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HYBRID INTELLIGENT OPTIMAL-SETTING CONTROL WITH MULTI-OBJECTIVES OF THE RAW SLURRY BLENDING PROCESS IN THE ALUMINA PRODUCTION

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Abstract. *Raw slurry blending process is one of the key producing processes in the sintering alumina production. Key technical indices of this blending process are the quality indices of the raw slurry and the load state of the mill. Operation control objectives are to control the quality indices into their targeted ranges and control the load state of the mill in the good state. However, due to the difficulty of measuring the quality indices and the load state on-line, and the complex dynamical characteristics between the technical indices and the control loops, these control objectives are difficult to be realized by using the existing control methods. A hybrid intelligent optimal-setting control of the raw slurry blending process is proposed. The proposed optimal-setting control with the hybrid intelligent approaches can automatically adjust the set-points in order to respond to the variation of the boundary condition. At last, the proposed control approach is applied in an alumina factory in China, and the application results have proven the validity and effectiveness of the proposed methods.*
Keywords: Raw slurry blending process, Optimal-setting control, Quality indices, Mill load, Hybrid intelligent control

1. **Introduction.** Key technical indices of the industrial processes often represent the product quality, energy consumption, production efficiency, and so on [1]. Controlling these key technical indices with the satisfactory performance can make enterprises obtain the higher net return. From a process engineering point of view, the purpose of automatic control of the industrial processes is not only primarily to control the controlled variables in the control loops at their set-points as well as possible but also to control these key technical indices [1-4].

In recent years, optimal control for operation of the industrial process, whose control objectives are to control the technical indices, has attracted more and more researches in the academia and industry. In the optimal operation control, how to dynamically determine the appropriate set-points of control loops on-line is the key problem. Now, optimal operation control mainly includes the self-optimizing control [5,6], the real-time optimization (RTO) [7], the direct finite horizon optimizing control [8], and so on. There are some shortcomings in these existing methods mentioned above:

(1) Accurate process models are necessary [1,9]. However, it is difficult to obtain the accurate models of some complex industrial processes.

(2) Energy consumption index or its related index is not considered in the control objectives.

(3) One of the control objectives is that the actual quality index is accurately equal to its target value. This objective is difficult to be achieved in the actual processes [9]. In fact, when the actual quality indices are into their target ranges, the operation performance of the industrial processes is satisfactory [10].

Raw slurry blending process is a key process in the sintering alumina industry in China. There are two types of control objectives in this process. One is to control the quality indices into their targeted ranges, and the other is to control the load state of the mill in the good state. These control objectives are difficult to be realized by using the existing optimal operation control.

In this paper, a hybrid intelligent optimal-setting control with multi-objectives of the raw slurry blending process is proposed. The optimal-setting control is composed of the compensation model of feeding capacity of the mill, predictive models of the quality indices, pre-setting model, feed forward compensator and feedback compensator of the set-points, and the coordination model. Rule-based reasoning and case-based reasoning are utilized in the compensation model of feeding capacity of the mill. RBF neural network is utilized in the on-line predictive models of the quality indices. Fuzzy rules reasoning is utilized in the feedback and feed forward compensator. Although each control element is well known, their innovative combination can generate better and more reliable performance. At last, the proposed method is applied in an alumina factory in China, and the application results have proven the effectiveness of the proposed methods.

2. Description and Analysis of the Raw Slurry Blending Process.

2.1. Process description. Raw slurry blending process is shown in Figure 1. In the raw slurry blending process, raw materials are the alkali power, red mud, blending ore and limestone, and the product is the raw slurry. At first, alkali powder and red mud are translated into the alkali sump. In the alkali sump, alkali powder and red mud are blended to produce the alkali red mud. Alkali red mud is translated into the mill. Blending ore and limestone are also translated into the mill. In the mill, alkali red mud, blending ore and limestone are grinded and blended to produce the raw slurry. The raw slurry are translated and stored in the tanks. The quality indices of the raw slurry are calcium ratio, alkali ratio and water content. The load state of the mill is an important technical index which is closely related to the energy consumption.

$Q_i^*(t)$ $(i = 1, 2, 3)$ are the target values of the quality indices of the raw slurry. $Q_i(T)$ $(i = 1, 2, 3)$ are the actual values of the quality indices. These actual values are obtained by the manual chemical examination. T is the period of the manual chemical examination. $y_i^*(t)$ $(i = 1, \ldots, 5)$ are the set-points of the flow rates of the alkali powder, red slurry, blending ore, limestone and alkali red mud. $y_i(t)$ $(i = 1, \ldots, 5)$ are the actual flow rates. $L^*(t)$ are the total flow rates of the raw materials translated into the mill, i.e., the feeding capacity of the mill. $V(t)$ and $I(t)$ are the vibration and current of the mill. $B(t)$ is the boundary condition, which is the chemical composition of each raw material.

