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Recent Progress on Data-Based Optimization for Mineral Processing Plants

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ABSTRACT

In the globalized market environment, increasingly significant economic and environmental factors within complex industrial plants impose importance on the optimization of global production indices; such optimization includes improvements in production efficiency, product quality, and yield, along with reductions of energy and resource usage. This paper briefly overviews recent progress in data-driven hybrid intelligence optimization methods and technologies in improving the performance of global production indices in mineral processing. First, we provide the problem description. Next, we summarize recent progress in data-based optimization for mineral processing plants. This optimization consists of four layers: optimization of the target values for monthly global production indices, optimization of the target values for daily global production indices, optimization of the target values for operational indices, and automation systems for unit processes. We briefly overview recent progress in each of the different layers. Finally, we point out opportunities for future works in data-based optimization for mineral processing plants.

1. Introduction

The production process of mineral processing is a typical complex industrial process. It consists of multiple unit processes that are connected in series, where the outputs of each unit process are the inputs for the subsequent unit process [1]. Each unit process has its own task and uses different performance indices to evaluate its own product quality and production efficiency. The operation of each unit contains a higher-level operational optimization system to ensure that the operational indices (i.e., quality, efficiency, and consumptions during the production phase) fall into their target ranges, and to generate the setpoints for the controllers [2,3]. All the unit processes operate together to produce the final product. Here, we refer to the performance indices of each unit process as the *unified technical indices*; these represent the unit product quality, production efficiency, and so forth. The concentrate grade of the final product is called the *global production index*. In practice, the unified technical indices of each unit process directly affect the global production indices.

It is well known that local optimization of the unit processes does not guarantee plant-wide global optimization. Therefore, research has been carried out on coordinating the unified technical indices of various unit processes to gradually achieve plant-wide global optimization of the whole production process [4–8]. Thus, it is important to coordinate all these units to optimize the global production indices—that is, the final production quality, yield, and profit.

In recent years, the concept and practice of operational optimization and control for industrial processes have attracted increasing attention [4–6,9–12]. In the chemical industry, a two-layered system consisting of real-time optimization (RTO) and model predictive control (MPC) has been widely applied to ensure the optimal operation of unit processes [13]. A series of variations or an adaptation strategy based on RTO is adopted to cope with issues such as the RTO requiring a steady-state model [6–8,14]. However, RTO encounters many difficulties when it is applied to complex industrial processes without mathematical models. In large-scale continuous industrial processes such as mineral processing, the physical and chemical reactions cause the relationship between the operational indices and the controlled variables to be nonlinear and strongly

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coupled. Moreover, the character of the relationship between the operational indices and the controlled variables is uncertain, and thus difficult to describe in a mathematical model. Existing approaches mainly address unit optimization and do not consider correlations between the unit processes. Such approaches lead to local optimal operation, which cannot guarantee the global production indices optimization of the entire plant.

To solve these problems, many valuable data-driven hybrid intelligent optimization approaches for global production indices optimization have been proposed recently. These approaches aim to optimize the whole industrial process under uncertainty. They do not need a mathematical model, as they rely on the operator's experience in practice and the data produced in the production process. In addition, these approaches can adapt to a dynamic environment by means of the closed-loop strategy, which is composed of ideas from control theory—that is, feedback, prediction-based feedforward, and dynamic tuning. These data-driven hybrid intelligent optimization approaches have been evaluated by simulations or in practice at mineral processing plants.

This paper provides an overview of the recent progress in data-based optimization for mineral processing plants. The rest of this paper is organized as follows: Section 2 presents the problem description. Section 3 summarizes the recent progress in data-based optimization for mineral processing plants. The paper concludes in Section 4, which contains suggestions for possible research directions in this area.

