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Application of SF_6 Gas Concentration Temperature Compensation Based on Improved PSO-RBF

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ABSTRACT

For the temperature drift phenomenon of SF_6 gas concentration sensor in high-voltage electrical equipment, the compensation accuracy of the sensor is improved by establishing the temperature compensation model of gas concentration sensor with RBF neural network, and combining the particle swarm optimization algorithm for the optimization of parameters of RBF temperature compensation model. The experimental results show that the method can better compensate the temperature of the gas concentration sensor, and the output of the compensated sensor is less affected by the ambient temperature, with a maximum error of 20 ppm over the full scale range.

KEYWORDS

SF_6 gas sensor; Lambert-Beer law; PSO-RBF; Temperature compensation

1. INTRODUCTION

SF_6 gas is extensively employed in high-voltage and high-power equipment due to its outstanding insulation and arc-extinguishing characteristics. Considering the existing detection methods both domestically and internationally, it can be observed that the current SF_6 detection devices have several limitations. The detection accuracy of these devices is greatly influenced by external factors, leading to inadequate precision. They are unable to provide practical and effective concentration alerts based on existing historical data. To address this issue, this study introduces a temperature compensation model to counteract the nonlinear effects of environmental temperature fluctuations on Non-Dispersive infrared gas sensors. At present, there are three methods to eliminate the non-linear effect of ambient temperature change on Non-Dispersive infrared gas sensor: hardware temperature control method, empirical formula compensation method, and temperature compensation algorithm. Regarding the use of algorithms for temperature compensation works best, but still there are data quality problem, nonlinear problem, algorithm complexity problem , adaptability problem, and parameter selection problem.

Non-dispersive infrared gas detection devices are susceptible to ambient temperatures, resulting in biased measurement results [1]. In practice, the output characteristics of each electrochemical sensor are not exactly the same, and the drift of the characteristics can also lead to a decrease in sensor accuracy over time [2]. Gas concentrations are often affected by multiple factors, and these relationships can be non-linear. If the model only considers linear relationships, it may not be able to accurately predict complex concentration changes [3, 4]. Due to the characteristics of time-varying and nonlinear coupling of gas concentration, the prediction accuracy of harmful gas concentration prediction models is low [5]. The process of generating insulating gas in transformer is more complicated in normal and fault condition. When the fault occurs, the fault type has a strong nonlinear relationship with the gas content [6]. The experimental results show that the size of the sensor is inconsistent with the temperature [7]. These algorithms require a lot of computing resources and time to train models, so they may be limited in practical applications [8]. Not all scenarios need to choose support vector machine and RBF neural network prediction method two algorithms [9]. The parameters to evaluate the performance of a gas sensor include sensitivity, response time, recovery time, selectivity, and repeatability [10]. Used to solve the individual parameters of the network. The network parameters include the center c_j of the radial basis function, the field width δ_j, and the connection weight w_j from the hidden layer to the output layer [11]. Determines whether the output of the RBF neural network model is accurate with the data center c_i of the activation function (radial basis function), the width σ and the connection weights from the hidden layer to the output layer. In this paper, the k-means clustering algorithm and the improved particle swarm optimization algorithm are used to determine and optimize these parameters [12]. In this paper, we will use pso to further optimize the parameters on the basis of RBF algorithm to improve the speed and accuracy of temperature compensation according to the above existing problems.

2. MODELS AND ALGORITHMS

2.1. RBF Neural Network Model Construction and Parameter Setting

First prepare the input matrix (P) containing the training data and the target matrix (T) corresponding to the target output. RBF neural network structure, including the number of nodes in the input layer, hidden layer and output layer. Set the parameters of the RBF neural network: it mainly includes the node spread of the hidden layer and possible other parameters. Use the 'newrb' function of MATLAB to build the RBF neural network, and use the training data to train the RBF neural network.

