Data-based Compensation Method for Optimal Operation Setting of Gold Cyanide Leaching Process

Tan Liu, Qingyun Yuan*, Lina Wang, Yonggang Wang

***Abstract*—The reaction mechanism of gold cyanide leaching process is complex, and there are many factors affecting leaching process. These will lead to some errors between process model and actual process. Therefore, the operation setting point acquired through model-based optimization is not the actual optimal one. As a result, it is difficult for the process to operate under the minimum material consumption required by the hydrometallurgy process. Therefore, a data-based compensation method for optimal operation setting of gold cyanide leaching process is proposed. Firstly, the optimal operation setting point is obtained through model-based optimization. Then, near the setting point, using the idea of Just-In-Time Learning (JITL), the model is established to describe the relationship between setting point deviation and material consumption reduction. On the basis of this model, the deviation of the setting point from the actual optimal one can be obtained by optimization. Furthermore, through iterative compensation, the setting point gradually converges to the actual optimal one, and the material consumption is further reduced. Finally, the gold cyanide leaching process in a smelter is taken as study object, the results prove this method is effective.**

***Index Terms*—cyanide leaching, data, optimization compensation, JITL.**

I. Introduction

HYDROMETALLURGY is a typical gold smelting process, which has been widely used in the metallurgical industry. Although it includes many sub-processes, which are gold cyanide leaching process, zinc powder cementation process, thickening and washing process, etc. However, as the first sub-process of hydrometallurgy process, the optimal control of leaching process will directly affect the stable and reliable operation of the whole process [1]. In general, leaching rate is ensured by adding excessive leaching agent. However, such operation will increase the material consumption in leaching process. Meanwhile, as market competition intensifies and economic globalization, energy-saving and consumption-reducing has become the essential proposition of hydrometallurgy industry. Therefore, to decrease the production cost and enhance the competitiveness of enterprises, the research for optimal control of leaching process is quite necessary [2].

Many scholars have researched the optimal control methods of gold cyanide leaching process. For example, de Andrade studied a mathematical model that could describe the gold cyanide leaching process. And he applied this model in optimization to reduce the production cost of process [3]. In addition, he discussed the problem of adding leaching agent to a multistage leaching tank and got the following conclusion [4]. When the consumption of leaching agents is low and the dissolution rate of gold is fast, all leaching agents shall be put in the first leaching tank. If not, they shall be put in other leaching tanks except the first one. Aiming at the difficulty of online detection of leaching rate, Zhang et al. constructed a soft sensor prediction model for leaching rate [5]. To sum up, the optimization methods of leaching process mainly depends on process model, and the forecasting precision of model directly affects the reliability of optimization results. However, there exist numerous limitations such as the production process, measuring instruments and the field environment, and always fail to build an accurate mathematical model for describing leaching process. In other words, the model and the actual process cannot exactly match. Therefore, the operation setting point obtained through model-based optimization is not the actual optimal one. Moreover, the corresponding material consumption of this process is not the lowest, resulting in high production cost and waste of resources. And it is difficult for this optimization method to solve the problem caused by model mismatch.

With the improving of the automation level in leaching process, a large quantity of data has been stored. This provides conditions for using data to compensate for operation setting point obtained through model-based optimization. Based on this, some scholars put forward the optimization method of leaching process based on correction term [6]-[9]. This method use the actual measurement data to modify the original model-based optimization problem, and makes the setting point close to the actual optimal setting point. Although this method can achieve the actual optimal setting point in theory, it is very time-consuming. Because the optimization problem needs to be solved repeatedly. In addition, when there is measurement noise and the gradient of actual

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data cannot be accurately estimated, the reliability of this method cannot be guaranteed.

In view of the above problems, according to the successful application of data modeling in chemical processes [10]-[12], this paper presents a new optimization compensation method for leaching process. In this method, the operation setting point is first obtained through model-based optimization. Then, near the setting point, the quantitative relationship between setting point deviation and material consumption reduction is constructed by data modeling method. And the setting point deviation is obtained with maximizing the material consumption reduction. Furthermore, the operation setting point is compensated once. Through iterative compensation, the operation setting point gradually approaches the actual optimal one, thus further reducing the material consumption of leaching process.

This paper is divided into the following parts: The cyanide leaching process of gold is introduced in Section II. In Section III, the compensation problem for the operation setting point in cyanide leaching process is described. In Section IV, a new optimization compensation method for leaching process is put forward. In Section V, the example verification is made and results are analyzed. Lastly, the conclusion is given.

II. Gold Cyanide Leaching Process

This paper takes the leaching process of a gold smelter in China as a background, its producing flow is depicted in Fig. 1.

