



# Research on Coal Mine Gas Safety Evaluation Based on D-S Evidence Theory Data Fusion

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**Abstract.** In order to improve the accuracy of coal mine gas safety evaluation results, a gas safety evaluation model based on D-S evidence theory data fusion is proposed, and multi-sensor fusion of gas safety evaluation is realized. First, the prediction results of the weighted least squares support vector machine are used as the input of D-S evidence theory, and the basic probability assignment function of each sensor is calculated by using the posterior probability modeling method, and the similarity measure is introduced for optimization. Secondly, aiming at the problem of fusion failure in D-S evidence theory when fusing high-conflict evidence, the idea of assigning weights is used to allocate the importance of each evidence to weaken the impact of conflicting evidence on the evaluation results. In order to prevent the loss of the effective information of the original evidence after modifying the evidence source, a conflict allocation coefficient is introduced on the basis of fusion rules. Finally, a gas safety evaluation example analysis is carried out on the evaluation model established in this paper. The results show that the introduction of similarity measures can effectively eliminate high-conflict evidence sources; the accuracy of D-S evidence theory based on improved fusion rules is improved by 2.8% and 15.7% respectively compared to D-S evidence theory based on modified evidence sources and D-S evidence theory; as more sensors are fused, the accuracy of the evaluation results is higher; the multi-sensor data evaluation results are improved by 63.5% compared with the single sensor evaluation results.

**Keywords:** Data fusion · D-S evidence theory · Gas · Safety evaluation

## 1 Introduction

Coal mine gas safety evaluation has always been an important means of coal mine safety management. Through the monitoring of environmental data in the coal mine and the correct identification of the gas safety, gas accumulation, outburst, and explosion can be effectively avoided, which has important theoretical significance and practical value for suppressing the occurrence of gas disasters and promoting the safe and sustainable development of the coal industry [1].

At present, the commonly used safety evaluation methods are probabilistic risk evaluation [2–4], and the use of computer technology and databases to establish disaster databases for casualties. However, in actual evaluation, the structure, indexes and parameters of each evaluation model are very different. The commonly used evaluation methods in China mainly focus on fuzzy comprehensive evaluation [5], gray clustering [6–8], neural network [9–11] and game analysis evaluation based on data mining [12]. Although the qualitative evaluation process is simple, the differences in the professional background and operational capabilities of different participants may lead to differences in accident risk evaluation. The existing gas safety evaluation system only stores information in the database, and does not realize the correlation between the monitoring data of multiple sensors, therefore, a complete and coordinated operating system has not been formed in practice. At the same time, in the analysis of the coal mine gas safety influencing factor system, more studies have magnified the role of people and machines, while neglecting the occurrence of gas accidents mostly is the unfavorable monitoring of environmental factors, the lack of evaluation systems and the insufficient accuracy.

The gas safety evaluation model used in this paper divides the gas safety status into different safety levels. Then, using the various sensor monitoring data collected by the working face monitoring station, the predicted data is obtained based on weighted least squares support vector machine. Finally, multi-sensor data fusion is carried out to realize the evaluation of the gas safety state of the working face at the next moment, so as to realize the early warning of the gas safety state.

## 2 Weighted Least Squares Support Vector Machine

Suykens [13] proposed a weighted least squares support vector machine (WLSSVM) based on the least squares support vector machine (LSSVM). The Lagrange function of its optimization problem can be described as:

$$L(w, b, \xi, \alpha) = \frac{1}{2}w^T w + \frac{1}{2}C \sum_{i=1}^N v_i \xi_i^2 - \sum_{i=1}^N \alpha_i [w^T \varphi(x_i) + b + \xi_i - y_i] \tag{1}$$

In Eq. (1),  $w$  is the weight coefficient vector;  $\varphi(x_i)$  is the mapping input to the high-dimensional space;  $C$  is the regularization parameter;  $b$  is the threshold;  $x_i$  represents the Lagrange multiplier. According to the KKT (Karush-Khun-Tucker) condition, the function eliminate  $w$ ,  $\xi_i$ , and get Eq. (2):

$$\begin{bmatrix} 0 & l_{1 \times N} \\ l_{N \times 1} & R + \frac{1}{C}V \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{2}$$

