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Adaptive prediction system of sintering through point based on self-organize artificial neural network①

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[Abstract] A soft-sensing method of burning through point (BTP) was described and a new predictive parameter —the mathematics inflexion point of waste gas temperature curve in the middle of the strand was proposed. The artificial neural network was used in predicting BTP, modification on backpropagation algorithm was made in order to improve the convergence and self-organize the hidden-layer neurons. The adaptive prediction system developed on these techniques shows its characters such as fast, accuracy, less dependence on production data. The prediction of BTP can be used as operation guidance or control parameter.

[Key words] sintering process; burning through point; prediction; artificial neural network; BP algorithm
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1 INTRODUCTION

In sintering process, optimized operation mainly aims at improving the sinter quality, yield and stabling the process. The point at which the mix bed burned through completely is called burning through point(BTP), and the strand operation variables are mainly determined according to the location of BTP. The stabilization of BTP results in the increase of strength and the decrease of return fines, the potential capacity of the plant is also utilized[1,2]. To date, BTP judgement and adjustment have to depend on operators' experience. The vital problems are the difficulties of measuring the location of BTP, its complexity in dynamic characteristics and the long time delays. In sinter plants abroad, waste gas analysis under grate was used to judge BTP[3], a IRSID computing model[4] and a burning zone model[5] were applied to control the sintering process. However, the applications of these techniques are limited by the practical of sintering operation in China. In Refs.[6 ~8], adaptive prediction was induced into sintering process control, and qualitative prediction of BTP was proposed[9,10]. Under such circumstances, soft-sensing and adaptive prediction of BTP based on artificial neural network described in this paper can offer a promising solution.

2 SOFT-SENSING OF BTP

The location of BTP itself can not be tested on-line, the judgement according to the observation of discharge end by operators give rise to a lot of uncertainty. Soft-sensing method is used to solve this problem by establishing the relationship between the measurable waste gas temperature of windbox and the state of BTP.

The waste gas temperature is measured with thermometers under pallets or in wind legs. From common view, the waste gas of windbox presents the highest temperature while the mix bed is burned through completely. Three points ((x_1, θ_1), (x_2, θ_2), (x_3, θ_3)) including the highest temperature point selected from five points along the length of strand at the discharge end are used to fit a quadratic curve state as $\theta = Ax^2 + Bx + c$. The horizontal coordinate of the maximum point of the curve is BTP_0 as shown in Fig.1.

Fig.1 Calculation method of BTP from waste gas temperature

However, affected by the leakage of discharge end, the curve of waste gas temperature presents a maximum point while the bed has not burned through because the bed permeability falls or the fuel content is not sufficient. The calculated value of BTP should be feedback compensated by inducing the waste gas

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temperature of discharge end to ensure the judgement accuracy. In order to get the temperature, several thermometers are located under grate bar along the width of the pallet at the last 3rd windbox, the average of their temperature is compared with normal waste gas temperature of discharge end to get the error $\Delta\theta$, and the $\Delta\theta$ is then multiplied by a weight factor α, whose value is related to the scale of plant and the raw material features. BTP_0 is corrected to the soft-sensing value BTP_m as

$$BTP_m = BTP_0 - \alpha\Delta\theta \tag{1}$$

As stated above, the soft-sensing method of BTP is indicated in Fig.2.

Fig.2 Soft-sensing method of BTP

3 NEW PARAMETER FOR PREDICTING BTP

BTP should be predicted according to the available variables considering of the real-time application. The temperature of normal inflexion point of waste gas temperature curve determined by experience[9] and the permeability of raw material[11] were used to predict BTP respectively. The former relies on experience while the latter can not be tested on-line in our plants. So the author proposed a new thermal state parameter—the mathematics inflexion point of waste gas temperature curve in the middle of strand, which can trial the dynamic of the process better. It is the mathematics inflexion point of cubic curve fitted from waste gas temperature measured in the middle part of strand.

