Research Article

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

Zhenming Sun [1] and Dong Li [2]

[1]*School of Energy and Mining Engineering, China University of Mining and Technology (Beijing), Beijing 100083, China*
[2]*Beijing Longruan Technologies, Beijing 100190, China*

Correspondence should be addressed to Zhenming Sun; sun@cumtb.edu.cn

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/and 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

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

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–Khun–Tucker) condition, the function eliminates w, ξ_i, and obtains

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

In the previous equation, $V = \text{diag}(v_1^{-1}, v_2^{-1}, \ldots, v_N^{-1})$ represents the diagonal matrix, $l_{1 \times N}$ 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 α and b, inputting test samples to obtain WLS-SVM model as

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

The weight calculation formula is

$$
v_i = \begin{cases} 1, & \left| \dfrac{\xi_i}{\widehat{s}} \right| \leq s_1, \\[2ex] \dfrac{s_2 - |\xi_i / \widehat{s}|}{s_2 - s_1}, & s_1 < \left| \dfrac{\xi_i}{\widehat{s}} \right| \leq s_2, \\[2ex] 10^{-4}, & \text{otherwise.} \end{cases}
\tag{4}
$$

In the previous equation, the values of s_1 and s_2 are 2.5 and 3.0, respectively [28]; $\widehat{s}$ represents the standard estimated deviation of the error sequence; and its calculation function is

$$
\widehat{s} = \frac{\text{IQR}}{2 \times 0.6745}.
\tag{5}
$$

In the previous equation, IQR represents the difference between the first and third quartiles in the sequence of errors ξ_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^{ξ} of the i-th sample data is determined as
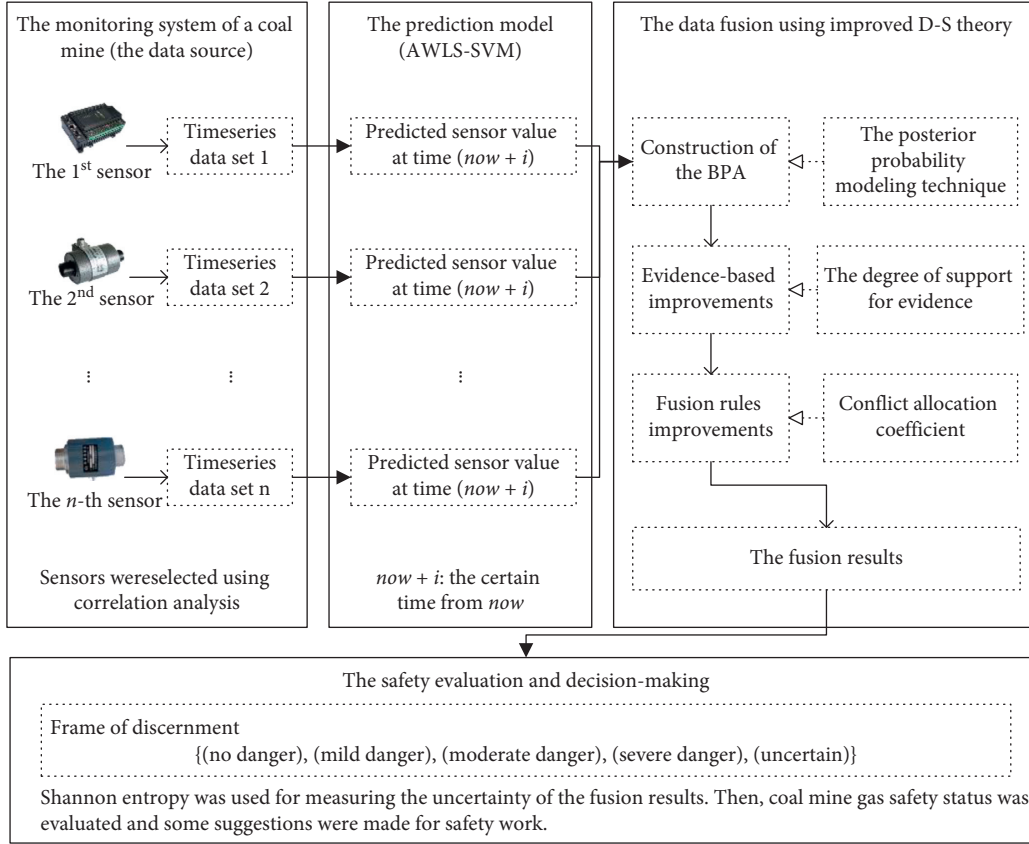
FIGURE 1: The gas safety evaluation model.