As seen in Fig. 1, firstly, the tailings after separation and flotation are mixed with water to form pulp. Then, the pulp is successively transported to 1# $\sim$ 7# pneumatic leaching tanks. In each pneumatic leaching tank, the leaching agent ($NaCN$) is added by the automatic dosing device, and the air is injected by the wind turbine. Then, they react with the gold in tailings, and the reaction equation is expressed as (1). After the reaction, the gold in tailings is dissolved into liquid phase with form of gold cyanide complex ion, realizing the transfer of gold components from solid phase to liquid phase. With increasing reaction time, gold cyanide ion concentration in liquid phase increases with the number of leaching tanks. While gold content in solid phase decreases with the number of leaching tanks, thus realizing the complete leaching. Finally, the leaching solution is transported to the tank of pregnant solution, and used for zinc dust precipitation.

$$4Au+8NaCN+2H_2O+O_2 \rightarrow 4NaAu(CN)_2+4NaOH \tag{1}$$

According to Fig.1 and works in literatures [13]-[15], the process model is established and expressed as follows:

$$\begin{cases} \frac{Q_{i,s}}{M_{i,s}}(C_{i-1,s0}-C_{i,s0})-r_{Au}=0 \\ \frac{Q_{i,l}}{M_{i,l}}(D_{i-1,s}-D_{i,s})-\frac{M_{i,s}}{M_{i,l}}r_{Au}=0 \\ \frac{Q_{i,l}}{M_{i,l}}(C_{(i-1),cn}-C_{i,cn})+\frac{Q_{i,cn}}{M_{i,l}}-r_{i,cn}=0 \end{cases} \tag{2}$$

where the subscript i represents the related quantity in the i-th leaching tank, $Q_{i,s}$ and $Q_{i,l}$ are quantities of ore and liquid respectively. $M_{i,s}$ and $M_{i,l}$ are the mass of ore and liquid stranded in the tank respectively. $C_{i,s0}$ is the initial gold grade of ore, and r_{Au} is the dissolution rate of gold. $D_{i,s}$ is the gold grade in liquid phase, $C_{i,cn}$ is the cyanogen ion concentration in liquid phase, and $Q_{i,cn}$ is the adding quantity of sodium cyanide. $r_{i,cn}$ is the cyanogen ion consumption rate [16], represented as follows:

$$r_{i,cn}=k_1+k_2C_{i,cn} \tag{3}$$

where k_1 and k_2 are unknowns, they are estimated by actual process data.

According to the process model, the operation vector of process is $\boldsymbol{Q}=[Q_{1,cn},Q_{2,cn},\cdots,Q_{7,cn}]^T$. It directly affects the leaching rate y, so Equation (2) can be expressed as follows:

$$y=\frac{C_{0,s0}-C_{7,s0}}{C_{0,s0}}\times 100\% = f(\boldsymbol{Q}) \tag{4}$$

III. Compensation Problem of Optimal Operation Setting in Gold Cyanide Leaching Process

According to the description in Section II, the material consumption of gold cyanide leaching process includes tail-

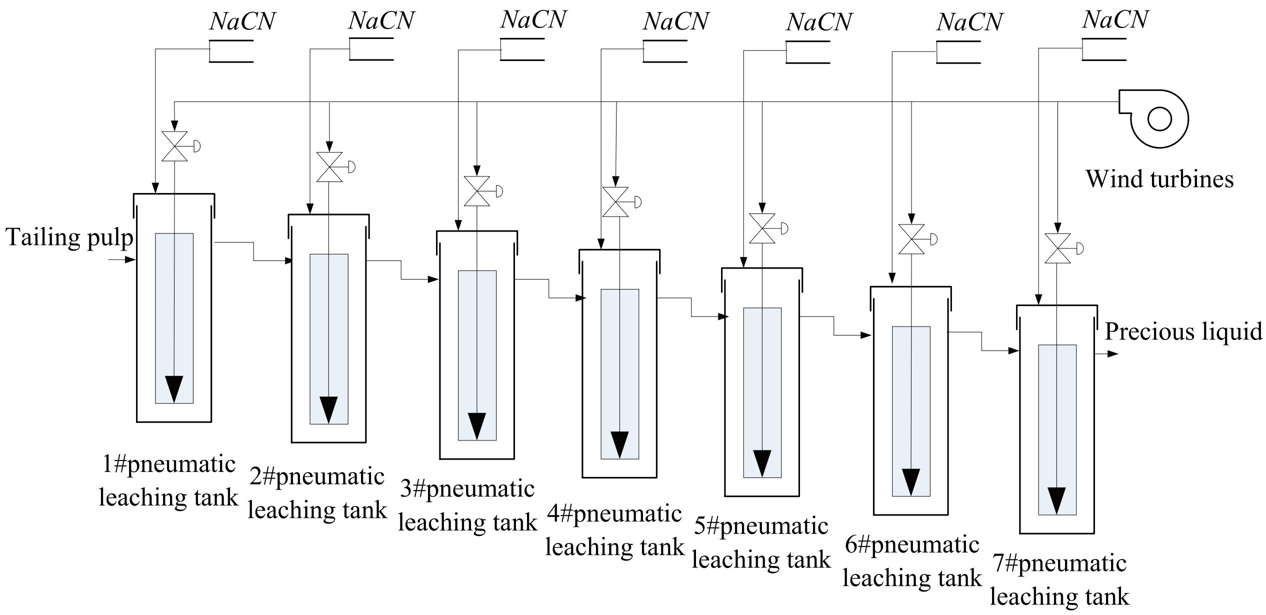

Fig. 1. Flow Chart of Cyanide Leaching Process

ings consumption, sodium cyanide consumption and electric energy consumption of wind turbine, as shown below.

$$W = Q_s \cdot P_s + \sum_{i=1}^{7} Q_{i,cn} \cdot P_{cn} + Q_e \cdot P_e \tag{5}$$

where Q_s is tailings quantity, Q_e is the electric energy consumption of wind turbine, P_s, P_{cn} and P_e are the unit prices of tailings, sodium cyanide and electric energy respectively.

