Research Article
Coal Mine Gas Safety Evaluation Based on Adaptive Weighted Least Squares Support Vector Machine and Improved Dempster–Shafer Evidence Theory

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Gas safety evaluation has always been vital for coal mine safety management. To enhance the accuracy of coal mine gas safety evaluation results, a new gas safety evaluation model is proposed based on the adaptive weighted least squares support vector machine (AWLS-SVM) and improved Dempster–Shafer (D-S) evidence theory. The AWLS-SVM is used to calculate the sensor value at the evaluation time, and the D-S evidence theory is used to evaluate the safety status. First, the sensor data of gas concentration, wind speed, dust, and temperature were obtained from the coal mine safety monitoring system, and the prediction results of sensor data are obtained using the AWLS-SVM; hence, the prediction results would be the input of the evaluation model. Second, because the basic probability assignment (BPA) function is the basis of D-S evidence theory calculation, the BPA function of each sensor is determined using the posterior probability modeling method, and the similarity is introduced for optimization. Then, regarding the problem of fusion failure in D-S evidence theory when fusing high-conflict evidence, using the idea of assigning weights, the importance of each evidence is allocated to weaken the effect of conflicting evidence on the evaluation results. To prevent the loss of the effective information of the original evidence followed by modifying the evidence source, a conflict allocation coefficient is introduced based on fusion rules. Ultimately, taking Qing Gang Ping coal mine located in Shaanxi province as the study area, a gas safety evaluation example analysis is performed for the assessment model developed in this paper. The results indicate that the similarity measures can effectively eliminate high-conflict evidence sources. Moreover, the accuracy of D-S evidence theory based on enhanced fusion rules is improved compared to the D-S evidence theory in terms of the modified evidence sources and the original D-S evidence theory. Since more sensors are fused, the evaluation results have higher accuracy. Furthermore, the multisensor data evaluation results are enhanced compared to the single sensor evaluation outcomes.

1. Introduction

China is a country with a large coal consumption and production where a large proportion of the production mines is related to the high gas mines. The gas accident is one of the major problems; hence, it is necessary to investigate and solve this problem for China’s coal industry. Coal mine gas safety evaluation has always been a key tool for coal mine safety management. In China, the coal mines are ordered to monitor the gas concentration, carbon monoxide concentration, carbon dioxide concentration, oxygen concentration, dust, wind speed, humidity, temperature, power state, and others by the National Coal Mine Safety Administration [1]. Through monitoring those data automatically and identifying the gas safety state timely in the coal mine, outburst, gas accumulation, and explosion can be effectively prevented. The work has important theoretical significance and practical value for suppressing the gas disasters occurrence [2, 3] and endorsing the safe and sustainable development of the coal industry.

Safety evaluation and risk assessment are important and systematic processes to assess the impact, occurrence, and
consequences of human activities on a system with hazardous characteristics, and they are necessary tools for the company’s safety policy. The risk types and data sources are many and various, so are the safety evaluation techniques to assess risks. Therefore, the choice of methods has become more and more important. Presently, safety evaluation techniques can be classified into qualitative and quantitative safety evaluation methods [4, 5].

1.1. Safety Evaluation Techniques

1.1.1. Qualitative Methods. The qualitative safety assessment methods are mainly to carry out qualitative analysis of the production system’s process, equipment, facilities, environment, personnel, and management based on experience and intuitive judgment ability. The results of qualitative safety assessment methods are some qualitative indicators, such as the type of an accident and the factors that may lead to the accident. The commonly used qualitative analysis methods [4] include checklist analysis, plant level safety analysis, process risk management audit, failure mode effect analysis, hazard, and operability. The qualitative evaluation process is simple and easy to understand and manage; however, the differences in the professional background and operational capabilities of various participants may lead to differences in safety assessment. For example, the structure of checklist analysis relies exclusively on the knowledge built into the checklists to identify potential problems [6]. If the checklist does not address a key issue, the analysis is likely to overlook potentially important weaknesses.

1.1.2. Quantitative Methods. The quantitative safety assessment methods are to quantify the status of the production system’s processes, equipment, environment, facilities, personnel, and management, based on statistical analysis of a large number of experimental results or accident data, using obtained indicators or laws (mathematical models). The commonly used quantitative analysis methods [5, 7] include fault tree analysis, event tree analysis, shortcut risk assessment, and maintenance analysis. The quantitative methods can evaluate the system more accurately than the qualitative methods, but they are still not perfect. Take the commonly used fault tree analysis as an example, this is a deductive technique that uses a fault tree to determine the cause of the accident event. All possible accident events are needed to construct the complete fault tree, but it is difficult to assess all possible accident events and their possibilities and consequences.

