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Cause-chain analysis of coal-mine gas explosion accident based on Bayesian network model

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Abstract

In order to prevent coal mining gas explosion accidents, it is considerable to understand the conditions and probabilities of casing process. This paper studied the cause of coal mining accidents and proposed a cause inference model of coal mining gas explosion accident based on Bayesian network. Firstly, the nodes and their domain in Bayesian network are determined by cause analysis. Secondly, we construct the Bayesian network through the accident samples and determine the conditional probability, and then attempt to build our Bayesian accident model. Finally, a GeNIe simulation software is adopted to analyze and verify the feasibility and effectiveness of our constructed model, and obtain the cause chain of coalmine gas explosion accident. The research results show that the inadequate technical management in the management elements has a relatively large impact on the accident. Technical management is not in place will result in many physical factors such as ventilation, electrical and other anomalies, and further cause coalmine gas explosion accident. Therefore, technical management should be strengthen to raise safety awareness and reduce equipment system abnormalities, to reduce such accidents and the hazards caused by explosion accident.

Keywords Mine gas explosion · Cause analysis · Bayesian network · GeNIe simulation

1 Introduction

Although the accident rate of coalmines has dropped significantly in China, the safety situation is still severer than the major coal-producing countries in abroad. Most coalmines in the country are underground mines with complex geological conditions and many disasters types, which threaten the lives and safety of employees. It is very important to understand hazards and risks associate with the process; perform risk assessment to identify them and take proper actions to remove or minimize hazards and risks; or else a catastrophic accident may occur. A small mistake by an operator or a problem in the process system may escalate into a disastrous event as the process area congests with process equipment and piping systems, and has limited ventilation and accidents escape routes. Case histories showed that catastrophic society as have a significant effect on people, environment, and they involved fatalities and great financial loss [1]. In coalmine accident, gas explosion accident is the casualty with the largest number of casualties, and cause great economic loss at the same time. The vast majority of mine in China are gas mines, some of them are high-gas mines. According to the statistics of the State Administration of Coal Mine Safety (SACMS) of China, the death toll from gas accidents always accounts for more than a half ratio in Chinese coal mines [2]. Therefore, doing well the prevention and control of gas accidents has the most prominent significance in reducing coalmine casualties and losses.

Aiming at the causes of gas explosion accidents in coalmine, many experts and scholars in the world have done some significant research. Zhou et al. [3] propose a causing model of gas explosion based on probability analysis. Yin et al. [4] found the main point and principle of coal mine explosion accident by statistical analysis. Sanmiquel et al. used Bayesian classifiers, decision trees among other data mining techniques to explore prevention measures for Spanish mining accidents [5]. Li divvied coal hazards into four categories and made a risk assessment

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based on the probability, loss and weight to find the key factors [6]. According to the specific behavior factors of coal miners, Paul [7] analyzed the causes of gas explosion accidents and built a model equation based on human behavior factors. Amyotte [8] analyzed and studied a large amount of gas explosion data and processed the data from the perspective of management, which pointed out that management defects are an important factor in the gas explosion accidents of coal mining; therefore, a management failure model is constructed. As one kind of probabilistic graphical model, approaches like Bayesian network have significant representational as well as computational advantages when treating large, highly complex systems [9]. Martin et al. used Bayesian network to identifying the causes that have the greatest bearing on accidents involving auxiliary equipment. It allow a causality model to be defined for workplace accidents in a more realistic way to a management model for labour risk prevention [10].

In recent years, Bayesian network (BN), a graphical model based on application of Bayes' theorem for probability reasoning to quantify complex dependencies, are being applied in engineering applications. A Bayesian network describes causal influence relations among variables via a directed acyclic graph. It represents a set of random variables in nodes and their conditional dependencies by drawing the edges from one node to another in a binary network, nodes and arcs represent variables and causal relationships among different nodes. Conditional probability tables or defined probabilistic relationships among nodes represent how one variable is linked another one or multi-variables. The nodes that influence other variables and have unconditional probability are called parent or root nodes. Nodes that are conditionally dependent on their direct parents are called intermediate nodes. The end node is defined as a leaf node.

