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Fuzzy mechanistic model with neural compensation for Estimation of shaft furnace's product quality

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Abstract: Usually grey-box modeling has better accuracy than black-box identification. The grey-box can be regarded as combination of mechanistic modelling and intelligent identification. But in many cases, mechanistic models are not available, for example the production quality of the shaft furnace which will be discussed in this paper, we can use fuzzy technique to obtain the mechanistic models that can be checked by the physical meanings. In this paper, we propose a novel modeling approach for complex nonlinear systems, it has a fuzzy mechanistic model and a neural compensator. For the training of the neural network, we propose a new fast and stable algorithm. Finally, the above method is successfully applied on estimation of the production quality of the shaft furnace.

1. INTRODUCTION

Over the past decades, a large number of soft computing models based on intelligent methods such as neural networks by Mitra et al. [2006], case-based reasoning by Fernandez et al. [2007], fuzzy logic by Zhang [2005], are extensively applied in modeling industrial processes. They are low-cost compared with the expensive hardware realization, see Lin et al. [2007]. The most used intelligent method, neural modeling, is black-box method. Sometime, when we have some prior knowledge, grey box identification may have better results. The grey box modeling can be regarded as combination of mechanistic modelling and intelligent identification, see Krishnaswamy et al. [2004], Boulvin et al. [2003] and Yang et al. [2003]. The mechanistic models usually represent the physical properties, which can be described by nonlinear functions or nonlinear dynamic equations. While the residual uncertainties between the mechanistic models and the plant can be modeled by black-box approach, for example neural networks.

It is well known that normal identification algorithms are stable for ideal plants (Ioannou et al. [1996]). In the presence of disturbance or unmodeled dynamics, these adaptive procedures can go to instability easily. Generally, we have to make some modifications to the normal gradient algorithm or backpropagation such that the learning process is stable see Jagannathan et al. [1996] and Suykens et al. [1997]. By using passivity theory, a time-varying learning rate is also stable without robust modification (Yu et al. [2003]). These algorithms can assure stability of neural identification, but the optimal properties are lost, sometimes they cannot arrive local minima. Gradient descent is a general algorithm that includes least-square and backpropagation as special cases. However the fixed learning rate yields poor performance. In contrast, time-varying rate as $\eta(k) = \frac{c}{k}$ can give optimally fast convergence in the sense of the misjudgment going to zero proportional to $\frac{1}{k}$, see Ljung et al. [1983]. But it results in slow convergence to bad solutions when c and k are small. So the "search then converge" approach is proposed by Darken et al. [1992], $\eta(k) = \eta_0 \frac{1}{1+a_1\frac{c}{k}+a_2\left(\frac{c}{k}\right)^2}$. But these two kinds of algorithms cannot guarantee stability. In this paper we propose a new learning rate as $\eta(k) = \frac{\eta_0}{1+a_1\frac{c}{k}+\|G(x_k)\|}$, which takes the advantages of Yu et al. [2003] and Darken et al. [1992] and assure stable and faster learning.

Magnetic separation is a general method for low-graded hematite iron ore, it is very popular in China because the majority of the China's iron ore is low-graded hematite. But it can hardly concentrate ores with standard grade. In light of this, an effective method is to employ a shaft furnace to give a kind of deoxidizing-magnetized roasting to the crude ores under a high temperature, see Yan et al. [2005].

The production quality of the shaft furnace is estimated by the technical index of magnetic tube recovery rate (MTRR), which is assayed off-line in long and irregular time intervals. Consequently, it is hard to give a good control for the production quality because the feedback signal MTRR cannot be obtained on-line, see Chai et al. [2006]. Therefore, the key problem of the production quality control is to model MTRR, or to give an effective

