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Intelligent Control for Flotation Process

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Abstract: In the flotation process, the concentrate grade and the tailing grade are crucial technical indices which reflect the product quality and efficiency. There are strong nonlinearity and uncertainty in such technical indices dynamic behaviors, which can hardly be described using accurate mathematical model. The technical indices which cannot be measured online continuously vary with boundary conditions. Therefore conventional control methods are incapable of keeping the actual the concentrate grade and the tailing grade within the target ranges. In this paper, an intelligent control method comprised of the setting layer and the closed loop control layer for the flotation reagent addition to the process has been presented. In flotation reagent feeding setting layer, a unit reagent pre-setting model, a feedback compensator and a feed forward compensator RBR based on (Rule-based reasoning) are integrated with a flotation reagent computation model to set the flotation reagent feeding. The control system updates automatically flotation reagent feeding when the boundary conditions changes. Successfully industrial application has shown that the concentrate grate has been increased by 0.52%, the tailing grade has been reduced by 4%, and the consumption of the flotation reagent feeding has been reduced by 17.5%. Significant application effect has been achieved.

1. INTRODUCTION

Flotation is used worldwide as an effective method to separate utilized ore from gangue according to the difference on the surface of physicochemical properties in mineral process so that the high concentrate grade and low tailing grade can be obtained. The purpose of flotation is to maximize the concentrate grades and minimize the tailing grades within their pre-specified technical indices ranges by controlling the flotation level, the input air and the chemical feeding (i.e., reagent), etc. This will improve the concentrate grade and the metal recovery so as to increase product quality and profit and enhance the competitiveness of this important industrial process.

In this regards, research into the modelling and controlling of flotation process has always been an important area in control engineering practice. Monitoring and control system (Bergh, Yianatos, Acuna, *ea al*, 1999) was established for the flotation process, and real application has improved the control performance for the concentrate grade and the metal recovery. In the analysis on the effect of the control loops on the concentrate grade and the metal recovery, a 3×3 matrix has been used to describe the dynamics of the flotation process (Maria, Antonio, Fabio, 2004). A fuzzy logic based technique was developed (Vieira, Sousa, Durao, 2005) based upon a MIMO model where the structure of the system model was established using a collection of T-S fuzzy rules. Since the air bubbles play an important role in flotation process, direct analysis of the images of the air bubbles have also been carried out (Cipriano, Guarini, Vidal, *et al*, 1998, Kaartinen, Hatonen, Hyotyniemi, Miettunen, 2006) which helps to monitor the operation and improve the control performance of flotation.

Such proposed methods have been applied and encouraging results have been obtained. However, flotation is complicated in terms of its operation and control. The concentrate grade and the tailing grade have strong nonlinearities and uncertainties with boundary conditions and operating variables, which is hard to describe using any mathematical models. Such technical indices are difficult to be measured online continuously. Besides these, the dynamics of each flotation circuit are unique, which are determined by the ore the plant processing, the process configuration and so on. Such proposed methods mentioned above are only useful for reference but not universal significance and they are difficult to transfer experience gained form one flotation plant to another. These limitations and the inherent complexity of the flotation process make automatic control of flotation be a difficult problem.

In this paper an intelligent control method for flotation process integrated the ideologies of both modelling and controlling (Chai, Tan, Chen, *et al,* 2002, Chai, Liu, Ding, and Su, 2007) is proposed to control the concentrate grade

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and the tailing grade within their respective target ranges. The proposed method has been applied to an actual flotation process. It has been shown per compared with manual control, that the concentrate grate has been increased by 0.52% and the tailing grade has been reduced by 4%. Also, the consumption of the flotation reagent feeding has been reduced by 17.5%. As such it can be concluded that a real application benefit has been achieved.

2. THE DESCRIPTION OF FLOTATION PROCESS

Flotation is a widely recognized effective methodology to separate useful ores from gangues according to the difference on the surface physicochemical properties. The principle of an actual flotation process for mineral processing in China is shown in Fig.1.

