Coal Spontaneous Combustion Temperature Prediction Based on Fuzzy Combined Kernel Relevance Vector Machine

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1. Introduction

With the continuous exploitation of coal resources, the coal spontaneous combustion disaster occurs from time to time, which seriously affects the safety production of coal mine and becomes one of the main disasters faced by the coal mine production. Coal spontaneous combustion is a complex dynamic oxidation process [1]. The occurrence of coal spontaneous combustion not only brings the great inconvenience to the coal production but also may cause an explosion, which will pose a great threat to the life safety of miners [2]. How to accurately predict the degree of coal spontaneous combustion through relevant conditions has always been a safety problem of widespread concern. The gas index of coal spontaneous combustion is the main basis for the prediction of coal spontaneous combustion in mines. Due to the limitations of temperature detection, and the index gas (e.g., O₂, N₂, CO, CH₄) concentrations will change in the process of coal spontaneous combustion, and the relevant indexes of gas produced by coal spontaneous combustion are widely used to predict coal spontaneous combustion in mines. Therefore, it can be seen that there is an inseparable relationship between the coal spontaneous combustion temperature and the index gas concentrations [3]. The risk of coal spontaneous combustion can be judged by studying some relationship between them [4], and the degree of coal spontaneous combustion can be predicted by analyzing the index gas concentrations [5].

In recent years, scholars have predicted the spontaneous combustion temperature of coal through machine learning...
methods. The radial basis function (RBF) neural network method has the advantages of the fast convergence speed, strong nonlinear mapping, and generalization ability when applied to the prediction of coal spontaneous combustion temperature \([6, 7]\). However, its network structure is complex and easy to fall into the local optimization. Although the least square support vector machine (LSSVM) can avoid the disaster of dimension and is suitable for a small sample data set, the kernel function is limited by the Mercer condition, and the prediction result is greatly affected by parameters \([8\textendash}11\]. As a machine learning method proposed in Bayesian theory, a relevance vector machine (RVM) has great advantages in prediction performance \([12, 13]\), but it has some shortcomings, such as the weak generalization ability of single kernel function and sensitivity to abnormal values. Therefore, this paper simulates the process of coal spontaneous combustion heating under actual production conditions and detects the changes of temperature distribution and the index gas concentrations, so as to obtain the relevant parameters of coal spontaneous combustion, and a coal spontaneous combustion combustion temperature prediction method based on fuzzy combined kernel RVM is proposed. After comparing and analyzing the experiment results with the RBF network, LSSVM, Gaussian kernel RVM, and combined kernel RVM, the fuzzy combined kernel RVM method has the highest accuracy for the coal spontaneous combustion combustion temperature prediction. The combined kernel function is composed of the Gaussian kernel function and the polynomial kernel function as an example in this paper. Actually, we can try different combinations in the combination kernel to determine the optimal prediction algorithm \([14\textendash}17]\). The purpose of this paper is to give the basic idea of a fuzzy combination kernel, which can be experimentally determined in different combinations of kernel functions in the future.

Compared with the existing coal spontaneous combustion temperature prediction methods, this paper makes the following main contributions:

1. The fuzzy combined kernel RVM method is proposed, which integrates fuzzy theory, combined kernel function, and RVM algorithm, to solve the problems of low prediction accuracy, weak generalization ability of single kernel function, and sensitivity to abnormal values in the existing machine learning methods, so as to realize the accurate prediction of coal spontaneous combustion temperature.

2. The laboratory built a coal spontaneous combustion platform to simulate various conditions under actual conditions and monitored the changes of index gas concentrations and temperatures at different positions in the process of coal spontaneous combustion, so as to obtain the modeling data.

3. Compared with the traditional prediction methods of coal spontaneous combustion temperature based on the RBF network, LSSVM, Gaussian kernel RVM, and combined kernel RVM, the results show that the proposed model in this paper not only has the highest prediction accuracy, but also is more sparse and easy to be generalized.