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

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^x of the i-th sample data is determined as

$$v_i^x = f\left(\frac{\|x_i - \text{median}(X)\|}{\text{median}(\|x_i - \text{median}(X)\|)}, c\right), \quad i = 1, 2, \ldots, n,$$

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

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

$$v_i = \sqrt{v_i^{\xi} v_i^x}. \tag{9}$$

The algorithm steps of AWLS-SVM are given in Algorithm 1.

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 data set, 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 ξ of each sample. The initialization weight value v is

---

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 ξ of each sample data and recalculate the weight v_i using equations (6), (8), and (9)

ALGORITHM 1: Algorithm steps.

calculated based on equations (4) and (5) and taking v into equations (2) and (3) to reach the WLS-SVM model.

Step 4. Recalculating the residual error ξ of each sample data based on the regression model. The weight value v is recalculated using equations (6), (8), and (9).

Step 5. Taking the weight value v into equations (2) and (3) to develop the AWLS-SVM as the prediction model.

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

$$X = \{X_1, X_2, X_3, \ldots, \Theta\}, \tag{10}$$

where X_i represents a possible result of the event and Θ 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: $2^X \longrightarrow [0, 1]$ and satisfies

$$\sum_{A \in 2^X} m(A) = 1, \quad m(\Theta) = 0. \tag{11}$$

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

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

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 $\text{Bel}(\Theta) = 0$ and $\text{Bel}(X) = 1$. 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: $2^X \longrightarrow [0, 1]$ is given as the basic probability assignment on X. If there are $A \in P(X)$, $B \in A$, then the function Pl: $2^X \longrightarrow [0, 1]$ is defined as

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

In the previous equation, $\text{Pl}(A)$ indicates that event A is true uncertainty and $\text{Bel}(\overline{A})$ shows the trust degree of event $\overline{A}$. The degree of mistrust $\text{Pl}(A)$ of A can be determined by equation (13).

The minimum level of trust of evidence theory for event A is $\mathrm{Bel}(A)$, the potential degree of trust in event A is stated as $\mathrm{Pl}(A)$, the support interval of event A is expressed as $[0, \mathrm{Bel}(A)]$, and the likelihood interval of event A is stated as $[0, \mathrm{Pl}(A)]$. 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:

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

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:

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

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

$$S_{ij} = 1 - d_{ij}. \tag{16}$$

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 degree of support for evidence m_i is

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

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 β

of the evidence is determined based on the level of support. The specific formula is as follows:

$$\beta(m_i) = \frac{T(m_i)}{\max(T(m_i))}. \tag{18}$$

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

$$\begin{aligned} m_i'(i) &= \beta(m_i) \cdot m_i, \\ m_i'(\Theta) &= \beta(m_i) \cdot m_i + (1 - \beta(m_i)). \end{aligned} \tag{19}$$

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 ($i = 1, 2, 3, \ldots, n; j = 1, 2, 3, \ldots, m$), and the basic probability assignment function value after their fusion is $m(A)$:

$$\begin{cases} m(A) = M_1 \oplus M_2 = \dfrac{1}{1-K} \displaystyle\sum_{B_i \cap C_j = A} m_1(B_i)m_2(C_j), \\[4mm] K(M_1, M_2) = \displaystyle\sum_{B_i \cap C_j = \Theta} m_1(B_i)m_2(C_j). \end{cases} \tag{20}$$

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

$$\omega(A_i) = \frac{\sum_{i=1}^{n} m_i'(A_{ij})}{\sum_{i=1}^{n} \sum_{j=1}^{p} m_i'(A_{ij})}. \tag{21}$$

The enhanced formula of D-S evidence theory fusion rule is expressed as

$$m(A) = \sum_{B_i \cap C_j = A} m_1(B_i) m_2(C_j) + K \cdot \omega(A_i). \qquad (22)$$

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 summary 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 $X = \{X_1 \text{ (no danger)}, X_2 \text{ (mild danger)}, X_3 \text{ (moderate danger)}, X_4 \text{ (severe danger)}, \text{ and } \Theta \text{ (uncertain)}\}$.

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

$$d_i(X_i, y) = |X_i - y|. \qquad (23)$$

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

$$c_i = \frac{(1/d_i)}{\sum_{i=1}^{4} (1/d_i)}. \qquad (24)$$

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

$$m(i) = \frac{c_i}{\sum c_i + E},$$

$$m(\Theta) = \frac{E}{\sum c_i + E}, \qquad (25)$$

$$E = \frac{1}{2}|y - x|^2,$$

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 gas 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

TABLE 1: The sample set of monitoring data.

