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Hybrid Intelligent Control for Optimal Operation of Shaft Furnace Process ⋆

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Abstract: The extensively used shaft furnace in the ore concentration industry is an important facility that turns the weak-magnetic low-grade hematite ore into strong-magnetic one. During the operation of the shaft furnace roasting process, the optimal control objective is to control the technique indices, namely the magnetic tube recovery ratio (MTRR) that represents the quality, the efficiency, and the consumption of the product processing, into its targeted ranges. However, due to the complex dynamics between the MTRR and the control loops, such a control objective is by far difficult to achieve by the existing control methods, thus only manual control is adopted. In this paper, a hybrid intelligent control method for the optimal process operation is proposed with the purpose of controlling the technique indices into the desired range by on-line adjusting the set-points of the control loops. The proposed method was applied to the roasting process undertaken by 22 shaft furnaces in the ore concentration plant of Jiuquan Steel & Iron Ltd in China. The application results show that the MTRR is controlled to the targeted range with 2% increase; the faulty working-conditions are eliminated, which boosts the equipment operation ratio by 2.98%, resulting in a raise of 0.57% in the concentrated grade and 2.01% in the metal recovery ratio.

1. INTRODUCTION

In the field of process control in metallurgic industry, research on automatic control and design of the controller usually focuses on the approaches of forcing the controlled variables to track the set-points of the control system as close as possible while ensuring the stability of closed loop systems(Skogestad [2000]). However, from the point of view of process engineering, the role of the automatic control or the manual control is not only to ensure the outputs of the control system desirably tracking its set-points, but also to control the technique indices, which reflect the quality, the efficiency and the consumption of the product processing, into its targeted ranges during the operation process (Engell [2007]).

In the widely used shaft furnace roasting system which is to turn the weak-magnetic low-grade ore into strong-magnetic one in order to use the conventional magnetic approach to obtain the concentrated iron ore in the hematite ore concentration industry of China, the technique indices, namely the magnetic tube recovery ratio (MTRR), indicates the quality, the efficiency and the consumption of the product processing. It is desirable to keep it in certain ranges (Chai et al. [2007a]). However, the MTRR is difficult to measure online and the dynamics between the MTRR and the outputs of the control loops of the temperature of the combustion chamber, the flow of the reduction gas, and the ore discharge time exhibit strong nonlinearities, coupling effects, and vary with the operation conditions. Therefore, it is difficult to describe the MTRR by a precise model. As a result, the set-points to be followed in these control loops can only be decided by the experience-dependant operator, which is expected to keep the technique indices within reasonable ranges. Since the ore size, categories, and integrants change frequently, the manual operation cannot accurately adjust the set-points in time, which in turn implies that the technique indices may not be controlled within the required ranges, leading to the habitual occurrence of faulty working-conditions such as Fire-emitting, Ore-melting and Under-deoxidization(Chai et al. [2007b]). In these instances, the operators, through observing the surface status of the furnace body and making judgment by experience, will correct the set-points for the control loops so as to drive the operation of the furnace away from the faulty working-conditions. As the operator cannot always draw correct conclusions to modify these set-points, the control performance could be degraded or even the system can be destroyed. Hence, the control of the process operations has a vital importance not only to the indices of the quality of the production, profit and consumption, but also to the safe and stable operations of the whole process. Therefore, the control of the technique indices, namely magnetic tube recovery ratio (MTRR), within the desired ranges becomes the key issue in the shaft furnace operation process that features integrated complexities.

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To address the above challenges, a hybrid intelligent control method is proposed, which can on-line adjust the set-points of the control loops in response to the operation work-conditions and control the technique indices into the desirable ranges. Here, the "hybrid" means the integration of modeling and control, the combination of prediction and feedback principle and the combination of the intelligent methods with the existing optimization method. The proposed method has been successfully applied to shaft furnace roasting process in the ore concentration plant of Jiuquan Steel & Iron Ltd in China. Practical applications show that alteration of the furnace working-conditions and upcoming faulty working-condition are responded by the automatically adjusted set-points of the combustion chamber temperature, the flow of the reduction gas and the ore discharge time. The tracking of the set-points by the loop control systems drives the operation away from the faulty working-conditions, making technique index, namely the MTRR, to the desirable range around its target value with 2% increase; eliminating the faulty working-conditions, which boosts the equipment operation ratio by 2.98%, resulting in a raise of 0.57% in the concentrated grade and 2.01% in the metal recovery ratio.

2. ROASTING PROCESS OF SHAFT FURNACE AND OPERATION CONTROL TARGET

2.1 Roasting Process of the Shaft Furnace

Although China is abundant in hematite ore resources, their grade is relatively low, making their separation difficult. Consequently the shaft furnace roasting process is adopted to carry out the high-temperature-reduction roasting in order to enhance the magnetism to obtain the concentrated iron ore in the following magnetic separation section. As shown in Fig. 1, the basic process of a shaft furnace consists of ore feeding, ore preheating, deoxidizing, cooling and discharge phases. Detailed operation of each of these phases is described in the following.

Ore feeding: In this phase the raw hematite ore is dropped into the furnace through an ore-store slot and a square funnel at the top of the shaft furnace.

Preheating: In this mode, ore are preheated to reach a temperature between 100°C and 150°C through their contacts with the ascending hot gas.

