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Underground Mine Flood Accidents Bayesian Network Learning and Inference

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Abstract:

In order to reduce the flood accidents in underground coal mine of China, a probabilistic inference model with machine learning method is proposed in this paper. Firstly, based on a dataset collected from 99 cases from year 2000 to 2018, the Fault tree analysis (FTA) and causal analysis are applied to determine the related factors of the flood accidents. Then an accurate Bayesian network (BN) model of flood accidents is obtained by structure learning and parameter learning. Finally, the sensitive factors and key factors are acquired by sensitivity analysis and maximum cause chain analysis, according to which the corresponding strategies for reducing flood accidents are put forward to reduce the risk.

Keywords*: Underground mine, Flood accidents, Bayesian network, Fault tree analysis, Machine learning.*

I. INTRODUCTION

In China, Coal plays a leading role in energy consumption [1, 2], but the frequent occurrence of mine accidents restricts the coal mine production seriously and bring tremendous life and property damage to the industry. The major accidents of coal mines are flood accidents, gas accidents, blasting accidents, roof accidents, haulage accidents, electrical & machinery accidents, and fire accidents [2]. Although the flood accidents in underground coal mines has declined dramatically in recent years in China, the casualties caused by flood accidents are next only to those caused by gas accidents and roof accidents. According to statistics of year 2000 to 2005, the death toll is 2812 caused by flood accidents; account for 7.6% of the total death toll caused by coal mine accidents. From 2006 to 2010, the death toll is 1385(7.9%) caused by flood accidents. And from 2011 to 2016, the death toll is 531 (8.1%).

Bayesian network (BN) was first proposed by Pearl in 1988, which is also known as belief network or directed acyclic graphical, is a probabilistic graph model [3]. BN show its superiorities on some aspects. By comparing BN with other techniques (classification trees, support vector machines and extreme learning machines) in terms of explanatory capacity and predictive potential, BN is proved to be the best all-round technique for this type of study [4]. Besides, compared with fault tree analysis (FTA), BN model has flexible structure and can adapt to various accident scenarios [5, 6].

BN has been used in the field of risk management widely, as an effective approach to study probabilistic reasoning. A casual network with key risk drives and enterprise risk can be developed by BN model, and then the signal lamp model is established to response to risks timely [7]. BN can also be introduced to railway systems for safety assessment [8] and used to get a risk early-warning system of surrounding rock instability [9]. In addition, a systemic decision approach with step-by-step procedures based on dynamic BN can be established to increase the likelihood of a successful project in a dynamic project environment [10].

There is no doubt that prevention of occupational hazards is very necessary, especially in mining, such a dangerous industry [11-13]. In order to achieve the early warning of coal mine accidents, a lot of researches have been done. For example, 746 unsafe acts are obtained after analyzing 160 flood accident cases [14]. However, the dynamic changes of influence factors are uncertain and complex, which compounds the difficulties of prevention and control of flood accidents. In recent years, BN has been used to evaluate the risk of coal mine accidents like gas explosion. More realistic evaluation for emergency decision-making and damage prevention of mine gas explosion disaster can be provided based on BN [15]. In this paper, BN is used to make an effective analysis of flood accidents, and the pertinence measures are proposed to help decrease its occurrence.

II. MATERIALS AND METHODS

2.1 Fault Tree analysis

(Fault Tree Analysis) FTA can identify the root causes of accidents accurately, and it is one of many symbolic logic analytical techniques [16, 17]. It uses Boolean logic to combine a series of lower-level events in a system or subsystem from top to bottom, as shown in Fig.1.

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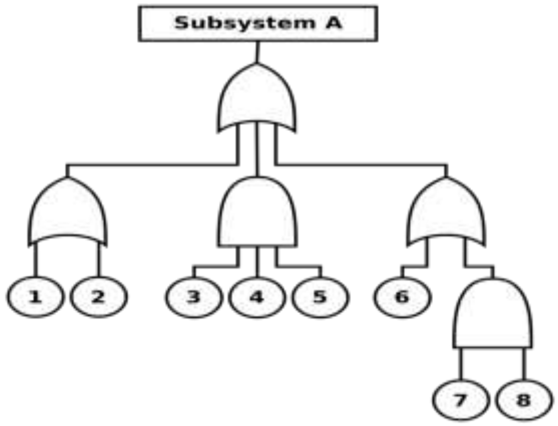

Fig 1: A fault tree diagram

FTA is a deductive method for identifying hazards leading to accidents, this method starts with the most undesirable event and traces back to the various scenarios that may lead to the accident. In the fault tree, the top, intermediate and basic events are connected by logic gates, of which AND-gates and OR-gates are the most widely used. AND gates combine input events, all of which must coexist in order to the output to occur, but for the OR gate, any event is sufficient to cause the output. (Fuzzy fault tree analysis for fire and explosion of crude oil tanks)

2.2 Bayesian Network

BN is a combination of graph theory and probability theory, which consists of directed acyclic graph (DAG) and joint probability distribution (JPD) [18]. It is an effective method to infer the relationship between multiple variables through causal and probabilistic structure.

FTA can identify the root causes of accidents accurately, and it is one of many symbolic logic analytical techniques [16, 17].

Cause analysis studies the environmental impact, management measures, human behaviors and other factors related to accidents, as well as the interaction between these factors, then puts forward a clear accident impact factors [19].

K2 algorithm solves the problem of model selection by Greedy search. The procedure takes as follows. First of all, a scoring function that evaluates the quality of network structure is determined. Then starting with one node of the network, the node with the highest score are

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selected as parent node of target node according to the order of determined nodes and the number of maximum parent nodes[20].