In Eq. (2),  $V = \text{diag}(v_1^{-1}, v_2^{-1}, \dots, v_N^{-1})$  is the diagonal matrix,  $l_{1 \times N}$  is the unit column vector,  $R = \{K(x_i, x_j) | i = 1, 2, \dots, N\}$  is the radial basis kernel function matrix,  $y = [y_1, y_2, \dots, y_N]^T$ . Equation (2) can be obtained  $b$  and  $\alpha$ , inputing test samples to get WLSSVM model as follows:

$$y = \sum_{i=0}^n \alpha K(x_i, x) + b \tag{3}$$

The weight calculation formula is as follows:

$$v_i = \begin{cases} 1, & \left| \frac{\xi_i}{\hat{s}} \right| \leq s_1 \\ \frac{s_2 - \left| \frac{\xi_i}{\hat{s}} \right|}{s_2 - s_1}, & s_1 < \left| \frac{\xi_i}{\hat{s}} \right| \leq s_2 \\ 10^{-4}, & \text{otherwise} \end{cases} \quad (4)$$

In Eq. (4), the values of  $s_1$  and  $s_2$  are 2.5 and 3.0 respectively;  $\hat{s}$  is the standard estimated deviation of the error sequence, and its calculation function is as follows:

$$\hat{s} = \frac{\text{IQR}}{2 \times 0.6745} \quad (5)$$

In Eq. (5), IQR is the difference between the third quartile and the first quartile in the sequence of errors  $\xi_i$  from small to large.

### 3 D-S Evidence Theory

#### 3.1 Basic Principles of D-S Evidence Theory

For the reasoning of uncertain problems, Dempster-Shafer (D-S) evidence theory has strong adaptability, and the reasoning process is simpler. Among them, the distribution of belief functions and the fusion of evidence are the basic knowledge of D-S evidence theory. The uncertainty of events can be expressed through the recognition framework and basic belief distribution functions.

#### Recognition Framework

The recognition framework represents a set  $X$  of possible situations of the event, and the elements it contains represent the degree of evaluation of the event status. In the gas safety evaluation system, every possible state is called a hypothesis, and all possible categories constitute a recognition framework. Therefore, the recognition framework contains all possible results of a particular problem. The recognition framework can be expressed in Eq. (6):

$$X = \{X_1, X_2, X_3, \dots, \Theta\} \quad (6)$$

In Eq. (6),  $X_i$  is called a possible result of the event, and the uncertainty represented by  $\Theta$ .

#### Basic Probability Assignment Function (BPA)

Suppose  $X$  is a recognition framework,  $2^X$  is a power set on  $X$ , if  $m: 2^X \rightarrow [0, 1]$ , and satisfy Eq. (7).

$$\sum_{A \in 2^X} m(A) = 1, m(\Theta) = 0 \quad (7)$$

In Eq. (7),  $m$  is called the BPA of the recognition frame  $X$ , it also known as the mass function,  $A$  is the element in the recognition frame. For  $\forall A \subseteq X$ , then  $m(A)$  is the basic belief, which indicates the degree of trust in proposition  $A$ .

### Belief Function

If there are  $A \in P(X)$  and  $B \in A$ , then define the function  $Bel$  as follows:

$$Bel(A) = \sum_{B \in A} m(B) \quad (8)$$

In Eq. (8),  $Bel$  represents the belief function, and the Eq. (8) represents the sum of the possibilities of all the subsets of  $A$ , which represents the overall degree of trust in  $A$ , so that it can be inferred that  $Bel(\Theta) = 0$  and  $Bel(X) = 1$ . The belief function represents the degree of trust of a certain thing. It is incomplete and untrustworthy to only use the belief function to describe the possibility of an event.

### Likelihood Function

In D-S evidence theory, the likelihood function is a measure used to express the degree of distrust of an event. Definition: Assuming that  $X$  is a recognition framework,  $m: 2^X \rightarrow [0, 1]$  is represented as the basic probability assignment on  $X$ . If there are  $A \in P(X)$ ,  $B \in A$ , then define the function  $Pl: 2^X \rightarrow [0, 1]$  as follows:

$$Pl(A) = 1 - Bel(\bar{A}) = \sum_{B \cap A \neq \Theta} m(B) \quad (9)$$

In Eq. (9),  $Pl(A)$  represents that event  $A$  is true uncertainty, and  $Bel(\bar{A})$  represents the trust degree of event  $\bar{A}$ . The degree of mistrust  $Pl(A)$  of  $A$  can be calculated by the Eq. (9).

