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TECHNICAL COMMUNICATION

A DEMATEL-ISM-BN Model of Mine Water Inrush Accidents

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Abstract
Large-scale mine water inrush accidents can be reduced in number and severity by better understanding the causes of these accidents and the internal relationships between the various causal factors. Based on 70 major events from 2010 to 2020, we constructed a multi-level hierarchical structural model using DEMATEL and ISM techniques, and then mapped the model to a BN network, using posterior probability computation to enable reverse diagnosis reasoning recognition. The results indicated that inadequate knowledge of water disasters and inadequate hydrogeological detection are the key factors, with posterior probabilities of 91 and 82%, and the highest centre degrees of 5.400 and 4.917. The fundamental contributing factors are disordered safety management and imperfect supervision, with causal degrees of 1.402 and 2.038. It is clear from the model's causal structure and maximum causal chain analysis that these factors are quite likely the cause of most water inrush accidents. Paying closer attention to these fundamental factors can help to more effectively control these accidents and minimize losses.

Keywords Mathematical model · Influencing factors · Safety engineering · Water disasters prevention

Introduction

Between 2010 and 2020, China experienced 5833 coal mine safety accidents, despite a significant decline in the annual total of such accidents. China is in a crucial phase in its infrastructural development and coal consumption is constantly increasing. Safe mining is the cornerstone for guaranteeing consistent coal mine output and is a prerequisite for China's sustainable economic growth (Zhang et al. 2021). An analysis of coal mine accidents across the country in 2021 revealed that the main accidents that year were water inrush accidents, with a death toll of 48, surpassing that of gas accidents that year and making up 27% of all deaths from coal mine accidents. Water inrush accidents are the third-largest category of coal mine accidents after gas accidents and roof accidents. They are incredibly destructive and provide a serious threat to mining personnel. Understanding the causes and nature of mine water inrush accidents bolsters safe coal mining.

Some studies have focused on the examination of the causes of mine water inrush accidents in fixed mining zones (Gu et al. 2020; Qi et al. 2017; Xu et al. 2020), while others have looked in-depth into the factors causing these accidents and the elements influencing mine water inrushes (Chen et al. 2020; Liu et al. 2021). However, considering the complex nature of mine water inrush accidents, paying attention to the influence of a single factor is often insufficient (Wu et al. 2022). Scholars have used analytic hierarchy process (AHP), fault tree analysis (FTA), Bayesian network (BN), or other research techniques to thoroughly analyse the causes of mine water inrush accidents based on human error, machinery failure, environment, and management (Chen and Yang 2011; Wu et al. 2016). However, these factors are often interdependent (Huang et al. 2020; Qin et al. 2021). It is necessary to conduct intensive research and expand existing knowledge to identify key factors, create targeted risk management countermeasures, and achieve stable and sustainable coal mine output. A more thorough and useful body of knowledge for the assessment and management of water inrush accidents can be obtained

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by examining the interdependent factors influencing complex systems.

The decision making trial and evaluation laboratory (DEMATEL) was proposed in the 1970s (Fontela and Gabus 1976). It uses graph theory and matrix theory to visualize the causal relationship between factors and calculates relevant indicators to determine the key factors of complex system by combining the experience and knowledge of experts (Kiakojuri et al. 2020) to create a visual structure model of the causal link between components (Garshasbi et al. 2022; Venugopal et al. 2022). The interpretative structural modelling method (ISM) can be used when DEMATEL cannot determine the hierarchical structure of complex systems to reflect the internal relationship between influencing factors in complex systems based on a reachability matrix (Liang et al. 2022; Meng et al. 2022). DEMATEL and ISM quantitatively investigate the interaction between factors, but there are many factors that can affect mine water inrush accidents, and their interactions are complicated (Li et al. 2019). Therefore, it is necessary to determine the dependency between factors qualitatively and quantitatively. Bayesian networks quantify the relationship strength in the accident system and determine the main path leading to system failure through model establishment (Zhang and Sheng 2019). Therefore, we combined DEMATEL and ISM to analyse accident-influencing factors, then examined the factors influencing mine water inrush accidents, built a multi-level hierarchical structure model, mapped it to a BN model, and extracted the key factors causing mine water inrush accidents using BN parameter learning.

Methodology

Various steps in the integrated DEMATEL-ISM-BN approach are given below.

Step 1. Select the influencing factor set $S=\{S_1, S_2, S_3 \ldots S_n\}$ and construct the initial direct influence matrix D. To ascertain the relationship between factors and obtain the direct impact matrix $D=[d_{ij}]_{n*n}$, several experts are asked to assign values according to the five degrees from "no influence" to "very high influence:, respectively, corresponding to 4, 3, 2, 1, and 0 (Liou 2015); "d_{ij}" stands for the degree of influence of "factor i" on "factor j"; when $i=j$, the value is 0.

