Research on Sensor Correction Method for Monitoring in Early Warning System of Coal Spontaneous Combustion

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Abstract. According to statistics, there are as many as 4000 coal spontaneous combustion accidents every year, causing heavy casualties and property losses. By accurately detecting the change of index gas concentration, it can provide reliable criteria for identifying and warning the early hidden dangers of coal spontaneous combustion. The improvement of sensor precision is the basis of intelligent monitoring. Modification of wireless multi-parameter sensor used in coal mine is of great significance for accurate monitoring of gas concentration in coal mine. In order to modify the wireless multi-parameter sensor, the high and low temperature experiments of the sensor were carried out at -5~45℃, and the real values of \textit{O}_2 concentration at 15%, 21%, 25% and \textit{CO} concentration at 175ppm, 250ppm and 375ppm were measured. Measurement data was Non-linear fitting and correction by using SVM (Support Vector Machine), BP neural network and Elastic Network regression method. The experimental results show that the Elastic Network regression compensation reduces the \textit{O}_2 sensor from the original maximum mean absolute percentage error (MAPE) of 18.4% to 0.52%, and the average MAPE decreases from 13.89% to 0.21%. Using the SVM nonlinear compensation, the \textit{CO} sensor is reduced from the original maximum MAPE of 43.2% to 1.6%, and the average MAPE is reduced from 21.38% to 1.4%. Elastic Network regression compensation excellent achieves nonlinear compensation of \textit{O}_2 sensor. The SVM better realizes the nonlinear compensation of the \textit{CO} sensor. Through non-linear compensation, wireless multi-parameter sensor can better meet the requirements of coal mine gas concentration monitoring.
1. Introduction
The coal spontaneous combustion in gob can easily give rise to coal mine gas explosion accidents, gas explosions and other major accidents, resulting in casualties and property losses. Therefore, the accurate monitoring of multi-parameter gas sensor for mining has important scientific significance and practical value for coal mine safety production.

In this paper, the wireless multi-parameter sensors are carbon monoxide sensor, methane sensor and oxygen sensor. In fact, the multi-parameter sensor that consists of carbon monoxide and oxygen sensors are electrochemical sensors, and their sensitive features will change with the temperature. The original data collected must undergo a process of temperature curve correction before it can be used. In recent years, scholars at home and abroad have studied the nonlinear correction in sensors. Based on the algorithm of least square SVM, Guo et.al. established the nonlinear error correction model of photoelectric displacement sensor and reduced the error of sensor between 0~1.5% [1]. Wang et.al. designed a back-propagation(BP) neural network model to establish the relationship between solar radiation and air temperature error [2]. Liu et al. applied the method of genetic support vector machine (GSVM) and BP neural network to sensor nonlinear correction and compared them, and found that GSVM method is better than BP neural network [3]. He et.al. proposed a nonlinear sensor correction method by grey GM (1, N) system based on neural network optimization, and verified its high accuracy of the optimized model [4]. Chen et al. proposed a nonlinear compensation model of temperature and humidity sensor based on Laguerre polynomial, and the results showed that the MAPE after compensation is less than 4.5576e-4% [5]. Wang et al. proposed a nonlinear compensation method of particle swarm optimization support vector machine (PSO-SVM) for mining sensors, and compared with BP neural network, the results showed that the MAPE of PSO-SVM was smaller [6].

Through a large number of studies, it can be found that the nonlinear error correction of the sensor can solve the problem of the nonlinear degree of sensor measurement to a certain extent, and it can also improve the measurement accuracy of the sensor, the application of the sensor in scientific research and the development of production. However, there is little research on the nonlinear compensation of multi-parameter gas sensors, so different correction methods are needed to find the optimal sensor correction method suitable for mine conditions.

So this paper use mine multi-parameter sensor for different temperature experiment, the measuring temperature range is from 5℃ to 45℃. At the same time, we collected oxygen concentration and the carbon monoxide concentration, and analyze the revised and the actual error value of three kinds of mathematical methods to modify the sensor, through the contrast analysis of the MAPE of each method, finally determined respectively suitable for multi-parameter, the revision method of oxygen sensor and carbon monoxide sensor. It improves the measurement accuracy of mine multi-parameter sensors and provides theoretical basis and technical support for accurate monitoring of gas concentration in coal spontaneous combustion in gob.