Number	A02 (%)	A01 (%)	A09 (m/s)	A11 (mg/m^3)	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.

	A02	A01	A09	A11	A07	A08
Predicted results	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
X_1	0.0646	0.2057	0.4939	0.5551	0.5664	0.5954
X_2	0.8079	0.2160	0.2358	0.2150	0.2106	0.1979
X_3	0.0557	0.2273	0.1549	0.1333	0.1294	0.1187
X_4	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
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
Θ	0.4526	0.2602	0.0051	0.0000	0.0040	0.0287

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 $m(X_2) = 0.8079$, 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, there is a great conflict between A09 and A07 and other sensors. Using one sensor evaluation result cannot accurately assess the safety state of coal mine gas. Hence, it is necessary to modify the evidence source before fusion.

This study adopts the improved technique of evidence source introduced in Section 4.2 and redistributes the weights for each sensor based on the BPA in Table 4, and the revised BPA is shown in Table 5.

According to Table 5, 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 considerably reduced, indicating that the modification method of

the evidence source is feasible and retains the excellent evidence of A02. At the same time, Table 5 shows that only using sensors A07 and A09 as evaluation evidence will fail decision-making. Moreover, 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 one sensor to assess the safety state of coal mine gas.

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 e_1, e_2, e_3, e_4, e_5, and e_6. 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 e_1 and e_2 are all highly conflicting pieces of evidence; hence, the decision results of D-S evidence theory and D-S-1 evidence
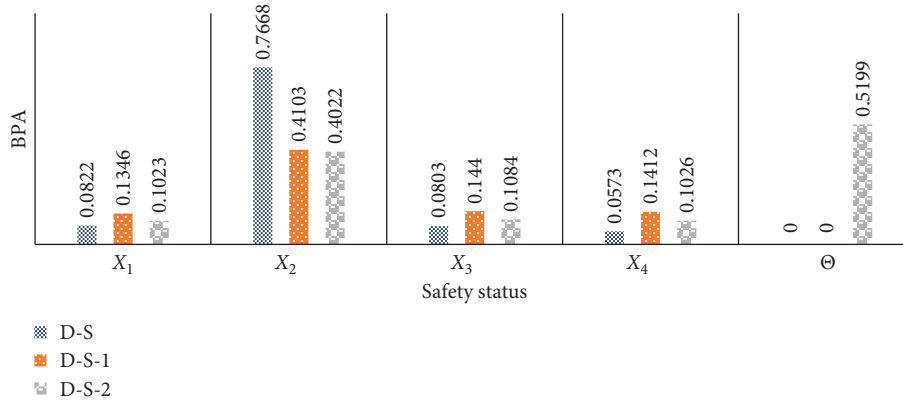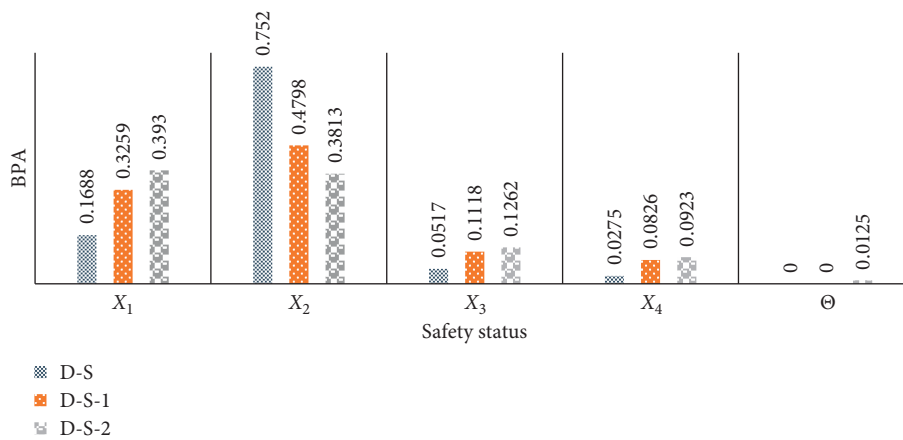
FIGURE 2: The comparative analysis of e_1e_2 fusion results.