(1) Network model construction

The parameters of the network are obtained through training. When the Gaussian function is adopted as the radial basis function, the parameters of the network include the number of basis functions, the central value of the basis function, the extension constant of the basis function, and the output weight [13] of the network. The number of neurons determines the structure of RBF neural network. When the number of neurons is 24, the network size is moderate and the compensation results are good. The SF_6 gas concentration sensor will inevitably be affected by the temperature during the working process, which leads to the deviation between the output concentration value of the SF_6 gas concentration sensor and the input value of the given concentration value, presenting a nonlinear state. The RBF can map the nonlinear function and establish the temperature compensation model of SF_6 gas concentration sensor. The two nodes in the input layer of the RBF are the target variable concentration C and the interference variable temperature T, and the one node in the output layer is the concentration value after compensation. The RBF-based temperature compensation model is shown in Figure 1.

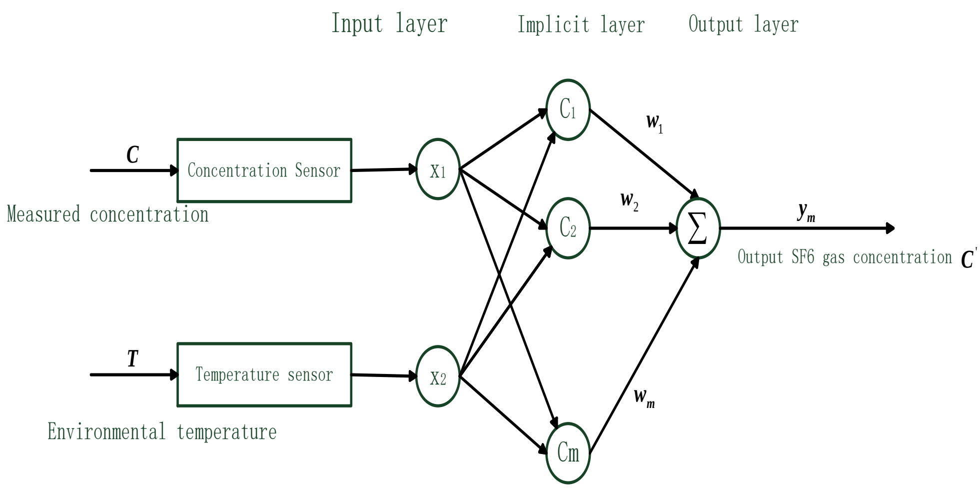


Figure 1. RBFNN temperature compensation model

(2) Network parameter setting

Let there exist M neurons in the input layer, where m denotes any neuron anywhere; if there exist N neurons in the hidden layer, where i denotes any neuron anywhere; $\phi_i(\bullet)$ denotes the radial basis function of the i denotes; w_{ij} denotes the connection weights between the hidden layer and the output layer; if there exist J neurons in the output layer, where j denotes any neuron anywhere.

Let the set of training samples X=[X_1,X_2,...,X,...,X]T, if the training samples $X_k = [x_{k1}, x_{k1}, \cdots x_{km}, \cdots x_{kM}](k = 1, 2, \cdots N)$, its corresponding actual output is $Y_k = [y_{k1}, y_{k1}, \cdots y_{km}, \cdots y_{kJ}](k = 1, 2, \cdots N)$. The output of the jth neuron of the RBF neural network when the input value is X_k is:

$$y_{kj}(X_k) = \sum_{i=1}^{N} w_{ij} e^{\frac{-|x_{ki} - c_i|^2}{2\sigma^2}}, j = 1, 2, 3 \ldots J \tag{1}$$

Where: c_i, denotes the data center value of the i node in the implied layer, and $e^{\frac{-|x_{ki} - c_i|^2}{2\sigma^2}}$ represents the output of that node, and σ denotes the standard deviation, also known as the width or expansion constant. The output layer nodes use a linear function, which is obtained by summing the output of the implied layer y_{kj}. From equation (1), it can be seen that determining the accuracy of the output of the RBF neural network model is related to the data center of the activation function (radial basis function c_i), the width σ, and the connection weights from the implicit layer to the output layer w_{ij}. In this paper, we use the k-mean clustering algorithm and the improved particle swarm algorithm to determine and optimize these parameters.

$$\begin{aligned} f(X) &= \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \\ &= \frac{1}{N} \sum_{i=1}^{N} (y_i - \sum_{j=1}^{N} w_j \exp(-\frac{\|X - C_j\|^2}{2\sigma^2_j}))^2 \end{aligned} \tag{2}$$

2.2. The introduction of Temperature Compensated PSO and Its Optimization Design Analysis

Speed and position are the two core elements of particle swarm optimization algorithm.