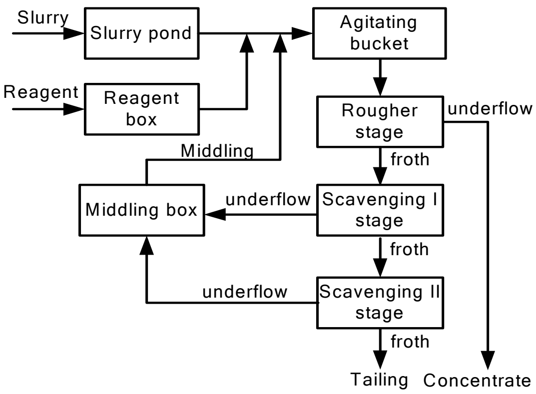

Fig. 1. The flow chart of the flotation process

At first the slurry from the upstream is conveyed into the slurry concentrate pond through the several pipes. The underflow slurry of appropriate density is then extracted and pumped to an agitating bucket. The slurry with added flotation reagent is agitated continuously so as to realize the required pre-processing in the bucket. This achieves a good mixing of the slurry with the added reagent. As soon as the slurry has been effectively pre-processed, it flows out and enters automatically into the rougher stage. The rougher underflow is the high concentrated grade ores which is sent to the concentrating pond as a final concentrated. The rougher froth overflow is inhaled to the scavenging I stage and the scavenging I froth overflow is inhaled to the scavenging II. The underflow of scavenging I are collected together with the underflow of scavenging II and the total collected underflow are returned to the agitating bucket as middling. The scavenging II froth is sent to the tailing pond as a flotation process final tailing.

The primary control objectives of such a flotation process are to maximize the process productivity and product quality in terms of the produced concentrated grade and tailing grade. The purpose of the flotation is to control such technical indices within the following ranges

$$\beta_{c\min} \le \beta_{ck}(t) \le \beta_{c\max} \text{ and } \beta_{wk}(t) \le \beta_{w\max} \quad (1)$$

where $\beta_{ck}(t)$ and $\beta_{wk}(t)$ are the actual values of concentrate grade and tailing grade, respectively, $\beta_{c\min}$ and $\beta_{c\max}$ are the lower and upper limits of the concentrate grade, $\beta_{w\max}$ is the upper limit of the tailing grade. These three limits values are decided by the actual processing technology.

As is mentioned in introduction, flotation is a complex industrial process with three fluid phases, namely solid, liquid and air. The concentrate grade and tailing grade are related to slurry consistency c, the supply ore mass M, the particle size d, the source ore grade α, the air flow rate Q_a, the flotation level h, the flotation reagent feeding rate V_r and the properties of ore etc. Such technical indices have strong nonlinearity and uncertainty with these factors and they are difficult to be measured online continuously which are hard to be described with any mathematical models.

In view of the condition of the low-level automation and lack of on-line sensors and grade analysis instruments in China, the process introduced in Fig.1 can only be controlled manually by the operator. Under the stable operation of the slurry consistency control, the supply ore control, the air flow rate control, the flotation level control, the operator sets and adjusts the flotation reagent feeding, which is the most important factor, according to the boundary conditions and the actual technical indices so as to control the concentrate grade and the tailing grade.

In fact, because of the complexity of the flotation process in terms of the difference between the different operators and the variations of boundary conditions from time to time, the operator cannot apply the correct flotation reagent feeding to the flotation. As a result, the actual added reagent feeding has always been either more than required or less than required. In specific, if less flotation reagent feeding is added, then the gangues would take affect partly with the reagent and only a portion of gangues can be adhered onto the air bubbles and float to the froth surface, leading to a low concentrate grate. On the other hand, if the flotation reagent feeding is more than required, the selectivity will be reduced and both the useful ore and the gangues would adhere to the air bubbles and float to surface. The froths will overflow and the performances of flotation are deteriorated, leading to a high tailing grade and low recovery. In real flotation process, to ensure a high concentrate grade the operator would normally add more flotation reagent feeding to the system. This causes a high tailing grade, a low metal recovery and results in the unnecessary waste of flotation reagent.