The specific flow of K2 algorithm is illustrated in the following pseudo codes [21].

$$
\begin{array}{l}
\textit{procedure } K2 \\
\{\textit{Input}: \textit{A set of } n \textit{ nodes, an ordering on the nodes,} \\
\quad\quad \textit{an upper bound } u \textit{ on the number of parents} \\
\quad\quad \textit{a node may have, and a database } D \\
\quad\quad \textit{containing } m \textit{ cases.}\} \\
\{\textit{Output}: \textit{For each node, a printout of the parents} \\
\quad\quad \textit{of the node.}\} \\
\textit{for } i := 1 \textit{ to } n \textit{ do} \\
\quad \pi_i := \Phi; \\
\quad P_{old} := g(i, \pi_i); \\
\quad \textit{OK TO Proceed} := \textit{true} \\
\quad \textit{while OK TO Proceed and } |\pi_i| < u \textit{ do} \\
\quad\quad\quad \textit{let } z \textit{ be the node in } \mathrm{Pred}(x_i) - \pi_i \textit{ that} \\
\quad\quad\quad\quad \mathrm{max}\textit{imizes } g(i, \pi_i \cup \{z\}); \\
\quad\quad P_{new} := g(i, \pi_i \cup \{z\}); \\
\quad\quad \textit{if } P_{new} > P_{old} \textit{ then} \\
\quad\quad\quad P_{old} := P_{new}; \\
\quad\quad\quad \pi_i := \pi_i \cup \{z\} \\
\quad\quad \textit{else OK TO Proceed} := \textit{false}; \\
\quad \textit{end } \{\textit{while}\} \\
\quad \textit{write}(\textit{'Node:'}, x_i, \textit{'Parents of this node:'}, \pi_i) \\
\textit{end } \{\textit{for}\}; \\
\textit{end}\{K2\};
\end{array}
$$

Where P_{new} represents the new measure obtained by the algorithm, and P_{old} represents the

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old measure; g refers to the scoring function, as shown in Eq. (1) [20].

$$g(i,\pi_i)=\prod_{j=1}^{q_i}\frac{(r_i-1)!}{(N_{ij}+r_i-1)!}\prod_{k=1}^{r_i}N_{ijk}! \quad (1)$$

Where π_i denotes the parent nodes of variable x_i, q_i represents the number of unique instantiations of π_i, N_{ij} is the number of cases in database D.

Expert evaluation method makes quantitative evaluation by scoring, and the result has the characteristics of mathematical statistics, on the basis of quantitative and qualitative analysis.

In this paper, Maximum likelihood estimation (MLE) is an effective apporach of parameter learning. And it requires four assumptions are as follows [22, 23].

(1)Discrete Bayesian network. This assumption means all variables (nodes) attributes in the problem domain are discrete.

(2)Global and local independence. Giving a BN topology and a set of variables, the probability of occurrence of samples in the training sample set is global and local independence, namely the parameter vector θ_{ij} are independent of each other, as shown in Eq. (2).

$$P(\theta/D,G)=\prod_{i=1}^{n}\prod_{j=1}^{q_i}P(\theta_{ij}/D,G) \quad (2)$$

(3)Polynomial distribution. Each sample in the training sample set is independently taken from the same polynomial distribution.

(4)Complete data set. There are no missing values for each sample in the training sample set.

Given BN topology G and training set D, the likelihood function L is defined as $L(D/\theta,G)=P(D/\theta,G)$. For convenience, $L(D/\theta,G)=\ln P(D/\theta,G)$. Basic Principles of MLE: the value of the parameter θ is chosen, the parameter θ^* that maximizes the value of the likelihood function $P(D/\theta,G)$ is the most suitable parameter for the BN [23]. The BN parameter θ^* using the maximum likelihood function method is expressed as Eq (3).

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$$\theta^{*}=\arg\max_{\theta} L(D/G,\theta)=\arg\max_{\theta} P(D/G,\theta)\propto\arg\max_{\theta}(\ln P(D/G,\theta)) \quad (3)$$

According Independent Identify Distribution (IID) hypothesis and structural characteristics of BNs is illustrated in Eq (4).

$$\ln P(D/G,\theta)=\ln\prod_{i=1}^{N}P(D/G,\theta)=\ln\prod_{l=1}^{N}\prod_{i=1}^{n}P(v_{li}/Pa(v_{i}),\theta_{i})=\sum_{i=1}^{n}\sum_{j=1}^{q_i}\sum_{k=1}^{m_i}N_{ijk}\ln(\theta_{ijk}) \quad (4)$$

Where, $q_i=\prod_{X_i\in Pa(X_i)}r_i$, N_{ijk} denotes the number of cases satisfying Eq. (5) in data set D

$$X_i=x_{ik};Pa(X_i)=Pa(X_i)_j \quad (5)$$

Sensitivity analysis (SA) is an essential index to measure the response of model output to input changes. It is useful for model analysis to know the nodes that are most influential and are unimportant [24].

III. CASE STUDY

3.1. Data Description and FTA

According to some typical examples of flood accidents, basic events of flood accidents are summarized, and flood fault tree is constructed [25]. In this paper, due to many cases are not announced, 99 flood accidents from 2000 to 2018 in various provinces of China are collected as the database. Based on the database, the fault tree of flood accidents which contains 51 nodes is developed (Fig. 2), and the nodes are illustrated in TABLE I.

TABLE I. Explanation of nodes of fault tree

Nodes	Name	Nodes	Name	Nodes	Name
T	flood accidents	M17	insufficient awareness about water control	X17	collapse columns
M1	existence of water	X1	Released water space	X18	illegal outsourcing

