Optimal control of end-port glass tank furnace regenerator temperature based on artificial neural network

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Abstract: In the paper, an artificial neural network (ANN) method is put forward to optimize melting temperature control, which reveals the nonlinear relationships of tank melting temperature disturbances with secondary wind flow and fuel pressure, implements dynamic feed-forward complementation and dynamic correctional ratio between air and fuel in the main control system. The application to Anhui Fuyang Glass Factory improved the control character of the melting temperature greatly.

Keywords: B-P network; topology structure; learning efficiency; momentum modulus

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1 Introduction

The principle controlled target of an end-port glass tank furnace regenerator is the melting temperature which is regulated by the flow of oil or gas. The disturbances stem from feed-in glass powder, the pressure, value and atomization of fuel, the secondary wind, the tank furnace pressure, etc. Among them, some can be controlled and some cannot. In order to keep the temperature steady, a cascade ratio regulating system is designed, in which the temperature adjustment functions as the main circuit, the fuel pressure as the subsidiary, and the secondary wind and the fuel pressure form a proportion. There are also other subsidiary regulating systems—the tank furnace pressure, the fuel pressure and the feed-in, in which PID control is generally used. However, in these controlling practices, exist the following problems:

1) The secondary wind and the fuel pressure make up a given proportion which is usually adjusted with the air plethora coefficient $\partial=1.2$ to 1.3. Because the air amount, the key element to the burning system, is related not only to the fuel value, the pressure and atomization, but also to the tank furnace pressure and burning direction, a given proportion cannot always satisfy the thorough combustion of fuel, which results in extra consumption at times.

2) Due to the lag of transfer and measurement, the control system cannot adjust timely, and the tank furnace temperature fluctuates greatly, which inevitably influences product quality.

3) Due to a regular commutation of the regenerator, there exists a speedy periodic interference in the long dead time control system [1]. But ordinary PID control will have a big overshoot and a long transient.

With the development of chemical production process, new demands are emerging in the precision and functions of process control. To accommodate technical requirements, improvements have been made in the schemes and functions of the control system, forming many special control systems [2]. In this paper, a method is put forward to optimize glass tank furnace temperature control, employing ANN [3], which reflects the nonlinear relationship between tank furnace temperature disturbances, secondary wind and fuel pressure. This method realizes dynamic feed-forward complementation and dynamic correctional ratio between air and fuel in the main control system [4], as is sketched in Fig. 1.

2 Network topology structure

The manufacturing process flow is as follows.

Powder glass materials are fed in batches by a feeder into the end-port glass tank furnace, therein are heated, subject to a series of chemical reactions and eventually melted into glass liquid by the radiant heat given off in the combustion of the fuel. The powder amount is of different composition and hence different heat
value. Since unilateral feeding is used in most tank furnaces and the secondary wind entering the two regenerators in the middle or final stage of furnace endurance may change, the combustion condition may not be the same at different directions inside the furnace. So, the fuel demand is also different. The tank furnace pressure will have a direct effect on conflagrant atmosphere. The combustion with either superfluous or deficient oxygen consumes more fuel.

As is shown in Fig. 2, in the network design, the four input layer neurons are set respectively to relate to the four parameters, material quantities, fuel number, combustion direction, and tank furnace pressure; the output layers have two neurons, relating to fuel and secondary wind flows respectively [5]. As no method is available for determining the numbers of the hiding layer and the hiding neurons in ANN, two hiding layers are set, each with four neurons. The coefficient matrix between the input layer and the hiding layer is expressed by $U$, that between the hiding layers $H1$ and $H2$ by $V$, and that between the hiding layer and output layer by $W$.

![Fig. 1 System diagram](image1)

![Fig. 2 BP nerve network topology structure](image2)

### 3 Training iterative process

#### 3.1 Network training initialization

**3.1.1 Collection of training samples and anticipant output:**

In order to collect a group of samples on-line ($\{x_i^{(p)}\}$, $p = 1,2,\ldots,50$, $i = 1,2,3,4$ for four input nodes) and a group of anticipant outputs ($\{t_k^{(p)}\}$, $p = 1,2,\ldots,50$, $k = 1,2$ for tow output nodes), the characteristic status of the tank furnace in a fixed cycle should be selected. **3.1.2 data change**

The samples collected and the anticipant values are changed linearly into real numbers between 0 and 1:

$$x_i^{(p)} = (\max_j - x_i^{(p)})/((\max_j - \min_j); \quad i = 1,2,3,4; \quad j = 1,2,3,4; \quad p = 1,2,\ldots,50.$$  \hspace{1cm} (1)

$$t_k^{(p)} = (t_{\max_k} - t_k^{(p)})/(t_{\max_k} - t_{\min_k}); \quad k = 1,2; \quad p = 1,2,\ldots,50.$$  \hspace{1cm} (2)

where $\max_i$ and $\min_i$ are the maximum and minimum of $x_i^{(p)}$ and $t_{\max_k}$ and $t_{\min_k}$ are the maximum and minimum of $t_k^{(p)}$, respectively. **3.1.3 set initial value**

The coefficient matrixes $U$, $V$ and $W$ are set with the initial values. Each factor is assigned a random value equally distributed between 0 and 1 in the beginning. It is known from experience that when the learning
efficiency $\eta$ is between 0.2 and 0.5 and the momentum modulus $a$ is assigned a value between 0.90 and 0.98, thus affects the convergence speed.

