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

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Abstract: To pursue 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. 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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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,
   \[
   Q_{kmin} \leq Q_k \leq Q_{kmax}, \quad k = 1, 2, 3, 4
   \]
   b) Limitations of Production Indices: Actual production indices $Q_k$ are restricted by its lower and upper limits as follows
   \[
   Q_{kmin} \leq Q_k \leq Q_{kmax}, \quad k = 1, 2, 3, 4
   \]
   c) Limitations of Operational Indices: The operational indices $r_{ij}$ that need to be decided are constrained by their lower and upper limits,
   \[
   r_{ij, min} \leq r_{ij} \leq r_{ij, max}, \quad i = 1, 2, ..., n; j = 1, 2, 3
   \]
   d) Equipment Capacity Constraints: The average of throughput per hour for the $i$th equipment $\pi_i$ is restricted by its upper limit as follows
   \[
   \pi_i \leq \pi_{imax}, \quad i = 1, 2, ..., n
   \]
   e) Raw Material Limitations: The quantity or quality of raw material is constrained by its lower and upper limits,
   \[
   p_{imin} \leq p_i \leq p_{imax}, \quad i = 1, 2, ..., n
   \]

3) Decision variables: The decision variables of operational indices optimization are the operational indices of each unit of a production line, $r \sim \{r_{ij}\} \sim \{r_{ij}\}$, 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:

\[
J \sim \{ \max |Q_1 - Q_1_{min}|, \max |Q_2 - Q_2_{min}|, \\
\max |Q_{3max} - Q_3|, \max |Q_{4max} - Q_4| \}
\]

subject to

\[
Q_k(t) = f_k(r_{ij}, \pi_i, p_i, v_k), \quad k = 1, 2, 3, 4
\]
\[
Q_{kmin} \leq Q_k \leq Q_{kmax}, \quad k = 1, 2, 3, 4
\]
\[
r_{ij, min} \leq r_{ij} \leq r_{ij, max}, \quad i = 1, 2, ..., n; j = 1, 2, 3
\]
\[
\pi_i \leq \pi_{imax}, \quad i = 1, 2, ..., n
\]
\[
p_{imin} \leq p_i \leq p_{imax}, \quad i = 1, 2, ..., n
\]
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 $\mathbf{r} \sim \{\mathbf{r}_i\}$ ($i = 1, 2, ..., n; j = 1, 2, 3$) 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 $\mathbf{r}$ as following,

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

where $\mathbf{r}_{CBR}$ and $\mathbf{r}_{EA}$ are the solution of CBR and MOEA, respectively, and $\lambda_0$ 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 representation, for operational indices and dynamic tuning.

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 $f_k$ for production indices $Q_k$ can be expressed as $f_k = |Q_k(t) - Q_k|$, where $Q_k$ is the actual value of $k$th production indices. The Pareto solution set is obtained 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 the optimal value of the operational indices, $\mathbf{r}_{CBR}$ (which is most suited for the actual operating condition) is selected.

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

<table>
<thead>
<tr>
<th>Case description</th>
<th>Case solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_1, c_2, c_3, c_4, c_5, c_6$</td>
<td>$B, r, r_{CBR}$</td>
</tr>
</tbody>
</table>

Fig. 2. Decision optimization strategy of operational indices

Whole production line

Constraints

Operational Indices

Actual values of production indices

Optimization of operational indices

Production indices and ranges

Prior-evaluation of production indices and dynamic tuning

Predictive model for production indices

Operational indices $\mathbf{r} \sim \{\mathbf{r}_i\}$ $i = 1, \ldots, n$ $j = 1, 2, 3$

Posterior-evaluation of production indices and dynamic tuning

$Q_{OOC}$ system

GCS

PCS
Table 2. Incremental association rules for operational indices tuning

<table>
<thead>
<tr>
<th>Condition</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Q_1(t))</td>
<td>(\bar{r}_{ij}(t)) + (\Delta t); ({ij} \in l)</td>
</tr>
<tr>
<td>(Q_2(t))</td>
<td>(\bar{r}_{ij}(t)); ({ij} \notin l)</td>
</tr>
<tr>
<td>(Q_3(t))</td>
<td>(\bar{r}_{ij}(t)) + (\Delta t); ({ij} \in l)</td>
</tr>
<tr>
<td>(Q_4(t))</td>
<td>(\bar{r}_{ij}(t)); ({ij} \notin l)</td>
</tr>
</tbody>
</table>

3) Weighting coefficient \(\lambda_0\): 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 \(r_{CBR}\) and that of MOEA \(r_{EA}\). This leads to

\[
\lambda_0 = \sum_{k=1}^{K_s} \frac{SIM(M, M_k)}{K_s} \tag{8}
\]

where \(\lambda_0\) is an important weight coefficient. Its selection as (8) means that if there are cases stored in the case base whose operating point is already near the current operation point so that \(\lambda_0\) will be close to 1; Otherwise, \(\lambda_0\) 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 \(Q_k(t+1)\).