1.2. Intelligent Methods for Coal Mine Safety Evaluation. With the enormous development of artificial intelligence (AI), more and more practical applications are available with the artificial intelligent algorithm in the field of engineering [8–12], and numerous attempts have also been carried out on coal spontaneous combustion [13, 14], gas explosions [15–18], etc. Moreover, there are some intelligent methods for coal mine safety evaluation to assess risks quantitatively and solve the problem above.

1.2.1. Improved Fuzzy Theory Methods. Sun [19] developed a comprehensive assessment model of coal mine safety risk in terms of the Fuzzy TOPSIS and integration operator technique. Dai [20] presented a method to use the gas density data by leveraging the fuzzy synthetic evaluation model, and an algorithm to select the weights assignment proposals. Peng [21] introduced linguistic intuitionistic fuzzy numbers to depict the necessary evaluation information. Wang [22] estimated and ranked all of these risk factors through the fuzzy analytic hierarchy process including managerial, environmental, individual, and operational criteria to develop a management model and direct the safety managers in mining procedure.

1.2.2. Improved Swarm Intelligence. He [23] integrated an ant colony algorithm with neural networks to develop a neural network security assessment model utilizing an ant colony algorithm to train the neural network weights. Li [24] optimized the neural net model of the right value (threshold) to overcome the neural net easily falling into the local minimum through quantum genetic algorithm.

1.2.3. Other Techniques. An improved factorization-machine supported neural networks (FNN) structure was designed by Zhang [25]. The fuzzy neurons of the improved FNN have decision-making and control properties with further enhanced error correction performance making the entire system adaptable and stable. Wang [26] integrating the gray correlation technique and the new gray correlation degree method introduced a dynamic resolution coefficient to decrease the error of the gray correlation technique. Li [27] extracted the causal chain of accidents through Bayesian Network analysis to develop the multilevel forecasting indicator system for safety situations and constructed the multilevel prediction model for the coal mine risk trend by combining rough set theory, Bayesian network, and support vector machine.

The occurrence reasons of gas accidents mostly include the unfavorable monitoring of environmental factors, the insufficient accuracy, and the lack of evaluation systems. Based on the Dempster–Shafer (D–S) evidence theory, a coal mine gas safety evaluation model is proposed to automatically get more accurate safety state information. Various sensor monitoring data were collected from the working face monitoring system and processed by adaptive weighted least squares support vector machine (AWLS-SVM) to obtain the prediction data as the input of the safety assessment model. Then, the gas safety state was divided into some different safety levels, and multisensor data fusion was carried out. By the comprehensive analysis of fusion results, the gas safety assessment would be realized assisting coal mine safety management.
2. Gas Safety Evaluation Model

The data source of the gas safety evaluation model is the monitoring system of a coal mine, including monitoring data of gas concentration, wind speed, dust, temperature, etc. The Pearson correlation was used to find the reasonable correlative sensors.

First, in order to evaluate the safety state of a coal mine after a certain time from now on, the predicted sensor values are acquired using the time series prediction model, and AWLS-SVM has been used as the prediction model in this paper. The predicted sensor values would be the evidence sources used in the next step.

Second, the sensor data need to be integrated using improved D-S evidence theory to produce more consistent, accurate, and useful information for safety assessment. The basic probability assignment (BPA) function, which is the basis of D-S evidence theory, is obtained through the posterior probability modeling technique and the similarity degree is presented for modifying the evidence source to reduce the conflicts and improve the accuracy.

Ultimately, multisensor data fusion is performed based on the introduced fusion rules, which are enhanced by the conflict assignment coefficients to prevent the distortion of evidence sources. The reasonable modification of fusion rules can also enhance the accuracy of fusion results.

The coal mine gas safety evaluation model based on AWLS-SVM and D-S evidence theory is shown in Figure 1.

3. Adaptive Weighted Least Squares Support Vector Machine

The evaluation model developed in this paper is aimed at the coal mine gas safety assessment after a definite time. It is essential to obtain the predicted values of the monitoring variables as the input of the evaluation model. Therefore, an adaptive weighted least squares support vector machine (AWLS-SVM) is proposed based on the weighted least squares support vector machine (WLS-SVM) with the adaptive weights calculated through the distribution characteristics of the discrete points.

3.1. Weighted Least Squares Support Vector Machine. Suykens [28] proposed a WLS-SVM in terms of the least squares support vector machine (LS-SVM). The Lagrange function of its optimization problem can be explained as

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

(1)

In the previous equation, \( w \) represents the weight coefficient vector; \( \varphi(x_i) \) shows the mapping input to the high-dimensional space; \( C \) denotes the regularization parameter; \( b \) represents the threshold; \( x_i \) is the Lagrange multiplier.

