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Multi-objective Hybrid Intelligent Optimization of Operational Indices for Industrial Processes and Application ⋆

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Abstract: To pursuit the plant-wide optimization of multiple units industrial process, a hybrid intelligent optimization approach under dynamic environment is proposed. The objective of optimization is that the production indices defined as the performance related to the final product quality, yield, energy and material consumption fall into their target ranges; whilst the decision variables are operational indices of each unit, which is related to units' intermediate product quality, efficiency and consumption. In this context, the domain knowledge of process engineers are mimicked and combined with the framework in terms of feedback, prediction and feed-forward schemes so as to realize the required optimization. The effectiveness of the proposed approach has been demonstrated by the practical application results.

1. INTRODUCTION

For large-scale industrial processes, most of them consist of multiple units. Each unit has different purpose and performs its own manufacturing task to ensure the intermediate product quality, efficiency, consumption of each unit-process (which are referred as the operational indices in this paper). On the other hand, these units also work in a collaborative way to form a process so as to fulfill the production mission of entire process and to ensure optimization of overall production indices, which characterize the final product quality, yield, energy and material consumption.

Recently, optimal operational control has attracted much attention (Engell [2007], Chai et al. [2011]). However, there is no one method that is applicable for all industrial processes. In chemical industry, a two layered structure consisting of real-time optimization (RTO) and single input and single output (SISO) control has been widely used to perform the optimal operation of unit process. RTO is a model-based method, where static process models are usually required, and its performance is the unit operating profit where the operational indices are taken as the constraints. The decision variables of RTO are set-points of SISO control systems. Since RTO uses static models of the process, once the set-points have been sent to control systems, RTO has to wait until the entire plant settles down before the next execution commences. Besides, there are some other shortcomings, such as model mismatch, etc. Indeed, there are numerous variants and adaptation strategies to tackle the shortages of this approach (Chachuat et al. [2009]). These methods need to establish mathematics models of a process and its constraints. Moreover, the optimization is performed in an open loop manner.

In other industries such as steel making and mineral processing, there always exist unmodelled dynamics and uncertain disturbances, which make the existing model-based methods very difficult to apply. For optimal operational control of such unit process, research results are usually problem based and focused on specific process. For instance, a hybrid intelligent control approach for optimal operation of the shaft furnace has been proposed by Chai et al. [2011], which adjusts the set-points of the control loops in real-time and at the same time the fault working situation diagnosis and tolerant control are considered.

However, these approaches have assumed that the target operational indices are known and no consideration has been made on the fact that the improper target operational cannot ensure global optimization of the production. In the globalized market environment, the ever growing incentive of improving product quality, production efficiency and reducing cost requires optimization of production indices for a whole production line (e.g. Tosukhowong et al. [2004]). Qin et al. [2006] has proposed a hierarchical fab-wide framework of process control and monitoring for semiconductor manufacturing. In this context, it is important to coordinate the target operational indices of units so as to realize optimization of production indices.

The decision making of operational indices involves multi-objectives in terms of product quality, yield, and consumption of energy and raw materials. The dynamic models between the operational indices and the production indices cannot be obtained easily. In addition, there are various uncertainties. Therefore, it is very difficult to solve using existing optimization methods. This leads to the situation

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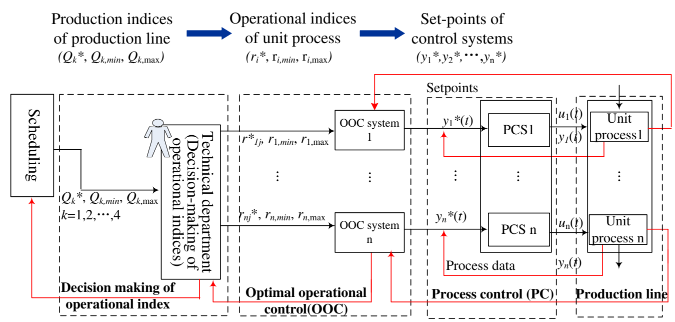

Fig. 1. Decision making of operational indices for a production line

that the decision making of the operational indices can only be performed manually according to the operator's experience in practice, which, however, cannot ensure global optimization.