2. Fuzzy Combined Kernel RVM Based Coal Spontaneous Combustion Temperature Prediction

2.1. Fuzzy Combined Kernel RVM Modeling. The existing kernel based machine learning methods have some problems, such as low prediction accuracy, weak generalization ability of single kernel function, and sensitivity to abnormal data. The ability of data mapping will be different from each kernel function, which will affect the construction of the model and the effect of prediction \([18]\). For example, for the Gaussian kernel function, the closer the sample point is to the test point, the greater the impact, and the further the distance is, the smaller the impact, so the learning ability is strong; as a global kernel function, the polynomial kernel function has a great impact on the data farther away from the test point, so it has strong generalization ability \([19, 20]\). On the other hand, in the process of machine learning model construction, it is generally considered that each sample point has the same contribution to the model, but the actual situation is not the case. When there is noise or outliers in the data, it may have a serious impact on the model construction and prediction, especially for sparse machine learning methods such as SVM and RVM, they only rely on a small part of data, and they may be very sensitive to noise or outliers \([21]\). The main methods of data processing based on fuzzy theory are as follows: first, define the upper and lower bounds of fuzzy membership, then select the appropriate calculation method of fuzzy membership according to the main attributes of the data set, finally assign each fuzzy membership to its corresponding sample points, and construct a machine learning model to make each sample point have different contribution to the model. Fuzzy theory can give different membership degrees to each group of data, so that each sample has a different contribution to the model, so as to reduce the influence of outliers on the model \([22]\).

Therefore, this paper proposes a prediction method of fuzzy combined kernel RVM, which integrates fuzzy theory \([23\textendash}25]\), combined kernel function, and RVM algorithm. Through fuzzy theory, different weights can be given to the sample data to reduce the influence of outliers on the model; the Gaussian kernel function and polynomial kernel function are weighted to make the model to overcome the problem of the weak generalization ability of a single kernel function. As for the determination of the weight of the kernel function in the combined kernel, it needs to be trained or obtained from experience for different data sets. Combined with the characteristics of the good sparsity and high prediction accuracy of RVM, the accurate prediction can be carried out.

Let the input vector and target vector of fuzzy combined kernel RVM be \(x = [x_1,\ldots,x_l,\ldots,x_N]^T\), and \(t = [t_1,\ldots,t_l,\ldots,t_N]^T\), respectively, where \(x_l, t_l \in \mathbb{R}^D\).
\( i = 1, \ldots , N, N \) is the number of input samples, and \( D \) is the characteristic number of samples. The fuzzy combined kernel RVM regression model can be constructed.

\[
y(x_i, w) = \sum_{i=1}^{N} w_i s_i k(x_i, x_i) + w_0, \tag{1}
\]

where \( k(x_i, x_i) \) is the kernel vector composed of the kernel function \( k(x_i, x_i) = [k(x_i, x_1), \ldots , k(x_i, x_N), \ldots , k(x_N, x_i), \ldots ] \), and

\[
k(x_i, x_i) = \beta e^{-x_i - x_i^2/2^2} + (1 - \beta)(rx_i, x_i)^H. \tag{3}
\]

It is the combined kernel function [26] composed of the Gaussian kernel function and the polynomial kernel function, where \( n = 1, \ldots , N, \lambda > 0 \) is the kernel width of the Gaussian kernel function, \( r \) and \( P \) are the coefficient and idempotent of the polynomial kernel function, respectively, \( r > 0 \) and \( P \) is a positive integer, and \( 1 - \beta \) represent the weights of the Gaussian kernel function and polynomial kernel function, respectively, \( \beta \in [0, 1], w = [w_0, w_1, \ldots , w_N]^T \) is the \( N + 1 \) dimensional weight, \( y(x_i, w) \) is the output of the prediction model, \( \epsilon_i \) is the additional Gaussian noise in the model, \( \epsilon_i = \epsilon_i - \mathcal{N}(0, \delta^2) \), \( \delta^2 \) is the variance of Gaussian noise, and \( s_i \) is the fuzzy membership of the training sample,

\[
s_i = \begin{cases} 
1 & h(x_i) > h_C \\
(1 - \sigma)[\frac{h(x_i) - h_T}{h_C - h_T}]^N + \sigma & h_T \leq h(x_i) \leq h_C, \\
\sigma & h(x_i) < h_T
\end{cases}
\tag{4}
\]

where \( h(x_i) = \sum_{j=1}^N y_j k(x_i, x_j) \) is the heuristic function for calculation of fuzzy membership degree with outliers in fuzzy theory [27]. \( y_j \) is the target value of the sample, \( h_C \) is the heuristic function of the last value, \( h_T \) is the heuristic function of the first value, and \( \sigma \) is the initial value of membership. The membership degree of training samples is calculated and given according to the type of prediction data, that is, the corresponding attention attitude of different training data. In this model, the kernel function \( k(x_i, x_j) \) map the data from the low-dimensional space to the high-dimensional one.