Regarding the KKT (Karush–Kuhn–Tucker) condition, the function eliminates \( w, \xi_i \), and obtains

\[
\begin{bmatrix}
0 \\
I_{1 \times N}
\end{bmatrix}
\begin{bmatrix}
w \\
\alpha
\end{bmatrix} =
\begin{bmatrix}
y \\
0
\end{bmatrix},
\]

(2)

In the previous equation, \( V = \text{diag}(v_1, v_2, \ldots, v_N) \) represents the diagonal matrix, \( I_{1 \times N} \) shows the unit column vector, \( R = \{K(x_i, x_j)\}_{i=1,2,\ldots,N} \) denotes the radial basis kernel function matrix, and \( y = [y_1, y_2, \ldots, y_N]^T \). Equation (2) can be obtained \( \alpha \) and \( b \), inputting test samples to obtain WLS-SVM model as

\[
y = \sum_{i=0}^{n} a_i K(x_i, x) + b.
\]

(3)

The weight calculation formula is

\[
v_i = \begin{cases} 
1, & \frac{\xi_i}{s_i} \leq s_1, \\
\frac{s_2 - \xi_i/s_i}{s_2 - s_1}, & s_1 \leq \frac{\xi_i}{s_i} \leq s_2, \\
10^{-4}, & \text{otherwise.}
\end{cases}
\]

(4)

In the previous equation, the values of \( s_1 \) and \( s_2 \) are 2.5 and 3.0, respectively [28]; \( \xi \) represents the standard estimated deviation of the error sequence; and its calculation function is

\[
\xi = \frac{\text{IQR}}{2 \times 0.6745}
\]

(5)

In the previous equation, \( \text{IQR} \) represents the difference between the first and third quartiles in the sequence of errors \( \xi_i \) from small to large.

3.2. Adaptive Weighted Least Squares Support Vector Machine. In the WLS-SVM algorithm, the weight is mainly used to eliminate the influence of gross error data in the sample, and whether its value is appropriate directly determines the performance of the model. The weights determined by equation (4) are linearly distributed, and the calculation results will include errors. Therefore, this paper adaptively determines the weight of each sample through iterative operations. The weights are adaptively calculated utilizing the distribution characteristics of discrete points divided into two categories: high leverage points far from the input data center, and high residual error points differing greatly from the actual value. The weighting technique in this paper is the key of the AWLS-SVM, the gross errors are judged simultaneously through sample leverage points and residual points, and it can minimize the adverse impacts of the discrete points.

The residual error weight \( v_i^\xi \) of the \( i \)-th sample data is determined as
where $T$ represents the robust scale estimate of the residual error defined as

$$T = \text{median} |\xi_i - \text{median} (\xi_i)|, \quad i = 1, 2, \ldots, n. \tag{7}$$

The leverage weight $v_i^e$ of the $i$-th sample data is determined as

$$v_i^e = \frac{2}{1 + e^{\xi_i/T}}, \quad i = 1, 2, \ldots, n. \tag{6}$$

$$f(z, c) = \frac{1}{(1 + |z/c|)^2} \tag{8}$$

where $|\cdot|$ represents the Euclidean distance, $\text{median}(X)$ shows the median value of $X$, $x_i$ denotes the $i$-th sample data, $X$ represents the vector of all input specimens, and $c$ denotes a constant usually taken as 4 [28, 29].

Comprehensively considering the leverage and residual error weights, the weight $v_i$ of the $i$-th sample data is determined as

$$v_i = \sqrt{v_i^e v_i^r}. \tag{9}$$

3.3. Prediction Model of Monitoring Variables. The steps to build a prediction model of monitoring variables in terms of AWLS-SVM include the following:

Step 1. Collecting the monitoring data of the mine working face, preprocessing the data, and obtaining the learning samples of the model.

For missing data in the time series, the interpolation method is utilized to supplement the missing data. For abnormal data, which are values of zero or beyond the theoretical range, the discarding method is used to delete the abnormal data from the original dataset, and the interpolation method is used again as a supplement. The ultimate objective is to prevent data problems resulting in the deviation of the counterintuitive results.

Step 2. Dividing the learning sample into a test set and a training set and selecting the proper fitness function, like the mean square error (MSE), neighborhood average method, and weighted arithmetic mean. The MSE is used in this paper.

