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Intelligent Operational Feedback Control for Fused Magnesium Furnace

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Abstract: Fused magnesium furnaces (FMF) are widely used in China to extract fused magnesia through a smelting process that has to be well controlled to assure high product output and low power consumption. With manual control, which is still widely used in practice, it is difficult to adjust the setpoints for control loop involved, thereby leading to compromised product output and increased power consumption. In this paper, an operational feedback control method is proposed to control the technical indices within their desired range. This is realized by on-line adjusting the setpoints of control loops for optimal operation of the FMF in response to changes in operating points. The techniques used consist of case based-reasoning (CBR), rule based-reasoning (RBR), neural network (NN), iterative learning control (ILC), in addition to classic PI and PID control. The proposed method and the developed control system have been applied to a real FMF. Industrial applications show the usefulness and effectiveness of the proposed operational feedback control method and its promises in other industrial processes with similar features.

1. INTRODUCTION

Design of industry process control is often focused on ensuring the controlled variables track the setpoint accurately while guaranteeing stability of the closed loop control system. However, the role of the control system is not only to ensure output tracking, but also to control the technical indices, such as product output, energy consumption to be within their target ranges (Chai, Ding, et al 2008). These technical indices are closely related to the outputs of the lower-level control loop. If the setpoints are not defined properly, the technical indices cannot be controlled well even when the lower-level controller achieves tracking perfectly. Currently, real-time optimization (RTO) and model predictive control (MPC) are often used to calculate the optimal setpoint of the loop controller in the chemical industry. For the metallurgic industry, however the technical indices cannot be measured online and models for those indices are difficult to obtain because of their complicated dynamic characteristics. Therefore, it is difficult to use the existing optimal control methods to perform the required control. Researchers usually try to explore the specific features of a given process in developing the control strategy. For example, Zhou, Chai et al, (2009) propose an intelligent optimal control method for grinding system to control the grind size and Qiao, Chai, et al, (2013) propose an intelligent setting control for clinker calcinations process to control the raw materials decomposition rate within the desirable range.

Fused magnesia is an important refractory for many industries such as metallurgical and chemical industry, and it is produced mainly by the three-phase ac fused magnesium furnace (FMF). The raw materials, namely the magnesite whose main ingredient is $MgCO_3$, are melted by the heat released by arcs in the FMF and then coagulated into the final products. In the FMF smelting process, the power consumed is the largest cost item, mounts typically to more than 20,000 kwh for a batch and accounts for more than 60 percent of the total cost. Therefore, reducing the energy consumption is of significant concern to the production enterprises. The technical index reflects the energy consumption for FMF is energy consumption per ton (ECPT, the ratio of the energy consumed in a complete smelting process to the total product) and it needs to be control effectively. The ECPT cannot be measured online, but it is directly related to the setpoints of electrode currents and the outputs of current control loop. Due to the complex relationship between ECPT and currents, the ECPT model is difficult to obtain. During the smelting process, if the current setpoints are not chosen properly or the output of the control loop fluctuate frequently, the product output will be reduced and the ECPT will be increased.

In the past few years, several theoretical and experimental studies have been carried out on the FMF. The heat distribution of the electrodes and its impact on crystallization process of fused magnesia are analyzed by Zhang, et al, (2005, 2006). Moreover, the arc resistance and molten pool resistance are adopted to simulate different stages of smelting process to obtain a reasonable feeding method and shape of molten pool by Tong, Zhang, et al, (2007). But those papers do not address the control problem. It is worth noting that Wu, Zhang, et al, (2008) introduces an intelligent control method for FMF based on case based reasoning (CBR) and Wu, Wu, et al (2009) introduces an intelligent control method based on rule based reasoning (RBR). In both cases, however, the production indices were not explicitly considered.

This paper presents an intelligent operational feedback control strategy for FMF. The proposed method consists of the closed loop optimization strategy for current setpoints and the current controller based on switching control. The closed loop optimization strategy consists of six modules, namely RBR based current persetting model, ECPT prediction model, PI control based setpoints feed-forward compensator, iterative learning control (ILC) and CBR based setpoints feedback compensator, RBR based abnormal conditions identification module and CBR based self-healing control module. The current controller consists of PID control based heating and melting controller, BRB based feeding controller, RBR based exhausting controller and their switching mechanism based on different conditions.

