Safety Pre-Control of Stope Roof Fall Accidents Using Combined Event Tree and Fuzzy Numbers in China’s Underground Noncoal Mines

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ABSTRACT Among the accidents in China’s underground noncoal mines including ferrous metal mines, nonferrous metal mines and nonmetallic mines, roof fall accidents are always extremely bad. The application of risk assessment to avoid roof fall accidents in coal mines is widespread. However, the traditional method has defects in its accuracy, cost, and simplicity. It cannot fundamentally ensure that workers survive a roof fall accident. Therefore, there is no great referential significance for noncoal mines. In this paper, supposing that roof fall accidents in underground noncoal mines are inevitable, we assess where we should start to take measures to prevent worker deaths. On the basis of a detailed investigation, units including those working far from the roof, noticing the signs, etc. were identified, and then a concise event tree model was built. Under this framework, the event tree model has 2 consequences, including being alive and death, and 13 scenarios related to accident occurrence. In this research, the probability of unit events was evaluated by using triangular fuzzy numbers. In addition, we found 3 scenarios with death, and then we calculated their respective probabilities. Finally, regarding the death scenario with the highest risk value, the paper recommends that priority measures should be taken to prevent deaths in roof fall accidents. The method in this paper provides a theoretical basis for pre-control measures and it is efficient, inexpensive, and simplified. Even if a roof fall accident is inevitable, we know where to start to take pre-control measures to prevent worker deaths.

INDEX TERMS Roof fall, event tree, fuzzy number, underground mines.

I. INTRODUCTION

Our daily lives depend on the minerals that are provided by mines. According to data on China’s mineral resources 2019 [1], a total of 173 kinds of minerals have been discovered in China. There are 162 kinds of minerals with identified reserves, and China is one of the few large countries in the world with complete mineral species and abundant mineral resources. In addition, China has become the world’s largest trading country for mineral products [1], [2]. A statistical analysis report of production safety accidents in China’s noncoal mines in 2013-2017 was issued in 2017 [3]. The boom of China’s mining industry has been accompanied by high casualties.

There were 193 accidents resulting in 260 deaths in 2017 in China’s noncoal mines including ferrous metal mines, nonferrous metal mines and nonmetallic mines. It is worth emphasizing that roof fall accidents are always extremely bad. Of these 193 accidents, 125 were roof fall accidents, which accounts for 64.77% of the total noncoal mine accidents, as shown in Fig. 1; and these 125 accidents resulted in 140 deaths. Regardless of whether the focus is on the number of accidents or the number of deaths, roof fall accidents are at the top from 2013 to 2017, as shown in Fig. 2 and
TABLE 1. A list of the roof fall studies in recent years.

| Mine types                | Application                                                                 | Reference |
|---------------------------|-----------------------------------------------------------------------------|-----------|
| Coal mine                 | Coal mine roof rating (CMRR) and rock mass rating (RMR)                     | [4]       |
| Tunnel face               | Use of virtual reality in underground roof fall hazard assessment          | [9]       |
| Coal mine                 | Investigation of the factors influencing roof stability using the coal mine roof rating (CMRR) | [10]      |
| Coal mine                 | Study of the fractal and seismic b-value during dynamic roof displacements (roof fall and surface blasting) | [11]      |
| Coal mine                 | Factors predictive of roof instability using the coal mine roof rating (CMRR) | [12]      |
| Coal mine                 | Application of the coal mine roof rating (CMRR)                            | [6]       |
| Coal mine                 | Assessment of roof stability using the three-dimensional distinct element method | [13]      |
| Coal mine                 | A novel fuzzy inference system for predicting the roof fall rate            | [14]      |
| Coal mine                 | Quantitative identification and analysis of the hazard sources of roof fall accidents | [15]      |
| Coal mine                 | Assessment of the roof fall risk                                           | [5]       |
| Coal mine                 | Identification of a tunnel roof fall using rock structure detection instrumentation | [16]      |
| Limestone mine            | Using classification techniques to predict roof falls                      | [17]      |
| Metal mine                | Evaluating the stability of a roof to avoid roof fall accidents             | [18]      |
| Coal mine                 | Using fault tree analysis to find the factors affecting roof fall accidents | [19]      |
| Gold mine                 | Using the fiber Bragg grating technology to monitor tunnel roofs           | [20]      |

Fig. 1. Percentage of different types of noncoal mine accidents in 2017 in China.

