Gas Overrun Risk Assessment in Coal Mining Face Based on Fuzzy Bayesian Network

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Abstract. A risk assessment technology based on a fuzzy Bayesian network is proposed to improve the degree of gas control management in the coal mining face and avoid gas overrun. Five characteristics of the coal mining working face, i.e., geological structure, ventilation conditions, gas extraction, mining activities, and coal mine management affecting the coal mining working face, were examined for 17 risk variables and a gas overrun assessment model was created. A priori information and sample data indicate that there is a 3% chance of gas overflow. The reverse reasoning test found that the main reasons for gas overrun were unreported gas anomalies, ventilation modes, gas content in coal seams, goaf extraction volume, and coal mining rate in coal mining face. The research results show that the approach can assess the risk of gas overflow in coal mining face.

1.Introduction

In the process of mine safety production, gas is one of the main threats, and its concentration is too high to prevent accidents such as gas explosions. The coal mine law stipulates that when the gas concentration in the return air duct exceeds 1%, underground production operations must be stopped, employees must be evacuated, and specific emergency measures must be taken to reduce the gas concentration. The diffusion of coal seam gas and the severity of the gas compound environment worsen with the increase of mine depth [1]. The largest gas leak in mining occurs during recovery operations, where gas concentrations are also high and prone to gas overruns, resulting in personal injury and property damage. Therefore, it is essential to carry out a risk assessment on gas overrun in the coal mining face to ensure safe and effective coal mining.

The two main categories of coal mine risk assessment are quantitative and qualitative techniques. Qualitative approaches include event tree analysis (ETA), fault tree analysis (FTA), hierarchical analysis, support vector machine, neural network, etc. Quantitative methods include pre-danger analysis, expert interviews, brainstorming, and fuzzy comprehensive assessment methods. The evaluation items include the assessment of coal mine geology [2] and water hazards [3], as well as human factors [4] and occupational risk [5].

Fuzzy Bayesian networks have currently been successfully applied in some fields, including the analysis of unsafe information regarding the transportation of road tankers [6], the risk assessment of shields under existing tunnels [7], and the assessment of the collision risk of the Floating Production Storage and Offloading (FPSO) oil and gas outbound transmission system [8]. The aforementioned findings suggest that further risk diagnosis and prediction studies on system hazards using fuzzy numbers combined with Bayesian networks are feasible when direct access to risk information is challenging.

There are more studies assessing gas hazards than gas overrun risks, although many factors influence gas overrun and a lack of accurate statistics make proper assessment challenging using conventional techniques. For this reason, this paper proposes a risk assessment method for gas overrun in coal mining face based on a fuzzy Bayesian network, using fuzzy numbers to describe the ambiguity of event occurrence state and probability of occurrence, and using the expert scoring method to obtain the occurrence probability of risk events, and determining the risk state and risk probability of various gas overrun in coal mining face through fuzzy Bayesian network.

2.Construction of the gas overrun likelihood index in coal mining faces

Developing consistent assessment models is challenging due to the complex factors affecting gas overrun and the diversity of evaluation techniques. In this research, an evaluation index system with five influencing variables, including ventilation conditions, geological structures, gas extraction, mining activities, and coal mine management of coal mining faces, was constructed in Mine Safety [2021] No. 9 notice.

Ventilation Conditions (Y1). Ventilation is a key means to prevent gas overrun, and the ventilation condition of the working face directly affects the occurrence of gas overrun at the working face. The

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amount of underground air distribution is directly affected by variations in mine ventilation resistance. In the mine, several ventilation methods such as U type, Y type, and U+L type are utilized, which affects the further leakage of gas. Therefore, the working face windage (Q1), air volume (Q2), and ventilation modes (Q3) are the key influencing factors of ventilation.

Geological Structures(Y2). The early gas composition of the coal seam accounts for a significant amount of gas flowing out of the mining face. The thicker the coal seam in a well site, the more gas in that well site. With the increase of the complexity of the coal seam, the coal gauge produced in the coal seam increases, which in turn has a certain impact on the gas emission [9]. As the degree of damage increases, the complexity of coal seam gas content (Q4), coal seam thickness (Q5), coal seam texture type (Q6), and coal seam failure type (Q7) also increases [10].