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M2	water flowing channels	X2	reservoirs	X19	cross-border mining
M3	water sources above mining area	X3	rivers	X20	illegal firing
M4	Poor surrounding environment of mining area	X4	meteoric water	X21	unprofessional teams
M5	hydrogeological conditions are adverse for mining	X5	water for production	X22	without specialized training
M6	hydrogeological data not update in time	X6	confined water	X23	unprofessional equipment
M7	groundwater	X7	ordovician limestone water	X24	unreasonable design of waterproof coal pillar
M8	insufficient water control technology	X8	goaf water	X25	waterproof coal pillar has collapsed
M9	Existing water flowing channels	X9	loosen layer water	X26	waterproof coal pillar is mined
M10	unnecessary water flow channels	X10	phreatic water	X27	improper site management command
M11	Unsafe mining behaviors	X11	tectonic water	X28	Poor sealing of boreholes
M12	delayed safety measures	X12	unreliable conclusion of geophysical exploration	X29	defective supervisory mechanism
M13	Illegal production	X13	incomplete hidden trouble investigation	X30	ambiguous entity responsibilities
M14	nonstandard surveying water	X14	Delayed water analysis and hydrological observations	X31	incomplete implementation of rules and regulations
M15	waterproof coal pillars lose efficacy	X15	faults	X32	lack of training about safety work
M16	defective security administrations	X16	cracks	X33	incomplete implementation of rules and regulations

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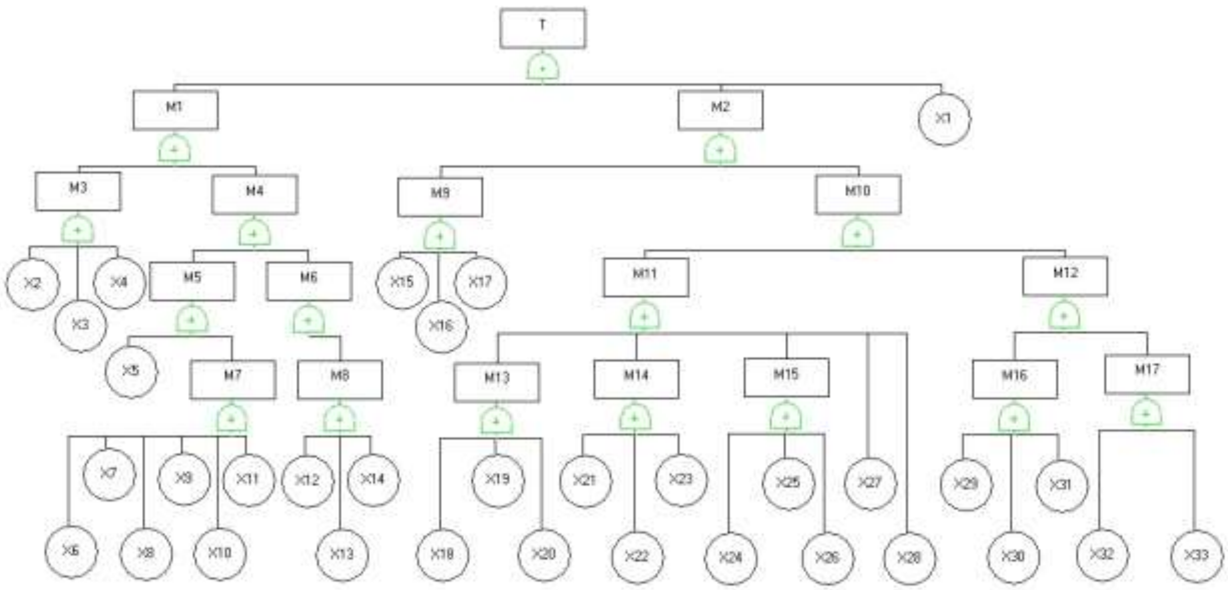

Fig 2: Flood accident fault tree

When all variables are complete in the training sample set, the maximum likelihood parameter θ* can be estimated by MLE in Eq (6).

$$\theta^{*} = \frac{N_{ijk}}{\sum_{k=1}^{m} N_{ijk}} = \frac{N_{ijk}}{N_{ij}} \tag{6}$$

3.2. Determine Risk Factors

In this paper, the risk factors of flood accidents are determined by causal analysis. Analyzing human factors, management factors and environmental factors of flood accidents, and then integrating those factors with the basic or intermediate events in fault tree, the specific risk factors are obtained as follows.

3.2.1 Human factors

Human factors mainly include non-prescribed manners, misoperations, and unsafe behaviors. By analyzing the collected cases, the following environmental factors causing floods are found.

Insufficient awareness about water control: Because of the insufficient train of water control, employees are less experienced. That makes them can't make an appropriate react to avoid the occurrence of accident, when there are hidden failures.

Nonstandard surveying water: Coal mines don't have a professional team to survey water. Staffs without professional trainings or staffs don't have professional equipments, etc.

Improper site management command: Due to spot managers make wrong commands; water-logged zone is exploited. Or when finding the signs of water permeation, they can't make right decisions, etc.

Unsafe mining behaviors: Unreasonable and unsafe behaviors happen in coal mining process.

Waterproof coal pillars lose efficacy: Unreasonable design of waterproof coal pillars. Waterproof coal pillar has collapsed. Or waterproof coal pillar is mined, etc.

Unnecessary water flow channels: Due to human factors, flowing water channels are formed in mining areas. And it distinguishes from existing water flowing channels.

Insufficient water control technology: The conclusion of geophysical exploration is unreliable. Or dynamic change of aquifer can't be found.

Delayed safety measures: It means that failure to detect irregular, unreasonable and illegal behaviors in Mining process timely, or failure to take appropriate measures to stop them.

3.2.2 Environmental factors

Environmental factors mainly include physical (light, humidity, and water), chemical (gas) and biological factors. By analyzing the collected cases, the following environmental factors causing floods are found.

Karst water, Goaf water, adverse hydrogeological conditions for mining, Surface water: It mainly includes meteoric water, surface pond, rivers, reservoirs, etc.

Existing water flowing channels: It mainly includes faults, cracks, collapse columns, etc. It distinguishes from water flowing channels caused by human factors.

Hydrogeological data not update in time: Technical data are compiled by

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non-hydrogeological technician. Or hydrogeological date can't be update timely.

3.2.3 Management factors

Management factors mainly include supervision, inspection, safety organization, and personnel arrangement and so on. By analyzing the collected cases, the following management factors causing floods are found.

Incomplete implementation of rules and regulations: Rules and Regulations can't be strictly implemented.

Defective supervisory mechanism: Local government has failed to find problems existing in coals.

