END-POINT TEMPERATURE PREDICTION BASED ON RBF NEURAL NETWORK

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Abstract: An end-point temperature prediction model based on RBF neural network is developed to reduce the measuring cost and improve the measuring accuracy in a vacuum induction furnace. It can give reliable predictions of tapping time and temperature of molten steel in the first-round prediction. And the prediction accuracy can be improved by the error correction in the second-round prediction. 120 set of data are used for model building and validation.The experimental results show that the proposed method is effective and the real-world application is potential.

Keywords: neural network method,prediction,error correction, k-means clustering,vacuum induction furnace

1. INTRODUCTION

Vacuum induction furnaces which are mostly used to produce super clean steel and alloy materials have been found numerous applications in aviation, navigation, nuclear power, military and chemical engineering. It can provide pure consumable electrode and precise casting for remelting. In order to guarantee the steel ingots' quality, the temperature of molten steel must reach a certain value which is generally 70-90 $^{\circ}C$ higher than the alloys' melting point when tapping, . Therefore, measurement of the molten steel temperature is of primary importance in the process of steel-smelting. At present, the thermoelectric couple or radiation measurements are applied in most vacuum induction furnaces. The thermoelectric couple measurements, however, may increase hardware consume seriously and the radiation measurements may lead to larger measuring errors(Greg,1997). In order to reduce the measuring cost and to improve the measuring accuracy, an end-point temperature prediction method based on RBF neural network is developed in this paper. This method can forecast the temperature with sufficient accuracy. The experimental results show that the proposed method is simple and applicable.

2. PREDICTION MODEL

During the process of steel-smelting in vacuum induction furnaces, it is difficult to describe the process using classical mathematical model because of some severe unknown nonlinear characteristic. Confessedly, Radial Basis Function (RBF) neural networks are increasingly applied in solving complex practical problems.Known as universal function approximators,they are capable of approximating any continuous nonlinear functions to arbitrary accuracy.

In order to avoid the limitation of the complex mechanics, an end-point temperature forecast model was built based on the RBF neural network. It can

build nonlinear maps between the inputs and the forecast results by self-learning from the actual data.This method, has high degree of accuracy and fast convergence property, obtains exact information of the molten steel temperature and achieves an effective control on the end-point temperature.

2.1 Input Parameter Analysis

There are many factors that can impact on the end-point temperature of the vacuum induction furnaces in the process of smelting. In order to build an effective prediction model of the molten steel temperature, it is necessary to master the mechanism of the smelting process and seek out the parameters that are relative to the temperature as input parameters. Vacuum induction furnace smelting can heat up metal material by generating electric and magnetic energy under a high vacuum circumstance. Such method is effective to eliminate impurities and gases and make the alloy components more homogeneous. Generally,vacuum induction furnace smelting process can be divided into periods of charging, melting, refining, alloying and tapping. During the melting period, the materials are quickly melted and the gas is sufficiently eliminated by high-power electricity. At the end of this period, the temperature is proper for refining and the process comes to the next period of refining and alloying. In order to shorten the steel-smelting period, we need to cut off the electricity to low down the temperature because many kinds of alloy elements are active and have a very low melting point. After adding the alloys at a lower temperature we must give high power stirring in order to make the alloys more homogeneous. Then, the deoxidation is perfect and alloying is completed.When the temperature of molten steel reaches the expected tapping temperature ,the smelting process comes to the end and it is time for tapping. After analyzing the smelting process and combining the field experiences, the prediction model should include following parameters as inputs:

- Electricity information: *power consumption during the refining period.*

The induction furnace smelting process is mainly dominated by controlling and adjusting the electricity power which directly impact on the temperature. So the power consumption is a necessary parameter for the prediction. We can get this parameter by multiplying the power by the cost time during the smelting period.

- Weight information: *amount of alloys.*

Alloying is an important step of vacuum induction furnace smelting. After the alloys are added to the molten steel, changes of the temperature rising,phase converting,melting and reacting with other elements take place. All these changes impact on the temperature of the molten steel. For instance, when adding the elements Al and Ti to the molten steel during the alloying period, it becomes a process giving out heat instead of one assimilating heat because of the existence of Al,Ti and the oxid on the crucible's wall. That is to say these elements generate deoxidation reactions which give off a large amount of heat and this cause the temperature of the molten steel rising very quickly. Knowing from Shun (1992), along with the amount of Al + Ti increasing 8%, the temperature of the molten steel rises 80-100 $^{\circ}C$. So it is important to select the amount of alloy as an input parameter for the prediction.

- Temperature information: *including liquid line temperature and full melting temperature.*

liquid line temperature is the temperature of the alloys' melting point. When casting, in order to guarantee the steel ingots' quality, the temperature of molten steel in the furnace is commonly 70-90 $^{\circ}C$ higher than the liquid line temperature. Different steels containing various alloys have different liquid line temperatures. The specific calculating method for it can be found in Fu (1982). When the material is totally melted, the temperature of molten steel should be measured.The measure result is called full melting temperature. All the input parameters are obtained after this measure.