In the optimization based on process model, when the treatment quantity is a certain value, the consumption of tailings and the electric energy consumption of wind turbine are usually constants. Therefore, in order to reduce the material consumption of process, the adding quantity of sodium cyanide should be as little as possible under the condition of meeting the given leaching rate. So the operation vector $\boldsymbol{Q}$ is chose as the decision-making vector, and the minimum recovery rate, process model and operation capacity are taken as constraints. The expression of the optimization problem for leaching process is as below.

$$\begin{aligned} & min\ W \\ & s.t.\ y \geq \eta \\ & \quad y = f(\boldsymbol{Q}) \\ & \quad Q_{cn,min} \leq Q_{i,cn} \leq Q_{cn,max}, i = 1, 2, \cdots, 7 \end{aligned} \tag{6}$$

where η is a specified value.

Through solving the problem in (6), the optimal operation setting point $\hat{\boldsymbol{Q}}$ is acquired. However, there exist numerous limitations such as process conditions, instrument performance and complex field environment, the model and the actual process cannot exactly match. As a result, the optimal setting point $\hat{\boldsymbol{Q}}$ is not the actual optimal setting point $\boldsymbol{Q}^*$, and the corresponding material consumption $W(\hat{\boldsymbol{Q}})$ is not the actual minimum consumption $W(\boldsymbol{Q}^*)$. Fortunately, the material consumption can be expanded as Taylor series near the optimal set point, it is represented as follows:

$$W(\hat{\boldsymbol{Q}}) = W(\boldsymbol{Q}^*) + \frac{\partial W}{\partial \boldsymbol{Q}}(\hat{\boldsymbol{Q}} - \boldsymbol{Q}^*) + \frac{\partial W^2}{\partial \boldsymbol{Q}^2}(\hat{\boldsymbol{Q}} - \boldsymbol{Q}^*)^2 + \sigma \tag{7}$$

where σ is high step infinitely small.

Suppose that $\Delta W = W(\hat{\boldsymbol{Q}}) - W(\boldsymbol{Q}^*)$ and $\Delta \boldsymbol{Q} = \hat{\boldsymbol{Q}} - \boldsymbol{Q}^*$, (7) can be expressed as follows:

$$\Delta W = \frac{\partial W}{\partial \boldsymbol{Q}} \Delta \boldsymbol{Q} + \frac{\partial W^2}{\partial \boldsymbol{Q}^2} \Delta \boldsymbol{Q}^2 + \sigma \tag{8}$$

Therefore, if the model between ΔW and $\Delta \boldsymbol{Q}$ is established near the optimal setting point and expressed as follows:

$$\Delta W = H(\Delta \boldsymbol{Q}) \tag{9}$$

Then, through solving the optimization problem in (10), the deviation between $\hat{\boldsymbol{Q}}$ and $\boldsymbol{Q}^*$ is received.

$$\begin{aligned} & max\ \Delta W = H(\Delta \boldsymbol{Q}) \\ & s.t.\ y \geq \eta \\ & \Delta \boldsymbol{Q}_L \leq \Delta \boldsymbol{Q} \leq \Delta \boldsymbol{Q}_U \end{aligned} \tag{10}$$

By subtracting the deviation $\Delta \boldsymbol{Q}$ from the current operation setting point $\hat{\boldsymbol{Q}}$, it is compensated once. Meanwhile, the compensated operation setting point is applied to leaching process. Then, the current setting point $\hat{\boldsymbol{Q}}$ gradually converges to the actual optimal setting point $\boldsymbol{Q}^*$ by iterative compensation, which helps to reduce the material consumption of process further.

IV. Optimization Compensation Method for Leaching Process Based on Data

Basing on the above idea, a new optimization compensation method for leaching process is proposed. Among them, considering the nonlinearity between ΔW and $\Delta \boldsymbol{Q}$ near the optimal operation setting point, a quantitative model describing their relationship is constructed by Least Square Support Vector Machine (LSSVM) [17]-[18]. Then, basing on this model, the deviation of the current operation setting point from the real optimal one is achieved by optimization method. This deviation is utilized to compensate the current operation setting point. After compensation, the setting point is applied to real producing process by the control of bottom level [19]-[20], and the implementation flow is given, as illustrated in Fig.2.