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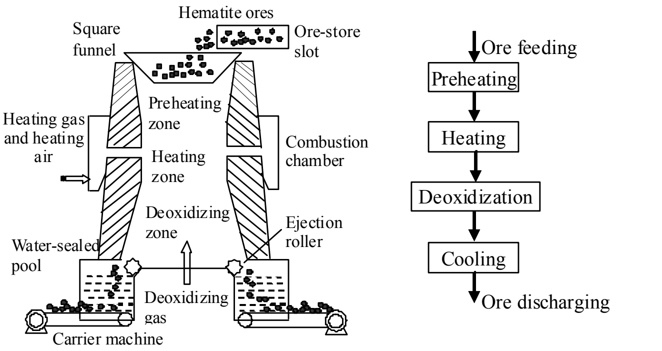


(a) The structure of the shaft furnace (b) The working flow of the shaft furnace

Fig. 1. Roasting process of shaft furnace

model for the shaft furnace process. But this process is extremely complex, it is a multiple variables, strong coupling, intensive nonlinear system. Until now there is not a mechanistic model for MTRR based on measurable signals. While the measurable signals represents the online in-time exterior status of the shaft furnace, the MTRR is obtained by assaying the samples from a small portion of the product of the shaft furnace after a batch of production has finished. As the shaft furnace roasting is a long-cycle process, the time consumption from the ores feed-in to they turning into the products varies from about 4 to 8 hours. Thereby the time delay from the measurable signals to the sampled point of MTRR is difficult to be determined. Moreover, another complexity lies in that the ores, after fed into the furnace, will move around and take part in certain chemical reactions simultaneously. Therefore, the exact status of these ores, such as the ore's temperature, position and the degree of their reactions, are unknown and difficult to be described by those measurable signals. All these uncertainties make it impossible to define the mechanistic relationship between MTRR and the measurable signals.

Although we cannot obtain the mechanistic model for the shaft furnace, but we can use fuzzy logic technique to analyze the experimental data, and obtain a fuzzy model by prior knowledge and fuzzy rules. We call it as fuzzy mechanistic model. Fuzzy modelling has many prominent advantages (Li et al. [2007]), including independent of the plant's mathematical models, reflecting the human's intellection, and relatively being intuitionists. The remaining unmodeled dynamic will be modeled by neural networks to improve modeling precision, which use the good approximation ability of neural modeling, see Scardovi et al. [2007], Lan et al. [2007] and Mangasarian et al. [2007]. This hybrid modelling strategy integrates fuzzy logic with neural networks approach, and has some advantages over fuzzy logic, neural networks and fuzzy neural networks for complex nonlinear system identification, such as MTRR modeling.

2. SHAFT FURNACE PROCESS

The shaft furnace roasting process is shown in Fig 1, its basic process consists the following units:

Ore feeding: The raw hematite ores are fed into the furnace through an ore-store slot and a square funnel at its top;

Preheating: in the preheating zone those ores contacting the ascending hot gas, their temperature rises to 100~150°C;

Heating: then in the heating zone, the ores' temperature comes up to 700~850°C, when attaining the heat produced by the inflammation of air-mixed heat gas in the combustion chamber;

Deoxidizing: the hot low magnetic ores flow down into the deoxidizing zone and are deoxidized to high magnetic ones;

Cooling and moving out: finally the ores are laid down into the water-sealed pool by two ore ejection rollers to be cooled and are consequentially moved out of the furnace by two carrier machines who running synchronously with their corresponding rollers.

During the process operation, a proper temperature range of the combustion chamber is needed (e.g. $[1000°\mathrm{C}, 1200°\mathrm{C}]$). The running-stop shift of the carrier machine and the flow rate of deoxidations gas may offer the temperature range as $570°\mathrm{C} \pm 20°\mathrm{C}$. The reactions are

$$\begin{array}{c} 3Fe_2O_3 + CO \xrightarrow{570°\mathrm{C}} 2Fe_3O_4 + CO_2 \\ 3Fe_2O_3 + H_2 \xrightarrow{570°\mathrm{C}} 2Fe_3O_4 + H_2O \end{array} \quad (1)$$

where the produced Fe_3O_4 contains intensive magnetism, which is required to achieve high grade extracted ores after the final mineral process. When the temperature of combustion chamber is relatively low or the flow rate of deoxidation gas is small, or the ores moving time quite long, the reactions are inadequate as they result in the production ores under deoxidation.

