

Assessment of Coal Mine Emergency Response Capability Based on Bayesian Network

Weizhong Zhang, Zetian Jia, Faqiang Zhang*

(School of Resources and Safety Engineering, Wuhan Institute of Technology, Wuhan 430073, China)

Abstract: Coal accounts for over 53% of China's primary energy consumption, making its production safety a critical pillar of national energy security. However, major coal mine accidents persist, largely attributable to inadequate emergency response capabilities. To address the challenges of information uncertainty and complex indicator interdependencies, this paper constructs a Bayesian Network (BN)-based evaluation model for coal mine emergency response capability. Following the Coal Mine Safety Regulations, an index system encompassing 4 dimensions—personnel, equipment, environment, and management—with 14 specific indicators was established. The BN structure, comprising 19 nodes and 21 directed edges, was built using GeNIe software, with Conditional Probability Tables parameterized via a logic-grading method based on expert-defined rules and indicator grading standards. A case study at a large Shandong mine demonstrates that the comprehensive capability is rated "Excellent" (probability 38%), with a cumulative probability of 70% for "Excellent" and "Good", consistent with the mine's actual safety status during its intelligent transformation. Sensitivity analysis identifies "safety violation inspections" as the most influential factor.

Keywords: Coal mine safety; Emergency response capability; Bayesian Network; Risk assessment; Energy security

1 Introduction

Coal dominates China's energy structure, accounting for over 53% of primary energy consumption in 2025. This massive production scale is accompanied by severe safety challenges. Hundreds of coal mine accidents still occurred between 2020 and 2025[1,2]. Although major accidents such as gas explosions, roof collapses, and water inrushes have declined in frequency, single incidents continue to cause heavy casualties, with water inrush accidents remaining a significant concern due to their high fatality rates[3]. A closer examination reveals that a considerable proportion of these accidents are attributable to inadequate emergency response capabilities—delayed response, misallocation of rescue resources, and on-site command failures. The weakness in emergency response capability has thus become a critical bottleneck constraining the safe development of the coal industry and threatening regional energy supply stability. A sudden shutdown due to major accidents may disrupt downstream industries such as power generation and metallurgy, triggering localized energy imbalances. Therefore, scientific assessment and continuous improvement of emergency response capability are of strategic importance for safeguarding national energy security and ensuring stable coal supply.

Extensive research has been conducted on coal mine emergency response capability assessment. In terms of index systems, researchers generally adopt the “human-machine-environment-management” framework. Cheng et al.[4] introduced the Capability Maturity Model (CMM) for emergency rescue capability evaluation; Zhou[5] further developed a CMM-based system specifically for coal mine emergency response capability; Wang[6] constructed evaluation models for the five major coal mine disasters; Zhang et al.[1] identified management loopholes and human operational errors as key accident-inducing factors. Regarding assessment methodologies, AHP, fuzzy comprehensive

DOI: 10.67762/aflyh628

Submission date: August 16, 2026

Corresponding author: Faqiang Zhang

E-mail: 523770688@qq.com

Fund Support: This work was supported by the 17th Graduate Education Innovation Fund of Wuhan Institute of Technology (CX2025201).

evaluation, and grey relational analysis are early commonly used tools[7], but they suffer from strong subjectivity and insufficient characterization of complex interactions. More recently, TOPSIS[8], deviation maximization[9], and cloud model[10] have been applied. Bayesian Networks have gained attention for their advantages in handling uncertainty and multi-factor coupling. Li et al.[11] constructed a fuzzy BN for gas explosion risk assessment; Zhang and Sheng[12] established a gas explosion causation model using GeNIe; Lin et al.[13] combined game theory with BN. Internationally, Shuang et al.[14] employed text mining and BN to identify safety risk factors; Li et al.[15] integrated fuzzy AHP with BN for gas explosion assessment. Xu et al.[16] constructed a systematic safety risk evaluation index system from macroeconomic perspectives. However, few studies have explicitly linked coal mine emergency response capability assessment to the broader goal of energy security, leaving a gap in understanding how improved emergency response can directly contribute to stable energy supply.

