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Greedy Kernel Components Acting on ANFIS to Predict BOF Steelmaking Endpoint

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Abstract: In order to make overall consideration of the information from the original variables in the basic oxygen furnace (BOF) steelmaking dynamic process, an adaptive neural network fuzzy inference system (ANFIS) model based on kernel and greedy components is proposed. This kind of model can improve the endpoint predicting precision of the steel carbon contents and temperature. After hidden information is exposed in the high feature space through the kernel function transformation, greedy algorithm is used to remove redundant information and reduce the dimensions. The extracted components are used as the new inputs of ANFIS, and the implication relation among the inputs is reflected by rules, which simulate the operators experience, and consequently reduce the influence resulted from different operators. When the practical data are simulated, the simulated results are close to the practical values. The method is effective.

1. INTRODUCTION

The impulse from the domestic market and the abundance of quality raw materials have favoured the development of the Chinese steel industry, which contributes to the process of industrialization and development. There are many large Iron and Steel Plant (ISP) in China, and this research studied on one of the largest steelmaking plant in China, with a production capacity of dozens million tons of various types of steel per year.

Steel in general is an alloy of iron and carbon(C), often with an admixture of other elements such as silicon(Si), manganese(Mn), sulphur(S), phosphorus(P) and nickel(Ni). Some alloys that are commercially called irons contain more carbon than commercial steels. Open-hearth iron and wrought iron contain only a few hundredths of 1% of carbon. Steels of various types contain from 0.04% to 2.25% of carbon (Fileti, Pacianotto et al. 2006), (Kurt, Orhan et al. 2007).

BOF is a widely preferred and effective steel making method due to its higher productivity and considerably low production cost. Therefore, today almost 65% of the total crude steel production in the world and 85% in China are met by using the BOF method. However, BOF steelmaking is a very complex chemical physical process. The amount, quality and component of scrap iron change from batch to batch; the grades of steel produced vary frequently; and also changes the height of the oxygen lance during each heat. As a result, controlling the steelmaking operation in the BOF is greatly difficult. The main objective of controlling oxygen converter steelmaking is to obtain the prescribed parameters for the steel when it is tapped from the furnace, including weight, temperature, and each element content. In the practical steelmaking process, the criterion whether the molten steel is acceptable or not are often decided by the endpoint carbon content $[C]$ and temperature T. In general, the main task of BOF is two: one is the carbon percentage decrease from approximately 4% in hot metal to less than 0.08% in liquid steel, and the other is the temperature increase from approximately 1250℃ in hot metal to more than 1650℃. The sketch map of smelting is presented on Fig. 1.

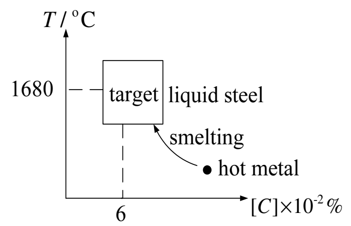

Fig. 1 the Sketch Map of Smelting

Generally, the large BOF steelmaking process with sublance system can be divided into two stages: static control and dynamic control. Static control is the basic control mode for the converter computer. Static models include terminal control model, oxygen supplying model, slagging model and bottom blowing model; dynamic models include decarbonization speed model, molten steel warming model and the model for the amount of refrigerant (Feng, Zhang et al. 2006), and the dynamic control for sublance is on the basis of static control.