- Time information: *including power-cut time and refining time.*

Because the power-cut causes the molten steel losing a large amount of heat, the temperature of the molten steel drops very quickly.The power-cut time is a very important input parameter when building a temperature prediction model.
The refining time is the period from the end of full melting to the beginning of the tapping. In order to make sure that the deoxidation is completely finished and the alloy components is well- homogeneous, we must guarantee a definite refining time. At the same time ,the impurities are also completely eliminated.

According to analysis hereinbefore, six parameters have been select as the input variables which are the power consumption during the refining period, amount of alloys,refining time,power-cut time,liquid line temperature and full melting temperature. A single output variable is tapping temperature,namely the end-point temperature. To sum up,the RBF neural network prediction model built in this paper has six input layer nodes and

one output layer node. The amount of hidden layer nodes should be determined by trained results.

2.2 data preprocessing

This paper use Z-score standardization method to normalize the input data. Let

$$x_i'(k) = \frac{x_i(k) - \bar{x}(k)}{\delta_k} \tag{1}$$

where

$$\bar{x}(k) = \frac{1}{N}\sum_{i=1}^{N} x_i(k) \tag{2}$$

$$\delta_k = \frac{1}{N-1}\sqrt{\sum_{i=1}^{N}[x_i(k) - \bar{x}(k)]^2} \tag{3}$$

where $k = 1, 2, \cdots, 6$ represents dimension of input samples, and $i = 1, 2, \cdots, N$ represents the number of input samples.

At the same time,the output values should also be disposed by normalization. After training, the outputs are transformed by following equation in order to obtain the actual training results.

$$\hat{y} = \bar{y} + \sigma\hat{y}' \tag{4}$$

Where $\hat{y}$ is the network output value after training, $\bar{y}$ is the average value by standardizing the expected outputs before training, σ is the variance of outputs before training and $\hat{y}'$ is the output of the trained network.

2.3 Training algorithm

A RBF network is a two-layer feed-forward neural network.Neurons at the first layer,namely hidden layer, is activated by a radial-basis function.The second layer of the network,namely output layer, takes the form of a linear combination of the hidden layer outputs.Therefore, to determine the center of the network is very important for the realization of the non-linear map.In this paper, a k-means clustering algorithm can solve the problem(Zhu,*et al.*,1999; Sing,*et al.*,2003; Chai,*et al.*,1999).It consists of following steps:

*Step 1.*initialization
Suppose there are N input samples $x_i(i = 1, 2, \cdots, N)$. Choose m samples randomly from x_i as the initial network center $c_j^o(j = 1, 2, \cdots, m)$;

Step 2. Group the input samples according to nearest neighbor rule.
That is to say ,for every input sample,calculate the distance between it and each clustering center with the equation

$$d_{ij}^l = \|x_i - c_j^l\| \tag{5}$$

Where l is the iterative index.Then,assign the input sample to the group of the least distance;

Step 3. compute new clustering centers as follows:

$$c_j^{l+1} = \frac{1}{n_j^l}\sum_{i=1}^{n_j^l} x_{j,i} \tag{6}$$

where n_j^l represents the number of the samples belonging to jth clustering at lth iterative, and $x_{j,i}$ represents the ith sample in the jth clustering;

Step 4. Calculate $\varepsilon_l = \|c_j^l - c_j^{l-1}\|$.
If ε_l is less than the given value, stop calculation. Otherwise continue from step 2.

When the network center has been determined, let$c_j = c_j^l$. Then,the width σ_j can be calculated by

$$\sigma_j = \frac{\sum_{b=1}^{B}\|c_b - c_j\|^2}{B^{1/2}}, \tag{7}$$

Where c_b is the nearest center to c_j ,and B is not greater than 3 in most common cases.

After determined the network center and the width, the connection weights W of the network should be adjusted. Relation between the hidden layer and output layer can be described as: $Y = \Phi W$ .It is a linear equation,and W can be calculated by means of recursive least square.

3. PREDICTION METHOD

3.1 first-round prediction

At the end of the full melting period, the first-round prediction is given based on the proposed RBF neural network.According to the practical experience, a shortest refining time is set as t_o , which is commonly shorter than any refining time in practical product. And then predict the temperature $\hat{T}_0$ at the time point t_o. If $\hat{T}_0$ does not reach the requirement of tapping, calculate the next prediction time point t_1 by following equation and predict the corresponding temperature at the point.

$$t_{n+1} = t_n + \alpha|T^* - \hat{T}_n| \tag{8}$$

where $n = 0, 1, 2, \cdots$, T^* is the target end-point temperature for tapping ,$\hat{T}_n$ is the prediction temperature at the time point of t_n, α is the experience constant and $0 < \alpha < 1$.