The organization of this paper is as follows. Section 2 discusses the smelting process of FMF. In section 3, the intelligent operational feedback control method is expounded especially. The performance of the application of the proposed control system in industrial field is analyzed in section 4. The paper is concluded in section 5.

2. DESCRIPTION OF FUSED MAGNESIUM FURNACE SMELTING PROCESS

2.1 Fused magnesium furnace smelting process

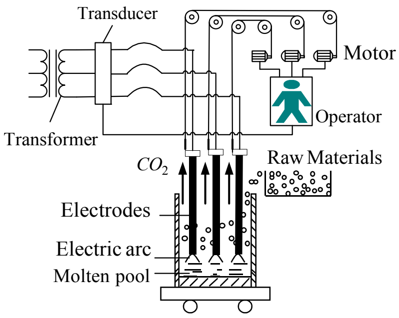


Fig. 1. Diagram of FMF smelting process.

The FMF smelting process is shown in Fig. 1 and often controlled manually. Three electrodes, powered by the three-phase ac power, are the main actuators, which are moved up and down based on the operating conditions. First, when the power is applied to the furnace, the electric arc will be generated. As operators fill the furnace with raw material, the molten pool will be formed with the raw material melted by electrical arc heating. During the smelting process, the electric arc is formed between the bottom of electrode and the upper surface of molten pool. The operators need to determine the current setpoints based largely on their experiences and adjust the electrode position using motors so that the arc length can be maintained within the desired range and the currents can track their setpoints.

The physical and chemical changes in smelting process are shown as follows:

$$MgCO_3 \xrightarrow{640^{o}C-800^{o}C} CO_2 + MgO\ (solid\ \ state) \qquad (1)$$

$$MgO\ (solid\ \ state) \xrightarrow{2800^{o}C} MgO\ (liquid\ \ state) \qquad (2)$$

The normal operation conditions of the smelting process are summarized as follows. Feeding condition S_1 : the raw magnesite is fed into the furnace; Heating and melting condition S_2 : the $MgCO_3$ is heated to 640℃-800℃ and decomposes into CO_2 and solid state of MgO. MgO continue to be heated up to 2800℃ when it turns into molten state. After natural cooling, the liquid becomes crystal gradually; Exhausting condition S_3 : the chemical reactions will produce a certain amount of CO_2 and has to be displaced. In the different conditions, the constant electric current setpionts cannot meet the needs of the smelting process. When the conditions or the production boundaries change, the operators therefore need to determine the amount of adjustment of the current setpoints based on their experiences, and then control the currents tracking the setpoints. Unfortunately, with the manual operation alone, the operators often cannot accurately adjust the setpoints in time and control the currents within the desired range, which can result in great fluctuations of the currents and thus have the impact on the quality of the product and ECPT. If large fluctuations last more than a certain threshold, they will lead to abnormal conditions which have greater consequences on product quality, process efficiency, and even plant safety.

2.2 The control objective for FMF smelting process

For effective operation of FMF, the objective is to control the product output within a desired range, while keeping the ECPT minimized, namely.

$$\begin{aligned} &Max\left(r_{\max}^{*} - r\right) \\ &st.m \ge m_{\min}^{*}, \end{aligned} \qquad (3)$$

where r denotes the actual values of ECPT and $r_{\max}^{*}$ denotes its upper limit, m denotes the product output and $m_{\min}^{*}$ denotes its lower limit. The dynamics of r can be described as follows

$$r = f\left(y(t), S_i, B_j, m\right), \quad i = 1,\cdots,3\,,\ j = 1,\cdots,5 \qquad (4)$$

where $f(\cdot)$ is an unknown nonlinear function varying with the electrode current $y(t)$, the product output m, the operation conditions S_i and the boundary conditions B_j which consist of the electrode diameter B_1, the smelting voltage B_2, the shell diameter B_3, the granularity of raw materials B_4 and the quality of raw materials B_5. Due to the fact that the product output m is difficult to measure online, the control system can only control the currents to track the proper setpoints to ensure the control objective shown in (3).