Gas Extraction (Y3). Gas extraction can greatly reduce the possibility of gas surges and gas overflows. During the whole extraction process, when the gas pressure in the coal seam gradually decreases, the gas volume can be effectively reduced. The amount of gas released is also affected by the separation between drill holes used for extraction. As the gas extraction increases, the gas concentration decreases and the gas outflow also decreases. The diameter of coal seam drilling and sealing holes is directly related to the efficiency of gas extraction [11]. Therefore, the variables affecting gas extraction are extraction time (Q8), sealing quality (Q9), borehole interval (Q10), and goaf extraction volume (Q11).

Mining Activities (Y4). During the mining process, the gas gushes out high or even abnormally, which leads to the situation of gas overrun. The coal left in the mining area will continuously release gas. Increasing the recovery rate can reduce the coal left, thereby reducing the gas gushing out [12]. The periodical incoming pressure is closely related to gas overrun at the working face, and the two have a consistent increasing and decreasing relationship. Meanwhile, due to the concentrated stress, the coal seam sheet side blocks the space, and the wind flow gushes into the mining area, resulting in gas overrun [13]. Mining is mainly affected by the coal mining rate of the coal mining face (Q12), weighting step (Q13), and coal seam spalling (Q14).

Coal Mine Management (Y5). The main reasons for gas overrun due to poor management and human error are non-reporting of non-reporting of gas abnormalities (Q15), poor implementation of gas management measures (Q16), and unreliable ventilation systems (Q17).

3.Safety risk assessment model based on fuzzy Bayesian network for coal mine gas overrun

A directed acyclic network called a Bayesian network (BN) consists of many conditional probability tables (CPT) and a directed acyclic graph (DAG). There are multiple nodes and control behaviors in a DAG. DAG is composed of many nodes and directed edges, where the nodes represent variables, and directed edges point from root nodes to the leaf nodes, reflecting the dependencies between the variables [14]. Each root node combination is represented by the conditional probability of each node. The following is the joint probability formula.

$$\begin{aligned} P(q_1,q_2,\cdots,q_n) &= P(q_1)P(q_2\,|\,q_1)\cdots P(q_n\,|\,q_1,q_2,\cdots q_{n-1}) \\ &= \prod_{i=1}^{n} P(q_i\,|\,q_1,q_2,\cdots q_{n-1}) \end{aligned} \tag{1}$$

Typically, the state node of the Bayesian network has two states: state0, indicating that the risk event specified by the node has not occurred (state0), which indicates that the risk event has occurred (state1). Having only two states does not adequately describe the situation because the state of the node cannot be assessed in a practical example. Therefore, this study uses three different types of node states (0, 1, and 2) to denote whether an event occurs, may occur, or does not occur.

3.1 Description of nodal probabilities

This study explores the use of fuzzy numbers to represent the probability of risk events, in order to solve the problem of the lack of a large number of correct data for risk events. Fuzzy numbers exist in various shapes [15], but the triangle fuzzy number operation is the most straightforward and user-friendly, therefore this work employs it to illustrate the likelihood of a gas overflow risk event. The following is a display of the affiliation function.

$$f(x)=\begin{cases} 0, x< a \\ (x-a)/(m-a), a \le x \le m \\ (b-x)/(b-m), m \le x \le b \\ 0, x> b \end{cases} \tag{2}$$

Where a denotes the minimum value of the state of this node, m denotes the most probable value of the node state, and b denotes the maximum value of the state of this node.

This study produced a questionnaire in which the language evaluation values of the four experts were divided into seven categories, from very low to very high: “low,” “On the low side,” “medium,” “On the high side,” “high,” and “very high.” This is done to integrate expert judgment with fuzzy numbers. The corresponding quantitative values are 0, 0.1, 0.3, 0.5, 0.7, 0.9, and 1. Fuzzy triangular numbers translate the expert language into fuzzy interval values, as shown in Table. 1. If an expert evaluates a node in a certain state as “high”, then the linguistic value corresponding to this level is 0.9, and its upper limit, most probable value, and lower limit of fuzzy number are 0.7, 0.9, and 1, respectively, as shown in Table 1.