Since Bayesian network has a unique indefinite form, rich probability expression ability, and comprehensive incremental characteristics of prior knowledge, its application field is very wide. Yong et al. adopted Bayesian networks for model diagnosis [11]; Ou researched the Bayesian learning on the urban transport multi-agent system [12]. Li et al. studied the Bayesian network model of coal mining roof accidents, and fully considered the dependencies between the elements [13]. Zhang and Xu used the Bayesian network model to study the cause of major gas accidents in coal mining, analyzed accident causes from the perspective of fault tree analysis (FTA), and then transferred it into Bayesian network model [14]. However, the researchers are based on the independent stratification of the factors in the fault tree and do not consider the interdependence of elements in the actual system. In view of this, this paper studies the causes of gas explosion accidents in coal mining based on the interdependence of accidents.

In this paper, the gas explosion accident is selected as the research object. In order to analyze the causes of gas explosion with dependencies relation, thus Bayesian network is adopted to establish a network model of gas accident. Finally, the constructed model is verified by GeNIe software and the cause chain is analyzed out to understand the coalmine gas explosion accident. In addition, the research results of the network model constructed in this paper can provide real-time and reliable decision-making information for coal mine safety production so as to prevent accidents.

2 Related works

2.1 Bayesian network model

The Bayesian network mainly consists of two parts: directed acyclic graph (DAG) and conditional probability table (CPT), which corresponds to the qualitative description and the quantitative description of the problem area respectively. DAG is the Bayesian network structure, is consisted of two elements: node and directed edge, where the node represents a variable in the network, each node corresponds to a variable; directional edge represents the probability relationship between variables or that the dependence or causal relation between nodes. The two endpoints of the directed edge are the parent node and the child node, respectively. The direction is from the former to the latter. The intensity between them is denoted by the corresponding probability, which is a qualitative analysis to the problem.

CPT is a set of local probability distributions reflecting the correlation between variables, which is probability parameters in other words. The probability value indicates the association strength or confidence degree between the child node and its parent node, and the node probability without parent node is its prior probability. The Bayesian network structure is the result of abstracting data instances and is a macroscopic description for the problem area. The probability parameter is an accurate expression of the correlation strength between variables (nodes), which belongs to the quantitative description.

Given a set of random variables that contain n variables, G, L and P represent the directed acyclic graph, the set of directed edges and the set of conditional probability distributions, respectively. Therefore, a Bayesian network model can be denoted as follows:

$$BN = (G, P) = (V, L, P) \quad (1)$$

where:

$$G = (V, L) \tag{2}$$

$$V = (V_1, V_2, \ldots, V_n) \tag{3}$$

$$L = \left\{ (V_i - V_j) \middle| V_i, V_j \in V \right\} \tag{4}$$

$$P = \{P(V_i | V_{i-1}, V_{i-2}, \ldots, V_1), V_i \in V\} \tag{5}$$

P represents probability distribution over V and V = $\{X_1, X_2, \ldots, X_n\}$ can be either discrete or continuous random variables. These random variables are assigned to the nodes and the edges. Bayesian networks can be represented by the joint probability distribution, $P(V)$,

$$\begin{aligned} P(V) &= \sum_{X \in V} P(X|pa(X)) = \\ P(X_1, X_2, \ldots, X_n) &= \sum_{i=1}^{n} P(X_i|pa(X_i)) \end{aligned} \tag{6}$$

In Bayesian networks, node V_i are conditional independent of any other set of non-child nodes given parent node. It is because of the assumption of conditional independence that greatly simplifies the computational and inference of Bayesian networks. In addition, there is a independence for causal relationship between parent and child nodes, which means that multiple reasons affect the same result independently.

2.2 Bayesian network learning

Bayesian network learning refers to the process of obtaining the Bayesian network by analyzing the data and is divided into two parts. First, the Bayesian network structure learning, namely, the relationship between nodes is qualitatively described to obtain a directed acyclic graph, which is structure learning; After the determination of Bayesian network structure, the parameter learning of conditional probability distribution is performed, thus the probability dependence between random variables is quantitatively described, which is parameter learning.