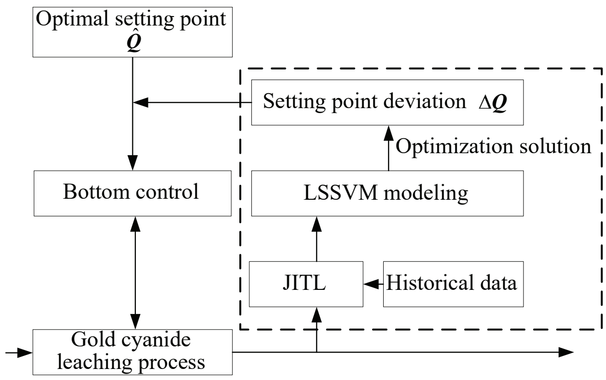

Fig. 2. Flow Chart of Compensation for Operation Setting Point

A. LSSVM Modeling Based on Just-In-Time Learning

With taking into account characteristics of model between ΔW and $\Delta \boldsymbol{Q}$ and wide application of Just-In-Time Learning (JITL) as a local nonlinear fitting algorithm [21], the main idea of JITL is used to choose data from historical data. The selected data needs to be very similar to the current data $(\hat{\boldsymbol{Q}}, \hat{W})$. The similarity between two groups of data is measured by s_i [22]-[24], which is expressed as follows:

$$s_i = \lambda \sqrt{e^{-d^2(\hat{\boldsymbol{Q}}, \boldsymbol{Q}_i)}} + (1 - \lambda) cos(\theta_i) \tag{11}$$

where $\lambda \in [0, 1]$, and

$$d(\hat{\boldsymbol{Q}}, \boldsymbol{Q}_i) = \|\hat{\boldsymbol{Q}} - \boldsymbol{Q}_i\|_2 \tag{12}$$

$$cos(\theta_i) = \frac{\Delta \hat{\boldsymbol{Q}}^T \Delta \boldsymbol{Q}_i}{\|\hat{\boldsymbol{Q}}\|_2 \|\boldsymbol{Q}_i\|_2} \tag{13}$$

From (11), it can be seen that if s_i is larger, the similarity between the two groups of data is stronger. And if s_i satisfies as follows:

$$s_i \geq \delta_s \tag{14}$$

The data $(\boldsymbol{Q}_i, W_i)$ will be selected from historical data. Through such judgement, $(\boldsymbol{Q}_j, W_j), j = 1, 2, \cdots, m$ are selected from historical data and processed as follows:

$$\begin{cases} \Delta \boldsymbol{Q}_j = \hat{\boldsymbol{Q}} - \boldsymbol{Q}_j \\ \Delta W_j = \hat{W} - W_j \end{cases} \tag{15}$$

Then, $(\Delta \boldsymbol{Q}_j, \Delta W_j), j = 1, 2, \cdots, m$ are acquired, and the model between ΔW and $\Delta \boldsymbol{Q}$ is established by using these data.

Assuming that $\boldsymbol{x}_j = \Delta \boldsymbol{Q}_j$ and $e_j = \Delta W_j$, the model established by LSSVM is as shown here.

$$e = \sum_{j=1}^{m} \alpha_j K(\boldsymbol{x}, \boldsymbol{x}_j) + b \tag{16}$$

where α_j is the Lagrange multiplier, $K(\cdot, \cdot)$ is the kernel function, and b is the offset.

B. Acquisition of Operation Setting Deviation

Based on (16), the deviation of the current operation setting point from the actual optimal one is acquired by solving this problem:

$$\begin{aligned} & max\ \Delta W = H(\Delta \boldsymbol{Q}) \\ & s.t.\ \boldsymbol{Q}_L \leq \hat{\boldsymbol{Q}} - \Delta \boldsymbol{Q} \leq \boldsymbol{Q}_U \\ & \Delta \boldsymbol{Q}_L \leq \Delta \boldsymbol{Q} \leq \Delta \boldsymbol{Q}_U \end{aligned} \tag{17}$$

Since the compensated operation setting point $\boldsymbol{Q}$ and the deviation $\Delta \boldsymbol{Q}$ must be within the capacity of the operation variable, the optimization problem contains two inequality constraints, namely $\boldsymbol{Q}_L \leq \hat{\boldsymbol{Q}} - \Delta \boldsymbol{Q} \leq \boldsymbol{Q}_U$ and $\Delta \boldsymbol{Q}_L \leq \Delta \boldsymbol{Q} \leq \Delta \boldsymbol{Q}_U$. Among them, $\boldsymbol{Q}_L$ and $\boldsymbol{Q}_U$ are the lowest and highest values of $\boldsymbol{Q}$ respectively. $\Delta \boldsymbol{Q}_L$ and $\Delta \boldsymbol{Q}_U$ are the lowest and highest values of $\Delta \boldsymbol{Q}$ respectively.

C. Iterative Compensation of Optimal Operation Setting Point

By solving the optimization problem in (17), the operation setting deviation $\Delta \boldsymbol{Q}$ and the corresponding material consumption reduction ΔW are obtained. If ΔW satisfies as follows:

$$\frac{\Delta W}{\hat{W}} > \delta_W \tag{18}$$

where δ_W is a threshold.

The current operation setting point is compensated by the deviation, and then applied to actual production process. Near the compensated setting point, data modeling is conducted again, and a new compensation value is obtained through optimization. If the corresponding material consumption reduction still meets (18), the setting point will be compensated again. And the above steps will be repeated until the material consumption reduction no longer satisfies (18). The corresponding iterative compensation flow is depicted in Fig. 3.

Fig. 3 consists of these steps:

Step 1: By solving the problem in (6), the current process data $(\hat{\boldsymbol{Q}}, \hat{W})$ is achieved.