2.3 ECPT Characteristic Analysis

The heat energy required to melt the raw materials in an entire FMF smelting process is from the electrical energy. In general, the smelting voltage and the smelting time are fixed, therefore the value of current has a direct impact on ECPT. When the current setpoint is too small, the power supply is insufficient, the temperature in the furnace is low, the raw materials melt inadequately, thereby leading to low product output and high ECPT. When the current setpoint increases, the furnace temperature is increased and therefore the product output. The increase in the product output will be faster than the increase rate of the energy consumption, consequently the ECPT will decrease. However, the product output will stop increasing when the limits of the smelting process and the equipment are reached, after the current setpoint is greater than a certain threshold. Further increase in current setpoint will lead to increase in energy consumption and thus an increase in ECPT.

3. INTELLIGENT OPERATIONAL FEEDBACK CONTROL METHOD FOR FUSED MAGNESIUM FURNACE

3.1 The Strategy for Intelligent Operational Feedback Control

In this paper, an operational feedback control system that achieves the control objective (3) is presented in Fig. 2. The proposed control system is comprised of the closed loop optimization strategy for current setpoints and the current controller based on switching control. The closed loop optimization strategy is comprised a current persetting model, an ECPT prediction model, a setpoint feed-forward compensator, a setpoint feedback compensator, an abnormal conditions identification module and a self-healing control module. The switching control system is comprised three controllers for different operating conditions. The functions of each unit are introduced as follows.

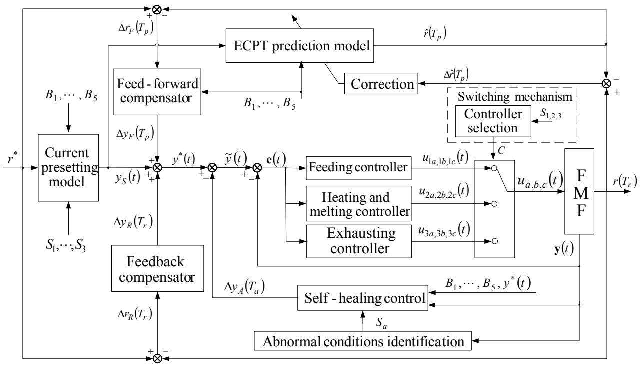


Fig. 2. The intelligent operational feedback control strategy.

Current persetting model: According to the target value of ECPT r^* , the boundary conditions B_j and the operating conditions S_i, the current presetting model generates the pre-setpoints $y_s(t)$ of current; ECPT prediction model: Given to the current pre-setpoints, a ECPT prediction model is developed to generates the predicted values of ECPT $\hat{r}(T_p)$; Setpoint feed-forward compensator: Acting upon the error $\Delta r_F(T_p)=r^*-\hat{r}(T_p)$, the feed-forward compensator computes the incremental changes of current setpoints $\Delta y_F(T_p)$; Setpoint feedback compensator: Given the ECPT error $\Delta r_R(T_r)=r-r(T_r)$, the feedback compensator computes the correction of current setpoints $\Delta y_R(T_r)$, and generates the desired current setpoints, $y^*(t)=y_S(t)+\Delta y_F(T_p)+\Delta y_R(T_r)$; Abnormal conditions identification and self-healing control: According to the fluctuation of currents $y(t)$, it identifies the abnormal condition S_a for different phases in the smelting process, and computes the correction $\Delta y_A(T_a)$ of the current setpoints. When the abnormal conditions are detected, the controller tracks the corrected setpoint $\tilde{y}(t)=y^*(t)+\Delta y_A(T_a)$ to achieve the expected control effects; Feeding controller, heating and melting controller, and exhausting controller: According to the tracking error $e(t)$ of control loop, the above three controllers are actuated to move the electrodes. The outputs of the three controllers are $u_{ia,ib,ic}(t)$, $i=1,\cdots,3$. The switching among different controllers according to the present conditions S_i , and the final outputs of switching controller is described as $u_{a,b,c}(t)$.