Step 2. Calculate the specification influence matrix B. The specification influence matrix B can be obtained by normalizing the initial direct influence matrix D, which can be calculated by

$$B=[b_{ij}]_{n*n}=\frac{1}{\max\limits_{1\le i\le n}\sum_{j}^{n} d_{ij}}D \tag{1}$$

Step 3. Calculate the comprehensive influence matrix T and identify key factors. Compared with the direct influence matrix D, the comprehensive influence matrix T further reflects the interaction between factors, including direct and indirect relationships, which is derived by

$$T=[t_{ij}]_{n*n}=B+B^2+B^3+B^4+\ldots+B^n=B(I-B)^{-1} \tag{2}$$

Step 4. Calculate the effect degree,f_i,be-affected degree, e_i, centre degree, z_i, and cause degree, y_i. The effect degree, f_i, describes the comprehensive impact of a certain factor i on other factors; the be-affected degree, e_i, describes the comprehensive impact of other factors on a certain factor i; the centre degree, z_i, of a certain factor in the system indicates how significant it is overall, higher values indicate greater importance; the cause degree y_i describes a certain factor's direct impact on other factors. Causal factors are represented by positive values, while result factors are represented by negative values. These parameters can be calculated by

$$f_i=\sum_{j=1}^{n} t_{ij}(i=1,2,\ldots,n) \tag{3}$$

$$e_i=\sum_{j=1}^{n} t_{ji}(i=1,2,\ldots,n) \tag{4}$$

$$z_i=f_i+e_i(i=1,2,\ldots,n) \tag{5}$$

$$y_i=f_i-e_i(i=1,2,\ldots,n) \tag{6}$$

Step 5. Calculate the reachability matrix, K. The overall impact matrix H can be calculated by Eq. 7. The element of the overall impact matrix H represents the influence information of factor i on factor j. The reachability matrix K in the ISM model can be calculated by Eq. 8 to verify a threshold λ.

$$H = [h_{ij}]_{n*n} = I + T \tag{7}$$

$$k_{ij} = \begin{cases} 1 & h_{ij} > \lambda \\ 0 & h_{ij} \leq \lambda \end{cases} \tag{8}$$

Step 6. The corresponding level of factors can be determined by calculating reachable set $Q(S_i)$, antecedent set $A(S_i)$ using Eqs. 9 and 10. After repeated calculation, we used Eq. 11 to get each iteration of the common set, C.

$$Q(S_i) = \left\{ S_j \middle| S_i \in S, h_{ij} = 1 \right\} (i = 1, 2, \ldots, n) \tag{9}$$

$$A(S_i) = \left\{ S_j \middle| S_i \in S, h_{ji} = 1 \right\} (i = 1, 2, \ldots, n) \tag{10}$$

$$C = \left\{ S_i \middle| S_i \in S, A(S_i) \cap Q(S_i) = Q(S_i) \right\} (i = 1, 2, 3, \ldots, n) \tag{11}$$

Step 7. Map the hierarchical network model to a BN. The hierarchical network model was established according to set C. By using GeNie3.0 software, the hierarchical network model was converted into a Bayesian network model.
Step 8. Assign prior probabilities for each node. Based on the accident report, the state of each node in each sample is counted and fed into Genie to derive the prior probability of each node.
Step 9. Bayesian network analysis. After determining the evidence variables, the risk identification and probability prediction were realized by calculating the posterior probability. The posterior probability is the revised or updated probability of an event occurring after considering new information and is calculated by updating the prior probability using Bayes' theorem.

Results and Discussions

Construction of an Index System for the Factors Influencing a Mine Water Inrush Accident

We collected reports of mine water inrush accidents for the years 2010 to 2020 on the coal mine safety website and safety management website and selected 70 reports of typical and large accidents as the data source of this study. The causes of mine water inrush accidents are numerous and complex. We extracted high-frequency keywords from these 70 accident investigation reports and counted their frequency of occurrence (Table 1).

The framework of factors influencing mine water inrush accidents was constructed using the characteristics of human factors, material factors, environmental factors, and management factors, considering the frequency of keywords and the actual situations. This is depicted in Fig. 1, along with the four characteristics.

Identifying the Connections and Hierarchical Structure Between all the Factors

In this study, ten experts in the field of coal mining were asked to fill out a questionnaire. They provided two-way scoring on the chosen influencing factors using their personal and professional experience, and then we chose the overall average value of each scoring component to create the direct impact matrix D based on the questionnaire responses and then the comprehensive influence matrix T was computed in accordance with steps 2 and 3 (Table 2).

Using a MATLAB program, we calculated the effect degree f_i, the be-affected degree e_i, centre degree z_i, and cause degree y_i (Table 3). A cause factor is considered to exist if the cause degree exceeds zero; otherwise, it is a

Table 1 Keywords and frequency statistics

Key word	Frequency	Key word	Frequency	Key word	Frequency
Not in place	51	Technical means	16	Cross-border mining	9
Security	42	Tunnel	14	Education	8
Water exploration and drainage	33	Train	14	safety consciousness	8
Water control	27	Permeability symptoms	13	Coal pillar fault	7
Ponding	23	Staffing	13	Drawing	6
Inadequate management	22	Chaos of management	10	Illegal	4
Supervision not implemented	21	Goaf	10	Violations	4
Illegal arrangement of heading face	18	Equipment	9	Geology	4