Step 2: The data similar to $(\hat{\boldsymbol{Q}}, \hat{W})$ is chose from historical data by using the judgement in (14), and based on these data, the model between ΔW and $\Delta \boldsymbol{Q}$ is established by using LSSVM.

Step 3: By using an improved particle swarm optimization (SOPSO) [25]-[27], the optimal setting point deviation and material consumption reduction is achieved by solving the problem in (17).

Step 4: If (18) is satisfied, the compensated setting point $\hat{\boldsymbol{Q}} - \Delta \boldsymbol{Q}$ shall be used in gold cyanide leaching process. Meanwhile, it needs to go back to Step 1. If not, the current optimal setting point should remain unchanged.

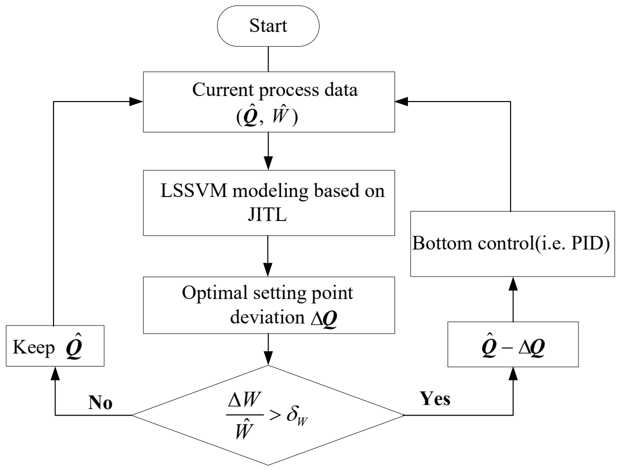

Fig. 3. Flow Chart of Iterative Compensation for Optimal Operation Setting Point

V. Example Validation and Result Analysis

To demonstrate the effectiveness and feasibility of the aforementioned method, firstly, the unknown parameters k_1 and k_2 in (4) are identified through process data, as shown in Table 1.

TABLE I
IDENTIFICATION RESULTS OF MODEL PARAMETERS

Number of groups	k_1	k_2
1	3.43	0.0147
2	3.46	0.0145

Based on the results of Table 1, k_1 is smaller and k_2 is larger in the first group of identification results than that in the second group of identification results. It indicates that when k_1 and k_2 are set to values in the first group, the corresponding gold reaction rate is slower, the reaction rate of cyanide ion is faster, and the consumption of cyanide is more. Therefore, the results in the first group are substituted into (4), which is taken as process model. The results of the other group are substituted into (4), which is taken as the actual process. Due to different values of parameters, the process model is different from the actual process, so they can be used to compare the gap between the compensated material consumption and the actual optimal material consumption.

SOPSO is applied for solving the problem in (6), and its parameters settings are as follows: the particle number is 50, the maximum iterative number of times is 20, the inertia weight $\omega = 0.8$, learning factors c_1 and c_2 are 1.2 and 0.9, respectively. According to solution of optimal model, the results based on process model and actual process are obtained, as shown in Table 2.

TABLE II
RESULTS BASED ON PROCESS MODEL AND ACTUAL PROCESS

Variables	Process model	Actual process
W(RMB/h)	6632.32	5395.19
$Q_{1,cn}(kg/h)$	115.92	123.12
$Q_{2,cn}(kg/h)$	113.35	117.06
$Q_{3,cn}(kg/h)$	110.26	112.47
$Q_{4,cn}(kg/h)$	105.54	94.52
$Q_{5,cn}(kg/h)$	89.99	72.31
$Q_{6,cn}(kg/h)$	35.19	16.26
$Q_{7,cn}(kg/h)$	30.69	8.45

Then, some data is randomly generated through the actual process. And 120 groups of data are selected from these data, which have strong similarity with the current data. Using these selected data, the model between ΔW and $\Delta \boldsymbol{Q}$ is established by using LSSVM. On this basis, the optimization problem in (17) is solved by using SOPSO algorithm, and the algorithm parameters are set the same as above. Since the optimization results of the first iteration satisfy (18), the deviation $\Delta \boldsymbol{Q}$ is used to compensate for the operation setting point obtained through model-based optimization. After compensation, the setting point is used in actual leaching process, and then the material consumption reduction $\Delta W = 256.76$(RMB/h) is obtained. Then, the iterative compensation is conducted until it no longer satisfies (18). At the same time, the iteration ends, and the number of iterations is 9. The material consumption reduction ΔW and setting point deviation $\Delta \boldsymbol{Q}$ of each iteration are given, as described in Table 3.

From the results in Table 3, with the increasing of iterations, ΔW and $\Delta \boldsymbol{Q}$ decreases until ΔW no longer meets (18). After the final iterative compensation, the operation setting point is obtained and compared with the actual optimal setting point, as shown in Table 4.