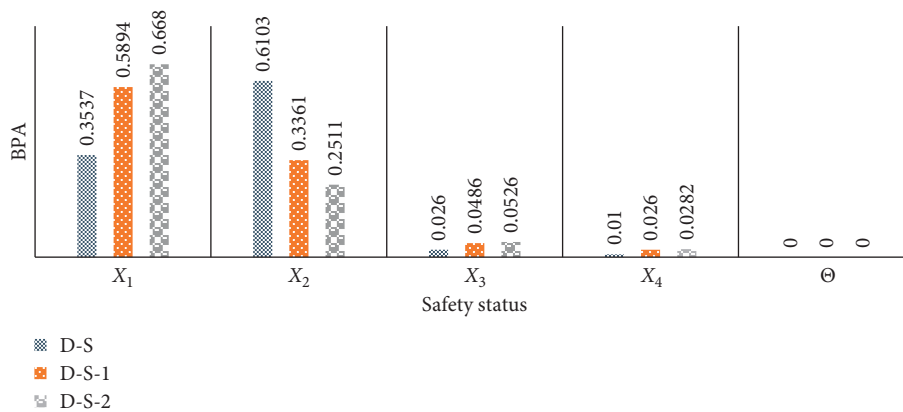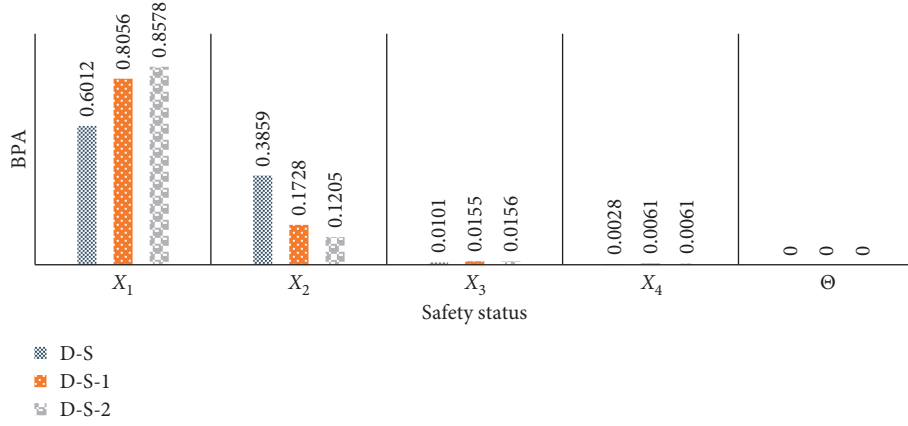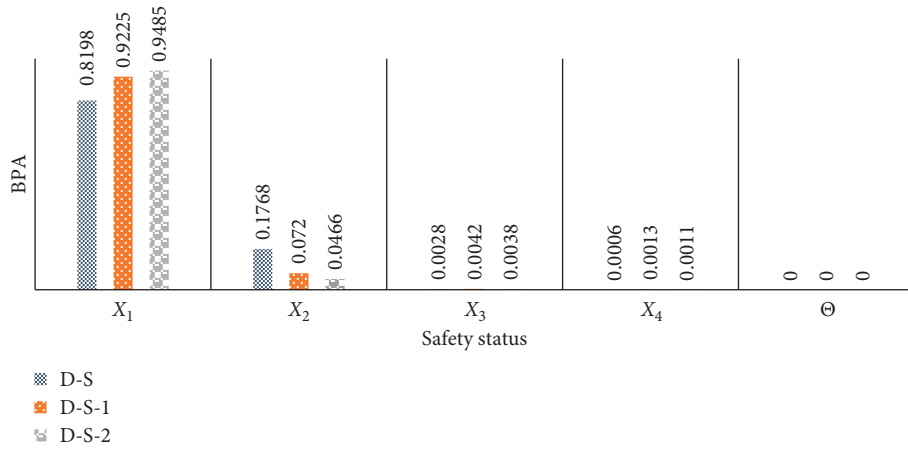FIGURE 3: The comparative analysis of $e_1e_2e_3$ fusion results.

FIGURE 4: The comparative analysis of $e_1e_2e_3e_4$ fusion results.

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

FIGURE 5: The comparative analysis of $e_1e_2e_3e_4e_5$ fusion results.

FIGURE 6: The comparative analysis of $e_1e_2e_3e_4e_5e_6$ fusion results.