Table 1 Expert linguistic evaluation.

No.	Semantic	Fuzzy number
1	Very low	(0, 0, 0.1)
2	Low	(0, 0.1, 0.3)
3	On the low side	(0.1, 0.3, 0.5)
4	Moderate	(0.3, 0.5, 0.7)
5	On the high side	(0.5, 0.7, 0.9)
6	High	(0.7, 0.9, 1)
7	Very high	(0.9, 1, 1)

3.2 Node probability calculation

Assume that the Bayesian model consists of m root nodes, denoted as ($X_1, X_2, \ldots, X_m$), and the root node X_i has K_j states, and its state space is $(0, 1, \ldots, K_{j-1})$. The probability that the root node is in a different state is determined by the judgment n experts, and the linguistic variables for determining the probability of the root node being in a certain X_i in a certain h state provided by the I experts are converted into a triangular fuzzy number with the following formula.

$$\tilde{n}^i_{j,h} = (a^i_{j,h}, b^i_{j,h}, c^i_{j,h}), i \in [1,n], j \in [1,m], h \in [1, k_j - 1] \tag{3}$$

Where $\tilde{n}^i_{j,h}$ denotes the score of an expert's judgment on the node state.

To more accurately quantify the probability of risk events using fuzzy quantification, the arithmetic average method is used to calculate the evaluation results given by each expert, and the formula is as follows

$$\tilde{n}^{`}_{j,h} = \tilde{n}^1_{j,h} \oplus \tilde{n}^2_{j,h} \oplus \cdots \oplus \tilde{n}^n_{j,h} = (a^{`}_{j,h}, b^{`}_{j,h}, c^{`}_{j,h}) \tag{4}$$

Where $\tilde{n}^i_{j,h}$ denotes the status score of the node after integrating all experts' opinions.

Since fuzzy numbers are not conducive to direct Bayesian network inference, it is necessary to defuzzify the fuzzy probability. The methods currently used for defuzzification include the center of gravity method, affiliation limit element averaging method, mean area method, weighted average method, integral method, etc. Among them, the mean area method is simple and convenient to calculate. This method is used to calculate the mean value of triangular fuzzy probability given by experts.

$$n^{`}_{j,h} = (a^{`}_{j,h} + 2b^{`}_{j,h} + c^{`}_{j,h}) / 4 \tag{5}$$

To ensure the normalization of the probability, the exact probability of the node needs to be normalized to ensure that under different risk levels, the sum of probability values is always 1, and the probability value is required for the final inference calculation. The formula is as follows.

$$n_{j,h} = \frac{n^{`}_{j,h}}{\sum_{k=0}^{k_j-1} n^{`}_{j,h}} \tag{6}$$

Where $n_{j,h}$ denotes the probability of occurrence of the state j at a point h after normalization, $n^{`}_{j,h}$ denotes the probability of occurrence of the j node h state before normalization.

After deriving the probability values, the subsequent inference calculation is completed with the help of Genie software. In the Bayesian network structure of gas overrun evaluation at the recovery face, "State0" means the event does not occur, "State1" means the event may occur, and "State2 " represents the event that must occur.

3.3 Construction of Bayesian network structure model

The existing gas overrun risk evaluation index system in mining face is shown in Table 2, and the Bayesian network structure is used to visually represent the coupling relationship between various risk factors and gas overflow events, as shown in Table 2.