The minimum degree of trust of evidence theory for event  $A$  is  $Bel(A)$ , the potential degree of trust in event  $A$  is expressed as  $Pl(A)$ , the support interval of event  $A$  can be expressed as  $[0, Bel(A)]$ , the likelihood interval of event  $A$  can be expressed as  $[0, Pl(A)]$ . When the evidence neither confirms nor denies the occurrence of event  $A$ , for this uncertain phenomenon, a trust interval can be used to represent the probability of event  $A$ .

## 3.2 Improved D-S Evidence Theory

D-S evidence theory has strong applicability in data fusion, but in the actual fusion process, there are still some deficiencies in dealing with uncertain problems. It is mainly manifested in the explosive problem, the limited problem of recognition framework, the independent problem between the evidences and the problem of conflicting evidence fusion. In this paper, the improvement of D-S evidence theory is mainly used to solve the problem of conflicting evidence sources.

### Evidence-Based Improvements

Modifying the evidence source can reduce the influence of interference factors on the fusion evaluation results and improve the accuracy of the evaluation results. In this paper, the idea of assigning weights is used to allocate the importance of each evidence, which can increase the reliability of the evidence on the decision result and weaken the impact of conflicting evidence. For the method of evidence-based improvement, this paper is called D-S-1 evidence theory.

For an uncertain event, there are  $n$  evidences, the corresponding recognition frame  $X$  contains  $N$  focal elements, and  $m_i$  represents the evidence set composed of the basic probability assignment function corresponding to the evidence under each focal element.

$$m_i = [m_i(A_1), m_i(A_2), \dots, m_i(A_n)]^T, i = 1, 2, \dots, n \tag{10}$$

Equation (11) is used to calculate the distance between  $m_i$  and  $m_j$ ,  $d_{ij}$  represents the distance of  $m_i$  and  $m_j$ . This distance function has a better reflection in describing the focal element and the reliability between evidences, and can better characterize the conflict between evidences.

$$d_{ij} = d(m_i, m_j) = \sqrt{\frac{1}{2} [\|m_i\|^2 + \|m_j\|^2 - 2(m_i, m_j)]} \tag{11}$$

The similarity function is further derived from the Eq. (11). The similarity between  $m_i$  and  $m_j$  can be expressed as  $S_{ij}$ . The expression of  $S_{ij}$  is as follows:

$$S_{ij} = 1 - d_{ij} \tag{12}$$

The smaller the distance between the evidences, the greater the mutual support. The degree of support for evidence can be expressed by the sum of other evidences, then the degree of support for evidence  $m_i$  can be expressed as:

$$T(m_i) = \sum_{j=1, j \neq i}^n S_{ij}, i = 1, 2, \dots, n \tag{13}$$

In this paper, the distance similarity matrix between evidences is used to give different weights to each sensor, so as to achieve the purpose of modifying the evidence source. In order to prevent the revised evidence source from being too conservative and losing the advantages of the original evidence, this paper adopts to retain the original set of more correct evidence to ensure the effect of data fusion. Based on the above ideas, according to the ratio of the degree of support of the evidence, under the condition of retaining a good set of evidence sources, the weight  $\beta$  of the evidence is calculated according to the degree of support. The specific formula is as follows:

$$\beta(m_i) = \frac{T(m_i)}{\max(T(m_i))} \tag{14}$$

After assigning weights, the modified basic probability assignment function corresponding to the evidence can be expressed as follows:

$$\begin{aligned} m'_i(i) &= \beta(m_i) \cdot m_i \\ m'_i(\ominus) &= \beta(m_i) \cdot m_i + (1 - \beta(m_i)) \end{aligned} \tag{15}$$

### Improvements Based on Fusion Rules

In this paper, the time series prediction value of the monitoring data of each sensor is used to calculate the basic probability assignment value. After the value of each sensor is fused, the mine gas safety status is judged. The fusion rules of D-S evidence theory are as follows:

Based on two independent evidences  $M_1, M_2$ , the focal elements of the two evidences are  $B_i$  and  $C_j (i = 1, 2, 3, \dots, n, j = 1, 2, 3, \dots, m)$ , the basic probability assignment function value after their fusion is  $m(A)$ :

$$\begin{cases} m(A) = M_1 \oplus M_2 = \frac{1}{1-K} \sum_{B_i \cap C_j = A} m_1(B_i)m_2(C_j) \\ K(M_1, M_2) = \sum_{B_i \cap C_j = \emptyset} m_1(B_i)m_2(C_j) \end{cases} \tag{16}$$

In Eq. (16),  $K(M_1, M_2)$  is called the conflict coefficient, which represents the degree of conflict between the two evidences  $M_1, M_2$ . When the conflict coefficient is 0, there is no conflict between the two evidences; when it is close to 1, the greater the conflict between the two evidences, there is a complete conflict.

Many scholars believe that the fusion rules of evidence theory are imperfect in the processing of evidence, so the reasonable modification of fusion rules can also improve the accuracy of fusion. After modifying the evidence source, simply modifying the evidence source data to prevent high conflicts between the evidences may cause the revised evidence to lose the effective information of the original evidence. The conflict allocation coefficient is introduced on the basis of the fusion rules to improve the accuracy of the decision stage. For the method of modifying the fusion rule, this paper is called D-S-2 evidence theory.

The conflict allocation coefficient  $\omega(A_i)$  can be defined as follows:

$$\omega(A_i) = \frac{\sum_{i=1}^n m'_i(A_{ij})}{\sum_{i=1}^n \sum_{j=1}^p m'_i(A_{ij})} \tag{17}$$

The improved formula of D-S evidence theory fusion rule is defined as follows:

$$m(A) = \sum_{B_i \cap C_j = A} m_1(B_i)m_2(C_j) + K \cdot \omega(A_i) \tag{18}$$

In Eq. (17): set  $A$  represents the intersection of focal element  $B_i$  and focal element  $C_j$ .

## 4 Construction of Gas Safety Evaluation Model

### 4.1 Construction of Recognition Framework

From the perspective of D-S evidence theory, the “gas safety state” can be regarded as a judgmental problem, and the summary of hypothetical results can be described as a recognition framework. According to the coal mine safety regulations and the value range of characteristic parameters under specific conditions, the gas safety state is divided into five states: no danger, mild danger, moderate danger, serious danger, and uncertain [14]. No danger indicates that the working face of the coal mine is in a good environment; mild danger indicates that the working face has a certain risk, and this danger value is within the acceptable range; moderate danger indicates that the working face is unsafe, and the indicates value has exceeded the accepted, this danger requires staff to conduct on-site inspection; serious danger indicates that the working face is very bad, and the staff should be evacuated. So the recognition framework of D-S evidence theory can be described as  $X = \{X_1 \text{ (no danger), } X_2 \text{ (mild danger), } X_3 \text{ (moderate danger), } X_4 \text{ (serious danger)}\}$ .

## 4.2 Construction of Basic Probability Assignment Function

This paper uses the posterior probability modeling method to find the basic probability assignment function, and introduces the similarity degree to modify the evidence source. The basic probability assignment function characterizes the support degree of each sensor to the safety status of mine gas. In this paper, a time series prediction model is constructed through the WLSSVM, and the prediction model is established with each influence factor as an input to obtain the prediction value of each sensor. The posterior probability modeling method calculates the basic probability assignment function of each sensor.

Taking a single sensor as an example, the basic probability assignment function value obtained by the posterior probability modeling method is  $y$ , the recognition framework is  $X = \{X_1, X_2, X_3, X_4\}$ . The distance between  $X$  and  $y$  can be expressed as follows:

$$d_i(X_i, y) = |X_i - y| \quad (19)$$

The correlation coefficient between the evidence and  $X_i$  can be expressed as follows:

$$c_i = \frac{1/d_i}{\sum_{i=1}^4 (1/d_i)} \quad (20)$$

Introducing Eq. (20), the basic probability assignment function  $m(i)$  and the uncertainty  $m(\Theta)$  of the corresponding evidence can be expressed as follows:

$$\begin{aligned} m(i) &= \frac{c_i}{\sum c_i + E} \\ m(\Theta) &= \frac{E}{\sum c_i + E} \\ E &= \frac{1}{2}|y - x|^2 \end{aligned} \quad (21)$$

In Eq. (21),  $y$  is the predicted value of the time series prediction model, and  $x$  is the expected output value of the prediction model.