Despite these achievements, several limitations remain. First, personnel-related indicators are relatively narrow, focusing on "positive" indicators such as training frequency while neglecting "bottom-line" indicators such as safety violations and certification compliance. Second, the coupling effects between management and personnel factors are not adequately considered. Third, there is a lack of interpretation of assessment results from the energy security perspective. To address these limitations and to enhance energy security through improved emergency preparedness, this study proposes a BN-based coal mine emergency response capability assessment model with three main contributions: (1) introducing safety violation inspection (C4) and special operation certification rate (C5) to better characterize personnel risk; (2) constructing a BN network with 19 nodes and 21 directed edges using GeNIe, with CPTs parameterized via logic grading; (3) validating the model through a case study at a large Shandong mine and interpreting results from an energy security perspective.

2 Methodology and Model Construction

A Bayesian Network (BN) is a probabilistic graphical model consisting of a Directed Acyclic Graph (DAG) and Conditional Probability Tables (CPTs)[12,17]. Nodes represent variables, directed edges represent causal dependencies, and CPTs quantify these dependencies. BN excels at handling uncertainty and reasoning under incomplete information. Its foundation is Bayes' theorem:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

For a BN with m nodes, the joint probability distribution is:

$$P(X_1, X_2, \dots, X_m) = \prod_{i=1}^m P(X_i | \pi(X_i))$$

Where $\pi(X_i)$ denotes the parent set of node X_i . Inputting indicator observations as evidence enables forward inference to compute the comprehensive emergency response capability distribution. Setting the target node to a specific state enables backward diagnostic inference to identify weak links.

The evaluation index system follows principles of scientific rigor, systematic coverage, feasibility, and independence. Literature frequency statistics were used for indicator screening[18], supplemented by mandatory requirements from the Coal Mine Safety Regulations. This process yielded a preliminary set of 32 indicators. These candidates were then evaluated against three screening criteria: (i) relevance to emergency response capability, (ii) availability in routine mine records, and (iii) independence from other selected indicators. Indicators that did not meet at least two criteria were removed. The remaining indicators were further reviewed and refined based on feedback from the cooperating mine's safety management team regarding data availability and practical relevance. This iterative process resulted in the final set of 14 indicators across four dimensions. The final system comprises a target layer (A), four criteria layers—personnel (B1), equipment (B2), environment (B3), and management (B4)—and 14 specific indicators. Personnel factors include safety training frequency (C1), drill participation rate (C2), technician experience (C3), which is included because experienced personnel are more capable of making timely and effective judgments during emergency situations and typically respond more quickly to abnormal conditions based on prior exposure to similar scenarios. violation inspection status (C4), and special operation certification rate (C5), with C4 and C5 newly introduced. C4 is defined as the number of human-factor safety violations recorded in the mine's monthly safety inspection logs, derived from the mine's safety reward and punishment ledgers. It is classified into three states: "Low" (rare violations, ≤ 2 per month), "Medium" (occasional violations, 3–5 per month),

and “High” (frequent violations, >5 per month). C5 is defined as the percentage of key positions (e.g., gas inspectors, safety inspectors) holding valid operation certificates, with states classified as “High” (100%), “Medium” (95–99%), and “Low” (<95%). Equipment factors include ventilation system integrity (C6), monitoring coverage (C7), and rescue equipment availability (C8). Environmental factors include gas concentration exceedance (C9) and geological complexity (C10), the latter influenced by coal seam gas occurrence and geological structures[19]. Geological complexity (C10) is included because more complex geological settings—such as extra-thick seams, fault zones, or high-stress regions—are associated with higher probabilities of roof falls, gas outbursts, or spontaneous combustion. These conditions also complicate rescue access and ventilation during emergencies. Therefore, higher geological complexity is treated as a factor that reduces overall emergency response capability. Management factors include emergency plan completeness (C11), safety investment ratio (C12), which reflects the financial resources allocated to safety equipment, training, and infrastructure maintenance. Adequate investment supports better preparedness and more effective emergency response, whereas insufficient funding may lead to degraded equipment performance and undertrained personnel. information sharing mechanism (C13), and command capability (C14). Quantitative indicators were graded based on mine records; qualitative indicators were scored by experts. All indicators were classified into three levels (“High/Medium/Low” or “Excellent/Good/Poor”), with the target node classified into four levels (“Excellent/Good/Medium/Poor”).