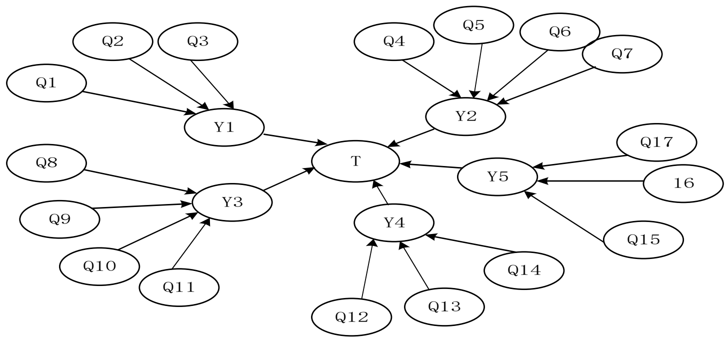

Figure 1 Bayesian network model of gas overrun at the recovery stage.

Table 2 Fuzzy Bayesian node indicators.

No.	Indicator	No.	Indicator
T	Gas overrun in coal mining face	Q7	Coal seam failure types
Y1	Ventilation conditions	Q8	Extraction time
Y2	Geologic structures	Q9	Sealing quality
Y3	Gas extraction	Q10	Borehole interval
Y4	Mining activities	Q11	Goaf extraction volume
Y5	Coal mine management	Q12	Coal mining rate of the coal mining face
Q1	Windage	Q13	Weighting step
Q2	Air volume	Q14	Coal seam spalling
Q3	Ventilation modes	Q15	Non-reporting of gas abnormalities
Q4	Coal seam gas content	Q16	Poor implementation of gas management measures
Q5	Coal seam thickness	Q17	Unreliable ventilation system
Q6	Coal seam texture types		

3.4 Calculation of a priori probability of the root node

Based on the fuzzy triangular numbers provided in Equation (3), four experts evaluate the prior probabilities of the nodes, which are then determined using Equations (4), (5), and (6). Taking the Q1 node as an example, the previous probability of various states of the Q1 root node is calculated, and the results are shown in Table 3.

Table 3 Prior probabilities of different states of the Q1 root node.

Condition	Triangular fuzzy probability of different experts				A priori probability
	A1	A2	A3	A4	
T0	(0.7,0.9,1)	(0.7,0.9,1)	(0.7,0.9,1)	(0.9,1，1)	0.77
T1	(0.1,0.3,0.5)	(0,0.1,0.3)	(0,0.1,0.3)	(0,0.1,0.3)	0.14
T2	(0,0.1,0.3)	(0,0,0.1)	(0,0.1,0.3)	(0,0.1,0.3)	0.08

4.Fuzzy Bayesian network model inference

4.1 Quantitative analysis

After building a Bayesian network through an indexing scheme, the prior probability of an accident at each root node must be established. Since the prior likelihood of a root node cannot be determined from the literature alone, the prior probability of each root node of gas overrun was determined by looking at mine production, talking to pertinent specialists, and synthesizing numerous reference sources, as shown in Table 4.

Table 4 Prior probability of each root node.

Symbol	Root node	Prior probability	Symbol	Root node	Prior probability
Q1	Windage	0.087	Q10	Borehole interval	0.023
Q2	Air volume	0.091	Q11	Goaf extraction volume	0.085
Q3	Ventilation modes	0.070	Q12	Coal mining rate of the coal mining face	0.067
Q4	Coal seam gas content	0.091	Q13	Weighting step	0.070
Q5	Coal seam thickness	0.068	Q14	Coal seam spalling	0.087
Q6	Coal seam texture types	0.089	Q15	Non-reporting of gas abnormalities	0.087
Q7	Coal seam failure types	0.070	Q16	Poor implementation of gas management measures	0.086
Q8	Extraction time	0.027	Q17	Unreliable ventilation system	0.087
Q9	Sealing quality	0.027			

Four senior experts were invited to evaluate the degree of correlation between the leaf nodes and root nodes, as well as to examine and evaluate expert linguistic factors and their associated triangular fuzzy numbers. The results are shown in Table 5. The information in Table 5 was homogenized and fuzzification to obtain the conditional probabilities of each leaf node. Taking ventilation (Y1) as an example, the results are shown in Table 6.

Table 5 Exert assessment results.