Given a given data set D, a collection of data instances is denoted as

$$D = \{D_k | k = 1, 2, \ldots, N\} \tag{7}$$

where D_k is a dataset. Assume there is a model used to describe the given data-set,so the model is a complete Bayesian network, namely:

$$M = (V, L, P) = (S, \Theta) \tag{8}$$

where V represents the set of variables determinated in the problem area, L is a directed connection set, and P is a conditional probability table. S represents a network structure corresponding to the directed connection set L, and Θ represents all the parameter vectors corresponding to the conditional probability table of a given structure S [15].

Structure learning refers to the network structure S learned and discovered from the data set, which is to determine the set L of dependencies between the variable set V and its variables, to realize the qualitative expression of the problem area. Therefore, we need to determine the variables and all the possible states or weights of the variables. Then, according to the observed data, we use the knowledge of relevant experts and their prior experience to evaluate the analysis results. Finally, we can judge the relationship between the variables and the graph direction.

2.3 Bayesian network inference

Using the conditional probabilities that learned in the Bayesian network structure and combining the Bayesian formula with the conditional probability formula, Bayesian network inference can calculate and get the posterior probability of each node. Under a certain BN model, we can obtain the probability of the node according to the corresponding calculation method.

There are mainly the following inference forms: (1) BN network model is used to deduce the probability of the event results for the known causes. (2) The known results from the event with the BN network are adopted to derive the probabilities of various causes. Fox example, the inference of the disease in the hospital, the cause of the machine failure in the factory all use the diagnostic inference. (3) According to partial causes or partial results of the known events, the dependencies between nodes are analyzed, whose result can support the phenomena that occurred in the events [16].

Bayesian network inference can be divided into precise inference and approximate inference. Precise inference methods include Poly tree algorithm, Clustering algorithm, Conditioning algorithm, etc.; approximate inference methods include simulation algorithm, transform algorithm, parameter approximation algorithm [13].

3 Causing model for coalmine gas explosion accident

Technically, there are two main types of coal mine explosions: methane explosions and coal dust explosions. Methane (gas) explosions occur in mines when a buildup of methane gas, a byproduct of coal, meets a heat source (over 650 °C), and there is not enough air to dilute the gas to levels below its explosion point. When air contains 5–16% of methane and there is over 12% oxygen, it can explode. Of course, these three factors are related with other factors by chain or networks physically.

Bayesian networks consist of nodes, directed arcs, and conditional probabilities of nodes. Establishing a Bayesian network requires identifying network nodes and structures as well as conditional probability tables. In order to establish a causal model of coalmine gas explosion accidents based on Bayesian network, firstly, the nodes and their ranges of Bayesian networks are determined. Secondly, the Bayesian network structure is determined based on the accident samples and the conditions of Bayesian network are determined again probability table, the ultimate establishment of coal mining gas explosion Bayesian network model.

3.1 Bayesian network nodes and their range

For developing dynamic operational risk assessment methodology based on the Bayesian network, it is important to identify the scope of work. It is also necessary to describe the system. According to the requirement, the scope can vary from small scale to large scale of the system. For system description, Bayesian network nodes and their range must be determined.

Combined with previous research results and gas explosion accident sample information [17], the following elements are determined as the model nodes. Coal mining gas explosion accident is considered as the destination-node of Bayesian network structure, where M is denoted as its number. The remaining nodes are classified according to human factors, material factors, environmental factors and management factors. Then, determine the value range of each node. The value range for each node is defined as two values {0,1}, where 0 is for no error and 1 for the errors. The detailed factors are shown in Table 1.

3.2 Our network structure

The next step is to identify the possible initiating event that can lead to accident. To identify possible initiating event, it is required to perform any hazards identification method which can be used to develop scenarios. Thus, Bayesian network can be detained by causal factors.

Firstly, aiming at each accident sample, the causal relationship between different mistakes is determined, so as to find the causal relationship chain, and then the causal relationship chain is integrated to determine the final Bayesian network model. Specific steps are described as follows:

(1) For the accident samples, identify the chain of the accident.
Based on the network nodes identified above, 243 gas explosion investigation reports of China are collected to determine the cause of the occurred accident so as to identify the causal chain of accidents in accordance with the direct cause of gas explosions caused by the fire source and gas accumulation.

