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Assessment Method of Coal and Gas Outburst: From the Perspective of TFN-MCS Theory

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Abstract: The prediction of coal and gas outburst risk can effectively prevent underground coal mine accidents. Due to the overlapping, coupling and complexity of coal and gas outburst in the development process, coal and gas outburst is generally Gaussian distribution or nearly Gaussian distribution, especially when the sample data in the research area is not accurate or the information is insufficient, the traditional evaluation model and method have certain limitations. To further improve the scientific and accurate prediction of coal and gas outburst risk level, a coupling model of coal and gas outburst risk assessment is established based on Monte Carlo stochastic simulation (MCS) and triangular fuzzy number (TFN) theory. Firstly, the index weight measurement value is determined by using expert opinions and AHP method. Then, the risk level and risk importance of coal and gas outburst risk assessment index are quantitatively described by using fuzzy semantics with five-level classification standards. Finally, the confidence interval of the comprehensive risk value of the coal mines to be evaluated in the research area is established. The research results show that after 20,000 simulation experiments with the coupling model, the calculation results have converged, and the confidence interval value of the system comprehensive risk simulation value of each coal mine is 95%, which can provide relevant decision support for the prevention and control planning of coal and gas outburst.

Keywords: Coal, Coal and Gas Outburst, Risk Assessment, Triangular Fuzzy Number Theory, Monte Carlo Stochastic Simulation

1. Introduction

As a major industrial feedstock, coal is deeply involved in global economic activities such as steel production and chemical manufacturing. Coal is also increasingly used to produce graphene and hydrogen and many other products used in the global economy [1]. As such, it is an important resource for the global economy. For many countries and regions, coal is a very important strategic core resource [2]. From this perspective, the sustainable and safe production of coal has affected the energy security of many countries. Underground mining is very dangerous due to the peculiarity and unpredictability of its environment, because the balance in the rock mass is disturbed in the process, which can lead to various types of natural disasters. For example, coal and gas eruption is a dynamic disaster in which the gas-bearing coal in the mine suddenly moves rapidly from the coal seam to the mine workings in the form of crushed powder, accompanied by a large number of gas jets. It is mainly driven by gas pressure, which is caused by geological factors, gas pressure and physical properties of coal [3, 4]. Coal and gas outburst disaster is recognized as one of the potentially fatal hazards to be controlled in the process of deep coal mining in the world, which seriously threatens the lives and property of miners [5]. Major coal producing countries such as China, India, Russia, Poland and the Czech Republic are constantly investing a lot of human and material resources to actively solve the outstanding problems [6, 7]. In order to effectively prevent coal and gas outburst accidents, it is necessary to carry out risk prevention and control in advance. At present, risk prediction is one of the most effective methods to prevent accidents [8]. From the perspective of coal mine production, reliable and accurate risk prediction is an important part of coal mine safety management. The key to advance risk prevention and control is to evaluate the risk of coal and gas eruption in production coal mines.

The existing literature on coal mine safety risk assessment provides examples of application experience, assessment model and calculation method. Generally speaking, there are three methods for coal and gas outburst risk assessment: qualitative analysis, semi-quantitative analysis and quantitative analysis. Qualitative analysis is mainly based on the subjective experience of risk assessors to evaluate the safety status of equipment, facilities, process flow, personnel positions and environmental atmosphere, such as PHA, FMEA, HAZOP and Bow-tie analysis. Semi-quantitative evaluation method is based on the subjective experience of evaluators, reasonably evaluate all kinds of risks, and apply tools such as risk classification table and risk matrix table to classify risks. This kind of method has strong operability and clear results, and is widely used in coal mining, metallurgy, transportation, electric power and other fields with relatively simple production systems and relatively few uncertain factors. LEC method, accident tree analysis method and MES method are the main methods. Quantitative analysis method is a method to calculate the quantitative risk value by assigning values to the risk factors involved in the evaluation object by using quantitative mathematical evaluation model. With clear risk factors, accurate data quantification and reasonable evaluation model, the risk grade can be accurately calculated, and different risk control objects can be compared horizontally, including TOPSIS [9], VIKOR [10], DEMATEL [11], fuzzy mathematics method [12] and various risk evaluation based on neural network algorithm [13, 14]. Although there are all kinds of decision analysis tools, practitioners usually do not know all the methods in the literature, and they can't estimate the benefits of specific methods for their specific problems. Each method has unique characteristics, and choosing the "best" method among too many available tools is really challenging. Therefore, more and more researchers choose to use hybrid techniques.

Due to the complexity of the coal and gas outburst process, the uncertainty, fuzziness and non-linearity of the influencing factors, especially in the process of secondary asphyxiation accidents caused by coal and gas outburst, and the complexity, overlapping and coupling of the accident evolution process, the asphyxiation characteristics are generally Gaussian distribution or approximate Gaussian distribution, especially when the sample data in the research area is not accurate or the information is insufficient, it is difficult to evaluate and simulate the risk of coal and gas outburst. Triangular fuzzy number (TFN) can be effectively used to express and process fuzzy information [15, 16] and it has good applicability when data and information are insufficient. However, the existing research on the relevant algorithms of TFN is not in-depth enough, and the calculation and simulation process are cumbersome, and some errors may occur. The Monte Carlo method is a stochastic simulation technology, which can deal with uncertainty and randomness well [17]. Using stochastic simulation method to simulate triangular fuzzy numbers and convert them into operations between ordinary real numbers can effectively deal with various uncertain information of coal and gas outburst risk systems, and it has good applicability for evaluation objects with less data and low accuracy.