3. THE INTELLIGENT CONTROL METHOD FOR FLOTATION PROCESS

To solve the problems described above, an intelligent control method is developed. This method combines modelling and controlling, feedback and feed forward compensators together in order to control $\beta_{ck}(t)$ and $\beta_{wk}(t)$ within their target ranges. The so-formed closed loop system is presented in Fig. 2, where the system is comprised of a slurry consistency control, a supply ore control, an air flow rate control, a flotation level control and a flotation reagent hybrid intelligent controller.

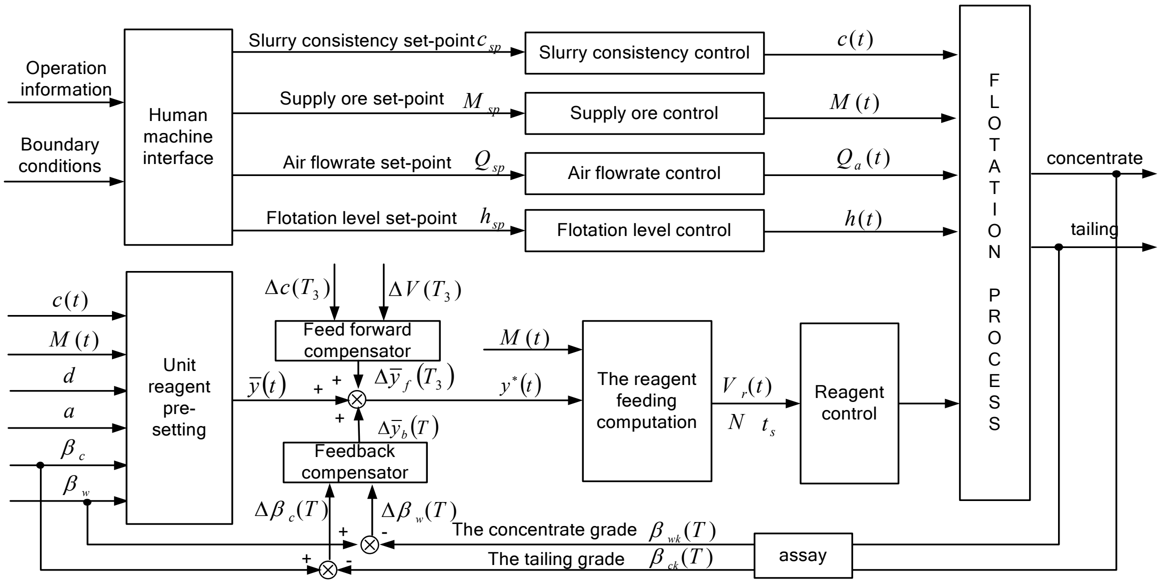

Fig. 2. The intelligent control strategy for flotation process

To control the actual values of the slurry consistency, the supply ore, the air flow rate and the flotation level close to their set-points, the well-known PID controllers have been used on individual basis to form the required closed loop control for these four systems.

Apart from these typical controllers, the proposed flotation reagent feeding controller is comprised of a unit reagent pre-setting model, a feedback compensator and a feed forward compensator, a reagent feeding computation model and a reagent controller. In this context, the unit reagent pre-setting model is established using rule based reasoning (RBR) technique. This model produces the initial value of the unit reagent as denoted by $\bar{y}(t)$ using the slurry consistency c, the supply ore mass M, the particle size d, the source ore grade α, the concentrate grade target β_c and the tailing grade target β_w, respectively.

The feedback compensator is also based on the RBR technique to produce a feedback compensating values $\Delta\bar{y}_b(T)$ applied to the unit reagent pre-setting model using the errors of concentrate grade and the tailing grade as denoted by $\Delta\beta_c(T)=\beta_c-\beta_{ck}(T)$ and $\Delta\beta_w(T)=\beta_w-\beta_{wk}(T)$, where $\beta_{ck}(T)$ and $\beta_{wk}(T)$ are the on-site laboratory measured values, T is the sampling interval of the feedback compensator.