(2) Find the causal chain based on more accidents
Taking the sample in step one as an example, the two causal chains are integrated to obtain the causal chain of accidents, as shown in Fig. 1.

(3) Establish Bayesian network structure
As shown in Step 2, the causal relationship chains of all the accident samples are integrated to form a

Table 1 Bayesian network node and range

Category	Reason name	Symbol	Range	
			No	Yes
Accident	Gas explosion	M	0	1
Human factor	Low safety awareness	R1	0	1
	Unsafe behavior	R2	0	1
Material factor	Gas monitoring system failure	W1	0	1
	Ventilation system chaos	W2	0	1
	Blasting cause	W3	0	1
	No explosion protection	W4	0	1
	Collision spark and open fire	W5	0	1
Management factor	Faultiness regulations	G1	0	1
	Unfulfillment safety training	G2	0	1
	Weak security enforcement	G3	0	1
	Improper technical management	G4	0	1
Environmental factor	Gas accumulation	H1	0	1
	Sufficient oxygen	H2	0	1
	Spontaneous combustion	H3	0	1

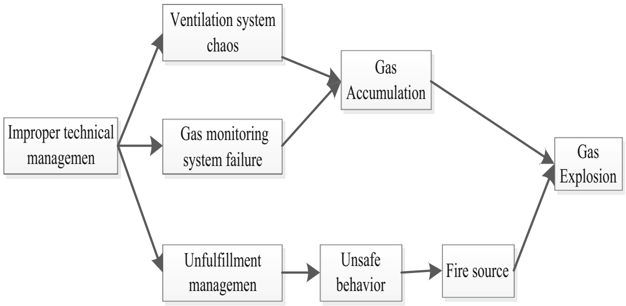

Fig. 1 Cause-and-effect diagram for gas explosion accident

Bayesian network structure. In addition, it is found that the causal relationship with spontaneous combustion factors exists only in rare cases. In order to reduce the complexity of the network model, the Bayesian network structure with 11 nodes is ultimately determined as shown in Fig. 2.

3.3 Conditional probability between nodes

The determined conditional probabilities between nodes in this paper are calculated from the occurred accident samples. All the samples are based on gas explosion accidents, and the conditional probability is obtained by continuously learning 243 gas explosion sample data. The probability values in the conditional probability table indicate the probability of occurrence of child nodes according to two states of the parent node. Through the statistical calculation of 243 coal-mine gas explosion accidents in China mining history, the conditional probability table is obtained, as

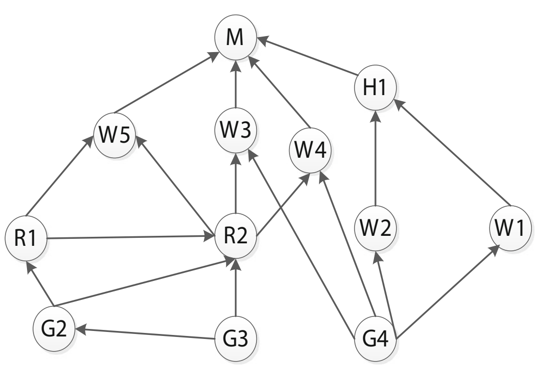

Fig. 2 Bayesian network structure for gas explosion accident

Table 2 Conditional probability table

G3	0	1	G4	0	1			
G3	0.55	0.45	G4	0.51	0.49			
G3	0	1	G4	0	1	G4	0	1
G2	0	0.73	W1	0.28	0.74	W2	0.33	0.52

Table 3 Conditional probability table

R2	0		1		G4	0		1	
G4	0	1	0	1	R2	0	1	0	1
W3	0	0.14	1	1	W4	0.33	0.45	0.60	0.90
R2	0		1		W2	0		1	
R1	0	1	0	1	W1	0	1	0	1
W5	0	0.67	0.26	0.63	H1	0	0.53	1	1
G2	0		1						
G3	0	1	0	1					
R1	0	0.58	0.63	1					

Table 4 Conditional probability table

R1	0				1			
G2	0		1		0		1	
G3	0	1	0	1	0	1	0	1
R2	0	0.09	0.75	0.91	0.75	1	0.97	1

Table 5 Conditional probability table

H1	0							
W4	0				1			
W3	0		1		0		1	
W5	0	1	0	1	0	1	0	1
M	0.06	0.02	0	0	0	0	0	0
H1	1							
W4	0				1			
W3	0		1		0		1	
W5	0	1	0	1	0	1	0	1
M	0	0.67	0.91	0.97	0.68	0.56	0.97	1

shown in Tables 1, 2, 3, 4 and 5. The probability values of the sub-nodes in the table are the values of state 1, namely, the probability of occurrence.

