PID Parameter Tuning for Electric Arc Furnace Electrode Regulation System Based on RBF Neural Network (Postprint)

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Abstract

Since conventional PID control struggles to meet the complex operating conditions of arc furnace electrode regulation systems, this paper combines radial basis function (RBF) neural networks with PID control to propose an RBF-PID parameter tuning method. By utilizing RBF neural networks to identify the Jacobian information of the controlled object and adopting an incremental PID gradient descent algorithm to tune existing PID parameters, an RBF-PID electrode regulation system controller is designed. Simulation results verify that the RBF-PID controller can tune PID parameters in real time, enabling fast and accurate control of the electrode regulation system.

Full Text

PID Parameter Tuning for Electrode Adjustment System of Electric Arc Furnace Based on RBF Neural Network

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Abstract

Conventional PID control struggles to meet the complex operating conditions of electric arc furnace electrode adjustment systems. This paper integrates radial basis function (RBF) neural networks with PID control and proposes an RBF-PID parameter tuning method. By using an RBF neural network to identify the Jacobian information of the controlled object, the existing PID parameters are tuned via an incremental PID gradient descent algorithm, resulting in the design of an RBF-PID controller for the electrode adjustment system. Simulation

results verify that the RBF-PID controller can tune PID parameters in real time, enabling rapid and accurate control of the electrode adjustment system.

Keywords: Electric arc furnace, electrode adjustment system, radial basis function neural network, PID control, parameter tuning

1. Introduction

In electric arc furnace steelmaking, the electrode adjustment system plays a critical role, as the vertical position of electrodes must be regulated in real time and with high precision to adapt to changing furnace conditions. Electric arc furnace electrode adjustment systems typically employ PID control [1]. PID control is the most classical, widely applicable, and straightforward control method, relying on a mathematical model of the object and particularly suitable for control systems where an accurate mathematical model can be established. Its advantages include simple algorithms, good robustness, and high reliability. However, actual industrial production processes often exhibit nonlinear and time-varying uncertainties, making it difficult to determine precise mathematical models. Consequently, conventional PID controllers cannot achieve ideal control performance [2]. Moreover, in practical electric arc furnace steelmaking operations, the complexity of parameter tuning methods often leads to poorly tuned conventional PID parameters, suboptimal performance, and poor adaptability to operating conditions. As a result, actual control system design still relies on trial-and-error coefficient adjustment, which inevitably constrains control precision. With continuous technological development in related fields, control system performance requirements have become increasingly demanding. Researchers have been seeking adaptive PID controller parameter tuning techniques to accommodate complex operating conditions and high-performance requirements, and the advancement of neural network theory has made this vision achievable.

This paper introduces radial basis function (RBF) neural networks into PID control. By identifying the Jacobian information of the controlled object through RBF neural networks, PID control parameters are tuned, enabling real-time and rapid parameter adjustment.

3. PID Parameter Tuning Based on RBF Neural Network Identification

The RBF neural network structure is shown in [Figure 1: see original paper]. The first layer is the input layer, where the number of nodes equals the dimension of the input. The second layer is the hidden layer, with the number of nodes determined by problem complexity. The third layer is the output layer, where the number of nodes equals the dimension of the output data. Unlike multilayer perceptrons, RBF networks have distinct functions across layers: the hidden layer is nonlinear, employing radial basis functions as basis functions to transform the input vector space into the hidden layer space, thereby making originally linearly inseparable problems linearly separable, while the output layer is linear [3]. Based on these structural characteristics of RBF neural networks, this paper adopts this method for identifying the Jacobian information of the controlled object, which is also a prerequisite for PID parameter tuning.

There are many common radial basis functions, among which the Gaussian function is the most typical, as shown in [Figure 2: see original paper]. The Gaussian function curve is radially symmetric, and its value decreases rapidly when the independent variable deviates from the center position.

In actual electric arc furnace production, furnace conditions and system models are time-varying and change rapidly. PID controller parameters determined from prior experience become ineffective after a period of time. To maintain satisfactory control performance throughout the electric arc furnace operation, online tuning and optimization of PID controller parameters are necessary. To achieve this, an intelligent PID controller based on RBF neural networks with these characteristics has been developed. Compared with traditional modeling methods, the self-tuning model for nonlinear time-varying systems established by RBF neural networks is not only extremely convenient but also offers high stability and accuracy, making it widely applicable in production process modeling. This paper uses an RBF neural network as an identifier and focuses on PID control parameter tuning for electric arc furnace electrode adjustment systems based on RBF neural network identification.

The RBF neural network PID controller consists of two components: an RBF neural network identifier that can obtain the Jacobian information of the object by identifying its characteristics, and an RBF neural network controller that achieves online adjustment and optimization of PID parameters based on the identification information [4].