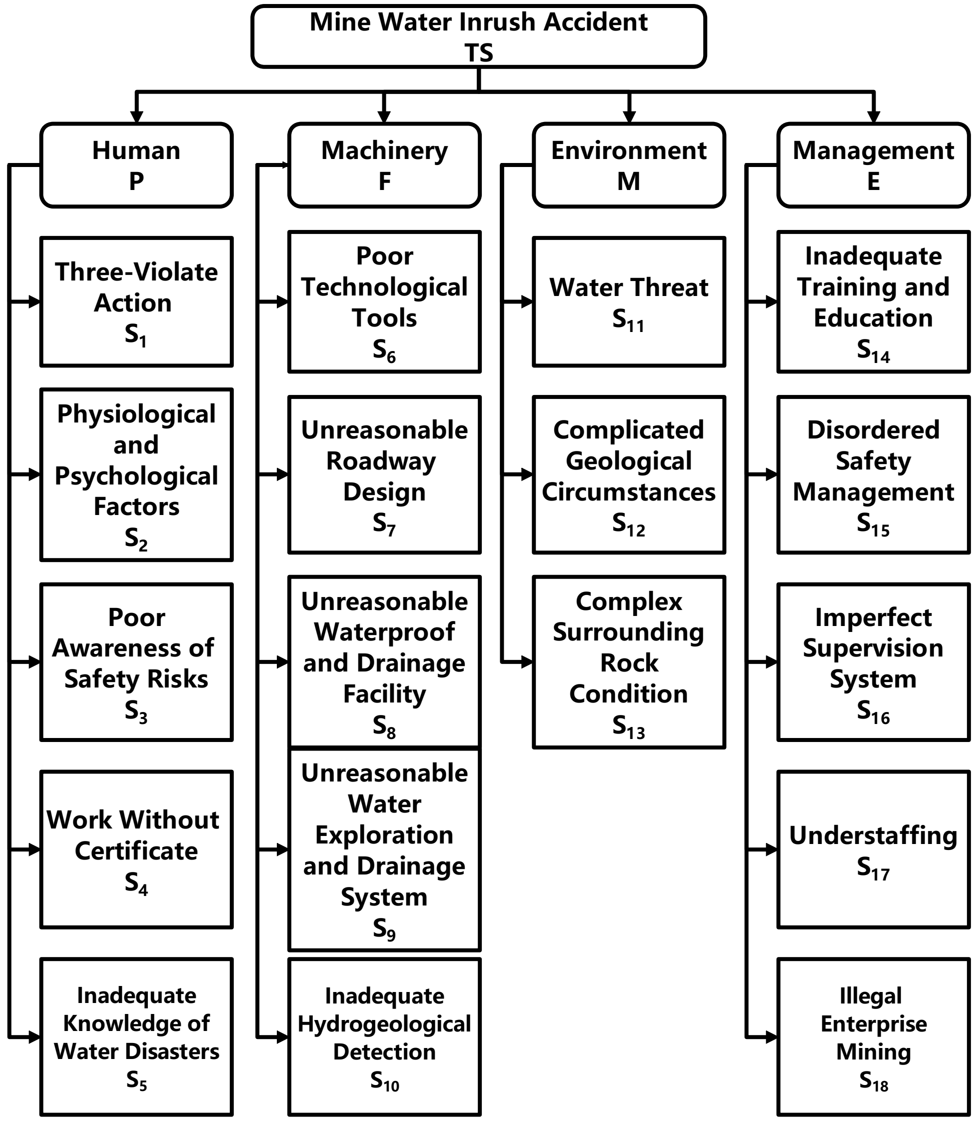

Fig. 1 Frame diagram of the mine water inrush accident's relevant factors

result factor. The occurrence of other factors is greatly influenced by the cause factors, and result factors are susceptible to the influence of the cause factors in the system. Table 3 shows that, from greatest to smallest, S_{16}, S_{15}, $S_{14,}$ S_{12}, S_4, S_6, S_{18}, and S_{17} are the cause factors of coal mine flooding incidents; S_1, S_7, S_2, S_8, S_{11}, S_9, S_{10}, S_{13}, S_3, and S_5 are the result factors. Among them, imperfect supervision and disordered safety management are the primary causes. Violation of commands, violation of regulations, and technical violations (three-violate actions) are more susceptible to the influence of other factors. A factor's importance increases with its centre degree. According to the centre degree ranking in Table 3, inadequate knowledge of water disasters and hydrogeological detection are what causes most mine water inrush accidents, followed by disordered safety management and poor technological tools.

The comprehensive influence matrix's arithmetic mean value and standard deviation were added to determine the value of threshold λ, which is 0.15. The reachability matrix was calculated using the MATLAB program, and all factors were separated into levels, which allowed us to establish the hierarchical network model of mine water inrush accident (Fig. 2).