Step 3. Using 3-fold cross-validation, performing the regression analysis by WLS-SVM with the training sample data, and determining the fitting residual error $\xi$ of each sample. The initialization weight value $v$ is determined in Algorithm 1.
Step 1. Based on the modeled sample data, determine the fitting residual of each sample using least squares support vector machine regression.
Step 2. Initialize the weight $v_i$ using equations (6), (8), and (9).
Step 3. Perform weighted least squares support vector machine regression on the sample data to obtain a regression model.
Step 4. According to the regression model, calculate the residual error $\xi$ of each sample data and recalculate the weight $v_i$ using equations (6), (8), and (9).

Algorithm 1: Algorithm steps.

| Step | Description |
|------|-------------|
| 1.   | Based on the modeled sample data, determine the fitting residual of each sample using least squares support vector machine regression. |
| 2.   | Initialize the weight $v_i$ using equations (6), (8), and (9). |
| 3.   | Perform weighted least squares support vector machine regression on the sample data to obtain a regression model. |
| 4.   | According to the regression model, calculate the residual error $\xi$ of each sample data and recalculate the weight $v_i$ using equations (6), (8), and (9). |

4. Improved Dempster–Shafer Evidence Theory

Dempster–Shafer (D-S) theory has strong applicability in data fusion; however, there are still some deficiencies in the actual fusion process in dealing with uncertain problems. The high conflicts of uncertain information may make the data fusion results inconsistent with the facts [30], resulting in the inability to assess the event. The problems are mainly manifested in the following three aspects:

- One-vote veto problem: when there is a complete contradiction between the pieces of evidence, there will be a veto problem.
- General conflict problem: when the belief functions of the evidence are very different, unreasonable results appear after fusion.
- Robustness problem: when the belief functions of the evidence change, the results after data fusion will change drastically.

In this study, the enhancement of D-S evidence theory is mostly considered to solve the problem of conflicting evidence sources.

4.1. Basic Principles of D-S Evidence Theory

For reasoning, the uncertain problems, D-S evidence theory has robust adaptability with a simpler reasoning process. 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 frame of discernment and basic probability assignment function.

4.1.1. Frame of Discernment

A set $X$ of possible situations of the event is represented by the frame of discernment with the elements representing the degree of evaluation of the event state. In the gas safety evaluation system, every possible state is known as a hypothesis, and all possible categories constitute a frame of discernment. Hence, the frame of discernment includes all possible results of a particular problem. The frame of discernment can be expressed in

$$X = \{X_1, X_2, X_3, \ldots, \Theta\},$$

where $X_i$ represents a possible result of the event and $\Theta$ denotes the uncertainty.

4.1.2. Basic Probability Assignment (BPA) Function

Suppose that $X$ is a frame of discernment; $2^X$ represents a power set on $X$, if $m: 2^X \rightarrow [0, 1]$ and satisfies

$$\sum_{A \subseteq X} m(A) = 1, \quad m(\Theta) = 0. \quad (11)$$

In the previous equation, $m$ is known as the BPA of the discernment frame $X$ and it is also known as the mass function and $A$ represents the element in the discernment frame. For $\forall A \subseteq X$, $m(A)$ shows the basic belief indicating the level of trust in proposition $A$.

4.1.3. Belief Function

If there are $A \in P(X)$ and $B \in A$, the function Bel is defined as

$$Bel(A) = \sum_{B \in A} m(B). \quad (12)$$

In the previous equation, Bel shows the belief function, and equation (11) is the sum of the possibilities of all the subsets of $A$ representing the overall degree of trust in $A$; hence, it can be inferred that Bel($\Theta$) = 0 and Bel($X$) = 1. The belief function shows the trust degree of a certain thing. It is incomplete and untrustworthy to only use the belief function to explain the possibility of an event.

4.1.4. Likelihood Function

In D-S evidence theory, the likelihood function is a measure expressing the degree of distrust of an event. Definition: $X$ is a frame of discernment, $m: 2^X \rightarrow [0, 1]$ is given as the basic probability assignment on $X$. If there are $A \in P(X)$, $B \in A$, then the function Pl: $2^X \rightarrow [0, 1]$ is defined as

$$Pl(A) = 1 - Bel(\overline{A}) = \sum_{B \in A \cap \Theta} m(B). \quad (13)$$

In the previous equation, Pl($A$) indicates that event $A$ is true uncertainty and Bel($\overline{A}$) shows the trust degree of event $\overline{A}$. The degree of mistrust Pl($A$) of $A$ can be determined by equation (13).
The minimum level of trust of evidence theory for event $A$ is $\text{Bel}(A)$, the potential degree of trust in event $A$ is stated as $\text{Pl}(A)$, the support interval of event $A$ is expressed as $[0, \text{Bel}(A)]$, and the likelihood interval of event $A$ is stated as $[0, \text{Pl}(A)]$. When the evidence neither confirms nor denies the occurrence of event $A$, a trust interval can be used for this uncertain phenomenon, to represent the probability of event $A$.