Identification Algorithm: In the RBF neural network structure, the input vector is $X = [x_1, x_2, \dots, x_n]^T$, and the radial basis vector is set as $H = [h_1, h_2, \dots, h_j, \dots, h_n]^T$, where h_j is the Gaussian function expressed as:

$$h_j = \exp\left(-\frac{\|X - C_j\|^2}{2b_j^2}\right), \quad j = 1, 2, \dots, m$$

where $C_j = [c_{j1}, c_{j2}, \dots, c_{ji}, \dots, c_{jn}]^T$ is the center vector of the j-th node in the RBF network hidden layer, $j = 1, 2, \dots, n$; $w = [w_1, w_2, \dots, w_j, \dots, w_n]^T$ is the weight vector; b_j is the base width of the hidden layer nodes with $b_j > 0$; and the base width vector is $B = [b_1, b_2, \dots, b_m]$.

The identifier output $y_m(k)$ is the sum of the products of the corresponding weight vector and radial basis vector:

$$y_m(k) = w_1 h_1 + w_2 h_2 + \dots + w_m h_m$$

The output performance index J of the identification network is:

$$J = \frac{1}{2}[y(k) - y_m(k)]2$$

The algorithms for RBF network output weights w, center vector c, and base width vector b are:

$$w_j(k) = w_j(k-1) + \eta[y(k) - y_m(k)]h_j + \alpha[w_j(k-1) - w_j(k-2)]$$

$$b_j(k) = b_j(k-1) + \eta\Delta b_j + \alpha[b_j(k-1) - b_j(k-2)]$$

$$c_{ji}(k) = c_{ji}(k-1) + \eta\Delta c_{ji} + \alpha[c_{ji}(k-1) - c_{ji}(k-2)]$$

where α is the momentum factor, η is the learning rate, and w is an indicator of control effectiveness. The smaller the value, the smoother the control effect. Increasing w may cause system instability and, in severe cases, oscillation. Therefore, selecting an appropriate w value is significant for control stability [5].

The adjustment algorithms for the three parameters k_p, k_i, and k_d adopt the gradient descent method:

$$\Delta k_p = -\eta\frac{\partial E}{\partial k_p} = \eta e(k)\frac{\partial y_{out}}{\partial u}x_c(1)$$

$$\Delta k_i = -\eta\frac{\partial E}{\partial k_i} = \eta e(k)\frac{\partial y_{out}}{\partial u}x_c(2)$$

$$\Delta k_d = -\eta\frac{\partial E}{\partial k_d} = \eta e(k)\frac{\partial y_{out}}{\partial u}x_c(3)$$

4. Simulation Results Analysis

Taking a 75t/10MV·A electric arc furnace electrode adjustment system as an example, the system mainly comprises a hydraulic system, proportional valve actuator system, mechanical transmission system, main circuit voltage, and control system rectification section. The electric arc furnace hydraulic system regulates electrode lifting speed and can be considered as an underdamped second-order system [6-7] with the transfer function:

$$G_1(s) = \frac{342.25}{s^2 + 7.4s + 342.25}$$

The proportional valve actuator system can be approximated as a proportional element with transfer function:

$$G_2(s) = 0.5$$

The mechanical transmission system outputs electrode position, primarily representing velocity changes, which can be described by an integral element [8] with transfer function:

$$G_3(s) = \frac{1}{s}$$

The main circuit voltage of the control system can be described as:

$$f(u) = 1.25u + 0.5$$

The transfer function of the control system rectification section is:

$$G_4(s) = \frac{1}{0.5s + 1}$$

The RBF neural network PID control block diagram is shown in [Figure 3: see original paper]. The PID controller employs the incremental form. The error $e(k)$ is:

$$e(k) = r_{in}(k) - y_{out}(k)$$

The PID controller inputs are:

$$x_c(1) = e(k) - e(k-1)$$

$$x_c(2) = e(k)$$

$$x_c(3) = e(k) - 2e(k-1) + e(k-2)$$

The control algorithm is:

$$u(k) = u(k-1) + k_p[e(k) - e(k-1)] + k_i e(k) + k_d[e(k) - 2e(k-1) + e(k-2)]$$

The PID parameter tuning index function is:

$$E(k) = e^2(k)$$

The parameter tuning principle is as follows: the RBF neural network can identify the parameters of the controlled object and, through learning the system Jacobian information, quickly tune the three parameters k_p, k_i, and k_d in the PID control algorithm online via the gradient descent method, compensating for the shortcomings of slow parameter adjustment and poor model adaptability in traditional PID controllers [9-10].

Simulation results are shown in [Figure 4: see original paper]. When a step input signal is applied, the RBF-PID controller reduces the settling time by 1.5 seconds and decreases system overshoot by 8.6% compared with conventional PID control.

The PID parameter tuning curves are shown in [Figure 5: see original paper]. The RBF neural network can identify the controlled object parameters and, by learning the system Jacobian information, rapidly perform online tuning of the k_p, k_i, and k_d parameters through the gradient descent method.

5. Conclusion

Due to limitations in traditional PID control parameter tuning methods and the complex operating conditions of electric arc furnaces, conventional PID control performance is suboptimal. This paper introduces RBF neural networks into PID control, tuning PID parameters through RBF neural network identification of the controlled object' s Jacobian information. Simulation results demonstrate that RBF-PID control can achieve real-time and rapid tuning of PID parameters.

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Note: Figure translations are in progress. See original paper for figures.