Heating: This is an important phase in the operation of the shaft furnace where two combustion chambers are used to heat the ore to the required temperature range 700 $\sim$ 850°C. This is realized through the heat produced by the ignition of air-mixed heating gas in these combustion chambers.

Deoxidizing: This part of the process is used to realize a chemical reaction so that the hot low- magnetic ore from the heating zone are deoxidized to a high magnetic one.

Cooling and moving out: This is the final stage where the ore are cooled by pouring them into a water-sealed pool via two ore-ejection rollers. Then the ore is discharged out of the furnace by two belt-conveyer machines that run synchronously with their corresponding ejection rollers.

2.2 Control Objective

The operation objective of the shaft furnace roasting process is to raise the metal recovery ratio of the roasted ore as high as possible, under the precondition of ensuring its safety operation. In addition, the bigger the value of the MTRR (within the range of 0$\sim$1) is, the more easily the high grade of concentrate ore may be attained. Thus, the control objective is to achieve the highest possible MTRR.

Technically, the MTRR $\gamma(t)$ is closely related to the temperature of combustion chamber y_1, the flow rate of deoxidization gas y_2, and the ore discharge time y_3. The dynamics of the system can therefore be described as:

$$\gamma(t) = f(y_1, y_2, y_3, B_1, ..., B_5). \tag{1}$$

where $f(\cdot)$ is an unknown nonlinear function varying with the boundary conditions $\boldsymbol{B}$ that consists of ore types B_1, nature B_2, size B_3, the general status of the furnace B_4 and ore discharging quantity B_5. Moreover, it should be noted that the MTRR $\gamma(t)$ cannot be measured online.

To obtain the highest possible magnetic tube recovery ratio (MTRR) $\gamma(t)$, the control objective is specified as:

$$max(\gamma(t) - \gamma^*). \tag{2}$$

where γ^* is the targeted value decided by the production requirement.

3. HYBRID INTELLIGENT CONTROL METHOD FOR THE OPERATION PROCESS OF SHAFT FURNACE ROASTING PROCESS

3.1 Problems on the operation control

The operation control on the shaft furnace roasting process is shown in Fig. 1, where operators choose the set-points $\{y_1^*, y_2^*, y_3^*\}$ for the combustion chamber temperature y_1, the flow rate of reduction gas y_2, and the ore discharge time y_3 by watching the fire in combustion chamber and reading the assayed off-line value of the MTRR γ^*. Then y_1, y_2 and y_3 are controlled to follow their set-points y_1^*, y_2^* and y_3^* by means of cascade PI controllers (Yan et al. [2005]). However, a delayed adjustment and improper set-points $\{y_1^*, y_2^*, y_3^*\}$ resulting from the varying boundary condition $\boldsymbol{B}$ will not only bring about the impossibility to meet the control objective (2), but also lead to an even worse result of the following faulty work-conditions:

Fire-emitting (S_1) stands for the fires emit out of the combustion chamber.

Flame-out (S_2) refers to the flames reaching out of the top of the furnace.

Ore-melting (S_3) represents the fault that the iron ores stick to the inner side of the furnace which causes difficulty for further entry of ores.

Under-deoxidization (S_4) denotes the fault of under deoxidization.

Over-deoxidization (S_5) stands for the fault of over deoxidization.

Over a long period of time, these faulty work-conditions could only be diagnosed by observing the surface status

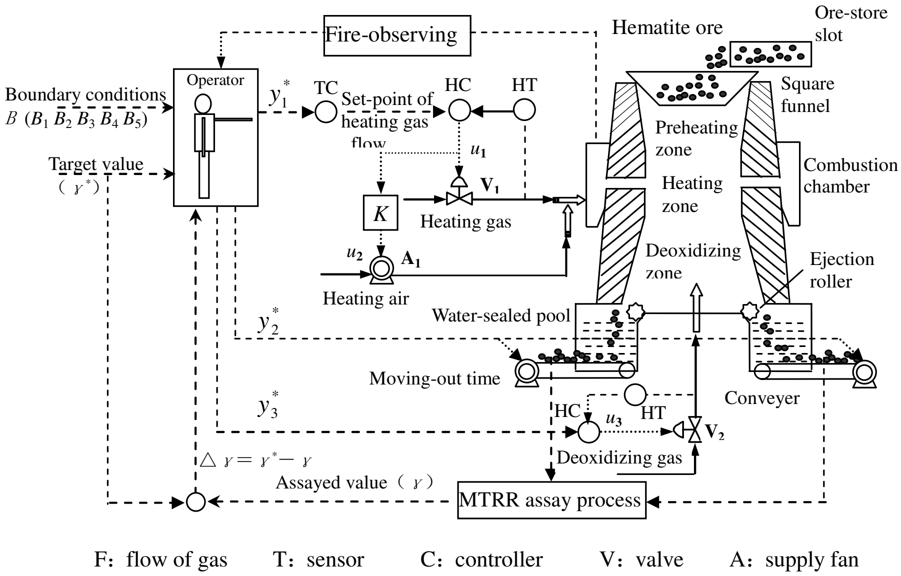

Fig. 1. Technical process and control of the shaft furnace

of the furnace body and judgment is made by experienced operators, who will adjust the set-points of the control loops on a trial and error basis to avoid some faulty working-conditions, which still occurred frequently for the improperness and delay of some manual operations. Therefore, the quality, efficiency and personnel safety were impacted fiercely.