Traditionally, the process can be effectively controlled through the use of mathematical models. Aiming at the effects of complex factors in the course of smelting, a set of steelmaking math-mode has been developed in a math way. However unfortunately, there exist a lot of theoretical assumptions, and too many parameters are involved in the traditional control methods, such as mechanism models based on heat balance and material balance, or statistic models based on regression analysis. Therefore, these models are often difficult in modelling precisely. Moreover, most of the models that have been used have been statistical and thus are not suited for continuously changing conditions. As the development of the intelligent technology, various kinds of neural network model have been applied more and more. The concept of fuzzy logic and artificial neural network for control problem has been grown into a popular research topic. The reason is that the classical control theory usually requires a mathematical model for designing the controller, which usually degrades the performance, especially for nonlinear and complex control problems(Lin, Lee et al. 2006). On the contrary, the fuzzy logic controller and the artificial neural network controller, they offer a key advantage over traditional adaptive control systems. That is, they do not require mathematical models of the plants. The traditional neural networks can learn from data and feedback, but the meaning associated with each neuron and each weight in the network is not easily understood. Alternatively, the fuzzy logical models are easy to appreciate, because it uses linguistic terms and the structure of if-then rules. As the mixture of neural network and fuzzy system, the fuzzy neural network representations have emerged as a powerful approach to the solution of many problems(Liu, Yuan et al. 2005). (Kubat, Taskin et al. 2004) proposed a fuzzy modelling for the control of BOF process. As a result of the application of the proposed modelling, acceptable levels of compatibility were achieved compared to the empirical BOF data in an integrated steel plant based in Turkey and targeted steel composition. (Xie, Tao et al. 2003), (Bigeev and Baitman 2006) also adopted different intelligent model to describe the BOF steelmaking process. Though these aforementioned intelligent models make up the deficiencies of the traditional models to some degree, they ignore the influence of the input simplifying on the predicting precision. According to (Szekely 2003), it is very necessary to simplify the input variables to reduce the complexity and improve the generalized capacity of the industrial model.

The main contribution of the present work is improving the predicting precision with less dimensional and more effective inputs to establish simpler and more accurate endpoint predicting model.

2. METHODS

2.1 Description Steelmaking Steps

BOF are main device of steelmaking process. Hot metal from blast furnace, and scrap iron are converted into steel by exothermic oxidation of all elements dissolved in the iron. Oxygen are kept blowing into the converter to eliminate the impurities by oxidation reactions.

There are various steps in steelmaking process from raw materials up to the final products. These steps can be summarized as follows.

Step 1: Charging raw materials into the furnace as being either iron ore or scrap iron, depending on the process. These are converted into molten steel. The ore-based process uses a blast furnace + BOF and the scrap-based process uses an electric arc furnace only.

Step 2: for both routes is pouring the molten steel from the furnace and it is eventually solidified in a continuous caster.

Step 3: these semi-finished products are transformed, or "rolled" into finished products. Some of these undergo a heat treatment, known as "hot rolling". More than half of the hot-rolled sheet is subsequently rolled again at ambient temperatures (known as "cold rolling"). It can then be coated with an anti-corrosion protective material.

In this investigation, fuzzy modelling for the control of BOF process is studied.

2.2 BOF Description

BOF comprises a vertical solid-bottom crucible with a vertical water-cooled oxygen lance entering the vessel from above. The vessel is tiltable for charging and tapping. The charge is normally made up of molten pig iron ("hot metal"), plus scrap and fluxes. Small quantities of cold pig iron and iron ore may also be charged. The distinguishing feature is that the heat produced by reaction of the various constituents of the charge is used without other sources of energy to bring the metal to the desired final conditions of compositions and temperature. General view of BOF is given in Fig. 2.

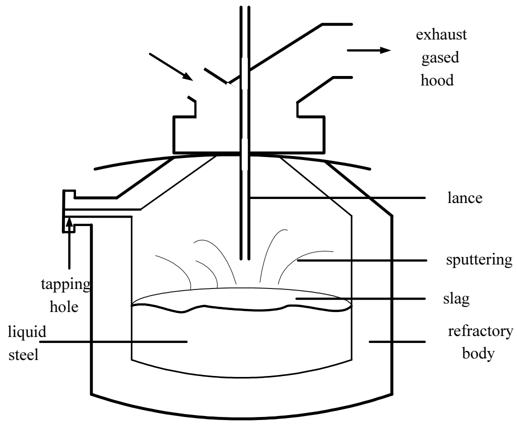

Fig. 2 General View of BOF

BOF can produce steel with wide range of carbon, alloy, and special alloy steels. Average molten steel capacity of BOF is normally between 100 tonnes and 400 tonnes of steel. When the molten iron arrives at the BOF via rail, it is processed through a desulphurization facility before being poured into a ladle in preparation for charging. In BOF steelmaking, hot metal and scrap are charged into a converter, along with lime and other fluxing materials. Oxygen is blown, and carbon, silicon, phosphorus, manganese, and some iron are oxidized.