According to Bayesian reasoning, when the target values \( t_i \) are independent of each other, the likelihood function of the training sample can be written.

\[
p(t_i|\alpha, \delta^2) = \prod_{i=0}^{N} N(t_i|y(x_i, w), \delta^2)
\]

where \( \varphi \) is an \( N \times (N + 1) \)-dimensional kernel matrix composed of kernel function \( k(x, x_i) \),

\[
\varphi = \begin{bmatrix}
1 & k(x_1, x_1) & k(x_1, x_2) & \cdots & k(x_1, x_N) \\
1 & k(x_2, x_1) & k(x_2, x_2) & \cdots & k(x_2, x_N) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
1 & k(x_N, x_1) & k(x_N, x_2) & \cdots & k(x_N, x_N)
\end{bmatrix}. \tag{6}
\]

In order to avoid the phenomenon of overfitting when solving \( w \) and \( \delta^2 \) directly by the maximum likelihood method, the likelihood function of weight \( w \) can be written.

\[
p(w|\alpha) = \prod_{m=0}^{N} N(w_m|0, \alpha_m^2), \tag{7}
\]

where \( \alpha \) is an \( N + 1 \)-dimensional hyper-parametric vector, and \( \alpha = [\alpha_0, \alpha_1, \alpha_2, \ldots , \alpha_N]^T \).

Through derivation, the conditional distribution of \( t \) is

\[
p(t|\alpha, \delta^2) = (2\pi)^{-N/2}|\Omega|^{-1/2} \exp \left[ \frac{t^T \Omega^{-1} t}{2} \right], \tag{8}
\]

and, the variance is

\[
\Omega = \delta^2 I + G\varphi A^{-1} \varphi^T G^T, \tag{9}
\]

where \( G = \text{diag}(s_1, s_2, \ldots , s_N) \), that is, the diagonal matrix is composed of fuzzy membership \( s_i \), and parameter \( A = \text{diag}(\alpha_0, \alpha_1, \ldots , \alpha_N) \).

The posterior probability distribution \( p(w|t, \alpha, \delta^2) \) is

\[
P(w|t, \alpha, \delta^2) = (2\pi)^{-N/2} \sum_{t} \exp \left[ \frac{(w - \mu)^T \Sigma^{-1}(w - \mu)}{2} \right], \tag{10}
\]

where the mean of a posteriori probability distribution \( \mu \) and covariance \( \Sigma \) can be written.

\[
\mu = \delta^2 \sum \varphi^T G t, \tag{11}
\]

\[
\Sigma = (\delta^2 - \varphi^T G \varphi + A)^{-1}. \tag{12}
\]

The updating formula of the fuzzy combined kernel RVM model can be obtained by the maximum likelihood method, which is the same as that in the classical RVM, and it is

\[
\hat{\alpha}_i^{\text{new}} = \frac{y_i}{\mu_i}, \tag{13}
\]

where \( \mu_i \) is the i-th posterior mean weight in (11), \( y_i \) is

\[
y_i = 1 - \alpha_i \sum_{i+j} \tag{14}
\]

and, \( \sum_{i+j} \) is the i-th diagonal element of the posterior weight covariance of formula (12), which is calculated from the current \( \alpha \) and \( \delta^2 \) values. The iterative formula for the noise variance \( \delta^2 \) shall be
Step 3. Fuzzy theory is used to process each group of index gas concentration data in the training set so that each group of data has different membership degrees by equation (4).

Step 4. Set the initial value of a posteriori parameter $\alpha$ and noise variance $\delta^2$ and the maximum number of iterations.

Step 5. Update the values of a posteriori parameter $\alpha_{\text{MP}}^{\text{new}}$ and noise variance $(\delta^2)_{\text{MP}}^{\text{new}}$ through formulas (13) and (15).

Step 6. If the error of the two parameter values in the iteration process is less than the set parameter accuracy, the training is completed. Otherwise, return to Step 6 to continue the iteration and update the corresponding parameters to obtain the relevant vectors and parameters completed by training to obtain the predicted coal spontaneous combustion temperature.

3. Experiments

3.1. Coal Spontaneous Combustion Data Acquisition. In order to simulate the coal spontaneous combustion environment, this experiment takes coal samples from the Tingnan coal mine in China and establishes a coal spontaneous combustion experimental platform. The experiment starts from the normal temperature environment, through the real simulation of the spontaneous combustion process of coal in the Tingnan coal mine, creates a good environment for the oxygen supply and heat storage similar to the actual process, and detects the changes of coal spontaneous combustion temperature and the index gas concentrations in the process. The experimental platform consists of a furnace body, gas circuit, and control detection, which is shown in Figure 2.