The purpose of the study is to put forward a risk assessment method, which can reflect the current risk level of coal and gas outburst of the assessed object more comprehensively and accurately. This method uses triangular fuzzy theory to analyze the interdependence between evaluation indexes and determine the index weight more reasonably, which can fully express the expert's experience knowledge and fuzzy judgment. At the same time, Monte Carlo stochastic simulation is applied to the evaluation of coal and gas outburst to help decision makers determine the final evaluation level with more accurate evaluation value. The results of risk assessment can determine whether a specific mine needs to adjust its risk management policy and determine the priority objectives of risk prevention and control.

This paper puts forward an innovative method to evaluate the risk of coal and gas outburst. Its originality lies in that it can provide intuitive and accurate risk assessment results for the safety managers of coal mine production enterprises, help managers identify the weak links in the risk prevention and control of coal and gas outburst quickly and cheaply, and put limited safety management resources into the risk prevention and control dimension of high-risk coal and gas outburst accurately and efficiently. This is very important for coal mining enterprises to realize high quality and sustainable safety production.

2. Qualitative Analysis of Fuzzy Bow-Tie Model for Coal and Gas Outburst

2.1. Bow-Tie Model

Bow-tie analysis method [18] is based on the "triangle model" to conduct risk analysis in the form of bow, analyze how hazards are released and the serious consequences caused, identify the preventive measures before the release of hazards and mitigation measures after the release, and maintain the effectiveness of preventive and mitigation measures. As a hybrid qualitative risk analysis technique, bow-tie analysis can be regarded as an extended combination between fault tree and event tree, and the risks considered are the top events in fault tree and the initial events in event tree [19]. Bow-tie model graphically shows the relationship between hazard sources, harmful factors, preventive control measures, top-level events, mitigation measures and consequences in the form of a bow-tie, as shown in Figure 1.

On the left side, it is constructed according to the principle of fault tree analysis, enumerating the hazards and harmful factors that may develop or lead to certain top-level events, and enumerating the control measures that should be taken for the harmful factors corresponding to each hazard source; on the right side, it is constructed according to the principle of event tree analysis, and at the same time, the mitigation measures and consequences caused by the further development of hazardous events are listed. The model can better explain the situation of specific risks and help people understand the risk system and the system of prevention and control measures.