Thus, the issue to be pursued in this paper is how to adjust online the set-points of the control loops under the variation of the working-conditions or in the presence of faulty working-conditions, so that the faulty work-conditions would be avoided during the process of the set-points tracking and that objective (2) would be reliably met.

3.2 Operation process control strategy

Based on the intelligent control methods, a hybrid intelligent optimal method to achieve the control objective (2) is presented in (Fig. 2) by integrating the modeling with control, the feedback and feed forward with the prediction. The proposed control system for the optimal operation is comprised of a control loop pre-setting model, a MTRR prediction model, feedforward and feedback compensators and a faulty work-condition diagnosis unit with a fault-tolerant controller (FTC).

Control loop presetting model: According to the target value $\gamma^*(t)$ of the MTRR, the outputs of the loop controls $\boldsymbol{y}(t)$, and the boundary conditions $\boldsymbol{B}$,the pre-set-points $\tilde{\boldsymbol{y}}(t)$ is generated for the control loops to follow. These pre-set-points are the set-point of temperature of combustion chamber $\tilde{y}_1(t)$, the set-point of flow rate of deoxidization gas $\tilde{y}_2(t)$, and the set-point of ore discharge time $\tilde{y}_3(t)$.

MTRR prediction model: Based on the output of the control loops $\boldsymbol{y}(t)$, a predicting value $\overline{\gamma}(t)$ is generated by the MTRR prediction model. This model is corrected using the output of a neural-network-based correction unit that takes the prediction error, $\Delta\gamma(T) = \bar{\gamma}(T) - \gamma(T)$, between the MTRR value $\gamma(T)$ processed by statistic process control (SPC) from assayed value $\tilde{\gamma}_k(T)$ and the predicted MTRR $\overline{\gamma}(t)$ as the input, where T is the sampling period that meets $T = nt$.

Feed-forward compensator: The feedforward compensator is used in response to the error between the target value of MTRR and the predicted one (i.e. $\Delta\gamma_F(t) = \gamma^* - \overline{\gamma}(t)$) so as to produce the compensation value $\Delta\tilde{\boldsymbol{y}}_F(t)$ for the pre-set-points $\tilde{\boldsymbol{y}}(t)$.

Feedback compensator: The feedback compensator produces feedback signals $\Delta\tilde{\boldsymbol{y}}_B(T)$ according to the error signals $\Delta\gamma_B(T) = \gamma^* - \gamma(T)$ between the target value of the MTRR and the processed value $\gamma(T)$. As such, the modified set-points can be produced to give $\bar{y}(t) = \tilde{y}(t) + \tilde{y}_F(t) + \tilde{y}_B(T)$.

Faulty work-condition diagnosis model: When the faulty working-conditions occur, the faulty working-condition diagnosis model identifies the faulty working-conditions types based on the prediction $\bar{\gamma}(t)$ of the MTRR, the output $\boldsymbol{y}(t)$ (i.e., $y_1(t), y_2(t)$ and $y_3(t)$) and $\Delta y_1(t)$, control variables $\boldsymbol{u}(t)$ (frequency of fan $u_1(t)$ and opening percentage of heating gas valve $u_2(t)$), process values of the shaft furnace $\boldsymbol{P}$ and the ore size B_1. Here $\boldsymbol{P}$ is the vector of the process variables including the temperature of waste gas on the top of the furnace p_1, the inner negative pressure p_2, the calorific power of heating gas p_3, the heating air pressure p_4, the flow rate of the heating gas p_5 and its variation rate Δp_5. The types of faulty working-conditions are described by $\boldsymbol{S} = \{S_1, S_2, S_3, S_4, S_5\}$.

Fault-tolerant controller (FTC): Based on the faulty work-conditions $\boldsymbol{S}$, the outputs of control loops $\boldsymbol{y}(t)$, control variables $\boldsymbol{u}(t)$, the loop tracking error $\boldsymbol{e}(t) = \boldsymbol{y}^*(t) - \boldsymbol{y}(t)$, process values $\boldsymbol{P}$, boundary conditions $\boldsymbol{B}$, the correcting values $\Delta\overline{\boldsymbol{y}}(t)$ for the set-points $\overline{\boldsymbol{y}}(t)$ will be produced by the FTC to generate set point values $\boldsymbol{y}^*(t)=\overline{\boldsymbol{y}}(t)+\Delta\overline{\boldsymbol{y}}(t)$ that drive the process away from the faulty work-situation. Therefore, the control objective (2) can be achieved.

