

# Study on the Risk Evaluation Method of Ground Collapse in the Mined-Out Area Based on D-S Evidence Theory

Zheng Yang<sup>1,\*</sup>, Guangyao Yang<sup>1</sup>, Feng Guo<sup>1</sup>, Zhongqiang Wang<sup>1</sup> and Chenkang Wei<sup>2</sup>

<sup>1</sup>*Shaanxi Xiaobaodang Mining Company, Dabaodang Town, Shenmu City, Shaanxi Province 719302, China*

<sup>2</sup>*College of Computer Science and Technology, Xi'an University of Science and Technology, Xi'an City, Shaanxi Province, 710054, China*

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**Abstract:** In the process of coal mining, it is easy to cause geological disasters such as ground collapse, so as to reduce the loss caused by ground collapse, so it is necessary to evaluate the stability evaluation of the mining area and the prediction of ground collapse. Ground subsidence is affected by geological, hydrological and weather, the evaluation of ground subsidence based on multi-source information fusion, with the help of machine learning, data fusion, integrates geological exploration drilling data, coal mining data and hydrological data. Based on the mining area, this paper establishes the risk identification framework of 4 states, establishes the stability evaluation index system with 9 influencing factors, calculates the basic probability distribution of the indexes and distributes the information entropy, and finally integrates the probability distribution of the indexes. It provides a new feasible way for risk assessment of mine mining area.

## 1 INTRODUCTION

China is rich in mineral resources and has a history of thousands of years of coal mining. Depending on relevant data, as of December 2004, the total mining subsidence area of coal mines in China has exceeded 7,000 square kilometers, with a loss of more than 50 billion yuan. The average mining collapse area of key coal mines accounts for about 10% of the coal containing area. At present, the mined-out area has become one of the main hazardous resource affecting mine production safety (State Administration for Work Safety, 2003), and it is also one of the two hidden dangers in production safety. It impacts on mineral development, life safety, and the natural environment so seriously that the establishment of this system has its necessity and urgency.

At present, multi-source information fusion technology (MSIF: Multi. Source Information Fusion) is mostly used in this direction. In the field of research assessment of ground subsidence risk in the mining area, many scholars use a single machine learning model and empirical formula to evaluate, without considering the uncertainty and correlation between factors, so data fusion can solve this problem well. Some scholars also use the information fusion

technology to conduct the risk assessment of the mined space area, and make full use of the complementarity and comprehensiveness of the multi-source data to greatly improve the quality of the evaluation index information. For example, they use the hierarchical analysis method (Liu, 2020) to assess the risk. This algorithm determines the weight ratio of individual factors mainly based on the relationship between their respective influence factors and historical disaster points. It has the advantage of less quantitative information required, but also, the results are not convincing. And when there are too many indicators, the accuracy is also difficult to guarantee. Another example is the risk matrix evaluation method. (Liu, Bhote, 2020) Making a subjective judgment on the risk importance level standard, risk possibility, and severity of the consequences may affect the accuracy of the use. (Jin, 1998)

Therefore, this paper adopts the multi-source information analysis and fusion based on D-S evidence theory (Wang, 2005) to calculate the stability level according to the fusion results, and provides a new way for the stability evaluation of the mining area. (Jin, 2006)

## 2 A MULTI-SOURCE INFORMATION FUSION MODEL BASED ON DS EVIDENCE THEORY

Let all the possibilities of the problem or event be expressed in a set, and the results are mutually exclusive and can fully cover all the results of the problem or event, and the answer to the question we study is a subset of this set. The identification framework  $\theta$  is a non-empty and limited set, which meets the collection algorithm. The identification framework is the foundation of evidence reasoning.