The objective is to produce a desired amount of steel, of specified chemical composition, at the proper tapping temperature. Control is difficult because the entire refining period takes only half an hour and there are no opportunities for sampling and analysis during this time. The BOF generally operates on a charge of 75% hot metal and 25% scrap. The scrap is loaded into a vessel via crane, and then the molten iron is poured into the vessel. A water-cooled oxygen lance is lowered into the vessel and high-purity oxygen is blown into the top of the metal at a speed of

16,000 cubic feet a minute. The oxygen combines with carbon and other elements to reduce impurities in the molten metal and convert it into clean, high-quality liquid steel. The steel is poured into a ladle and sent to the ladle metallurgy facility.

In the BOF steelmaking process, when oxygen lance blows the oxygen to the bath surface, the hot metal impurities are removed and the temperature keeps increasing, accompany with the slags, gases, and released energies that are product by continually happening physical and chemical reactions. Impurities such as sulphur, phosphorus, and silicon are removed in the preprocessing time and prior blowing period, as a result, the main task of the BOF is decarbonization and temperature rising. Before blowing, the static model estimates the oxygen consumption value of the total steelmaking process. When the blowing reaches 85% of the value, the sublance goes down to the liquid steel to detect [C] and T. Comparing these values with the target values, the second blow oxygen volume and the re-added coolant weight are recalculated, then continue blowing until steel component and temperature are acceptable. The BOF endpoint predicting model mentioned here uses carbon content detected by sublance [C_f], second blow oxygen volume and re-added coolant as original input, to predict endpoint [C] and T.

2.3 Refined Mechanics

The preparation of the charge can be efficiently controlled by using a statistical model based on the material and heat balances, but a dynamic model is needed to control the blowing process. The second blow oxygen and re-re-added coolant weight are two important parameters (Zhang, Xiao et al. 1993).

Assume that k stands for the current heat, t stands for the sublance time. The second blown oxygen volume $u_{1\mathrm{set},k}(t+\vartriangle t)$ can be expressed as follows:

$$\begin{aligned} & u_{1\mathrm{set},k}(t+\vartriangle t) = \\ & u_{1,k}(t) + \frac{W_{\mathrm{ST},k}}{\gamma_k}\left\{k_0\left[u_{2,k}(t+\vartriangle t) - u_{2,k}(t)\right]\right. \\ & +\left[y_{2\mathrm{aim},k}(t+\vartriangle t) - y_{2,k}(t)\right] - f_k(t)\delta_k \\ & \left.-\varepsilon_k\left[y_{1\mathrm{aim},k}(t+\vartriangle t) - y_{1,k}(t)\right]\right\} \end{aligned} \tag{1}$$

where $u_{1,\,k}(t)$ denotes the second blow oxygen volume at t; $u_{2,k}(t)$ denotes the re-added coolant at t; W_{ST} is the target tapping weight (t); γ_k, δ_k, ε_k is the warming coefficient (°C/t); k_0 is the cooling coefficient(°C/t); $y_{1,k}(t)$, $y_{2,k}(t)$ respectively denotes the carbon content and temperature of the liquid steel at t; if t=0, $f(t)$=1, else $f(t)$=0.