Conditions	The first exert			The second exert			The third exert			The fourth exert		
	state 0	state 1	state 2	state 0	state 1	state 2	state 0	state 1	state 2	state 0	state 1	state 2
P(Y1=0|Q1=0,Q2=0,Q3=0)	VH	VL	VL	VH	VL	VL	VH	VL	VL	VH	VL	VL
P(Y1=0|Q1=0,Q2=0,Q3=1)	VH	L	VL	VH	VL	VL	VH	L	L	H	L	L
P(Y1=0|Q1=0,Q2=0,Q3=2)	VH	L	VL	VH	L	L	H	FL	L	H	L	L
P(Y1=0|Q1=0,Q2=1,Q3=0)	H	VL	VL	VH	L	VL	H	L	L	VH	L	L
P(Y1=0|Q1=0,Q2=1,Q3=1)	H	L	VL	VH	L	L	VH	FL	L	H	L	L
P(Y1=0|Q1=0,Q2=1,Q3=2)	H	L	L	VH	L	L	H	L	L	H	VL	FL
P(Y1=0|Q1=0,Q2=2,Q3=0)	H	VL	VL	H	L	VL	H	FL	VL	FH	L	L
P(Y1=0|Q1=0,Q2=2,Q3=1)	H	L	L	FH	FL	FL	H	M	L	FH	L	L
P(Y1=0|Q1=0,Q2=2,Q3=2)	H	FL	L	FH	FL	L	H	L	L	H	L	L
P(Y1=1|Q1=1,Q2=0,Q3=0)	VH	VL	VL	VH	VL	VL	VH	L	VL	VH	VL	VL

Conditions	The first exert			The second exert			The third exert			The fourth exert		
	state 0	state 1	state 2	state 0	state 1	state 2	state 0	state 1	state 2	state 0	state 1	state 2
P(Y1=1|Q1=1,Q2=0,Q3=1)	H	VL	VL	H	VL	L	VH	L	L	VH	L	L
P(Y1=1|Q1=1,Q2=0,Q3=2)	VH	L	FL	VH	L	L	H	L	FL	H	L	L
P(Y1=1|Q1=1,Q2=1,Q3=0)	H	L	VL	H	FL	L	H	FL	L	H	L	L
P(Y1=1|Q1=1,Q2=1,Q3=1)	H	L	L	H	L	VL	H	L	VL	FH	L	L
P(Y1=1|Q1=1,Q2=1,Q3=2)	H	VL	L	H	L	L	H	L	L	H	L	L
P(Y1=1|Q1=1,Q2=2,Q3=0)	H	L	L	FH	FL	VL	H	L	L	VH	L	L
P(Y1=1|Q1=1,Q2=2,Q3=1)	H	L	L	FH	L	VL	H	FL	L	VH	L	L
P(Y1=1|Q1=1,Q2=2,Q3=2)	H	L	L	H	L	L	H	L	L	VH	L	FL
P(Y1=2|Q1=2,Q2=0,Q3=0)	VH	VL	VL	VH	VL	VL	H	VL	L	VH	L	VL
P(Y1=2|Q1=2,Q2=0,Q3=1)	H	L	VL	H	L	L	FH	L	L	H	FL	L
P(Y1=2|Q1=2,Q2=0,Q3=2)	VH	L	L	H	L	VL	H	L	L	H	L	VL
P(Y1=2|Q1=2,Q2=1,Q3=0)	H	VL	VL	H	VL	VL	H	L	VL	VH	L	VL
P(Y1=2|Q1=2,Q2=1,Q3=1)	H	VL	VL	FH	VL	VL	H	L	VL	VH	L	VL
P(Y1=2|Q1=2,Q2=1,Q3=2)	H	VL	VL	FH	VL	VL	H	L	VL	H	VL	VL
P(Y1=2|Q1=2,Q2=2,Q3=0)	H	L	L	H	L	L	H	VL	VL	H	VL	VL
P(Y1=2|Q1=2,Q2=2,Q3=1)	H	L	L	H	FL	L	H	FL	L	H	L	L
Y1=2|Q1=2,Q2=2,Q3=2)	H	FL	L	H	FL	L	H	FL	L	FH	FL	L

Table 6 Conditional probabilities of each leaf node. (a)