\[
\begin{align*}
\hat{Q}_k(t+1) &= \hat{Q}_{kL}(t+1) + \hat{e}(t+1) \tag{9} \\
\hat{Q}_{kL}(t+1) &= \theta_k \cdot [r_{ij}(t), Q_i(t), p_i, \pi_i] \tag{10} \\
\hat{e}(t+1) &= \xi(r_{ij}(t), Q_i(t), p_i, \pi_i, \vartheta) \tag{11}
\end{align*}
\]

where \(\theta_k\) is a vector and its dimension is the sum of the dimension of \(r_{ij}(t), Q_i(t), p_i\) and \(\pi_i\). \(\xi(\cdot)\) 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 \(\vartheta\) 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 \(\Delta \hat{r}(t)\) or \(\Delta r(T)\) 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

\[
\begin{align*}
\Delta \hat{Q}_k(t) &= Q^*_k - \hat{Q}_k(t) \\
\Delta Q_k(T) &= Q^*_k - Q_k(T), k = 1, 2, 3, 4 
\end{align*} \tag{12}
\]

Then, the evaluation is carried out as follows:

(1) If \(\exists k \in \{1, 2, 3, 4\}, \Delta \hat{Q}_k(t) \geq \Delta Q^*_{k_{min}}\), then go to the tuning phase, otherwise standby.

(2) If \(\exists k \in \{1, 2, 3, 4\}, \Delta Q_k(T) \geq \Delta Q^*_{k_{min}}\), then go to the tuning phase, otherwise standby.

where \(\Delta Q^*_{k_{min}}\) and \(\Delta Q^*_{k_{min}}\) 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

\[
W(r_m) = \gamma_{r_{ij}}(Q_k) - \gamma_{r_{ij}}(Q_k) \cdot r_m \in r_{ij} \tag{13}
\]

\[
\gamma_{r_{ij}}(Q_k) = \text{POS}_{r_{ij}}(Q_k)/|U| \tag{14}
\]

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 \(r_{ij} \Rightarrow \gamma_{r_{ij}}(Q_k)\). \(POS_{r_{ij}}(Q_k)\) 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 \(\hat{r}_{ij}(t)\) 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 \(\Delta r_l\) (\(\Delta \hat{r}_l(t)\) 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 \(\Delta Q_k(T)\)). Then the tuning on \(r \sim \{r_{ij}\}\) can be carried out.

Priori-evaluation and dynamic tuning is expressed as

\[
r'_{ij}(t) = \begin{cases} r_{ij}(t) + \Delta \hat{r}_l(t), & \{ij\} \in l \\ r_{ij}(t), & \{ij\} \notin l \end{cases} \tag{15}
\]
Fig. 3. Scheme of mineral processing production process
Posteriors-evaluation and dynamic tuning is given by

\[ r_{ij}^*(t) = \begin{cases} r_{ij}(t) + \Delta r_i(t), & t = T & \{ij\} \in \varnothing \\ \alpha r_{ij}(t), & t \neq T & \{ij\} \in \varnothing \\ \beta r_{ij}(t), & \{ij\} \notin \varnothing \end{cases} \]  \hspace{1cm} (16)

Finally, the operational indices of each unit \( r^* \sim \{r_{ij}^*\} \) can be generated from \( r, \Delta r(t) \) and \( \Delta r(T) \) 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 high-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 tailing 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 \( r_{ij}, t = 1, 2, ..., 5; j = 1, 2 \) are shown in Table 3 and they are the decision variables of the operational indices optimization. The targets are \( Q_1(d) = 20.5\% \) and \( Q_2(d) = 15\% \). The thresholds in the priori- and posteriori-evaluation are obtained as \( \Delta Q_{ij} = 0.1\% \) and \( \Delta Q_{ij} = 0.1\% \), respectively. The significance of the operational indices \( r_{ij} \) to the production indices \( Q_k \) are given by \( \{0.2, 0.05, 0.06, 0.06, 0.18, 0.04, 0.06\} \) and the operational indices to be tuned are \( r_1, r_2, r_3, r_4, r_5, r_6, r_7 \), and the decision of CBR. The number of the initial cases in the base is 80 and the threshold for case similarity is 0.8. The predictive model has been established and used to produce \( Q_1(t + 1) \) and \( Q_2(t + 1) \). The thresholds in the priori- and posteriori-evaluation are obtained as \( \Delta Q_{ij} = 0.1\% \) and \( \Delta Q_{ij} = 0.1\% \), respectively. The significance of the operational indices \( r_{ij} \) to the production indices \( Q_k \) are given by \( \{0.2, 0.05, 0.06, 0.06, 0.18, 0.04, 0.06\} \) and the operational indices to be tuned are \( r_1, r_2, r_3 \), and \( r_4 \) with significance no less than 0.15. Their correction values are generated through rule reasoning. Examples are \( \Delta r_i = [0.4, 0.5, 0.4] \) and \( \Delta r_l = [0.5, 0.6, 0.7] \) 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 \( r^* \) 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 \( r_1, r_2, r_3, r_4, r_5, r_6, r_7 \), and \( r_8 \) are enhanced by \( 2, 1.98, 1.26, 1.49 \) and \( 0.57 \), and \( r_3, r_4, r_5 \) are cut down by \( 0.69 \) and \( 0.31 \), respectively.

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

<table>
<thead>
<tr>
<th>Case description</th>
<th>Case solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c_1 )</td>
<td>( c_2 )</td>
</tr>
<tr>
<td>( Q_1 )</td>
<td>( Q_2 )</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Decision variable</th>
<th>Case description</th>
<th>Case solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta Q_{ij} )</td>
<td>( \Delta Q_{ij} )</td>
<td>( \Delta Q_{ij} )</td>
</tr>
</tbody>
</table>
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 132.37 t/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.

REFERENCES