2.2. Multiple control objectives of the optimal-setting control. The operation control objectives are to control the quality indices of the raw slurry into their targeted ranges, and to control the load state of the mill in the good state. These multiple control

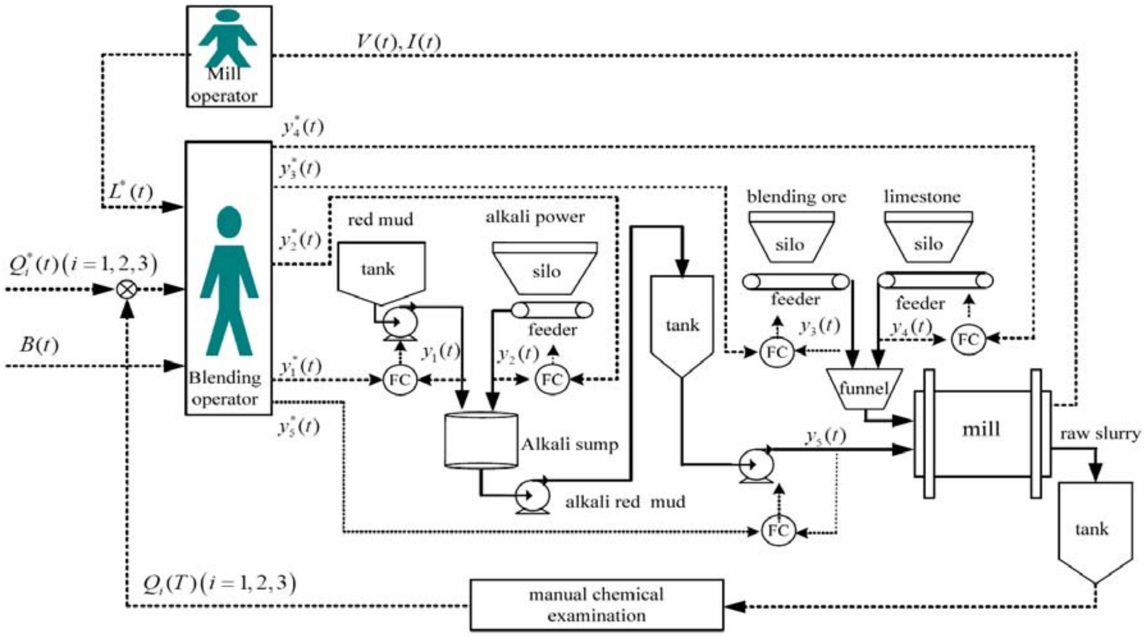


FIGURE 1. Schematic diagram of the raw slurry blending process and manual setting control

objectives are shown in Equations (1)-(4):

$$S(t) = S^*(t) \tag{1}$$

$$Q_1^*(t) - \Delta_1(t) \le Q_1(t) \le Q_1^*(t) + \Delta_1(t) \tag{2}$$

$$Q_2^*(t) - \Delta_2(t) \le Q_2(t) \le Q_2^*(t) + \Delta_2(t) \tag{3}$$

$$Q_3(t) \le Q_3^*(t) \tag{4}$$

where $S(t)$ is the actual load state of the mill; $S^*(t)$ is the good load state of the mill; $\Delta_1(t)$ and $\Delta_2(t)$ are the allowable max errors of the calcium ratio and alkali ratio.

There are two differences in the control objectives between the optimal-setting control proposed in this paper and the existing methods:

(1) The load state of mill, which is closely related to the energy consumption, is presented in the control objectives. Moreover, there are three quality indices should be controlled. As shown in Equations (1)-(4), this is a multi-objectives optimal-setting control.

(2) The quality indices are controlled into their target ranges, not to be equal accurately to their target values. The range control means that it can reduce unnecessary adjustments in response to allowable errors.

2.3. **Process characteristic analysis.** There are some complex dynamic characteristics during the operation of the raw slurry blending process:

(1) Load state of the mill $S(t)$ is difficult to be measured.

(2) Mil load is controlled by the adjustment of the feeding capacity of the mill $L(t)$. There are no accurate model between $S(t)$ and $L(t)$.

(3) It is difficult to measure the quality indices of the raw slurry on-line. $Q_i(T)$ is measured by the manual chemical examination with the long cycle T.

(4) There are strong coupling, nonlinear and large time delay characteristics between $Q_i(t)$ and $y_i(t)$.

For the shortcomings of the existing methods and the complex characteristics of the raw slurry blending process, the control objectives shown in Equations (1)-(4) are difficult to be achieved by the existing control methods. In order to realize the control objectives, there are two important points should be solved. One is how to determine $L^*(t)$ on-line according to the control objective shown in Equation (1), and the other is how to determine the $y_i^*(t)$ on-line according to the control objectives shown in Equations (2)-(4).

3. **Setting Control Strategy of the Raw Slurry Blending Process.** The proposed optimal-setting control strategy is shown in Figure 2, which can realize the multiple control objectives shown in Equations (1)-(4).