Conditional probability	State 0	State 1	State 2
P(Y1=0|Q1=0,Q2=0,Q3=0)	0.95121951	0.024390244	0.024390244
P(Y1=0|Q1=0,Q2=0,Q3=1)	0.84444444	0.088888889	0.066666671
P(Y1=0|Q1=0,Q2=0,Q3=2)	0.7628866	0.13917526	0.097938144
P(Y1=0|Q1=0,Q2=1,Q3=0)	0.84090909	0.090909091	0.068181818
P(Y1=0|Q1=0,Q2=1,Q3=1)	0.77486911	0.14136126	0.083769633
P(Y1=0|Q1=0,Q2=1,Q3=2)	0.77005348	0.085561497	0.14438503
P(Y1=0|Q1=0,Q2=2,Q3=0)	0.81097561	0.1402439	0.048780488
P(Y1=0|Q1=0,Q2=2,Q3=1)	0.68478261	0.22826087	0.08695652
P(Y1=0|Q1=0,Q2=2,Q3=2)	0.71122995	0.18181818	0.10695187
P(Y1=1|Q1=1,Q2=0,Q3=0)	0.92857143	0.047619048	0.023809523
P(Y1=1|Q1=1,Q2=0,Q3=1)	0.83333333	0.095238095	0.071428572
P(Y1=1|Q1=1,Q2=0,Q3=2)	0.73267327	0.16831683	0.099009901
P(Y1=1|Q1=1,Q2=1,Q3=0)	0.73684211	0.17894737	0.084210527
P(Y1=1|Q1=1,Q2=1,Q3=1)	0.80606061	0.12121212	0.072727273
P(Y1=1|Q1=1,Q2=1,Q3=2)	0.79545455	0.11363636	0.090909091
P(Y1=1|Q1=1,Q2=2,Q3=0)	0.76111111	0.15	0.088888889
P(Y1=1|Q1=1,Q2=2,Q3=1)	0.77486911	0.14136126	0.083769633
P(Y1=1|Q1=1,Q2=2,Q3=2)	0.7539267	0.14136126	0.10471204
P(Y1=2|Q1=2,Q2=0,Q3=0)	0.9047619	0.047619048	0.047619047
P(Y1=2|Q1=2,Q2=0,Q3=1)	0.76111111	0.15	0.088888889
P(Y1=2|Q1=2,Q2=0,Q3=2)	0.81818182	0.11363636	0.068181818

(b)

P(Y1=2|Q1=2,Q2=1,Q3=0)	0.77005348	0.14438503	0.085561497
P(Y1=2|Q1=2,Q2=1,Q3=1)	0.69191919	0.17171717	0.13636364
P(Y1=2|Q1=2,Q2=1,Q3=2)	0.73888889	0.15	0.11111111
P(Y1=2|Q1=2,Q2=2,Q3=0)	0.81395349	0.11627907	0.069767442
P(Y1=2|Q1=2,Q2=2,Q3=1)	0.72164949	0.17525773	0.10309278
P(Y1=2|Q1=2,Q2=2,Q3=2)	0.66169154	0.23880597	0.099502488

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4.2 Positive reasoning

Figure 2 illustrates the forward inference of the Bayesian network used in this study to determine the probabilities of events occurring at T0, T1, and T2, respectively. Since the likelihood of gas overrun in this functioning face is generally considered to be less than 5%, the probability of gas spillage at this working face is very low.