## 4.3 Construction of Gas Safety Evaluation Model

Five classification indicators of gas safety status can be obtained through Sect. 4.1. The construction process of data fusion model based on D-S evidence theory mainly includes three parts: time series prediction of each sensor, construction of basic probability assignment function, fusion between evidences and decision-making. First, each sensor obtains the predicted value through the time series prediction model. The basic probability assignment function is obtained through the posterior probability modeling method. The similarity degree is introduced to modify the evidence source to obtain the basic probability assignment function. In order to improve the accuracy of decision-making, multi-sensor data fusion was carried out according to the fusion rules. The coal mine gas safety evaluation model based on D-S evidence theory data fusion is shown in Fig. 1.

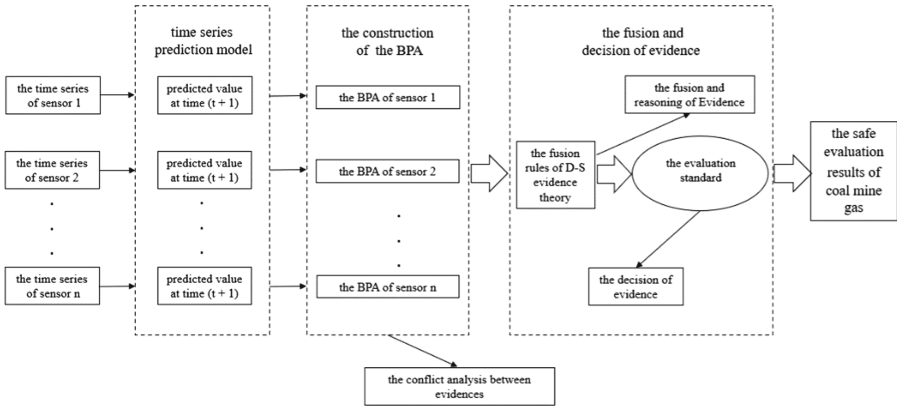


Fig. 1. Gas safety evaluation model

## 5 Case Analysis

### 5.1 Data Sources

The data in this paper comes from the gas concentration at the upper corner (No. A02), the gas concentration at the working face 10 m (No. A01), the wind speed (No. A09), the dust (No. A11), the return air 15 m temperature (No. A07), the return air 15 m gas concentration (No. A08) of the a coal mine. The original data sampling interval is 1 min, and the data distribution has obvious jagged characteristics. Therefore, this paper uses 5 min as the sampling interval to obtain 1500 groups of samples, select the first 1400 samples for model training, and the remaining samples for model testing. Some data is shown in Table 1.

Table 1. Sample set of monitoring data.

No.	A02/(%)	A01/(%)	A09/(m/s)	A11/(mg/m <sup>3</sup> )	A07/(°C)	A08/(%)
1	0.224	0.262	1.952	0.02	21.332	0.35
2	0.226	0.26	1.992	0.014	21.3	0.342
3	0.218	0.26	1.97	0.08	21.306	0.342
4	0.218	0.27	1.98	0.082	21.3	0.342
5	0.212	0.276	2.016	0.068	21.304	0.34
.	.	.	.	.	.	.
.	.	.	.	.	.	.
1497	0.368	0.408	1.926	0.086	22.026	0.502
1498	0.37	0.406	1.916	0.084	22	0.518
1499	0.362	0.4	1.944	0.076	22	0.496
1500	0.352	0.396	1.944	0.074	22	0.482



### 5.2 The Predicted Results of the Time Series Prediction Model

This paper uses the multivariable WLSSVM time series prediction model introduced in Sect. 2 to predict the monitoring value of each sensor at the next moment. This paper uses the target sensor as the output and other sensors as the input for model training. SPSS software was used to analyze the Pearson correlation of A02, A01, A09, A11, A07 and A08 monitoring points. The analysis results are shown in Table 2.