Motivated by this problem, a novel hybrid intelligent optimization approach of operational indices for industrial process is proposed, which combines the multi-objective optimization, performance indices prediction, evaluation and dynamic tuning. Its effectiveness has been demonstrated by the application results.

2. PROBLEM DESCRIPTION OF OPERATIONAL INDICES DECISION MAKING

2.1 Decision making of operational indices for whole production line

As shown in Fig. 1, the operational indices decision making of a production line (which composes of multiple units denoted as from unit-process 1 to unit-process n) involves the scheduling, the technical department decision making, the optimal operational control (OOC) systems, and the process control systems (PCSs). The scheduling determines production indices of as denoted by $Q_k^*(k = 1, 2, 3, 4)$ and their ranges (Q_{kmin}, Q_{kmax}), where $Q_k^*(k = 1, 2, 3, 4)$ is the target of the product quality, yield, energy and raw materials consumption, respectively. Q_{kmin} and Q_{kmax} are the lower and upper limits of Q_k. According to the obtained production indices, Q_k^*, and ranges, the technical department generates the operational indices for each unit process as denoted by $\mathbf{r}_i^* \sim \{r_{ij}^*\}$, where $i = 1, 2, ..., n$ represents the number of units and $j = 1, 2, 3$ represents the target of the product quality, efficiency and consumption index, respectively. Taking $\mathbf{r}_i^*$ as the target, the OOC system of ith unit generates the set-points $y_i^*(t)$ of PCSs, which track their set-points $y_i^*(t)$ so as to make the actual production indices, Q_k, be inside their target ranges.

2.2 Description of operational indices optimization

1) Performance index: The objective of the optimization of operational indices is to determine a set of proper operational indices to optimize the production indices, i.e. the product quality and yield are made as high as possible, and the energy and material consumptions are made as low as possible. Its objective functions are as follows:

a)Product Quality Objective: Product quality $Q_1(t)$ should be made as high as possible, i.e., $\max |Q_1(t) - Q_{1min}|$.

b) Yield Objective: Yield of the whole production process $Q_2(t)$ is made as high as possible, i.e., $\max |Q_2(t) - Q_{2min}|$.

c) Energy Consumption Objective: Energy consumption $Q_3(t)$ is made as low as possible, i.e., $\max |Q_{3max} - Q_3(t)|$.

d) Raw Material Consumption Objective: Raw material consumption $Q_4(t)$ is made as low as possible, i.e., $\max |Q_{4max} - Q_4(t)|$.

2) Constraints: *a) Production Indices Constraint:* The production indices $Q_k(t)(k = 1, 2, 3, 4)$ and the operational indices of each unit $r_{ij}(r = 1, 2, ..., n; j = 1, 2, 3)$ should all satisfy their relationship models,

$$Q_k(t) = f_k(r_{ij}, \pi_i, p_i, v_k), \quad k = 1, 2, 3, 4 \tag{1}$$

where π_i and p_i denote the equipment capability and the raw material resource of ith unit, respectively, and v_k the disturbance (e.g. environment and material variation).

b) Limitations of Production Indices: Actual production indices Q_k are restricted by its lower and upper limits as follows

$$Q_{kmin} \leq Q_k \leq Q_{kmax}, \quad k = 1, 2, 3, 4 \tag{2}$$

c) Limitations of Operational Indices: The operational indices r_{ij} that need to be decided are constrained by their lower and upper limits,

$$r_{ij,min} \leq r_{ij} \leq r_{ij,max}, \quad i = 1, 2, ..., n; j = 1, 2, 3 \tag{3}$$

d) Equipment Capacity Constraints: The average of throughput per hour for the ith equipment π_i is restricted by its upper limit as follows

$$\pi_i \leq \pi_{imax}, \quad i = 1, 2, ..., n \tag{4}$$

e) Raw Material Limitations: The quantity or quality of raw material is constrained by its lower and upper limits,

$$p_{imin} \leq p_i \leq p_{imax}, \quad i = 1, 2, ..., n \tag{5}$$

3) Decision variables: The decision variables of operational indices optimization are the operational indices of each unit of a production line, $\mathbf{r} \sim \{\mathbf{r}_i\} \sim \{r_{ij}\}$, where $i = 1, 2, ..., n$ is the number of units, and $j = 1, 2, 3$ represents the product quality, production efficiency and consumption, respectively.