4 Bayesian network model verification and analysis

4.1 Model verification for coalmine gas explosion

In order to determine our Bayesian network model, GeNIe is adopted to construct the theoretical model for graphical decisions, which is a software developed by the Decision Systems Laboratory, Pittsburgh University in USA. According to the proposed Bayesian model for coalmine gas explosion accident above, a model simulation diagram is constructed by using node tools and directed edges in GeNIe. The simulation model is shown in Fig. 3.

In order to verify the validity of our model, 25 cases of gas explosion are selected to verify the model. Taking gas explosion investigation report in a mine as an example, the causes of the accident are analyzed as "unsafe behavior R2", "frictional impact W3", "Unfulfillment equipment or fire zone management G3" and "gas accumulation H1". The four factors are set as "evidence node", and its node condition has the "state1" probability with 100% input model. Then, run the simulation model, whose result is shown in Fig. 3

According to the simulation results of the model, the probability of the accident is 98%. Similarly, the remaining 24 samples in the accident sample are researched, where we are found there are 7 accidents greater than or equal to 95%; 11 cases occurred between 90 and 95%; three accidents occurred in 85–90%; No accident occurred is below 85%. Therefore, under the model inference established in this paper, 25 groups of accident samples all have an accident rate higher than 85%; in other words, the occurrence probability of an accident is extremely high, which is consistent with the fact that the accident has occurred. Therefore, the model established in this paper has some validity in the analysis of gas explosion accidents, and can perform Bayesian model inference.

4.2 Cause analysis

Based on the Bayesian network model established by GeNIe software, the posterior probability of each network node under the condition of accident can be deduced to find out the most likely causal chain. The gas explosion node M is set to occurrence state, namely, p (M = 1) = 100%. Then, we run the inference to get the posterior probability of each node under the condition of gas explosion accident, as shown in Fig. 4. Finally, reversely find a parent node with the highest posterior probability from node M. It should be noted that the gas explosion must have two conditions: gas accumulation and fire source, so we need to find the cause of the chain [14].

(1) Gas accumulation.
The parent node of the gas accumulation is H1 in M, so the chain is {H1-M}; the two parent nodes of H1 are W1, W2, where the posterior probability of W2 is the largest, so the chain is {W2-H1-M}; G4 is only a parent node, so the chain is {G4-W2-H1-M}. It can be concluded that the most likely causal chain for gas accumulation is {G4-W2-H1-M}, as shown by the bold line in Fig. 4.

(2) Fire source problem.
There are three parents that can become fire source in M, the posterior probability of W4 is larger than W5 and W3, so the chain is {W4-M}; W4 has only one parent node G4, so the chain is {G4-W4-M}; we can also find other causes chain on the basis of the