On the other hand, when the temperature is too high, and the flow rate of deoxidation gas is over abundant or the moving time is excessively short, it may lead to an over deoxidation reaction as follows:

$$\begin{array}{c} Fe_3O_4 + CO \xrightarrow{\geq 570°\mathrm{C}} 3FeO + CO_2 \\ Fe_3O_4 + H_2 \xrightarrow{\geq 570°\mathrm{C}} 3FeO + H_2O \end{array} \quad (2)$$

Here the production FeO is another type of low magnetic ores. The relationship between MTRR and the ingredients in the ore can be described as follows:

$$MTRR = f\left[Fe_2O_3, Fe_3O_4, FeO, \Theta\right] \quad (3)$$

where f represents a certain function with unknown parameters; Θ is the other inert gradients in the ore, such as the gangue. From the foregoing analysis, the highest and most desirable MTRR happens when there are no contents of Fe_2O_3 and FeO in the ore, except for the Θ, but only contents of Fe_3O_4. In other words, it is most ideal position that the ore is carried out of the furnace when it has thoroughly completed the reaction (1), but has not start the reaction (2).

As is mentioned above, the production quality of the shaft furnace is examined by the magnetic tube recovery rate (MTRR), whose value is within $[0, 1]$, the higher of the MTRR, the better ores grades is. Normally, MTRR is controlled within the target range.

3. FUZZY MECHANISTIC MODEL FOR MTRR

We want to generate fuzzy rules from data set, the standard clustering method is applied. Let us formulate the fuzzy clustering problem. Consider a finite set of elements $X = \{x_1, x_2, \ldots, x_n\}$ as being elements of the $p-$ dimensional Euclidian space $\mathbb{R}^p$, that is, $x_i \in \mathbb{R}^p$. The problem is to perform a partition of this data set into l fuzzy sets. The criterion is usually to optimize an objective function. The final result of fuzzy clustering can be expressed by a partition matrix U such that $U = [u_{ij}]$, $i = 1 \ldots n$, $j = 1 \ldots l$, u_{ij} is a numeric value in $[0, 1]$. There are two constraints on the value of u_{ij}. Firstly, a total membership of the element $x_i \in X$ in all classes is equal to 1. Secondly, every constructed cluster is non-empty. That is

$$\begin{aligned} &\sum\nolimits_{j=1}^{l} u_{ij} = 1, \quad \text{for all } i = 1, 2, \ldots, n \\ &0 < \sum\nolimits_{i=1}^{n} u_{ij} < n, \quad \text{for all } j = 1, 2, \ldots l \end{aligned} \tag{4}$$

A standard form of the objective function is

$$J(u_{ij}, \mathbf{v}_k) = \sum_{j=1}^{l} \sum_{i=1}^{n} \sum_{k=1}^{l} g[w(x_j), u_{ij}] \ d(x_i, v_k),$$

where $w(x_j)$ is the a prior weight for each x_j, $d(x_i, v_k)$ is the degree of dissimilarity between the data x_i and the supplemental element v_k, which can be considered as the central vector of the k-th cluster. The degree of dissimilarity is defined as a measure that satisfies two axioms: 1) $d(x_i, v_k) \geq 0$, 2) $d(x_i, v_k) = d(x_k, v_i)$. So the fuzzy clustering can be formulated as an optimization problem:

$$\begin{aligned} &\min J(u_{ij}, v_k), \\ &\text{Subject: } \sum_{j=1}^{l} u_{ij} = 1, \quad 0 < \sum_{i=1}^{n} u_{ij} < n \end{aligned} \tag{5}$$

where $i, k = 1, 2 \ldots l$, $i = 1, 2 \ldots n$. The objective function of the fuzzy C-means (FCM) is