Definition 1: Make  $\theta$  the identification framework,  $R$  a set class in the power set  $2^\theta$ , and  $A$  a subset of  $\theta$ . If the function  $m:R \rightarrow [0,1]$

Meet the following conditions:

$$\begin{cases} m(\phi) = 0 \\ \sum m(A) = 1 \end{cases} \quad (1)$$

Definition 2: Make  $\theta$  the identification framework,  $R$  a set class in the power set  $2^\theta$ ,  $A$  a subset of  $\theta$ , and  $m$  a mass function on  $\theta$ , and  $Bel: R \rightarrow [0,1]$  meets:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad (2)$$

$Bel$  is called the probability assignment function on the identification framework  $\theta$ . To any proposition  $A$ ,  $Bel(A)$  is called the confidence of proposition  $A$ , suggesting the full degree of confidence of proposition  $A$ .

Definition 3: Make  $\theta$  the identification framework,  $R$  a set class in the power set  $2^\theta$ , and  $A$  a subset of  $\theta$ , and  $m$  a mass function on  $\theta$ , and  $Pl: R \rightarrow [0,1]$  meets:

$$Pl(A) = \sum_{B \cap A \neq \phi} m(B) \quad (3)$$

Then  $Pl$  is referred to as the plausible function on the recognition framework. And for any proposition  $A$ ,  $Pl(A)$  is called the plausibility of the proposition  $A$ . The function  $Pl$  represents the degree not opposed to the proposition  $A$ .  $[Bel(A), Pl(A)]$  indicates the uncertainty interval of the evidence, which is also the uncertainty of the evidence. One of the purposes of evidentiary inference is to reduce the uncertainty interval.

Definition 4: assuming that two different pieces of evidence  $A$  and  $B$  focal elements are summed respectively, and the mass function is sum respectively, the D-S combinatorial formula of the result of  $m=m_1 \oplus m_2$  is as follows:

$$\begin{aligned} m(A) &= \frac{1}{1-k} \sum_{A_i \cap B_i = A, A_i \cap B_i \subseteq \theta} m_1(A_i) \cdot m_2(B_i) \quad (4) \\ &= \sum_{A_i \cap B_i = \phi} m_1(A_i) \cdot m_2(B_i) \quad (5) \end{aligned}$$

The  $k$  conflict coefficient, which reflects the degree of conflict between the evidence. The greater the  $k$ , the greater the conflict; when  $k = 1$ , it is a complete conflict and is not suitable for this formula.

## 3 ANALYSIS OF THE STABILITY FACTORS IN THE MINED-OUT AREA

The factors causing geological disasters in the mined-out area are various and a complex problem.(Gong, 2008) The data in the geological report are processed and classified, and the influencing factors are divided into the ore body factors and the collection parameters of the mined-out area. The evaluation indicator system of the mined-out area is established as shown in Figure 1.

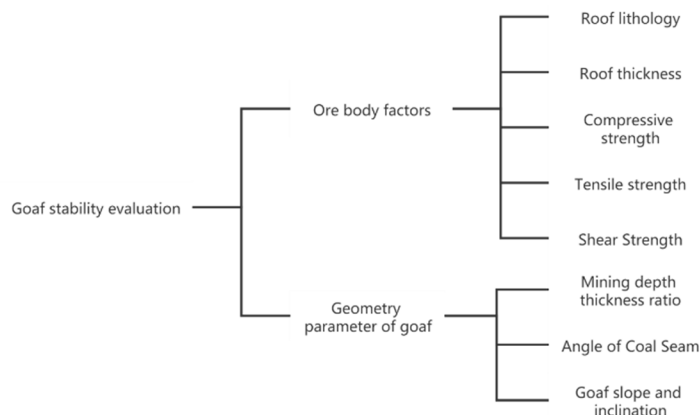


Figure 1: Stability evaluation index system of mined space area.

## 4 THE RISK EVALUATION METHOD BASED ON D-S EVIDENCE THEORY

Based on D-S evidence theory, the risk evaluation method with evidential reasoning is proposed. With data from a coal mined in Yulin, this part gives the main experimental processes of the method.

