Research on Combination Forecasting Model of Mine Gas Emission

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Abstract—This paper focuses on the effective analysis of the mine gas emission monitoring data, so as to realize the accurate and reliable mine gas emission prediction. Firstly, a weighted multiple computing models based on parametric *t*–norm is constructed. And a new mine gas emission combination forecasting method is proposed. The BP neural network model and the support vector machine were used as the single prediction models. Finally, genetic algorithm and least square method were used to determine the parameters of t-norm in the combination forecasting model, and realized the optimal combination of single models. The experimental analysis shows that the new model has less error than BP neural network model and support vector machine model in the evaluation indexes. It can be concluded that the new combined forecasting model is more suitable for the coal mine gas emission forecast.

Keywords-Mine gas emission; Combination forecasting; Parametric t–norm; LS-SVM; BP neural network

I. INTRODUCTION

Mine gas emission is a very complex dynamic phenomenon; it is comprehensive affected by the Coal seam burial depth, coal seam thickness, mining intensity, the original gas content and other factors. The interaction of various factors make the change of gas emission is dynamic non-linear characteristics. Gas emission forecast is the important reference for mine ventilation system design and gas control management. According to the collected data, establishing a suitable forecasting model to forecast gas hazards, during the early phase of gas accumulation and concentration overrun. Then it can guide the relevant department to take preventive measures to prevent the occurrence of disaster accidents, to ensure the safety of coal production.

There are four main ways to forecast the current gas emission:

1) Statistical analysis. According to received lots of gas emission actually from the previous mine production and mining depth of the data, using the laws of mathematical statistics promotes the forecast to the new mine.

2) Coal seam gas content method. According to the gas content of coal seam and the residual gas content in coal after mining to calculate relative gas emission.

3) Source calculation method. According to the law of gas emission, calculated separately coal mining face, excavation face, mining area and mine gas emission.

4) Analogy method. According to the known mine gas emission to predict the mine with the same or similar geological conditions and mining conditions [1].

With the rapid development of science and technology, especially the development of mathematics and computer technology, the original prediction methods and application fields have been expanded, and some new or further optimized prediction methods have emerged. It mainly uses regression analysis[2,3], BP neural network[4-6], support vector machines[7,8], wavelet analysis[9,10]etc. These models have made some predictive effects when predicting the amount of gas emission. However, in view of the application of a single prediction model, the modeling mechanism is different and will have some limitations in different degrees. Therefore, the generalization ability is poor.

Since the t-norm can improve the generalization ability of the system, based on the prediction model of individual gas emission, the author proposes a combined forecasting model based on parametric *t*-norm to forecast the amount of gas emitted by a number of factors.

II. WEIGHTED MULTIVARIATE COMPUTING MODEL BASED ON T-NORM

A. Parametric T-norm

Definition 1[11] Set binary operator $t(x,y)$ is the binary operation of $[0,1]\times[0,1]\rightarrow[0,1]$. The $t(x,y)$ that satisfies the following conditions is t-norm:

1) Boundary conditions: $t(0,y)=0, t(1,y)=y$;

2) *Monotonic:* $t(x, y)$ *on* x, y *monotonically increasing;*

3) *Associative law:* $t(t(x, y), z) = t(x, t(y, z))$;

4) *Commutative law:* $t(x, y) = t(y, x)$.

Gas emission is the important parameters of prevention and control of gas explosion and gas outburst warning. In view of the complexity of the application area, the concept of *t*-norm needs to be appropriately expanded. Since the computation and the operation itself can be continuously changed, a parametric *t*-norm is proposed. The parameterized *t*-norm is the extend of the And operation and the Or operation, and satisfies the four conditions in the *t*-norm definition. The form of the *t*-norm with parameters is determined by the parameters, using different *t*-norm generation functions, various t-norms and parametric *t*-norm can be generated. So, *t*-norm has good generalization ability.

B. Multivariate Parameterization T-norm

From the definition of *t*-norm, it is a binary operator. In application, the *t*-norm must be extended to a multivariate function.

Theorem 1 the *t*-norm can be generalized to a multivariate function.

By the Associative Property $t(x_1, x_2, ..., x_n) = t(t_{n-1}(x_1, x_2, ..., x_{n-1}), x_n)$, Theorem 1 is established.

C. Weighted Multivariate Computing Model

The current *t*-norm arithmetic model describes an equal condition in an ideal state. And many of the influential factors in the actual complex system generally have different weights. So we introduce the weight parameter for the parameterized *t*-norm as follows:

Theorem 2 Set *f(x)* is the generation function of *t*-norm, then

$$G(x_1, x_2, ..., x_n, \alpha_1, \alpha_2, ..., \alpha_n) = f^{-1}(\max(f(0), \sum_{i=1}^{n} \alpha_i f(x_i) - 1)) \tag{1}$$

is a weighted multivariate computing model based on parametric *t*-norm. Among that, $x_i \in R^+ (i = 1, 2, ..., n)$, α_i is the weight of $f(x_i)$, $\alpha_i \in [0,1]$ and $\sum_{i=1}^{n} \alpha_i = 1$.