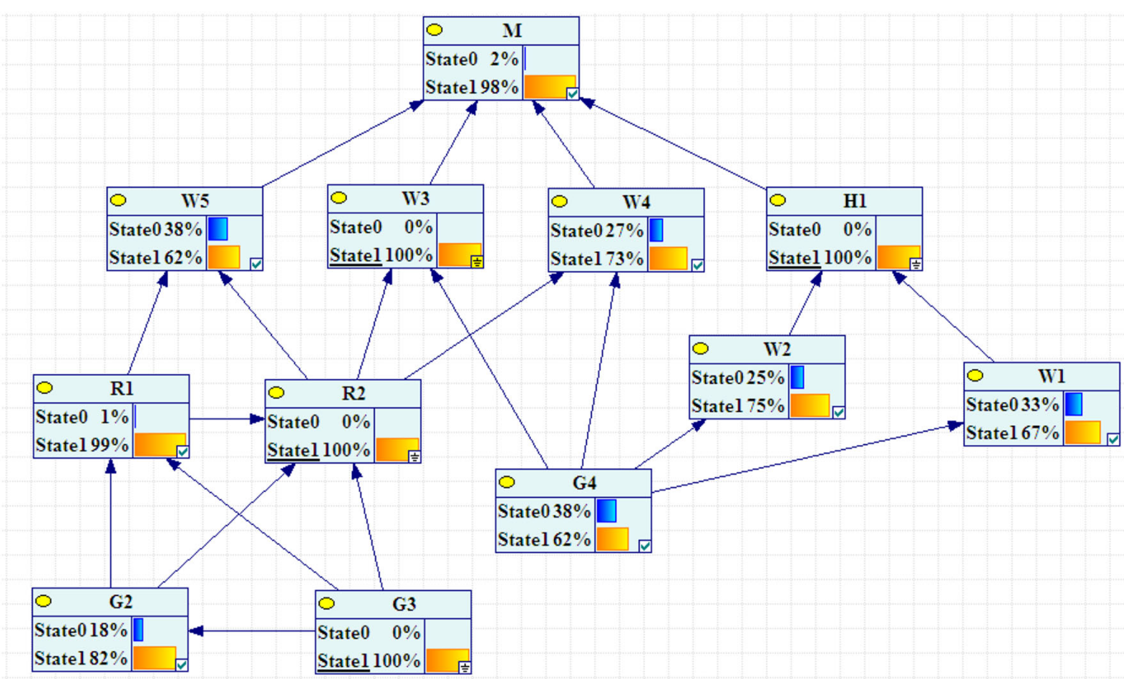

Fig. 3 Model verification

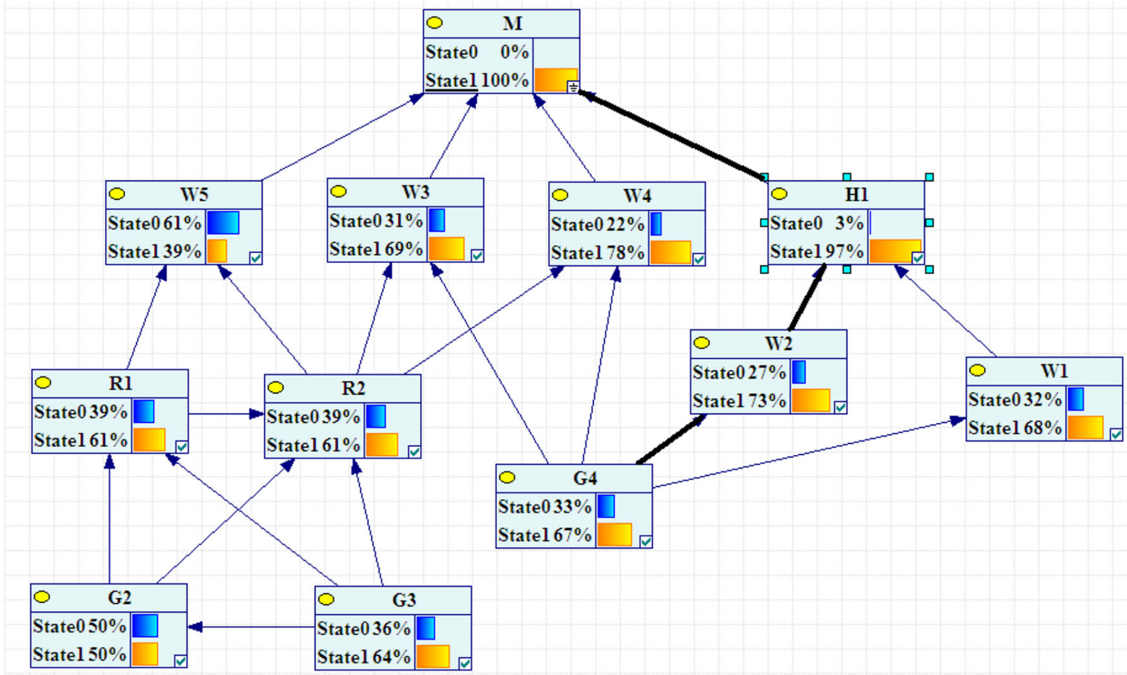

Fig. 4 Mine gas explosion accident Bayesian network

above step, such as {G3-R2-G4-W4-M} and {G3-R1-R2-G4-W4-M}.