BN Model

As shown in Fig. 3, the Bayesian network model was built based on the multi-level hierarchical network model

Table 2 The comprehensive influence matrix T

Factor	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}	S_{17}	S_{18}
S_1	0.05	0.12	0.04	0.08	0.05	0.04	0.05	0.05	0.05	0.09	0.09	0.02	0.03	0.03	0.08	0.02	0.08	0.07
S_2	0.15	0.08	0.08	0.09	0.11	0.05	0.09	0.08	0.08	0.09	0.07	0.03	0.04	0.08	0.07	0.05	0.09	0.09
S_3	0.18	0.19	0.08	0.13	0.14	0.08	0.11	0.11	0.10	0.14	0.09	0.04	0.06	0.09	0.10	0.06	0.11	0.10
S_4	0.15	0.17	0.16	0.08	0.21	0.13	0.18	0.18	0.18	0.20	0.15	0.06	0.12	0.08	0.11	0.07	0.12	0.11
S_5	0.20	0.21	0.18	0.12	0.13	0.11	0.21	0.20	0.20	0.15	0.21	0.08	0.12	0.10	0.10	0.07	0.13	0.11
S_6	0.13	0.19	0.13	0.12	0.18	0.10	0.20	0.21	0.18	0.21	0.20	0.13	0.18	0.08	0.11	0.07	0.13	0.08
S_7	0.05	0.08	0.07	0.04	0.13	0.09	0.07	0.11	0.11	0.10	0.16	0.08	0.10	0.03	0.03	0.02	0.04	0.03
S_8	0.05	0.08	0.06	0.03	0.13	0.09	0.11	0.06	0.10	0.10	0.15	0.06	0.07	0.02	0.03	0.02	0.04	0.02
S_9	0.06	0.09	0.07	0.04	0.13	0.10	0.12	0.11	0.07	0.11	0.16	0.06	0.07	0.03	0.06	0.04	0.05	0.03
S_{10}	0.15	0.19	0.10	0.08	0.14	0.13	0.20	0.19	0.18	0.11	0.19	0.12	0.16	0.05	0.10	0.06	0.10	0.05
S_{11}	0.08	0.09	0.07	0.06	0.12	0.10	0.14	0.14	0.14	0.12	0.09	0.08	0.10	0.03	0.04	0.02	0.09	0.03
S_{12}	0.10	0.12	0.07	0.06	0.17	0.16	0.15	0.12	0.12	0.16	0.20	0.06	0.16	0.06	0.08	0.03	0.15	0.05
S_{13}	0.08	0.09	0.05	0.04	0.14	0.12	0.16	0.10	0.09	0.09	0.17	0.09	0.06	0.05	0.06	0.02	0.05	0.03
S_{14}	0.19	0.21	0.19	0.14	0.22	0.13	0.17	0.17	0.16	0.19	0.15	0.06	0.08	0.07	0.15	0.12	0.14	0.14
S_{15}	0.20	0.22	0.18	0.18	0.22	0.17	0.19	0.18	0.18	0.21	0.18	0.09	0.12	0.16	0.09	0.10	0.17	0.15
S_{16}	0.21	0.22	0.19	0.19	0.22	0.15	0.19	0.18	0.18	0.21	0.19	0.09	0.12	0.16	0.14	0.06	0.19	0.17
S_{17}	0.15	0.17	0.16	0.12	0.21	0.13	0.18	0.18	0.18	0.20	0.15	0.06	0.12	0.08	0.11	0.07	0.08	0.11
S_{18}	0.19	0.20	0.17	0.12	0.13	0.07	0.12	0.11	0.11	0.15	0.09	0.04	0.06	0.12	0.13	0.11	0.12	0.07

Table 3 DEMEATEL analysis results

	Influence factor	Effect degree	Be-affected degree	Centre degree	Centre degree ranking	Cause degree	Factor attributes
S_1	Three-violate action	1.044	2.365	3.410	16	− 1.321	Result factor
S_2	Physiological and psychological factors	1.422	2.706	4.127	8	− 1.284	Result factor
S_3	Poor awareness of safety risks	1.892	2.051	3.942	12	− 0.159	Result factor
S_4	Work without certificate	2.441	1.728	4.169	7	0.713	Cause factor
S_5	Inadequate knowledge of water disasters	2.621	2.778	5.399	1	− 0.157	Result factor
S_6	Poor technological tools	2.622	1.943	4.565	4	0.680	Cause factor
S_7	Unreasonable roadway design	1.346	2.639	3.985	11	− 1.293	Result factor
S_8	Unreasonable waterproof and drainage facility	1.228	2.477	3.705	14	− 1.248	Result factor
S_9	Unreasonable water exploration and drainage system	1.400	2.414	3.814	13	− 1.014	Result factor
S_{10}	Inadequate hydrogeological detection	2.292	2.625	4.917	2	− 0.332	Result factor
S_{11}	Water threat	1.571	2.685	4.257	6	− 1.114	Result factor
S_{12}	Complicated geological circumstances	2.016	1.226	3.242	18	0.790	Cause factor
S_{13}	Complex surrounding rock condition	1.500	1.780	3.279	17	− 0.280	Result factor
S_{14}	Inadequate training and education	2.674	1.341	4.016	10	1.333	Cause factor
S_{15}	Disordered safety management	2.990	1.588	4.578	3	1.402	Cause factor
S_{16}	Imperfect supervision system	3.052	1.014	4.067	9	2.038	Cause factor
S_{17}	Understaffing	2.441	1.876	4.317	5	0.565	Cause factor
S_{18}	Illegal enterprise mining	2.122	1.440	3.563	15	0.683	Cause factor

after the real case sample data of mine water inrush accidents was imported into the Genie Bayesian network software.