2. Problem description

The decision-making methods used for complex mineral processing often contain time-scale and space-scale decompositions of the global production indices, as shown in Fig. 1. First, the decision-making department of the plant determines the monthly global production indices, Q_j (t_m) (where j = 1, 2, …, J, J is the number of global production indices, and t_m is the monthly time scale), as well as their target ranges based on their operational experience. The planning and scheduling department then generates the daily global production indices, Q_j (t_d) (where j = 1, 2, …, J, and t_d is the daily time scale), according to the monthly global production indices, Q_j (t_m). Finally, the technical department decomposes the daily global production indices, Q_j (t_d), into the operational indices, $r^*_{i,j}$ (t_h) (where, i = 1, 2, …, I, and t_h is the hourly time scale), of each unit process. The operational optimal control systems generate the setpoints y^* for the control loops, and the control systems track the setpoints. The ultimate aim is to make the global production indices fall into their target ranges. Ref. [12] contains a more detailed description.

3. Data-driven hybrid intelligent modeling and optimization

To realize optimization of the manual-based decision-making process described above, Ref. [12] proposes a hierarchical optimization structure of different time scales that aims at optimizing the global production indices of mineral processing, as shown in Fig. 2. The optimization structure consists of four layers: optimization of the target values for monthly global production indices, optimization of the target values for daily global production indices, optimization of the target values for operational indices, and automation systems for unit processes. For a detailed description and for the functions of the different layers, refer to Ref. [12]. In this paper, we mainly outline recent progress in data-based modeling and optimization approaches.

3.1. Optimization of the global production indices

Optimization of the global production indices involves two layers

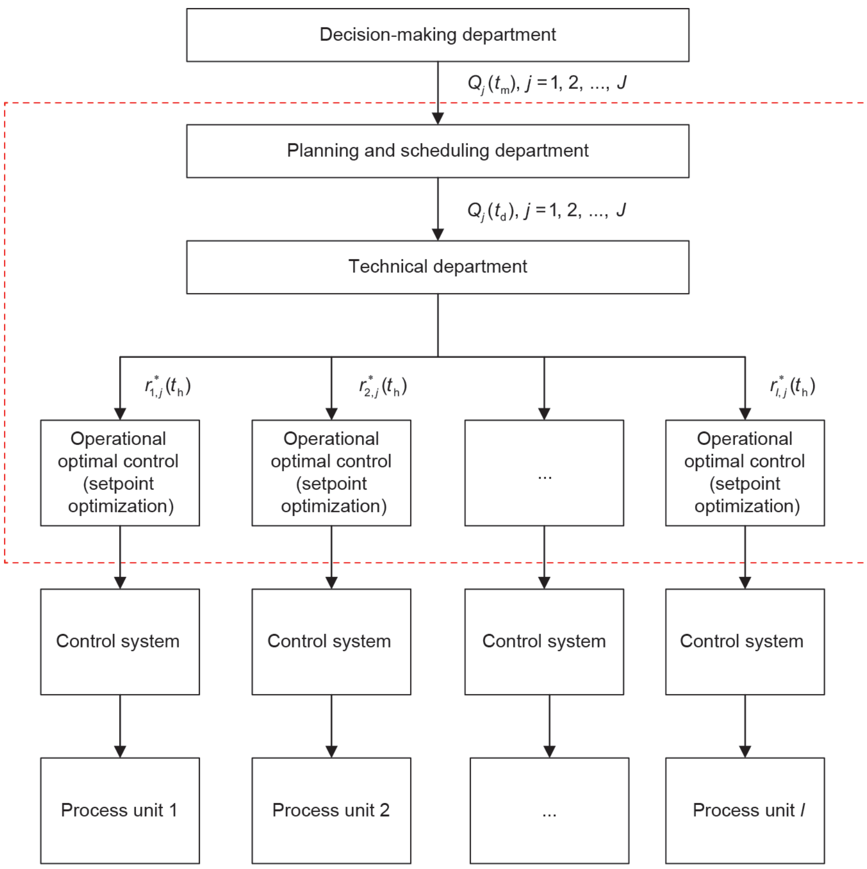

Fig. 1. Problem description of the multiple-layer optimization of mineral processing.

