{i}},\mathrm{X})] \tag{1}$$

In the fault tree analysis of coal mine gas explosion accidents, some basic events appear repeatedly owing to the causal logical relationships among accident factors. Such repetition does not constitute logical redundancy; instead, it arises from the multiple roles that these events play in the accident chain. Accordingly, the core logic of the minimal cut set method is adopted to compute the occurrence probability of the top event.

Probability importance reflects the degree to which the actual influence of the occurrence probability of basic events is fully considered. To comprehensively evaluate the contribution of each basic event, a more in-depth analysis must be performed on the fault tree of coal mine gas explosion accidents. The formula for calculating probability importance is presented as follows:

$$\mathrm{I_g(i)}=\frac{\partial \mathrm{P(T)}}{\partial \mathrm{q_i}}\ (\mathrm{i}=1,2,\ldots,\mathrm{n}) \tag{2}$$

Where $P(T)$ denotes the occurrence probability of the top event, and q_i denotes the occurrence probability of the i-th basic event.

Critical importance analysis characterizes the variation in the top event probability caused by a change in the occurrence probability of the i-th basic event. It enables the quantification of the contribution of different risk factors to coal mine gas explosion accidents. The formula for calculating critical importance is presented as follows:

$$\mathrm{I_g^c(i)}=\frac{\mathrm{q_i}}{\mathrm{P(T)}}\mathrm{I_g(i)} \tag{3}$$

Where $P(T)$ denotes the occurrence probability of the top event, and qi denotes the occurrence probability of the i-th basic event, $I_g(i)$denotes the probability importance.

2.2 Analytic Hierarchy Process

The Analytic Hierarchy Process is a multi-criteria decision-making method that integrates qualitative and quantitative analyses for comprehensive evaluation.

First, a hierarchical structure model is constructed as the core framework of AHP, and its basic three-layer structure is presented as follows:

- Target level: The overall decision objective is the risk assessment of coal mine gas explosion.
- Criterion Level: It represents the core evaluation dimensions for the overall objective, the intermediate events in the fault tree.
- Solution Level: The decision alternatives corresponding to the overall objective, namely the basic events in the fault tree.

Subsequently, a judgment matrix is constructed, where the structural importance or probability importance derived from FTA serves as the basis for pairwise comparisons within the AHP framework. The weight vector is then calculated accordingly. A consistency test is performed to verify the logical consistency of the subjective pairwise comparisons in the judgment matrix and avoid severe contradictions, so as to guarantee the rationality and reliability of the weight results. Ultimately, a comprehensive evaluation is conducted to obtain the comprehensive risk contribution of each basic event to the overall objective. On this basis, risk levels are classified and the priority sequence for risk prevention and control is determined.

2.3 Bayesian Network

Bayesian Network is a probabilistic graphical model that uses a directed acyclic graph to represent causal dependencies among variables, employs a conditional probability table to quantify the strength of these dependencies, and performs probabilistic inference and prediction under uncertainty via Bayes' theorem.

First, the basic events, intermediate events, and top event of the fault tree are mapped to the nodes of the Bayesian network, respectively. Logical relationships such as AND gates and OR gates are converted into conditional dependency edges between nodes, thereby constructing an initial logically consistent Bayesian network. A structural learning algorithm is adopted to optimize the network structure, and maximum likelihood estimation or Bayesian estimation is employed to learn the conditional probability tables (CPTs) for all network nodes - namely, the probability distribution of each state of child nodes given the states of their parent nodes. The dataset is repeatedly split into training and test sets via cross-validation, and the model's performance on unseen data is verified iteratively to effectively evaluate its generalization ability and mitigate the risk of overfitting.