**Table 2.** Correlation analysis results of various influencing factors

	A02	A01	A09	A11	A07	A08
A08	0.572	0.910	0.668	0.324	0.788	1

It can be seen from Table 2 that the correlation coefficients are all greater than 0.3, and it is reasonable for each other sensor to be the input of the target sensor. The prediction results are shown in Table 3.

**Table 3.** Predicted results of various sensors

	A02	A01	A09	A11	A07	A08
Predicted results	0.380	0.422	1.912	0.094	22.086	0.504

### 5.3 Experimental Results and Analysis

#### Contrast Analysis of Conflict Degree

This paper uses the posterior probability modeling method introduced in Sect. 3.2 to calculate the basic probability assignment function of each sensor. The BPA of each sensor is shown in Table 4.

**Table 4.** Basic probability assignment functions

	A09	A07	A11	A02	A01	A08
X <sub>1</sub>	0.0646	0.2057	0.4939	0.5551	0.5664	0.5954
X <sub>2</sub>	0.8079	0.2160	0.2358	0.2150	0.2106	0.1979
X <sub>3</sub>	0.0557	0.2273	0.1549	0.1333	0.1294	0.1187
X <sub>4</sub>	0.0288	0.2399	0.1153	0.0966	0.0934	0.0848
⊖	0.0431	0.1111	0.0000	0.0000	0.0002	0.0032

It can be seen from Table 2 that the results of single sensor recognition are A09  $m(X_2) = 0.8079$ , A07  $m(X_4) = 0.2399$ , A11  $m(X_1) = 0.4939$ , A02  $m(X_1) = 0.5551$ , A01  $m(X_1) = 0.5664$  and A08  $m(X_1) = 0.5954$ . Obviously, A09 and A07 have a great conflict with other sensors. Using a single sensor evaluation result can not accurately evaluate the safety status of coal mine gas. Therefore, it is necessary to modify the evidence source before fusion.

This paper adopts the improved method of evidence source introduced in Sect. 4.2, redistributes the weights for each sensor according to the BPA in Table 4, the revised BPA is shown in Table 5.

**Table 5.** Basic probability assignment function after modifying the evidence source

	A09	A07	A11	A02	A01	A08
$X_1$	0.0369	0.1712	0.4914	0.5551	0.5643	0.5801
$X_2$	0.4622	0.1797	0.2357	0.2150	0.2098	0.1929
$X_3$	0.0318	0.1892	0.1541	0.1333	0.1298	0.1157
$X_4$	0.0165	0.1997	0.1148	0.0966	0.0930	0.0826
$\Theta$	0.4526	0.2602	0.0051	0.0000	0.0040	0.0287

It can be seen from Table 5 that A09 is revised from  $m(X_2) = 0.8079$  to  $m(X_2) = 0.4622$ , and A07 is revised from  $m(X_4) = 0.2399$  to  $m(X_4) = 0.1997$ . The conflict is significantly reduced, indicating that the method of modify the source of evidence is feasible and retains the excellent evidence of A02. At the same time, the Table 5 shows that only using sensors A09 and A07 as evaluation evidence will lead to failure of decision-making, and only using A11, A02, A01 and A08 as evaluation evidence has low recognition accuracy and makes decision reliability low. Therefore, it is not reliable to use only a single sensor to evaluate the safety status of coal mine gas.

**Comparative Analysis of Evaluation Results**

Through the comparative analysis of the degree of conflict above, we can see that data fusion plays an important role in the decision-making results. Sensors A09, A07, A11, A02, A01, A08 are recorded as evidence  $e_1, e_2, e_3, e_4, e_5, e_6$ . The fusion process of multi-sensors is the fusion process of two sensors in sequence. The comparison results of the multi-sensor fusion of the three methods are shown in Table 6, 7, 8, 9 and 10.