Speed update formula:

$$v_i^d = wv_i^{d-1} + c_1 r_1 (pbest_i^d - x_i^d) + c_2 r_2 (gbest^d - x_i^d) \tag{3}$$

Position update formula:

$$x_i^{d+1} = x_i^k + v_i^d \tag{4}$$

In the formula(3), c_1 represents the individual acceleration factor, c_2 presents the social acceleration factor, w is the inertia weight of the velocity. v_i^d represents the velocity of particle i at the d iteration; x_i^d represents the position of the particle at the d iteration; $pbest_i^d$ represents the best position passed by the particle up to the d iteration; $gbest^d$ represents the best position for all particles to up to the d iteration

The flow chart of particle swarm optimization algorithm is shown in Figure 2. Firstly, initialize the particle population. After initialization, each particle will have different initial speed and initial position. According to the appropriate function built for practical application, calculate the fitness value of the individual in the particle population; Compare the current fitness value of each individual with the best position above, and select the best position; For each individual, the fitness value of its current position is compared with the fitness value corresponding to its global best position (gbest). If the fitness value of the current position is higher, the global best position is updated with the current position; Update the speed and position of each particle according to; If the conditions are not met, recalculate.

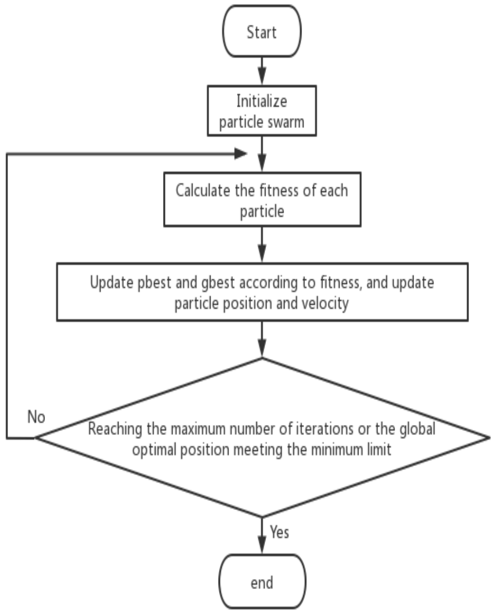


Figure 2. Flow chart of Particle Optimization Algorithm

So far, PSO has been successfully applied in some aspects of life. The particle swarm optimization algorithm is used to optimize the BP neural network and RBF neural network, which makes up for the inherent deficiency of the RBF neural network and solves the defect that the BP neural network and RBF neural network needs to adjust some parameters.

In particle swarm optimization (PSO) algorithms, learning factors and weights are important parameters that affect the performance of the algorithm. Optimizing these parameters can help improve the convergence speed and search effect of the algorithm.

2.3. Optimized Design of Improved PSO-RBF Neural Network Algorithm

At present, RBF neural networks usually use K-means clustering algorithm to initialize the central value of the basis function [14]. The K-means clustering algorithm is simple to implement, but its clustering results are often closely related to the initial random K samples, and the clustering results are not satisfactory, which affects the network performance. Particle swarm optimization algorithm is used to obtain the optimal parameters of RBF network.

Initialize the size, initial position and initial velocity of the particle swarm, and set the inertia factor, learning factor, iteration times, maximum velocity and other related parameters. Find out the best position of the initial individual and the best position of the particle swarm. According to the flow of particle swarm optimization algorithm, the particle velocity and position are continuously updated until the optimal solution is obtained.

According to the above analysis, the algorithm flow of PSO optimized RBF can be obtained to normalize the target data; Initializing the parameters of the particle population and giving each particle a random initial position and initial velocity; The mean square deviation of RBF neural network is selected as the evaluation function of particle swarm optimization; Calculate the fitness value of each particle function, compare the current fitness value of each particle with the fitness value corresponding to its historical best position (pbest), and update the historical best position with the current position if the fitness value of the current position is higher; For each particle, the fitness value of its current position is compared with the fitness value corresponding to its global best position (gbest). If the fitness value of the current position is higher, the global best position is updated with the current position; Finally, the RBF neural network training model is built with the best particle. The learning factor and weight coefficient of PSO are dynamically changed according to the number of iterations [15, 16]. The specific process is shown in Figure 3.