### 4.1 Identification of the Risk Assessment and Identification Framework of the Mined-Out Area

According to D-S evidence theory, assuming that all possible results we can recognize after the problem occurs can be expressed in terms of a set called the identification framework  $\theta$ . For the risk assessment of coal mined-out area (Ding, 2009; Chen, 2013), based on the fact that we want to know the current safety of an area of the mined-out area, all possible results of the problem obtain the identification framework for the mined-out area hazard assessment of this problem  $\theta = \{\text{safety state, basic safety state, critical state, failure state}\}$ . The identification framework can basically comprehensively express the judgment of the slope safety assessment. Conclusions reached using evidential reasoning methods, it is a confidence measure vector on a subset of evaluation objects in the recognition framework. In the research conducted in this paper, the result is the confidence vector of a certain mined-out region on the identification

framework (safe state, basic safety state, critical state, failure state).

### 4.2 The D-S Evidence Argument Synthetic

#### 4.2.1 Division of the Basic Index Interval

Combined with the risk assessment indicator system of the mined-out area and the basic probability division based on interval number, the collected 8 indexes are divided according to the four states of the identification framework. See in Table 1.

#### 4.2.2 Probability Allocation

Similarly, the basic index selected on the identification framework, giving the basic probability distribution process of the mining thickness ratio:

(1) Determines the number of intervals. According to Table 1 the result of thickness ratio on identification frame is: [25,35], [15,25], [10,15], [0,10], using the four interval number as the interval number model.

(2) Determines the identification interval. The mining thickness ratio of mined out area No. 1 is 22.74.

The identification interval of the thickness ratio is: [22.74,22.74].

(3) Calculates the interval distance. The distance of the deep mining thickness ratio under the identification framework  $\theta$  is calculated, and the results are as shown in Table 2:

Table 1: Division of the risk assessment index interval in the mining space area.

Evaluation indicators	Highest Security level	Normal Security level	Hidden dangers	Damage state
Deep mining and thickness ratio	[25, 35]	[15, 25]	[10,15]	[0,10]
Top plate thickness (m)	[15, 25]	[10, 15]	[5, 10]	[0, 5]
Coal seam inclination angle(°)	[0,15]	[15, 30]	[30, 45]	[45,60]
Slope-dip angle is (°)	[0, 15]	[15, 25]	[25, 45]	[45,60]
Compressive Strength (Mpa)	[70, 100]	[50, 70]	[30, 50]	[0, 30]
Tensile strength (Mpa)	[5,10]	[3, 5]	[1.5, 3]	[0, 1.5]
Shear off strength (Mpa)	[6, 10]	[4,6]	[2, 4]	[0, 2]

Note: In some index interval division, the maximum interval value cannot be given. For example, the compressive strength is considered greater than 70, but a determined interval is needed in the calculation, so a maximum value is set artificially, which does not affect the calculation result.

Table 2: Interval distance.

Identification framework	Highest Security level	Normal Security level	Hidden dangers	Damage state
Basic probability matching	0.1595	0.3992	0.2565	0.1847

Table 3: Interval similarity.

Identification framework	Highest Security level	Normal Security level	Hidden dangers	Damage state
Distance	10.1459	9.2748	12.0798	14.9161

Table 4: Basic probability allocation of all indicators in the mined space area No. 1.

Evaluation indicators	Highest Security level	Normal Security level	Hidden dangers	Damage state
Deep mining and thickness ratio	0.1595	0.3992	0.2565	0.1847
Top plate thickness	0.1522	0.3838	0.2872	0.1768
Coal seam inclination angle	0.4242	0.2949	0.1633	0.1177
Slope inclination angle	0.3615	0.3554	0.219	0.0642
Compressive strength	0.1889	0.3921	0.2606	0.1585
Tensile strength	0.1356	0.3785	0.3179	0.1679
Shear-off strength	0.1528	0.3793	0.2888	0.1791
Lithology	0.25	0.35	0.2	0.2

Table 5: Credibility of the risk grade of some mined-out areas.