The BN structure was constructed using GeNIe via causal reasoning, drawing on the established “human-machine-environment-management” framework commonly used in coal mine safety research. The parent-child relationships between indicators and criteria nodes were determined based on domain knowledge from the literature and validated through discussions with mine safety practitioners. This approach reflects a knowledge-driven structure, consistent with common practice in BN applications where data-driven learning is not feasible due to limited sample sizes. The 14 bottom-level indicators point to their respective criteria nodes, and the four criteria nodes collectively point to the target node. The final network contains 19 nodes and 21 directed edges, with no directed cycles.

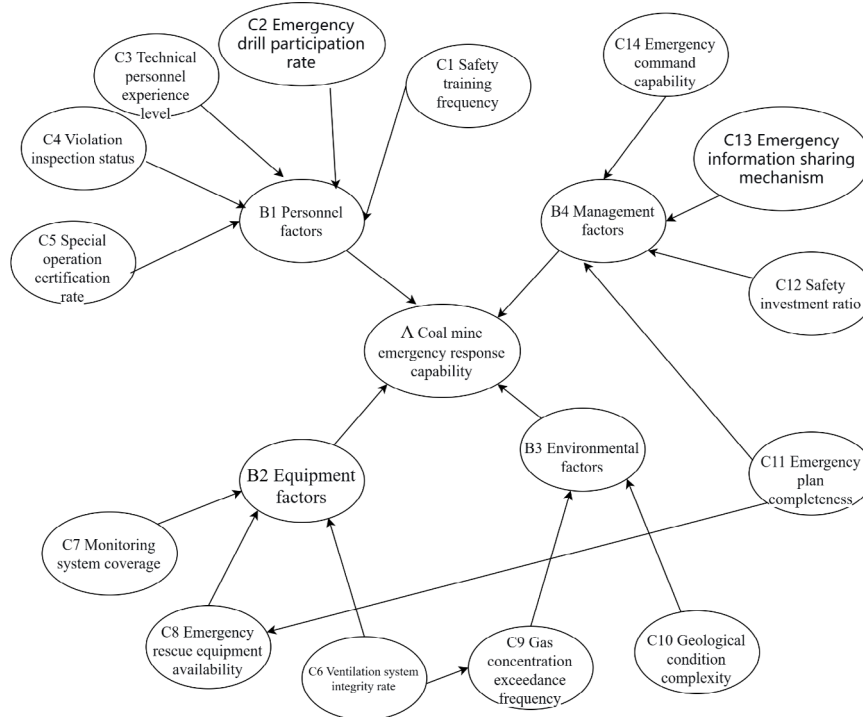


Fig. 1. Bayesian Network structure for coal mine emergency response capability assessment

CPT parameterization is a critical step. For the 14 root nodes, prior probabilities were assigned based on industry averages where available, or using uniform distribution (1/3 each) where data were insufficient. For non-root nodes, CPT size grows exponentially with parent count—the target node A has four parents, requiring $34=8134=81$ conditional probability sets. To avoid subjective manual assignment, this study adopted a “logic grading method”[11,13,20], based on the “short board” principle: if B1 or B4 is “Poor,” A is “Poor” with probability ≥ 0.90 ; if B1 and B4 are both “Good” and B2 and B3 are at least “Medium,” A is “Good” with probability ≥ 0.80 ; only when all four criteria are

“Excellent” is A “Excellent” with probability ≥ 0.85 . Remaining combinations were assigned by linear interpolation. CPTs were batch-generated via Excel and imported into GeNIe for normalization. Criteria-layer CPTs followed similar logic, with C4 and C5 assigned higher weights. The probability thresholds in the CPTs were assigned according to the logic-grading rules defined by the indicator state combinations. These rules were developed based on domain knowledge and standard practices in coal mine safety assessment, drawing on both the existing literature and expert input during the indicator design phase. For example, a high probability (≥ 0.90) was assigned when a critical criterion (B1 or B4) was in the “Poor” state, reflecting the dominant influence of personnel and management factors on overall emergency capability. Lower probabilities were distributed by linear interpolation across remaining state combinations. To further examine the influence of parameter settings on model outputs, a perturbation analysis was performed by varying the key probability thresholds by $\pm 10\%$ and observing the corresponding changes in the target node probability distribution. This analysis is presented in the Results and Discussion section. To validate robustness, sensitivity analysis and extreme-condition tests were employed.