The furnace body is round. The maximum coal loading height is 150 cm, and the inner diameter is 120 cm. The total coal loading is about 1.5 T. The thermal insulation layer and the temperature control water layer tracking the outer coal temperature can ensure that the coal in the furnace is in a good heat storage environment. The water layer is equipped with the electric heating pipe and inlet preheating copper pipe, and an air intake pipe is set at the central axis of the furnace. There are air flow buffer layers at the top and bottom of the furnace to make the air flow pass through the experimental coal evenly from bottom to top. The air is preheated by the temperature control water layer to make it the same as the created coal spontaneous combustion ambient temperature and then sent from the bottom of the furnace. In addition, temperature measuring probes and gas sampling points are arranged in the furnace.

SP3430 gas chromatograph is selected for gas collection and analysis, as shown in Figure 3. The automatic gas
chromatograph adopts a combined overall structure and is mainly composed of a special gas chromatograph with a double column box, an automatic sampler, and a chromatographic data processing workstation.

The sample data of experimental coal spontaneous combustion are shown in Table 1.

The temperature changes of 38 consecutive days during the experiment process and the changes of various gases were detected by the gas detection and analysis system. 38 groups of temperature and gas concentration data are summarized, in which 30 groups of data are selected as the training samples, and 8 groups of data are the test samples to verify the trained model.

3.2. Construction and Verification of the Model. After normalizing the gas concentration data in the training samples and test samples with the min-max method [28, 29], this paper gives different membership degrees to each group of data in the training set through fuzzy calculation and then builds a coal spontaneous combustion temperature prediction model based on combined kernel RVM to verify its effectiveness.

Step 1. Construct a combined kernel weighted by fourth-order polynomial kernel function and Gaussian kernel function and map the data in low-dimensional space to the high-dimensional one. In this experimental data set, it is found that the error of the model is small when the coefficient $r$ of polynomial kernel function is 7.9, the kernel width of the Gaussian kernel function $\lambda = 0.9$ and weight $\beta = 0.55$.

Step 2. Set the minimum value of fuzzy membership degree as 0.1 and the maximum value as 1 and then calculate different membership degrees by equation (4) and the order $d = 4$, and give them to each group of data in the training set.

Step 3. Initialize $\alpha = 0.01$, $\delta^2 = 0.001$, and the maximum number of iterations is 1000.

Step 4. Set the maximum value of superparameters as 10000 and the threshold of variance $\delta^2$ is 0.01. During the iteration, if $\alpha$ exceeds the set value, the
corresponding \( w \) is zero, and the corresponding sample points can be ignored. Minority \( \alpha \) will approach the finite value, and the corresponding weight is the relevance vector. When iterating, if the relative error of variance is less than the set threshold or reaches the maximum number of iterations, it is considered that the training has met the requirements and the iterative process is ended.

**Step 5**: Substitute the index gas concentration data in the test sample into the trained model to predict the corresponding coal spontaneous combustion temperature value and compare it with the measured value.

### 3.3. Performance Index

In order to analyze and evaluate the prediction effect of different methods on the coal spontaneous combustion temperature, it is necessary to compare the prediction results of various models through various evaluation indexes. In this paper, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean...
Mathematical Problems in Engineering 7

Table 2: The number of relevance vectors of the three methods.

| Prediction methods | Gaussian kernel RVM | Combined nuclear RVM | Fuzzy combined kernel RVM |
|--------------------|---------------------|-----------------------|---------------------------|
| Number of relevance vectors | 10                  | 11                    | 10                        |

The number of relevance vectors is compared in the training process of the Gaussian kernel RVM, combined kernel RVM, and fuzzy combined kernel RVM, as shown in Table 2.

where $y_i'$ is the predicted value, $y_i$ is the actual value, $y_{mean}$ is the average value of the real value, and $N$ is the number of test samples.

MAE, MAPE, and RMSE are important methods to judge the closeness between the predicted value and the actual value. The closer the value is to 0, the closer the predicted value is to the actual value, and the better the prediction effect of the model is; on the contrary, the prediction effect of the model is poor. The relevance coefficient $R^2$ is to reflect the relevance degree of the predicted value and the actual value. When $R^2$ is closer to 1, it indicates that the fitting effect is better; otherwise, the effect is worse.