A posterior probability analysis is a crucial component of Bayesian network reasoning since it not only predicts the likelihood of an outcome when the cause factor is known,

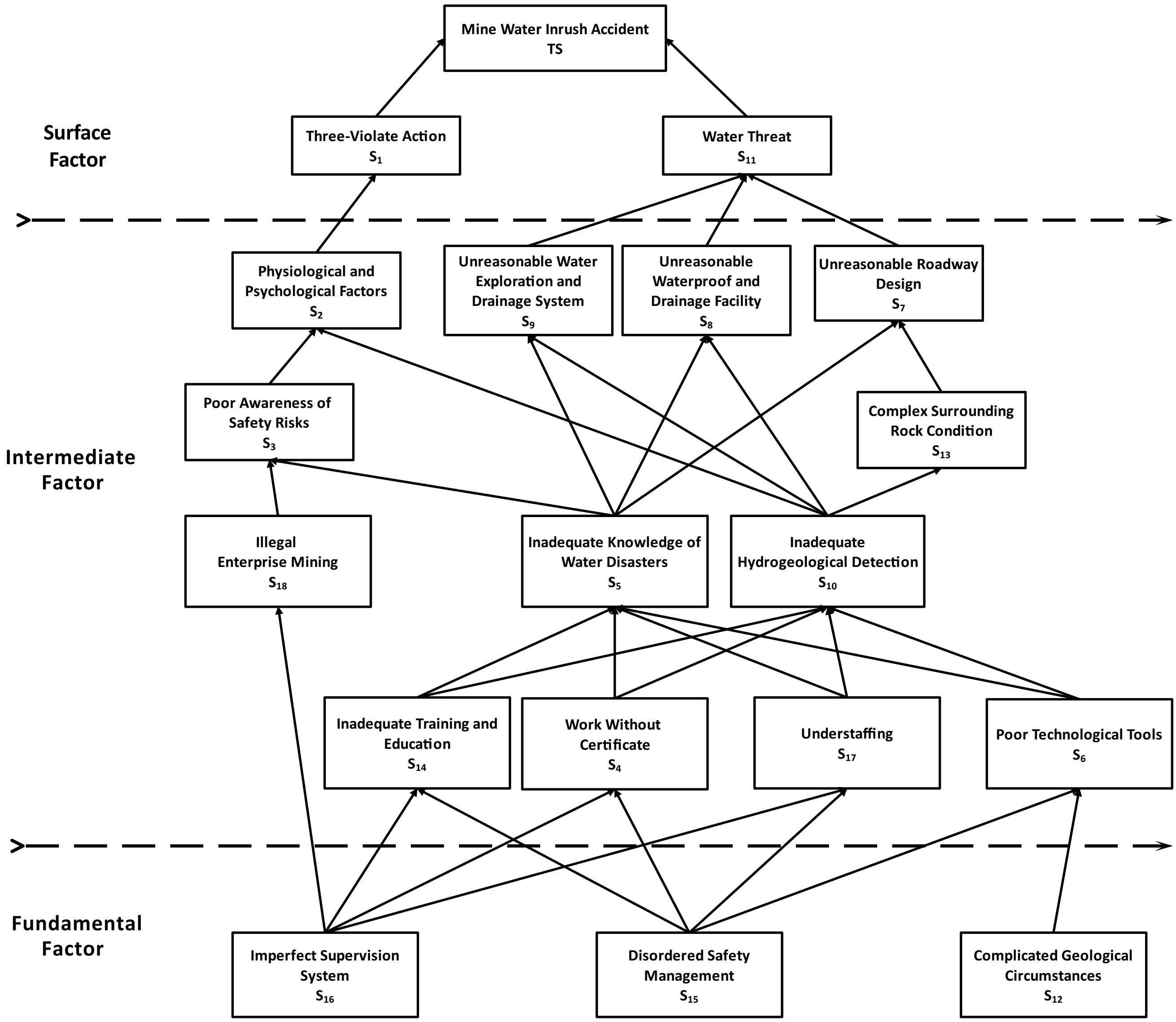

Fig. 2 The hierarchical network model

but also determines the most likely causes of an outcome when the outcome is known for fault diagnosis. The posterior probability distribution of the node was calculated using the fault diagnosis function of BN and the root node TS was set as the evidence node (in other words, when the chance of a coal mine flooding accident was 100%). The outcomes are displayed in Fig. 4.