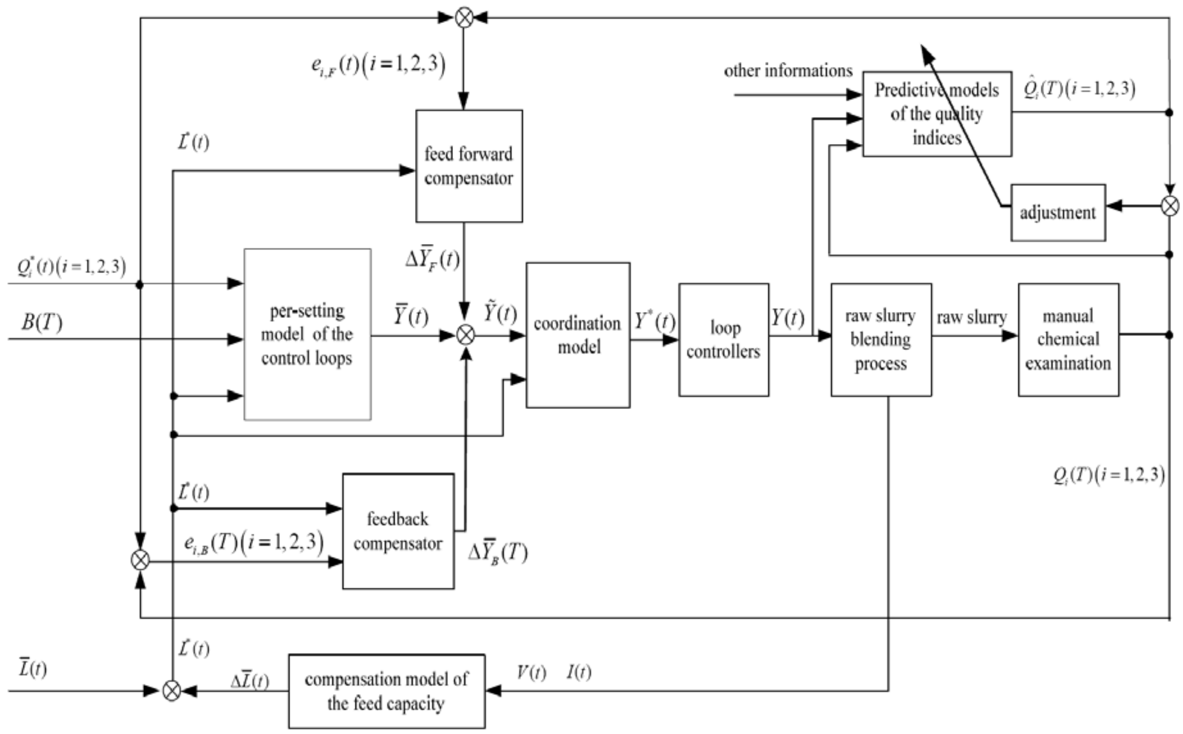


FIGURE 2. Strategy diagram of the optimal-setting control

$\bar{L}(t)$ is the initial feeding capacity of the mill. $\Delta\bar{L}(t)$ is the compensation value of the feeding capacity. $\hat{Q}_i(t)$ is the on-line predictive values of the calcium ratio, alkali ratio and water content. $\bar{Y}(t) = [\bar{y}_1(t), \ldots, \bar{y}_5(t)]$ are the initial set-points of flow rates. $\tilde{Y}(t) = [\tilde{y}_1(t), \ldots, \tilde{y}_5(t)]$ are the intermediate set-points of flow rates. $Y^*(t) = [y_1^*(t), \ldots, y_5^*(t)]$ are the final appropriate set-points of the flow rates. $\Delta\bar{Y}_F(t) = [\Delta\bar{y}_{1F}(t), \ldots, \Delta\bar{y}_{5F}(t)]$ are the feed forward compensation values of the initial set-points. $\Delta\bar{Y}_B(T) = [\Delta\bar{y}_{1,B}(T), \ldots, \Delta\bar{y}_{5,B}(T)]$ are the feedback compensation values of the initial set-points. $e_{1,F}(t)$, $e_{2,F}(t)$, $e_{3,F}(t)$ are the errors between the predictive and target quality indices. $e_{1,B}(T)$, $e_{2,B}(T)$, $e_{3,B}(T)$ are the errors between the actual and target quality indices. Their definitions are shown in Equations (5)-(8):

$$e_{i,F}(t) = \hat{Q}_i(t) - Q_i^*(t) \quad i = 1, 2 \tag{5}$$

$$e_{3,F}(t) = \begin{cases} \hat{Q}_3(t) - Q_3^*(t) & \hat{Q}_3(t) > Q_3^*(t) \\ 0 & \hat{Q}_3(t) \le Q_3^*(t) \end{cases} \tag{6}$$

$$e_{i,B}(T) = Q_i(T) - Q_i^*(T) \quad i = 1, 2 \tag{7}$$

$$e_{3,B}(T) = \begin{cases} Q_3(T) - Q_3^*(T) & Q_3(T) > Q_3^*(T) \\ 0 & Q_3(T) \le Q_3^*(t) \end{cases} \tag{8}$$

where T is the long period of manual chemical examination and $T = nt$.

The function of the each part in Figure 2 is described as follows:

(1) Compensation model of the feeding capacity: This compensation model can automatically adjust the feeding capacity of the mill on-line. According to $V(t)$ and $I(t)$, $\Delta\bar{L}(t)$ can be obtained by using this model. $L^*(t)$ also can be obtained by using Equation (9):

$$L^*(t) = \bar{L}(t) + \Delta\bar{L}(t) \tag{9}$$

(2) Predictive models of the quality indices: Predictive values of the calcium ratio, alkali ratio and water content, i.e., $\hat{Q}_i(t)$ can be on-line obtained based-on these models. In each predictive model, RBF neural network is adopted to predict the quality index. The detail design process of the RBF neural network is in [11].

(3) Pre-setting model of the control loops: According to $Q_i^*(t)$, $B(t)$ and $L^*(t)$, the initial set-points $\bar{Y}(t)$ can be obtained by using this model. The technical computation model with experiences is adopted in this model. The detail process of the pre-setting model is in [12].

In this pre-setting model, boundary condition $B(t)$ is assumed to be stable and known. When the unknown fluctuation of $B(t)$ occurs, the initial set-points are not appropriate. So, the initial set-points should be compensated by using the feed forward compensator and the feedback compensator.

(4) Feed forward compensator of the set-points: According to $e_{1,F}(t)$, $e_{2,F}(t)$, $e_{3,F}(t)$ and $L^*(t)$, $\Delta\bar{Y}_F(t)$ can be obtained by using this compensator. This is a short period compensator for the initial set-points, and the compensation period is t.