According to the errors between the slurry consistency set-point and its actual value $\Delta c(T_3)=c_{sp}-c(T_3)$, and the slurry flow rate error $\Delta V(T_3)=V_{sp}-V(T_3)$, respectively, where T_3 is the sampling interval of the feed forward compensator, the feed forward compensator is established using again the RBR technique. This feed forward compensator will generate a compensating signal denoted by $\Delta\bar{y}_f(T_3)$ in order to attenuate the interference caused by the variations of boundary conditions. Therefore using the outputs generated from above three models, the unit reagent optimal set-point $y^*(t)$ can be obtained to given

$$y^*(t)=\bar{y}(t)+\Delta\bar{y}_b(T)+\Delta\bar{y}_f(T_3) \tag{2}$$

The reagent feeding computation model firstly generates the reagent feeding V_r according to a certain time interval per denoted by T_1. Then the number of operational electro-magnetism valves N and the flotation reagent adding time interval t_s with respect to the work cycle duration T_2 of the related electro-magnetism valve are determined using the flow rate of the valve capacity V_0. In the end the reagent controller operates these electro-magnetism valves to realize the control of the actual reagent feeding so as to track the flotation reagent set point V_r.

3.1 *The Arithmetic of the Unit Reagent Pre-setting Model*

A method of protocol analysis (Neli, 1998; Wagner, Ottto, and Chung, 2002), together with the veteran experiences about the flotation reagent operation is adopted in the unit reagent pre-setting model, the feedback compensator and the feed forward compensator to extract the protocols. These protocols are transformed to a series of expert rules and they are stored in the knowledge base of the expert system. The knowledge is presented as production rules (Wu, Nakano, and She, 1999) as follows.

If <*promise*> then <*conclusion*>

In the rule base for the unit reagent pre-setting model, the promises of each rule are defined as the consistency c, the supply ore mass M, the slurry particle size d and the ore grade a together with the concentrate grade target β_c and the tailing grade β_w, respectively. The conclusion of each rule is the unit reagent pre-setting $\bar{y}(t)$ that is applied to the selected valve. For the feedback compensator, the promises are the tracking errors denoted by $\Delta\beta_c(T)$ and $\Delta\beta_c(T)$, and the rule conclusion is $\Delta\overline{y}_b(T)$. As for the feed forward compensator the promises are the tracking errors denoted by $\Delta c(T_3)$ and $\Delta V(T_3)$, and the rule conclusion is $\Delta\overline{y}_f(T_3)$.

In the rule base for the unit reagent pre-setting model, according to the operational experiences, the ranges of the slurry consistency c, the supply ore mass M, the slurry particle size d and the ore grade a are classified, respectively. The results of variables in the promise are shown in table1

Table 1 The limits of variables of c, M, d, a

variable	lower	upper
	c_{11}	c_{21}
	c_{12}	c_{22}
c	c_{13}	c_{23}
	c_{14}	c_{24}
	c_{15}	c_{25}
	M_{11}	M_{21}
M	M_{12}	M_{22}
	M_{13}	M_{23}
	$d_{\max}$	
d	$d_{\min}$	$d_{\max}$
	$d_{\min}$	
	$\alpha_{\max}$	
a	$\alpha_{\min}$	$\alpha_{\max}$
	$\alpha_{\min}$	

In table 1, c_{1j} and c_{2j} (*j=1,2,...,5*) are the lower and upper limits of each relevant intervals of variable c, M_{1j} and M_{2j} (*j=1,2,3*) are the lower and upper limits of M, $d_{\min}$ and $d_{\max}$ are the lower and upper limits of d, $\alpha_{\min}$ and $\alpha_{\max}$ are the lower and upper limits of a.