2. Experimental equipment and process

2.1. Experimental equipment
In the laboratory, the basic device of the experimental system for temperature correction of oxygen and carbon monoxide is shown in Fig. 1. Multi-parameter gas sensors placed in incubator, the standard concentration gas through gas cylinders to entrance glass rotor flowmeter, glass rotor flowmeter export standard concentration gas transmission through a rubber hose to incubator at the bottom of the internal sensor connected to the mouth on the air inlet gas, different temperature gas for heating or cooling, will travel through the air flow of gas from outside. The acquired data is transmitted to the signal processing and display module outside the incubator box for data recording. The acquired data is transmitted to the signal processing and display module outside the incubator box for data recording.
2.2. The experimental process

The incubator box adopts SETH-8-042l constant temperature and humidity test box produced by ESPEC as the container to simulate the closed environment. The inner volume of the test box is 306L, and the adjustable temperature range is -40~150℃. The temperature and humidity in the box can be adjusted by touching the panel. In this experiment, the temperature of the gas, to be tested, is changed by adjusting the temperature of the test chamber.

The range of the test temperature is -5~45℃, and the interval is 5℃. The multi-parameter gas sensors in this system are O₂, CO and CH₄, respectively. Because the CH₄ sensor has its own data correction function, the temperature correction of O₂ and CO sensors is carried out in this experiment. The standard concentration selected by O₂ is 15%, 21% and 25%, and the standard concentration selected by CO is 175ppm, 250ppm and 375ppm.

3. Nonlinear compensation method and analysis

For the three methods in this paper, the measured concentrations of O₂, 175ppm and 250ppm at different temperatures with standard concentrations of 15% and 21% were selected as sample training sets. The measured concentrations of O₂ with standard concentration of 25% and CO with 375ppm at different temperatures were selected as sample test sets for nonlinear correction.

3.1. Support vector machine nonlinear compensation method

Support vector machines is a machine learning method developed in the mid-1990s. The processing method of SVM for nonlinear data is to select a kernel function, and then map the data to a higher dimensional space and make it linearly separable through the transformation of the kernel function, so as to solve the problem of linearly indivisible data in the original space and realize the prediction of the data. The kernel function used in this paper is the radial basis kernel function, and the expression is [7-9]:

\[ K(x, x_i) = \exp \left( -\frac{|x - x_i|^2}{\sigma^2} \right) \]  

Combined with the actual contents of this section, the main steps of SVM prediction are as follows [10, 11]. Prediction and error compensation of O₂ and CO concentrations: The experimental temperature conditions were set to -5~45℃ with an interval of 5℃. The measured concentrations of O₂ standard concentration of 15% and 21%, and CO standard concentration of 175ppm and 250ppm were selected as training data sets, each training samples being 22 data sets. The measured concentrations with O₂ standard concentration of 25% and CO standard concentration of 375ppm were used as the test samples. The trained SVM model was used to output the predicted values of the test samples, and the deviation between the predicted values and the standard values was used to compensate and modify the measured values. The type of SVM was selected as nu-svr, the type of
kernel function was selected as radial basis kernel function, the O\textsubscript{2} penalty factor coefficient was set as 160, and the parameter \( \sigma \) was set as 15.8. The CO penalty factor coefficient is set to 2300, and the \( \sigma \) parameter is set to 50.

**Figure 2.** Fitting model of SVR nonlinear calibration test data and comparison between standard concentration and measured concentration.

**Figure 3.** Comparison between SVR nonlinear calibration standard value and measured value and correction value.

**Table 1.** Comparison of MAPE and correction error before O\textsubscript{2} and CO correction from SVR nonlinear correction method.