TABLE IV
COMPARISON OF SETTING POINT AFTER COMPENSATION AND ACTUAL OPTIMAL SETTING POINT

Variables	Setting point after compensation	Actual optimal setting point
$Q_{1,cn}(kg/h)$	122.35	123.12
$Q_{2,cn}(kg/h)$	116.84	117.06
$Q_{3,cn}(kg/h)$	112.32	112.47
$Q_{4,cn}(kg/h)$	94.59	94.52
$Q_{5,cn}(kg/h)$	73.43	72.31
$Q_{6,cn}(kg/h)$	17.20	16.26
$Q_{7,cn}(kg/h)$	9.52	8.45

As Table 4 shows, after 9 iterations of compensation, the operation setting point approaches the actual optimal operation setting point.

To display the compensated results more intuitively, the material consumption obtained by the proposed optimization compensation is shown in Fig. 4.

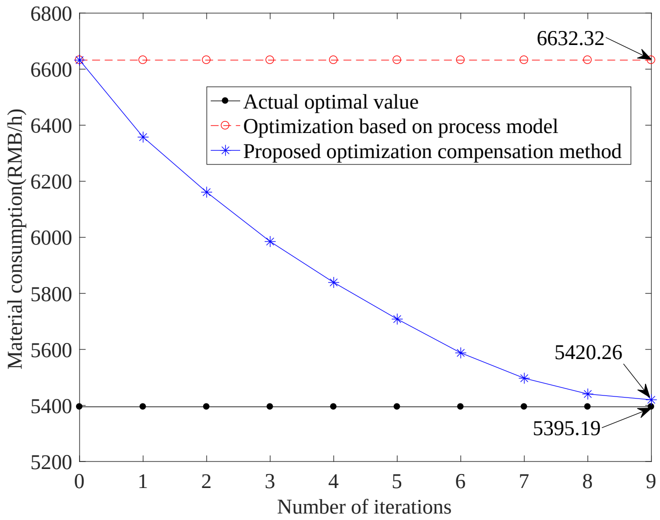

Fig. 4. Material Consumption Obtained by the Proposed Optimization Compensation Method

From Fig. 4, it shows that when leaching process operates at the operation setting point obtained through model-based optimization, the material consumption is 6632.32(RMB/h). Leaching process runs at a new operation setting point by iterative compensation, and the material consumption is 5420.26 (RMB/h), decreasing by 18%. The change of sodium cyanide adding quantity of the corresponding seven leaching tanks with iteration times is shown in Figs. 5-11.

It can be seen that after 9 iterations of compensation, the operation setting point of leaching process approaches the actual optimal one, which helps to decrease the material consumption.

To prove the superiority of the proposed method, the optimization method based on correction [6] is also applied for solving the problem in (6). And the obtained results are given, as described in Fig. 12.

As seen in Fig. 12, when the optimization method based on correction is applied for optimizing the material consumption of leaching process, after 16 iterations of compensation, the material consumption converges to actual optimal value. The model-based optimization problem is corrected by using the actual process data, so that the operation setting point approaches the actual optimal one. However, the optimization solution only uses process current information, and does not use process historical information. Therefore, compared with

TABLE III
RESULTS OF ITERATION COMPENSATION

Number of iterations	ΔW	$\Delta Q_{1,cn}$	$\Delta Q_{2,cn}$	$\Delta Q_{3,cn}$	$\Delta Q_{4,cn}$	$\Delta Q_{5,cn}$	$\Delta Q_{6,cn}$	$\Delta Q_{7,cn}$
1	256.76	-1.36	-0.75	-0.44	2.28	3.53	3.86	4.48
2	214.49	-1.14	-0.61	-0.37	1.96	2.91	3.23	3.71
3	176.18	-0.93	-0.49	-0.31	1.56	2.39	2.59	3.15
4	145.99	-0.78	-0.42	-0.25	1.33	2.03	2.13	2.56
5	130.73	-0.69	-0.38	-0.22	1.21	1.77	1.90	2.32
6	120.58	-0.64	-0.35	-0.19	1.09	1.65	1.81	2.08
7	90.49	-0.48	-0.26	-0.15	0.81	1.24	1.33	1.59
8	56.28	-0.31	-0.17	-0.09	0.51	0.77	0.84	0.98
9	20.63	-0.11	-0.06	-0.03	0.19	0.28	0.31	0.36

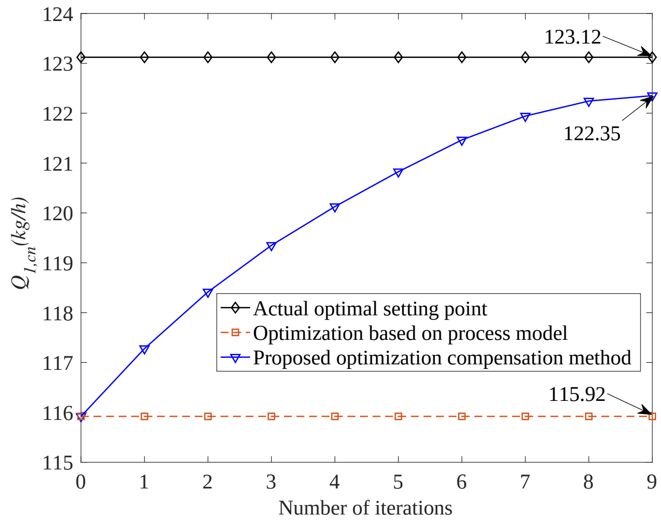

Fig. 5. Change of Sodium Cyanide Adding Quantity of the First Leaching Tank with Iteration Times