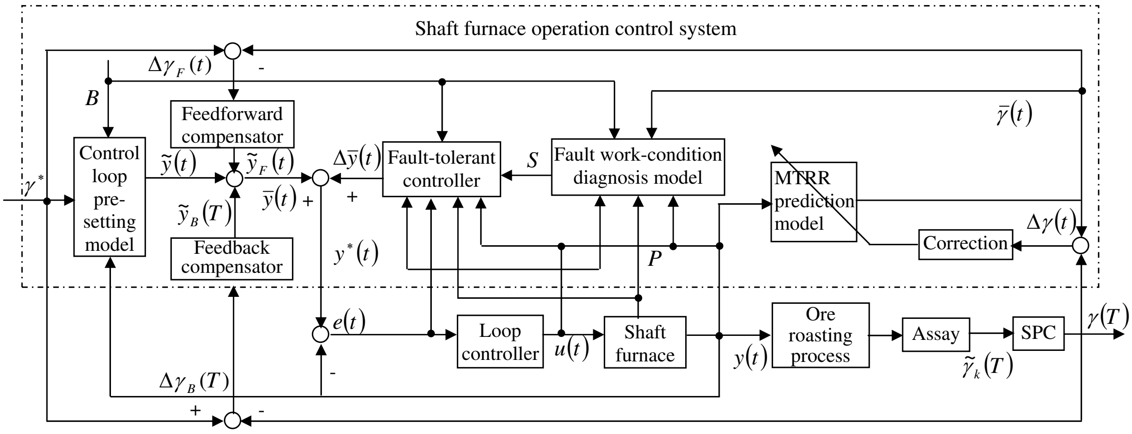

Fig. 2. Operation control strategy for the roasting process of shaft furnace

3.3 Hybrid intelligent control algorithm

The hybrid intelligent control algorithm that realizes the above operation process control strategy is described in detail as follows.

A. Algorithm for control loop presetting model The loop presetting model, consisting of case production, case retrieval, case reuse, case revision and case retain, is obtained by adopting case-based reasoning (Soumitra et al. [1997]) and expert experiences on the operations of shaft furnace.

Case Production: The Case Production is to create the initial cases in the case base for the production of the set-points, based on the operational experiences from the process of shaft furnace. These cases are constituted in the form of Table 1, in which *Case description* and *Case Solutions* are filled. The former includes the target value of MTRR γ^*, the boundary conditions $\boldsymbol{B}$ and the output of control loop $\boldsymbol{y}(t)$. The *Case Solution* $\tilde{\boldsymbol{y}}(t)$=[$\tilde{y}_1(t)$, $\tilde{y}_2(t)$, $\tilde{y}_3(t)$] includes the presetting points for the temperature, the flow rate of deoxidization gas and the ore discharge time.

The *Case description* is expressed as $C = \{c_i\}$,(i=1,2,...,9), where c_i is a description feature of an operation condition. In this context, $\{c_1,c_7,...,c_9\}$ are numerical values. Also, c_7, c_8 and c_9 represent the output of control loop, i.e. $y_1(t), y_2(t)$ and $y_3(t)$. Other case descriptions $\{c_2,...,c_6\}$ are of enumerative style. c_2 describes the ore types B_1. If the fed ore is the source ore its value is set to 1. Otherwise, if the fed ore is recycled its value will be set to 2. Similarly, the values of $\{c_3,...,c_6\}$ have each been assigned number "1", "2" and "3" which are employed to illuminate the fact that ore nature B_2 is "good", "ordinary" or "bad", the ore size B_3 is "big", "moderate" or "small", the furnace status B_4 is "good", "ordinary" or "bad" and the ore output quantity B_5 "abundant", "ordinary" or "low".

In general eight intact cases were stored in the case base and have been exerted to the follow-up operation.

Case Retrieval: Suppose that the current work-condition is M, and its description feature is $C = \{c_i\}$,(i=1,2,...,9), the cases in the case base hold the feature of $C_k = \{c_{i,k}\}$,(k=1,2,...,K) with K being the number of stored cases. The similarity value $SIM(M, M_k)$ between M and M_k is given by:

$$SIM(M, M_k) = \frac{\sum_{i=1}^{9} \lambda_i sim(c_i, c_{i,k})}{\sum_{i=1}^{9} \lambda_i} \qquad (3)$$
$$i = 1, 2, ...9,\ k = 1, 2, ...K$$

where λ_i denotes the weight of each case description feature attained by experiences and $sim(c_i, c_{i,k})$ is the similarity between the description feature of current working-condition c_i and the feature of stored case $c_{i,k}$ and is defined as:

$$sim(c_i, c_{i,k}) = \begin{cases} 1-|c_i-c_{i,k}|/\max(c_i, c_{i,k}), & i = 1, 7, 8, 9 \\ 1-|c_i-c_{i,k}|/E, & i = 2, \ldots, 6 \end{cases} \qquad (4)$$

where E is the style number of the enumerative variables. Defined a threshold $\theta(0 < \theta \leq 1)$, r cases $C_j (j = 1, \cdots, r)$ with the similarity value not less than the threshold are retrieved for the Case reuse.

Case Reuse: This unit calculates the case solution $\tilde{\boldsymbol{y}}(t)$ for current work-condition M by using:

$$\tilde{\boldsymbol{y}}(t) = \frac{\sum_{i=1}^{j} SIM(M, M_j)\bar{y}_j}{\sum_{i=1}^{j} SIM(M, M_j)} \qquad (5)$$

where $\bar{y}_j$,$(j = 1, 2, \ldots, r)$ are the case solutions of the jth stored cases.

Case Revision and Case Retain: In this unit, $\tilde{\boldsymbol{y}}(t)$ is employed as the new set-points for the control system and can be tuned according to experiences. Case retain is fulfilled in the same manner as in (Zhou P. et al., 2006).