Therefore the operational indices optimization problem is formulated as the following constrained multi-objective optimization problem:

$$\begin{aligned} J \sim \{ & \max |Q_1 - Q_{1min}|, \max |Q_2 - Q_{2min}|, \\ & \max |Q_{3max} - Q_3|, \max |Q_{4max} - Q_4|\} \end{aligned} \tag{6}$$

$$\begin{aligned} s.t. \quad & \\ & Q_k(t) = f_k(r_{ij}, \pi_i, p_i, v_k), \quad k = 1, 2, 3, 4 \\ & Q_{kmin} \leq Q_k \leq Q_{kmax}, \quad k = 1, 2, 3, 4 \\ & r_{ij,min} \leq r_{ij} \leq r_{ij,max}, \quad i = 1, 2, ..., n; j = 1, 2, 3 \\ & \pi_i \leq \pi_{imax}, \quad i = 1, 2, ..., n \\ & p_{imin} \leq p_i \leq p_{imax}, \quad i = 1, 2, ..., n \end{aligned}$$

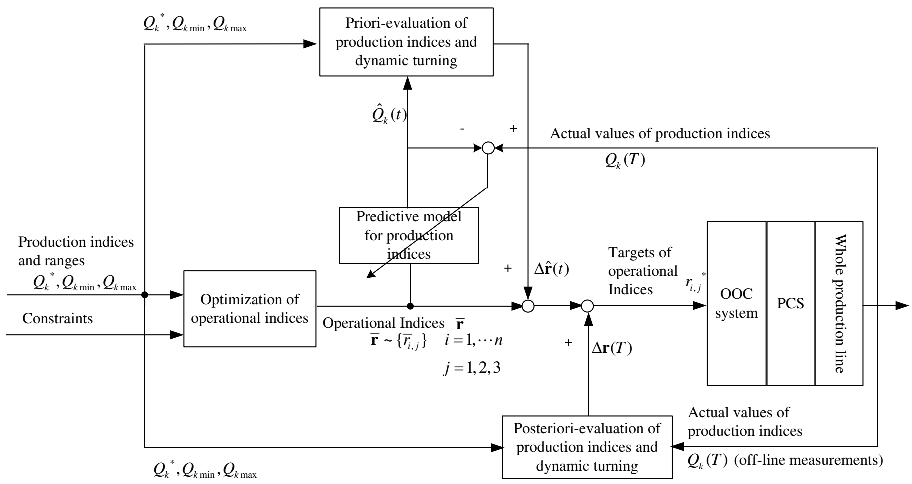

Fig. 2. Decision optimization strategy of operational indices

3. OPTIMIZATION OF OPERATIONAL INDICES

To solve the problem (6), a novel strategy of operational indices optimization is proposed as shown in Fig. 2, where the evolutionary algorithm is combined with the case-based reasoning (CBR) to generate the near-optimal solution. Then the performance prediction, evaluation and dynamic tuning are adopted to solve this optimization problem. It is composed of four modules (see Fig. 2), including a module of optimization operational indices , a predictive model for production indices, a priori-evaluation and a posteriori-evaluation with dynamic tuning module. The purpose of this structure is to cope with the uncertainty caused by v_k. A detailed description for each module is described in the following.

3.1 Optimization of operational indices

This is to determine the operational indices $\bar{\mathbf{r}} \sim \{\bar{r}_{ij}\}$ ($i = 1, 2, ..., n$; $j = 1, 2, 3$) according to the targets of production indices Q_k^* and the constraints (1)-(5). In this study, a hybrid optimization approach integrating CBR and MOEA is proposed, which produces $\bar{\mathbf{r}}$ as following,

$$\bar{\mathbf{r}} = \lambda_0 \bar{\mathbf{r}}_{CBR} + (1 - \lambda_0)\bar{\mathbf{r}}_{EA}, \ \lambda_0 \in [0, 1] \tag{7}$$

where $\bar{\mathbf{r}}_{CBR}$ and $\bar{\mathbf{r}}_{EA}$ are the solution of CBR and MOEA, respectively, and λ_0 is a weight coefficient to be determined.