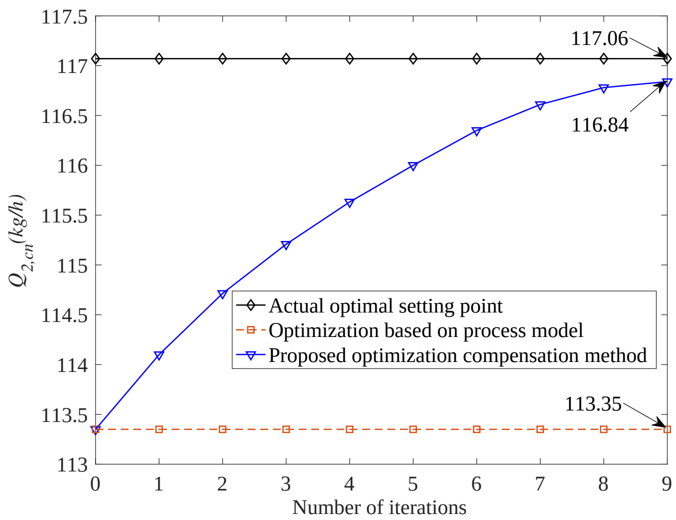

Fig. 6. Change of Sodium Cyanide Adding Quantity of the Second Leaching Tank with Iteration Times

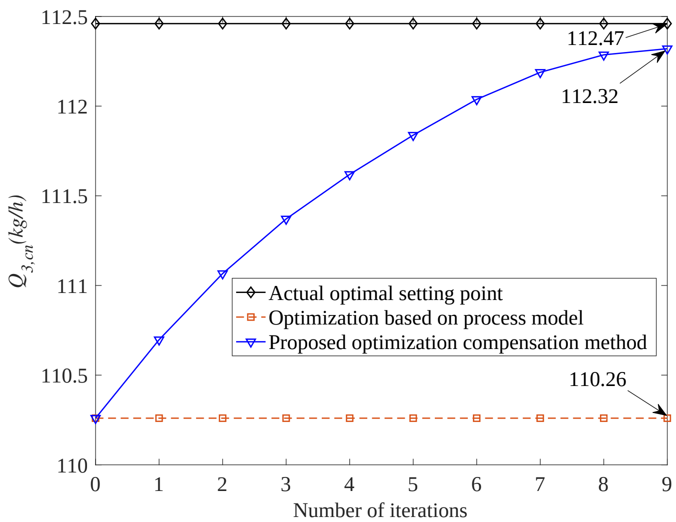

Fig. 7. Change of Sodium Cyanide Adding Quantity of the Third Leaching Tank with Iteration Times

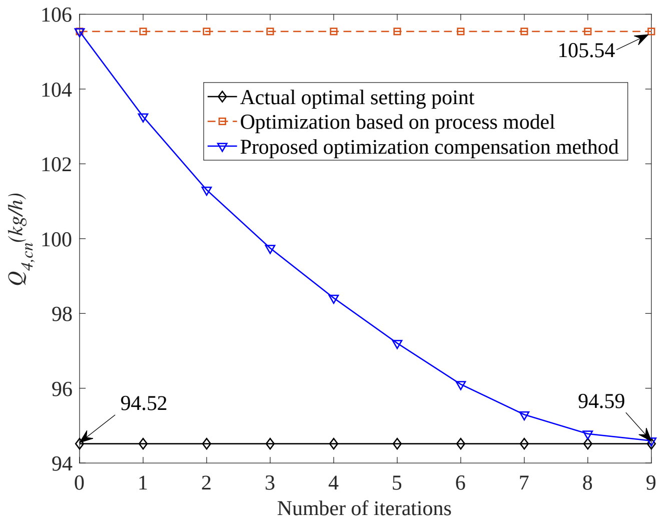

Fig. 8. Change of Sodium Cyanide Adding Quantity of the Forth Leaching Tank with Iteration Times

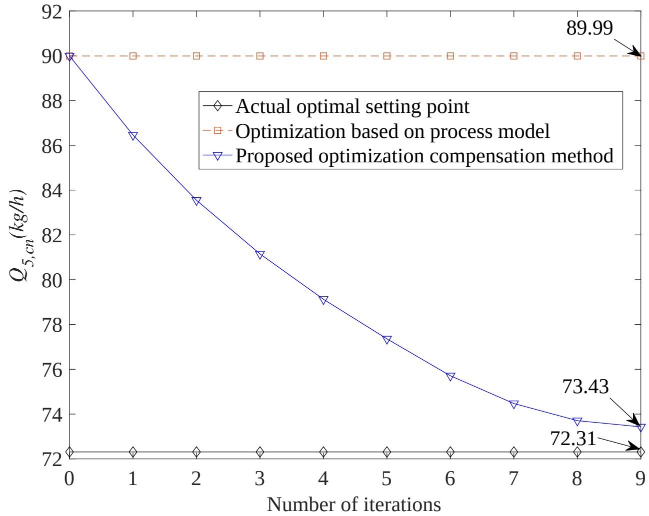

Fig. 9. Change of Sodium Cyanide Adding Quantity of the Fifth Leaching Tank with Iteration Times