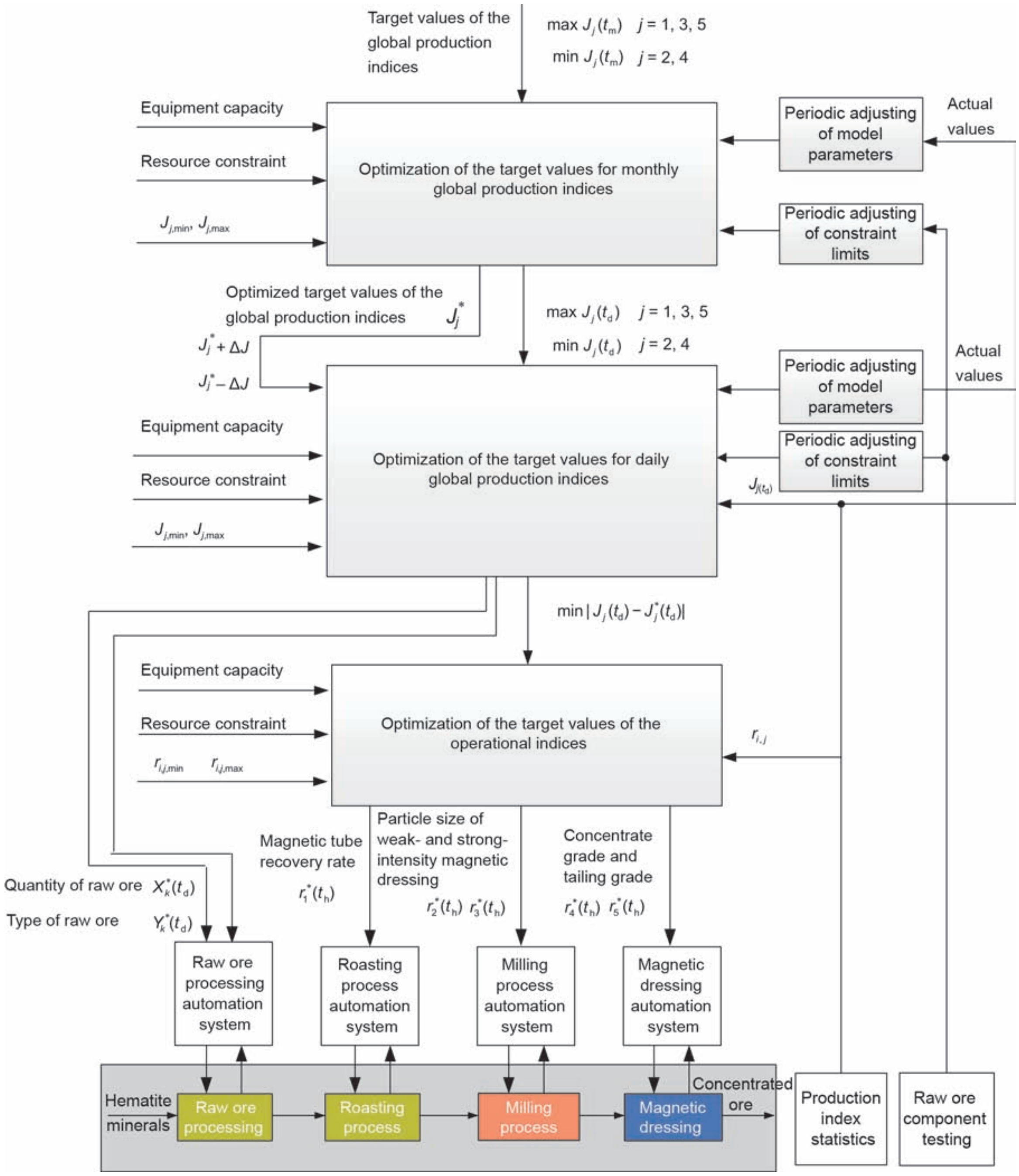

Fig. 2. The structure of integrated optimization for the automation systems of mineral processing. $X_k^*(t_d)$ is a real number and represents the quantity of the kth type of raw ore that should be used to realize the daily global production indices optimization. $Y_k^*(t_d)$ = 1 or 0, representing whether or not the kth type of raw ore is used to realize the daily global production indices optimization [12].

of decomposition decision-making methods regarding the global production indices, based on different time scales. The upper-layer decision aims to achieve a set of desired production objectives (mainly on a monthly time scale), while the lower-layer decision aims to achieve a further decomposition within each specific period (mainly on a daily time scale) to meet the target production objectives generated by the upper layer.