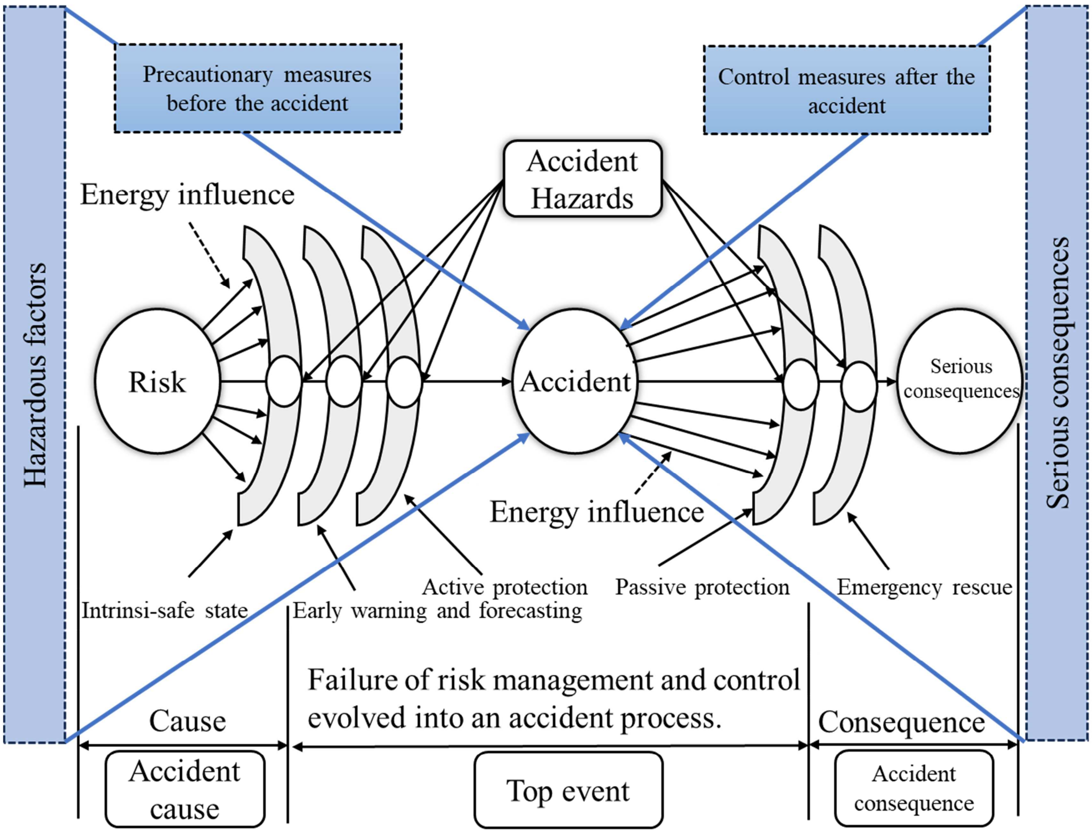


Figure 1. *Bow-tie model used in qualitative risk analysis.*

2.2. Establishment of Fuzzy Bow-Tie Model for Coal and Gas Outburst

Due to the peculiarities of coal and gas outburst accidents, there are uncertainties in the investigation of outburst disasters. At present, people's understanding of coal and gas outburst mechanism is not completely clear. The influential research on the outburst mechanism at home and abroad can be divided into four categories [20-24]. The "comprehensive action hypothesis" is recognized by most people, which states that coal and gas outburst is caused by the comprehensive action of gas, in-situ stress and physical and mechanical properties of coal. Therefore, this paper mainly draws the fault tree of coal and gas outburst according to the "comprehensive action hypothesis" and the actual situation of a mine. At the moment of coal and gas outburst in a coal mine, a large amount of coal and gas flow will be ejected from the mining working area, which will not only seriously destroy the roadway equipment and ventilation system, but also make all the wells in the nearby area full of gas and pulverized coal, resulting in gas suffocation or coal flow burial, and even serious consequences such as coal dust and gas outburst. In this study, the system state of outburst accident consequences is set as accident and no accident, and the event tree of coal and gas outburst is drawn. According to the above analysis, the bow-tie model of coal and gas outburst can be drawn based on the bow-tie model combined with the accident tree and event tree of coal and gas outburst, as shown in Figure 2. The corresponding static evaluation index system is also formed, including 3 qualitative indicators and 6 quantitative parameters. The critical value (or state) of these indicators has a significant impact on the potential danger of coal and gas outburst. In this study, the risk levels of coal and gas outburst are divided into five levels: safety I, low risk II, general risk III, high risk IV and extremely high risk V, and the division criteria are shown in Figure 3.

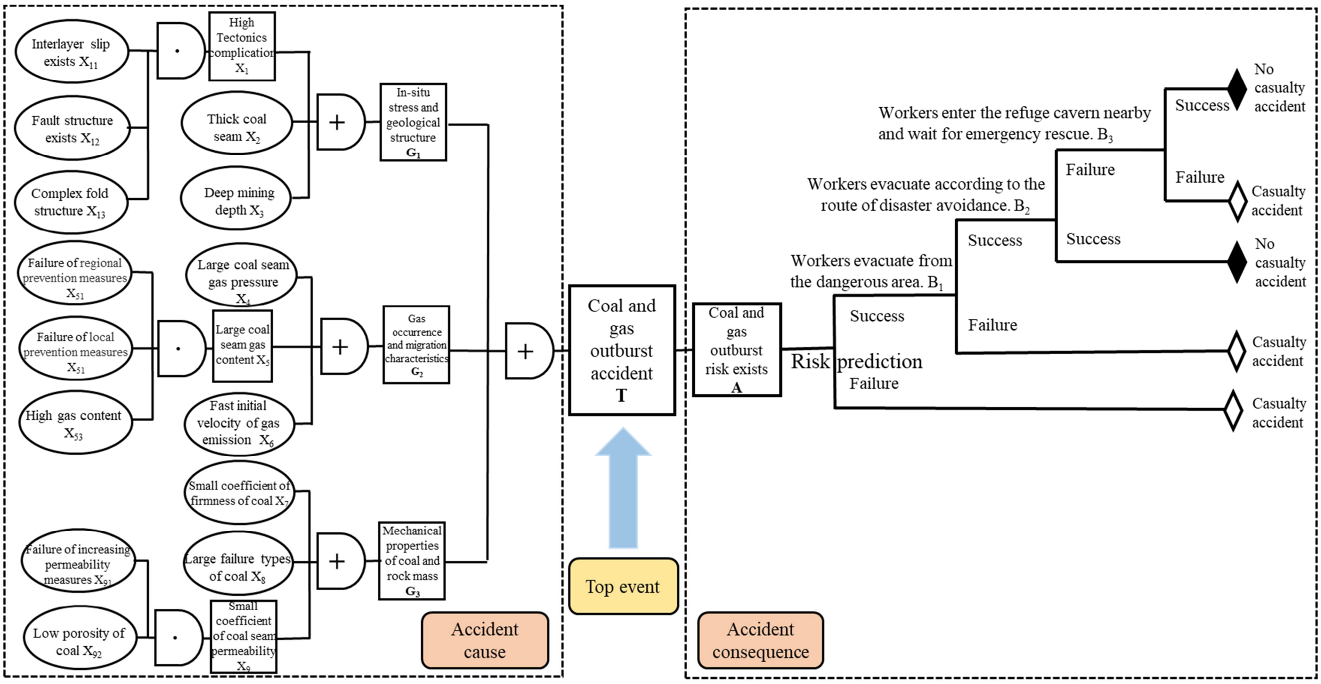


Figure 2. *Bow-tie analysis diagram of coal and gas outburst.*

Risk Levels		I	II	III	IV	V
In-situ stress and geological structure	Tectonics complication	None	Simple	A few faults and folds	Many faults and folds	Geological structure zone with gas-rich area
	Thickness of coal seam (m)	<1.5m	1.5~4m	4~8m	8~12m	>12m
	Mining depth (m)	<400m	[400m,600m)	[600m,700m)	[700m,800m)	≥ 800m
Gas occurrence and migration characteristics	Coal seam gas pressure (MPa)	<0.74MPa	[0.74,1)	[1,2)	[2,3)	≥3MPa
	Coal seam gas content (m^3/t)	<8m^3/t	[8,10)	[10,12)	[12,15)	≥15 m^3/t
	Initial velocity of gas emission (mmHg)	<10mmHg	[10,14)	[14,18)	[18,20)	≥20
Mechanical properties of coal and rock mass	Coefficient of firmness of coal	[0.8,1)	[0.6,0.8)	[0.4,0.6)	[0.2,0.4)	[0.2,0)
	Failure types of coal	I	II	III	IV	V
	Coefficient of coal seam permeability[m^3/(MPa^2·d)]	≥3 [m^3/(MPa^2·d)]	[2,3)	[1,2)	[0.5,1)	<0.5 [m^3/(MPa^2·d)]

Figure 3. *Risk criterion of coal and gas outburst.*

2.3. Triangular Fuzzy Probability Analysis

Since most of the accident statistical data are not timely, it is impossible to obtain the exact probability of each event. Therefore, this study adopts the method of combining subjective probability with fuzzy mathematics. Common fuzzy numbers include triangular fuzzy number, trapezoidal fuzzy number, normal fuzzy number, etc. In this study, the most commonly used triangular fuzzy number [25] is selected. Triangular fuzzy number is a concept of fuzzy set put forward by Zadeh [26] in 1965, which is applied to quality management and risk management, and fuzzy sorting is carried out by combining the logarithmic regression method [27, 28]. Its working principle is to describe the possible range of information values on the basis of geometric triangle [29]. The relationship between triangular fuzzy number and the criteria of risk grade and risk importance grade is shown in Table 1, and the transformation between these language variables and the membership function and triangular fuzzy number is shown in Figure 4.