3.2 Realization of Intelligent Operational Feedback Control

3.2.1 The current persetting model based on RBR

In this paper, the algorithm based on RBR (Wang, Wang et al, 2011; Astrom, Anton, et al, 1986) is used for generating the pre-setpoints $y_s(t)$ of the control loop in different operating conditions. The RBR uses rules of the form “IF” <promise> “THEN” <conclusion>, the premises in this case are r^*, S_i and B_j. Considering the FMF smelting process characteristics, the current condition S_i, the boundary conditions B_4 and B_5 are taken values in the set {1,2,3} (1, 2, 3 for S_i represents the current condition is feeding, heating and melting or exhausting, B_4 represents the granularity of the raw material being big, medium, small, and B_5 represents the quality of the raw material being good, medium, poor, respectively). And the limited values of antecedent variables r^* and $B_1,\cdots,B_3$ are H_{r^*} , H_{11} , H_{21} , H_{22} and H_{31} . The H_{r^*} is the limit of r^* , the H_{11} is the limit of graphite electrode diameter, the H_{21} and the H_{22} are the lower and upper limits of the rated voltage, and the H_{31} is the limit of furnace shell diameter. Based on the relationship between the antecedent variables and the limits, different current values can be pre set. For example, there is a smelting process with lower target value of the ECPT, thick graphite electrode, large diameter furnace shell and smelting with high rated voltage. When this smelting process is in feeding condition, the granularity of raw material is medium and quality of raw materials is good, then the smelting process needs a lower current setpoint. The persetting rules in this state can be expressed as follows:

If $r^*<H_{r^*}$, $B_1\geq H_{11}$, $B_2\geq H_{22}$, $B_3\geq H_{31}$, $B_4=2$, $B_5=1$, and $S_i=1$ then $y_S(t)=I_{S1}$.

Similarly, based on the relationship between the antecedent variables and the limits, different current values can be preset according to the following rule.

If $r^*<H_{r^*}$, $B_1\geq H_{11}$, $B_2\geq H_{22}$, $B_3\geq H_{31}$, $B_4=3$, $B_5=1$ and $S_i=1$ then $y_S(t)=I_{S2}$,

$$\vdots$$

If $r^*\geq H_{r^*}$, $B_1<H_{11}$, $B_2<H_{21}$, $B_3<H_{31}$, $B_4=3$, $B_5=3$ and $S_i=3$ then $y_S(t)=I_{S8}$,

where $I_{S1},\cdots,I_{S8}$ denote the current pre-setpoints in different conditions, and the values for $I_{S1},\cdots,I_{S8}$ are from small to large.

3.3.2 ECPT prediction model

ECPT for FMF is the ratio of the energy consumed in a complete smelting process to the total product. Since the product can only be assayed after the end of the smelting process, the value of the ECPT for this batch cannot be measured online. Using the actual values of the ECPT to guide production has issues associated with time delay.

By analyzing the FMF smelting process, the main prediction model of ECPT is acquired by using the law of conservation of energy, as shown in (5):

$$\hat{r}_m(T_p)=\frac{W_i(t)+\sqrt{3}U\cos\varphi\bar{y}(T_p)(T-T_s)}{\dfrac{\alpha\left(\dfrac{(Ay_S(t)+BC)^2}{Vy_S(T_p)}-k_1\left[\dfrac{VI}{\left(A+\dfrac{BC}{y_S(T_p)}\right)^2}\right]^{-\beta}\dfrac{C}{y_S(t)}\right)T}{9.4\times 10^6}+(1-\varepsilon)\dfrac{TD_a}{\Delta t_a\varsigma}},$$

where $V=\dfrac{100\rho_{m.A}}{\sqrt{3}(\rho_{m.A}+0.92\rho_{m.B})}$, $\varepsilon=\begin{cases}1 & when\ m_{\Delta t_a}\le D_a/\varsigma,\\ 0 & when\ m_{\Delta t_a}> D_a/\varsigma.\end{cases}$ (5)

with $W_i(t)$ being the current consumption of energy, $\cos\varphi$ the power factor, T_s the smelting time that has elapsed, $\bar{y}(T_p)$ the average value of the currents before the current time, T the total smelting time, α the thermal efficiency of FMF, A the voltage drop between the cathode and anode, B the arc voltage gradient, C the factor of the arc length, $\rho_{m.A}$, $\rho_{m.B}$ the resistivity of arc and molten pool, V the arc voltage, k_1, β the adjustable parameters that are affected by the electrode material and electrode diameter, ε the factor of product, Δt_a the feeding time interval, D_a the weight of raw materials which added in a feeding time interval, and ς the input-output ratio of raw materials.