B. Algorithm for MTRR prediction model As the MTRR $\gamma(t)$ cannot be measured online, it can only be assayed by sampling the roasted ore in long time intervals. From (1), the MTRR $\gamma(t)$ is a nonlinear function of the temperature of the combustion chamber $y_1(t)$, the flow of reduction gas $y_2(t)$, and the ore discharge time $y_3(t)$. As such, the MTRR prediction model is established as shown in (Fig. 3) which illustrates the Neural Network(NN) based MTRR prediction model with the structure of 3-13-1. This means that the NN consists of 3 layers: namely the input, the

Table 1 Case structure in the loop presetting model of the shaft furnace's roasting process

Case description (C)									Case Solutions		
γ^*	B_1	B_2	B_3	B_4	B_5	$y_1(t)$	$y_2(t)$	$y_3(t)$	$\tilde{y}(t)$		
c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	$\tilde{y}_1(t)$	$\tilde{y}_2(t)$	$\tilde{y}_3(t)$

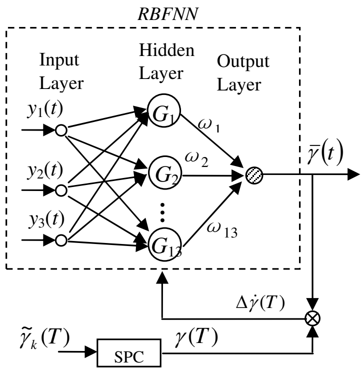

Fig. 3. MTRR Prediction Model based on RBF neural network

hidden and the output layers. The nodes in the input layer is set to 3, presenting $y_1(t), y_2(t)$ *and* $y_3(t)$. The hidden layer includes 13 nodes, and the output is the MTRR $\bar{\gamma}(t)$(Yan and Chai [2005]).

C. Algorithm for feed-forward/feedback compensators
When the pre-set-points of the loops works, the MTRR can still be lower than its target value, for the sake of long-cycle assay of the MTRR and the frequent fluctuation of the process boundary conditions which impacts on the accuracy of the presetting model. Therefore, the feedfoward and feedback compensators with nonlinear parameters are designed by combining the Case-based reasoning (CBR) with the PI controller in order to compensate the characteristics of nonlinear work-condition variation.

The feedforward compensator is realized as follows:

If $\Delta\gamma_F(t) = \gamma^* - \bar{\gamma}(k) > 0$, then

$$\begin{aligned}\tilde{y}_F(t) = \tilde{y}_F(t-1) + k_{fp}(\Delta\gamma_F(t) - \Delta\gamma_F(t-1)) \\ + k_{fi}\Delta\gamma_F(t)\end{aligned} \tag{6}$$

If $\Delta\gamma_F(t) \leq 0$, *let* $\tilde{y}_F(t) = 0$

The feedback compensator is achieved as follows:

If $\Delta\gamma_B(T) > 0$, then

$$\begin{aligned}\tilde{y}_B(T) = \tilde{y}_B(T-1) + k_{bp}(\Delta\gamma_B(T) - \Delta\gamma_B(T-1)) \\ + k_{bi}\Delta\gamma_B(T)\end{aligned} \tag{7}$$

If $\Delta\gamma_B(T) \leq 0$, $\tilde{y}_B(T)$ is set to 0.

where k_{fp}, k_{fi}, k_{bp} and k_{bi} are the parameters of the feedforward and feedback PI compensator, respectively. These parameters are corrected online by using the CBR technology given in (3)-(5).

D. Algorithm for faulty working-conditions diagnosis model
A method of protocol analysis (Wagner et al. [2002]) along with the experts' experiments on resolving the work-situation faults is adopted in the expert system to extract the *protocols* of the faulty working-condition. Then these *protocols* are re-arranged into the expert rules before they are stored in the knowledge base of the expert system. The knowledge base can be updated and upgraded during the system operation so as to ensure the consistency of the knowledge and the effective validation of the reasoning result (Neli [1998]). The presentation of the knowledge is classified into production rules (Gui and Liu [2002]) and time constrained production rules (Qian et al. [1998]) that are shown in Table 2, where there are 34 rules in total according to the different limits.

From Table 2, the two faulty working-conditions, namely S_4 and S_5, should be identified by using the prediction value of MTRR $\bar{\gamma}(t)$, MTRR that is under the lower limit γ_L means that the faulty working-condition is inclined to emerge. Therefore, the prediction value of MTRR needs to be introduced to the expert system. This expert system adopts the forward reasoning, which compares the data set in the database with the preconditions in the expert rules. When some rules are triggered, the reasoning results about the faulty working-condition can be obtained.

E. Algorithm for CBR-based fault-tolerant controller
With the purpose of taking the advantage of both case-based reasoning and expert experiences to ensure that the fault-tolerance control can consistently absorb the experts' experiments during the reasoning, the following fault-tolerant controller is proposed.

Case Production: The case production for fault-tolerance control can create the initial cases for the fault case-base based on the operational experiences from the process of shaft furnace. These cases are constituted in the form of Table 3, in which *Case description* and *Case Solutions* are filled. The former includes faulty working-condition $\boldsymbol{S}$, the output of control loop $\boldsymbol{y}(t)$, control variables $\boldsymbol{u}(t)$, loop tracking error $\boldsymbol{e}(t)$, process valuables $\boldsymbol{P}$ and boundary conditions $\boldsymbol{B}$. The *Case Solution* $\Delta\bar{\boldsymbol{y}}(t)$=$[\Delta\bar{y}_1(t), \Delta\bar{y}_2(t), \Delta\bar{y}_3(t)]$ are the adjusting values to be added to the set-points for the temperature, the flow rate of deoxidization gas and the ore discharge time.