3 Case Study

To validate the proposed model, a large modern coal mine in Shandong Province was selected. The mine has an approved capacity of 6.6 million tons/year, mining the No. 3 coal seam with an average thickness of 8.5 m (extra-thick seam). It is a low-gas mine with Class II spontaneous combustion propensity. The mine has maintained a generally stable safety record, achieving eight consecutive years without fatalities, although over 20 spontaneous combustion hazards were documented during slice mining. An intelligent emergency command platform and a “three-level linkage + grid-based” responsibility system have been established. The mine is currently undergoing an intelligent system upgrade, with some senior employees still adapting and cross-departmental information flow experiencing delays. The mine has also emphasized safety culture development, which positively influences emergency management[22].

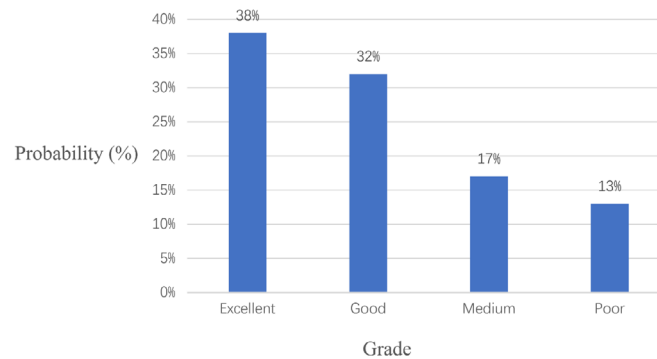
The data utilized in this study were primarily derived from routine operational archives and internal management documents of the cooperating mine, supplemented by publicly accessible safety records. Quantitative indicators, such as ventilation system performance and gas concentration, were obtained from the mine's continuous monitoring systems. Qualitative indicators, including emergency plan completeness and command capability, were assessed against the criteria specified in the Guidelines for Emergency Plan Assessment through expert evaluation. All 14 indicators were standardized according to the classification criteria defined in Section 2, and the entire assignment process was systematically documented to ensure traceability.

Table 1 summarizes the state assignments. The mine performs well in equipment and environmental control: ventilation integrity $>95\%$, full monitoring coverage, rescue equipment qualification 100%, and zero annual gas exceedance. However, weaknesses exist in personnel and management: intelligent platform proficiency is approximately 85%, training frequency is medium, cross-departmental emergency response lags, and grassroots command efficiency has room for improvement. The extra-thick seam with spontaneous combustion risk makes geological complexity “Complex.” The mine represents a typical “strong hardware, weak software” case during its transformation period.

With all indicator state assignments entered as evidence into the GeNIe model, the output node “coal mine emergency response capability” shows: “Excellent” at 38%, “Good” at 32%, “Medium” at 17%, and “Poor” at 13%. The cumulative probability of “Excellent” and “Good” reaches 70%. In this study, the grade is determined by the maximum membership principle, i.e., the grade with the highest probability is selected as the final rating. Since 38% (“Excellent”) is higher than 32% (“Good”), 17% (“Medium”), and 13% (“Poor”), the comprehensive capability is rated as “Excellent”. This criterion is applied consistently across all cases. The mine analyzed in this case study is officially recognized as a Grade I safety standardization mine under China’s national standards, which require an overall score of 90 or above in the standardized assessment system. The fact that the BN model assigns an overall rating of “Excellent” to this mine is therefore consistent with its official safety designation. The 70% cumulative probability reflects the model’s confidence in assigning the mine to the top two capability grades rather than a direct numerical equivalent to the standardized scoring system. This result reflects the mine's actual safety status—strong hardware and complete systems provide a solid foundation, but spontaneous combustion risk and personnel-management running-in issues during intelligent transformation prevent “Excellent” from exceeding 40%, while “Medium” and “Poor” still account for 30% (Fig. 2).