In the FMF smelting process, the values of α , D_a , $\rho_{m.A}$ and $\rho_{m.B}$ will change randomly, their true value cannot be acquired. Therefore, these parameters can only be replaced with some fixed values. This will lead to a prediction error $\hat{r}_e(T_p)$ between the true value of ECPT and $\hat{r}_m(T_p)$. In order to eliminate the impact of $\hat{r}_e(T_p)$, a prediction error model is established based an improved ELMAN neural network model, with input $y_s(t)$, Δt_a , B_4 and B_5 , output $\hat{r}_e(T_p)$, and 4 input layer nodes and 10 hidden layer nodes. Thus, the output of ECPT prediction model is $\hat{r}(T_p)=\hat{r}_m(T_p)+\hat{r}_e(T_p)$. The detailed modelling process is introduced in Wu, Chai, et al, 2013b.

3.2.3 Current setpoint feed-forward compensator

In smelting process, when the boundary conditions change, the outputs of the current presetting model cannot be easily tracked. Compensation with a PI control was designed to accommodate the changing characteristics of the smelting process. According to the error $\Delta r_F(T_p)$, feed-forward compensator computes $\Delta y_F(T_p)$ as follows:

$$\Delta y_F(T_p)=\begin{cases}\Delta y_F(T_p-1)+[k_1(\Delta r_F(T_p)-\Delta r_F(T_p-1)) & \\ \quad +k_2\Delta r_F(T_p)], & if\quad \Delta r_F(T_p)\ge 100,\\ 0, & else\ \Delta r_F(T_p)<100.\end{cases} \qquad (6)$$

where k_1 and k_2 are adjustable parameters adjusted using RBR, whose extraction process is similar to that described in Section 3.2.1.

3.2.4 Current setpoint feedback compensator

The smelting process for FMF is a typical batch process. The current setpoint feed-forward compensator can be used to correct the improper current setpoints in one smelting process, but it cannot correct the setpoints in response to the actual ECPT of different batches as the boundary conditions have been changed. It is necessary to design the feedback compensator in order to improve the control accuracy to compensate for deviation of setpoints. ILC, (Saab, 1994; Xiong, Zhang, 2005) is adapted for the batch smelting process of fused magnesium furnace. For simplicity, The ILC with P type is used for feedback

$$\Delta y_R(T_{r,L_f})=\Delta y_R(T_r-1)+L(T_r)\Delta r_R(T_r-1), \qquad (7)$$

where $\Delta y_R(T_r)$ is the compensation for the current presetting values, and $L(T_r)$ is the learning gain which is determined by CBR(Liu, Chen, 2012; Fernandez, Diaz, et al, 2007). In the CBR method, according to the expert experiences and the characteristics of smelting process, the cases are denoted by, r^* and $B_1,\cdots,B_5$. The case solution y_{sk} is presented by the value of learning gain $L(T_r)$. The solution procedure for $L(T_r)$ is similar to that described in Wu, Zhang, et al, (2008).

3.2.5 Abnormal Condition Identification and Self-healing Control System based on RBR and CBR

Abnormal conditions can arise when the current setpoints are not properly adjusted on time. This paper uses an abnormal condition identification based on RBR and self-healing controller based on CBR for the FMF (Wu, Wu, et al, 2013a) to automatically adjusts the currents setpoints when the abnormal conditions occur. The corrected setpoints are well tracked by the control loop so that the abnormal conditions can be eliminated.

3.2.6 Switching control for current tracking

In this paper, a switching control system consists of a feeding controller, a heating and melting controller, an exhausting controller and the switching mechanism is designed to hurdle the different working conditions. According to the control requirements of the FMF and the operators' experience, a switching mechanism is established. When the smelting process is in the heating and smelting condition, the loop controller uses the PID algorithm to control the currents to track the setpoints. In the vicinity of operating point of current, an approximate first order plus dead time (FOPDT) model between the currents and motor speed is given by,

$$G(s)=\frac{Ke^{-\tau s}}{Ts+1}. \qquad (8)$$

During the heating and smelting conditions, the characteristic of current change near the operating point is almost linear, thereby justifying the PID control. This paper uses Ziegler-Nichols (ZN) method to tune the PID parameters and gives $K_p=1.2T/K\tau$, $T_i=2.2\tau$, $T_d=0.5\tau$. When the smelting process is in the feeding and exhausting condition, the RBR based controllers (Wu, Wu, et al 2009) are used to ensure the stability of the FMF smelting process.