The core of prediction using Bayesian networks lies in updating probabilities via Bayes' theorem, which integrates prior knowledge and observed evidence to derive the posterior probability of the target variable. Ultimately, prediction is performed based on the posterior probability distribution, with the state corresponding to the maximum posterior probability selected as the prediction result. Risk levels are classified according to predefined posterior probability thresholds. The calculation of posterior probability is essentially an application of Bayes' theorem. For a target variable H and an evidence variable E, the posterior probability is given by the following formula:

$$P(H|E)=\frac{P(E|H)\cdot P(H)}{P(E)} \tag{4}$$

In this formula:$P(H)$ denotes the prior probability, referring to the initial probability distribution of the target variable when no evidence is observed (the initial risk probability based on historical accident rates). $P(E/H)$ represents the likelihood, defined as the probability of observing evidence given a particular state of the target variable. $P(E)$ is the marginal probability of the evidence, corresponding to the total probability of observing the evidence across all possible states of the target variable; it serves as a normalization term to ensure the posterior probabilities sum to 1. $P(H/E)$ stands for the posterior probability, which is the updated probability of the target variable H taking each state after evidence E is observed, and forms the core of the prediction.

3. Experiments

3.1 Overall Framework

In this experiment, an integrated modular architecture of "cause identification - weight quantification - risk prediction" is proposed. It integrates fault tree analysis, the analytic hierarchy process, and Bayesian networks, and an integrated model framework for coal mine gas explosion risk is thereby established. The overall experimental flowchart is illustrated in Figure 1.

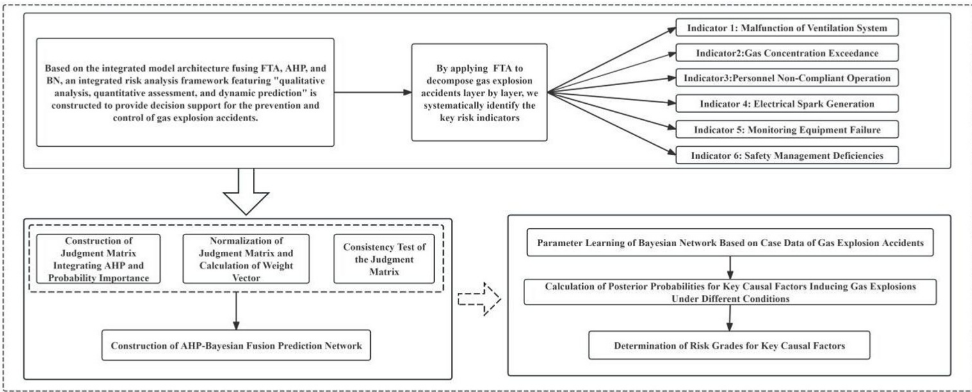

Figure 1 Experimental Flowchart

3.2 Risk Index Analysis

Based on incomplete statistics in this study, 64 coal mine gas explosion accidents occurred in China during 2016-2026. Using these accident data, combined with qualitative and quantitative analyses of the gas explosion fault tree, and referring to the actual values of the three importance coefficients, we followed the principle that factors effectively controllable at the coal mine site through equipment monitoring and system management should cover the core causal dimensions of gas explosion accidents. Accordingly, 6 key causal indicators and their corresponding coefficient results were finally determined, as shown in Table 1.

Table 1 Six Key Indicators and Corresponding Coefficients

Indicators	Structural Importance Index	Probability Importance Index	Critical Importance Index
Ventilation system failure	0.325	0.289	0.296
Gas concentration over-limit	0.318	0.276	0.281
Personnel operating violations	0.297	0.268	0.259
Generation of electrical sparks	0.256	0.215	0.198
Monitoring equipment malfunction	0.234	0.192	0.185
Deficiencies in safety management	0.212	0.178	0.169

3.3 Based on the AHP-Bayesian fused evaluation and prediction network

This module takes the six causal indicators for coal mine gas explosions identified via FTA as its research objects. It combines the analytic hierarchy process with the probability importance index to determine the weighted quantification results. Subsequently, it is deeply integrated with the probabilistic inference capability of Bayesian networks to construct an integrated risk prediction network, realizing a closed-loop analysis ranging from the ranking of causal weights to the prediction of accident risk probabilities.