At $(t+\vartriangle t)$, the re-added coolant $u_{2\mathrm{set},k}(t+\vartriangle t)$ can be expressed as follows:

$$\begin{aligned} & u_{2\mathrm{set},k}(t+\vartriangle t) = u_{2,k}(t) + \\ & \{\frac{\gamma_k\beta_k}{\alpha_k}\ln\left[\frac{\exp\left(\dfrac{y_{1,k}(t)-C_0}{\beta_k}\right)-1}{\exp\left(\dfrac{y_{1\mathrm{aim},k}(t+\vartriangle t)-C_0}{\beta_k}\right)-1}\right] \\ & -\left[y_{2\mathrm{aim},k}(t+\vartriangle t) - y_{2,k}(t)\right] + f_k(t)\delta_k \\ & -\varepsilon_k\left[y_{1\mathrm{aim},k}(t+\vartriangle t) - y_{1,k}(t)\right]\} / \left[k_0 + \frac{\gamma_k h_0}{W_{\mathrm{ST},k}}\right] \end{aligned} \tag{2}$$

where α_k and β_k are decarbonazition coefficient; C_0 is a constant(critical constant); h_0 denotes the unit oxygen content of accessories (Nm^3/t).

According to (1) and (2), we calculate the theoretical value to estimate the abnormal data pairs and remove them. This is essential to assure the accurate modeling from the data source.

3. ENDPOINT PREDICTING MODEL

3.1 Question Proposed

As the complexity of the BOF steelmaking process, it's hard to acquire the intermediate information by real-time and continuous detection, the data gathered are practically important. Generally, the original variables of the BOF endpoint predicting model are these seven factors: second blow oxygen volume Vo, iron strap W_{tp}, lime W_{sh}, mixture W_{hl}, ore W_{ks}, dolomite W_{by}, and carbon content detected by sublance [C_f] or temperature T_f. In the ordinary intelligent models, such as radial basis function RBF network, back propagation BP network, they use these all variables as inputs to establish models based on input-output data. As a result, the distributed characteristics of the data are ignored. This paper emphasize the characteristic of the input data, for example, data from variables V_O or [C_f] are concentrated and without value zero, therefore, it is necessary to expanding dimensions to mining the hidden information; while data from variables W_{tp} or W_{hl} are sparse and zero value is frequently present, so we reduce the dimension to remove the redundant information. In order to reduce the complexity and improve the adaptability of the model, we take all the original input variables together into consideration when expanding or reducing the dimension.

3.2 Extraction Components Based on Greedy Kernel

Extraction Kernel Principal Components is a nonlinear expansion of principal component analysis (PCA) (Müller, Mika et al. 2001). Supplying T_{X} is a subset of the n-dimensional training set. l stands for the number of inputs:

$$T_{\mathrm{X}} = \{x_1, \ldots, x_l\}, x_i \in \chi \subseteq \mathbb{R}^n, i = 1, \cdots, l \tag{3}$$

T_X is mapped into a high dimensional feature space by $\phi : \chi \to F$, and the training set becomes

$T_\phi = \{\phi(x_1), \cdots, \phi(x_l)\}$. In general, the exact form of ϕ is hardly estimated, so the kernel functions are introduced, which convert the nonlinear problem in the sample space to the inner multiplication in the feature space.

$$k(x_i, x_j) = <\phi(x_i), \phi(x_j)> \tag{4}$$

where *i, j*=1,…,*l*, and $i \neq j$; $<\cdot,\cdot>$ donates inner production. Then the kernel vector can be expressed as:

$$\mathbf{k}(\mathbf{x}) = [k(x_i, x_1), \cdots, k(x_i, x_l)]^T \tag{5}$$

After reducing to m-dimensional, $\mathbf{z} \in \mathbb{R}^m$ and satisfies: $\mathbf{z} = \mathbf{A}^T\mathbf{k}(\mathbf{x}) + \mathbf{b}$, where $\mathbf{A}_{[l\times m]}$ is parameter matrix, $\mathbf{b}_{[m\times 1]}$ is bias vector.