Lack of training about safety work, Defective security administrations, Ambiguous entity responsibilities, Illegal production: It includes illegal outsourcing, cross-border mining, illegal firing, etc.

3.3. Bayesian Network Model

The BN can be established by structure learning and parameter learning based on the sufficient data [26].

3.3.1. Bayesian network structure learning

For different research, the methods of learning Bayesian network structure are also different [27]. When sample data is complete, search scoring methods or statistical test methods are used. Such methods include two parts: selecting scoring function and formulating search strategy. When the sample data is incomplete, small data set or Bayesian network learning with noise are adopted [20]. Due to data is relatively complete, the paper adopts K2 algorithm to preliminarily establish Bayesian network structure model. K2 algorithm is a representative algorithm in search scoring methods.

In the paper, we use GeNIe2.0 sofware to complete the BN structure learning. The specific steps are as follows.

3.3.1.1 Input data

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In order to finish the structure learning, we need to import data collected and select the learning algorithm of Bayesian network. In this paper, K2 algorithm is chosen as the method of structure learning, Greedy method is selected as the search strategy, and K2 is selected as the scoring function.

3.3.1.2 Import background knowledge

In order to simplify Bayesian network structure and improve the modeling efficiency, 24 groups of relative relations are selected as the background knowledge based fault tree (Fig. 3). The details are as follows.

(1) Defective supervisory mechanism →Ambiguous entity responsibilities (2)Incomplete implementation of rules and regulations →Defective security administrations (3)Ambiguous entity responsibilities →Defective security administrations (4)Defective supervisory mechanism →Defective security administrations (5)Defective security administrations →Delayed safety measures (6) Insufficient awareness about water control →Delayed safety measures (7)Lack of training about safety work → Insufficient awareness about water control (8)Delayed safety measures → Unnecessary water flow channels (9)Unsafe mining behaviors →Unnecessary water flow channels (10)Insufficient awareness about water control →Unsafe mining behaviors (11)Improper site management command →Unsafe mining behaviors (12)Waterproof coal pillars lose efficacy →Unsafe mining behaviors (13)Nonstandard surveying water →Unsafe mining behaviors (14)Illegal production →Unsafe mining behaviors (15)Existing water flowing channels →Water flowing channels (16)Unnecessary water flow channels →Water flowing channels (17)Insufficient water control technology →Hydrogeological data not update in time (18) Goaf water →Adverse hydrogeological conditions for mining (19) Karst water →Adverse hydrogeological conditions for mining (20)Adverse hydrogeological conditions for mining → Existence water source (21)Hydrogeological data not update in time →Existence water source (22)Surface water →Existence water source (23)Existence water source →Flood accidents (24)Water flowing channels →Flood accidents.

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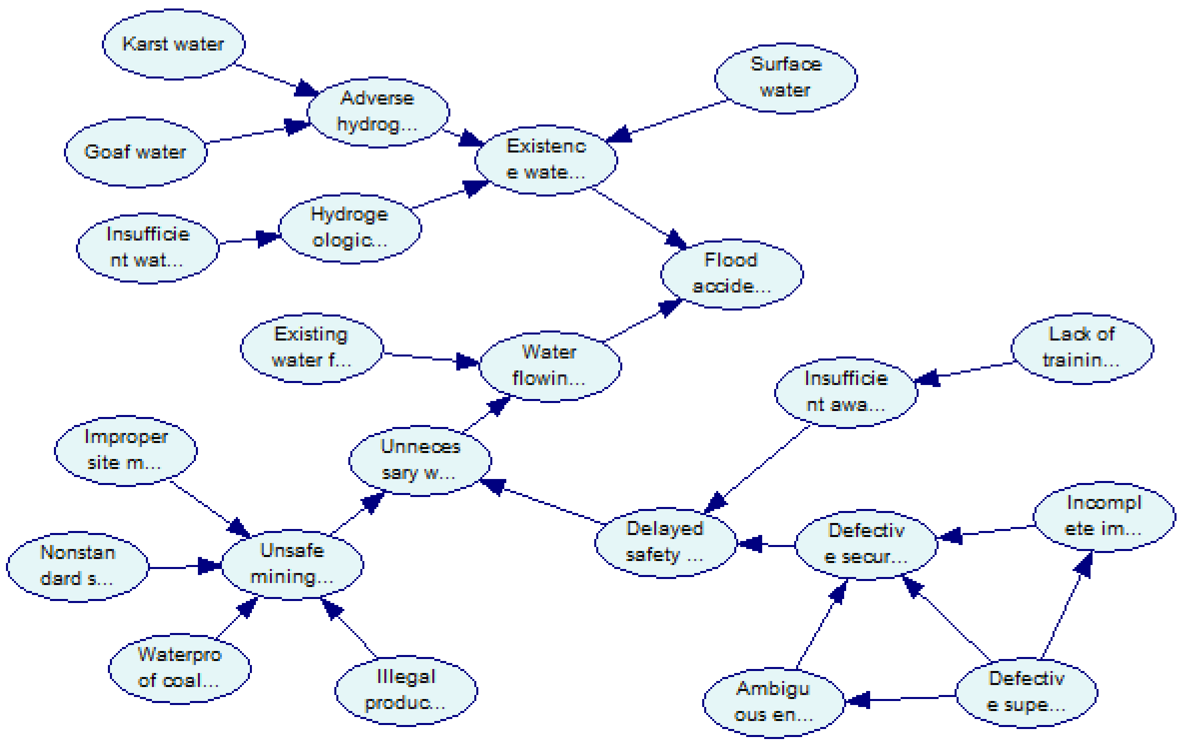

Fig 3: Background knowledge

3.3.1.3 Initial Bayesian network

The initial BN is shown in Fig. 4.