$$J(u_{ij}, v_k) = \sum_{j=1}^{l} \sum_{i=1}^{n} u_{ij}^m \|x_i, v_j\|^2 \tag{6}$$

where u_{ij}^m denotes the membership grade of x_i in the cluster A_k, v_j denotes the center of A_k, and $\|x_i, v_j\|$ is the distance of x_i to center v_j, x_i and v_j are $p-$dimension vectors, $m > 1$, is called an exponential weight which influences the degree of fuzziness of the membership function, m influences the degree of fuzziness of the membership function. Note that the total membership of the element x_i in all classes is 1, *i.e.*, $\sum\nolimits_{k=1}^{l} u_{ki} = 1$, $i = 1 \cdots n$.

To solve the minimization problem (5) with respect to the objective function (6), we can fix u_{ij} and v_i and apply the conditions (4), that is

$$\begin{aligned} v_j &= \frac{1}{\sum\nolimits_{i=1}^{n} (u_{ij})^m} \sum_{i=1}^{n} (u_{ij})^m x_i \\ u_{ij} &= \frac{\left(1/\|x_i, v_i\|^2\right)^{1/m-1}}{\sum\nolimits_{k=1}^{c} \left(1/\|x_i - v_k\|^2\right)^{1/m-1}} \end{aligned} \tag{7}$$

Although the system described by (7) cannot be solved analytically, a fast FCM algorithm for MTRR is summarized as follows:

Step 1: Select a number of clusters l $(2 \leq l \leq n)$ and exponential weight m $(1 < m < \infty)$, choose an initial partition matrix $U^{(0)}$ and a termination criterion ϵ.

Step 2: Calculate the fuzzy cluster centers $\left\{v_j^{(k)} \mid j = 1, 2, \ldots, l\right\}$ using $U^{(k)}$ and (7).

Step 3: Calculate the new partition matrix $U^{(k+1)}$ using $\left\{v_j^{(k)} \mid j = 1, 2, \ldots, l\right\}$ and (7).

Step 4: Calculate $\Delta = \left\|U^{(k+1)} - U^{(k)}\right\| = \max_{i,j} \left|u_{ij}^{k+1} - u_{ij}^{(k)}\right|$. If $\Delta > \epsilon$, then $k = k+1$ and go to Step 2. If $\Delta \leq \epsilon$, then stop.

We start from a state-space discrete-time multivariable NARMA model

$$y(k) = h[x(k)] = \Psi[X(k)] \tag{8}$$

where

$$\begin{aligned} &X(k) = [y(k-1), y(k-2), \cdots u(k-d), \\ &u(k-d-1), \cdots]^T \end{aligned} \tag{9}$$

$\Psi(\cdot)$ is an unknown nonlinear function representing the plant dynamics, $u(k)$ and $y(k)$ are measurable scalar input and output, d is time delay.

A generic fuzzy model is presented as a collection of fuzzy rules in the following form (Mamdani type, see Mamdani [1976])

$$\begin{aligned} &\mathrm{R}^j\text{: IF } x_1 \text{ is } A_1^j \text{ and } x_2 \text{ is } A_2^j \text{ and } \cdots x_n \text{ is } A_n^j \\ &\text{THEN } \widehat{y} \text{ is } B^j \end{aligned} \tag{10}$$

We use $l(j = 1, 2 \cdots l)$ fuzzy IF-THEN rules to perform a mapping from the input linguistic vector $X = [x_1 \cdots x_n] \in \Re^n$ to the output linguistic scalar $\widehat{y}(k)$. $A_1^j, \cdots A_n^j$ and B^j is standard fuzzy sets. Each input variable x_j has l_j fuzzy sets. In the case of full connection, $l = l_1 \times l_2 \times \cdots l_n$. From Wang et al. [1992] we know, by using product inference, center-average and singleton fuzzifier, the output of the fuzzy logic system can be expressed as

$$\widehat{y} = \left(\sum_{j=1}^{l} w_j \left[\prod_{i=1}^{n} \mu_{A_i^j}\right]\right) \Big/ \left(\sum_{j=1}^{l} \left[\prod_{i=1}^{n} \mu_{A_i^j}\right]\right) \tag{11}$$

where $\mu_{A_i^j}$ is the membership functions of the fuzzy sets A_i^j, w_j is the point at which $\mu_{B_j} = 1$.