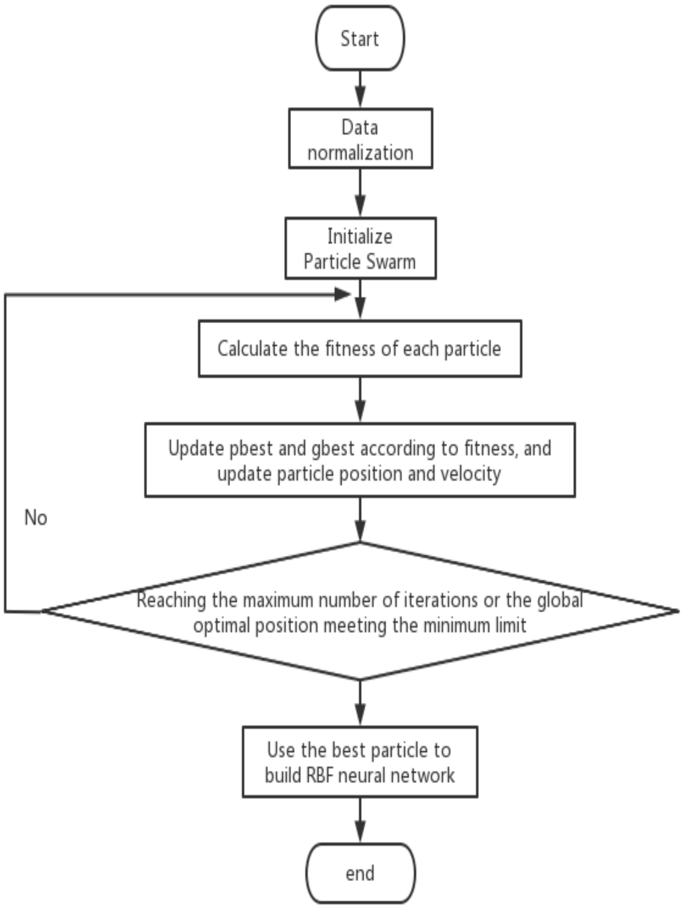


Figure 3. Flow chart of PSO - RBF neural network

3. EXPERIMENT OF OPTIMIZED RBF NEURAL NETWORK BASED ON PSO

The main idea of this topic based on the temperature compensation method of PSO-RBF neural network is to develop the algorithm using Matlab software according to the results of the temperature compensation model design in Section 2, so as to correct the nonlinear influence of detecting the environmental temperature change on the SF_6 gas sensor. The main process is divided into two parts: learning and training of PSO-RBF neural network and simulation calculation. The key steps are as follows [17-19]:

The core idea of PSO algorithm to optimize the neural network is to continuously optimize the iterative parameters b1 and W1 to minimize the error between the model prediction output value c0 and the calibrated gas concentration value c (b2 and W2 can be directly calculated by b1 and W1), that is, the fitness function of PSO algorithm is

$$\boldsymbol{F} = \boldsymbol{p} - \boldsymbol{p}_0 \tag{5}$$

Where the value of the optimization objective function is used to evaluate the quality of the particle position determines whether the history to update the optimal position of the individual particle and the historical optimal position of the group ensures that the particle searches in the direction of the optimal solution.

For the general problem, the particle population size is taken in the range of 20 to 40, In this paper, taking the particle population size of 30, Take the w=0.5, c1s=2.5, c1e= 0.5, c2s =0.5, c2e=2.5. In the hybrid algorithm, learning rate η has a large impact on the performance of the algorithm, When the learning rate is large, Will cause the fitness values to fluctuate around the minimum, it can even vary widely. When the learning rate is small, at this point, the algorithm has a stronger local optimization ability, but not conducive to improve the precocious maturity of particle population, The convergence rate is slow. 0 When the learning rate is 0.001, Therefore, the neural network parameters to be optimized are 96, However, in solving high-dimensional complex optimization problems, besides, The particle swarm algorithm itself has the advantage of fast solution speed, Multiple experiments showed that, After 100 iterations, the particle is concentrated in a small region, Therefore, the number of iterations in the PSO algorithm were all set to 100, Taking into account the initial state of the network as well as the stochastic factors in the particle update process.