Fig. 2. Number for different types of noncoal mine accidents in 2013-2017 in China.

Fig. 3. Number of deaths for different types of noncoal mine accidents in 2013-2017 in China.

For roof fall accidents in both coal and noncoal mines via Table 1.

To prevent the occurrence of roof fall accidents, roof stability is undoubtedly the most direct factor. However, regardless of which method is adopted, there is much preliminary work to be done, and the accuracy is difficult to guarantee. Taking the most widely applied the Coal Mine Roof Rating(CMRR) method in coal mines as an example, in order to obtain the CMRR value, we need much actual exposed observation data. Examples of this necessary data include data on the strata distribution, number of strata, groundwater, and moisture sensitivity and the measured data of the roof drilling core in the early stage [6]. However, little historical data being available is a great obstacle for the mines. Much measured data mean increased costs and time. Some scholars have warned that the CMRR has negative implications for strata control [7], [8]. Hence, another method is required for noncoal mines with little historic data or measured data to apply. Viewing from another Angle, if a roof fall accident is inevitable, we address where we should start to take measures to prevent worker deaths. The application of event tree analysis (ETA) and fuzzy number theory in other fields has been mature. Traditional ETA relies on the probability calculation for quantitative analysis without considering other factors. In this study, the risk value, which is equal to the scenario probability multiplied by extent of injuries, was introduced for ETA.
The rest of this study is organized as follows: In section II.A, we introduce fuzzy number theory. An event tree model for stope roof fall accidents, which is composed of 13 scenarios, is presented in section II.B. In addition, the method of assessing the risk value of a scenario, which is composed of the probability and extent of injuries, is proposed in II.B. In section III, a copper mine is analyzed by using the event tree model and proposed assessment method. Finally, in Section IV, discussion and conclusions are given.

II. MATERIALS AND METHODS

A. FUZZY NUMBER THEORY

1) FUZZY NUMBER OPERATION AND FUZZY LINGUISTIC TERMS

Zadeh first introduced fuzzy set theory to express the subjectivity and vagueness of human judgment [21]–[23]. Jain, and Dubois et al. [24], [25] presented the concept of fuzzy numbers.

We define a triangular fuzzy number \( A = (a, b, c) \) as a fuzzy subset with left membership function \( f^L_A \) and right membership function \( f^R_A \). If \( A^\lambda \) represents that \( \lambda \) is the cut set of triangular fuzzy number \( A \), then \( A^\lambda = \{ A^L, A^R \} = \{ (b - a) \lambda + a, (b-c) \lambda + c \} \). It is supposed that there are two triangular fuzzy numbers \( A \) and \( B \), then, the algebraic operational rules are shown as follows:

\[
\begin{align*}
[A \oplus B]^\lambda &= [A^L \oplus B^L, A^R \oplus B^R] \\
[A \ominus B]^\lambda &= [A^L \ominus B^L, A^R \ominus B^R] \\
[A \otimes B]^\lambda &= [A^L \otimes B^L, A^R \otimes B^R] \\
[A \odot B]^\lambda &= [A^L \odot B^L, A^R \odot B^R]
\end{align*}
\] (1)

2) DEFUZZIFICATION METHOD

To conduct quantitative analysis of the possibility of an event, a fuzzy number needs to be converted into a definite value, which is called defuzzification [26].

Many scholars have conducted in-depth studies related to this topic. For example, Chen proposed the method of the maximizing and minimizing set [27], and Kim et al proposed the optimism index method [28]. In this paper, the widely applied integral value method [29], [30] proposed by Liu et al. is adopted. According to section II.A.1., “A” represents a fuzzy number with left membership function \( f^L_A \) and right membership function \( f^R_A \), and the defuzzification value of the fuzzy number can be obtained as follows:

\[
I = \alpha I^R (A) + (1 - \alpha) I^L (A) \tag{2}
\]

where \( I^L (A) \) is the integral value of the inverse of the left membership function \( f^L_A \). Similarly, \( I^R (A) \) is the integral value of the inverse of the right membership function \( f^R_A \). The index of optimism is \( \alpha \in [0, 1] \). Specifically, when \( \alpha = 0 \) and 1, \( I \) is equal to \( I^L (A) \) and \( I^R (A) \), respectively. For a typical value with \( \alpha = 0.5 \), the defuzzification value of the fuzzy number becomes

\[
I = \frac{1}{2}[I^R (A) + I^L (A)] \tag{3}
\]