Commonly, the technologist of the unit reagent pre-setting value can be attained by the laws and methods of the reagent feeding according to on site laboratory test and industrial test. Summarizing these laws and methods, the unit reagent pre-setting rules can be acquired and stored in the unit pre-setting base. The expert rules for the unit reagent pre-setting model are formulated using the following procedure.

For example, if at present the slurry consistency c is greater than c_{13} and less than c_{23}, the supply ore mass M is greater than M_{12} and less than M_{22}, the concentrate grade target and tailing grade target are β_c and β_w, the particle size d is greater than $d_{\min}$ and less than $d_{\max}$, and the supply ore grade a is greater than $a_{\min}$ and less than $a_{\max}$, respectively, then according to process knowledge and expert experiences the unit reagent pre-setting value is set to $\overline{y}(t)=r_1$. This can be described by rule1 as follows

Rule1:IF $c_{13} \leqslant c < c_{23}$ and $M_{12} \leqslant M < M_{22}$ and β_c and β_w and $d_{\min} \leqslant d < d_{\max}$ and $a_{\min} \leqslant a < a_{\max}$ THEN $\overline{y}(t)=r_1$

The other knowledge protocols and the corresponding rules can be expressed as follows. Assume at present c is greater than c_{12} and less than c_{22}, M is greater than M_{12} and less than M_{22}, the technical indices target are β_c and β_w, d is greater than $d_{\min}$ and less than $d_{\max}$, and a is greater than $a_{\min}$ and less than $a_{\max}$, respective. In this case, the slurry consistency c is a bit high and others are normal. The unit reagent pre-setting value $\overline{y}(t)=r_1$ is acquired, leading to the following expert rule 2

Rule2:IF $c_{12} \leqslant c < c_{22}$ and $M_{12} \leqslant M < M_{22}$ and β_c and β_w and $d_{\min} \leqslant d < d_{\max}$ and $a_{\min} \leqslant a < a_{\max}$ THEN $\overline{y}(t)=r_1$

These rules can be combined into a rule base along with all the possible gained operational experiences of the flotation reagent pre-setting. Such a rule base of the unit reagent pre-setting model constitutes the following table 2

Table 2 The expert rules for the unit reagent pre-setting

Rules	*Antecedents*	*Conclusions*
Rule1	$c_{13} \le c < c_{23}$ *and* $M_{12} \le M < M_{22}$ *and* β_c *and* β_w *and* $d_{\min} \le d < d_{\max}$ *and* $a_{\min} \le a < a_{\max}$	$\overline{y}(t) = r_1$
Rule2	$c_{12} \le c < c_{22}$ *and* $M_{12} \le M < M_{22}$ *and* β_c *and* β_w *and* $d_{\min} \le d < d_{\max}$ *and* $a_{\min} \le a < a_{\max}$	$\overline{y}(t) = r_1$
…	…	
Rule i	$c_{12} \le c < c_{22}$ *and* $M_{13} \le M < M_{23}$ *and* β_c *and* β_w *and* $d_{\max} \le d$ *and* $a_{\min} \le a < a_{\max}$	$\overline{y}(t) = r_1$
…	…	

In response to the variations of the input variables and their combinations, all rules have been obtained. As a result, the pre-setting value $\overline{y}(t) = r_1$ can be obtained with respect to different inputs. In practice all the data from the process is stored in a data base which works collaboratively with the established rule base. Once particular data information is collected, they will be used to activate the corresponding rule so as to generate the required $\overline{y}(t)$.

In the same way, the rule bases of the feedback compensator and the feed forward compensator are established which are listed in table 3 and table 4.