According to the above method, the temperature at time points of $t_0, t_1, t_1 \cdots$ can be forecast as $\hat{T}_0, \hat{T}_1, \hat{T}_2, \cdots$ respectively. Stop the prediction, once a predicted temperature at these time points is proper for tapping.As a result, reliable predictions of tapping time and temperature can be obtained in the first-round prediction.

3.2 Error correction

The first-round prediction is given at the end of full melting stage, using the above method. The predictions are, however, not very accurate because some of the aforementioned parameters are only available after the last power-cut. In order to reduce the final predicted error, second-round prediction is necessary at the end of the last power-cut.

For the purpose of simply and fast computation, the second-round prediction need not be as same as the first-round. The RBF neural network builded previously was linearized and the errors of those parameters which not very accurate in the first prediction were computed . In this paper,these parameters consist of the power consumption during the refining period,the amount of alloys and the power-cut time. The calculated errors are used as inputs of the linearized network, and the network outputs are the output errors.

Assuming that the output of the RBF network is formed as

$$y = \sum_{i=1}^{m} \omega_i \Phi_i \tag{9}$$

where

$$\Phi_i = e^{-\frac{1}{2\sigma_i}\|x-c_i\|^2} \tag{10}$$

after linearization, the network model can be written as

$$\Delta y = \sum_{j=1}^{k} \frac{\partial y}{\partial x_j} \Delta x_j \tag{11}$$

$$= \sum_{j=1}^{k} [\sum_{i=1}^{m} \omega_i \Phi_i (-\frac{1}{\sigma_i})(x_j - c_i)] \Delta x_j \tag{12}$$

The second-round prediction is then calculated by

$$\hat{y}_2 = \hat{y}_1 + \Delta y \tag{13}$$

where $\hat{y}_1$ is the first-round prediction.

The main advantages of the above method are twofold. It can give reliable predictions of tapping time and temperature of molten steel in the first-round prediction. And the prediction accuracy can be improved by the error correction in the second-round prediction.

4. EXPERIMENT RESULTS AND ANALYSIS

120 set of data had been obtained from the steel-smelting records of a vacuum induction furnace, in which 90 records had been chosen as training data to build a prediction model(Kane,*et al.*,1999).The optimal number of the hidden layer nodes is finally confirmed as 26 and the training times are 104.Then the end-point temperature of other 30 heats was predicted based on this model.The actual and predicted outputs after training at first-round prediction are shown in Fig.1,while the actual and predicted outputs after error correction at second-round are shown in Fig.2.

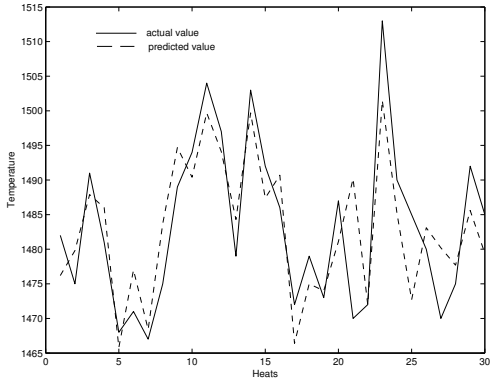

Fig. 1. The actual and predicted outputs at first prediction

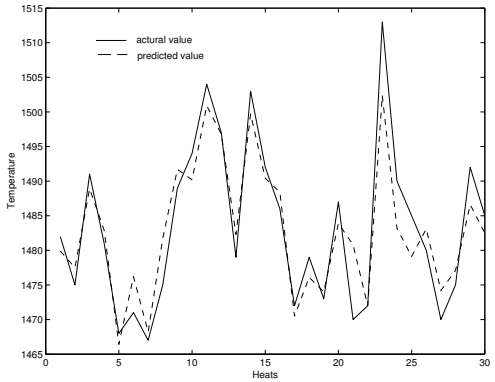

Fig. 2. The actual and predicted outputs after error correction

It is found that the method is able to forecast the temperature with sufficient accuracy. For the first-round prediction shown in Fig.1, in the 30 heats, there are 26 heats that the differences between actual and predicted values are less than 10^oC ,the hit rate is 86.7%. For the second-round prediction shown in Fig.2, there are 28 heats that the differences between actual and predicted values are less than 10 ^oC, the hit rate is 93.3%. Compared with the first-round prediction, the hit rate improved 6.7% after error correction.

5. CONCLUSION

Prediction of the end-point temperature is a great significance for steel-smelting process.Moreover, guaranteeing a certain refining time is also necessary for vacuum induction furnace smelting. The proposed method can not only predict the temperature of molten steel accurately but also fix the refining ending time in advance. The experiment clearly demonstrate that it is reasonable to predict the end-point temperature of vacuum induction furnace smelting based on RBF neural networks.It can improve productivity of the furnace and give guidance to actual production.

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