According to the causal chain analysis, When a mine water inrush accident has happened, the likelihood of a water threat is highest, with a chance of 95%,and this is also obvious in reality, the probability of inadequate hydrogeological detection is 91%, the two factors mentioned above have a strong causal link, this shows that there is a strong correlation between a water threat, inadequate hydrogeological detection and the occurrence of accidents; inadequate knowledge of water disasters, three-violate action, physiological and psychological factors, and poor awareness of safety risks have high probabilities of occurrence (80%, 86%, 84%, and 85%). Additionally, there is a clear causal link among them; as fundamental factors, the probability of disordered safety management was 89% and the probability of imperfect supervision was 83%. The cause chain analysis revealed that the largest cause chain of water seepage accidents is inadequate hydrogeological detection → water threat → water inrush accident. We need to pay attention to these factors, while

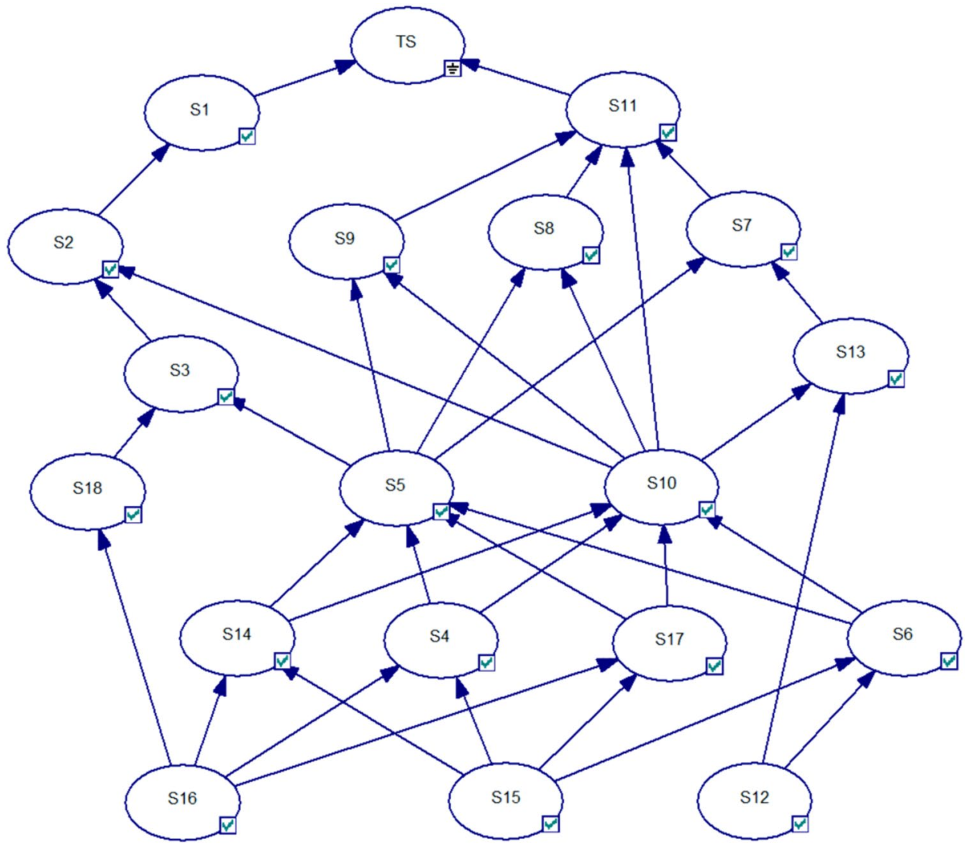

Fig. 3 The Bayesian network model

recognizing that the factors allowing hydrogeological detection are more complex.

General Analysis

Inadequate knowledge of water disasters and inadequate hydrogeological detection have a significant node position in the hierarchical structure model and are at the top of the DEMATEL centrality ranking. These two factors have numerous intersecting edges, which significantly influences their relationship, and have a high probability of occurrence in the posterior probability analysis of the BN network. Inadequate hydrogeological detection enhances the likelihood of a water threat while inadequate knowledge of water disasters has a strong causal relationship with a poor awareness of safety risks and ultimately the emergence of three-violate action. Our general analysis revealed that inadequate knowledge of water disasters and inadequate hydrogeological detection lie in the middle layer of the model structure, are susceptible to appear due to fundamental factors, and strongly affect the surface factors.

Complicated geological circumstances, disordered safety management, and imperfect supervision, which are all fundamental factors in the hierarchical network model, lead to all the other factors. According to the BN network's posterior probability analysis, disordered safety management and imperfect supervision are highly likely and contribute to inadequate training and education; the posterior probability of complicated geology is low but has a strong causal relationship with complex surrounding rock condition. Other factors are significantly influenced by the result factors; in the long run, focusing on these factors will help reduce mine water inrushes. The regulatory authorities should step up their oversight and supervision of illegal organizations and strictly investigate their mining activities. Strict oversight and well-ordered safety management can better monitor undocumented employment and insufficient staffing, ensure that operators receive better training in emergency handling skills and safety knowledge, and improve water hazard awareness.

Three-violate action and water threats, which are at the top level of the hierarchical network model, directly cause water inrush accidents. Improved staff understanding of water hazards and strict enforcement of hydrogeological work can quickly reduce the occurrence of three-violate action and water threat, based on posterior probability and causal chain analysis of the BN network. This will prevent many water inrush events.