(5) Feedback compensator of the set-points: According to $e_{1,B}(T)$, $e_{2,B}(T)$, $e_{3,B}(T)$ and $L^*(t)$, $\Delta\bar{Y}_B(T)$ can be obtained by using this model. This is a long period compensator for the initial set-points, and the compensation period is T.

According to the output variables of the pre-setting model, feedback and feed forward compensator, we can obtain the intermediate set-points:

$$\tilde{Y}(t) = \bar{Y}(t) + \Delta\bar{Y}_F(t) + \Delta\bar{Y}_B(T) \tag{10}$$

$\tilde{Y}(t)$ can realize the control objectives shown in Equations (2)-(4). However, after these compensations, the load state of the mill may be not good, that is to say:

$$\tilde{y}_1(t) + \tilde{y}_2(t) + \tilde{y}_3(t) + \tilde{y}_4(t) \neq L^*(t) \tag{11}$$

The set-points $\tilde{Y}(t)$ should be regulated again by using the coordination model.

(6) Coordination model: According to the $\tilde{Y}(t)$ and $L^*(t)$, the final appropriate set-points $y_i^*(t)$ can be obtained, and the control objectives shown in Equations (1)-(4) can be realized. Being different with $\tilde{y}_i(t)$, $y_i^*(t)$ is satisfactory to Equation (12):

$$y_1^*(t) + y_2^*(t) + y_3^*(t) + y_4^*(t) = L^*(t) \tag{12}$$

4. Realization of the Setting Control Strategy.

4.1. Compensation model of the feeding capacity.

The compensation model of the feeding capacity consists of two sub-models including the estimate model of the load state and the regulation model of the mill load, which is shown in Figure 3.

There are some definitions:

$$G_1(t) = \frac{T_1}{T_2} \sum_{\tau=t-T_2}^{t} V(\tau) \tag{13}$$

$$G_2(t) = \frac{T_1}{T_2} \sum_{\tau=t-T_2}^{t} I(\tau) \tag{14}$$

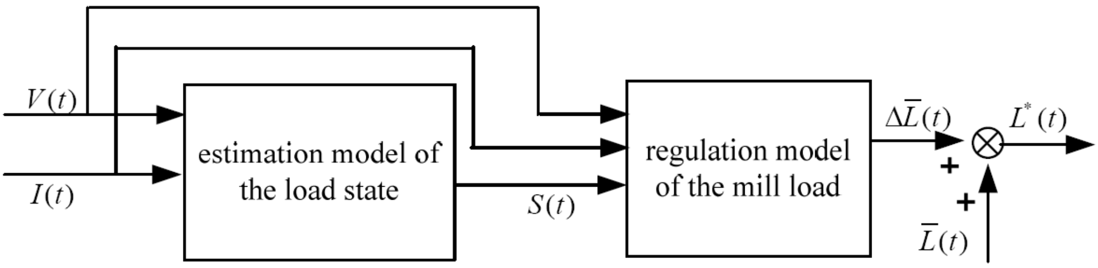


FIGURE 3. Strategy diagram of the compensation model of the feeding capacity

where T_1 is the sampling period of the vibration and current sensor; T_2 is the calculation period of $G_1(t)$ and $G_2(t)$.

As described in Subsection 2.3, the load state of the mill is difficult to be measured. Rule reasoning is adopted in the estimation model of the load state to solve this characteristic. The feeding capacity is the key variable to control the load state of the mill. There are also no accurate model between the load state and the feeding capacity of the mill. Case-based reasoning is adopted in the regulation model of the mill load to solve this characteristic.

4.1.1. *Estimation model of the load state.* According to the current ranges of $G_1(t)$ and $G_2(t)$, expert rules can be utilized to estimate the load state of mill $S(t)$. In this paper, the load state of the mill is divided into five states. S_1 represents the low load state. S_2 represents the quasi-low load state. S_3 represents the good load state, which is also the target load state S^*. S_4 represents the quasi-high load state, and S_5 represents the high load state.

At first, $G_1(t)$ is divided into three intervals and $G_2(t)$ is divided into four intervals. The intervals of $G_1(t)$ and $G_2(t)$ are shown in Table 1.

TABLE 1. Intervals of the vibration and current of the mill

variables	intervals
$G_1(t)$	$G_1(t) \geq A_2$
	$A_1 < G_1(t) < A_2$
	$G_1(t) \leq A_1$
$G_2(t)$	$G_2(t) \geq B_3$
	$B_2 \leq G_2(t) < B_3$
	$B_1 \leq G_2(t) < B_2$
	$G_2(t) < B_1$

In this paper, $A_1 = 800$, $A_2 = 900$, $B_1 = 65$, $B_2 = 70$, $B_3 = 75$.

According to the experience and knowledge of the excellent mill operators, and many results of the industrial experiments, the expert rules are determined. The expert rules are shown in Table 2.

TABLE 2. Expert rules

rules	conditions	conclusions
Rule 1	$G_1(t) > A_2$ and $G_2(t) < B_1$	S_1
Rule 2	$G_1(t) > A_2$ and $B_1 \leq G_2(t) \leq B_2$	S_2
$\vdots$	$\vdots$	$\vdots$
Rule 12	$G_1(t) < A_1$ and $G_2(t) > B_3$	S_4

4.1.2. *Regulation model of the mill load.* The input variables of the regulation model are the current load state $S(t)$, $G_1(t)$ and $G_2(t)$, and the output variable is the compensation value of the feeding capacity $\Delta\bar{L}(t)$. Case-based reasoning mainly includes case representation, case retrieval, case matching and case reuse [13]. The case representation can be described as Table 3. Each case is composed of two parts including the case description and the case solution.