**Table 6.** Comparative analysis of  $e_1e_2$  fusion results

	$m(X_1)$	$m(X_2)$	$m(X_3)$	$m(X_4)$	$m(\Theta)$	Identify result	Safety status
D-S	0.0822	0.7668	0.0803	0.0573	0.0000	$X_2$	$X_1$
D-S-1	0.1346	0.4103	0.1440	0.1412	0.0000	$X_2$	$X_1$
D-S-2	0.1023	0.4022	0.1084	0.1026	0.5199	$\Theta$	$X_1$

**Table 7.** Comparative analysis of  $e_1e_2e_3$  fusion results

	$m(X_1)$	$m(X_2)$	$m(X_3)$	$m(X_4)$	$m(\Theta)$	Identify result	Safety status
D-S	0.1688	0.7520	0.0517	0.0275	0.0000	$X_2$	$X_1$
D-S-1	0.3259	0.4798	0.1118	0.0826	0.0000	$X_2$	$X_1$
D-S-2	0.3930	0.3813	0.1262	0.0923	0.0125	$X_1$	$X_1$

**Table 8.** Comparative analysis of  $e_1e_2e_3e_4$  fusion results

	$m(X_1)$	$m(X_2)$	$m(X_3)$	$m(X_4)$	$m(\Theta)$	Identify result	Safety status
D-S	0.3537	0.6103	0.0260	0.0100	0.0000	$X_2$	$X_1$
D-S-1	0.5894	0.3361	0.0486	0.0260	0.0000	$X_1$	$X_1$
D-S-2	0.6680	0.2511	0.0526	0.0282	0.0000	$X_1$	$X_1$

**Table 9.** Comparative analysis of  $e_1e_2e_3e_4e_5$  fusion results

	$m(X_1)$	$m(X_2)$	$m(X_3)$	$m(X_4)$	$m(\Theta)$	Identify result	Safety status
D-S	0.6012	0.3859	0.0101	0.0028	0.0000	$X_1$	$X_1$
D-S-1	0.8056	0.1728	0.0155	0.0061	0.0000	$X_1$	$X_1$
D-S-2	0.8578	0.1205	0.0156	0.0061	0.0000	$X_1$	$X_1$

**Table 10.** Comparative analysis of  $e_1e_2e_3e_4e_5e_6$  fusion results

	$m(X_1)$	$m(X_2)$	$m(X_3)$	$m(X_4)$	$m(\Theta)$	Identify result	Safety status
D-S	0.8198	0.1768	0.0028	0.0006	0.0000	$X_1$	$X_1$
D-S-1	0.9225	0.0720	0.0042	0.0013	0.0000	$X_1$	$X_1$
D-S-2	0.9485	0.0466	0.0038	0.0011	0.0000	$X_1$	$X_1$

As shown in Table 6 above, the fusion evidence sources  $e_1$  and  $e_2$  are all highly conflicting evidences, so the decision results of D-S evidence theory and D-S-1 evidence theory are invalidated, and the recognition results of D-S-2 evidence theory are uncertain. After introducing the evidence source  $e_3$  in Table 7, the recognition results of the D-S evidence theory and D-S-1 evidence theory are wrong, and the D-S-2 evidence theory recognition results are accurate, which proves that the improved fusion rule in this paper is effective, and retains the revised evidence source. Effective information in Table 8,  $e_1e_2e_3e_4$  fusion, D-S evidence theory recognition result is wrong, D-S-1 evidence theory and D-S-2 evidence theory recognition results are accurate, which proves that the modified method of the evidence source improved in this paper is correct, eliminating

the inter-evidence Highly conflicting. Tables 9 and 10 show that the D-S-2 evidence theory method for the modification of evidence source and fusion rules in this paper is reasonable. The recognition accuracy of D-S-2 evidence theory is higher than that of D-S evidence theory and D-S-1 evidence theory. The accuracy rate of mine gas safety status recognition has been improved. At the same time, the fusion rule satisfies the exchange law, and it can be concluded that as the evidence increases during the fusion process, the accuracy of the identification in the decision stage is higher. The problem that the single sensor is difficult to accurately characterize the gas safety state is solved.

Through the above analysis, it can be concluded that the multi-sensor data fusion gas safety status evaluation system proposed in this section has high practical value in field applications, and has important theoretical significance for suppressing the occurrence of gas disasters and promoting the safe and sustainable development of the coal industry. In Table 10, the accuracy of D-S evidence theory based on improved fusion rules is improved by 2.8% and 15.7% respectively compared to D-S evidence theory based on modified evidence sources and D-S evidence theory, as more sensors are fused, the accuracy of the evaluation results is higher; the multi-sensor data evaluation results are improved by 63.5% compared with the single sensor evaluation results.