Table 1. *Relationship between triangular fuzzy number and risk grade.*

Evaluation grade	Fuzzy scale	Semantic abbreviation	Risk grade	Importance grade
1	(0,0,0.25)	VL	Very low	Very unimportant
2	(0,0.25,0.50)	L	Low	Unimportant
3	(0.25,0.50,0.75)	M	Middle	Middle
4	(0.50,0.75,1)	H	High	Important
5	(0.75,1,1)	VH	Very High	Very important

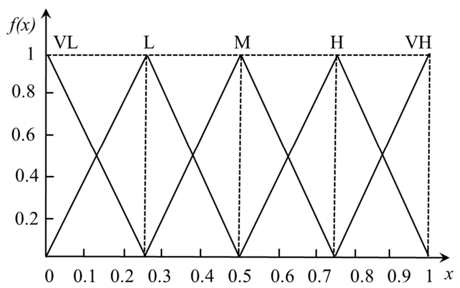


Figure 4. *Curve of mapping function of triangular fuzzy numbers.*

Definition of TFN [30] If M can be expressed by the following membership function $f_M(x)$, it is called a triangular fuzzy number, and the expression of this triangular fuzzy number is $M=(l,m,u)$.

$$f_M(x)=\begin{cases}\frac{(x-l)}{(m-l)}, l\leqslant x\leqslant m;\\ \frac{(u-x)}{(u-m)}, m\leqslant x\leqslant u;\\ 0, \text{otherwise}\end{cases} \tag{1}$$

Where: l and u are the upper and lower limits of triangular fuzzy numbers, respectively; m is the value of fuzzy number M when its membership degree is 1.

To aggregate fuzzy numbers, different experts must evaluate each basic event separately. To establish the conversion relationship between experts' linguistic variables and fuzzy numbers, hierarchical linguistic variables can be established to convert experts' linguistic evaluations into triangular fuzzy numbers. Since different experts may have different evaluations of the same basic event, in order to reduce the subjective influence of a single expert and achieve the consistency of the overall view, it is necessary to assign different weights to each expert according to the differences in the experts' own experience and knowledge reserves, and to linearly integrate and calculate the formulas of each expert's linguistic evaluation.

$$M_i=\sum_{j=1}^{p} W_j M_{ij} \tag{2}$$

Where: M_i is the fuzzy sum, $i=1, 2, 3, n$ (n is the number of events); W_j is the weight of the first expert, $j=1, 2, 3, p$ (p is the number of experts); M_{ij} is the fuzzy score of events i by the j expert.

According to Table 1, experts' linguistic evaluation can be converted into triangular fuzzy number, but it is still a fuzzy value. In the actual situation, risk assessment needs a clear value of event factors, so it is necessary to use deblurring method to convert triangular fuzzy number into corresponding probability value. The deblurring method can not only reduce the influence of subjective factors, but also improve the accuracy of risk assessment. At present, the commonly used deblurring methods include maximum-minimum set method, maximum membership method and barycenter method. The maximum-minimum set method is widely used, so this paper chooses the maximum-minimum set method proposed by CHEN [31] for deblurring. The maximum fuzzy set and minimum fuzzy set can be expressed as:

$$f_{\max}(x)=\begin{cases}\left(\frac{x-x_{\min}}{x_{\max}-x_{min}}\right)^r, x_{\min}\leqslant x\leqslant x_{\max};\\ 0, \text{otherwise.}\end{cases} \tag{3}$$

$$f_{min}(x)=\begin{cases}\left(\frac{x_{max}-x}{x_{max}-x_{min}}\right)^r, x_{\min}\leqslant x\leqslant x_{\max};\\ 0, \text{otherwise.}\end{cases} \tag{4}$$

Where: r is a constant, which can be adjusted according to the attitude towards risk. r=1; If $x_{\min}=0$ and $x_{max}=1$, the simplified maximum fuzzy set and minimum fuzzy set are:

$$f_{max}(x)=\begin{cases}x, 0\leqslant x\leqslant 1;\\ 0, \text{otherwise.}\end{cases} \tag{5}$$

$$f_{\min}(x)=\begin{cases}1-x, 0\leqslant x\leqslant 1;\\ 0, \text{otherwise.}\end{cases} \tag{6}$$

The possible formulas for the left and right fuzzy probabilities of fuzzy number M are as follows:

$$P_{\mathrm{RM}}=sup[f_M(x)\Lambda f_{max}(x)] \tag{7}$$

$$P_{\mathrm{LM}}=sup[f_M(x)\Lambda f_{min}(x)] \tag{8}$$

Where: P_{RM} is right fuzzy probability; P_{LM} is left fuzzy probability; $f_M(x)$ is integrated fuzzy probability. Then the fuzzy probability value of fuzzy number m can be obtained by equation (9).

$$P_M=(P_{\mathrm{R}}+1-P_{\mathrm{L}})/2 \tag{9}$$

To ensure that the true and fuzzy probabilities of an event are the same, it is also necessary to transform the fuzzy probability into a fuzzy failure probability, and the transformation formula is:

$$P=\begin{cases}\frac{1}{10^k}, P_M\neq 0;\\ 0, P_M=0\end{cases} \tag{10}$$

Where: P is the fuzzy failure probability, where $k=[(1-P_M)/P_M]^{1/3}\times 2.301$.