Mined-out Area Num	Caularea risk level credibility			
	Level I	Level II	Level III	Level IV
Mined-out Area No.1	0.0502	0.4278	0.5132	0.0087
Mined-out Area No.10	0.1392	0.7222	0.1359	0.0026
Mined-out Area No.11	0.1335	0.7332	0.1308	0.0025
Mined-out Area No.34	0.5687	0.3505	0.0783	0.0024
Mined-out Area No.35	0.5854	0.3354	0.0766	0.0025

(4) Calculates the interval similarity. The similarity between the mining thickness ratio and the four intervals is calculated by formula. Results are shown in Table 3.

(5) The normalization treatment of interval similarity obtains the probability allocation of each state under the recognition framework and get the result.

This probability distribution is shown in Table 4.

Through the judgment matrix obtained from the basic probability allocation function, the index weight is:

$$w = [0.1171, 0.0496, 0.2988, 0.2587, 0.1090, 0.0265, 0.0659, 0.0743].$$

We weighted evidence fusion for mined-out area 1, and the mass function for the influence indicators of mined-out area 1 is as follows:

Mining thickness ratio ( $m_1$ ),  $m_1$  {Level I, Level II, Level III and Level IV}=(0.1595,0.3992,0.2565,0.1847);

Top plate thickness is ( $m_2$ ),  $m_2$  {Level I, Level II, Level III and Level IV}=(0.1522,0.3838,0.2872,0.1768);

Coal seam dip angle ( $m_3$ ),  $m_3$  {Level I, Level II, Level III and Level IV}=(0.4242,0.2949,0.1633,0.1177);

Slope angle ( $m_4$ ),  $m_4$  {Level I, Level II, Level III and Level IV}=(0.3615,0.3554,0.2190,0.0642);

Compressive strength ( $m_5$ ),  $m_5$  {Level I, Level II, Level III and Level IV}=(0.1889,0.3921,0.2606,0.1585);

Tensile strength ( $m_6$ ),  $m_6$  {Level I, Level II, Level III and Level IV}=(0.1356,0.3785,0.3179,0.1679);

Shear strength ( $m_7$ ),  $m_7$  {Level I, Level II, Level III and Level IV}=(0.4242,0.2949,0.1633,0.1177);

Top slab lithology ( $m_8$ ),  $m_8$  {Level I, Level II, Level III and Level IV}=(0.25,0.35,0.20,0.20).

The mass functions on 4 identification frameworks are fused, so the  $m_1 - m_2 -$  fusing result is  $M, M\{I\} = 0.08, M\{II\} = 0.54, M\{III\} = 0.26, M\{IV\} = 0.12$ , then the new mass function is  $M\{I, II, III, IV\} = (0.08, 0.54, 0.26, 0.12)$ . According to the fusion results of the first two mass functions and the third mass function, the results of the second fusion and the fourth mass function, thus the security level credibility of the final No.1 on the identification framework  $\theta$  after n-1 fusion, and the No.10,11,34 and 35 are randomly selected for the above fusion calculation. The results are shown in Table 5.

### 4.3 DS Evidence Theory Fusion Result Analysis

Combining the above calculation results, the multi-source information fusion based on D-S evidence theory is used to determine the selected 5 mined-out areas, and to get the basic credibility on the identification framework  $\theta$ . As it appears from Table 5, the credibility of No.1 is 0.0502. From the perspective of probability, the probability that mined-out area No.1 is safe is 5.02%. The probability of relative safety is 42.78%. The probability of being in a dangerous state is 51.32%, The probability of being in very dangerous is 0.87%, Therefore, the final risk assessment result of No.1 mined-out area is relatively dangerous, which means Col collapse may occur. Similarly, the evaluation result of No.10 is level II, which is relatively safe; the evaluation result of No.11 is level II and is relatively safe. The evaluation result of No.34 and 35 is level I and they are in a very safe state.

## 5 CONCLUSIONS

According to the method proposed in this paper, the risk identification framework of four states was established using data from a mine in YuLin, nine influencing factors were selected to establish the stability evaluation index system, and the D-S evidence theory is used to weight the probability distribution of the index. At last, the experimental result is consistent with the actual situation of the mine,

The effectiveness of the multi-source information fusion method is verified, and a new feasible way is provided for the mine mining area Hazard assessment.

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