1) Decision making of the operational indices based on CBR: To employ the operational experience of on-site process engineers during the decision making of the operational indices, a CBR based algorithm is proposed which consists of five components: namely the Case representation, the Case retrieval, the Case re-use, the Case revision and the Case retain. The case representation for decision making of the operational indices are constructed as shown in Table 1 including the case description and the case solution. The Case description is expressed as $C = \{c_i\}(i = 1, 2, ..., 6$, the actual value of i related to dimensions of the vectors $\boldsymbol{B}$ and $\mathbf{r}$ in case description), where c_1, c_2, c_3 and c_4 are the feature descriptions of the production indices, Q_k, respectively. c_5 is the boundary

Table 1. Case structure of the decision making for operational indices

Case description						Case solution
c_1	c_2	c_3	c_4	c_5	c_6	s
Q_1	Q_2	Q_3	Q_4	$\boldsymbol{B}$	$\mathbf{r}$	$\bar{\mathbf{r}}_{CBR}$

conditions, $\boldsymbol{B}$ stands for the component and category of raw material, and c_6 is the actual value of current operational indices $\mathbf{r}$. The case solution is the expected operational indices $\bar{\mathbf{r}}_{CBR}$.

Initial cases are obtained from abstraction of the operational experiences and stored in the case base. K-nearest neighbor case retrieval (Chai et al. [2011]) and replacement based case re-use are adopted to generate the case solution (i.e., the operational indices as denoted by $\bar{\mathbf{r}}_{CBR}$) for the current operating point. $\bar{\mathbf{r}}_{CBR}$ is adopted as the new target of operational indices and can be tuned according to experiences. Case retain is fulfilled in the same manner as in Chai et al. [2011].

2) Multi-objective optimization of operational indices based on NSGA-II: The NSGA-II (Deb et al. [2002]) is adopted to solve the multi-objective optimization problem (6). The NSGA-II has characteristics of fast non-dominated sorting, diversity maintaining mechanism and elitist strategy.

The fitness function f_s can be formulated as $f_{s1} = |Q_1(t) - Q_{1,min}|, f_{s2} = |Q_1(t) - Q_{2,min}|, f_{s3} = |Q_{3,max} - Q_3(t)|, f_{s4} = |Q_{4,max} - Q_4(t)|$, where $Q_k(t)$ can be generated by the linear approximate model of (1) established through regression of the process data. The initial population with N individuals is generated randomly based on the decision variables of optimization problem (6) and the constraints (1)-(5).

Through the procedures of NSGA-II [i.e. non-dominated sorting and selection, crossover and mutation (standard algorithm in Deb et al. [2002])], the Pareto solution set is achieved and then the optimal value of the operational indices, $\bar{\mathbf{r}}_{EA}$ (which is most suited for the actual operating condition) is selected.

Table 2. Incremental association rules for operational indices tuning

Condition					Conclustion		
$Q_1^*(t)$	...	$Q_4^*(t)$	...	$\Delta Q_4(t)$	$\Delta r_{l=1}$	...	$\Delta r_{l=L}$

3) Weighting coefficient λ_0: To fully use the experience of on-site engineers (i.e., the results of CBR), the average of the similarity of the retrieved cases in CBR is taken as the weight coefficient between the solution of CBR $\bar{\mathbf{r}}_{CBR}$ and that of MOEA $\bar{\mathbf{r}}_{EA}$. This leads to

$$\lambda_0 = \sum_{k_s=1}^{K_s} SIM(M, M_{k_s})/K_s \tag{8}$$

where λ_0 is an important weight coefficient. Its selection as (8) means that if there are cases stored in the case base whose operating point is close to the current operation point so that λ_0 will be close to 1; Otherwise, λ_0 will be close to 0 which represents that the result of MOEA has a large weight.