2.4. Monte Carlo Stochastic Simulation

Monte Carlo simulation is a method of analysis based on statistical theory that uses computers to simulate the actual possible situation and study the risk. It was first proposed by Stanislaw Ulam and John von Neumann. This simulation method builds a mathematical model based on the quantitative logical relationship between random variables and target variables, and uses relevant tools and software to simulate a large number of results according to the probability distribution of random variables, that is, through repeated experiments, the relevant data and probability distribution of target variables are obtained. In general, the simulation method refers to a process of understanding a system through a large number of random samples and finding a result that gradually approaches it. As the sample size increases, it becomes more stable in the position close to the result, and then the value to be calculated is obtained. Monte Carlo simulation method is widely used in many fields [32-34]. The simulation principle is as follows:

For *n* objects or indicators to be evaluated, N-dimensional vectors $X = \{X_1, X_2, \cdots, X_n\}$ are used to represent the state of the disaster system. Let $x = \{x_1, x_2, \cdots, x_n\}$ be the number of samples of *X*, and *g(x)* be the value of the function of the disaster system, and its mathematical expectation μ is as follows:

$$\mu = E[g(x)] = \int_{\Omega} g(x) f(x) \mathrm{d}x \tag{11}$$

Where: Ω is the spatial set of all disaster systems; $f(x)$ is the probability density function of the variable *X*. If the objects or indicators to be evaluated are independent of each other, there are:

$$f(x) = P(X = x) = \prod_{i=1}^{n} f(x_i) \tag{12}$$

Where: $f(x_i)$ is the probability density function of the random variable X_i. It is not difficult to see that equation (11) is a multiple integration problem. For high-dimensional complex catastrophe systems, the Monte Carlo random simulation method can be used to estimate the expected value μ of the function *g(x)*. After *N* independent repeated samples, the estimated expected value $\hat{\mu}$ and variance $V(\hat{\mu})$ are as follows:

$$\hat{\mu} = \& \frac{1}{N} \sum_{k=1}^{N} g[x(k)] \tag{13}$$

$$V(\hat{\mu}) = \& V\left[\frac{1}{N} \sum_{k=1}^{N} g[x(k)]\right] = \frac{1}{N^2} \sum_{k=1}^{N} V\{g[x(k)]\} = \frac{V[g(x)]}{N} \tag{14}$$

Where: $x(k) = \{x_1(k), x_2(k), \cdots, x_n(k)\}$ is the sample value obtained after the kth sampling of the variable x, and *V[x)]* is the variance of *g(x)*.

The method of x(k) value can be defined as: randomly generating n evenly distributed numbers of [0,1] intervals $a(k) = \{a_1(k), a_2(k), \cdots, a_n(k)$, and combining the formula $x(k) = F^{-1}[a(k)]$, then the value function of the object to be evaluated can be obtained as follows:

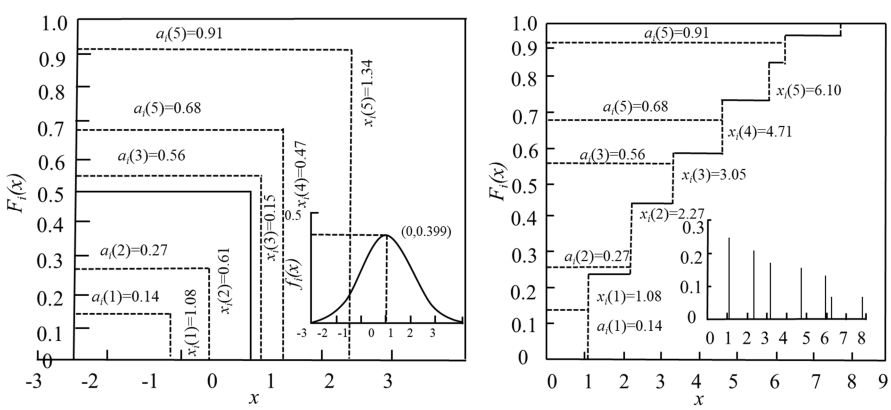
$$x(k) = \{x_1(k), x_2(k), \cdots, x_n(k)\} = \{F_1^{-1}[a_1(k)], F_2^{-1}[a_2(k)], \cdots, F_n^{-1}[a_n(k)] \tag{15}$$

Where: $F_i(x_i)$ is the probability distribution function of X_i, and $F_i^{-1}(x_i)$ is the inverse function. An example of random state generation of x(k) is shown in Figure 5, where Figure 5(a) and Figure 5(b) are the results of independent sampling of continuous and discrete one-dimensional random variables for five times, and the number of states of the variable X_i in Figure 5(b) is *m*(*i*)=7.

In the process of Monte Carlo random simulation, the variation coefficient $\hat{\beta}$ of the expected estimated value $\hat{\mu}$ is generally used as the basis of simulation accuracy and calculation convergence, and its value is

$$\hat{\beta} = \frac{\sqrt{V(\hat{\mu})}}{\hat{E}(\hat{\mu})} = \frac{1}{\hat{\mu}} \sqrt{\frac{V[g(x)]}{N}} \tag{16}$$

It can be seen from equation (16) that the error value generated by random simulation is directly proportional to the variance and inversely proportional to the simulation times. Therefore, to improve the simulation accuracy, it can be achieved by increasing the sampling number *N* or reducing the variance of the function *g(x)*. In the process of coal and gas outburst risk assessment, it is generally believed that the simulation times of random sampling should be more than 2000 times. The simulation times of Monte Carlo random sampling based on TFN model are *N*=20,000.