Table 3. Case representations

case description			case solution
f_1	f_2	f_3	f_s
$S(t)$	$G_1(t)$	$G_2(t)$	$\Delta\bar{L}(t)$

In the regulation model, case attributes include $S(t)$, $G_1(t)$ and $G_2(t)$. f_s represents the case solution, which is the $\Delta\bar{L}(t)$ in the regulation model.

We assume that the description characteristics of the current mill system is $C' = (f_1', f_2', f_3')$. The cases stored in the case base are C^k $(k = 1, \ldots, m)$, and m is the number of the cases in the case base. The case description of C^k is $\left(f_1^k, f_2^k, f_3^k\right)$, and the case solution of the C^k is f_s^k.

We define the case similarity between C' and C^k is $sim^k(C', C_k)$:

$$sim^k(C', C^k) = sim_1(f_1', f_1^k) \times \left[\alpha \times sim_2(f_2', f_2^k) + \beta \times sim_3(f_3', f_3^k)\right] \tag{15}$$

$$sim_1(f_1', f_1^k) = \begin{cases} 0 & f_1' \neq f_1^k \\ 1 & f_1' = f_1^k \end{cases} \tag{16}$$

$$sim_2(f_2', f_2^k) = 1 - \frac{\left|f_2' - f_2^k\right|}{\max(f_2', f_2^k)} \tag{17}$$

$$sim_3(f_3', f_3^k) = 1 - \frac{\left|f_3' - f_3^k\right|}{\max(f_3', f_3^k)} \tag{18}$$

where α and β are the weighted coefficients. In this paper, $\alpha = 0.57$, $\beta = 0.43$.

The definition of the max similarity of C' and C^k $(1 \leq k \leq m)$ is:

$$sim_{\max} = \max_{k \in \{1, \ldots, m\}} sim^k\left(C', C^k\right) \tag{19}$$

The definition of the threshold of similarity between C' and C^k is:

$$sim_{th} = \begin{cases} 0.91 & sim_{\max} \geq 0.91 \\ sim_{\max} & \text{else} \end{cases} \tag{20}$$

In Equation (20), 0.91 is the threshold that is determined by the expert experience.

The cases that satisfy the following Equation (21) will be retrieved as the matching cases with ranking in ascending order of sim_k.

$$sim^k(C', C_k) \geq sim_{th} \tag{21}$$

Now, we assume that the matching cases are $\{C^1, C^2, \ldots, C^r\}$. The similarity between C' and $\{C^1, C^2, \ldots, C^r\}$ are $\{sim^1, sim^2, \ldots, sim^r\}$. The solutions of the matching cases are $\{f_s^1, f_s^2, \ldots, f_s^r\}$. We assume that $sim^1 \leq sim^2 \leq \ldots \leq sim^r$. The solution of the current case C' is:

$$f_s' = \left(\sum_{k=1}^{r} a_k \times f_s^k\right) \Big/ \left(\sum_{k=1}^{r} a_k\right) \tag{22}$$

In Equation (22), a_k is determined by using Equation (23):

$$\begin{array}{ll} \text{if} & sim^r = 1 \\ \text{then} & a_k = \begin{cases} 1 & k = r \\ 0 & k \neq r \end{cases} \\ \text{else} & a_k = sim^r \quad k = 1, \ldots, r \end{array} \tag{23}$$

f'_s also is the compensation value of feeding capacity, i.e., $\Delta\bar{L}(t)$. At last, by using Equation (9), we can obtain the appropriate feeding capacity of mill $L^*(t) = \bar{L}(t) + \Delta\bar{L}(t)$.

4.2. **Feedback compensator of the set-points.** Fuzzy rule reasoning is utilized in the feedback compensator. In this compensator, the input variables are $e_{1B}(T)$, $e_{2B}(T)$ and $e_{3B}(T)$, and the output variables are $\Delta\bar{y}_{1,B}(T)$, $\Delta\bar{y}_{2,B}(T)$, $\Delta\bar{y}_{3,B}(T)$ and $\Delta\bar{y}_{4,B}(T)$. The fuzzy sets of the input and output variables are shown in Figure 4. According to the experience of the excellent operator and the result of industrial experiment, we finally determined 147 fuzzy rules in the fuzzy reasoning system. By using the singleton fuzzifier, max-min reasoning and weighted mean defuzzification [14,15], the fuzzy reasoning system can derive the $\Delta\bar{y}_{i,B}(T)\,(i = 1, 2, 3, 4)$. From $\Delta\bar{y}_{1,B}(T)$ and $\Delta\bar{y}_{2,B}(T)$, we can obtain $\Delta\bar{y}_{5,B}(T)$:

$$\Delta\bar{y}_{5,B}(T) = \Delta\bar{y}_{1,B}(T) + \Delta\bar{y}_{2,B}(T) \tag{24}$$

4.3. **Feed forward compensator of the set points.** Feed forward compensator uses the predictive values of the quality indices of the raw slurry obtained by the predictive models, so the feed forward compensator has the short cycle. Being same with the feedback compensator, fuzzy rules reasoning is also utilized in this compensator. The input variables of the fuzzy system are $e_{1,F}(t)$, $e_{2,F}(t)$ and $e_{3,F}(t)$. The output variables of the fuzzy system are $\Delta\bar{y}_{1,F}(t)$, $\Delta\bar{y}_{2,F}(t)$, $\Delta\bar{y}_{3,F}(t)$ and $\Delta\bar{y}_{4,F}(t)$. The fuzzy sets and rules in the feed forward compensator are same with ones in the feedback compensator. According to the output variables of the pre-setting model, feedback and feed forward compensator, we can obtain the intermediate set-points $\tilde{Y}(t)$ by using Equation (10).