3.2 Predictive model for production indices

Since it is difficult to establish $f_k(r_{ij}, \pi_i, p_i, v_k)$ using the first principle, a predictive model consisting of a linear main model and a nonlinear compensation model is adopted. The output of the predictive model is the production indices $\hat{Q}_k(t+1)$.

$$\hat{Q}_k(t+1) = \hat{Q}_{kL}(t+1) + \hat{e}(t+1) \tag{9}$$

$$\hat{Q}_{kL}(t+1) = \theta_k \cdot [r_{ij}(t), Q_i(t), p_i, \pi_i] \tag{10}$$

$$\hat{e}(t+1) = \xi(r_{ij}(t), Q_i(t), p_i, \pi_i, \vartheta) \tag{11}$$

where θ_k is a vector and its dimension is the sum of the dimension of $r_{ij}(t), Q_i(t), p_i$ and π_i. $\xi(\cdot)$ is the error between the actual operational indices and the output of linear predictive model.

The error compensation model $\xi(\cdot)$ is nonlinear and the least square support vector machine is used to approximate it. Moreover, since there exists uncertain disturbance in $\xi(\cdot)$, its parameter ϑ is selected by the modelling error probability density function (PDF) shaping method (Ding et al. [2010(accepted]).

3.3 Priori- and Posteriori-evaluation, and dynamic tuning

This is to produce the adjustment value either $\Delta\hat{\mathbf{r}}(t)$ or $\Delta\mathbf{r}(T)$ for the operational indices according to the targets Q_k^* and either predictions $\hat{Q}_k(t)$ or the actual values $Q_k(T)$ of the production indices. Here, T is the sampling period of the production indices. Its main procedure can be outlined as follows:

1) Priori- and posteriori-evaluation of production indices: According to the target value Q_k^* and either the predictive value $\hat{Q}_k(t)$ or the actual value $Q_k(T)$, the following errors are calculated

$$\Delta\hat{Q}_k(t) = Q_k^* - \hat{Q}_k(t)$$
$$\Delta Q_k(T) = Q_k^* - Q_k(T), k = 1, 2, 3, 4 \tag{12}$$

Then, the evaluation is carried out as follows:

(1) If $\exists k \in \{1, 2, 3, 4\}$, $\Delta\hat{Q}_k(t) \geq \Delta\hat{Q}_{kmin}$, then go to the tuning phase, otherwise standby;
(2) If $\exists k \in \{1, 2, 3, 4\}$, $\Delta Q_k(T) \geq \Delta Q_{kmin}$, then go to the tuning phase, otherwise standby.

where $\Delta\hat{Q}_{kmin}$ and ΔQ_{kmin} are the lower limits of the errors calculated by (12). These limits are positive and are determined by the experiences of on-site engineers.

2) Determine the operational indices that need to be tuned: As industrial processes are generally composed by many unit-processes, the number of operational indices is large. Moreover, these indices have different effect to the production indices. Therefore, the influence of operational indices to the production indices needs to be studied first, where the operational indices which are closely related to the production indices are selected using the significance of attributes in the rough set theory (Pawlak [1982]). The main procedures of the algorithm are given as follows.

Based on (Pawlak [1982]) the attributes significance is calculated from

$$W(r_m) = \gamma_{r_{ij}}(Q_k) - \gamma_{r_{ij}-r_m}(Q_k), \quad r_m \in r_{ij} \tag{13}$$

$$\gamma_{r_{ij}}(Q_k) = POS_{r_{ij}}(Q_k)/|U| \tag{14}$$

where $\gamma_{r_{ij}}(Q_k)$ is a much general concept of dependency of attributes, called a *partial dependency* of attributes. Q_k depends in degree $\gamma_{r_{ij}}(Q_k)$, $0 \leq \gamma_{r_{ij}}(Q_k) \leq 1$, on r_{ij}, denoted as $r_{ij} \Rightarrow_{\gamma_{r_{ij}}(Q_k)} Q_k$. $POS_{r_{ij}}(Q_k)$ is named as a positive region with respect to r_{ij} and it is a set of all elements of U that can be uniquely classified to blocks of the partition U/Q_k by means of r_{ij} .

The significance $W(r_{ij})(i = 1, 2, ..., n; j = 1, 2, 3)$ of each operational index r_{ij} can be achieved by (13). Therefore the operational indices that need to be tuned, $r_l(l = 1, 2, ..., L)$, can be selected via the threshold of the significance which is pre-defined.