The Analytic Hierarchy Process adopts a hierarchical structure consisting of the target layer, criterion layer, and scheme layer. Taking the probability importance index as the basis for pairwise comparisons, the importance degree among indicators is evaluated using the AHP 1-9 scale method. The corresponding sixth-order judgment matrix is constructed as follows:

$$\text{A}=\begin{bmatrix} 1 & \cdots & 5 \\ \vdots & \ddots & \vdots \\ \frac{1}{5} & \cdots & 1 \end{bmatrix} \tag{5}$$

Following column normalization of the judgment matrix A, the normalized matrix is obtained as follows:

$$A_1 = \begin{bmatrix} 0.3774 & 0.4286 & \cdots & 0.2941 \\ 0.1887 & 0.2143 & \cdots & 0.2353 \\ \vdots & \vdots & \ddots & \vdots \\ 0.0755 & 0.0536 & \cdots & 0.0588 \end{bmatrix} \tag{6}$$

Based on this normalized matrix, the weight of the ventilation system failure indicator is determined as follows:

$$\text{w}_1=(0.3774+0.4286+0.4286+0.333+0.250+0.2941)/6=0.353 \tag{7}$$

Similarly, the weights of the remaining five indicators are 0.298, 0.291, 0.167, 0.126, and 0.119, respectively. The comprehensive weight vector is W_1=(0.353,0.298,0.291,0.167,0.126,0.119). Since the judgment matrix is constructed based on subjective comparisons, a consistency test is required. The calculation process for its maximum eigenvalue is as follows:

$$\text{A}\cdot\text{W}=\begin{bmatrix} 1 & \cdots & 5 \\ \vdots & \ddots & \vdots \\ \frac{1}{5} & \cdots & 1 \end{bmatrix}\cdot\begin{bmatrix} 0.353 \\ 0.298 \\ 0.291 \\ 0.167 \\ 0.126 \\ 0.119 \end{bmatrix}=\begin{bmatrix} 2.156 \\ 1.820 \\ 1.779 \\ 1.028 \\ 0.774 \\ 0.728 \end{bmatrix} \tag{8}$$

$$\lambda_{\max}=\frac{1}{6}\left(\frac{2.156}{0.353}+\ldots+\frac{0.728}{0.119}\right)=6.1241 \tag{9}$$

The consistency index is calculated as $CI=\frac{\lambda_{max}-n}{n-1}=0.043$, and the consistency ratio is $CR=\frac{CI}{RI}=0.0347<0.1$. The results demonstrate that the judgment matrix satisfies the consistency requirement, verifying the validity of the weight calculation results.

In the Bayesian network, the comprehensive weight vector W is adopted as the prior probability of the causal factors. Under the assumption of conditional independence among features, the formula for the joint likelihood probability is given as follows:

$$P(y|x) = \prod_{i=1}^{n} P(y|x_i) \tag{10}$$

In the formula, y denotes the occurrence of the top event (gas explosion), $T = 1$, x_i represents the occurrence of the i-th key causal factor, $C_i = 1$, $P(x_i|y)$ is the conditional probability of the i-th causal factor occurring given a gas explosion, corresponding to $P(T = 1|C_i = 1)$.

When a single causal factor occurs, the conditional probability $P(T = 1|C_i = 1)$ of a gas explosion is equal to the comprehensive weight, with specific values of 0.353, 0.298, 0.291, 0.167, 0.126, and 0.119, respectively. The joint likelihood probability refers to the conditional probability $P(T=1|C_1=1,\ldots,C_6=1)$ under the simultaneous occurrence of all six causal factors, which is 7.6651×10^{-5}.