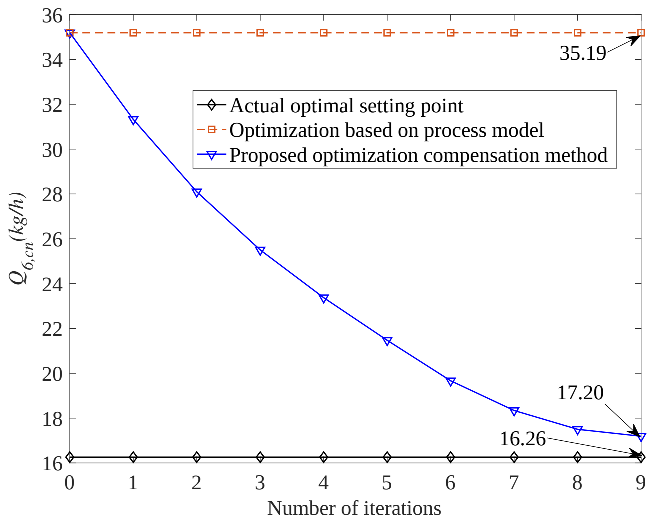

Fig. 10. Change of Sodium Cyanide Adding Quantity of the Sixth Leaching Tank with Iteration Times

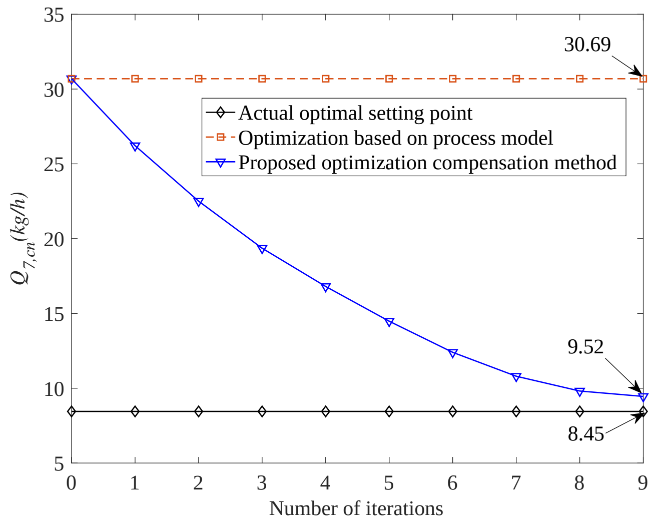

Fig. 11. Change of Sodium Cyanide Adding Quantity of the Seventh Leaching Tank with Iteration Times

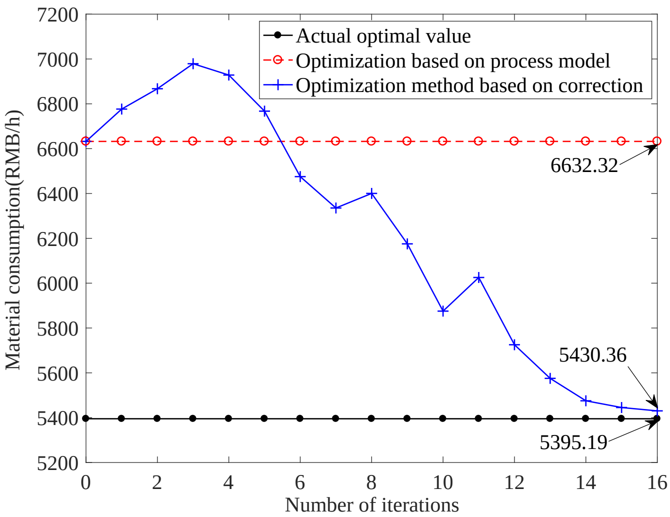

Fig. 12. Material Consumption obtained by Optimization Method Based on Correction

the proposed optimization compensation method, this method needs more iterations and has slower convergence speed.

To quantitatively compare the optimization method based on correction with the proposed method, both are used for solving the optimization problem of leaching process for 100 times. The corresponding performance indexes of the two methods are listed in Table 5.

TABLE V
COMPARATIVE RESULTS OF TWO METHODS

Indexes	Optimization method based on correction	Proposed method
m	16	9
$T_{average}(min)$	0.165	0.232
$T_{total}(min)$	2.64	2.09

In the table above, m indicates the minimum number of iterations to achieve the global optimal value with probability 95%, $T_{average}$ represents the average calculation time of one iteration, and T_{total} represents the calculation time of receiving the global optimum.

As seen from Table 5, compared with the optimization method based on correction, the proposed method requires fewer iterations and can quickly obtain the optimal value.

VI. CONCLUSION

Owing to the characteristics of cyanide leaching process, it is hard to find the actual minimum material consumption just by model-based optimization. Consequently, basing on the obtained operation setting point, the iterative compensation for the optimal operation setting point is realized by using process data, data modeling and optimize method. The proposed method uses not only mechanism information in process model but also other information in process data. Furthermore, the operation setting point approaches the actual optimal one, and the material consumption of leaching process is efficiently reduced.

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