Find the reconstructive vector $\phi(x_i)$ which makes the error of reconstruction lowest. Thus the error of reconstruction can be expressed as:

$$\varepsilon_{\text{KMS}}(\mathbf{A}, \mathbf{b}) = \frac{1}{l}\sum_{i=1}^{l} \| \phi(x_i) - \tilde{\phi}(x_i) \|^2 \tag{6}$$

Greedy method is employed to select the principal component. Greedy method comes from the idea of greedy, which makes the best decision and gets the largest profit. The greedy method constructs the optimal solution step by step. In each step, the optimal decision is chose and the local optimal solution is evaluated following the decision. Once the decision has been made, it has never been changed. An alternative optimization algorithm is genetic algorithm, compared to the greedy algorithm: the next generation consists of new individuals while the next generation consists of the optimal individuals in the greedy algorithm. Therefore, the greedy algorithm converges faster than the genetic algorithm. The details of the greedy algorithm are following:

Step 1: A random possible principal component is selected as current principal component x .

Step 2: Find a new principal component x^* by searching the neighbourhood of the current principal component x with greedy method.

Step3: If x^* is closer to the optimal solution x_{opt}, the current principal component is set to x^* .In fact, x_{opt} is unknown.

Step 4: Repeat step 2 and 3, until all principal components have been found and the quality of them is unchanged.

The idea of combining the greedy algorithm and kernel principal component not only detects the hidden information of the intensive variables, such as V_{O}, $[C_{\text{f}}]$, but also compress the sparse variables, such as W_{tp}, W_{hl}. All inputs are normalized by this algorithm to control the complexity of the model and improve the generalization performance. Compared to the traditional model, the normalized inputs are applied to the predictive model which gets a better performance.

Input $T_{\mathbf{X}}$ satisfied

$$\mathbf{z} = \mathbf{A}^T\mathbf{k}_{\mathbf{S}}(\mathbf{x}) + \mathbf{b} \tag{7}$$

introducing

$$\mathbf{k}_{\mathbf{S}}(\mathbf{x}) = [k(x_i, s_1), \cdots, k(x_i, s_l)]^T \tag{8}$$

where $\mathbf{A}_{[l\times m]}$ is the parameter matrix, $\mathbf{k}_{\mathbf{S}}(\mathbf{x})$ are kernel functions whose centres are $T_{\mathbf{S}} = \{s_1, \cdots, s_d\}$ and $T_{\mathbf{S}}$ is a subset of $T_{\mathbf{X}}$, d is the size of $T_{\mathbf{S}}$.

The interests of the greedy kernel principal component are $T_{\mathbf{S}}$ instead of $T_{\mathbf{X}}$, which reduces the complexity of (7).

Therefore, the specified steps to extract components are:

The input variables are mapped into the high dimensional feature space by ϕ .

According to (7), map the feature space $\mathbb{R}^n$ into lower dimensional space $\mathbb{R}^m$;

Evaluate $\mathbf{x}_{\text{out}} \in \mathbb{R}^n$, which satisfied (9), where $\tilde{\phi}(\mathbf{x}_{\text{in}})$ denotes the optimal closed reconstruct vector.:

$$\mathbf{x}_{\text{out}} = \arg\min_{\mathbf{x}} \| \phi(\mathbf{x}) - \tilde{\phi}(\mathbf{x}_{\text{in}}) \|^2 \tag{9}$$

Kernel functions include linear kernel function, polynomial kernel function and sigmoid kernel function. In this paper, RBF kernel function is employed, which can be expressed as:

$$\mathbf{k}(\mathbf{x}, \mathbf{y}) = \exp(-\frac{\| \mathbf{x} - \mathbf{y} \|^2}{2\sigma^2}) \tag{10}$$

3.3 Fuzzy Neural Network

After kernel transformation and greedy optimization methods, the original variables are expressed as three inputs, and then act on the fuzzy neural network to establish the BOF endpoint modelling. The fuzzy neural network used here is adaptive neural network fuzzy inference system ANFIS (Jang 1993). ANFIS is a mixed product which has both advantages of fuzzy inference system FIS and neural network NN: FIS can extract the rules in the data, which is capable of handling the structured knowledge; NN is of great learning adaptive capacity. The 5 layers architecture of ANFIS is shown on Fig. 3.