| O\textsubscript{2} observed value | MAPE\textsubscript{a} (%) | MAPE\textsubscript{b} (%) | CO observed value | MAPE\textsubscript{a} (%) | MAPE\textsubscript{b} (%) |
|----------------------------------|--------------------------|--------------------------|--------------------|--------------------------|--------------------------|
| 20.4                             | 18.4                     | 2.6                      | 357                | 4.8                      | 1.1                      |
| 20.6                             | 17.6                     | 2.2                      | 368                | 1.87                     | 1.2                      |
| 20.8                             | 16.8                     | 1.9                      | 386                | 2.93                     | 1.2                      |
| 21.1                             | 15.6                     | 2.3                      | 409                | 9.07                     | 1.3                      |
| 21.4                             | 14.4                     | 2.6                      | 434                | 15.73                    | 1.4                      |
| 21.6                             | 13.6                     | 2.6                      | 458                | 22.13                    | 1.4                      |
| 21.9                             | 12.4                     | 3.1                      | 476                | 26.93                    | 1.5                      |
| 22.1                             | 11.6                     | 3.2                      | 494                | 31.73                    | 1.5                      |
| 22.2                             | 11.2                     | 2.9                      | 510                | 36                       | 1.6                      |
| 22.3                             | 10.8                     | 2.8                      | 528                | 40.8                     | 1.6                      |
| 22.4                             | 10.4                     | 3.0                      | 537                | 43.2                     | 1.6                      |

Note: a: Before correction; b: After correction
According to above steps, Matlab was used to prepare the program for the prediction model training, and the test data fitting model of O\textsubscript{2} and CO and the comparison between the standard concentration and the measured concentration were obtained. Through the above steps, the predicted output value of O\textsubscript{2} concentration with a standard concentration of 25% and the predicted output value of CO concentration with a standard concentration of 375ppm were obtained at different temperatures. Then, the MAPE was obtained through comparative analysis with the standard value. The MAPE before and after correction of O\textsubscript{2} and CO are shown in table 1. It can be seen that the maximum MAPE between the predicted concentration of O\textsubscript{2} sensor and the standard concentration by using SVM is 3.2% and the average MAPE is 2.65%. The maximum MAPE between the predicted CO sensor concentration and the standard concentration is 1.6% and the average MAPE is 1.4%.

3.2. BP neural network nonlinear compensation method

BP neural network is a multi-layer feedforward neural network. The network has an input layer, a hidden layer and an output layer, and its main characteristics are the forward transmission of signals and the back propagation of errors [12-14]. In this paper, temperature and standard concentration were taken as input, and the error between the measured value and the predicted value was taken as the back-propagation error to modify the model. The predicted value was taken as the output. The topology of BP network is shown in fig.4 [15-17]:

![Figure 4. Topology of BP neural network.](image)

The BP neural network has 2 neurons in the input layer, 1 neuron in the output layer, 4 neurons in the O\textsubscript{2} hidden layer and 15 neurons in the CO hidden layer. The learning rate is set to 0.01 and the number of iterations is set to 1000. X1 and X2 are input values of BP neural network, that is, temperature and true concentration before correction. Y is the output data of the output layer, that is, the concentration predicted value. Wij is the weight from the input layer to the hidden layer, and Wkl is the weight from the hidden layer to the output layer. The transfer function of the hidden layer selects the sigmoid function, and the transfer function of the output layer selects the pure linear function.

In the process of building the model, all thresholds and weights in the network are randomly initialized within the range of (0, 1), and temperature and standard concentration are taken as the input of the network until the result of the output layer is produced, then the error of the output layer is calculated, and then the error is reversed-propagated to the hidden layer nerve. Finally, the threshold value and weight are adjusted according to the error of the neurons in the hidden layer, and the iterative process is repeated until the error with the standard value is minimized. According to the above BP neural network structure, Matlab is used to prepare the program to conduct the prediction model training, and obtain the O\textsubscript{2} and CO test data fitting model and the comparison between the standard concentration and the measured concentration, as shown in fig.5. The comparison between the standard value of O\textsubscript{2} and CO and the measured value and the modified value is shown in fig.6.
Figure 5. Test data fitting model and comparison of standard concentration and measured concentration from BP nonlinear correction.

Figure 6. Comparison of standard values with measured and corrected values based on BP nonlinear correction.