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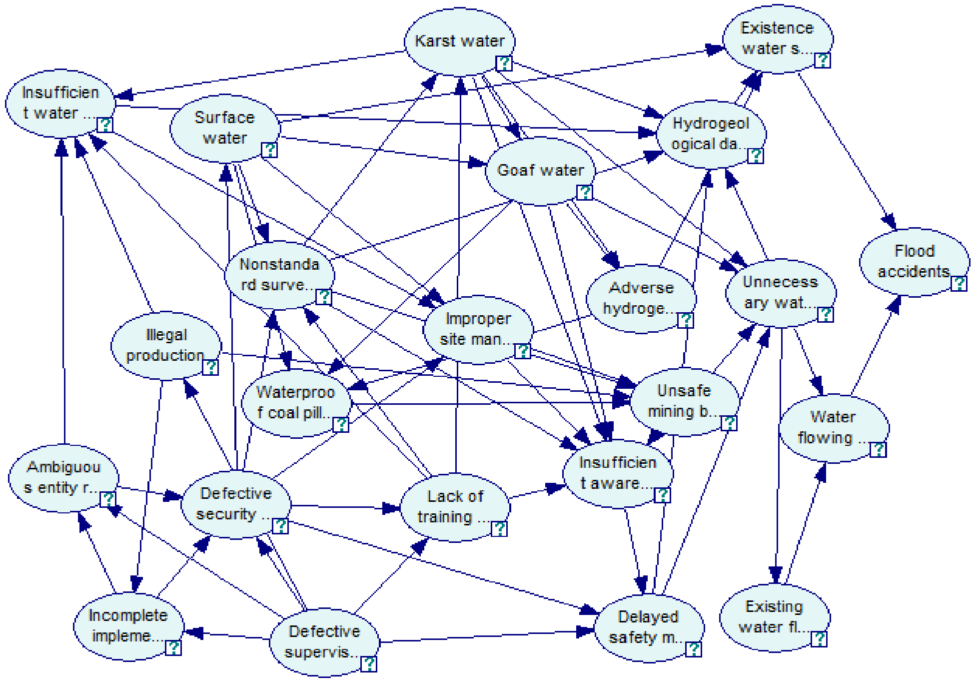

Fig. 4: Initial Bayesian network

3.3.1.4 Optimizing initial Bayesian network

The initially BN structure is likely to be quite different from the final version [28]. The initial Bayesian network structure obtained by GeNIe2.0 is complex, and there are many unrelated connection sets in the network structure. Therefore, the initial Bayesian network need to be modified.

In this paper, expert assessment method is used to optimize the initial Bayesian network. Due to weak correlation, the following 22 groups of relative relations are deleted.

(1)Unnecessary water flow channels →Existing water flowing channels (2) Defective security administrations →Surface water (3) Surface water →Improper site management command (4) Surface water →Nonstandard surveying water (5)Unnecessary water flow channels →Hydrogeological data not update in time (6)Delayed safety measures →Hydrogeological data not update in time (7)Nonstandard surveying water →Hydrogeological data not update in time (8)Karst water →Hydrogeological data not update in time (9)Adverse hydrogeological conditions for mining →Waterproof coal pillars lose efficacy (10)Karst water → Insufficient water control technology (11) Karst water → Goaf water (12)Nonstandard surveying water → Karst water (13)Lack of training about safety work → Karst water

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(14)Karst water → Unnecessary water flow channels (15)Karst water →Insufficient awareness about water control (16)Goaf water →Unnecessary water flow channels (17)Goaf water →Insufficient awareness about water control (18)Goaf water →Waterproof coal pillars lose efficacy (19)Insufficient water control technology →Improper site management command (20) Unsafe mining behaviors →Insufficient awareness about water control (21)Improper site management command →Insufficient awareness about water control (22)Nonstandard surveying water →Insufficient awareness about water control.

At the end of the above steps, we get the optimized Bayesian Networks. As shown in Fig. 5.

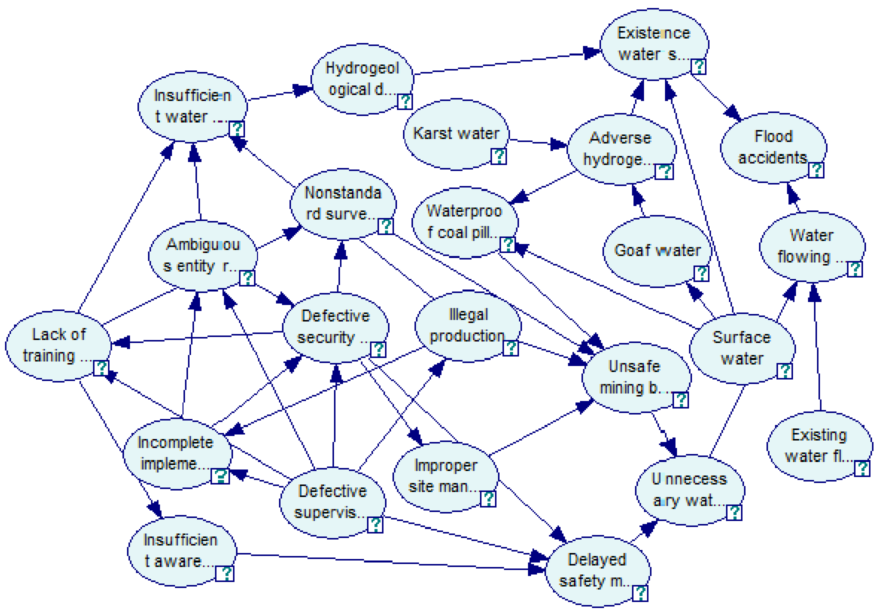

Fig. 5: Optimized Bayesian Networks

3.3.2. Bayesian network Parameter learning

Parameter learning of Bayesian network is the quantization process of the dependence relation between the random variables. Parameter learning that learns probability change of parameters in the network based the given BN structure and sample data.

MLE or Monte Carlo based methods can be used to Bayesian network parameter learning [29]. In this paper, Bayesian network parameter learning is finished based on MLE (Fig. 6), TABLE 2 shows the probability of each node, where Y means nodes occurrence, N means that nodes don’t occur[30].