### 3.2 Forward transmission

#### 3.2.1 Work out a set of $\{O_k^{(p)}\}$

\[ h_{j,k}^{(p)} = \frac{1}{1 + \exp\left(-\sum_{q} U_{j,k}^{(q)} x_{j}^{(p)}\right)}; \quad i = 1, 2, 3, 4; \]
\[ j = 1, 2, 3, 4; \quad p = 1, 2, \ldots, 50. \]  

### 3.2.2 Output of half square difference

\[ E^{(p)} = \frac{1}{2} \sum_k (t_{k}^{(p)} - O_{k}^{(p)})^2; \quad k = 1, 2; \quad p = 1, 2, \ldots, 50. \]  

#### 3.3 Backward transmission

#### 3.3.1 Reversal modification of the coefficient matrixes through an algorithm of the deviation.

By the link-differential theorem, the differential with regard to link-coefficient error function will be returned along the original passage. By adjusting every layer coefficients the errors will be reduced. In order to achieve the goal, adjustment of the link-coefficient in every layer will be made correspondingly on the basis of error function. A gradient descent algorithm to speed up the coefficient adjustment has been adopted in traditional algorithm study. For example, the adjustment of $W$ to an increment at a time is

\[ \Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} \quad (0 < \eta < 1) \]  

The formula to modify the increment is:

\[ \Delta W_{ij} = -\eta \delta_{i} O_{j} \]
\[ \delta_{i} = (t_{i} - O_{i}) O_{i} (1 - O_{i}) \quad k = 1, 2. \]  

In the process of the iterative $p$-th and $(p-1)$-th time, the formula to modify a link-coefficient increment is:

\[ \Delta W_{ij}^{(p)} = -\eta \delta_{i} O_{j} + \partial \Delta W_{ij}^{(p-1)} \]  

In the study, dynamic adjustment of $\eta$ and $a$ makes $\eta$ change continuously with error $E$ to avoid a small $\Delta W$, and thus affects the convergence speed.

The coefficient matrix $V$ and $U$ adjusting to an increment at a time are

\[ \Delta V_{ij}^{(p)} = \eta \delta_{i} h_{j} + \partial \Delta V_{ij}^{(p-1)} \]
\[ \Delta \delta_{j} = h_{j} (1 - h_{j}) \sum_k \delta_{i} W_{ij} \]
\[ \Delta U_{ij}^{(p)} = \eta \delta_{i} h_{j} + \partial \Delta U_{ij}^{(p-1)} \]
\[ \Delta \delta_{j} = h_{j} (1 - h_{j}) \sum_k \Delta V_{ij} \]  

#### 3.3.2 Recording the iterative time

If it is convergent, it turns to the forward transmission to calculate the next $\{O_k^{(p)}\}$.

#### 3.4 Parameter modification

1) The output of the different mean square of the system is

\[ E = \frac{1}{2p} \sum_k \left(t_{k}^{(p)} - O_{k}^{(p)}\right)^2; \quad k = 1, 2. \]  

2) To judge if the performance of the requirement is achieved. If not, adjust $\eta$ and $a$.

3) To modify the numbers of the hiding neurons, observe the iterative times and training errors and optimize the network structure.

After the network training performance, a test is carried out to see if the technological demand is met.

### 4 Network training and testing results

Experiment revealed that a bigger $\eta$ realizes a quicker study speed before $\eta$ is too big and causes oscillation. With the increase of $a$, the convergence speed is quickened and the system errors increase. If there are only a few hiding neurons, the precision of the system will be affected. However, it doesn’t mean the more the better because too many neurons cause slow convergence speed. Training and testing results indicated that when the number of hiding neurons is 4, $\eta = 0.3$, and $a = 0.94$, the B-P network is not only of higher precision and simpler structure but also of quicker training speed, as is shown in Table 1.

<table>
<thead>
<tr>
<th>Serial numbers</th>
<th>$\eta$</th>
<th>$a$</th>
<th>Hiding neuron numbers</th>
<th>Iterative numbers</th>
<th>System error/%</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>0.2</td>
<td>0.92</td>
<td>4</td>
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</tr>
<tr>
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<td>0.94</td>
<td>4</td>
<td>9 230</td>
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</tr>
<tr>
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<td>0.96</td>
<td>4</td>
<td>4 540</td>
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</tr>
<tr>
<td>4</td>
<td>0.5</td>
<td>0.98</td>
<td>4</td>
<td>1 208</td>
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<tr>
<td>5</td>
<td>0.3</td>
<td>0.94</td>
<td>3</td>
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</tr>
<tr>
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<td>0.3</td>
<td>0.94</td>
<td>5</td>
<td>88 960</td>
<td>-7.75</td>
</tr>
</tbody>
</table>

### 5 Application result of the ANN model

The dynamic complementary feedforward of the ANN was applied to Anhui Fuyang Glass Factory of
China, which improved the control character of the melting tank furnace temperature enormously. Fig. 3 shows the curves of the output responses, in which the melting tank furnace temperature is under the disturbance of a timely commutation.

Fig. 3 Comparison of control results

The application of the ANN optimizing the regenerator end-port glass tank furnace control is still in the preliminary stage. As to the selection of the network structure and the original coefficient values, further study is needed. With the rapid development of computer technology and optimal control theory, the automatic adaptation of the study and the intelligence control will perfect the glass tank furnace control consummate gradually.

References