The prior probability $P(T=1)$ of the top event refers to the marginal occurrence probability of a gas explosion without observational evidence. As the basis for calculating the posterior probability, it is derived via the law of total probability under the independence assumption of the causal factors. The calculation formula is given as follows:

$$P(T=1) = \sum_{i=1}^{6} P(T=1 \mid C_i=1) \cdot P(C_i=1) \tag{11}$$

Accordingly, the prior probability of the top event can be calculated as $P(T=1)=0.35602$.

The posterior probability $P(C_i=1|T=1)$ refers to the conditional probability of a single causal factor occurring given that a gas explosion has taken place. It reflects the root-cause probability of each causal factor after an explosion occurs. The calculation formula is given as follows:

$$\mathrm{P(C_i=1|T=1)} = \frac{\mathrm{P(T=1 \mid C_i=1) \cdot P(C_i=1)}}{\mathrm{P(T=1)}} \tag{12}$$

In the formula, $P(T=1 \mid C_i=1)$ denotes the single-factor likelihood probability, $P(C_i=1)$ denotes the prior probability of occurrence of the i-th causal factor, and $P(T=1)$ denotes the prior probability of the top event.

Based on this, the posterior probability of ventilation system failure can be calculated as $P(C_1=1|T=1)=\frac{0.353\times0.353}{0.35602}=0.355396$. Similarly, the posterior probabilities of the other five causal factors are 0.253277, 0.237854, 0.078335, 0.044593, and 0.039775, respectively.

Based on the posterior probability results obtained from the Bayesian network, together with the AHP weight ranking, the systematic safety accident risks arising from specific links in coal mine gas explosions are clearly identified. Let the risk factor row vector be $C=[C_1,C_2,C_3,C_4,C_5,C_6]$, where the specific elements are defined as follows:

1) C_1: Ventilation system failure is the primary cause and acts as the fundamental prerequisite for gas accumulation.

2) C_2: Excessive gas concentration directly satisfies the explosion limit criteria and constitutes one of the necessary conditions for a gas explosion.

3) C_3: Personnel violations of operating procedures constitute an active ignition source and directly trigger the occurrence of a gas explosion.

4) C_4: Electrical sparks serve as a typical ignition source, and the associated hazard is particularly pronounced in zones with critically excessive gas concentrations.

5) C_5: Monitoring equipment failure delays risk detection and compromises the early warning function, thereby indirectly elevating the accident occurrence probability.

C_6: Safety management inadequacies compromise the control effectiveness of other risk factors, thereby indirectly elevating the overall accident occurrence probability.

4. Results

4.1 Experimental Configuration

(a) Dataset: The empirical survey data adopted in this study span the period from 2016 to 2026, comprising 64 coal mine gas explosion accidents documented by China's national coal mine safety information platforms and 24 provincial-level coal mine safety supervision authorities.

(b) Algorithm: This study employs an integrated risk analysis approach combining FTA, AHP and BN, which follows a complete logical chain: hazard cause identification, weight quantification, risk prediction, and root-cause traceability.

(c) Experimental Setup: All algorithmic operations and model validation experiments in this study were performed on the Windows 10 operating system, with Python (Version 3.12) as the primary programming language. Core third-party libraries including NumPy, pandas, pgmpy, and SciPy were utilized for implementation; the hardware specifications of the experimental computer were as follows: an Intel(R) Core(TM) i5-7200U central processing unit operating at 2.50 GHz, a 238 GB solid-state drive, and a graphics processing unit with 128 MB of video memory. Collectively, these hardware and software configurations fully met the core computational requirements of this study.

4.2 The results indicate

This study adopts the FTA-AHP-BN integrated risk analysis model. To intuitively present the quantitative distribution characteristics of each key factor in terms of structural importance, probabilistic importance, critical importance, comprehensive weight, and single-factor explosion probability, a multidimensional quantitative analysis bar chart for the key causes of coal mine gas explosions was constructed, as illustrated in Figure 2.