Table 1 Summary of indicator state assignments for the case coal mine

Criterion Layer	Indicator ID	Indicator Name	Empirical Data Basis (Reference)	State Assignment
Personnel (B1)	C1	Safety training frequency	6 annual sessions, 100% coverage	Medium
	C2	Emergency drill participation rate	Full coverage in practical drills	High
	C3	Technical personnel experience level	Intelligent platform proficiency ~85%	Medium
	C4	Violation inspection status	Occasional violation records in annual safety reward/punishment ledger	Medium
	C5	Special operation certification rate	100% certification per mine special operation personnel records	High
Equipment (B2)	C6	Ventilation system integrity rate	Routine maintenance above 95%	High
	C7	Monitoring system coverage	Full coverage via intelligent control platform	High
	C8	Emergency rescue equipment availability	100% qualification rate through regular calibration	High
Environment (B3)	C9	Gas concentration exceedance frequency	Low-gas mine, 0 exceedances per year	Normal
	C10	Geological condition complexity	Extra-thick seam with spontaneous combustion risk	Complex
Management (B4)	C11	Emergency plan completeness	“1+13+13” plan system, dynamically updated	High
	C12	Safety investment ratio	Sufficient ton-coal safety fee extraction and intelligent investment	High
	C13	Emergency information sharing mechanism	Cross-departmental transmission delays during platform transition	Good
	C14	Emergency command capability	Grid-based management with room for grassroots response improvement	Good

**Fig. 2.** Probability distribution of coal mine emergency response capability grades

To further analyze the influence degree of each indicator on the assessment results, sensitivity analysis was conducted. The results show that violation inspection status (C4) exhibits the highest sensitivity, followed by special operation certification rate (C5) and emergency information sharing mechanism (C13)[11,13]. A sensitivity test was performed: changing C4 from “Medium (occasional)” to “High (frequent)” while keeping other indicators unchanged increased the probability of “Poor” from 13% to 28%, and decreased “Excellent” from 38% to 22%, indicating that safety violations significantly weaken emergency response capability. This finding is consistent with the conclusion that “violation of operating procedures is the direct cause of accidents” [4,1].

4 Results and Discussion

The case calculation results above indicate that the comprehensive emergency response capability of the mine

is rated as “Excellent” (38%), with a cumulative probability of “Excellent” and “Good” reaching 70%. To further validate the reliability of the model, this section proceeds from three aspects: model robustness testing, comparative analysis of assessment results, and discussion from the energy security perspective.

4.1 Model robustness testing

To examine the influence of CPT parameter settings on assessment conclusions, a perturbation analysis was conducted following the approach outlined in Section 2. The major probability values in the CPTs of the personnel factors node and management factors node were individually varied by $\pm 10\%$, and the model was re-run. The perturbation test results show that even with these variations, the comprehensive emergency capability grade remains “Excellent,” and the probability changes for each state do not exceed 5 percentage points. This indicates that the model’s overall conclusions are stable with respect to reasonable uncertainties in the CPT parameters.

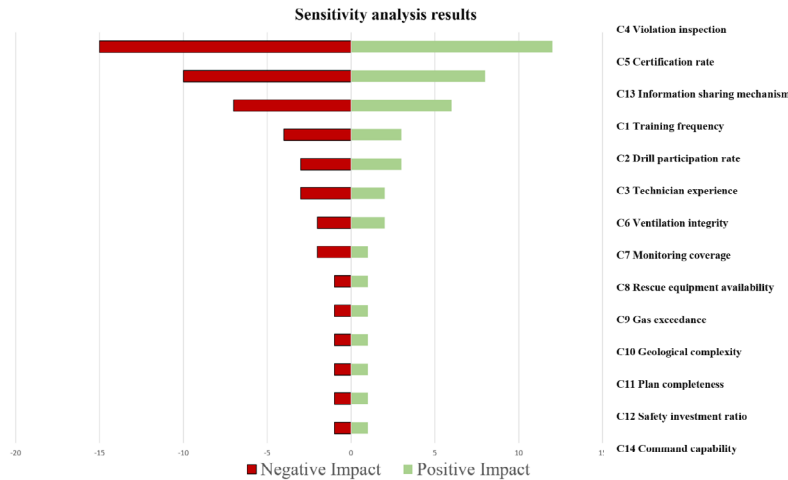


Fig.3 Sensitivity analysis results

Regarding network structure uncertainty, an auxiliary edge from C3 (technical personnel experience level) to B2 (equipment factors) was added to the network, and the model was re-evaluated[21]. The results show that the probability of “Excellent” changes from 38% to 36%, a variation of only 2 percentage points, and the assessment conclusion remains stable, indicating strong structural stability.