For the triangular fuzzy number \( A \), \( I^R (A) \) and \( I^L (A) \) can be calculated as follows:

\[
\begin{align*}
I^L (A) &= \frac{1}{2} \left[ \sum_{\lambda=0.1}^{0.9} n^L \lambda + \sum_{\lambda=0.9}^{1} n^L \lambda \right] \tag{4} \\
I^R (A) &= \frac{1}{2} \left[ \sum_{\lambda=0}^{0.9} n^R \lambda + \sum_{\lambda=0.9}^{1} n^R \lambda \right] \tag{5}
\end{align*}
\]

where \( \lambda = 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, \) and 1.0; \( \Delta \lambda = 0.1 \); \( n^L \) denotes the lower limits of \( A^L \) and \( n^R \) denotes the upper limits of \( A^R \).

B. EVENT TREE ANALYSIS

1) UNIT IDENTIFICATION

The occurrence of an accident is the result of a succession of events. The unit identification mainly considers the following aspects:

(1) Accident case investigations. To identify unit events, it is necessary to understand the development process of the whole accidents that previously occurred. We communicated with the miners who have been working in the stope, especially those who had experienced roof fall incidents. In addition, we consulted the reports on the roof fall accidents in detail. Then, we identified the critical unit events.

(2) Expert consultation. On the basis of (1), we consulted 6 experts in the industry. To ensure independence and simplicity of unit events, the Delphi method [31] was employed. After four rounds of feedback, the experts came to a consensus.

The sign of a stope roof fall is chosen to be initiating event. A total of 6 units are selected for subsequent events including working far from the roof (unit 1), noticing the sign (unit 2), reminding to evacuate (unit 3), successful evacuation (unit 4), successful self-help (unit 5), and successful rescue (unit 6).

2) THE ESTABLISHMENT OF AN EVENT TREE

After the units are determined, the event tree can be established, as shown in Fig. 4. Each unit can take two completely opposite states, which represents whether it was successful or not (S = Success and F = Failure, respectively). It is obvious that there are 13 scenarios in the event tree with 2 consequences, death and being alive, respectively. Note that the consequences in scenario 5, scenario 9, and scenario 13 are “death”. The others are “being alive”. Every scenario consists of at most 6 units and at least 1 unit. Every scenario describes the complete process of the event.

More specifically, as an example, scenario 13 is comprised of 6 units including working far from the roof (F), noticing the sign (F), reminding to evacuate (F), successful evacuation (F), successful self-help (F), and successful rescue (F). The event process is illustrated as follows.

When the sign of a stope roof fall came up, workers were working close to the roof, but the workers did not notice the roof fall sign. Later, they were still not reminded to evacuate. After the failed evacuation, the workers still failed to save themselves and failed to receive external rescue, ultimately resulting in the death of the workers.
FIGURE 4. Event tree of roof fall accidents in China's underground noncoal mines.

TABLE 2. Expert fuzzy linguistic terms.

| Fuzzy linguistic term | Triangular fuzzy number     | λ cut set            |
|-----------------------|----------------------------|---------------------|
| Very Low (VL)         | (0.0,0,1.0,3)              | [0.16, -0.2λ+0.3]   |
| Low (L)               | (0.1,0.3,0.5)              | [0.2λ+0.1, -0.2λ+0.5]|
| Medium (M)            | (0.3,0.5,0.7)              | [0.2λ+0.3, -0.2λ+0.7]|
| High (H)              | (0.5,0.7,0.9)              | [0.2λ+0.5, -0.2λ+0.9]|
| Very High (VH)        | (0.7,0.9,1.0)              | [0.2λ+0.7, -0.1λ+1.0]|

3) UNIT PROBABILITY ASSESSMENT

(1) Expert fuzzy linguistic terms

Suppose that the probability of success for a unit event is expressed in terms of $P_S$, and the probability of failure is expressed in terms of $P_F$, the details of which are shown in Fig. 4. It is obvious that the equation "$P_S = 1 - P_F$" can be obtained for the same unit.