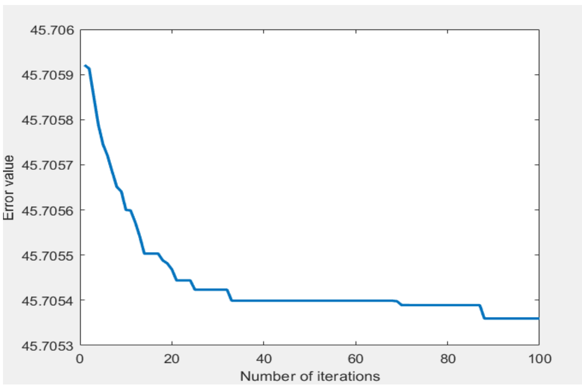


Figure 4. Optimal number of iterations

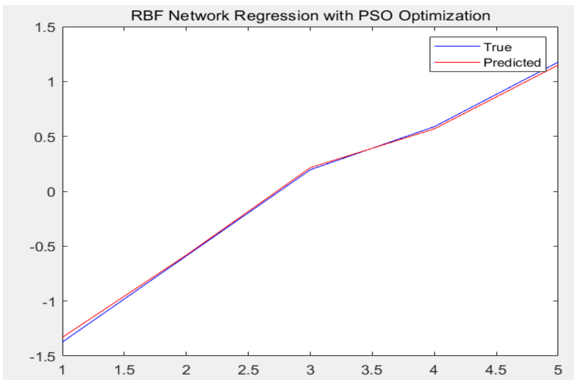
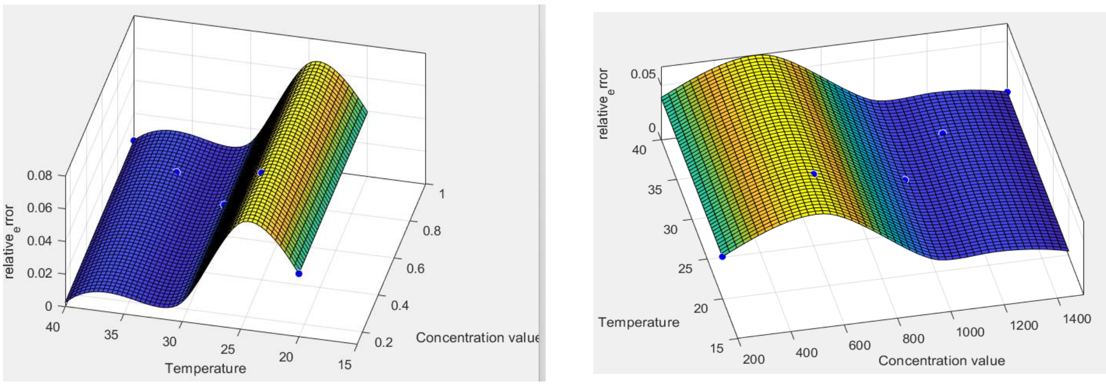


Figure 5. Compensation results



(a) Normalized Concentration (b) Concentration

Figure 6. PSO-RBF Temperature Compensation Error Surface

In order to reduce the error caused by the chance of neural network optimization, this experiment uses 2 repeated independent experiments to take the mean and its prediction. The results are shown in Figure 4, Figure 5, Figure 6. The results after compensation by PSO-RBF algorithms are shown in Table 1.

Table 1. PSO-RBF and PSO-BP temperature compensation comparison

NO	Actual (ppm)	Merament/ Normalize Merament(ppm)	PSO-RBF(ppm)*1000	Normalize PSO-RBF(ppm)
1	0	10/0.0004	0.0078	0.0525
2	200	168/0	0.1807	0.1205
3	600	634/0.2742	0.5947	0.3964
4	1000	939/0.5848	1.0020	0.6680
5	1200	1134/0.762	1.1973	0.7982
6	1500	1438/0.9629	1.4939	0.9959

4. CONCLUSION

From the above, it can be seen that the predicted concentration after temperature compensation by PSO-RBF algorithm has a minimum error of 20 ppm, which is basically close to the actual value, and the compensation effect is the best relative to other algorithms.

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