Extreme-condition tests were also conducted: with all indicators set to optimal states, the probability of “Excellent” exceeds 94%; with all indicators set to worst states, the probability of “Poor” exceeds 90%. Under both scenarios, the model outputs conform to logical expectations.

4.2 Comparative analysis of assessment results

The model results were compared with the mine’s annual safety self-inspection report and supervisory authority conclusions. The mine has maintained zero gas exceedance for three consecutive years, with stable ventilation and monitoring systems and comprehensive emergency plans—findings highly consistent with the model’s 70% cumulative probability of “Excellent” and “Good.” The self-inspection report explicitly identified issues such as “proficiency of some personnel in the early stage of intelligent platform application needs improvement” and “cross-departmental emergency information transmission efficiency requires optimization,” which correspond precisely to the high sensitivity of C4 and C13 identified by the model.

Reverse diagnostic inference was performed: with the target node set to “Poor” ($P(A=\text{Poor})=100\%$), the model computed the posterior probabilities of each bottom-level indicator. The results show that the posterior probability of C4 being “Frequent” rises from a prior of 33% to 72%, and C5 being “Low” rises from 33% to 65%. This indicates that the most likely causes of “Poor” emergency response capability are frequent violations and substandard certification rates, rather than equipment or environmental problems.

4.3 Discussion from the energy security perspective

From the energy security perspective, the significance of emergency response capability assessment lies in preventing production capacity interruptions caused by sudden accidents from impacting regional energy supply[14]. This model can transform qualitative indicators into quantifiable probability distributions, enabling enterprises and regulatory authorities to intuitively grasp the overall level of emergency response capability. When the cumulative probability of “Excellent” and “Good” falls below 50%, the risk of emergency failure increases significantly, allowing

early intervention.

The high sensitivity of C4 indicates that safety management should prioritize behavioral control at the operational level. A practical implication for mine operators is to strengthen day-to-day supervision of frontline safety compliance and establish timely feedback mechanisms for identified violations, rather than relying solely on training frequency or other input-based indicators.

Three managerial implications emerge from the assessment results. First, the findings confirm that behavioral factors—particularly safety violations—exert a stronger influence on emergency response capability than conventional input-based metrics such as training frequency or equipment integrity. This suggests that safety management should place greater emphasis on frontline behavior monitoring and violation feedback systems, rather than focusing primarily on resource inputs. Second, the high sensitivity of information sharing (C13) and command capability (C14) indicates that organizational factors are as critical as individual-level factors. Improving cross-departmental communication and clarifying command responsibilities during emergencies may yield measurable improvements in overall capability. Third, the model's structure and indicator requirements make it suitable for routine application in mine safety management. Since the input data are derived from standard operational records, the assessment can be repeated periodically with relatively low effort, allowing mines to track changes in capability over time and evaluate the effectiveness of targeted interventions.

Beyond the case-specific findings, the broader implication of this study lies in its methodological contribution to energy safety assessment. The BN framework offers a transparent and quantifiable approach to integrating diverse safety indicators—ranging from equipment conditions to organizational procedures—into a single probabilistic evaluation. This addresses a key gap in current practice, where safety assessments often rely on separate, uncoordinated checklists that do not capture the cumulative or interacting effects of multiple risk factors. By providing a systematic, evidence-based tool, the proposed model supports more informed decision-making in both operational and regulatory contexts. When applied periodically, it can also help identify deteriorating trends before they result in critical failures, contributing to proactive rather than reactive safety management. In the broader context of energy security, such preventive capability is essential for reducing the likelihood of unplanned production stoppages that could affect regional energy supply stability.

In summary, the model achieves effective transformation from qualitative indicators to quantitative probabilities, can precisely identify weak links, and provides decision-making references for self-assessment and safety supervision, helping to reduce the probability of sudden production stoppages caused by inadequate emergency response capability.