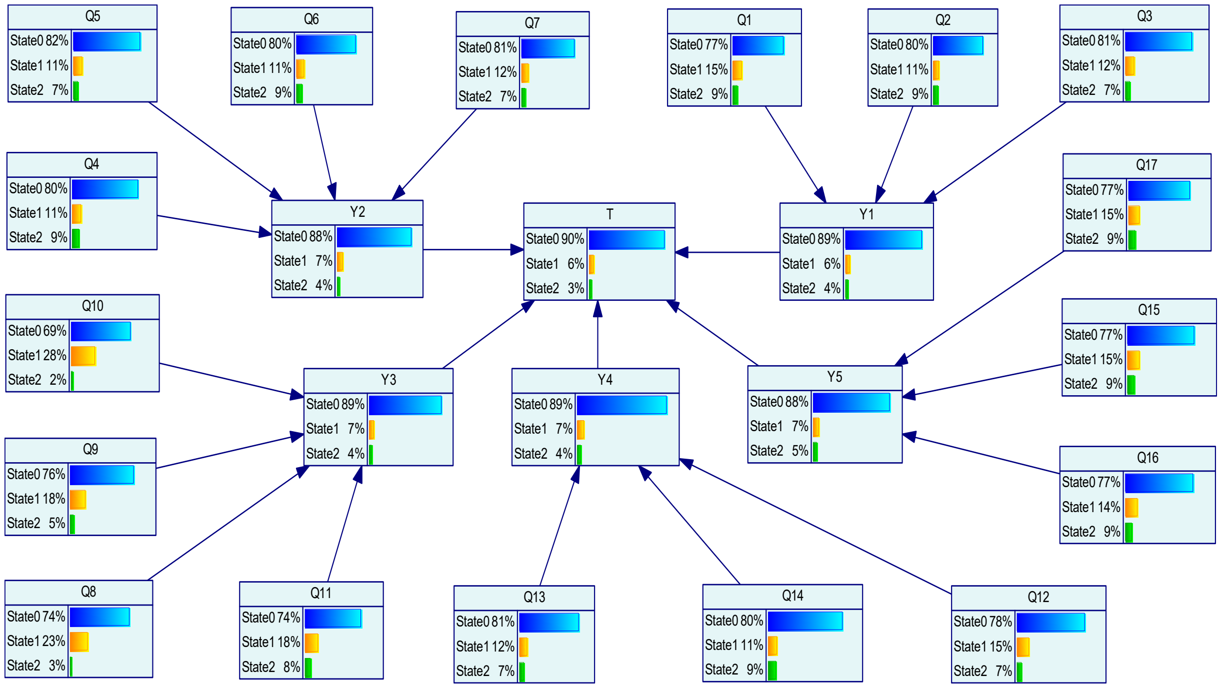

Figure 2 Bayesian network prior probability distribution.

4.3 Backward reasoning

This paper uses the diagnostic inference function of the Bayesian network to carry out reverse inference to find out the main reasons for the gas overrun risk in the coal mining face and the key factors affecting the occurrence of the event. Starting from the target node, the probability of occurrence of the target node T, i.e., gas overrun at the coal mining face, and its parent nodes Y1, Y2, Y3, Y4, and Y5 with state-level T2 are set to 100% at the same time, while the other risk state values are 0, as shown in Figure 3.

From the perspectives of ventilation technology, non-reporting of gas anomalies, ventilation methods, coal seam gas content, goaf extraction volume, and coal mining face at phase 2, the posterior probability of non-reporting of gas abnormal is greater than 15%. it can be seen that the factors that have the greatest impact on gas overrun in the 312 coal mining faces are non-reporting of gas anomalies, ventilation modes, coal seam gas content, goaf extraction volume, and coal mining rate of the coal mining face.

To prevent gas overrun in the coal mining face, the management should be strengthened, and the main measures are as follows.

(1) We should standardize the operator specifications, pay attention to the impact of gas overrun in the coal mining faces, and collect on-site gas anomaly information. To reduce accidents related to human error, technical managers and plant inspectors must properly apply gas control and prevention procedures.

(2) To reduce the gas gushing before the initial pressure or periodic pressure of the old roof, it is needed to select the appropriate ventilation method, strengthen the observation and evaluation of mine pressure in the mining face, and increase the ventilation rate appropriately.

(3) It is necessary to understand the gas transfer situation in geological structure belts, adjust measures to local conditions in a timely manner, and reduce the likelihood of uncontrollable gas disasters. When the gas concentration increases, we ought to increase the number of local ventilators and select the power of the ventilators to increase the air supply volume.

(4) To satisfy the requirements of the extracted gas pressure, it is important to use any type of hole, including waste holes, to increase the sealing of the quality of the hole and prevent the gas from escaping from the holes.