3) Tuning algorithm: Based on the rough sets and the association rule mining methods, the incremental association rules (Ma et al. [2000]) (i.e., the dynamic correction rules) are obtained from the actual operation data. Through these rules, rule-based reasoning is carried out to achieve the tuning value and then to correct the operational indices $\bar{r}_{ij}(t)$ which is produced by the operational indices optimization. The formulation of the obtained rules is shown in Table 2. The condition attributes includes the target value of the production indices Q_k^* and the prediction error $\Delta\hat{Q}_k(t)$ or the actual error $\Delta Q_k(T)$ for $k = 1, 2, 3, 4$. The conclusion attributes is the correction value Δr_l ($\Delta\hat{r}_l(t)$ or $\Delta r_l(T)$).The details of above algorithm can be found in (Ding et al. [2009]).

While error $\Delta\hat{Q}_k(t)$ or $\Delta Q_k(T)$ is calculated and evaluated, the correcting value $\Delta\hat{r}_l(t)$ or $\Delta r_l(T)$ is obtained through the rule-based reasoning according to Q_k^* and $\Delta\hat{Q}_k(t)$ (or Q_k^* and $\Delta Q_k(T)$). Then the tuning on $\bar{\mathbf{r}} \sim \{\bar{r}_{ij}(t)\}$ can be carried out.

Priori-evaluation and dynamic tuning is expressed as

$$r'_{ij}(t) = \begin{cases} \bar{r}_{ij}(t) + \Delta\hat{r}_l(t), & \{ij\} \in l \\ \bar{r}_{ij}(t), & \{ij\} \notin l \end{cases} \tag{15}$$

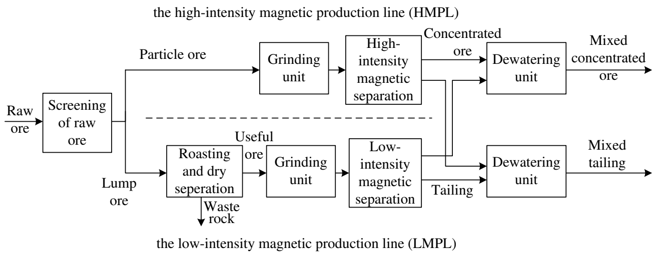

Fig. 3. Scheme of mineral processing production process

Posteriori-evaluation and dynamic tuning is given by

$$r^*_{ij}(t) = \begin{cases} r'_{ij}(t) + \Delta r_l(T), & t = T \ \& \ \{ij\} \in l \\ r'_{ij}(t), & t \neq T \ \& \ \{ij\} \in l \\ \bar{r}_{ij}(t), & \{ij\} \notin l \end{cases} \tag{16}$$

Finally, the operational indices of each unit $\mathbf{r}^* \sim \{r^*_{ij}\}$ can be generated from $\bar{\mathbf{r}}$, $\Delta\hat{\mathbf{r}}(t)$ and $\Delta\mathbf{r}(T)$ as shown in Fig. 2.

4. AN INDUSTRIAL APPLICATION

4.1 Operational indices optimization of a hematite iron ore mineral processing plant

1) Mineral processing of hematite iron ore The production structure of the biggest mineral processing factory of hematite iron ore in China with the production capability of 5 million ton per year is shown in Figs. 3. The production includes the units: screening, shaft furnace roasting, grinding and low-intensity and high-intensity magnetic separation. In addition, there are two dewatering units for concentrated ores and tailing.

The screening unit classifies the raw ore into particle ore of 0-15mm in size and lump ore larger than 15mm in size. The lump ore is sent into the roasting unit and roasted in the shaft furnace. The roasted ore discharged from the furnace is then separated into useful ore and waste rock. The useful ore is then sent to the grinding unit and produces the ore pulp with suitable particle size. Then the ore pulp is sent into the low-intensity magnetic separator to be separated into concentrated ore and tailing. The particle ore is firstly ground in the grinding unit and generates ore pulp which is sent into the high-intensity magnetic separator to be separated into concentrated ore and tailing. The mixed concentrated ore and tailings are dewatered to produce the final mixed concentrated and tailing, respectively.