### Model Uncertainty Measure

This paper uses Shannon entropy to measure the uncertainty of the above three D-S evidence theories. Let  $n$  signal sources make up the signal  $X = \{x_1, x_2, x_3, \dots, x_n\}$ , the probability that each signal source provides corresponding information for an event is  $P = \{p(x_1), p(x_2), p(x_3), \dots, p(x_n)\}$ , then the system structure  $S$  of the signal can be expressed as:

$$S = \begin{pmatrix} X \\ P \end{pmatrix} = \begin{pmatrix} x_1 & x_2 & \dots & x_n \\ p(x_1) & p(x_2) & \dots & p(x_n) \end{pmatrix} \quad (22)$$

Therefore, the Shannon entropy of the signal is expressed as follows:

$$H(x) = - \sum_{i=1}^n p(x_i) \ln p(x_i) \quad (23)$$

The uncertainty of D-S evidence theory fusion is:

$$\begin{aligned} & -0.8198 * \ln 0.8198 - 0.1768 * \ln 0.1768 - 0.0028 * \ln 0.0028 \\ & - 0.0006 * \ln 0.0006 = 0.4901 \end{aligned}$$

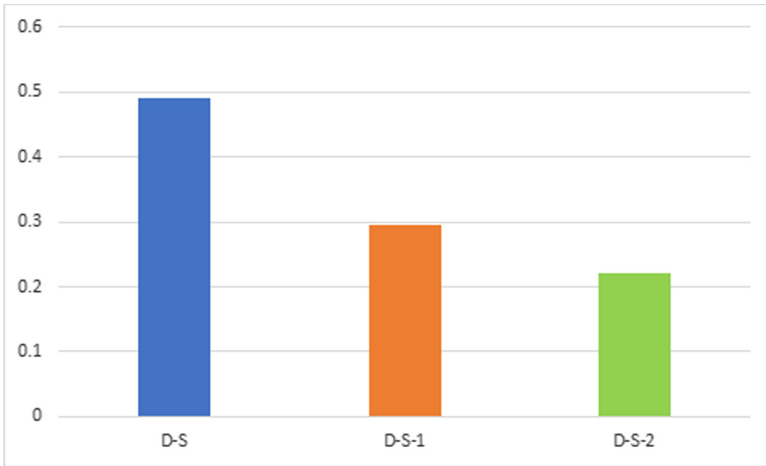
The uncertainty of D-S-1 evidence theory fusion is:

$$\begin{aligned} & -0.9225 * \ln 0.9225 - 0.0720 * \ln 0.0720 - 0.0042 * \ln 0.0042 \\ & - 0.0013 * \ln 0.0013 = 0.2955 \end{aligned}$$

The uncertainty of D-S-2 evidence theory fusion is:

$$\begin{aligned} & -0.9485 * \ln 0.9485 - 0.0466 * \ln 0.0466 - 0.0038 * \ln 0.0038 \\ & - 0.0011 * \ln 0.0011 = 0.2217 \end{aligned}$$

From the comparison of the above results (Fig. 2), we can see that the improved D-S-2 evidence theory has lower uncertainty than D-S evidence theory and D-S-1 evidence theory, and can better evaluate the safety of coal mine gas.



**Fig. 2.** Uncertainty for three types of D-S evidence theory

## 6 Conclusion

- (1) According to the characteristics of coal mine monitoring data, an index system is constructed. By acquiring the predicted values of each sensor, the basic probability assignment function of each sensor is calculated using the posterior probability modeling method.
- (2) A safe evaluation model of coal mine gas status is constructed, and multi-sensor data fusion is realized. As more sensors are fused, the evaluation results are more accurate. The model in this paper effectively solves the problem that it is difficult for a single sensor to accurately characterize the gas safety state.
- (3) Aiming at the problem of evidence fusion failure caused by high conflict data, this paper introduces the similarity to modify the evidence source of conflict data, which effectively reduces the conflict between the evidence. At the same time, in order to prevent distortion of evidence sources, the conflict allocation coefficients are introduced to improve the fusion rules, and the accuracy of evaluation results is improved. It proves that the improved D-S evidence theory has higher accuracy and better generalization ability for coal mine gas safety evaluation, which can provide theoretical basis for gas disaster accident prevention.

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