The *Case description* is expressed as $C = \{c_i\}$,(i=1,2,...,21) where c_i is a description feature of a work-condition. In this case, $\{c_6, ..., c_{18}\}$ are numerical values and c_6, c_7 *and* c_8 represent the output of loop control variables $y_1(t), y_2(t)$ and $y_3(t)$. c_9, c_{10} and c_{11} are affected by control inputs $u_1(t), u_2(t)$ and $u_3(t)$, and c_{12} and c_{13} denote the tracking

Table.2 Expert rules for work-situation fault diagnosis

Rules	*Antecedents*	*Conclusions*
Rule11	$y_1(t) > H_1$ AND $u_1(t) > W_1$ AND $p_4 < A_0$	S_1
Rule12	$y_1(t) > H_1$ AND $u_2(t) > V_1$ AND $p_4 < A_0$	
Rule13	$y_1(t) > H_1$ AND $p_3 < R_0$	
Rule21	$y_1(t) > H_1$ AND $p_1 > G_1$	S_2
Rule22	$y_1(t) > H_1$ AND $p_2 > N_1$ AND $p_4 > A_1$	
Rule31	$y_1(t) > H_2$ AND $y_3(t) < M_0$ AND $\Delta y_1(t) > \Psi_1$ AND abs $(\Delta p_5(t)) < \Phi_1$ AND $(B_1 = b_{1,1}$ OR $B_1 = b_{1,2})$	S_3
Rule41	$\bar{\gamma}(t) < \gamma_L$ AND $y_1(t) < H_0$	S_4
Rule42	$\bar{\gamma}(t) < \gamma_L$ AND $y_2(t) < F_0$	
Rule43	$\bar{\gamma}(t) < \gamma_L$ AND $y_3(t) > M_1$	
Rule51	$\bar{\gamma}(t) < \gamma_L$ AND $y_1(t) > H_1$	S_5
Rule52	$\bar{\gamma}(t) < \gamma_L$ AND $y_2(t) > F_1$	
Rule53	$\bar{\gamma}(t) < \gamma_L$ AND $y_3(t) < M_0$	

Table.3 Structure of work-situation fault cases

Case description																		Case Solution		
S			$y(t)$			$u(t)$			$e(t)$		P			B				$\Delta\bar{y}(t)$		
c_1	…	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}	…	c_{18}	c_{19}	c_{20}	c_{21}	$\Delta\bar{y}_1(t)$	$\Delta\bar{y}_2(t)$	$\Delta\bar{y}_3(t)$	

errors of the temperature of combustion chamber $e_1(t)$, and the tracking errors of the flow rate of the deoxidization gas $e_2(t)$. Also, $c_{14}, c_{15}, c_{16}, c_{17}$ and c_{18} list the process parameters from p_1 to p_5. The other species, $c_1, ..., c_5, c_{19}, c_{20}$ and c_{21} possess enumerative style. $\{c_1, ..., c_5\}$ describe the $\{S_1, ..., S_5\}$, respectively. If faulty working-conditions happen, their values are set to 1. Otherwise their values will be set to 2. Similarly, the values of c_{19}, c_{20} and c_{21} have each been assigned number "1", "2" and "3" which are employed to illuminate the fact that ore size is "big", "medium" or "little", the ore grade is "high", "moderate" or "low", and the ore output quantity "abundant", "ordinary" or "low".

In general eight initial cases were stored in the case base and they have been exerted to the follow-up operation.

Corrected by $\Delta\bar{\boldsymbol{y}}(t)$, $\boldsymbol{y}^*(t) = \bar{\boldsymbol{y}}(t) + \Delta\bar{\boldsymbol{y}}(t)$ is used as the updated set-points for the control system.

4. INDUSTRIAL APPLICATIONS

The proposed hybrid intelligent control method has been applied to the operation of the shaft furnace roasting process consisting of the 22 shaft furnaces in the biggest hematite ore concentrator in China, as shown in Fig. 4, Fig. 5 and Fig. 6 illustrates the shaft furnaces and some tableaus of corresponding control software.

According to the production requirement, the target value of the MTRR in this plant is set to γ^*=0.82.

In the control loop pre-setting model, the weight values in (3) for each case features are defined as $\lambda = \{\lambda_1, ..., \lambda_i, ..., \lambda_9\}$={0.6212, 0.4659, 0.4633, 0.4823, 0.4158, 0.4269, 0.5612, 0.5584, 0.5482}. The limited values