Table 2. Comparison of MAPE and correction error before O\textsubscript{2} and CO correction comes from BP nonlinear correction.

| O\textsubscript{2} observed value | MAPE\textsubscript{a} (%) | MAPE\textsubscript{b} (%) | CO observed value | MAPE\textsubscript{c} (%) | MAPE\textsubscript{d} (%) |
|---------------------------------|--------------------------|--------------------------|----------------------|--------------------------|--------------------------|
| 20.4                            | 18.4                     | 1                        | 357                  | 4.80                     | 8.6                      |
| 20.6                            | 17.6                     | 1.1                      | 368                  | 1.87                     | 8.7                      |
| 20.8                            | 16.8                     | 1.3                      | 386                  | 2.93                     | 6.7                      |
| 21.1                            | 15.6                     | 1.9                      | 409                  | 9.07                     | 3.6                      |
| 21.4                            | 14.4                     | 2.5                      | 434                  | 15.73                    | 0.2                      |
| 21.6                            | 13.6                     | 2.7                      | 458                  | 22.13                    | 2.6                      |
| 21.9                            | 12.4                     | 3.3                      | 476                  | 26.93                    | 4.1                      |
| 22.1                            | 11.6                     | 3.5                      | 494                  | 31.73                    | 5.6                      |
| 22.2                            | 11.2                     | 3.3                      | 510                  | 36.00                    | 6.7                      |
| 22.3                            | 10.8                     | 3.1                      | 528                  | 40.80                    | 8.2                      |
| 22.4                            | 10.4                     | 2.9                      | 537                  | 43.20                    | 8.2                      |

Note: a: Before correction; b: After correction

The MAPE and correction error pair before modification of O\textsubscript{2} and CO are shown in table 2. It can be seen from the table that the maximum MAPE between the predicted concentration of O\textsubscript{2} sensor and the standard concentration is 3.5% and the average MAPE is 2.4%. The maximum MAPE between the
predicted CO sensor concentration and the standard concentration is 8.7%, and the average MAPE is 5.74%.

3.3. Elastic network regression nonlinear compensation method

Ridge regression is a regularized version of linear regression, that is, adding regularization terms to the original cost function of linear regression, so as to make the model weight as small as possible while fitting data. Lasso regression is another regularized version of linear regression. The regularization term is the $l_1$ norm of the weight vector. Elastic network regression is a compromise between ridge regression and Lasso regression, which is controlled by mixing ratio $r$.

Combined with the actual contents of this chapter, the main steps for elastic network prediction are as follows: The polynomial fitting model was determined, and super parameters such as learning rate, penalty factor and number of iterations were set. The batch gradient descent formula of the model was derived through loss function. Then the objective function value was improved through iteration. According to the above elastic network regression structure, Matlab is used to prepare the program to conduct the prediction model training, and obtain the O$_2$ and CO test data fitting model and the comparison between the standard concentration and the measured concentration, as shown in fig.7. The comparison between the standard value of O$_2$ and CO and the measured value and the modified value is shown in fig.8.

![Figure 7](image1)

**Figure 7.** Test data fitting model and comparison of standard concentration and measured concentration based on elastic network regression nonlinear correction.

![Figure 8](image2)

**Figure 8.** The comparison of the standard value with the measured value and the corrected value from Nonlinear correction of elastic network regression.
Table 3. Comparison of MAPE and correction error before O\textsubscript{2} and CO correction comes from elastic network regression nonlinear correction.

| O\textsubscript{2} observed value | MAPE\textsubscript{a} (%) | MAPE\textsubscript{b} (%) | CO observed value | MAPE\textsubscript{a} (%) | MAPE\textsubscript{b} (%) |
|----------------------------------|--------------------------|--------------------------|------------------|--------------------------|--------------------------|
| 20.4                             | 18.40                    | 0.04                     | 357              | 4.80                     | 1.60                     |
| 20.6                             | 17.60                    | 0.21                     | 368              | 1.87                     | 3.40                     |
| 20.8                             | 16.80                    | 0.39                     | 386              | 2.93                     | 3.10                     |
| 21.1                             | 15.60                    | 0.10                     | 409              | 9.07                     | 1.50                     |
| 21.4                             | 14.40                    | 0.20                     | 434              | 15.73                    | 0.40                     |
| 21.6                             | 13.60                    | 0.08                     | 458              | 22.13                    | 1.90                     |
| 21.9                             | 12.40                    | 0.48                     | 476              | 26.93                    | 2.10                     |
| 22.1                             | 11.60                    | 0.52                     | 494              | 31.73                    | 2.30                     |
| 22.2                             | 11.20                    | 0.22                     | 510              | 36.00                    | 2.10                     |
| 22.3                             | 10.80                    | 0.04                     | 528              | 40.80                    | 2.40                     |
| 22.4                             | 10.40                    | 0.02                     | 537              | 43.20                    | 1.00                     |

Note: a: Before correction; b: After correction

The MAPEs before and after correction of O\textsubscript{2} and CO are shown in table 3. It can be seen from table 3 that the maximum MAPE between the predicted concentration of O\textsubscript{2} sensor and the standard concentration is 0.52% and the average MAPE is 0.21% when the elastic network regression nonlinear compensation method is used to correct. The maximum MAPE between the predicted CO sensor concentration and the standard concentration is 3.4%, and the average MAPE is 1.98%.