4 PREDICTION OF BTP USING ARTIFICIAL NEURAL NETWORK

4.1 Statement of problem

The objective is to evaluated steps ahead (d is the number of sample intervals ahead) prediction of process output based on the available information on the input and the output measurement at the current time. For this purpose, let the on-strand process be represented by the discrete time model:

$$\begin{aligned} y(t) = f[&y(t-l), y(t-l-1), \cdots, \\ &y(t-l-n+1), u_1(t-k), \\ &u_1(t-k-1), \cdots, \\ &u_1(t-k-n-l+1), u_2(t-k), \\ &\cdots, u_2(t-k-n-l+1), \\ &u_p(t-k), \cdots, \\ &u_p(t-k-n-l+1)] + \xi(t) \end{aligned}$$

where y is the output(BTP); u is the input parameters; l is the lagging of autoregression; n is the rank of moving average elements; p is the number of input parameters; k is the time delay; t is the discrete sampling time index; $\xi(t)$ is a white noise series with zero mean.

So the problem focuses on realizing the nonlinear mapping $f: y_n \times u_{p\times n} \rightarrow y$.

The prediction of BTP transforms to dynamic system identification of nonlinear system. Relying on the self-learning, self-adaptive, nonlinear function approximation and parallel computation capabilities of artificial neural network[12], the function f can be approximated by a neural network with appropriate architecture and algorithm. So the d step ahead prediction of BTP using neural network may be expressed as

$$\begin{aligned} \hat{y}(t+d) = NN_f(&y(t), y(t-1), \cdots, \\ &y(t-n+1), u_1(t+d-k), \\ &u_1(t+d-k-1), \cdots, \\ &u_1(t-k-n+1), u_2(t), \cdots, \\ &u_2(t-k-n+1), \cdots, u_p(t), \\ &\cdots, u_p(t-k-n+1)) \end{aligned}$$

$\hat{y}(t+d)$ is the d step ahead predicted value of y. The cost function is

$$E = \frac{1}{2}(y - y_a)^2 \tag{2}$$

where y_a is the actual measured value of BTP. The study objective is to minimizes E, i.e. to make the nonlinear mapping approximate the desired mapping f.

4.2 Multilayer feedforward neural network with self-organize modified backpropagation algorithm

In this research, a multilayer feedforward neural network(FNN) is used, and the lag factor z^{-1} is induced to represent the dynamic of process. A diagram of this type of neural network with single-output(SO) and one hidden-layer is shown in Fig.3, where ω_{ij} is the weight which connects the input component i to neuron j; R is the number of hidden neurons.

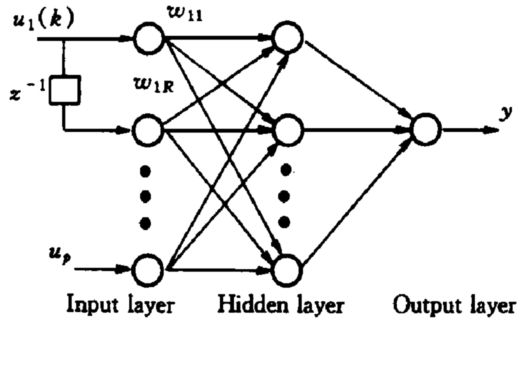

Fig.3 Topology of SO-FNN with single hidden-layer

Individual neurons of hidden-layer and output layer perform the following sigmoid function:

$$f(x) = (1 + \exp(-x))^{-1} - 0.5$$

Suppose there are k groups of input-output patterns that are to be used to train the network, the input of the jth neuron for the pth training pattern is

$$\mathrm{Net}_j^p = \sum_i \omega_{ij} O_i^p + b_j$$

O_i^p is the output of the ith neuron of former layer; b_j denotes the bias of the neuron.

The activation of the jth neuron is computed as follows:

$$O_j^p = f(\mathrm{Net}_j^p)$$

Provided that the cost function is defined as Eqn.(2), then the error of the jth neuron is given by

$$\delta_j^p = \frac{\partial E}{\partial \mathrm{Net}} = \begin{cases} (t_j^p - O_j^p) O_j^p (1 - O_j^p) \\ (j\text{—Output neuron}) \\ \sum_k \delta_k^p \omega_{kj} O_j^p (1 - O_j^p) \\ (i\text{—Hidden neuron}) \end{cases}$$

k denotes the former layer neurons.