4.4. **Coordination model of the set-points and the feed capacity.** Taking the flow rate of the limestone as the benchmark, the blending ratio is:

$$\tilde{y}_1 : \tilde{y}_2 : \tilde{y}_3 : \tilde{y}_4 = k_1 : k_2 : k_3 : k_4 \tag{25}$$

where $k_4 = 1$.

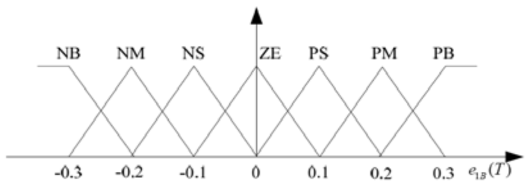
The output variables of the coordination model are:

$$y_i^*(t) = \frac{k_i}{k_1 + k_2 + k_3 + k_4} \times L^*(t) \quad i = 1, \ldots, 4 \tag{26}$$

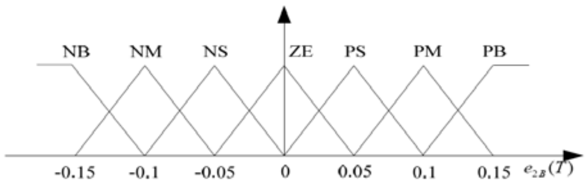
$$y_5^*(t) = y_1^*(t) + y_2^*(t) \tag{27}$$

5. **Industrial Applications.** The hybrid intelligent optimal-setting control presented in Sections 3 and 4 is applied in the Shanxi alumina factory in China.

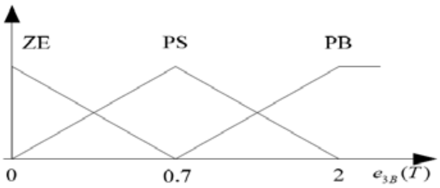
For example, in a period of time, the current work state of the mill is $L(t) = 189t/h$, $G_1(t) = 1176.8$ and $G_2(t) = 67.3$. By using the estimation model of the load state, we can know that the current load state is the quasi-low load state S_2. By using the regulation model, the compensation value of the feed capacity is $\Delta\bar{L}(t) = 18.6$, and the revised feed capacity is $L^*(t) = 189 + 18.6 = 207.6$. When the feeding capacity is revised, the curves of the vibration and current are shown in Figures 5 and 6, and we can know that $G_1(t) \in [800, 900]$ and $G_2(t) > 75$, and the load state is the good load state $S^*(t)$. Long-term application results show that the 3.5% reduction of the energy consumption has been achieved by using the compensation model of the feed capacity.



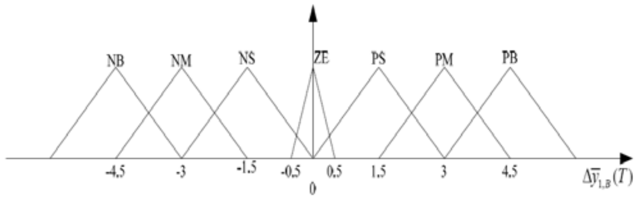
(a) Fuzzy sets of $e_{1B}(T)$



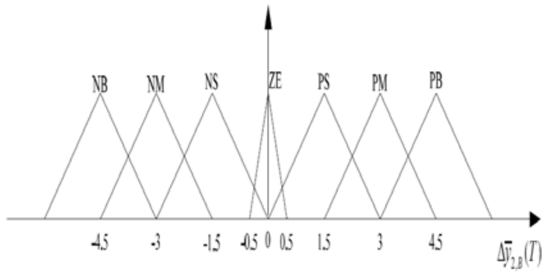
(b) Fuzzy sets of $e_{2B}(T)$



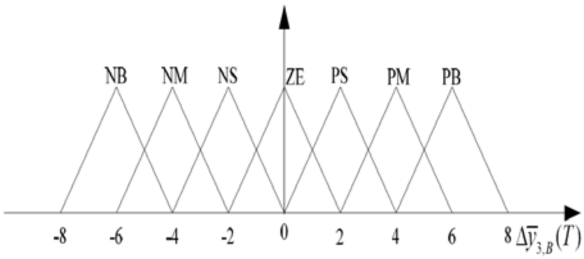
(c) Fuzzy sets of $e_{3B}(T)$



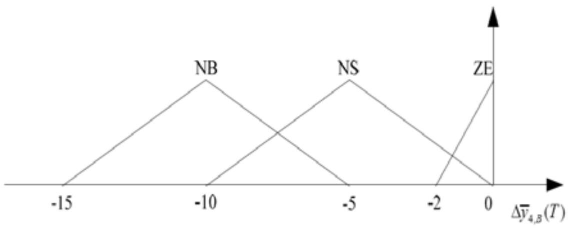
(d) Fuzzy sets of $\Delta\bar{y}_{1,B}(T)$



(e) Fuzzy sets of $\Delta\bar{y}_{2,B}(T)$



(f) Fuzzy sets of $\Delta\bar{y}_{3,B}(T)$



(g) Fuzzy sets of $\Delta\bar{y}_{4,B}(T)$

FIGURE 4. Fuzzy sets of the input and output variables

For example, in a period of time, $\Delta_1(t)$ in Equation (2) is 0.06, and the error of the calcium ratio by using the manual setting control and the intelligent optimal-setting control are shown as Figures 7 and 8. In Figure 7, the qualified rate of the calcium ratio is 74%. In Figure 8, the qualified rate of the calcium ratio is 86%. A lot of application results show that by using the intelligent optimal-setting control, the qualified rates of the calcium ratio, alkali ratio and water content are increased to 86%, 84% and 90% respectively. So, the quality of the raw slurry is improved.