4. INDUSTRIAL APPLICATION

The proposed method is applied to a real fused magnesia factory in China. According to the production requirements and operation experience, the upper limit of ECPT in this factory is $r^*_{\max} = 2800 kwh/t$ .The limit values in the current persetting model are $H_{r^*} = 2600$, $H_{11} = 300$, $H_{21} = 100$, $H_{22} = 110$ and $H_{31} = 2.4$. In the PID based heating and smelting controller, the parameters of FOPDT model are identified based on step response method. The model parameters are $K = 3$, $T = 4$ and $\tau = 1.8$. Using Z-N method to acquire the PID parameter offline and adjust them online, the final values are $K_p = 0.7$, $T_i = 4.1$ and $T_d = 0.8$.

Before implementing the automation system presented in this paper, the whole smelting process was operated manually solely based on human experience. The control effect for currents (the setpoint is 13500A) is shown in Fig.3.

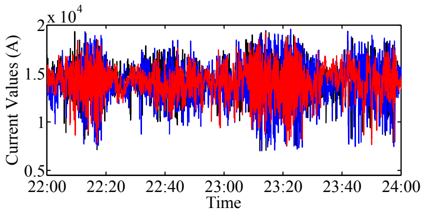


Fig. 3. The control effect for currents with manual control.

It can be seen in Fig. 3 that the current cannot track the setpoints very well and the range of current variation is large. During 22:06-22:18 the maximum tracking error of the currents is up to 6717A which greatly exceeds the acceptable range for tracking error ([1500A, -1500A]). The currents fluctuate in a large range caused unacceptable temperature distribution in the furnace, deteriorated product qualities, and increased ECPT. The extended period of the large current fluctuations led to abnormal conditions during 23:08-23:26. The large and frequent current fluctuation and the occurrence of abnormal feeding condition indicate that manual adjustment of the setpoints cannot guarantee a satisfactory smelting process.

In order to better verify the method, the proposed current controller based on switching control method is applied to the smelting process alone first and the control effect is shown in Fig.4. Current setpoint in this process is given manually by the operator and same as in Fig.3.

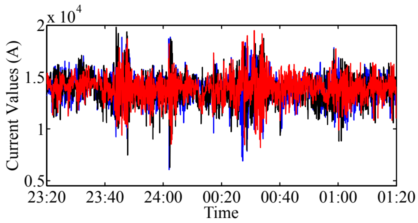


Fig. 4. The control effect for currents with loop control only.

It can be seen from Fig.4 that with the proposed switching control strategy, the control effect has been improved compared to the manual control, and the time period during which the current tracking error exceeds the acceptable range is significantly reduced. However, since the same current setpoints are used, the tracking errors still overstep into the unacceptable range sometimes.

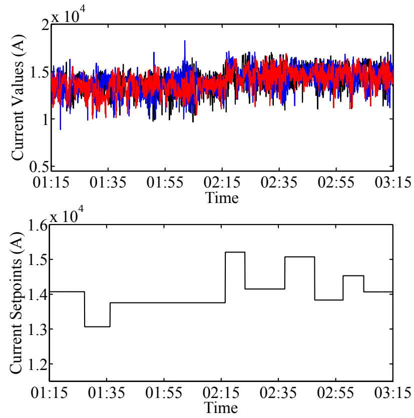
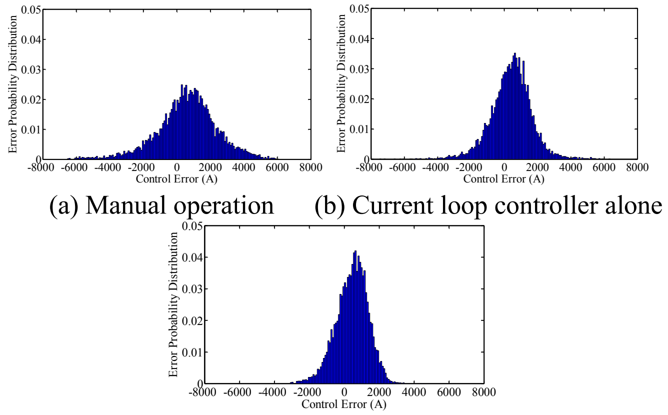


Fig. 5. The control effect for currents with proposed method.