For MTRR modeling, $\widehat{y} = MTRR$, $X = \{x_1, x_2, x_3\} = \{t, h, c\}$

Takagi [1985] gave the Takagi-Sugeno-Kang fuzzy model ,

$$\begin{aligned} &\mathrm{R}^i\text{: IF } x_1 \text{ is } A_{1i} \text{ and } x_2 \text{ is } A_{2i} \text{ and } \cdots x_n \text{ is } A_{ni} \\ &\text{THEN } \widehat{y}_j = p_{j0}^i + p_{j1}^i x_1 + \cdots p_{jn}^i x_n \end{aligned} \tag{12}$$

where $j = 1 \cdots m$. The qth output of the fuzzy logic system can be expressed as

$$\widehat{y}_q = \sum_{i=1}^{l} \left(p_{q0}^i + p_{q1}^i x_1 + \cdots p_{qn}^i x_n\right) \phi_i \tag{13}$$

where ϕ_i is defined as in (8). (13) can be also expressed in the form of the Mamdani type (14),

$$\widehat{Y}(k) = W(k) \Phi[X(k)] \tag{14}$$

where $\widehat{Y}(k) = [\widehat{y}_1 \cdots \widehat{y}_m]^T$

$$W(k) = \begin{bmatrix} p_{10}^1 \cdots p_{10}^l & p_{11}^1 \cdots p_{11}^l & \cdots & p_{1n}^1 \cdots p_{1n}^l \\ \vdots & \vdots & & \vdots \\ p_{m0}^1 \cdots p_{m0}^l & p_{m1}^1 \cdots p_{m1}^l & \cdots & p_{mn}^1 \cdots p_{mn}^l \end{bmatrix}$$

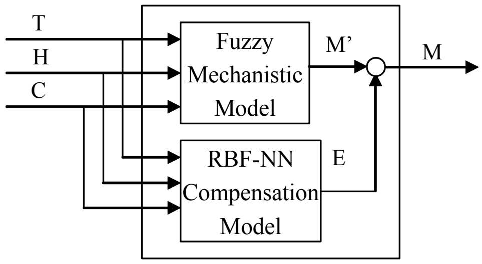


Fig. 2. Structure of MTRR prediction model

$$\Phi\left[X\left(k\right)\right] = \left[\,\phi_1 \cdots \phi_l \;\; x_1\phi_1 \cdots x_1\phi_l \;\; \cdots \;\; x_n\phi_1 \cdots x_n\phi_l\,\right]^T$$

At the beginning of modelling, the process parameters that impose the greatest impact on the MTRR should be picked out from a variety of parameters. In previous work by Chai et al. [2006], this has been fulfilled by combining the PCA method with mechanistic analysis. As a result, the temperature of the combination chamber T, the flow of reducing gas H and the moving time C are selected as the main parameters influencing the MTRR(M).

4. NEURAL COMPENSATION

The structure of the hybrid approach is illustrated in Fig.2. Here, $M\prime$ is the output of the fuzzy mechanistic model; $\triangle M$ means the compensation value of the RBF-NN compensation model; and $M = M' + \triangle M$ gives the final predicted value of the MTRR.