Fig. 4. The shaft furnaces

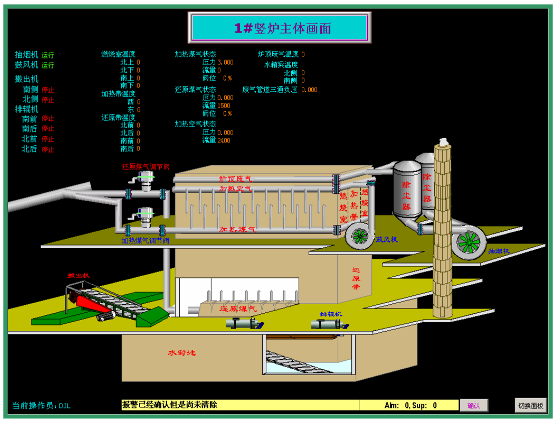

Fig. 5. Monitoring view of shaft furnace

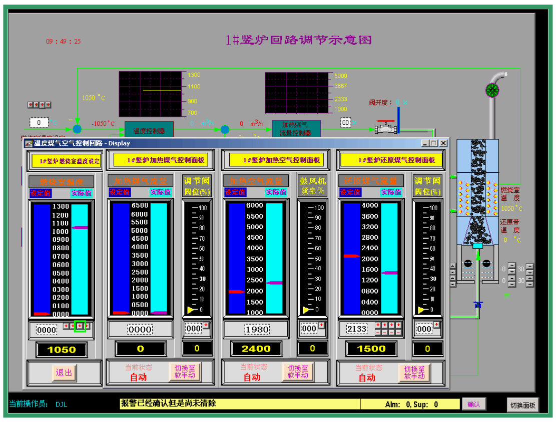

Fig. 6. Operation panel of control system

in Table 2 are determined as: γ_L=0.82, H_1=1150°C, H_2=1160°C, F_0=2200m^3/h, M_0=280s, G_1= 100°C, Ψ_1=10°C, Φ_1=15 m^3/h.

Application results of the proposed system on one shaft furnace are shown in Fig 7, which illustrates the time-varying trends of the MTRR, the temperature of combustion chamber, the flow rate of the deoxidization gas, and the ore discharge time from 7:00 to 12:00.

At 7:00: Control loop pre-setting model generated the pre-setting points, $\tilde{\boldsymbol{y}}(7:00)$=[1140°C, 2230$m^3/h$, 280$s$], for the control loops according to the desired value of the MTRR γ^*.

At this moment, the predicted value of the MTRR was $\bar{\gamma}(7:00)$=0.822 and the actual value was $\gamma(7:00)$=0.821. Since $\Delta\gamma_F(7:00) = \gamma^* - \bar{\gamma}(7:00) < 0$, the output of the feedforward compensator was $\tilde{\boldsymbol{y}}_F(7:00)$=0; Similarly, the feedback compensator produced $\tilde{\boldsymbol{y}}_B(7:00) = 0$ as $\Delta\gamma_B(7:00) = \gamma^* - \gamma(7:00) < 0$. Therefore, $\boldsymbol{y}^*(7:00)$ =$\tilde{\boldsymbol{y}}(7:00)$=[1140°C, 2230$m^3/h$, 280$s$] was adopted as the set-points of the control systems to be followed.

At 7:50: The predicted value of MTRR was $\bar{\gamma}(7:50)$ =0.819, its actual value became $\gamma(7:50)$=0.82, and $\Delta\gamma_F$ changed to $\Delta\gamma_F(7:50) > 0$, the feedforward compensator was $\Delta\tilde{\boldsymbol{y}}_F(7:50)$=[15,-40,-4], which indicates its healthy operation. In addition, the $\Delta\gamma_B(7:50) < 0$ implied the feedback compensation value $\Delta\tilde{\boldsymbol{y}}_B(7:50)$=0. Thereby the compensated set-points were modified to $\boldsymbol{y}^*(7:50)$=$\bar{\boldsymbol{y}}(7:50)$=[1155°C,2190$m^3/h$,276$s$].

At 8:30: The MTRR $\gamma(8:30)$=0.824>γ^* implied a normal work condition.

At 9:00: Sequentially an abnormal work-conditions showed in Table 4 occurred. At this moment, the MTRR $\gamma(9:00)$ =0.799< γ_L in Table 2. It can also be noticed that the temperature of combustion chamber was $y_1(9:00)$=1170°C which exceeds its top limits of H_1 and H_2. Also, it was observed that the flow rate of the deoxidization gas was 2196m^3/h which is lower than its bottom limit F_0. Moreover, the discharge time was 276s which does not catch its minimum limit M_0. The temperature of the waste gas p_1 was 134°C which is higher than its upper limit G_1 and the increase of the temperature of combustion chamber within half an hour ($\Delta y_1(9:00)$) was 26°C which is greater than its maximum limit Ψ_1 as the change of heating gas (12m^3/h) within the allowed arrange (top limit Φ_1=15m^3/h). As a result, the conclusion of the fault diagnosis was that S_2, S_3 and S_4 will happen.

Then the fault-tolerant controller figured out the correcting values for the set-points of the loops $\Delta\bar{\boldsymbol{y}}(9:00)$= [-53°C, 176$m^3/h$, 7$s$]. Therefore the updated temperature set-point of combustion chamber can be obtained: $y_1^*(9:00)$=$\bar{y}_1(9:00)$+$\Delta\bar{y}_1(9:00)$=1155-53=1102°C; the updated flow rate set-point of the deoxidization gas was therefore set by y_2^*=$\bar{y}_2(9:00)$+$\Delta\bar{y}_2(9:00)$ =2190+176=2366m^3/h; the updated set-point for the ore discharge time was changed to $y_3^*(9:00)$=$\bar{y}_3$+ $\Delta\bar{y}_3(9:00)$=276+7=283s.

Then these updated set-points at 9:00 were used as those of the control loop as substitutes.

At 12:00: The MTRR $\gamma(12:00)$=0.824> γ^*, and other variables and variety ratios are all within their ranges. The above-mentioned faulty work-conditions have vanished and a normal work condition is resumed.