2) Operational indices optimization of mineral processing of hematite iron ore The decision making system of operational indices for the mineral processing of hematite iron ore is developed. This system consists of the optimization of operational indices and five OOC systems of the shaft furnace, two grinding units, the high- and low-intensity magnetic separation units. The operational indices of each unit and the set-points of control systems are shown in Table 3.

The performance of the operational indices optimization are the production indices: the daily mixed concentrate grade Q_1, and the daily yield of concentrated ore Q_2. The operational indices of each unit process ($r_{ij}, i = 1, 2, ..., 5; j = 1, 2$) are shown in Table 3 and they are the

Table 3. The operational indices and set-points of control system of mineral processing

Unit	Operational indices
Shaft furnace	r_1: Magnetic tube recovery rate (%)
Grinding unit I	r_2: Grinding particle size(%)
Separation(low)	r_{31}: Concentrate grade(%) r_{32}: Tailing grade(%)
Grinding unit II	r_4: Grinding particle size(%)
Separation(high)	r_{51}: Concentrate grade (%) r_{52}: Tailing grade (%)

Table 4. Case structure of the decision making for operational indices of mineral process

Case description									Case solution
c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	s
Q_1	Q_2	π_1	π_2	p_1	p_2	Rg	Rt	$\mathbf{r}$	$\bar{\mathbf{r}}_{CBR}$

decision variables of the operational indices optimization. The targets are $Q_1(d)$=52.5% ($d = 1, 2, ..., 7$) and $Q_2(d)$ is $6850t/d$, $6610t/d$, $6650t/d$, $6810t/d$, $6890t/d$, $7100t/d$, and $7100t/d$ for $d = 1, 2, ..., 7$, respectively, where d in $Q_i(d)$ represents its sample duration is one day.

NSGA II is adopted to perform the multi-objective evolution optimization, where the population size is selected as $N = 200$ and the maximum generation is 200. The pool size is 100 and the tour size is 2. The crossover probability is set to 0.9 and the mutation probability is selected as 0.1. The structure of the case base is shown in Table 4, where Rg and Rt represent the grade and type of raw ore, respectively, and $\mathbf{r}$ and $\bar{\mathbf{r}}_{CBR}$ are vectors of the current operational indices, $\mathbf{r} \sim \{r_1, r_2, r_{31}, r_{32}, r_4, r_{51}, r_{52}\}$, and the decision of CBR. The number of the initial cases in the case base is 80 and the threshold for case similarity is 0.8. The predictive model has been established and used to produce $\hat{Q}_1(t+1)$ and $\hat{Q}_2(t+1)$. The thresholds in the priori- and the posteriori-evaluation are obtained as $\Delta\hat{Q}_{kmin}$ =0.3% and ΔQ_{kmin} =340t/d, respectively. The significance of the operational indices r_{ij} to the production indices Q_k are given by $\{0.2, 0.15, 0.06, 0.06, 0.18, 0.04, 0.06\}$ and the operational indices to be tuned are r_1, r_2 and r_4 with significance no less than 0.15. Their correction values are generated through rule reasoning. Examples are $\Delta r_l = [0.4, 0.5, 0.4]$ and $\Delta\hat{r}_l = [0.5, 0.6, 0.7]$ at first tuning circle.

4.2 Application results and analysis

The industrial application results over one week's operation are shown in Fig. 4 when the 8 series of the production are all in the normal condition. The sampling and statistical periods of all the indices are of two hours. Fig. 4(a)-(g) show the operational indices $\mathbf{r}^*$ produced by the proposed approach and compared with the actual values.

Over one week's operation, it is can be seen that when the production conditions vary the proposed approach can provide the optimal operational indices and are taken as the targets of the lower level systems. The comparison results between the proposed approach and the manual decision making are shown in Table 5. The performance of the proposed approach is superior to that of the manual decision making. The operational indices r_1, r_2, r_{31}, r_4 and r_{51} are enhanced by 2, 1.98, 1.26, 1.49 and 0.57, and r_{32} and r_{52} are cut down by 0.69 and 0.31, respectively.