3.4. Results analysis

The O\textsubscript{2} sensor and CO sensor are nonlinear compensated by SVM, BP neural network and elastic network regression compensation method. The nonlinear compensation error is shown in fig.9. The maximum MAPE and average MAPE are shown in table 4.

Table 4. Error comparison of nonlinear compensation results between O\textsubscript{2} and CO sensors.

| Error indicator         | O\textsubscript{2} Maximum MAPE (%) | O\textsubscript{2} Average MAPE (%) | CO Maximum MAPE (%) | CO Average MAPE (%) |
|-------------------------|------------------------------------|------------------------------------|---------------------|---------------------|
| Original Error          | 18.4                               | 13.89                              | 43.20               | 21.38               |
| SVM                     | 3.20                               | 2.65                               | 1.60                | 1.40                |
| BP neural network       | 3.50                               | 2.40                               | 8.70                | 5.74                |
| Elastic network         | 0.52                               | 0.21                               | 3.40                | 1.98                |

From Fig. 9, it can be obtained that: among the three methods, the overall nonlinear compensation error of the elastic network regression to the O\textsubscript{2} sensor is small, and the error fluctuation is small; the overall nonlinear compensation error of the SVM to the CO sensor is relatively uniform, and all of them are less than 2%.
According to Table 4, the original maximum MAPE of O$_2$ sensor was reduced from 18.4% to 3.2%, and the average MAPE was reduced from 13.89% to 2.65% by using SVM nonlinear compensation. The original maximum MAPE of CO sensor decreased from 43.2% to 1.6%, and the average MAPE decreased from 21.38% to 1.4%. Using BP neural network nonlinear compensation, the original maximum MAPE of O$_2$ sensor was reduced from 18.4% to 3.5%, and the average MAPE was reduced from 13.89% to 2.4%. The original maximum MAPE of CO sensor decreased from 43.2% to 8.7%, and the average MAPE decreased from 21.38% to 5.74%. The use of elastic network regression compensation reduced the original maximum MAPE of O$_2$ sensor from 18.40% to 0.52%, and the average MAPE from 13.89% to 0.21%. The original maximum MAPE of CO sensor decreased from 43.2% to 3.4%, and the average MAPE decreased from 21.38% to 1.98%.

Based on the above analysis, it is found that the nonlinear compensation of O$_2$ sensor is well realized by elastic network regression compensation, and the nonlinear compensation of CO sensor is well realized by SVM.

4. Conclusion

In this study of reliability correction method for monitoring mechanism of wireless multi-parameter sensor in mining, a SVM, BP neural network (BP) and elastic network regression compensation method were proposed to perform nonlinear compensation for O$_2$ sensor and CO sensor, determine the nonlinear compensation method and find the optimal compensation model according to the principle.

The original average MAPE of O$_2$ sensor was reduced from 13.89% to 2.68% by the nonlinear compensation of SVM. CO sensor decreased from 21.38% to 1.4%. The original mean MAPE of O$_2$ sensor was reduced from 13.89% to 2.25% by using BP neural network nonlinear compensation. CO sensor decreased from 21.38% to 6.53%. The original average MAPE of O$_2$ sensor was reduced from 13.89% to 0.19% by elastic network regression compensation. CO sensor decreased from 21.38% to 2.28%.

The SVM has the worst nonlinear compensation effect for O$_2$ sensor, the BP neural network has the worst nonlinear compensation effect for CO sensor, the elastic network regression has the best nonlinear compensation effect for O$_2$ sensor, and the SVM has the best nonlinear compensation effect for CO sensor. Nonlinear compensation can improve the measurement accuracy of multi-parameter sensor and realize accurate early warning of coal spontaneous combustion in gob.

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