The optimization of global production indices mainly focuses on cost minimization or profit maximization within a certain period of time. Refs. [15–18] provide single-objective scheduling methods based on global production indices optimization, where the objective is one of production rate, concentrate grade, production costs, or profits. Yu et al. [9] propose a nonlinear multi-objective programming model for mineral processing production planning. Five conflicting global production indices, including the iron concentrate output, the concentrate grade, the concentration ratio, the metal recovery, and the production cost, are considered. At the same time, a gradient-based hybrid operator is proposed to make a decision-making set of the established multi-objective problem. Similarly, Ref. [10] proposes a three-objectives scheduling approach for electric smelting furnaces, and Ref. [11] presents a two-level structure that integrates planning and scheduling. The proposed method in Ref. [11] is demonstrated to be able to provide efficient raw ore combinations for decision-makers. Refs. [19,20] present detailed descriptions of similar work in chemical processing, such as planning and scheduling for single-stage, multi-stage continuous, and multi-product process approaches.

3.2. Operation of the operational indices

Operational indices are a space-scale decomposition of the global production indices, and are obtained by the optimization of the global production indices; they represent the performance (i.e., quality, efficiency, and consumption during the production phase) of a unit process. The relationships between the unit processes are usually unknown. Therefore, it is important to coordinate the decisions that are made regarding the target operational indices of individual unit processes, to realize the optimization of the overall plant global production indices. Ref. [21] proposes an approach (Fig. 3) that is a typical framework of operational indices optimization. This closed-loop dynamic optimization strategy contains four modules: optimization of the initial operational indices, a predictive model of the global production indices, an *a priori* evaluation of the global production indices and dynamic tuning, and an *a posteriori* evaluation of the global production indices and dynamic tuning. The functions of each module are described below.

- **Optimization of the initial operational indices.** This module generates a set of pre-set operational indices, $r_{i,j}$ (where i = 1, 2, …, I), and their targets, $[r_{i,\min}, r_{i,\max}]$, based on the global production indices, $Q_j(t_d)$ (where j = 1, 2, …, J).
- **A predictive model of the global production indices.** This module produces a predicted value of the global production indices, $\hat{Q}_k(t)$, using the actual operational data at time t.
- **An *a priori* evaluation of the global production indices and dynamic tuning**. This module uses the target operational indices, $r_i^*(t)$, and the predictive operational indices, $\bar{r}(t)$, to generate the compensation value, $\Delta\hat{r}(t)$.
- **An *a posteriori* evaluation of the global production indices and dynamic tuning**. This module generates another operational indices compensation value, $\Delta r(T)$, by determining the difference between the actual global production indices, $Q_j(T)$, and the target production value, Q_j^* (where t is the sample interval, T is the test interval, $T = nt$, and n is an integer).

3.2.1. Optimization of operational indices

Refs. [21,22] propose a hybrid optimization approach that integrates case-based reasoning (CBR) with a multi-objective evolutionary algorithm (MOEA). In this approach, the decision-making for the operational indices, which uses CBR, is based on the operational experience of onsite process engineers, while the MOEA is the optimization of multiple global production indices. To achieve optimal operation, Ref. [23] solves a multi-stage beneficiation process optimization problem, and proposes a multi-objective operational optimization approach. Ref. [24] presents an operational indices decision-making approach that combines the dynamic multi-objective method with the CBR method. In practice, operational indices optimization is usually a dynamic problem. To solve this problem, Ref. [25] presents a dynamic multi-objective approach that considers the uncertainties of equipment capacity in the processing.

3.2.2. Prediction of global production indices

The predictive model for the global production indices adopts a hybrid model structure that consists of a linear main model and a nonlinear compensation model [21,22,24]. The linear main model provides the main relationship between the global production indices and the operational indices, while the nonlinear compensation model, which is established by a least-squares support vector machine (LSSVM) [26], is used to provide additional corrections for better prediction. Moreover, the parameters of the nonlinear compensation model are selected by minimizing the probability density function (PDF) of the modeling error [1]. This is the first time that the PDF control method is introduced to model parameter selection. Ref. [27] develops a multiple-models strategy-based prediction model, which integrates the fuzzy clustering algorithm with the machine-learning algorithm. To achieve online prediction for plant-wide global production indices, Ref. [28] proposes a data-based adaptive online prediction model that is achieved by updating the model's parameters online using the statistical properties of the training samples method. Ref. [29] presents a robust prediction method that is based on modifying the weight of the AdaBoost algorithm, which can reduce the model's sensitivity to outliers.