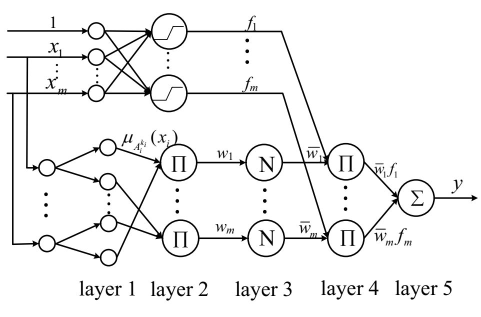

Fig.3 Architecture of ANFIS

Lay 1: signal fuzzification. The output is

$$o_{ik_i}^{(1)} = \mu_{A_i^{k_i}}(x_i) \tag{11}$$

Where xi denotes the input of note i, $\mu_{A_i^{k_i}}(x_i)$ denotes the membership degree that xi belongs to $A_i^{k_i}$, $o_{ik_i}^{(1)}$ is the output.

Lay 2: calculate the confidence of the rules:

$$w_i = \mu_{A_1^{k1}}(x_1)\mu_{A_2^{k2}}(x_2)\cdots\mu_{A_m^{km}}(x_m) \tag{12}$$

Lay 3: normalizing:

$$\bar{w}_i = w_i / \sum_i w_i \tag{13}$$

Lay 4: calculate the output of the rules:

$$o_i^{(4)} = \bar{w}_i f_i \tag{14}$$

Lay 5: calculate the final output:

$$o_1^{(5)} = \sum_i \bar{w}_i f_i \tag{15}$$

3.4 Algorithm Flow

BOF steelmaking process is greatly influenced by input. The changing tendency of the inputs will has determined the endpoint hitting rate. Consideration of the distributed characteristics of the original variables present, it is helpful for reflecting the BOF steelmaking essence if we can handle the input data properly. The input variables are projected into high dimensional feature space using kernel function, so that the latent information can be extract, then greedy algorithm is used to select principal components, remove redundant information and reduce the input dimensions. In view of the large quantity of manual experience in the process, the ANFIS model is used here to analogue the experience through rules. Therefore, the BOF steelmaking endpoint predicting model is established by two structure similarity ANFIS. Fig. 4 is the flow chart of the greedy kernel component ANFIS.

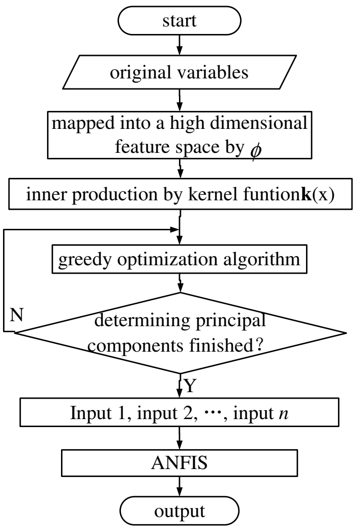

Fig.4 GKC-ANFIS flow chart

When smelting, some heats need re-added and re-blow several times, which cause to the data according to these heats are dense, therefore it is necessary to expanding these data, so as to mining the hidden information, while other heats do not need the re-added coolant or slag former, if these data remain in the modelling, they are probably become disturbance in modelling. In this paper, we expand the variables and compress them at the same time to get the effective and simple inputs. The theoretical support is detailed in part 3.2.

4. SIMULATION

To determine the accuracy of values of finishing endpoint carbon content and temperature predicted by the model, we conducts 60 groups of the practical data from some Iron and Steel Plant in China. The heats were made in converters with a capacity of 180 tons.

The first 50 groups are the training data set, and the last 10 groups are the testing data set of GKC-ANFIS model. When training, we normalize all the data firstly to eliminate the adverse effect by different order among the variables.