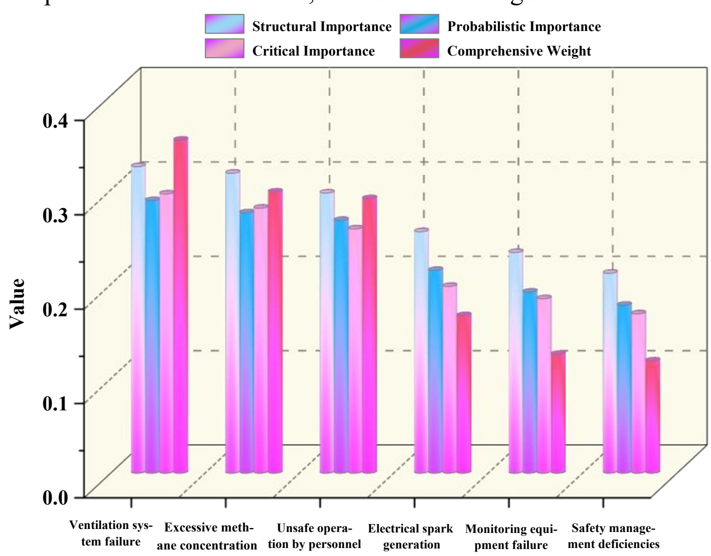

Figure 2 Multidimensional Quantitative Analysis of Key Causal Indicators in Coal Mine Gas Explosions

As shown in Figure 2, the six causal indicators exhibit consistent variation trends across all evaluation dimensions. Specifically, ventilation system failure attains the highest values across all dimensions, followed by excessive gas concentration, while personnel violations of operating procedures rank third. The corresponding values for electrical spark generation, monitoring equipment failure, and safety management deficiencies decline sequentially. This observation demonstrates that the multidimensional evaluation framework established on the basis of fault tree structure, probability characteristics, and the analytic hierarchy process effectively verifies the scientific validity and reliability of the quantitative results in this study. Regarding the dimensional discrepancies, ventilation system failure reaches the peak value in all dimensions, presenting a substantial gap in comparison with safety management deficiencies. This directly reflects the hierarchical disparities in the contribution degrees of different causal factors to gas explosion accidents, providing a clear and intuitive basis for the prioritization of risk prevention and control.

To systematically present the specific quantitative values of the six key causal indicators across all evaluation dimensions and provide support for risk assessment, prediction, and decision-making, the core quantitative results of this study are listed in Table 2.

Table 2 Multidimensional Quantitative Results of Key Causal Factors in Coal Mine Gas Explosions

Causal Factors of the Phenomenon	Structural Importance	Probability Importance	Critical Importance	Comprehensive Weight	Single-Factor Explosion Probability
Ventilation system failure	0.325	0.289	0.296	0.353	0.353
Gas concentration over-limit	0.318	0.276	0.281	0.298	0.298
Personnel operating violations	0.297	0.268	0.259	0.291	0.291
Generation of electrical sparks	0.256	0.215	0.198	0.167	0.167
Monitoring equipment malfunction	0.234	0.192	0.185	0.126	0.126
Deficiencies in safety management	0.212	0.178	0.169	0.119	0.119

As shown in Table 2, the importance hierarchy of causal factors in coal mine gas explosions is clearly delineated. All three importance metrics derived from fault tree analysis identify ventilation system failure as the primary causal factor, and the comprehensive weights validated via consistency checks further corroborate its dominant role. Excessive gas concentration, personnel violations of operating procedures, and ventilation system failure collectively form the core causal system. The single-factor explosion probability aligns with the comprehensive weight values and is consistent with the root-cause traceability results obtained from Bayesian network posterior probability analysis. Monitoring equipment failure and safety management deficiencies represent indirect causal factors with relatively lower quantitative magnitudes. The quantitative results across all dimensions are mutually corroborative, providing a scientific quantitative foundation for formulating differentiated prevention and control strategies for coal mine gas explosions.