In this paper, expert fuzzy linguistic terms are used to evaluate the unit probability [22], [32], [33]. The fuzzy linguistic terms have the corresponding triangular fuzzy number and λ cut set, as shown in Table 2.

(2) Expert weights

Since the evaluation results of experts are subjective, three or more experts are consulted in order to avoid the defects of a single expert.

The experts’ backgrounds should be checked in advance, including their ages, occupations, levels of education, etc. Then, the scale method can be used to determine each expert weight $w_i$. For example, suppose that Q represents the degree of importance in the expert judgment matrix, which is actually the value of $Q_a$ with respect to $Q_b$. The rules are shown in detail in Table 3. By comparing $n$ experts to each other, the judgment matrix $T_{n\times n}$ can be formed as follows:

$$T_{n\times n} = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ t_{21} & t_{22} & \cdots & t_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{n1} & t_{n2} & \cdots & t_{nn} \end{bmatrix}$$ (6)

In the next step, $\sigma_{\text{max}}$ (the maximum eigenvalue) and $\omega = (\omega_1, \omega_2, \omega_3, \ldots, \omega_n)$ (the eigenvector) of the matrix $T_{n\times n}$ can be calculated. Obviously, $w_i (i = 1, 2, \ldots, n)$ is the weights of the experts.

In addition, the matrix $T_{n\times n}$ needs to be verified. According to Table 4, the value of the average random consistency index $RCI$ can be obtained. Furthermore, the consistency index $CI$ can be obtained through (7). Based on (8) and Table 4, it is not difficult to get the value of the consistency ratio $CR$. $CR < 0.1$ must be satisfied, which represents that the consistency of the judgment matrix $T_{n\times n}$ consistency is qualified. Otherwise, the judgment matrix $T_{n\times n}$ needs to be rebuilt.

$$CI = \frac{\sigma_{\text{max}} - n}{n - 1} \quad (7)$$

$$CR = \frac{CI}{RCI} \quad (8)$$

(3) Experts’ judgment cut set

It is assumed that the number of experts is $n$. According to Table 2, the λ cut set corresponds to the experts’ fuzzy
linguistic terms, and its general formula is represented by $[e_i, \lambda_i, f_i, g_i, h_i]$ ($e_i, f_i, g_i, h_i$ are real numbers, and $1 \leq i \leq n$). Therefore, based on (1), the comprehensive fuzzy linguistic term of $n$ experts for a specific unit can be obtained as follows:

$$P_{ui} = \omega_1 \times [e_1, \lambda_1, f_1, g_1, h_1] + \omega_2 \times [e_2, \lambda_2, f_2, g_2, h_2] + \ldots + \omega_n \times [e_n, \lambda_n, f_n, g_n, h_n]$$

(4) Unit probability

Then, according to formula (4) and formula (5), $I_L$ and $I_R$ can be calculated. At last, the unit probability $P_{ui} = I_i (1 \leq i \leq n)$ can be obtained by (1).

**TABLE 4.** The RCI value.

| $n$ | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  |
|-----|----|----|----|----|----|----|----|----|----|
| RCI | 0  | 0  | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 |

**TABLE 5.** Extent of the deaths and quantification values of a scenario.

| Extent of injury | Values |
|------------------|--------|
| More than 5 deaths | 3 |
| 3 to 5 deaths | 2 |
| Less than 3 deaths | 1 |

Five men who are familiar with the conditions of the mine are selected as experts, and their characteristics are shown in Table 6.

The results of the judgment matrix, the maximum eigenvalues, and the corresponding weight vector are listed as follows:

$$T_{5 \times 5} = \begin{bmatrix} 1 & 3 & 7 & 2 & 6 \\ 1/3 & 1 & 5 & 3 & 2 \\ 1/7 & 1/5 & 1 & 1/2 & 1 \\ 1/2 & 1/3 & 2 & 1 & 2 \\ 1/6 & 1/2 & 1 & 1/2 & 1 \end{bmatrix}$$

$$\sigma_{max} = 5.22519$$

$$\omega = (0.45718, 0.25239, 0.06473, 0.14682, 0.07888)^T$$

According to the following formula, the judgment matrix is qualified when $CR < 0.10$. Therefore, the judgment matrix $T_{5 \times 5}$ is reasonable.

$$CR = 0.0503 < 0.1$$

In this paper, 5 experts are selected to evaluate the possibility of unit events using fuzzy linguistic terms, and the evaluation results and expert weights are shown in Table 7.