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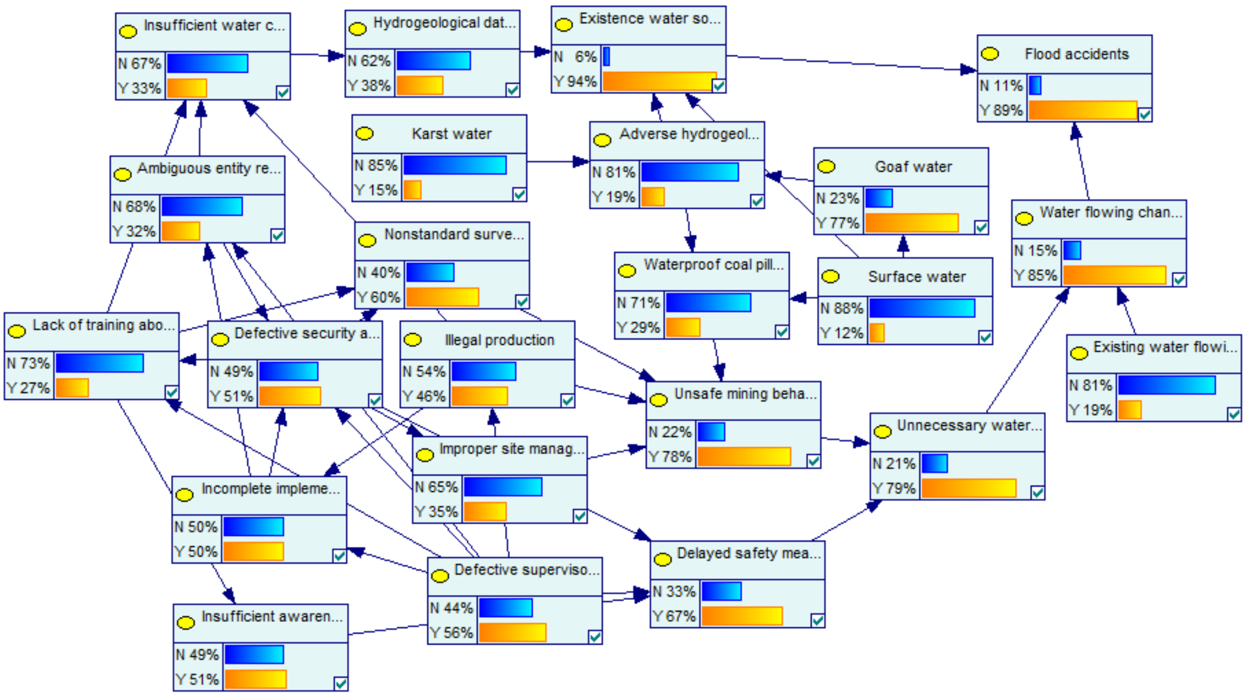

Fig 6: Bayesian Networks after Parameter Learning

TABLE 2 Results after parameter learning

Nodes	Probability of occurrence(Y)/%	Probability of non-occurrence(Y)/%
Goaf water	77	23
Karst water	15	85
Insufficient water control technology	51	49
Adverse hydrogeological conditions for mining	19	81
Hydrogeological data not update in time	38	62
Surface water	12	88
Existence water source	94	6
Existing water flowing channels	19	81
Illegal production	46	54
Nonstandard surveying water	60	40
Waterproof coal pillars lose efficacy	29	71
Improper site management command	35	65
Insufficient awareness about water control	51	49

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Unsafe mining behaviors	78	22
Unnecessary water flow channels	79	21
Delayed safety measures	67	33
Lack of training about safety work	27	73
Defective security administrations	51	49
Defective supervisory mechanism	56	44
Incomplete implementation of rules and regulations	50	50
Ambiguous entity responsibilities	32	68
Water flowing channels	85	15
Flood accidents	89	11

IV. RESULT

4.1. Sensitivity analysis

Sensitivity analysis is a powerful tool that can be applied to explore the behavior of the flood accident model, such a complex model that contains various factors and multiple hidden connections among the factors. It can help to study the variation in the output of a model how to be apportioned to different sources of variation in the input. And then, the variables which have the greatest influence on the target can be identified. Generally, sensitivity analysis can be used in evaluating a BN by considering how the BN's posterior distributions change under different conditions.

In this section, the node flood accidents is set to the target, for which the sensitive factors can be identified in Fig. 7 where the darker the node color, the more sensitive the node is. As depicted in Fig. 7, these nodes (Existence water source, Water flowing channels, Existing water flowing channels, Surface water, Unnecessary water flow channels, and Adverse hydrogeological conditions for mining) are the sensitive factors for the target and the sensitivity of each node is shown in TABLE 3.