According to practical probability of occurrence, the two chains are not the most likely cause of the network, but this does not mean that gas explosion will not follow these causal chains. Therefore, the cause chain of gas explosion accident is {G4-W4-M}.

4.3 Summary and recommendations

Application of Bayesian network in the field of coalmine process safety and risk analysis offers number of advantages. Bayesian network can combine the expert judgment and quantitative knowledge to estimate risk. In addition, it demonstrates changes of variables with time through the reasoning process. Application of Bayesian network is very much helpful for the area where the availability of data is limited.

Firstly, it is reasonable to select the parent node with the highest posterior probability in turn to constitute the chain of accident causes, which is based on the occurrence probability of node itself and the conditional probability between nodes. GeNIe mainly adopt the joint tree algorithm to perform inference. The posterior probability of each node needs to be propagated through the message and gradually calculated by the conditional probability in the joint tree inference algorithm. It showed that the posterior probability of each node contains the relationship between the child nodes and the parent nodes, so the posterior probabilities of the child nodes and the parent nodes are not independent but related to each other [18].

Secondly, starting from the top-level node, the parent node with the highest posterior probability will be found by diagnostic inference mode using Bayesian network. In Bayesian networks, the parent node and the child nodes are causal relationships. Starting from the child node which represents the result, the parent node with the highest posterior probability was found in the process of the diagnostic inference and causal analysis of the accident.

The parent node with the highest posterior probability is selected from several parent nodes of a child-node, which is equivalent to choosing the one with the highest occurrence probability from several reasons leading to the result, and further determine the chain of the selected nodes, where the chain has also become the most likely cause of the accident chain.

Finally, the most likely causal chain selected in this paper represents the most probable path leading to the accident, which does not preclude other causal chains at all, and only demonstrate the occurrence probability of other causal chains is relatively small. However, the root cause of these probabilities comes from the statistical results of accidental samples. After all, the number of accidental samples is limited and the accident itself is a small probability event. Therefore, it does not exclude that the accident occurs according to the path of other causes.

Through data verification and experiment, it is found that our proposed method is feasible. In addition, the probability comparison between nodes can be more intuitively carried out from the visual interface of software to find out the cause chain which causes the accident. This study demonstrates time dynamic Bayesian network for dynamic operational risk assessment. This methodology has the ability to provide updated probability with time, to incorporate inspection and testing time interval, which shows its effect on the critical event probability. As this technique is based on Bayesian network, it has the advantages of flexibility in modeling. This technique is very efficient to estimate risk in comparison to other techniques with respect to time and efforts.

5 Conclusion

In this paper, Bayesian network is used to establish a causal analysis model of coal mine gas explosion. The direct impact factors of gas explosion accidents are gas accumulation, electrical without explosion protection, frictional impact and open flame. It is very important and has a greater significance for preventing and controlling coal mine gas explosion. The Bayesian network model is validated by GeNIe software. The test experiment shows that the model has high prediction accuracy and can be used to effectively analyze the causal factors of accidents. Then, the GeNIe software is used to calculate the Bayesian network model. Starting from the two conditions of gas accumulation and fire source that the gas explosion accident must possess, the most likely causes of the coalmine gas explosion accidents are obtained. The most probable cause of the coal-mine gas explosion accident shows that the inadequate technical management in the management elements has a relatively large impact on the accident. Technical management is not in place will result in many physical factors such as ventilation, electrical and other anomalies, and further occur coalmine gas explosion accident. Therefore, technical management should be strengthened to raise safety awareness and reduce equipment system abnormalities, to reduce such accidents and the hazards caused by explosion accident.

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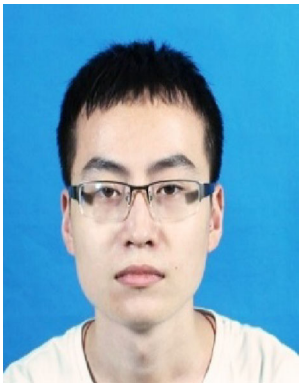

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