### 4.2. Improvements of D-S Evidence Theory

#### 4.2.1. Evidence-Based Improvements

Modifying the evidence source can reduce the effect of interference factors on the fusion assessment results and improve the evaluation results’ accuracy. In this study, the idea of assigning weights is utilized to allocate each evidence’s importance to increase the reliability of the evidence on the decision result and weaken the effect of conflicting evidence.

For an uncertain event, there are $n$ pieces of evidence, and the corresponding discernment frame $X$ contains $N$ focal elements with $m_i$ representing the evidence set composed of the basic probability assignment function equivalent to the evidence under each focal element:

$$m_i = [m_i(A_1), m_i(A_2), \ldots, m_i(A_n)]^T, \quad i = 1, 2, \ldots, n.$$  \hspace{1cm} (14)

Equation (14) is utilized to determine the distance between $m_i$ and $m_j$, and $d_{ij}$ represents the distance of $m_i$ and $m_j$. This distance function with a better reflection in explaining the focal element and the reliability between pieces of evidence can better determine the conflict between pieces of evidence:

$$d_{ij} = d(m_i, m_j) = \sqrt{\frac{1}{2} \left( \|m_i\|^2 + \|m_j\|^2 - 2(m_i, m_j) \right)}.$$  \hspace{1cm} (15)

The similarity function is further derived from equation (15). The similarity between $m_i$ and $m_j$ can be expressed as $S_{ij}$ and the expression of $S_{ij}$ is

$$S_{ij} = 1 - d_{ij}.$$  \hspace{1cm} (16)

The smaller the distance between the pieces of evidence, the higher the mutual support. The degree of support for evidence can be stated by the sum of other evidence; then the degree of support for evidence $m_i$ is

$$T(m_i) = \sum_{j=1, j\neq i}^{n} S_{ij}, \quad i = 1, 2, \ldots, n.$$  \hspace{1cm} (17)

In this paper, the distance similarity matrix between pieces of evidence is utilized to allocate various weights to each sensor to meet the purpose of modifying the evidence source. To prevent the conservative revised evidence source and losing the advantages of the original evidence, this study adopts retaining the original set of more accurate evidence to guarantee the impact of data fusion. Based on the above ideas and the ratio of the degree of support of the evidence, under retaining a good set of evidence sources, the weight $\beta$ of the evidence is determined based on the level of support. The specific formula is as follows:

$$\beta(m_i) = \frac{T(m_i)}{\max(T(m))}.$$  \hspace{1cm} (18)

After allocating the weights, the modified basic probability assignment function equivalent to the evidence can be stated as follows:

$$m'_i(i) = \beta(m_i) \cdot m_i,$$

$$m'_i(\Theta) = \beta(m_i) \cdot m_i + (1 - \beta(m_i)).$$  \hspace{1cm} (19)

#### 4.2.2. Improvements Based on Fusion Rules

In this paper, using the time series prediction value of the monitoring data of each sensor, the basic probability assignment function value is calculated. After fusing the value of each sensor, the mine gas safety state is judged. The fusion rules of D-S evidence theory are as follows.

According to two independent pieces of evidence $M_1$ and $M_2$, the focal elements of the two pieces of evidence are $B_i$ and $C_j (i = 1, 2, 3, \ldots, m; j = 1, 2, 3, \ldots, n)$, and the basic probability assignment function value after their fusion is $m(A)$:

$$m(A) = M_1 \oplus M_2 = \frac{1}{1 - K} \sum_{B_i \cap C_j = A} m_1(B_i)m_2(C_j),$$

$$K(M_1, M_2) = \sum_{B_i \cup C_j = \Theta} m_1(B_i)m_2(C_j).$$  \hspace{1cm} (20)

In the previous equation, $K(M_1, M_2)$ is known as the conflict coefficient representing the degree of conflict between the two pieces of evidence $M_1$ and $M_2$. There is no conflict between the two pieces of evidence when the conflict coefficient is 0. However, when it is closer to 1, greater conflict exists between the two pieces of evidence, as a complete conflict.

Many scholars [30–32] believe that the fusion rules of evidence theory are imperfect in the processing of evidence; hence, the reasonable modification of fusion rules can also enhance the accuracy of fusion. After modification of the evidence source, the simple modification of the evidence source data to prevent high conflicts between the pieces of evidence may result in the revised evidence to lose the effective information of the original evidence. The conflict allocation coefficient is introduced based on the fusion rules to enhance the decision stage accuracy.