Table 3 The expert rules for the feedback compensator

Rules	*Antecedents*	*Conclusions*
Rule1	$-M_1 \le \Delta\beta_c < M_1$ *and* $-N_1 \le \Delta\beta_w < N_1$	$\Delta\overline{y}_b(T) = r_2 = 0$
Rule2	$M_1 \le \Delta\beta_c < M_2$ *and* $-N_1 \le \Delta\beta_w < N_1$	$\Delta\overline{y}_b(T) = r_2$
…	…	
Rule i	$M_2 \le \Delta\beta_c < M_3$ *and* $N_1 \le \Delta\beta_w < N_2$	$\Delta\overline{y}_b(T) = r_2$
…	…	

In table 3, M_i (*i=1,2,3*) and N_i (*i=1,2*) are the lower and upper limits of each relevant intervals of the $\Delta\beta_c(T)$ and $\Delta\beta_w(T)$, r_2 is the feedback compensating value of $\Delta\bar{y}_b(T)$.

Table 4 The expert rules for the feed forward compensator

Rules	Antecedents	Conclusions
Rule1	$-N_{11} \le \Delta c < N_{11}$ and $-N_{21} \le \Delta V < N_{21}$	$\Delta\bar{y}_f(T_3) = r_3 = 0$
Rule2	$N_{11} \le \Delta c < N_{12}$ and $-N_{21} \le \Delta V < N_{21}$	$\Delta\bar{y}_f(T_3) = r_3$
…	…	
Rule i	$N_{12} < \Delta c$ and $N_{21} \le \Delta V < N_{22}$	$\Delta\bar{y}_f(T_3) = r_3$
…	…	

In table 4, N_{11} and N_{12} are limits of each relevant intervals of the $\Delta c(T_3)$, and N_{21} and N_{22} are limits of each relevant intervals of the $\Delta V(T_3)$, r_3 is the feed forward compensating value of the $\Delta\bar{y}_f(T_3)$.

3.2 The Flotation Reagent Feeding Computation Model

Refer to (2), it can be seen that $y^*(t)$ has been calculated in terms of the unit reagent pre-setting value, the feedback compensating value and the feed forward compensating value. However, the added reagent is applied to the system as a flow rate V_r. Therefore there is a transformation that need to be performed so as to transfer $y^*(t)$ into the required flow rate V_r. This leads to the following equation

$$V_r(t) = \frac{M(t)\cdot y^*(T_1)\cdot T_1}{3600c_r} \tag{3}$$

where c_r is the consistency of the flotation reagent confected ahead, T_1 is the reagent setting cycle and $M(t)$ is the statistical value of the supply ore mass with the following

$$M(t) = \frac{1}{m}\sum_{1}^{m} M^*(k) \tag{4}$$

where $M^*(k)$ is the instantaneous ore mass at sample time which can be acquired as follows(Zhang, He, Chen, Wang, 2002)

$$M^*(k) = \frac{V(k)}{1/\delta + (1-c(k))/c(k)} \tag{5}$$

where δ is the consistency of feeding ore commonly regarded as a constant for a certain type of ore.

The reagent added in the flotation process is mainly a froth collector mixed with twelve amine and hydrochloric acid. This kind of flotation reagent exhibit some undesired properties such as small mobility, high viscosity and corrosive. The feedback control could not be realized because the actuator does not operate for blocked reagent. Therefore the electro-magnetism valve, which has two switching modes namely "on" and "off", has been applied to control the reagent as an actuator. According to the above obtained feeding rate V_r, one can choose an appropriate operation number of valve to realize the required control input with each valve operates in "on" and "off" working mode so that the actual reagent feeding can be made equal to the reagent feeding setting V_r, leading to an approximated continuous feeding of the reagent.

For a given V_r, the required operating number of electro-magnetism valves N is determined from

$$N = \begin{cases} Int(V_r/V_0)+1 & 0 < x < V_0 \\ Int(V_r/V_0) & x = 0 \end{cases} \tag{6}$$

where V_0 is the electro-magnetism valve capacity, $Int(\cdot)$ is integral function, and x is error defined as

$$x = V_r/T_1 - Int(V_r/T_1\cdot V_0)\times V_0 \tag{7}$$

Using these calculations the actual opening duration of each selected operating valve is given by

$$t_s = {V_r T_2}\big/(N\cdot T_1\cdot V_0) \tag{8}$$

4. INDUSTRIAL APPLICATION

The proposed hybrid intelligent control method has been applied to a cationic reverse flotation process of magnetite iron ore in a mineral plant in China. The actual flotation process is illustrated in Fig 3 which is composed of three flotation stages, named as the rougher stage, the scavenging I stage and the scavenging II stage.