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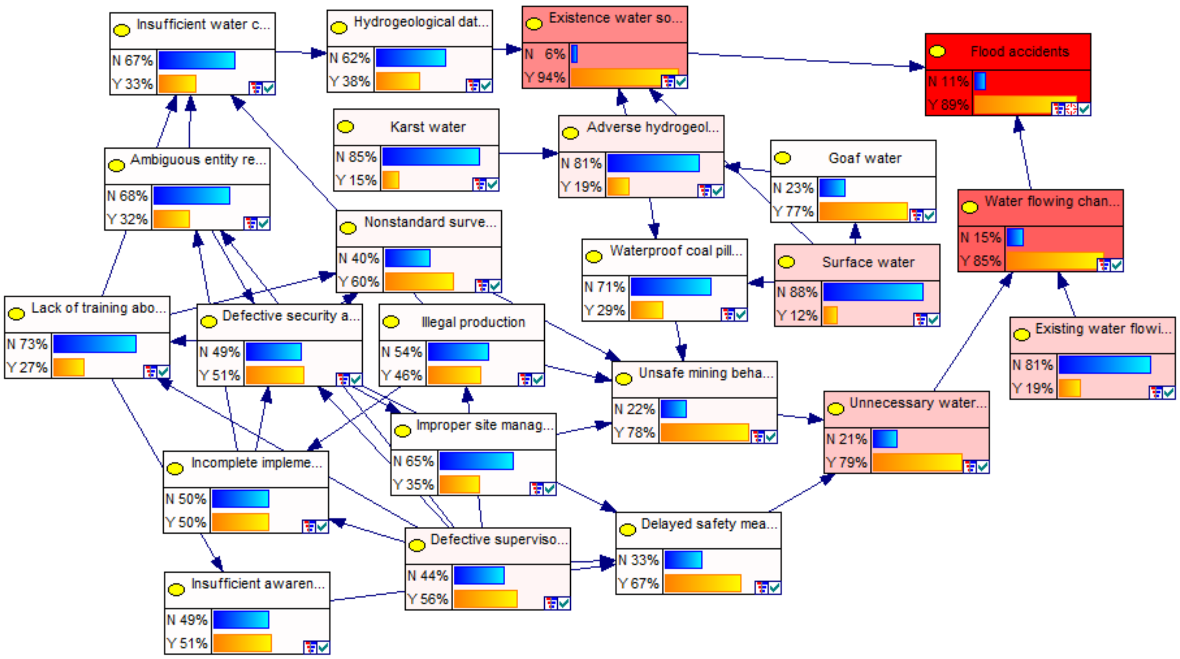

Fig 7: Sensibility analysis

TABLE 3. Sensitive values of sensitive factors

Name of node	Existence water source	Water flowing channels	Existing water flowing channels	Surface water	Unnecessary water flow channels	Adverse hydrogeological conditions for mining
Sensitive values	0.214	0.315	0.078	0.069	0.092	0.028
ranking	2	1	5	4	3	6

As shown in TABLE 3, compared with the node existence water source, the node water flowing channels has a greater sensitivity for the flood accidents, and the node unnecessary water flow channels is more sensitive than the node existing water flowing channels. Therefore, coal mines should take some measures to standardize production and avoid illegal production, then the safety level of mining process can be improved to some extents.

4.2. Maximum Cause Chain Analysis

Generally speaking, the process of Maximum cause chain is divided into three steps. Firstly, the target should be determined, where the relationships that nodes related to the target also need to take into account. It is noteworthy that the nodes exist water source and water flowing

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channels are both the necessary conditions for the occurrence of flood accidents. Under this situation, these two nodes (Existence water source and Water flowing channels) should be set to a same condition with the target node flood accidents. Accordingly, the occurrence probabilities (Y) of these nodes (Flood accidents, Existence water source, Water flowing channels) need to be adjusted to 100% at the same time. Then running the BN model, the probability of each node can be obtained (Fig. 8). Finally, starting from the nodes existence water source and water flowing channels respectively, the parent nodes that has the greatest influence on them can be identified. Similarly, the process is looped until the root nodes consist in and the maximum cause is obtained as depicted in Fig. 9.

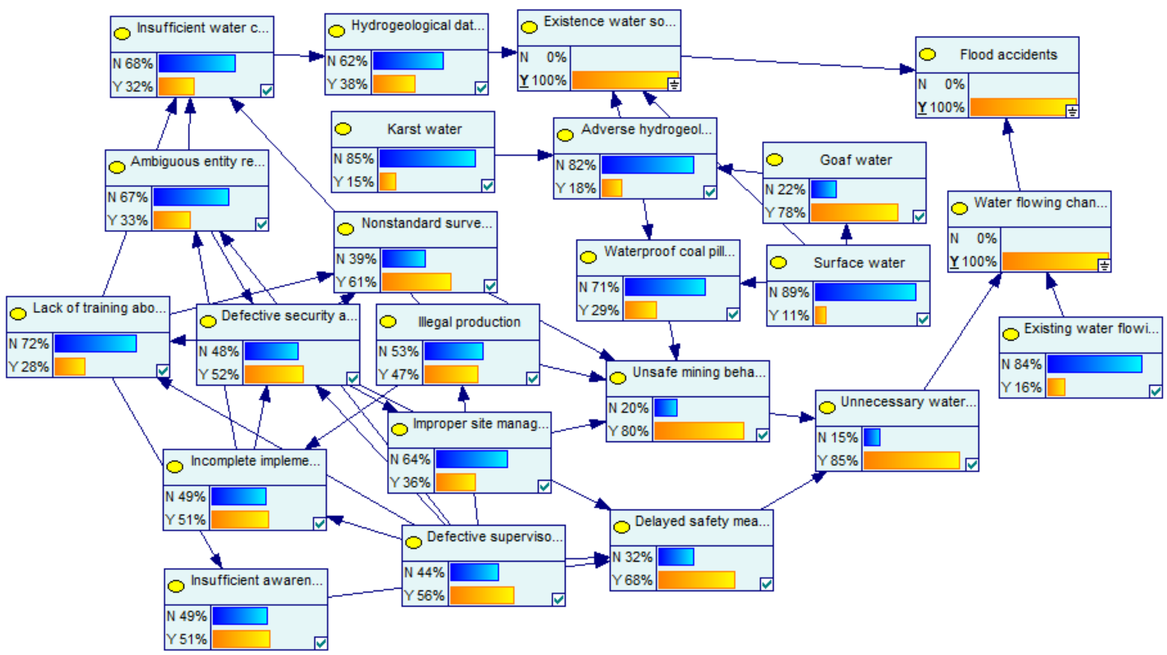

Fig 8: The maximum cause chain analysis

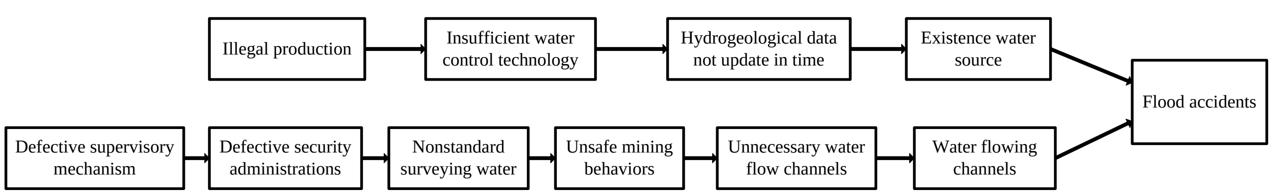

Fig 9: The maximum cause chain of flood accident

The maximum cause chain of flood accidents obtained only reflects the formation mechanism of most accidents. Actually, any node in BN may lead to flood accidents.