The weights and biases are adjusted according to the rule based on gradient descent:

$$\Delta \omega_{ij}(t+1) = \eta_j(t) \delta_j^p O_j^p + \Delta \alpha \omega_{ij}(t)$$

$$\Delta b_j(t+1) = \eta_j(t) \delta_j^p + \beta \Delta b_j(t)$$

where β is a threshold memory factor ($0 < \alpha, \beta < 1$) working as a momentary. η is a learning rate which governs the step of adjustment. In order to improve the convergence, the learning rate η is adaptive updated as

$$\eta_j(t) = \lambda \eta_j(t-1),$$

where

$$\begin{cases} 0 < \lambda < 1, \text{ if } E(t) - E(t-1) > 0 \\ \lambda > 1, \text{ if } E(t) - E(t-1) < 0 \\ \lambda = 1, \text{ if } E(t) - E(t-1) = 0 \end{cases}$$

Frequently, the number of hidden neurons is determined by trial and error, which takes much of the design time. In present, Algorithms with self-organizing network architecture is highly attentive[13]. A method of constructing appropriate hidden neurons is pruning, which starts out with superfluous hidden neurons depending on the complexity of the problem to be solved. In training period, those neurons that have weak influence on the network output are removed or emerged by other neurons, the appropriate architecture is obtained then. The details are described in the following part.

The average output of hidden neuron i after learning k patterns is defined as

$$\overline{O_i} = \frac{1}{k} \sum_{p=1}^{k} O_i^p$$

Evaluate the output distribution of i by:

$$S_i = \frac{1}{k} \sum_{p=1}^{k} O_i^{p^2} - \overline{O_i^2}$$

If $|S_i| < \varepsilon_1$, $\varepsilon_1 \in [0.001, 0.01]$, i should be removed for its output has little change in training. Whether two hidden neurons i and j in the same layer ($|S_i| > \varepsilon_1$, $|S_j| < \varepsilon_1$) can be combined or not depends on their similitude defined as

$$\gamma_{ij} = \frac{\frac{1}{k} \sum_{p=1}^{k} O_i^p O_j^p - \overline{O_i}\,\overline{O_j}}{S_i S_j}$$

If $|\gamma_{ij}| \geqslant \varepsilon_2$, $\varepsilon_2 \in [0.8, 0.9]$, i and j should be combined to one neuron because they have similar contribution for training.

4.3 Training of neural network

The initial architecture of the multiple feedforward neural network is 5-15-1. For 5 steps ahead prediction, the input vectors include the current position of the mathematics inflexion point of waste gas temperature curve and its delay value, the current and delay position of $\mathrm{BTP_m}$ and the current pallet travelling speed. The supervised signal is BTP position after 5 sample time. The training set consists 600 groups of input and output data and the neural network is trained with OMBP algorithm. In training iterations the weight factors in the network and the bias of nodes are adjusted, the architecture of network is self-organized meanwhile. The optimum number of nodes in the hidden-layer is 5-10-1 determined by training. The approximation output of neural network is shown in Fig.4.

Fig.4 Approximated output of neural network

4.4 Prediction of BTP using neural network

The testing set is made of 450 groups of data, the input vector is presented to the trained neural network, the output of neural network is the predicted value of BTP 5 steps ahead. The predicted result of testing set is shown in Fig.5, the predictive error is defined as Eqn.(2). Noted that the prediction error E is below 0.15.

Fig.5 Predicted output of testing set by trained neural network

5 CONCLUTIONS

1) The soft-sensing method can be used to realize the on-line measurement of BTP.

2) The mathematics inflexion point of waste gas temperature curve can be made as predictive parameter.

3) Multi-layer feedforward neural network with OMBP algorithm can be trained as predictor.

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