The number of primary components is 3, that is the inputs of the ANFIS is 3; the width of RBF kernel is 0.05; the linguistic values of input are equal 3; the error criterion is 0. After training, the nodes number of the model is 38, and the total rule number is 5. The predicting results of GKC-ANFIS about BOF endpoint [*C*] and T are shown in Fig. 5, and Fig. 6.

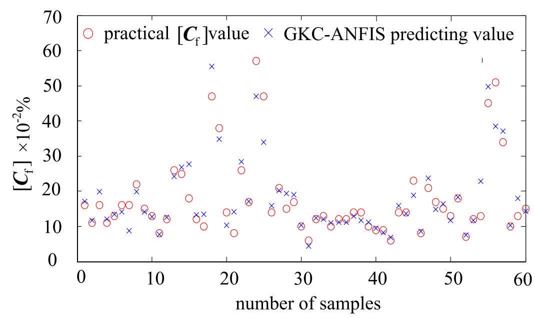

Fig.5 Predicting endpoint carbon content

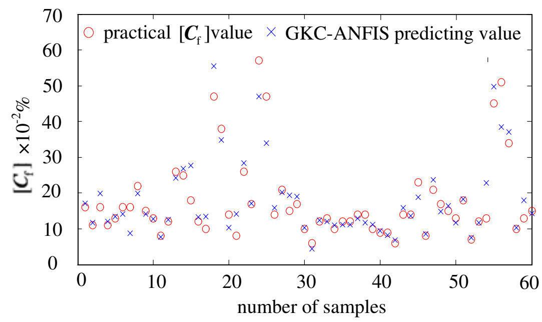

Fig.6 Predicting endpoint temperature

Comparing the GKC-ANFIS with the RBF and ANFIS models, mean squared error MSE and relative error RE are shown in Table 1. The structure and predicting accuracy of ANFIS models after changing are shown in Table 2.

Table 1 Error Comparison of the Three Models

predicting model	temperature		carbon content	
	MSE(°C)	RE	MSE(%)	RE
RBF	12.0916	0.0038	0.0678	1.7404
ANFIS	10.8888	0.0052	0.0634	0.1584
GKC-ANFIS	9.8382	0.0046	0.0406	0.1469

Table 2 Comparison of ANFIS and GKC-ANFIS

[*C*] predicting models	number of nodes	number of rules	accuracy
ANFIS	90	11	80.0%
GKC-ANFIS	38	5	88.3%

It can be seen from Table 1 that when RBF model is used to predict the endpoint temperature, the MSE is around 12°C; when ANFIS model is used, the MSE decreased, resulted from excellent ability to analogue manual experience. When GKC-ANFIS model is adopted, the MSE is less than 10°C. In the predicting of [*C*], the GKC-ANFIS model also achieves higher accuracy, and the predicting values are more approach to practical values. From Table 2, after simplified the original variables, the predicting model becomes simpler, with the network scale from 90 to 38 and rules number from 11 to 5. When specifying the [*C*] error is ±0.05%, the predicting accuracy rises from 80.0% to 88.3%.

5. CONCLUSION

The paper indicates how the extracted components acting on ANFIS would be effectively used for improved process control of BOF in steelmaking industry. This paper studies the BOF steelmaking endpoint predicting model with a new way, which is not on model itself, but on the original variables. The new way different from the literatures and research before is to expand and to compress the original variables at the same time, taking as full consideration of the data as possible to describe the complex BOF steelmaking process in the severe environment and limited detection facilities. Original variables own their unique characteristics, which may help us understand the essence of the BOF steelmaking process profoundly. Compare to traditional models, GKC-ANFIS is more understandable with strikingly physical meaning, simple inputs, effective result and accurate output. This research proves that the original variables may have great effect on the endpoint [*C*] and *T*, even to the final hitting rate. Higher steel output at lower cost is one of the main objectives of modern steelmaking methods. This model should be accurate enough so that the parameters of the tapped steel will deviate as little as possible from the specified values.

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