Radial Basis Function (RBF) neural networks have recently gained considerable attention, which can be used to compensate the errors of the fuzzy mechanistic model. The advantages of the RBF approach, such as the linearity in the parameters and the availability of the fast and efficient training methods, have been noted in several publications, see Constantinopoulos et al. [2006]. RBF neural networks has one hidden layer and a linear output layer. The output of neural networks may be presented as

$$\widehat{y}_n = \sum_{i=1}^{N} \omega_i G_i(X\left(k\right)) + b \tag{15}$$

where N is hidden nodes number, ω_i is the weight connecting Gaussian function and output layer, $X\left(k\right)$ is input vector is defined in (9), b is the threshold. The significance of the threshold is that the output values have nonzero mean. It can be combined with the first term as $w_0 = b$, $G_i(x) = 1$, so $\widehat{y}_n = \sum_{i=0}^{N} \omega_i G_i(x)$. $G_i(Vx)$ is radial basis function which we select it as Gaussian function

$$G_i(x) = \exp\left\{\frac{\|x - c_i\|}{2\sigma_i^2}\right\}$$

where c_i and σ_i^2 represent the center and spread of the basis function. Finally, the RBF neural compensator is

$$\widehat{y}_n\left(k\right) = \Omega_k G\left[X\left(k\right)\right] \tag{16}$$

where $\Omega_k = \left[\omega_1 \cdots \omega_N\right]$, G is $n-$dimension vector function.

We use this RBF neural networks to compensate the modeling error of the fuzzy mechanistic model (11). According to the Stone-Weierstrass theorem, see Cybenko [1989], this general nonlinear smooth function (8) can be written as

$$y\left(k\right) - \widehat{y}_m = \Omega^* G\left[X\left(k\right)\right] - \mu\left(k\right) \tag{17}$$

where Ω^* is optimal weight, $\mu\left(k\right)$ is the modeling error. Since G is bounded function and the output of the plant is assumed bounded, $\mu\left(k\right)$ is bounded as $\mu^2\left(k\right) \leq \overline{\mu}$, $\overline{\mu}$ is an unknown positive constant. The neuro compensation error is defined as

$$e\left(k\right) = \widehat{y}\left(k\right) - \left(y\left(k\right) - \widehat{y}_m\right) \tag{18}$$

The dynamic can be represented as

$$\begin{aligned} e\left(k\right) &= \Omega_k G\left[X\left(k\right)\right] - \Omega^* G\left[X\left(k\right)\right] - \widehat{y}_m + \mu\left(k\right) + \widehat{y}_m \\ &= \widetilde{\Omega}_k G\left[X\left(k\right)\right] + \mu\left(k\right) \end{aligned} \tag{19}$$

where $\widetilde{\Omega}_k = \Omega_k - \Omega^*$. The following theorem gives a stable fast learning algorithm of the RBF compensator.

Theorem 1. If we use the RBF neural networks (16) to compensate fuzzy mechanistic model error $y\left(k\right) - \widehat{y}_m$, the following gradient updating with time-varying rate can make identification error $e\left(k\right)$ bounded (stable in an L_∞ sense)

$$\Omega_{k+1} = \Omega_k - \eta_k G\left[X\left(k\right)\right] e\left(k\right) \tag{20}$$

where $\eta_k = \dfrac{\eta_0}{1 + \left\|G\left[X\left(k\right)\right]\right\|^2 + \frac{c}{k}}$, $0 < \eta_0 \leq 1$, $c > 0$. The average of the identification error satisfies

$$J = \limsup_{T\to\infty} \frac{1}{T}\sum_{k=1}^{T} e^2\left(k\right) \leq \frac{2+c}{1-\eta_0}\overline{\mu} \tag{21}$$

where $\overline{\mu} = \max_k \left[\mu^2\left(k\right)\right]$

Remark 1. (20) is the gradient descent algorithm, which the normalizing learning rate η_k is time-varying in order to assure the identification process is stable. This learning law is simpler to use, because we do not need to care about how to select a better learning rate to assure both fast convergence and stability. No any previous information is required.