When the function *f (x)* changes, the model generates a new operator cluster, and more variability, so that the model has good generalization ability. Set $f(x)=x^p$, so the generated weighted multivariate computing model from (1) is:

$$G(x_1, x_2, ..., x_n, \alpha_1, \alpha_2, ..., \alpha_n) = f^{-1}(\sum_{i=1}^{n} \alpha_i x_i^p - 1) \tag{2}$$

Among them, $p \in (-\infty, 0) \cup (0, +\infty)$, the composite forecasting model is constructed according to (2).

III. Modeling Method of Gas Emission Prediction

A. BP Neural Network Modeling Method

There is a nonlinear relationship between gas emission and many influencing factors. Therefore, BP neural network can be used to predict the gas emission [12]. In this paper, Single prediction model of BP neural network for gas emission quantity is based on three layers BP neural network, the input layer is composed of 6 nodes, which is used to input different kinds of influence factors; and the output layer has 1 node, which is for the prediction value of the gas emission quantity. During the comparison of multiple training models for gas emission prediction models, and finally determined to adopt one hidden layer, the incentive function uses logarithm sigmoid function. Hidden node number using for 4 has better training effect. The initial weight set among the (-1,1). Convergence error is set to 1e-3.Construction of BP neural network predictive model structure is showed by Fig .1.

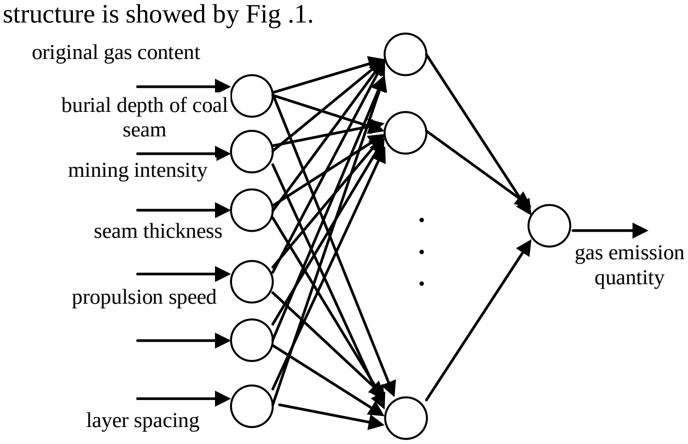

Figure 1. The neural network prediction model for mine gas emission

B. SVM Regression Model Modeling Method

Support Vector Machines (SVM)is a new approach of learning machine based on VC dimension theory and structural risk minimization principle of statistical learning theory. It shows unique advantages in the solution of limited samples, non-linear and high-dimensional pattern recognition, learning and local minimum and other issues. The basic thought of using SVM to estimate the regression function is through non - linear mapping φ, and input the data x for the space mapped to a high-dimensional feature space, then in this high-dimensional space for linear regression.

Least Squares Support Vector Machines (LS-SVM) is one of the method bases on SVM, and replaces the traditional SVM with the least-square method system, using quadratic programming method to solve the problem of pattern recognition. It changes the quadratic programming problem of the algorithm of the original SVM to system of linear equations by constructing a new quadratic loss function. So that it can effectively reduce the computational complexity. So, the paper uses LS-SVM as the single prediction model to forecast the gas emission.

The step of establishment of LS-SVM prediction model of gas emission is as following:

1) Given a training set made by a sample data of N gas emission factors $\{x_k, y_k\}_{K=1}^{N}$ *,inputs data* $x_k \in R^m$ *,outputs data* $y_k \in R$ *,the function fitting problem can be described as the following optimization problem:*

$$\min_{w,e} J(w,e) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{k=1}^{N} e_k^2 \quad (3)$$

$$S.\ T.\ y_k = w^T \phi(x_k) + b + e_k (k = 1,2,\ldots,N) \quad (4)$$

In (4), $\phi(x_k)$ is used to map input data from space R^m to high dimensional feature space R^{mh} ,and $w \in R^{mh}$ is the weighted variable. $\gamma > 0$ is penalty factor to use for adjust error; $e_k \in R$ is error variable, $b \in R$ is offset value.