(a) X_i obeys standard normal distribution. (b) X_i obeys discrete distribution. [*m*(*i*)=7]

Figure 5. *Schematic diagram of one-dimensional random variables.*

3. Risk Assessment Steps and Examples

3.1. Risk Assessment Steps

By combining Monte Carlo stochastic model and triangular fuzzy theory, the risk assessment model of coal and gas outburst is constructed. The realization steps of the model mainly include the following five steps, as shown in Figure 6.

Step 1 As the risk assessment of coal and gas outburst involves many factors, such as disaster-causing factors, disaster-bearing bodies and pregnant environment, and there is no unified quantitative standard for each influencing factor in the actual modeling process, the risk assessment index system will be too complicated, which will affect its operability and implementation. Based on the theory of disaster system management, following the principles of system, completeness, representativeness, practicability, simple quantifiability and generality, the risk assessment index system of coal and gas outburst is established from the characteristics of coal and gas outburst risk and its own formation mechanism, as shown in Table 2.

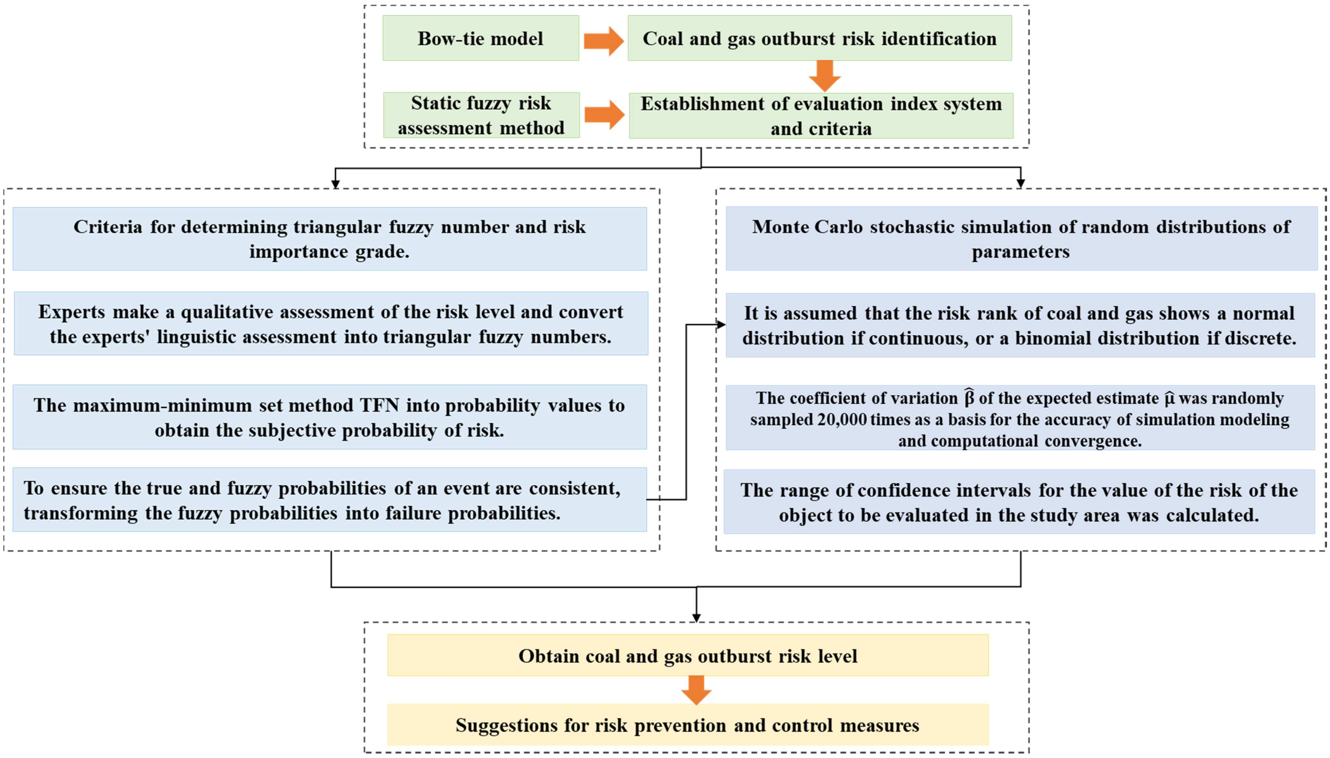


Figure 6. *Process diagram of risk assessment method for coal and gas outburst.*

Table 2. *Risk index system of coal and gas outburst.*

Target layer	Criterion layer	Weight	Index layer	Weight	Integrated weight
Risk grade of coal and gas outburst	In-situ stress and geological structure G1	0.242	X1	0.091	0.022
			X2	0.091	0.022
			X3	0.091	0.022
	Gas occurrence and migration characteristics G2	0.566	X4	0.181	0.102
			X5	0.181	0.102
			X6	0.092	0.052
	Mechanical properties of coal and rock mass G3	0.192	X7	0.091	0.017
			X8	0.091	0.017
			X9	0.091	0.017

Step 2 Calculate the weight of each index in the risk assessment system. Expert opinion and AHP method are used to determine the weight of criterion layer, individual index weight and total index weight. Among them, $w_1(i,j)$ $(j=1\sim n_i)$ is the weight value of each index in the risk assessment index layer of coal and gas outburst; $w_2(i)$ $(i=1\sim n)$ is the weight value of each index in the risk assessment criterion layer of coal and gas outburst; $w(i,j)$ is the total weight of each evaluation index in the comprehensive risk assessment of coal and gas outburst.

$$w(i,j)=w_2(i)w_1(i,j) \tag{17}$$

In formula (17), n is the number of evaluation indices at the standard level, and n=3; n_i is the number in the index level of the *i* criterion, and n_i= {1, 2, 3}.