5. INDUSTRIAL APPLICATIONS

5.1 Algorithm realization

The fast FCM algorithm mentioned in Section 3 is adopted to obtain the fuzzy reasoning rules. For $T, H, C, and\ M$, the parameters are chosen as number of clusters $l = 5$, expediential weight $m = 2$,initial partition matrix $U^{(0)} = \begin{bmatrix} 0.5 & 1 & 0.5 & 0 & 0 \\ 0 & 0.5 & 1 & 0.5 & 0 \\ 0 & 0 & 0.5 & 1 & 0.5 \end{bmatrix}$,termination criterion $\epsilon = 0.1$. By the end of the iteration, the fuzzy rules are obtained and some of them are listed in the following table:

Cases				Fuzzy Rules
MTRR values	Temperature	Flow	Time	
-0.31	1050	2400	4	R1
-0.32	1100	2400	3	R2
-0.31	1200	2000	2	R3

R1:IF t is T_2 and h is H_5 and c is C_3 THEN m is $-Ml$

R2:IF t is T_3 and h is H_5 and c is C_2 THEN m is $-Ml$

R3:IF t is T_5 and h is H_1 and c is C_1 THEN m is $-Ml$

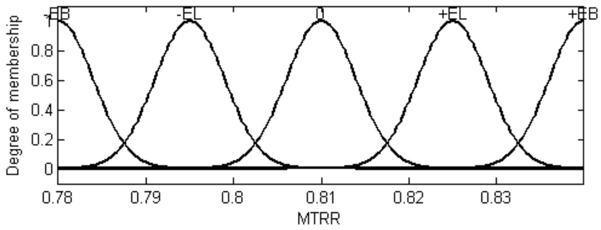


Fig. 3. Membership functions of MTRR

Through this method, 35 rules are produced and added into the fuzzy mechanistic model to produce a generic fuzzy model which is presented as a collection of fuzzy rules in the following form (Mamdani type fuzzy model)

$$\text{R}^i\text{: IF } t \text{ is } T_i \text{ and } h \text{ is } H_i \text{ and } c \text{ is } C_i \text{ THEN } m \text{ is } M_i \tag{22}$$

We use $35(i = 1, 2 \cdots 35)$ fuzzy IF-THEN rules to perform a mapping from an input linguistic vector $X = [t, h, c] \in \Re^3$ to an output linguistic vector $\widehat{M}(k) = [\widehat{m}]^T \in R$. T_i, H_i and $C_i$are standard fuzzy sets. Each input variable t, h, and c has 5 fuzzy sets as shown in Fig 3.

From Wang et al. [1992] we know, by using product inference, center-average and singleton fuzzifier, the output $\widehat{m}$ of the fuzzy logic system can be expressed as

$$\widehat{m} = \left(\sum_{i=1}^{35} w_i \left[\prod_{j=1}^{3} \mu_{A_{ji}} \right] \right) / \left(\sum_{i=1}^{35} \left[\prod_{j=1}^{3} \mu_{A_{ji}} \right] \right) = \sum_{i=1}^{35} w_i \phi_i \tag{23}$$

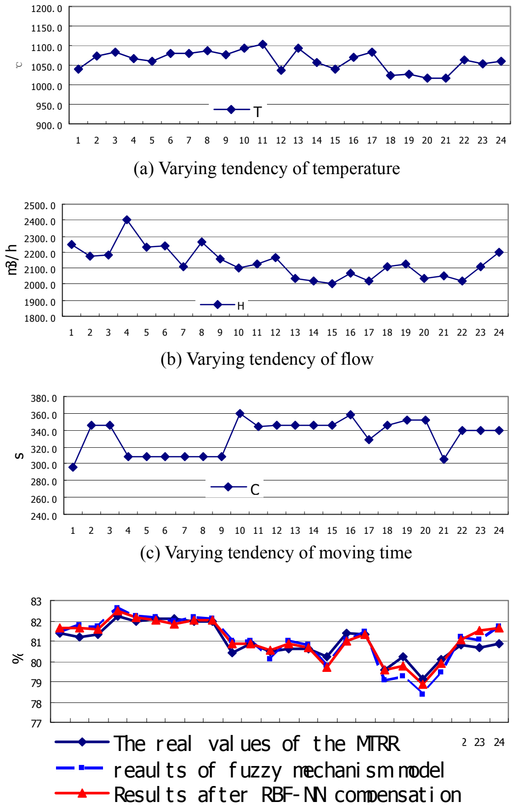
where $\mu_{A_{ji}}$ is the membership functions of the fuzzy sets $A_{ji} = [T_i, H_i, C_i]$, w_i is the point at which $\mu_{M_i} = 1$.