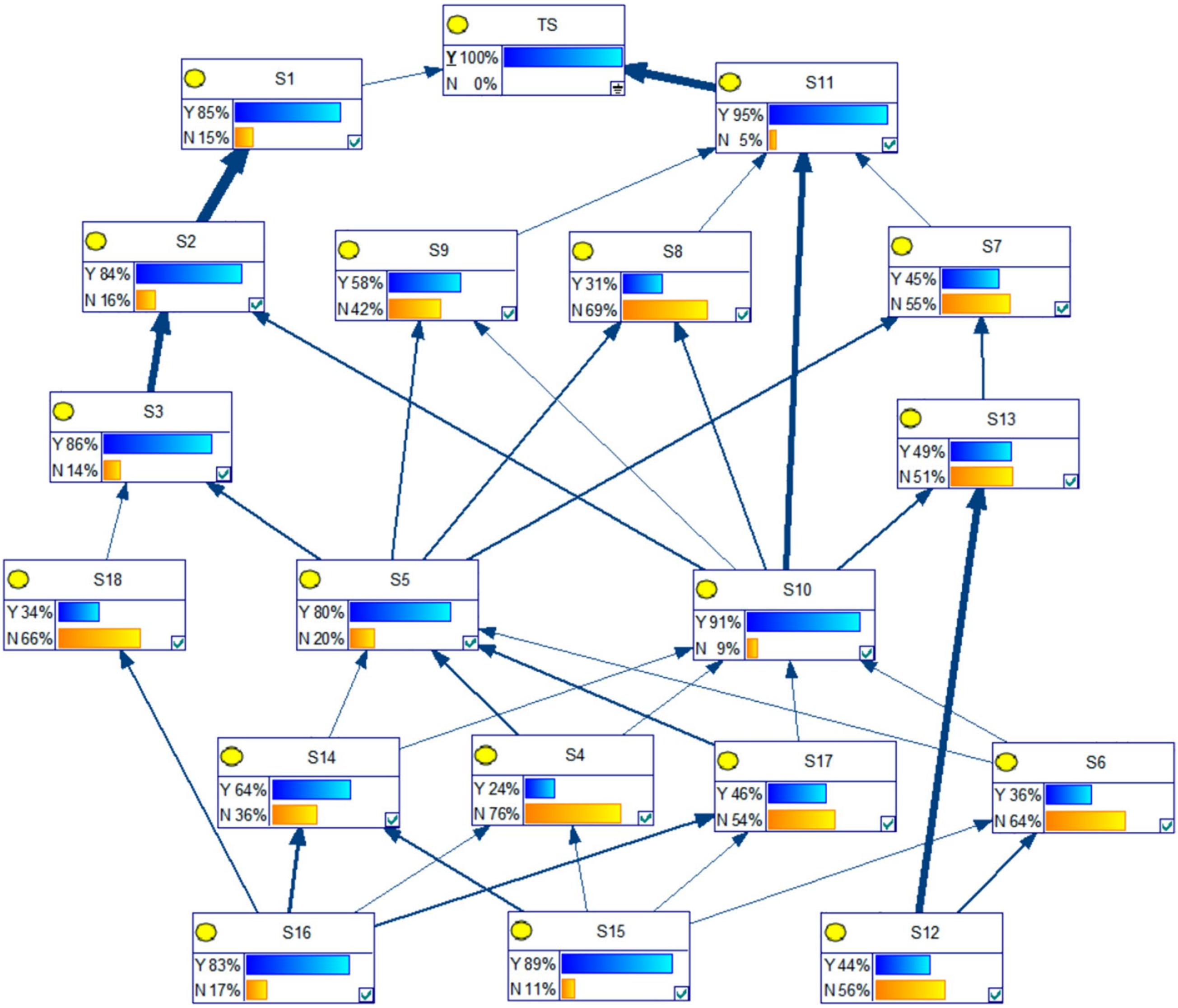

Fig. 4 Bayesian network posterior probability distribution

Conclusions

We analysed mine water inrush accidents by systematically combining DEMATEL, ISM, and BN of the nonlinear interactions to identify the components that cause accidents. The main conclusions were:

(1) Implementation of the integrated DEMATEL-ISM method led to the creation of a hierarchical network model that could be represented by a cause-and-effect diagram.
(2) This model combining DEMATEL, ISM and BN quantifies and visually examines the node weight and the correlation strength between factors, not limited by the system theory of human, machinery, management, and environment.
(3) The safety management and supervision departments must strictly verify the hydrogeological work, following the principle that if there is any doubt, it is necessary to explore first, then excavate, and remediate before mining; mining operations should be stopped when appropriate to effectively reduce the frequency of mine water inrush accidents.