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

$$S = \begin{pmatrix} X \\ P \end{pmatrix} = \begin{pmatrix} x_1 & x_2 & \cdots & x_n \\ p(x_1) & p(x_2) & \cdots & p(x_n) \end{pmatrix}. \tag{26}$$

Therefore, the Shannon entropy of the signal is given as

$$H(x) = -\sum_{i=1}^{n} p(x_i)\ln p(x_i). \tag{27}$$

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

$$-0.8198 * \ln 0.8198 - 0.1768 * \ln 0.1768 - 0.0028 \\ * \ln 0.0028 - 0.0006 * \ln 0.0006 = 0.4901. \tag{28}$$

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

$$-0.9225 * \ln 0.9225 - 0.0720 * \ln 0.0720 - 0.0042 \\ * \ln 0.0042 - 0.0013 * \ln 0.0013 = 0.2955. \tag{29}$$

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

$$-0.9485 * \ln 0.9485 - 0.0466 * \ln 0.0466 - 0.0038 \\ * \ln 0.0038 - 0.0011 * \ln 0.0011 = 0.2217. \quad (30)$$

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 D-S-1 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.

Acknowledgments

References

[1] National Coal Mine Safety Administration, "Coal mine safety regulation," 2020, http://www.chinacoal-safety.gov.cn/xw/zt/lszt/mkaqgc/.

[2] Q. G. Sun, "Current situation of coal mine gas disasters in China and countermeasures," *China Coal*, vol. 40, no. 3, pp. 116–119, 2014.

[3] C. Cai, "Analysis method of gas warning results of coal mine safety monitoring and control system," *Industry and Mine Automation*, vol. 44, pp. 15–18, 2018.

[4] F. Tian, M. Zhang, L. Zhou, H. Zou, A. Wang, and M. Hao, "Qualitative and quantitative differences between common occupational health risk assessment models in typical industries," *Journal of Occupational Health*, vol. 60, no. 5, pp. 337–347, 2018.

[5] P. K. Marhavilas, D. Koulouriotis, and V. Gemeni, "Risk analysis and assessment methodologies in the work sites: on a review, classification and comparative study of the scientific literature of the period 2000–2009," *Journal of Loss Prevention in the Process Industries*, vol. 24, no. 5, pp. 477–523, 2011.

[6] P. K. Marhavilas and D. E. Koulouriotis, "A risk-estimation methodological framework using quantitative assessment techniques and real accidents' data: application in an aluminum extrusion industry," *Journal of Loss Prevention in the Process Industries*, vol. 21, no. 6, pp. 596–603, 2008.

[7] Y. Li and F. W. Guldenmund, "Safety management systems: a broad overview of the literature," *Safety Science*, vol. 103, pp. 94–123, 2018.

[8] A. A. Rassafi, S. S. Ganji, and H. Pourkhani, "Road safety assessment under uncertainty using a multi attribute decision analysis based on Dempster-Shafer theory," *KSCE Journal of Civil Engineering*, vol. 22, no. 8, pp. 3137–3152, 2018.

[9] C.-H. Chen, F.-J. Hwang, and H.-Y. Kung, "Travel time prediction system based on data clustering for waste collection vehicles," *IEICE Transactions on Information and Systems*, vol. E102.D, no. 7, pp. 1374–1383, 2019.

[10] C.-H. Chen, "A cell probe-based method for vehicle speed estimation," *IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences*, vol. E103.A, no. 1, pp. 265–267, 2020.

[11] C. H. Chen, F. Y. Song, F. J. Hwang, and L. Wu, "A probability density function generator based on neural networks," *Physica A: Statistical Mechanics and Its Applications*, vol. 541, Article ID 123344, 2020.

[12] Y. Chen, C. Gu, C. Shao et al., "An approach using adaptive weighted least squares support vector machines coupled with modified ant lion optimizer for dam deformation prediction," *Mathematical Problems in Engineering*, vol. 2020, 23 pages, Article ID 9434065, 2020.

[13] Q. Zhang, H. G. Li, and H. Li, "An improved least squares SVM with adaptive PSO for the prediction of coal spontaneous combustion," *Mathematical Biosciences and Engineering*, vol. 16, no. 4, pp. 3169–3182, 2019.

[14] S. Zhang, J. Q. Chen, and D. Zhang, "Gob spontaneous combustion prediction based on neural network," *Transducer and Microsystem Technology*, vol. 31, no. 5, pp. 10–12, 2012.

[15] X. Tong, W. Fang, S. Yuan, J. Ma, and Y. Bai, "Application of Bayesian approach to the assessment of mine gas explosion," *Journal of Loss Prevention in the Process Industries*, vol. 54, pp. 238–245, 2018.