5 Conclusions

This study constructed a Bayesian Network-based assessment model for coal mine emergency response capability and validated it through a case study at a large modern coal mine in Shandong Province. The main conclusions are as follows:

(1) An evaluation index system comprising 4 criterion layers and 14 specific indicators was developed. Based on the conventional "human-machine-environment-management" framework, two indicators—violation inspection status (C4) and special operation certification rate (C5)—were introduced to enhance the characterization of personnel behavioral risk and compliance levels.

(2) A Bayesian Network assessment model with 19 nodes and 21 directed edges was established, with Conditional Probability Tables parameterized via a logic-grading method, achieving effective transformation from qualitative indicators to quantitative probability distributions. The model supports both forward inference and reverse diagnostic inference.

(3) Case validation results show that the comprehensive emergency response capability of the mine is rated as "Excellent" (probability 38%), with a cumulative probability of "Excellent" and "Good" reaching 70%, consistent with the mine's actual safety status during its intelligent transformation period. Both sensitivity analysis and reverse diagnostic inference indicate that violation inspection status (C4) is the most critical factor, followed by special operation certification rate (C5) and emergency information sharing mechanism (C13). This suggests that the focus of emergency response capability improvement should shift from hardware investment toward balancing "personnel behavioral control" and "management information coordination."

From the perspective of energy security assurance, this model can help coal mining enterprises and regulatory authorities identify weak links in the emergency system in advance, shifting the risk management threshold forward and reducing the probability of production capacity interruption due to inadequate emergency response capability.

Limitations: CPT parameters could be further refined with more industry data; the current model primarily assesses static time points and has not yet considered dynamic evolution; validation has only been conducted on a single mine, and the generalizability of the model needs further testing across mines with different geological conditions and production scales[23]. In addition, the current CPTs are derived from expert knowledge and reflect normal operating conditions. When mine conditions deviate significantly from this baseline—such as in the case of gas anomalies or water inrush accidents—the applicability of these CPTs may be constrained. This highlights a boundary condition of the model's applicability. Future work will explore integration with real-time monitoring data and the adoption of Dynamic Bayesian Networks to allow the model to adapt to evolving conditions, thereby improving its responsiveness to emerging hazards. Future research will expand the sample range, explore real-time data integration with monitoring systems, and attempt to introduce Dynamic Bayesian Networks to capture temporal evolution characteristics.

References

- [1] Zhang Peisen, Li Fuxing, Zhu Huicong, Niu Hui, Li Xiaohe. Statistical analysis and prevention countermeasures of coal mine accidents from 2008 to 2020 [J]. *Mining Safety & Environmental Protection*, 2022,49 (1):128-134. DOI: 10.19835/j.issn.1008-4495.2022.01.022.
- [2] Wang Yungang, Cui Chunyang, Zhang Feiyan, Wang Yaru. Statistical analysis and research on major and above coal mine accidents in China from 2011 to 2020 [J]. *Journal of Safety and Environment*, 2023,23 (9):3269-3276. DOI: 10.13637/j.issn.1009-6094.2022.0963.
- [3] Zeng Yifan, Wu Qiang, Zhao Suqi, et al. Characteristics, causes and prevention countermeasures of coal mine water hazard accidents in China [J]. *Coal Science and Technology*, 2023,51 (7):1-14. DOI: 10.13199/j.cnki.cst.2023-0500.
- [4] Cheng Lianhua, Zhou Ruixue, Yan Jin, et al. Construction and application of CMM-based emergency rescue capability maturity model for coal mines [J]. *China Safety Science Journal*, 2021,31 (7):180-186. DOI: 10.16265/j.cnki.issn1003-3033.2021.07.025.
- [5] Zhou Ruixue. Construction and application of evaluation system for coal mine emergency response capability based on CMM [D]. Xi'an: Xi'an University of Science and Technology, 2021. DOI: 10.27397/d.cnki.gxaku.2021.000809.
- [6] Wang Yalin. Research on emergency management capability evaluation based on five major disasters in coal mines [D]. Huainan: Anhui University of Science and Technology, 2021. DOI: 10.26918/d.cnki.gnhgc.2021.000961.
- [7] Zhang Xiaoxu, Fan Chaonan, Ma Guoliang. Application research of analytic hierarchy process in coal mine safety system [J]. *Energy and Environmental Protection*, 2022,44 (12):307-311. DOI: 10.19389/j.cnki.1003-0506.2022.12.055.
- [8] Yao Youli, Kou Jie, Zhang Menghao. Risk assessment of coal mine "ventilation, gas, dust and fire" based on game theory combination weighting-TOPSIS [J]. *Mining Safety & Environmental Protection*, 2024,51 (6):71-78. DOI: 10.19835/j.issn.1008-4495.20230694.
- [9] Bai Lili, Bai Shangwang, Dang Weichao, et al. Research on coal mine safety evaluation based on combination weighting of maximization of deviations [J]. *Computer Applications and Software*, 2021,38 (4):82-87.
- [10] Zhang Wenyu, Zhang Jianshe, Yuan Dongliang, et al. Comprehensive evaluation of emergency response capability of construction enterprises for safety accidents based on measurement-cloud model [J]. *Safety and Environmental Engineering*, 2021,28 (5):51-57, 64. DOI: 10.13578/j.cnki.issn.1671-1556.20200889.
- [11] Li Min, Lin Zhijun, Lu Yi, et al. Risk assessment of coal mine gas explosion based on fuzzy Bayesian network [J]. *Journal of China Coal Society*, 2023,48 (S2):626-637. DOI: 10.13225/j.cnki.jccs.2022.1485.
- [12] Zhang Ning, Sheng Wu. Causation analysis of coal mine gas explosion accidents based on Bayesian network [J]. *Industry and Mine Automation*, 2019,45 (7):53-58. DOI: 10.13272/j.issn.1671-251x.2019010049.
- [13] Lin Zhijun, Li Min, He Shan, et al. Risk assessment of coal mine gas explosion based on game theory-Bayesian