The conflict allocation coefficient $\omega(A_i)$ can be expressed as

$$\omega(A_i) = \frac{\sum_{j=1}^{n} m'_i(A_{ij})}{\sum_{j=1}^{n} \sum_{\Theta} m'_i(A_{ij})}.$$  \hspace{1cm} (21)
The enhanced formula of D-S evidence theory fusion rule is expressed as

\[ m(A) = \sum_{B_i \backslash C_j} m_1(B_i)m_2(C_j) + K \cdot \omega(A_i). \]  

(22)

In equation (22), set \( A \) denotes the intersection of the focal element \( B_i \) and focal element \( C_j \).

4.3. Settings for the Gas Safety Evaluation Model. The gas safety evaluation model includes AWLS-SVM and improved D-S evidence theory, which are explained in detail before. The frame of discernment and the basic probability assignment function are the bases of D-S evidence theory calculation, some settings should be done before to use the evaluation model.

4.3.1. Settings of Discernment Frame. From the perspective of D-S evidence theory, the gas safety state can be considered as a judgmental problem, and the sum of hypothetical results can be explained as a frame of discernment. Based on the coal mine safety regulations [1] and related literature [33, 34], the gas safety state is divided into five states: no danger implies that the working face of the coal mine is in a decent environment; mild danger represents that the working face possesses a certain risk, and this danger value is within the acceptable range, an on-site inspection should be completed; moderate danger implies that the working face is unsafe, the indicated value has exceeded the acceptable range, and an on-site inspection is required as soon as possible; severe danger represents that the working face is very bad, and the staff should be evacuated; and uncertain implies that the evacuated result is vague, and the work should be redone after checking the data source and the evaluation process. Hence, the frame of discernment for the coal mine gas safety evaluation model can be explained as \( X = \{ X_1 (\text{no danger}), X_2 (\text{mild danger}), X_3 (\text{moderate danger}), X_4 (\text{severe danger}), \Theta (\text{uncertain}) \} \).

4.3.2. Construction of Basic Probability Assignment Function. In this paper, the posterior probability modeling technique is utilized to construct the basic probability assignment function, and the similarity degree is introduced to modify the evidence source. The support degree of each sensor is characterized by the basic probability assignment function to the safety state of mine gas. In this paper, a time series prediction model is made through the AWLS-SVM, and the prediction model is developed with each influence factor as an input to obtain the prediction value of each sensor. The posterior probability modeling technique calculates the basic probability assignment function of each sensor.

Taking a sensor as an example, the basic probability assignment function value obtained by the posterior probability modeling method is \( y \), and the frame of discernment is \( X = \{ X_1, X_2, X_3, X_4, \Theta \} \). The distance between \( X \) and \( y \) can be stated as

\[ d_i(x, y) = |x_i - y|. \]

(23)

The correlation coefficient between the evidence and \( X_i \) can be stated as

\[ c_i = \frac{1}{\sum_i (1/d_i)}. \]

(24)

Introducing equation (24), the uncertainty \( m(\Theta) \) of the corresponding evidence and the basic probability assignment function \( m(i) \) can be expressed as

\[ m(i) = \frac{1}{c_i + E}, \]

\[ m(\Theta) = \frac{E}{\sum_c (1/c_i + E)}, \]

where \( y \) represents the predicted value of the time series prediction model and \( x \) shows the expected output value of the prediction model.

5. Case Analysis

5.1. Data Sources. Qing Gang Ping coal mine located in Shaanxi province is taken as the study area, and the data in this paper are obtained from the coal mine monitoring system, which includes the gas concentration at the upper corner (No. A02), the wind speed (No. A09), the air concentration at the working face 10 meters away (No. A01), the dust (No. A11), the return air tunnel gas concentration (No. A08), and the return air tunnel temperature 15 meters away (No. A07). The original data sampling interval is 1 minute, and the data distribution has obvious jagged characteristics. Hence, this paper uses 5 minutes as the sampling interval to obtain 1500 groups of samples and choose the first 1400 samples for model training and the remaining samples for model testing. The sample set of original monitoring data are shown in Table 1.

5.2. Predicted Results of the Time Series Prediction Model. To predict the monitoring value of each sensor at the next moment, this paper uses the multivariable AWLS-SVM time series prediction model introduced in Section 3. It also uses the target sensor as the output and other sensors as the input for model training. SPSS software was utilized to analyze the Pearson correlation of A02, A01, A09, A11, A07, and A08 monitoring sensors. The analysis results are represented in Table 2.