2) Using the way of Lagrange to solve this optimization problem, that is:

$$L(\omega, b, \zeta, \alpha, \gamma) = \frac{1}{2}\omega_g \omega + c\sum_{k=1}^{n} \zeta_k^2 - \sum_{k=1}^{n} \alpha_k (\varphi(x_k) + b + \zeta_k - y_k) \quad (5)$$

Among that , $\alpha_k (k = 1,2,\ldots,N)$ is Lagrange multiplier.

From $\frac{\partial L}{\partial \omega} = \frac{\partial L}{\partial \zeta} = \frac{\partial L}{\partial \alpha} = \frac{\partial L}{\partial \gamma} = 0$,it can calculate equation：

$$\omega = \sum_{k=1}^{n} \alpha_k \phi(x_k), \sum_{k=1}^{n} \alpha_k = 0, \alpha_k = c^{\zeta} k \quad (6)$$

Kernel function $K(x_i, x_j) = \phi(x_i) g^{\phi}(x_j)$ is symmetric functions satisfying Mercer condition. According to (6) and the constraint (4), the optimization problem can be transformed into solving linear equations.

$$\begin{bmatrix} 0 & 1 & \wedge & 1 \\ 1 & K(x_1,x_1)+1/c & \wedge & K(x_1,x_1) \\ M & M & M & M \\ 1 & K(x_1,x_1) & \wedge & K(x_1,x_1)+1/c \end{bmatrix} \begin{bmatrix} b \\ \alpha_1 \\ M \\ \alpha_1 \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ M \\ y_1 \end{bmatrix} \quad (7)$$

3) The LS-SVM fitting model is obtained

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x_k, x) + b \quad (8)$$

Thereinto, α_k is the support vector, α_k and b can be calculated according to the training sample data.

The training of LS-SVM model is mainly to solve the linear equations(7). When using LS-SVM model to forecast, just need to calculate the kernel function between the training samples and the tested samples $K(x_i, x_j)$, not involving the concrete form of the function $\phi(x_k)$.

4) Selected kernel function. Choosing kernel function is an important part of building model. Because Radial Basis Function(RBF) has good learning ability and wide convergence domain, RBF is chosen as the kernel function of the model. That is:

$$K(x_i, x_j) = \exp(-\left\| x_i - x_j \right\|^2 / \sigma^2) \quad (9)$$

Among that , σ is kernel function.

C. Combination Forecasting Modeling Method

The combined forecasting modeling method is a combination of two or more predictive methods to predict the same prediction problem. Theoretical research and practical application, the combination forecast makes full use of the advantages of each individual forecasting model, having the ability to adapt to the development of future forecast conditions. It can enhance the stability of prediction and improve the accuracy of prediction[13, 14].The key of the combined forecasting model lies in the generalization ability of the model. The combined forecasting model can be described as follows:

Assuming that the actual observed value of a predicted object at Time t is $y(t)(t = 1,2,...,m)$,there are n feasible predictive methods for this prediction problem, the corresponding prediction models are f_1 , f_2 ,…, f_n ,and the predicted values are $\hat{y}_i(t)(t = 1,2,...,m; i = 1,2,...,n)$, that is $\hat{y}_i(t) = f_i(t)$ .Weighted combination forecasting problem can be described as:

$$\hat{y}(t) = F(\hat{y}_1(t), \hat{y}_2(t), ..., \hat{y}_n(t), \alpha_1, \alpha_2, ..., \alpha_n) \quad (10)$$

Among that, combination forecast value is $\hat{y}(t)(t = 1,2,...,m)$, F is a way of combination. The purpose of using (10) is to make combination forecast value $\hat{y}(t)$ have better effect than single prediction $\hat{y}_i(t)$.

The combined forecasting model is based on BP neural network theory and Least Squares Support Vector Machines theory, the predicted values are: $\hat{y}_{BP}(t)$ and $\hat{y}_{LS-SVM}(t)$ .Combined with the characteristics and advantages of each single prediction model, the different weights α and $1-\alpha$ are assigned to the individual forecasting models for the combined model. Assuming the F in (10) is (2), so the mathematical expression of Combination Forecasting Model based on Parametric T-norm(CFMPT) is:

$$\hat{y}(t) = ((\alpha \hat{y}_{BP}(t)^p + (1-\alpha)\hat{y}_{LS-SVM}(t)^p - 1)^{1/p} \quad (11)$$

The genetic algorithm and the least squares are combined to estimate the parameters.

Because of the objectivity and inevitability of prediction error, there are some error between predicted value $\hat{y}(t)$ and actual value $y(t)$. Set error:

$$E = ((\hat{y}(t) - y(t))^2)^{1/2} \tag{12}$$

To minimize the error E as the objective function of the genetic algorithm, the two parameters of CFMPT model are obtained.