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V. DISCUSSION

According to sensitivity factors and key factors, corresponding measures are proposed as follows, which contribute to prevent or avoid the occurrence of flood accidents and reduce the losses caused by the accidents.

5.1 Implement Safety in Production and Strengthen Safety Supervision

Coal mine enterprises should take measures to implement safety production. Firstly, enhancing the education effectiveness of disaster prevention can improve staff awareness of water control to some extents. And then a better supervision of the sensitivity and key factors should be implemented, which can help to eliminate the occurrence of illegal behaviors.

Assuming that the measures mentioned above have been properly implemented, the occurrence of these nodes (Defective security administrations, Illegal production, Unsafe mining behaviors, unnecessary water flow channels, defective supervisory mechanism) will be close to zero. Accordingly, the non-occurrence probability (N) of the nodes to100%, the occurrence probability (Y) of the target node (Flood accidents) drops from 89% to 76%, a decrease of 13%.

5.2 Standardize Work Process

Coal mines should strengthen the standardization of all kinds of work, especially the water survey. Besides, professional personnel should be trained. At the same time, advanced equipment need to be installed and the strict implementation standards should also be formulated.

Accordingly, the non-occurrence probabilities (N) of the nodes (Insufficient water control technology, Nonstandard surveying water, Hydrogeological data not update in time, Unsafe mining behaviors, Existence water) are adjusted to 100%. The result shows that the probability of Y of flood accidents drops from 89% to 38%, down 51%.

Assuming the measures of the two aspects are implemented at the same time, the non-occurrence probabilities (N) of following 9 nodes defective security administrations, illegal production, defective supervisory mechanism, insufficient water control technology, nonstandard surveying water source, hydrogeological data not update in time, unsafe mining behaviors, unnecessary water flow channels, existence water) need to be adjusted to 100%. The

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result shows that the probability of flood accidents drops from 89% to 30%, down 59% (Fig. 10).

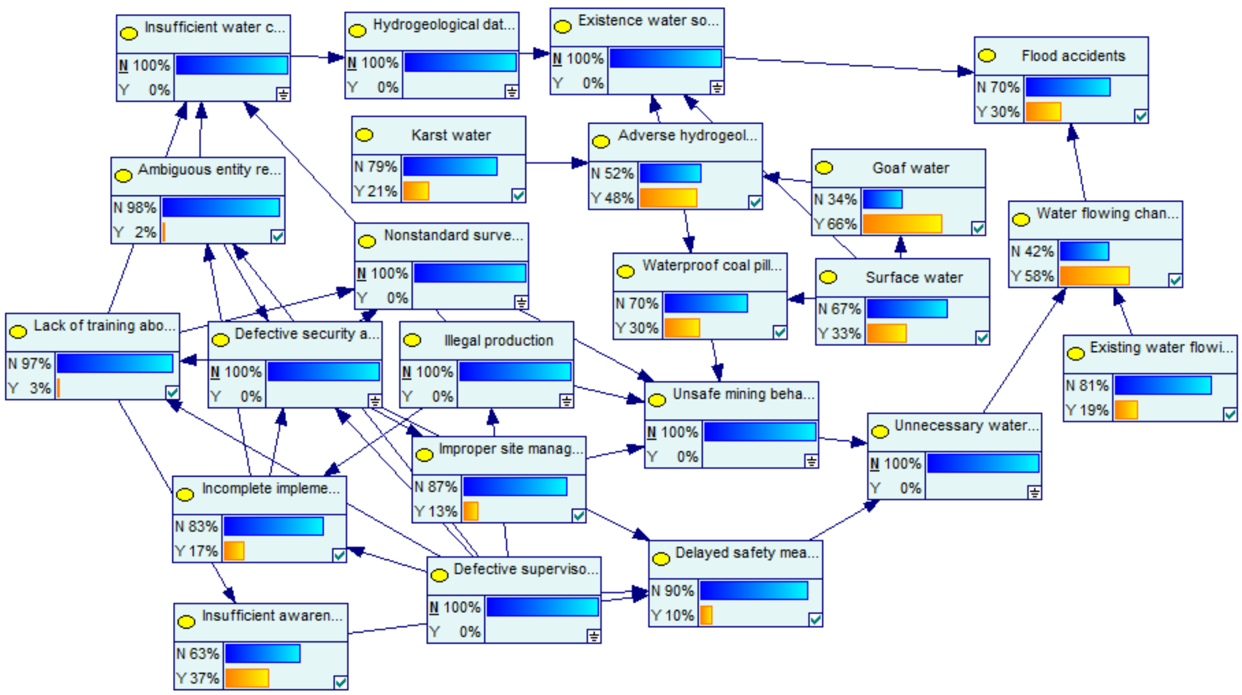

Fig. 10: Probability of nodes after measures are implemented

VI. CONCLUSION

In this paper, BN is applied to flood accidents in coal mines. Firstly, the fault tree of the flood accidents is established based on a database composed of 99 flood accidents from 2000 to 2018. Then the related factors of the flood accidents are determined as the nodes of BN model, based on FTA and causal analysis. After modification of nodes and determining of the relationships between nodes, the BN model of flood accidents is established. Finally, the key factors (Defective security administrations, Illegal production, Defective supervisory mechanism, Insufficient water control technology, Nonstandard surveying water, Hydrogeological data not update in time, Unsafe mining behaviors, Unnecessary water flow channels and Existence water) can be determined by result analysis. Accordingly, we put forward effective suggestions to reduce the occurrence of flood accidents in coal mines.

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