The interpretation of a correlation coefficient depends on the context and purposes. One of the common criteria used is \(|r| > 0.95\), significant degree; \(0.8 \leq |r| < 0.95\), high degree; \(0.5 \leq |r| < 0.8\), moderate degree; \(0.3 \leq |r| < 0.5\), low degree; and \(|r| < 0.3\), irrelevant. Thus, the correlation of 0.3 is regarded as the limit in this paper. According to Table 2, the correlation coefficients are all greater than 0.3, and it is
reasonable for each sensor to be as the input of the target sensor. The prediction results are shown in Table 3.

The prediction results were obtained undertaking the steps described in Section 3.3 using the data sources in Section 5.1 from the coal mine monitoring system, and those values would be the input of the data fusion using the improved D-S theory.

5.3. Experimental Results and Analysis

5.3.1. Contrast Analysis of Conflict Degree. The posterior probability modeling method introduced in Section 4.3 is used in this paper to calculate the basic probability assignment function of each sensor. The BPA of each sensor is shown in Table 4.

According to Table 2, the results of single sensor recognition are A09 (%) A07 (%) A09 (m/s) A11 (mg/m³) A07 (°C) A08 (%), and A08 = 0.572, 0.910, 0.668, 0.324, 0.788, 1.

5.3.2. Comparative Analysis of Evaluation Results. Based on the comparative analysis of the degree of conflict in Section 5.3, data fusion plays a key role in the decision-making results. For the modifying method of the evidence source, this paper calls the D-S-1 evidence theory. Moreover, the D-S-2 evidence theory is called for the method of modifying the fusion rule. Sensors A09, A07, A11, A02, A01, and A08 are recorded as pieces of evidence e₁, e₂, e₃, e₄, e₅, and e₆. The fusion procedure of multisensors is the fusion process of two sensors in sequence. The comparison outcomes of the multisensor data fusion of the three methods are provided in Figures 2–6.

According to Figure 2, the fusion evidence sources e₁ and e₂ are all highly conflicting pieces of evidence; hence, the decision results of D-S evidence theory and D-S-1 evidence

| Table 1: The sample set of monitoring data. |
|--------------------------------------------|
| Number | A02 (%) | A01 (%) | A09 (m/s) | A11 (mg/m³) | 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   |

| Table 2: The 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 |

| Table 3: The predicted results of various sensors. |
|-----------------------------------------------|
| Predicted results | A02 (%) | A01 (%) | A09 (m/s) | A11 (mg/m³) | A07 (°C) | A08 (%) |
|-------------------|---------|---------|-----------|-------------|---------|---------|
| 0.380            | 0.422   | 1.912   | 0.094     | 22.086      | 0.504   |

| Table 4: The basic probability assignment functions. |
|-----------------------------|----------------|--------|--------|--------|--------|--------|
| A09 | A07 | A11 | A02 | A01 | A08 |
| X₁ | 0.0646 | 0.2057 | 0.4939 | 0.5551 | 0.5664 | 0.5954 |
| X₂ | 0.8079 | 0.2160 | 0.2358 | 0.2150 | 0.2106 | 0.1979 |
| X₃ | 0.0557 | 0.2273 | 0.1549 | 0.1333 | 0.1294 | 0.1187 |
| X₄ | 0.0288 | 0.2399 | 0.1153 | 0.0966 | 0.0934 | 0.0848 |
| Θ | 0.0431 | 0.1111 | 0.0000 | 0.0000 | 0.0002 | 0.0032 |

| Table 5: The basic probability assignment function after modifying the evidence source. |
|-----------------------------|----------------|--------|--------|--------|--------|--------|
| A09 | A07 | A11 | A02 | A01 | A08 |
| X₁ | 0.0369 | 0.1712 | 0.4914 | 0.5551 | 0.5643 | 0.5801 |
| X₂ | 0.4622 | 0.1797 | 0.2357 | 0.2150 | 0.2098 | 0.1929 |
| X₃ | 0.0318 | 0.1892 | 0.1541 | 0.1333 | 0.1298 | 0.1157 |
| X₄ | 0.0165 | 0.1997 | 0.1148 | 0.0966 | 0.0930 | 0.0826 |
| Θ | 0.4526 | 0.2602 | 0.0051 | 0.0000 | 0.0040 | 0.0287 |
theory are invalidated, and the recognition results of D-S-2 evidence theory are uncertain. Followed by introducing the evidence source \( e_3 \) in Figure 3, the recognition results of the D-S-1 and D-S evidence theories are wrong, and the D-S-2 evidence theory recognition results are accurate. This proves that the enhanced fusion rule in this paper is effective in retaining the revised evidence source. In Figure 4, according to the fusion results of evidence sources \( e_1, e_2, e_3, \) and \( e_4 \), D-S evidence theory recognition result is inaccurate and D-S-2 evidence theory recognition results are accurate proving that the modified technique of the evidence source enhanced in this paper is correct, eliminating the interevidence high conflicts. Figures 5 and 6 show that the D-S-2 evidence theory technique for modifying the evidence source and fusion rules in this paper is reasonable. The recognition accuracy of the D-S-2 evidence theory is higher compared to
the D-S-1 evidence theory and D-S evidence theory. The accuracy of D-S evidence theory based on the improved fusion rules (D-S-2, the model proposed in this paper) is improved by 2.82% (from 0.9225 to 0.9485), respectively, compared to D-S evidence theory based on modified evidence sources (D-S-1) and improved by 15.70% (from 0.8198 to 0.9485) compared to the original D-S evidence theory (D-S).