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References

Chen J, Yang R (2011) Analysis of mine water inrush accident based on FTA. Proc Environ Sci 11:1550–1554. https://doi.org/10.1016/j.proenv.2011.12.233

Chen J, Li F, Lian ZC (2020) The hydrogeology of mine water inrush period using Dijkstra's algorithm. Arab J Geosci 13:825. https://doi.org/10.1007/s12517-020-05846-1

Fontela E, Gabus A (1976) The DEMATEL observer, DEMATEL 1976 report. Battelle Geneva Research Center, Geneva

Garshasbi M, KantiSen M, Kabir G, Dutta S (2022) Housing infrastructure resilience analysis against flood hazard using an intuitionistic fuzzy DEMATEL approach. In: de Oliveira F, Correia JA, Choudhury S, Dutta S (eds) Advances in structural mechanics and applications, structural integrity, vol 19. Springer, Cham. https://doi.org/10.1007/978-3-030-98335-2_13

Gu QX, Huang Z, Li SJ, Zeng W, Wu Y, Zhao K (2020) An approach for water-inrush risk assessment of deep coal seam mining: a case study in Xinlongzhuang coal mine. Environ Sci Pollut Res 27(34):43163–43176. https://doi.org/10.1007/s11356-020-10225-0

Huang WC, Zhang Y, Kou XY, Yin DZ, Mi RW, Li LQ (2020) Railway dangerous goods transportation system risk analysis: an Interpretive Structural Modeling and Bayesian Network combining approach. Reliab Eng Syst Saf 204:107220. https://doi.org/10.1016/j.ress.2020.107220

Kiakojuri D, Shamshirband S, Anuar NB, Abdullah J (2020) Retraction note: analysis of the social capital indicators by using DEMATEL approach: the case of Islamic Azad University. Qual Quant 54:191–192. https://doi.org/10.1007/s11135-019-00949-8

Li F, Wang WH, Dubljevic S, Khan F, Xu J, Yi J (2019) Analysis on accident-causing factors of urban buried gas pipeline network by combining DEMATEL, ISM and BN methods. J Loss Prev Process Ind 61:49–57. https://doi.org/10.1016/j.jlp.2019.06.001

Liang Y, Wang HC, Zhao XY (2022) Analysis of factors affecting economic operation of electric vehicle charging station based on DEMATEL-ISM. Comput Ind Eng. https://doi.org/10.1016/j.cie.2021.107818

Liou JJH (2015) Building an effective system for carbon reduction management. J Clean Prod 103:353–361. https://doi.org/10.1016/j.jclepro.2014.10.053

Liu SS, Peng GX, Yin GM (2021) A study on the in-situ stress conditions at the Kailuan mining area in China and their influence on coal mine water inrush. Arab J Geosci 14:2057. https://doi.org/10.1007/s12517-021-08276-9

Meng B, Lu N, Lin C, Zhang YJ, Si QM, Zhang JS (2022) Study on the influencing factors of the flight crew's TSA based on DEMATEL–ISM method. Cogn Tech Work 24:275–289. https://doi.org/10.1007/s10111-021-00688-7

Qi Y, Li M, Li K, Yeh TCJ (2017) Spatiotemporal development of mine water inrush and its mechanism—a case study in Ganhe coal mine, Shanxi, China. Arab J Geosci 10(19):433–441. https://doi.org/10.1007/s12517-017-3216-5

Qin M, Wang XR, Du YW (2021) Factors affecting marine ranching risk in China and their hierarchical relationships based on DEMATEL, ISM, and BN. Aquaculture 549:737802. https://doi.org/10.1016/j.aquaculture.2021.737802

Venugopal R, Veeramani C, Edalatpanah SA (2022) Analysis of fuzzy DEMATEL approach for financial ratio performance evaluation of NASDAQ exchange. In: Saraswat M, Roy S, Chowdhury C, Gandomi AH (eds) Proc, International Conf on Data Science and Applications. Lecture Notes in Networks and Systems, vol 287. Springer, Singapore. https://doi.org/10.1007/978-981-16-5348-3_51

Wu J, Xu S, Zhou R, Qin Y (2016) Scenario analysis of mine water inrush disasters hazard using Bayesian networks. Saf Sci 89:231–239. https://doi.org/10.1016/j.ssci.2016.06.013

Wu M, Ye Y, Hu N, Wang Q, Tan W (2022) Visualization analysis and progress of mine water inrush disaster-related research. Mine Water Environ. https://doi.org/10.1007/s10230-022-00876-5

Xu Y, Chang Q, Yan X, Han W, Chang B, Bai J (2020) Analysis and lessons of a mine water inrush accident resulted from the closed mines. Arab J Geosci 13(14):665. https://doi.org/10.1007/s12517-020-05613-2

Zhang N, Sheng W (2019) Causes analysis of coal mine gas explosion accidents based on Bayesian network. J Mine Autom 45(07):5358. https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2019&filename=MKZD201907011&uniplatform=NZKPT&v=b5DY9Sv0NzWpmXELWDjQL6r8Wix2hb0FVVL_1gYGcbcFtLi4jr3d6eXWXso-KXfz (**in Chinese**)

Zhang SL, Zhang MB, Zhu RH, Meng QL (2021) Analysis of the characteristics of China's mine accidents in the past five years and countermeasures for prevention and control. Coal Chem Ind 44(08):101–106+109. https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&dbname=CJFDLAST2021&filename=HHGZ202108033&uniplatform=NZKPT&v=MMYGm7KkZ27A7FJ-_WOINK1pRbyYkXzk9IRoYyEcXoAJRorLplVEnE8u_dBW2y8U (**in Chinese**)