- network [J].Journal of China Coal Society, 2024,49 (8):3484-3497. DOI: 10.13225/j.cnki.jccs.2023.0963.
- [14] Shuang Liu, Yang Mengjie, Liu Dingwei, et al. Identifying coal mine safety production risk factors by employing text mining and Bayesian network techniques [J].Process Safety and Environmental Protection, 2022,162:1067-1081. DOI: 10.1016/j.psep.2022.04.054.
- [15] Li Min, Wang Han, Wang Dong, et al. Risk assessment of gas explosion in coal mines based on fuzzy AHP and Bayesian network [J].Process Safety and Environmental Protection, 2020,135:207-218. DOI: 10.1016/j.psep.2020.01.003.
- [16] Xu Pengfei, Zhao Hao, Fu Enshan, et al. Coal mine systematic safety risk evaluation index system and application [J].Coal Engineering, 2023,55 (5):135-140.
- [17] Xue Sisheng. Analysis and control research on coal mine gas accident causation based on probabilistic reasoning [D].Xuzhou: China University of Mining and Technology, 2019. DOI: 10.27623/d.cnki.gzkyu.2019.000261.
- [18] You Mengjie. Research on coal mine safety risk identification and evaluation based on text mining [D].Xuzhou: China University of Mining and Technology, 2022. DOI: 10.27623/d.cnki.gzkyu.2022.000076.
- [19] Lu Jiexin, Shi Shiliang, Luo Xinrong, et al. Stability analysis and structure optimization of surface wells for CBM in Guqiao Mine [J].Mining Engineering Research, 2022,37 (3):31-38. DOI: 10.13582/j.cnki.1674-5876.2022.03.006.
- [21] Li Jinrong, Yang Yuzhong. Risk assessment of coal mine ventilation system based on DS theory-Bayesian network [J].China Safety Science Journal, 2022,32 (8):146-153. DOI: 10.16265/j.cnki.issn1003-3033.2022.08.1633.
- [22] Wang Pei, Wang Xiaoyu, Sun Zongjian. Brief analysis of safety production culture construction in Guqiao Mine [J].Metallurgical Management, 2019,(9):138-139.
- [23] LIU Ying. Research on dynamic capability evaluation of emergency management for safety production in coal enterprises[D]. Beijing: China University of Mining and Technology (Beijing), 2022. DOI: 10.27624/d.cnki.gzkb.2022.000098.