[16] L. M. Pejic, J. G. Torrent, E. Querol, and K. Lebecki, "A new simple methodology for evaluation of explosion risk in underground coal mines," *Journal of Loss Prevention in the Process Industries*, vol. 26, pp. 1524–1529, 2013.

[17] M. Li, H. Wang, D. Wang, Z. Shao, and S. He, "Risk assessment of gas explosion in coal mines based on fuzzy AHP and Bayesian network," *Process Safety and Environmental Protection*, vol. 135, pp. 207–218, 2020.

[18] Q. Zhang, "Risk assessment of gas explosion disaster based on random forest model," *IOP Conference Series: Earth and Environmental Science*, vol. 446, Article ID 22081, 2020.

[19] X. D. Sun, L. X. Zhang, and H. L. Qi, "Coal mine safety production risk assessment model based on fuzzy analytic hierarchy process," *Industrial Safety and Environmental Protection*, vol. 40, no. 1, pp. 65–68, 2014.

[20] Z. Dai, J. H. Liu, and W. Wang, "Collection and fusion of gas density data and its security warning for coal mine," *Computer Engineering and Design*, vol. 37, pp. 783–787, 2016.

[21] H.-g. Peng, J.-q. Wang, and P.-f. Cheng, "A linguistic intuitionistic multi-criteria decision-making method based on the Frank Heronian mean operator and its application in evaluating coal mine safety," *International Journal of Machine Learning and Cybernetics*, vol. 9, no. 6, pp. 1053–1068, 2018.

[22] Q. Wang, H. Wang, and Z. Qi, "An application of nonlinear fuzzy analytic hierarchy process in safety evaluation of coal mine," *Safety Science*, vol. 86, pp. 78–87, 2016.

[23] R. J. He and Y. H. Du, "Application of improved particle-swarm-optimization neural network in coalmine safety evaluation," *IOP Conference Series: Materials Science and Engineering*, vol. 423, Article ID 12007, 2018.

[24] X. Li, N. W. Li, and Z. Yang, "Coal mine safety evaluation model based on quantum genetic algorithm," *Computer Systems and Applications*, vol. 21, no. 7, pp. 101–105, 2012.

[25] J. A. Zhang, W. J. Li, and Y. L. Guan, "Application of improved FNN in coal mine safety production warning system," *Coal Engineering*, vol. 8, pp. 168–171, 2013.

[26] D. Wang, L. Liu, and X. M. Zhang, "The improvement and application of the grey correlation degree method in the evaluation of coal mine intrinsic safety," *Journal of Safety Science and Technology*, vol. 9, no. 1, pp. 151–154, 2013.

[27] D. W. Li, S. Li, and M. J. You, "Research on mine safety situation prediction model: the case of gas risk," in *Proceedings of the 2019 11th International Conference on Wireless Communications and Signal Processing (WCSP)*, pp. 1–6, Xi'an, China, October 2019.

[28] J. A. K. Suykens, J. De Brabanter, L. Lukas, and J. Vandewalle, "Weighted least squares support vector machines: robustness and sparse approximation," *Neurocomputing*, vol. 48, no. 1–4, pp. 85–105, 2002.

[29] D. J. Cummins and C. W. Andrews, "Iteratively reweighted partial least squares: a performance analysis by Monte Carlo simulation," *Journal of Chemometrics*, vol. 9, no. 6, pp. 489–507, 1995.

[30] L. Zadeh, "A simple view of the Dempster–Shafer theory of evidence and its implication for the rule of combination," *AI Magazine*, vol. 7, no. 2, pp. 85–90, 1986.

[31] J. An, M. Hu, L. Fu, and J. Zhan, "A novel fuzzy approach for combining uncertain conflict evidences in the Dempster-Shafer theory," *IEEE Access*, vol. 7, pp. 7481–7501, 2019.

[32] J. Schubert, "Conflict management in Dempster-Shafer theory using the degree of falsity," *International Journal of Approximate Reasoning*, vol. 52, no. 3, pp. 449–460, 2011.

[33] H. T. Liu and L. L. Li, "Comprehensive evaluation analysis of mine gas safety based on integrated method," in *Proceedings of the 2009 International Conference on Computational Intelligence and Software Engineering*, pp. 1–4, Wuhan, China, December 2009.

[34] Q. J. Qi, X. L. Zhao, and B. C. Song, "Pre-evaluation method of coal mine safety based on continental distance model with varying weight," *Procedia Earth and Planetary Science*, vol. 1, no. 1, pp. 180–185, 2009.

[35] C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, vol. 27, no. 4, pp. 623–656, 1948.