The consistency ratio CR=0.002<0.1 of the judgment matrix is calculated. Through the consistency test, the weights of the indicators can be obtained. From the weights in the table, it can be seen that coal seam gas content and coal seam gas pressure are the leading indicators. The higher the gas pressure and gas content, the higher the elastic potential of the gas, which can easily induce outburst when the stress state changes sharply, and provide power for outburst in the excitation and development stages, thus creating conditions for continuous coal stripping.

Step 3 First, the fuzzy semantics with five-level classification standards in Table 1 are used to quantitatively describe the risk level and risk importance of coal and gas outburst risk assessment indicators, and the triangular fuzzy numbers $R = \{a_R, b_R, c_R\}$ and $I = \{a_I, b_I, c_I\}$ are used to quantitatively describe them, where a, b and c are expressed respectively. Then, by interviewing experts or engineers who are familiar with the working conditions and disasters in coal mines in the study area, and combining with their own theoretical experience and knowledge level, the fuzzy quantitative values of risk level and risk importance for coal and gas outburst in the study area are given. Second, combined with $R = \{a_R, b_R, c_R\}$ and $I = \{a_I, b_I, c_I\}$, the stochastic simulation formula is as follows:

$$x = \begin{cases} a + [u(b-a)(c-a)]^{0.5}, u \leqslant (b-a)/(c-a) \\ c - [(1-u)(c-b)(c-a)]^{0.5}, u > (b-a)/(c-a) \end{cases} \tag{18}$$

Where: u is a uniformly distributed random number in the interval of [0,1], and N is the number of random simulation experiments. At the same time, a large number of simulation samples $x_{R1}, x_{R2}, \cdots, x_{RN}$ and $x_{I1}, x_{I2}, \cdots, x_{IN}$ with possible values of $R = \{a_R, b_R, c_R\}$ and $I = \{a_I, b_I, c_I\}$ can be obtained.

Step 4 The simulation value series of coal and gas outburst risk is as follows:

$$z_l = \sum_{i=1,j=1,k=1}^{n,n_i,n_{i,j}} \omega(i,j,k) x_{Rl}(i,j,k,l) x_{RI}(i,j,k,l) \tag{19}$$

Where: $l=1\sim N$, $x_{Rl}(i,j,k,l)$, and $x_{RI}(i,j,k,l)$ are the first simulation values of the triangular fuzzy number possible value variables in the I criterion layer and the j index layer, respectively.

Step 5 Establish the confidence interval range of comprehensive risk value of the object to be evaluated in the research area. For the simulation series $\{Z_l \mid l = 1 \sim N\}$ in descending order, according to empirical cumulative percentage's mathematical expectation formula:

$$P_l = l/(N+1) l = 1 \sim N \tag{20}$$

Its confidence interval range at confidence level α is:

$$\left[Z_{\mathrm{INT}\{[1-0.5(1-\alpha)](1+N)\}}, Z_{\mathrm{INT}[0.5(1-\alpha)](1+N)}\right] \tag{21}$$

Where: P_l is the corresponding empirical cumulative percentage in descending order of serial number l; INT () is an integer function.

3.2. Risk Assessment Examples

On the basis of the modeling idea of the evaluation model, the risk levels of coal and gas eruption in three coal mine, A, B and C, in a certain research region are fully assessed. According to the risk evaluation index system, the risk levels and risk importance levels of coal and gas outburst in coal mines are obtained as shown in Table 3, with experts or engineers and technicians making a quantitative description with reference to the risk level standard.

From the triangular fuzzy comments in Table 3, it can be seen that the risk level of A mine corresponding to the K index X4 of the J classification of the first I criterion is (0.50, 0.75, 1), and the risk importance level of A mine is (0.75, 1, 1). First, the simulated values of possible variable values are obtained according to formula (18), and then the probability diagram of comprehensive risk simulated values of coal and gas outburst system in urban areas is obtained according to formula (19), as shown in Figure 4. Finally, the confidence intervals of simulated values of coal and gas outburst risks in three coal mines A, B and C under the confidence level of 95% are calculated according to formula (20) and formula (21), respectively, [0.0244, 0.0582], [0.0987, 0.1390], [0.1619, 0.2166], During the coupling model in the simulation process, the calculation results have converged after 20,000 simulation experiments. This evaluation result is consistent with the result of grading the sticking schedule *Ci* based on TOPSIS ideal solution. For example, the average risk of the three cities is 0.0391, 0.1088 and 0.1792, and the risk ranking is approximately RA < RB < RC. This evaluation result can provide a scientific basis for decision-making for the departments in charge of prevention and control of coal and gas outbursts.