The neural compensation value $\triangle M$ is calculated by: $\triangle M = \sum_{i=1}^{13} \omega_i G_i$, where $G_i = \exp\left(-\frac{\|y-\xi_i\|^2}{2\sigma_i^2}\right)$, $i = 1, 2, \ldots, 13$

5.2 Experimental results

The biggest hematite ore concentrator of China owns 22 shaft furnaces. In the past, the MTRR can not be obtained on-line in real time and it is difficult to realize the closed loop control for the shaft furnace. Along with the development of the proposed hybrid intelligent MTRR prediction model, the DCS system is built up to collect all the measurable parameters, involving the three controlled variables (temperature T, flow H and moving time C, control variables u (consisting of the frequency of fan u_1, the opening percentage of heating gas valve u_2, and the opening percentage of heating gas valve u_3), process parameters p (comprising of the temperature of waste gas p_1, the inner negative pressure p_2, the heat gas composition p_3, the heating air pressure p_4, and the flow rate of heating gas p_5), and some boundary conditions B (i.e. the Ore size B_1, the ore grade B_2, and ore flow quantity B_3).

The solutions of the proposed MTRR prediction model serve as the basis for decision-making of optimal setting model that accepts the operating condition of the furnace and handles questions before producing the optimal setting value of the controlled parameters based on production indices. Thereby the intelligent optimal control system can adapt to outside conditions in real time, and



(a) Varying tendency of temperature

(b) Varying tendency of flow

(c) Varying tendency of moving time

(d) Varying tendency of MTRR

Fig. 4. Tendency of input and output of the MTRR prediction model

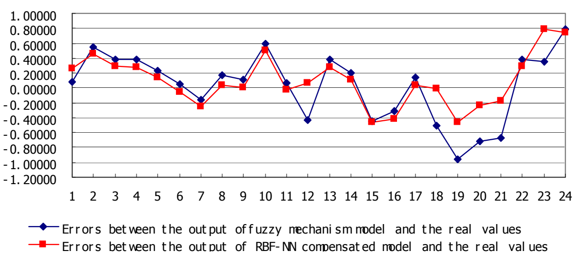


Fig. 5. Comparation of the two groups of errors

technical indices, namely the production quality, is ensured as reliably as possible.

The follow case is a real-world application of the proposed hybrid intelligent MTRR prediction model. 24 groups of data, contrasting the varying tendency of the temperature, the flow and the moving time to MTRR, are used to test the results of these models as shown in Fig 4.

From Fig.4, the curve of the RBF-NN compensated results (the red line) is more consistent to the real curve of the MTRR (the dark blue line) than the fuzzy logic model predicted one (the light blue line). For further survey, the errors of the fuzzy mechanistic model (e_1) and those of the RBF_NN compensated model (e_2) are compared in Fig 5.

The square sums of the two groups of errors in Fig 5 are calculated by: $E_i = \sum_{j=1}^{24} e_{ij}^2$, where e is the error of each point, $i = 1, 2$; E is the square sum of the errors. The calculation results is:$E_1 = 4.80$ and $E_2 = 2.82$ which indicate that the prediction accuracy of the BRF-NN compensated fuzzy mechanistic model is superior to the single fuzzy model.

6. CONCLUSIONS

The main contributions of the paper includes three parts: 1) a novel high accuracy modeling approach is proposed which has a fuzzy mechanistic model and a neural compensator. 2) A fast learning algorithm for the neural compensator is proven to be stable. 3) This identification method is successfully applied to estimate the production quality of shaft furnace (MTRR). The experimental results indicate that the grey-box model is superior to black-box model. This modelling strategy can be extended to many other complex industrial modelling.

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