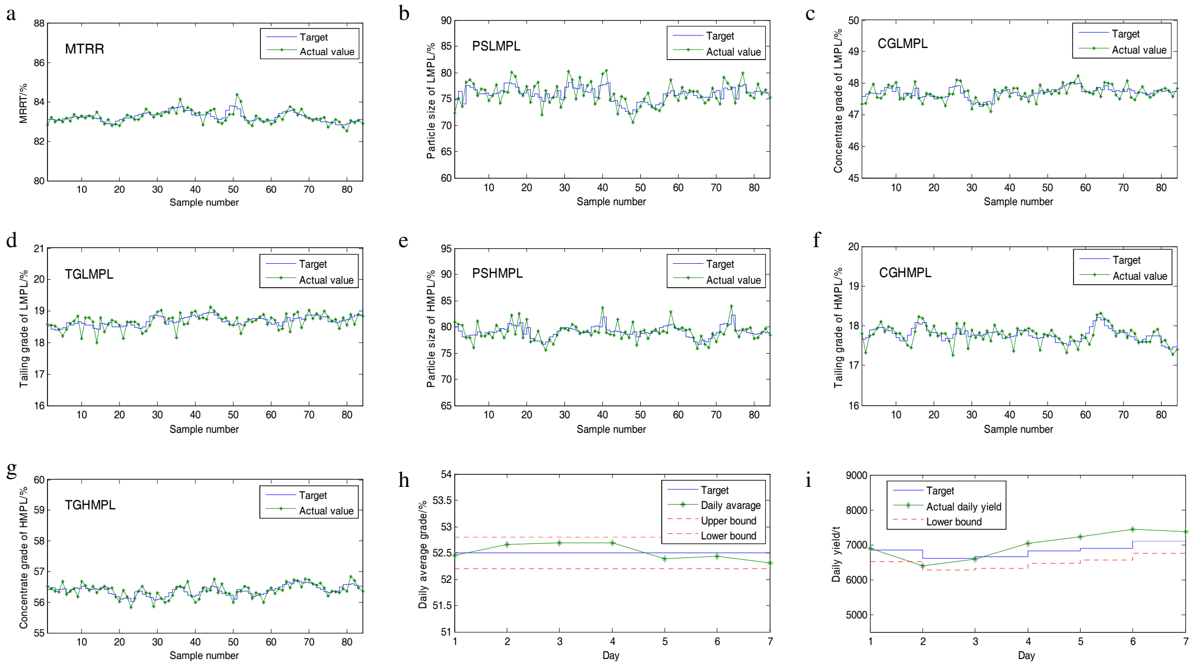

Fig. 4. Target and actual value of the operational indices and the production indices

Table 5. Results comparison between the proposed approach and manual decision making

Operational indices	r_1	r_2	r_{31}	r_{32}	r_4	r_{51}	r_{52}
Average of proposed approach	83.50	76.48	56.26	17.81	78.99	47.53	18.69
Manually decision making	81.5	74.5	55	18.5	77.5	47	19
Improvement (Decreasement)	2	1.98	1.26	$\underline{-0.69}$	1.49	0.57	$\underline{-0.31}$

This improvement(or reduction) leads to the finally improvements of the daily mixed concentrate grade and daily yield of concentrated ore of the whole production line as shown in Fig. 4(h)-(i). The statistical analysis results of one month show the averages of the daily mixed concentrate grade and daily yield are improved by 0.57% and 132.37t/d, respectively, as compared to those of manual operation.

5. CONCLUSION

Manual decision making of the operational indices cannot ensure global optimization of the industrial process. To solve this problem, a hybrid intelligent operational indices optimization approach is proposed. If the operating points vary or uncertain disturbances occur, the proposed approach will automatically adjust the operational indices of each unit-process. The modified operational indices are then taken as the targets and are tracked by the lower level systems to realize production's global optimization. Note that the proposed approach don't need the mathematics process model which usually difficult to achieved despite the prediction model which is data-based. The real application results shows the effectiveness of the proposed approach and the high potential of being further applied in the operational indices optimization of other complex industrial processes under dynamic environment.

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