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APSO-RBF Nonlinear Calibration Method in Carbon Anode Baking Temperature Measurement

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Abstract

A correcting nonlinear errors of the thermocouple sensor based on Radial Basis Function Neural Network using particle swarm optimization are introduced. It solves t he shortcoming of Thermocouple Sensor's application on large data. The result of experiment shows that the nonlinear calibration based on APSO-RBF has higher precision than the method based on RBF and ANFIS. Then, APSO-RBF is used to test fire path temperature in the anode baking. It is proved that the method is effective.

Keywords*: carbon anode temperature, particle swarm optimization, radial basis function neural network, N thermocouple sensor, nonlinear calibration*

1. Introduction

Carbon anode baking process of the anode carbon block temperature, flue temperature, furnace negative pressure, and the flue gas temperature and other physical quantity are the key parameters ensuring anode carbon block baking quality, wherein the accurate measurement and control of anode baking temperature (fire path and the carbon block) directly affect the quality performance parameters including the porosity, specific resistance, compressive strength, electrolysis, oxidation rate and back EMF of the anode carbon. And the accurate negative pressure measurement and control of furnace chamber is the crucial step to ensure the full combustion of the fuel and volatile, asphalt overflow, volatile decomposition and evaporation, concentration, while the temperature control of flue gas emission is the main factor of energy saving and consumption reducing. Therefore, Establishment of intelligent detection and correction method for these nonlinear physical quantities is the premise condition for realizing accurate control of key parameters in anode baking process.

The N type thermocouple is compared with the original K, S type thermocouple. The nonlinear error accounted for 1300 □ EMF in 0.4%, and the nonlinear error is also far less than that of K type thermocouple in the scope of 20-400□. Because N type thermocouple has shorter usage history, and its measurement principle is same as other thermocouple, nonlinear correction should also be done in N type thermocouple. At present the extensive research can be mainly classified into two directions, one is piecewise linearization of nonlinear analog circuit fitting method, which is mainly used for analog meters and temperature transmitters. Another adopts look-up table method by microprocessor to realize nonlinear correction and cold end temperature compensation. But these methods have the fitting and look-up table error, as well as the sensor periphery antioxidant protection layer and other reasons, in the anode baking under the special environment of actual have some problems.

Current correction methods include piecewise linearization of nonlinear analog circuit method, as well as the microprocessor (or single computer) look-up table method; but these methods due to the external temperature range, thermocouple, thermal resistance of the changes, especially in the thermocouple to take certain oxidation protection measures and other reasons, will cause the thermocouple or thermal resistance the output characteristics of the change, when being used in high precision temperature measurement and control system, cannot meet the actual measurement and control requirements [1-4].

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2. The Basic Principle of Thermocouple Nonlinear Correction

General thermocouple temperature measurement model can be expressed as:

$$E = f(T) \tag{1}$$

Where in E represents the thermocouple output voltage, T denotes thermocouple input (measured temperature) .

Usually the compensated output p can be drawn when output E undergoes a compensation model g (E).

$$p = g(E) \tag{2}$$

If for any E output, can be found on input output characteristic curve corresponding to the input T, that the compensated output with desired properties, P = T. Apparently g (E) also is nonlinear, and the actual process is very complicated, it is difficult to use the analytical expression, therefore, we use APSO-RBF method to carry on the study, then replace the g(E).

3. Correction Method of APSO-RBF Method

The first through the APSO algorithm for RBF network needs to determine the parameters for fast global optimization, so we can define an optimized search space, at this time, the APSO algorithm of RBF network optimization results as the initial values of parameters, and then play the RBF network local search ability, high precision, using gradient method is optimized further, thereby to achieve the required accuracy of correction model, namely APSO-RBF method. Using APSO to train the RBF neural network, takes the following as an indicator of fitness function:

$$J = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{m}\left(y_{j,i}^{d} - y_{j,i}\right)^2 \tag{3}$$

Among them, the training sample set is D = { (yi , xi)| i = 1 , 2 , □, N}, N is the training set samples; m is the number of hidden layer units. For the RBF network, because of its input vector components to a distance function combination, so the normalized input data is crucial. Here, using Matlab toolbox of premnmx function, the input data is normalized to (- 1 , 1). $y_{j,i}^{d}$ is the i samples of the j network output node outputs; $y_{j,i}$ is a sample of the j output nodes of the actual output value. The algorithm for the basic steps can be expressed as follows:

(1) Initialization: initial search point position and speed is usually in the range allowed randomly generated PSO algorithm. To determine the maximum number of iterations of Tmax = 100; population size 30; hidden layer center number is 8; weight factor C1 = C2 = 2; the weight function w from 0.9 linearization reduced to 0.4.
(2) Evaluation of adaptability: according to the training sample set and type (3), evaluation of every particle's fitness, if good on the particle current fitness value, the pbest is set to the position of the particle is updated, and the individual fitness value. If all the particles of the individual fitness value of the best better than the current all particles of optimal adaptive value, the gbest is set to the position of the particle, the particle number recording, and updates the best fitness value.
(3) The particle update: according to APSO theory for each particle velocity and position updating.
(4) Output decision: if the current iteration number reaches the predetermined maximum number, then stop the iteration, the output optimal solution, otherwise go to step 2.
(5) The RBF network learning: according to APSO algorithm positioning of an optimized search space, gradient descent method to the network parameters are modified iterative algorithm is as follows:

$$\omega_j(k) = \omega_{j-1}(k) + \eta(y^d(k) - y(k))h_j \\ +\alpha(\omega_{j-1}(k) - \omega_{j-2}(k)) \tag{4}$$

$$\Delta\sigma_j = \sigma_j(y^d(k) - y(k))\omega_j h_j \frac{\|X - C_j\|^2}{\sigma_j^2} \tag{5}$$

$$\sigma_j(k) = \sigma_j(k-1) + \eta\Delta\sigma_j \\ +\alpha(\sigma_j(k-1) - \sigma_j(k-2)) \tag{6}$$

$$\Delta c_j(k) = (y^d(k) - y(k))\omega_j \frac{x_j - c_j}{\sigma_j^2} \tag{7}$$

$$c_j(k) = c_j(k-1) + \eta\Delta c_j \\ +\alpha(c_j(k-1) - c_j(k-2)) \tag{8}$$

$$h_j = \exp\left[-\frac{\|X - C_j\|^2}{2\sigma_j^2}\right](j = 1, 2, \ldots, m) \tag{9}$$

Where in η is the learning speed,□□ is momentum factor. Here set η = 0. 01, □= 0. 05. j is the number of hidden layer units.

(6) End judging: test whether the maximum number of iterations (or minimum error), if achieved, will cease operations, if not, go to step fifth. The maximum number of iterations is 100, the minimum error requirement is 0.001.

4. APSO-RBF Method Simulation and Application

Because APSO-RBF is directed to a large sample of the solution to the problem, so according to the indexing table, from 1-1000℃ at 1℃ take a sample, calculate the corresponding thermoelectric potential, and to the thermal potential temperature as input, output, 1000 groups of training samples. Use APSO-RBF method to undertake training, and with the RBF, ANFIS training method to compare. By simulation and comparison results show that APSO-RBF method convergence is faster, the training precision reached 0.001 to 8 generation (Figure 1), and RBF reach 0.1 to 40 generation, ANFIS reached 0.01 to 400 generation.

APSO-RBF network training from1.5~1000.5□check each 1°C select a sample, results as shown in Figure 2, the error of calibration stability in 0 to0.04 °C.

The APSO-RBF correction method is applied to the anode roasting chamber temperature measurement, the in situ measurement of nearly 400 groups using PSO-RBF method for the correction of data with the international standard N type thermocouple measurement value, error correction, as shown in Figure 3.

From the graph 3, the APSO-RBF method for the correction of type N thermocouple measurement error within -0.55, has a relatively high accuracy.

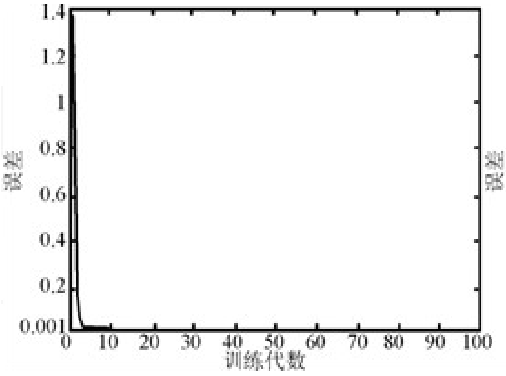

Figure 1. APSO-RBF training results

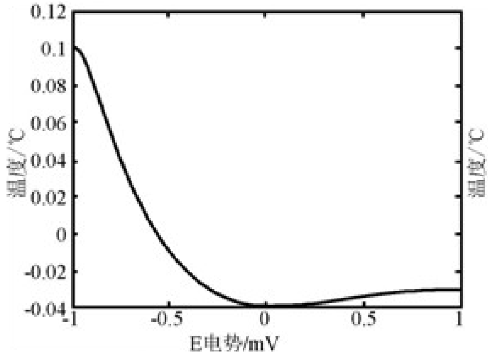

Figure 2. APSO-RBF parity error

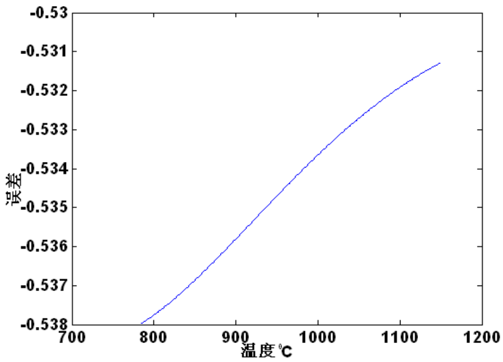

Figure 3. APSO-RBF results of application error

5. Conclusion

The research takes the anode baking process N thermocouple temperature sensor calibration for the precision measurement as the objective. Through the actual data by collecting in scene identify and optimizing the measurement model parameters, realize precision measurement of anode baking temperature. For N type thermocouple temperature sensor calibration method. According to the size of the sample size, APSO-RBF N-type thermocouple correction methods are presented. By comparison, as well as simulation and application in temperature precision measurement of anode baking process shows that APSO-RBF correction methods can solve to the precise measurement problem. APSO-RBF correction methods are better than the original method.

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