The accuracy rate of mine gas safety state recognition was enhanced. At the same time, the fusion rule satisfies the exchange law; moreover, it can be concluded that increasing the evidence during the fusion process leads to the higher accuracy of the identification in the decision stage. The problem regarding the difficulty in accurately characterizing the gas safety state in the single sensor is solved. It can be concluded that the multisensor data fusion gas safety state evaluation system suggested in this paper possesses high practical value in field applications with important theoretical significance for overwhelming the occurrence of gas disasters and enhancing the safe and sustainable development of the coal industry.

5.3.3. Model Uncertainty Measure. This paper utilizes Shannon entropy [35] for measuring the uncertainty of the above three D-S evidence theories. Let $n$ signal sources make up the signal $X = \{x_1, x_2, x_3, \ldots, x_n\}$; the probability that each signal source represents the equivalent information for an event is $P = \{p(x_1), p(x_2), p(x_3), \ldots, p(x_n)\}$; then the system structure $S$ of the signal can be stated as

$$S = \left( \begin{array}{c} X \\ P \end{array} \right) = \left( \begin{array}{cccc} x_1 & x_2 & \ldots & x_n \\ p(x_1) & p(x_2) & \ldots & p(x_n) \end{array} \right).$$  

(26)

Therefore, the Shannon entropy of the signal is given as

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

(27)

The uncertainty of fusion data using D-S evidence theory is

$$-0.8198 \times \ln 0.8198 - 0.1768 \times \ln 0.1768 - 0.0028 \times \ln 0.0028 - 0.0006 \times \ln 0.0006 = 0.4901.$$  

(28)

The uncertainty of fusion data using D-S-1 evidence theory is

$$-0.9225 \times \ln 0.9225 - 0.0720 \times \ln 0.0720 - 0.0042 \times \ln 0.0042 - 0.0013 \times \ln 0.0013 = 0.2955.$$  

(29)
The uncertainty of fusion data using D-S-2 evidence theory is

\[-0.9485 \ast \ln 0.9485 - 0.0466 \ast \ln 0.0466 - 0.0038 \ast \ln 0.0038 - 0.0011 \ast \ln 0.0011 = 0.2217.\]  

(30)

From the above results, it is deduced that the enhanced D-S-2 evidence theory has lower uncertainty compared to the D-S evidence theory and can better assess the safety of coal mine gas.

6. Conclusions

According to the features of coal mine monitoring data, a prediction model is made. By obtaining the predicted values of each sensor, the basic probability assignment function of each sensor is determined to utilize the posterior probability modeling method.

Moreover, a safe assessment model of coal mine gas state is made, and multisensor data fusion is realized. Fusing more sensors, the evaluation results are more accurate. The model in this paper effectively solves the problem of difficulty in accurately characterizing the gas safety state by one sensor.

Furthermore, regarding the problem of evidence fusion failure caused by high-conflict data, this paper represents the similarity for modifying the evidence source of conflict data, which effectively decreases the conflict between the evidence sources. At the same time, to prevent distortion of evidence sources, the conflict assignment coefficients are presented to enhance the fusion rules, and the accuracy of evaluation results is improved. It proves that the enhanced D-S evidence theory can improve accuracy by 15.70% compared to the original D-S evidence theory.

The enhanced method has better generalization ability and higher accuracy for coal mine gas safety evaluation providing a theoretical basis for gas disaster accident prevention. According to the results of coal mine gas safety evaluation, there are some policy implications for coal mine safety in China: although reducing gas in underground coal mine has a positive effect on coal mine safety, it is impossible to completely avoid gas production in the short term. Thus, one available choice is to promote the research of gas monitoring and related safety evaluation technologies and to advocate the use of more efficient and accurate technical means.

Data Availability

The data used to support the findings of this study have been deposited in https://github.com/sun-zhenming/CoalMineMonitoringData.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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