Table 3. *Expert evaluation values of risk importance grades corresponding to three coal mines.*

Indicators	Risk level of A	Risk importance of A	Risk level of B	Risk importance of B	Risk level of C	Risk importance of C
X1	4(0.50, 0.75, 1)	3(0.25, 0.50, 0.75)	3(0.25, 0.50, 0.75)	3(0.25, 0.50, 0.75)	4(0.50, 0.75, 1)	3(0.25, 0.50, 0.75)
X2	4(0.50, 0.75, 1)	4(0.50, 0.75, 1)	4(0.50, 0.75, 1)	4(0.50, 0.75, 1)	4(0.50, 0.75, 1)	4(0.50, 0.75, 1)
X3	5(0.75, 1, 1)	5(0.75, 1, 1)	3(0.25, 0.50, 0.75)	2(0, 0.25, 0.50)	3(0.25, 0.50, 0.75)	3(0.25, 0.50, 0.75)
X4	4(0.50, 0.75, 1)	5(0.75, 1, 1)	4(0.50, 0.75, 1)	5(0.75, 1, 1)	5(0.75, 1, 1)	5(0.75, 1, 1)
X5	4(0.50, 0.75, 1)	4(0.50, 0.75, 1)	4(0.50, 0.75, 1)	5(0.75, 1, 1)	5(0.75, 1, 1)	5(0.75, 1, 1)
X6	2(0, 0.25, 0.50)	2(0, 0.25, 0.50)	3(0.25, 0.50, 0.75)	2(0, 0.25, 0.50)	4(0.50, 0.75, 1)	5(0.75, 1, 1)
X7	3(0.25, 0.50, 0.75)	3(0.25, 0.50, 0.75)	4(0.50, 0.75, 1)	3(0.25, 0.50, 0.75)	3(0.25, 0.50, 0.75)	3(0.25, 0.50, 0.75)
X8	2(0, 0.25, 0.50)	2(0, 0.25, 0.50)	3(0.25, 0.50, 0.75)	2(0, 0.25, 0.50)	2(0, 0.25, 0.50)	2(0, 0.25, 0.50)
X9	2(0, 0.25, 0.50)	2(0, 0.25, 0.50)	2(0, 0.25, 0.50)	3(0.25, 0.50, 0.75)	2(0, 0.25, 0.50)	3(0.25, 0.50, 0.75)

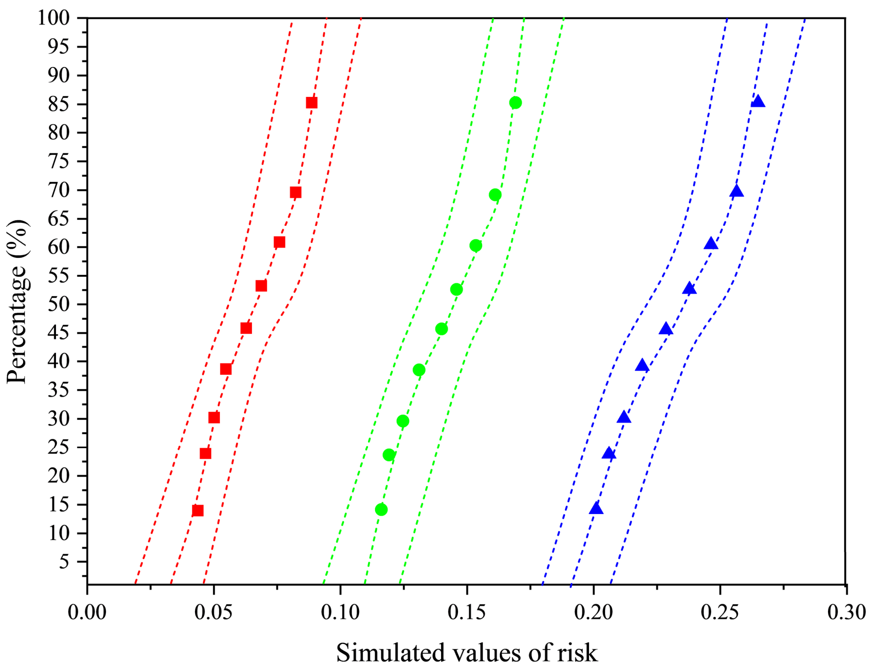


Figure 7. *Probability diagram of simulated values of coal and gas outburst risk in three coal mines.*

The Monte Carlo stochastic simulation model that represents the quantitative value of the risk in the form of a confidence range provides more information about the reliability of the assessment outcome, and the assessment outcome is more consistent with reality. The results evaluated by the existing risk assessment methods of coal and gas outburst are often a certain value, which cannot better reflect the actual situation of coal and gas outburst risk analysis, which is affected by various uncertain factors. For example, the evaluation results of coal and gas outburst risk value think that 95% of the probability is [0.1619, 0.2166], which is obviously more reasonable than the single number of 0.1792 evaluated by the conventional evaluation model, which verifies the scientific and reasonable Monte Carlo random simulation based on the TFN theory. It is worth noting that the quality of the data and expert opinions used determines the reliability and accuracy of the valuation model. Ensuring the accuracy and integrity of data and the representativeness of expert opinions is very important in practical applications of the TFN-MCS model.

4. Conclusion

In this study, the fuzzy bow-tie model of coal and gas outburst is established, and the basic events and accident consequences of coal and gas outburst accidents are intuitively determined by qualitative analysis, which provides reference for similar research. Second, Monte Carlo stochastic simulation theory and triangular fuzzy theory are coupled to the model and applied to the risk assessment of coal and gas outburst, and the evaluation index system is established from three aspects: in-situ stress, gas, and physical and mechanical properties of coal and rock mass. Thirdly, by introducing the difference coefficient to sort the combined weights obtained by combining subjective and objective weights, the one-sidedness of subjective weights is corrected. The results show that the gas characterized by coal seam gas pressure and coal seam gas content is the dominant factor influencing the outburst risk, and the role of geo-stress and coal rock mass cannot be ignored. Finally, through the simulation calculation of Monte Carlo random simulation method, the final risk quantification value of coal and gas outburst accidents in each coal mine is represented in the form of confidence interval, which makes the evaluation result more objective and credible, more objective and practical than traditional fuzzy evaluation theory and random simulation theory, and can provide scientific decision-making basis for coal and gas outburst prevention and management.

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