6. **Conclusions.** In response to the difficulties in the controlling set-points manually, a hybrid intelligent optimal-setting control approach with the multiple objectives has

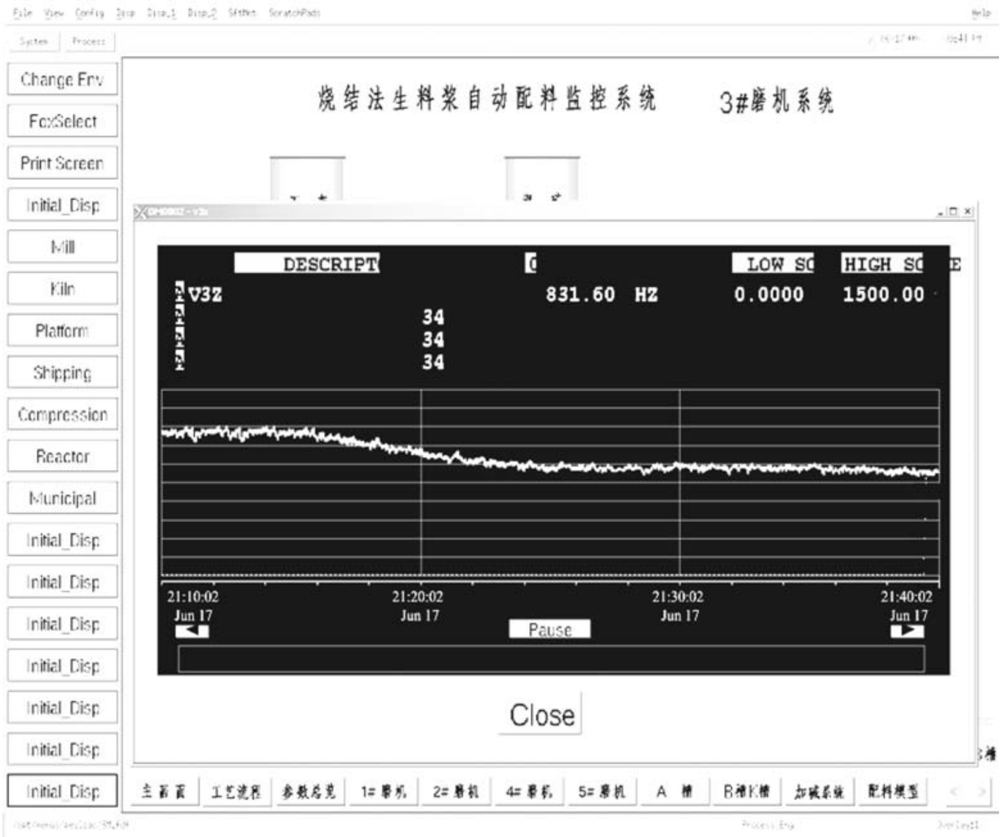


FIGURE 5. Curve of the vibration of the mill

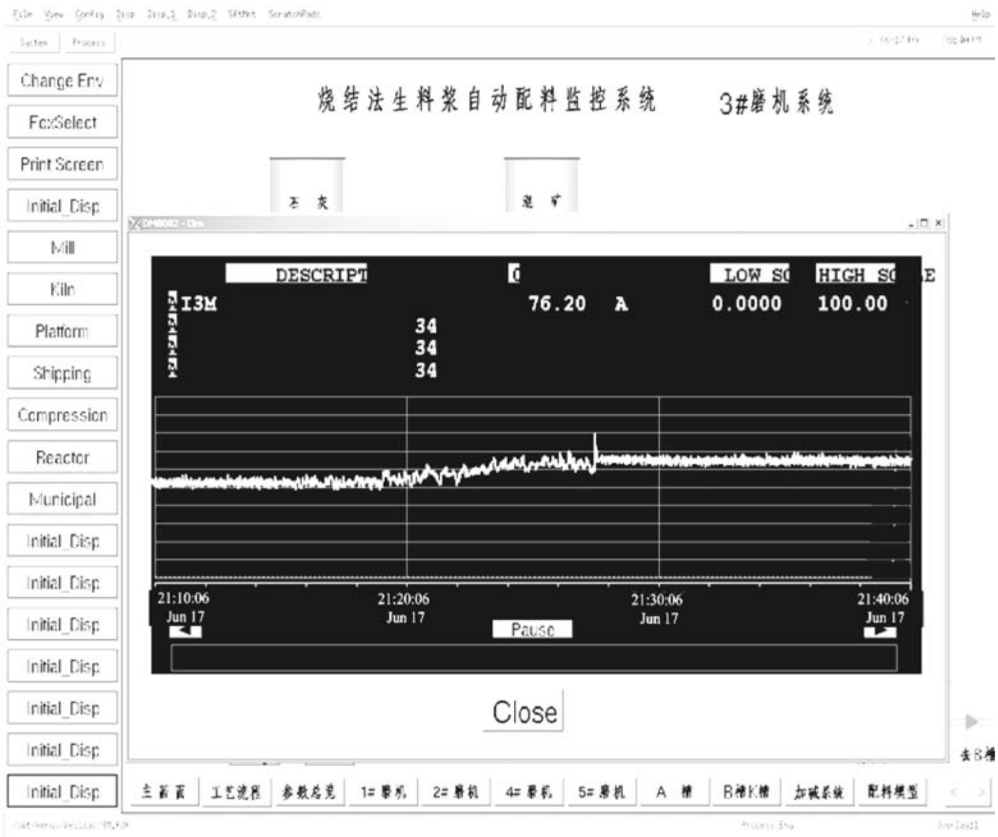


FIGURE 6. Curve of the current of the mill

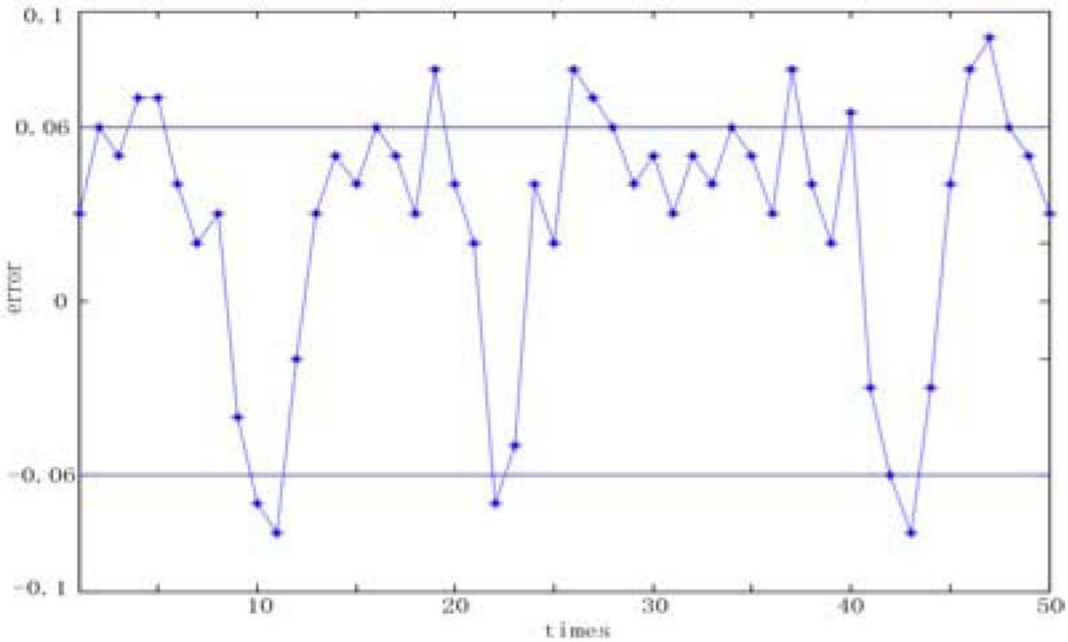


FIGURE 7. Error of the calcium ratio with the manual setting control

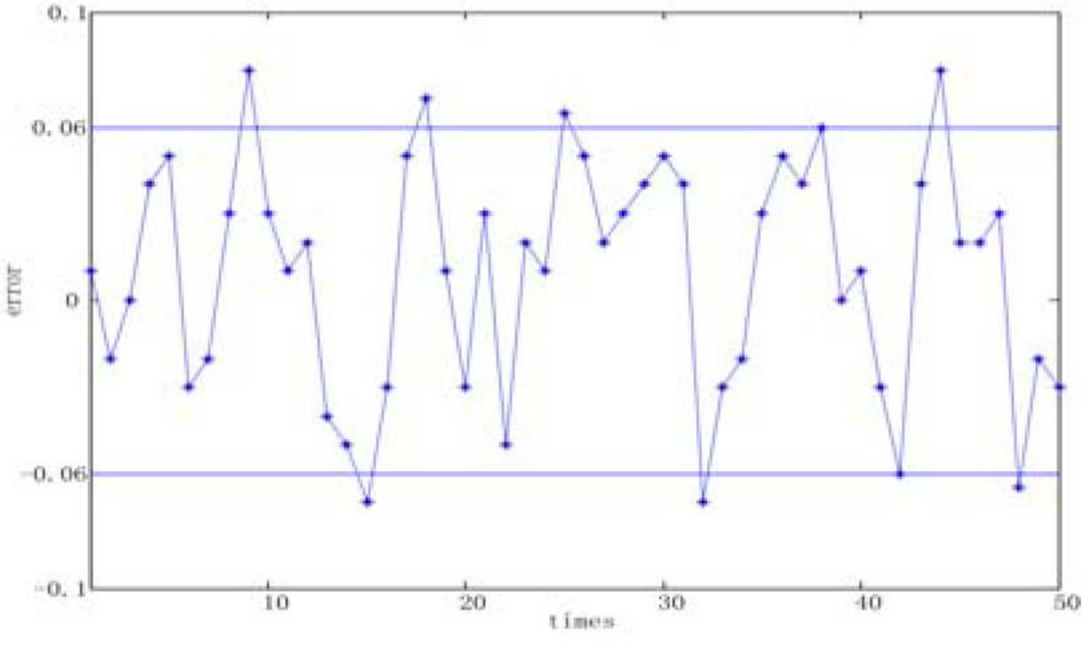


FIGURE 8. Error of the calcium ratio with the intelligent optimal-setting control

been proposed for a raw slurry blending process. Via the innovative combination of the compensation model of the feeding capacity, the predictive models of the quality indices, pre-setting model, feed forward and feedback compensator of the set-points and the coordination model, some complex dynamic characteristics can be overcame and the set-points of the raw materials can be adjusted automatically. This approach has been successfully applied in an alumina factory in China. The presented approach can be extended to a wide range of processes with the similar features.

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