Fig. 3. The flotation process at site

Based on the method proposed in this paper, an intelligent control system has been developed. To fully observe the advantages of using the proposed control structure, two experiments were carried out under the same conditions, where one experiment was for the manual control and the other for the intelligent control system. The results of distributions of the technical indices of these two experiments are shown in Fig 4 and Fig 5, respectively.

As shown in Fig.4, it can be seen that when the manual control was applied, the variations of the controlled technical indices represented by the concentrate grade and the tailing grate are of large values. In particular, the variation of the tailing grate is very large and thus leads to heavy metal losses. In comparison, it can be seen from Figure 5 that these variations are clearly small when the proposed intelligent control strategy was applied, leading to a stabilized response of the concentrate grate. In this case, the technical indices are both controlled within their targeted ranges albeit there are still some variations for the tailing grate which has still been controlled inside its target range. This indicates that the proposed h intelligent control can cope with the variations of the boundary conditions of the flotation process via an automated closed loop control so that the influence from the varying boundary conditions on the technical indices is much reduced and that the final concentrate grade and the tailing grade meet the target requirements.

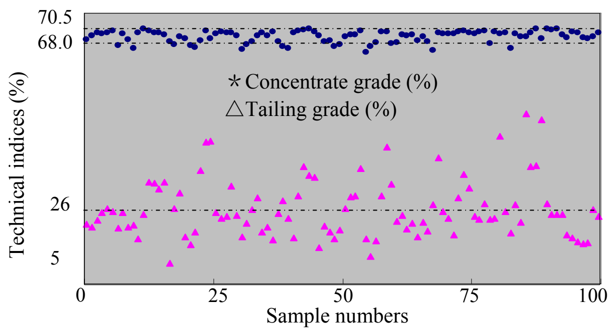

Fig. 4. Distributions of the technical indices of manual control

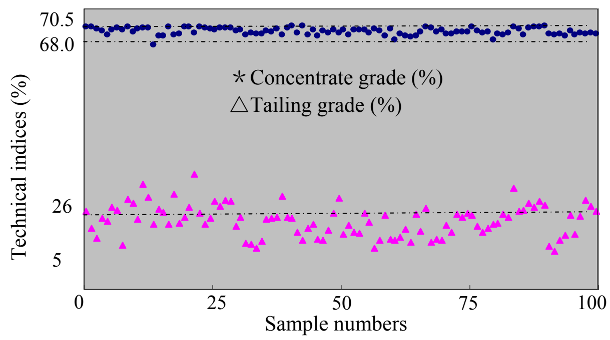

Fig. 5. Distribution of the technical indices of intelligent control system

A long term operation of such an intelligent control strategy on the flotation process have shown, per compared with manual control, that the concentrate grate has been increased by 0.52% and the tailing grade has been reduced by 4%. Also, the consumption of the flotation reagent feeding has been reduced by 17.5%. As such it can be concluded that a real application benefit has been achieved.

5. CONCLUSIONS

Due to the difficulties for the manual operation to achieve an effective control of the concentrate grade and the tailing grade within their targeted ranges for flotation process, this paper has proposed a novel intelligent control strategy which consists of the setting layer and the closed loop control layer for the flotation reagent addition to the process. The flotation reagent feeding setting layer is composed of a unit reagent pre-setting model, a feedback compensator and a feed forward compensator, a reagent feeding computation model for the addition of the reagent whilst the reagent real-time control is realized by automatically selected number of the electro-magnetism valves which are of a switching control mode. This ensures that the actual reagent feeding can follow its setting. Thus the concentrate grade and the tailing grade can both be controlled within their target ranges. Through the real application of the proposed method to an actual floatation process, it can be seen that the proposed intelligent control strategy will have a high potential of being further applied to mineral processing.

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