4. Results and Discussion

The number of relevance vectors is compared in the training process of the Gaussian kernel RVM, combined kernel RVM, and fuzzy combined kernel RVM.
It can be seen that the Gaussian kernel RVM and fuzzy combined kernel RVM are more sparser than the combined kernel RVM in predicting coal spontaneous combustion temperature.

The proposed fuzzy combined kernel RVM for the prediction of coal spontaneous combustion temperature (F-CK-RVM-TP) is compared with the RBF network (RBF-TP), LSSVM (LSSVM-TP), Gaussian kernel RVM (GK-RVM-TP), and combined kernel RVM (CK-RVM-TP). The simulation is shown in Figure 4.

As can be seen from Figure 4, the coal temperature prediction values of the fuzzy combined kernel RVM, combined kernel RVM, and Gaussian kernel RVM are close to the measured temperature values, and their prediction accuracy is higher than LSSVM and RBF.

The relative errors of the above five prediction methods are plotted into a box diagram shown in Figure 5.

As can be seen from Figure 5, although the maximum error of the Gaussian kernel RVM prediction is the smallest of the five methods, the median error is large, so the overall effect of this method is not good. The median of the relative error of the prediction of the fuzzy combined kernel RVM is less than that of the other four methods, so the fuzzy combined kernel RVM method has the highest accuracy in the prediction of coal spontaneous combustion temperature. On the other hand, as can be seen from Table 3, the fuzzy combination kernel RVM model has the highest prediction accuracy and the best fitting effect.

### 5. Conclusions

In this paper, a coal spontaneous combustion temperature prediction method based on fuzzy combined kernel RVM is proposed. Firstly, the sample data are mapped to the high-dimensional space through the combined kernel function weighted by the polynomial kernel function and Gaussian kernel function. Secondly, the fuzzy algorithm is used to calculate and give different membership degrees to each group of training samples, and then the combined kernel RVM model is constructed to obtain the optimal parameters. Finally, the coal spontaneous combustion temperature of the test samples is predicted by the optimal fuzzy combined kernel RVM model.

The prediction results of the proposed method are compared with those of the RBF network, LSSVM, Gaussian kernel RVM, and combined kernel RVM. The results show that the proposed method has the highest accuracy in predicting coal spontaneous combustion temperature, and the correlation vector is less than the combined kernel RVM method. Therefore, the proposed method is more suitable for predicting coal spontaneous combustion temperature and other complex environments.

The proposed method in this paper enhances the accuracy of prediction because of the introduction of fuzzy theory, but at the same time, there are also some challenges. On the one hand, this method is suitable for the scene with relatively stable data set noise. On the other hand, there are some parameters of the algorithm, which need to be determined by experiments based on a large number of training set data.

### Abbreviations and Symbols

| Abbreviation | Description            |
|--------------|------------------------|
| RBF          | Radial basis function  |
| LSSVM        | Least square support vector machine |
| RVM          | Relevance vector machine |

### Table 3: Prediction results of the five models.

| Prediction methods | RBF  | LSSVM | Gaussian kernel RVM | Combined kernel RVM | Fuzzy combined kernel RVM |
|--------------------|------|-------|---------------------|---------------------|---------------------------|
| MAPE (%)           | 5.66 | 5.11  | 4.92                | 4.81                | 4.57                       |
| MAE (°C)           | 2.7569 | 2.6663 | 2.5396             | 2.4701              | 2.2704                    |
| RMSE               | 3.3278 | 3.5193 | 3.3158             | 3.2323              | 2.9235                    |
| $R^2$              | 0.9489 | 0.9429 | 0.9493             | 0.9517              | 0.9518                    |
MAE: Mean absolute error
MAPE: Mean absolute percentage error
RMSE: Root mean square error
$R^2$: Coefficient of determination
F-CK: Fuzzy combined kernel RVM for coal spontaneous combustion temperature prediction
RVM-TP: RVM for coal spontaneous combustion temperature prediction
RBF-TP: RBF network for coal spontaneous combustion temperature prediction
LSSVM-TP: LSSVM for coal spontaneous combustion temperature prediction
GK-RVM-TP: Gaussian kernel RVM for coal spontaneous combustion temperature prediction
CK-RVM-TP: Combined kernel RVM for coal spontaneous combustion temperature prediction
$x$: The input vector of fuzzy combined kernel RVM
$t$: The target vector of fuzzy combined kernel RVM
$y$: The output of the prediction model
$k$: The kernel vector.

Data Availability

The data that support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

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

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