According to Table 7, the comprehensive fuzzy linguistic terms of the 5 experts for unit 1 (state $F_1$) can be obtained as follows:

$$P_{i1} = \sum_{i=1}^{n} \omega_i [e_i, \lambda_i, f_i, g_i, h_i] = 0.45718 + 0.14682 + 0.06473 + 0.14682 + 0.07888 = 0.68305$$

Furthermore, the corresponding $I_R (F_1)$, $I_L (F_1)$, and defuzzification value of $I(F_1)$ can be calculated as follows:

$$I_L (F_1) = \frac{1}{2} \left[ \sum_{\lambda=0}^{1} n^\lambda \Delta \lambda + \sum_{\lambda=0}^{0.9} n^\lambda \Delta \lambda \right] = 0.5366$$

$$I_R (F_1) = \frac{1}{2} \left[ \sum_{\lambda=0}^{1} n^\lambda \Delta \lambda + \sum_{\lambda=0}^{0.9} n^\lambda \Delta \lambda \right] = 0.7366$$

$$I(F_1) = \frac{1}{2} [I_R (F_1) + I_L (F_1)] = 0.6366$$

Similarly, the defuzzification values of other units can also be obtained using the above methods, which are shown in Table 8. In this case, the defuzzification value is the unit probability.

According to (13), the scenario probability $P_{13}$ can be obtained as follows:

$$P_{13} = P_{F_1} \times P_{F_2} \times P_{F_6} \times P_{F_7} \times P_{F_8} \times P_{F_9}$$

$$= 0.6366 \times 0.5253 \times 0.7395 \times 0.8355 \times 0.8750 \times 0.7508 = 0.13572$$

The risk value of scenario $R_{13} = P_{13} \times L = 0.13572L$.

In the same way, the risk value of scenario $R_9 = 0.02732L$, $R_5 = 0.06240L$ can also be obtained. $L$ is the extent of death in the scenarios. According to the actual working condition of the stope and Table 5, its value is 1 in this case. Obviously, $R_{13} > R_9 > R_5$. Therefore, priority should be given to taking measures against scenario 13 to prevent casualties.

**III. CASE STUDY**

The roof fall accident in the Hubei Tonglv copper mine in 2018 in China is taken as an example to conduct event tree analysis.
As shown in Fig. 4, all the unit states for scenario 13 are “F”. If we change any of the unit states, we can stop scenario 13 from happening. Taking a successful rescue (F) as an example, mining enterprises can install personnel positioning and communication systems to ensure that workers be saved in a roof fall accident [35], [36]. Just from that, the state of a successful rescue becomes “S” and scenario 13 is converted to scenario 12 (the consequence is being alive).

IV. DISCUSSION AND CONCLUSION
Roof fall accidents are always extremely bad in China’s underground noncoal mines. However, most research has focused on the stability of the roofs in coal mines and the traditional method has defects related to its accuracy, costs, and simplicity. the application of ETA for roof fall accidents is rare in both coal and noncoal mines.

In this research, a concise event tree model for roof fall accidents in China’s underground noncoal mines, which has 2 consequences and 13 scenarios, was built. Moreover, the probability assessment of the unit events using triangular fuzzy numbers was studied based on event tree analysis. Specialy, traditional ETA was improved by introducing the risk value, which is equal to the scenario probability multiplied by extent of death, to ETA.

Finally, regarding the death scenario with the highest risk value, priority measures should be taken to prevent the death in roof fall accidents. The method in this paper provides a theoretical basis for pre-control measures and it is efficient, inexpensive, and simple. Even if a roof fall accident is inevitable, we know where to start to take pre-control measures to prevent worker deaths.

The defuzzification method is highly dependent on assessing the unit probability. Many scholars have conducted in-depth studies on defuzzification methods. At present, the integral value method has been widely applied. Therefore, we chose this method in this paper. In addition, we selected 5 experts from different departments who are familiar with mine conditions and adopted the scale method to determine the weights of different experts. We did our best to ensure that the results are in line with reality. However, this process is very involved and relies greatly on experts. Further study is required to find a more simplified method without any accuracy loss.

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