Since it was installed in Oct, 2003, the proposed system can provide the set-points for the control loops in time under the variation of work-conditions or faulty work-conditions. As the control system tracks the modified set-points, faulty work-conditions disappear. The application results of the proposed system have shown that the total frequency of faulty work-conditions is cut down by over 50%, the production rate per furnace is elevated with 0.72 T/h (from 24.9 T/h to 25.62T/h), the magnetic tube recovery rate rises 2%, the equipment operation rate is enhanced by 2.98%, the concentrated grade is raised by 0.57% and the metal recovery ratio improved by 2.01%.

5. CONCLUSIONS

In view of the difficulties in the manual setting-points control, this paper proposes a hybrid intelligent control method for the optimal process operation to control the technique indices, namely the magnetic tube recovery ratio (MTRR) within the desirable ranges by on-line adjusting the set-points of the control loops. If the work-conditions vary or even faulty work-conditions occur, this method will automatically adjust the set-points of the combustion chamber temperature, the flow of reduction and the ore discharge time. In the process of control system tracking the set-points, the work-conditions in the shaft furnace roasting process moves away from the diagnosed work-situation, and the MTRR is controlled into the targeted range. Successful applications in the largest minerals processing factory of China show that the proposed technique has high potential of being further applied in the optimal operation of complex industries.

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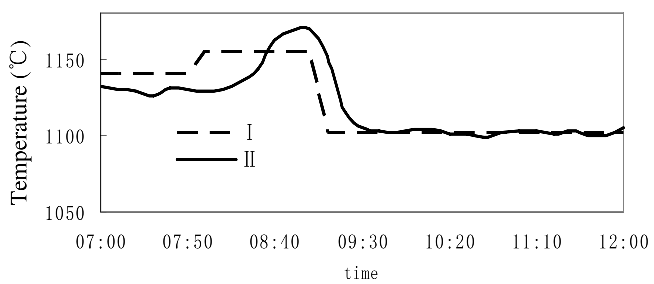
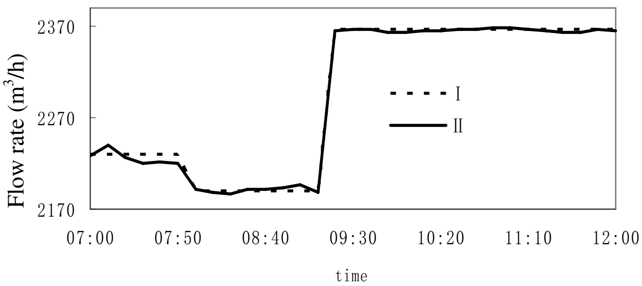
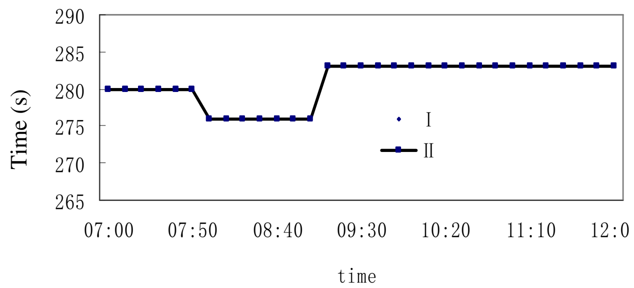


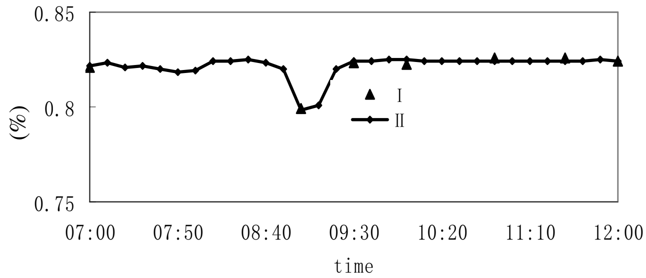
Ⅰ) Temperature set-point of combustion chamber
Ⅱ) Output of temperature control loop of combustion chamber
(a) Temperature trend of combustion chamber



Ⅰ) Flow rate set-point of deoxidization gas
Ⅱ) Output of flow control loop of deoxidization gas
(b) Flow rate trend of deoxidization gas



Ⅰ) Set-point of ore discharge time
Ⅱ) Practical value of ore discharge time
(c) Trend of ore discharge time



Ⅰ) Prediction of MTRR
Ⅱ) Practical value of MTRR
(d) Trend of MTRR

Fig. 7. Optimizing control effects of the shaft furnace roasting process

Table 4 Work condition of the shaft furnace at 9:00 a.m.

$y^*(t)$			B			P					
$y_1^*(t)$	$y_2^*(t)$	$y_3^*(t)$	B_1	B_2	B_3	p_1	p_2	p_3	p_4	p_5	p_6
1155	2190	276	2	1	2	134	1.16	4791	10.3	4008	9
$y(t)$			$u(t)$			$e(t)$		$\bar{\gamma}(t)$		$\gamma(t)$	
$y_1(t)$	$y_2(t)$	$y_3(t)$	$u_1(t)$	$u_2(t)$	$u_3(t)$	$e_1(t)$	$e_2(t)$	0.798		0.799	
1170	2196	276	44	64	68	-12	2				

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