With the intelligent operational feedback control method proposed in this paper, the current setpoints and the responses of the electrical currents are shown in Fig. 5. The target value of ECPT $r^* = 2650\, kwh/t$. At 01:15am, the smelting process is in heating and melting condition, and the current setpoint is $y^*(01{:}15) = 14072A$. At 01:26, the CO_2 gas in the furnace need to be displaced, the smelting process is in exhaust condition. According to the rules for current persetting, $y_S(01{:}26) = 13450\,A$. Given this value, ECPT prediction model generate the predicted value $\hat{r}(01{:}26) = 2621 kwh/t$, the feed-forward compensator produced $\Delta y_F(01{:}26) = 0A$ because $|\Delta r_F(01{:}26)| = 29 < 100$. The feedback compensator executes CBR for learning gain $L(T_r)$ .The case solution can be determined as $L(01{:}26) = 0.08$. Then the feedback compensator produced $\Delta y_R(01{:}26) = -105A$ with the equation (7). The setpoint of current is adjusted to $y^*(01{:}26) = 13450 + 0 - 105 = 13345A$. At this point, the current tracking error is larger than the acceptable range, and the current change rate is very large, the abnormal exhausting condition happened. The self-healing controller adopts the identification result and case solution at the time 01:26 can be determined as $\Delta y_A(01{:}26) = -280A$ by executes CBR. The setpoint at this time is $\tilde{y}(01{:}26) = 13345 - 280 = 13065A$. The control system tracks the corrected setpoint and the smelting process recovers to normal condition. At other time, the operating conditions change again, and the operating parameters are shown in Table 1.

Table 1. Operating points of the smelting process

	02:17	02:22	02:38	02:47	02:59
S_i	2	2	2	1	2
B_4	2	2	2	2	2
B_5	1	1	2	2	2
$y_s(t)$	14950	14950	15250	14600	15250
$\Delta y_F(T_P)$	409	-644	-644	-1232	-1182
$\Delta y_R(T_r)$	-156	-156	465	465	465
$\Delta y_A(T_a)$	0	0	0	0	0
$y^*(t)$	15203	14150	15701	13833	14533



(a) Manual operation (b) Current loop controller alone

(c) Proposed method

Fig. 6. The control error probability distribution.

The control error probability distributions with the proposed method, the current loop controller used alone and with the manual operation are shown in Fig. 6. The current tracking errors within the acceptable range [-1500A, 1500A] is 86 percent with the proposed method, compared to 79 percent and 59 percent with the current loop alone and manual operation respectively. This shows that the proposed control strategy significantly improves the performance.

The proposed control strategy has been applied to a real fused magnesia factory, the control system has been in safe and reliable operation. The results shown in Fig.7 is the comparison of ECPT in August 2012 using the proposed control strategy and another month before under manual control for FMF. The result shows that the product of actual energy consumption can track the target and the obvious advantages compared to manual control. Compared with the previous manual control, the operation of the proposed control strategy can ensure the product output while reducing ECPT decreases by more than 6 percent.

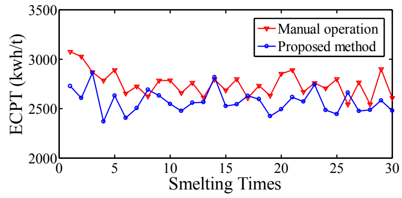


Fig. 7. The control effect for ECPT.

5. CONCLUSION

This paper proposes an intelligent operational feedback control method for the optimal process operation to control the technical index, namely the energy consumption per ton (ECPT), within the desirable ranges. The proposed method consists of closed loop optimization strategy for current setpoint and current controller based on switching control. When the conditions or the production boundaries change, the proposed method can adjust the current setpoints on-line and make the currents track the setpoints well. This strategy has been used in fused magnesia production enterprises successfully and the successful applications show that the proposed strategy of the intelligent feedback control holds great promise in automating complex industrial process.

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