Genetic algorithm is an adaptive global optimization search algorithm to simulate the genetic and evolutionary processes of biological organisms in the natural environment. In view of its global search ability, CFMPT parameter estimation module use genetic algorithm. Set the following genetic algorithm parameters for parameter optimization: the initial population is 20; Using binary encoding, the number of encoding is 8; Select the operation using a stochastic uniform distribution model; the crossover operation uses a distributed cross. The mutation operation uses Gaussian function variation[15].

IV. Experiment and Result Analysis

A. Experimental Design

The main factors influencing the gas emission (m^3/ min) include: burial depth of coal seam(m), mining intensity(average daily output, t/d), seam thickness(m), propulsion speed (average daily progress, m/d), original coal seam gas content(m^3/t) and layer spacing(m).These are used as input. Gas emission is used as output. Using the No. 1-15 data as the training sample, which from the Table. V in the [1] named monitoring data of absolute gas emission in a coal mine, the No. 16-18 is used as prediction sample to forecast.

The experimental steps are as follows:

1) For comparison, the sample is normalized and the data is normalized to [0,1].The normalized formula is as follows:

$$norm(x_i) = \frac{x_i - \min(X)}{\max(X) - \min(X)} \tag{13}$$

2) Training the individual prediction methods BP and LS-SVM on the training set prediction results $y_{BP}(t)$ and $y_{LS-SVM}(t)$ are obtained on the test set.

3) Using CFMPT model: genetic algorithm is used to estimate the parameters in the training set, prediction results of CFMPT is reached in the test set.

4) All regression results are subjected to an anti-normalization process as follows:

$$y_i = \hat{y}_i \times (\max(X) - \min(X)) + \min(X) \tag{14}$$

5) Evaluation by evaluation index.

B. Result and Analysis

Using CFMPT model to forecast, the results are shown as Table. I, according to the genetic algorithm to find the optimal Equation (11). That is, the parameter of the combination forecasting model is $\alpha = 0.982$, $p = 3.649$. For comparison, the results of the single prediction model and the results of [1] and [9] are also listed into the table. The results of the comparison on the error evaluation index are shown in Table. II.

TABLE I. COMPARISON OF TEST RESULTS

Sample No	Real value	Improvement BP[1]	Wavelet Analysis [9]	BP (Article)	LS-SVM (Article)	CFMPT
1	4.06	3.99	4.02	4.0616	4.6759	4.0708
2	4.92	4.58	4.98	4.9328	4.7882	4.9301
3	8.04	8.08	8.09	8.0828	7.4782	8.0387

TABLE II. COMPARISON OF THE ERRORS OF VARIOUS ALGORITHMS (%)

Sample No	Improvement BP[1]	Wavelet Analysis[9]	BP (Article)	LS-SVM (Article)	CFMPT
1	1.72	0.99	0.04	15.17	0.27
2	6.91	1.21	0.26	2.68	0.20
3	0.50	0.62	0.53	6.99	0.02
Aver-age Errors	3.043	0.94	0.277	8.28	0.163

It can be seen from the Table. II, when it uses various prediction models to forecast the gas emission, The average relative error of improved BP[1] is 3.043%.The average relative error of the BP prediction model proposed in this paper is 0.277%.The average relative error of the wavelet neural network[9] is 0.94%.The average relative error of LS-SVM model in this article is 8.28%.The average relative error of CFMPT model is the lowest, as 0.163%.

Prediction results show, BP neural network, wavelet neural network and LS-SVM all can be used to forecast gas emission. But for small sample, number of hidden layers of BP neural network will lead to a large difference between the predicted results. For example, improved BP neural network in [1] and using the BP neural network in this article, all lead to differential production , because of the difference between the training method and the number difference of hidden layers. But the number of hidden layers of the current selection has no theoretical guidance. most of them are selected by experience, and the number of training is too much, it is easy to be fitting situation. Regardless of BP model, wavelet neural network model or LS-SVM model, because of the limitation of single model, it is hard to be sued into all cases. In another words, the generalization ability is weak. The combined forecasting model compensates the shortcomings of the single model, learns from each other, and obtains the best forecasting effect.

The single prediction model in the CFMPT prediction model can adopt any linear, nonlinear model. Due to the variability of CFMPT, it is single event prediction model can be established. And the CFMPT model is most suitable for predicting the characteristics of time series data.

V. CONCLUSION

A combined forecasting model of gas emission based on parametric t-norm is proposed. CFMPT model has the ability to change, generalization ability. It can use the way of training to find the best combination model for the characteristics of data sets. That overcomes the limitation of the weak ability of small sample of individual forecasting method.

Experimental results show that the result from CFMPT model is better than the result from single prediction model, which verifies the effectiveness of the method. Moreover, it has strong reliability for time series prediction, and has good practical application value.

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