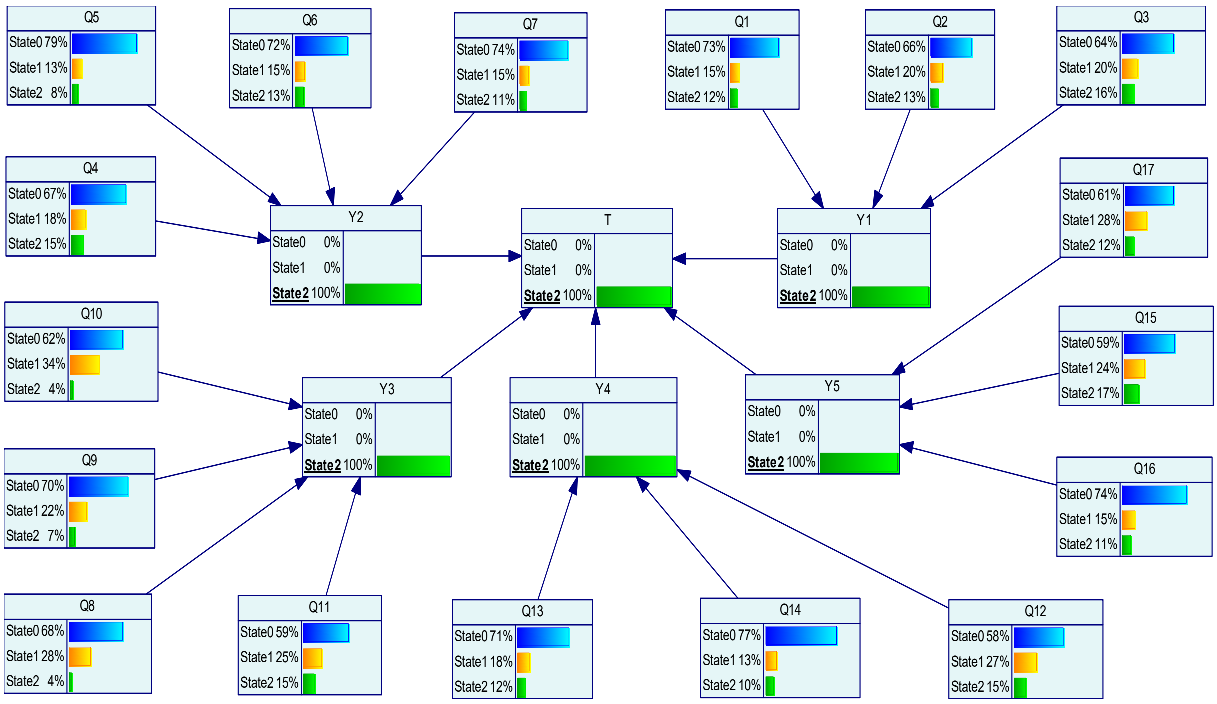

Figure 3 Bayesian network posterior probability distribution.

5.Summary

Based on the empirical analysis of a mine in Sichuan, this study proposes a gas overrun risk assessment method for coal mining face based on a fuzzy Bayesian network and draws the following conclusions.

(1) Gas overrun in coal mining face is affected by various risk factors. An in-depth analysis of the coal mining faces reveals 17 risk factors in five categories including geological structures, ventilation conditions, gas extraction, mining activities, and coal mining management, and constructs coal mining faces based on a fuzzy polymorphic Bayesian network.

(2) According to the favorable inference evaluation results, the coal mining face gas overrun grades are divided into the probabilities for T0, T1, and T2, corresponding to 90%, 6%, and 3%, respectively. It proves that the model has real-world application value when combined with the actual circumstance.

(3) The results of reverse reasoning show that the influencing variables that lead to gas overrun the limit include non-reporting of gas anomalies, ventilation modes, coal seam gas content, goaf extraction volume, and coal mining rate of the coal mining face. Combining these aspects with the assessment model will help the investigation of accident causes and procedures, which will also lay the foundation for reducing gas overrun in the coal mining face.

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