5. Conclusion

This study proposes an FTA-AHP-BN integrated model for the risk assessment and prediction of coal mine gas explosions. This model effectively overcomes the limitations of conventional single-method risk analyses for gas explosions, including insufficient assessment accuracy and poor linkage between causal factor identification and risk prediction. It exhibits superior performance in terms of multi-method synergy and the efficiency of risk assessment and prediction. In future applications, this model will not only provide quantitative analytical approaches and technical support for the precise prevention and control of gas explosion accidents in coal mine safety engineering, but also furnish a scientific foundation for optimizing mine safety production management and accident prevention and control systems.

References

1. Lu Jintao, Ren Licheng, Rong Dan, et al. Risk Assessment of Coal Mine Gas Explosion Based on Grey Element Model [J]. Chinese Journal of Safety Science, 2021, 31(2): 99-105.
2. Wen Xinxin, Kong Xiangbo. Risk Pattern Recognition of Coal Mine Gas Explosion Based on KPCA-GA-BP [J]. Journal of Safety and Environment, 2021, 21(1): 19-26.
3. Wang Shengwei, Li Xijian, Dai Fangrui, et al. Risk Evaluation of Coal Mine Gas Explosion Based on Improved AHP-SPA [J]. Mining Research and Development, 2021, 41(4): 113-117.
4. Li Min, Lin Zhijun, Lu Yi, et al. Risk Assessment of Coal Mine Gas Explosion Based on Fuzzy Bayesian Network [J]. Journal of Coal Science, 2023, 48(Suppl. 2): 626-637.
5. Wu Lianhua, Zhang Yiping, Liu Kechen. Risk Assessment of Coal Mine Gas Explosion Based on Game Theory-Uncertain Measure Theory [J]. Chemical Industry and Processing, 2023, 52(6): 13-19.
6. LI Li, GUO Huimin, CHENG Lianhua, et al. Research on causes of coal mine gas explosion accidents based on association rule [J]. Journal of Loss Prevention in the Process Industries, 2022, 80: 104879-104886.
7. QIU Zunxiang, LIU Quanlong, LI Xinchun, et al. Construction and analysis of a coal mine accident causation network based on text mining [J]. Process Safety and Environment Protection, 2021,153: 320-328.
8. Ye Guangli. Application of Qualitative Comparative Analysis Method in Gas Explosion Accident Analysis [J]. Coal Technology, 2022, 41(2): 125-127.
9. Li Li, Guo Huimin, Cheng Lianhua, Li Shugang, Lin Haifei. Research on causes of coal mine gas explosion accidents based on association rule [J]. Journal of Loss Prevention in the Process Industries,2022,80.
10. Jing Guoxun, Mu Lulu. Statistical Analysis and Emergency Management of Coal Mine Gas Explosion Accidents [J]. Journal of Safety and Environment, 2023, 23(10): 3657-3665.
11. Shao Liangshan, Yang Jinhui. Coal Mine Gas Explosion Prediction Based on Accident Characterization and Case-Based Reasoning [J]. Journal of Safety and Environment, 2024, 24(1): 221-228.
12. LI L, GUO H M, CHENG L H, et al. Research on causes of coal mine gas explosion accidents based on association rule [J]. Journal of Loss Prevention in the Process Industries, 2022, 80: 104879.
13. WANG Y X, FU G, Q L Y, et al. Modelling and analysis of unsafe acts in coal mine gas explosion accidents based on network theory [J]. Process Safety and Environmental Protection, 2023, 170: 28-44.
14. Guo Huimin, Cheng Lianhua, Li Shugang. Causal Analysis of Coal Mine Gas Explosions Based on DEMATEL-ISM-MICMAC [J]. Mining Safety and Environmental Protection, 2023, 50(2): 114-119.
15. Lin Zhijun, Li Min, He Shan, et al. Risk Assessment of Coal Mine Gas Explosion Based on Game Theory-Based Bayesian Network [J]. Journal of Coal Science, 2024, 49(8): 3484-3497.