3.2.3. Dynamic tuning approach

Regarding dynamic tuning, a knowledge-based global operation

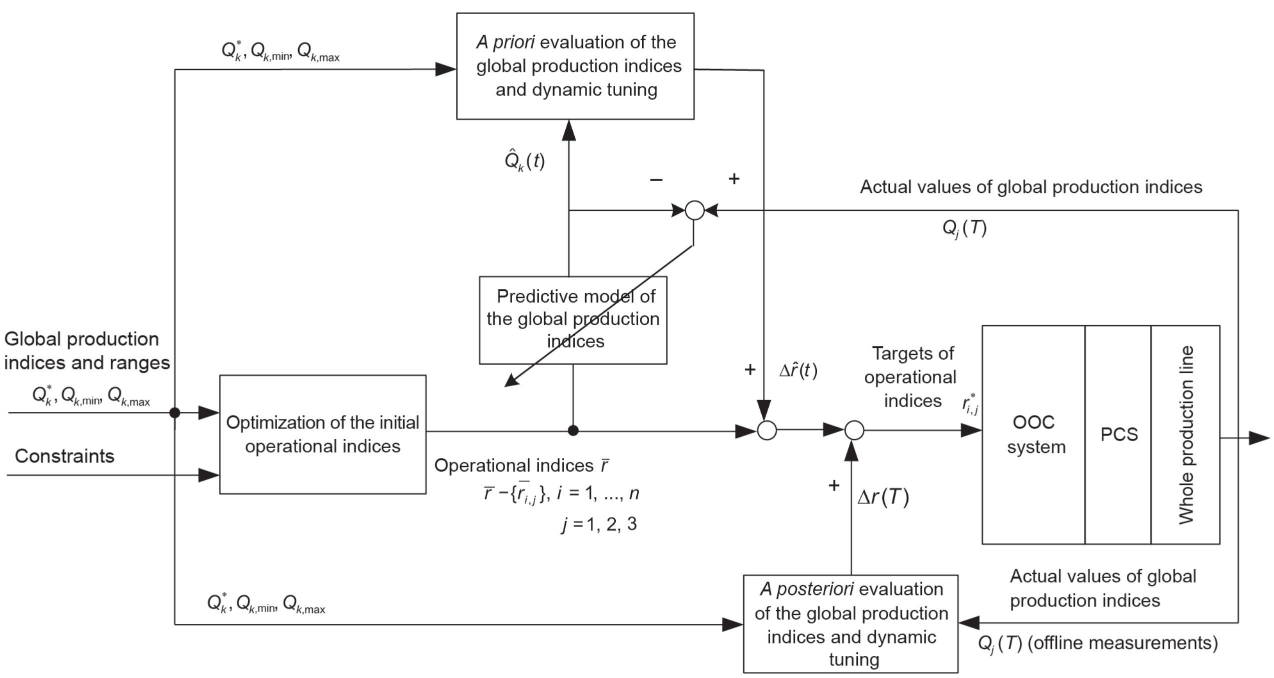

Fig. 3. Framework of operational indices optimization. OOC: optimal operational control; PCS: process control system. Q_k^* represents the target value of the kth production index. Q_k is the actual value of the kth production index. $\hat{Q}_k(t)$ represents the predictive value of the kth production index [21].

approach is proposed to minimize the effect on production performance that is caused by unexpected variations in the operation of a mineral processing plant [30]. An adaptation signal discovered from the process operational data is employed to construct a closed-loop dynamic operation strategy. A rough set-based rule extraction approach is developed to generate the compensation rules. Furthermore, a reinforcement learning algorithm is used to compensate for uncertainties and correct baseline operational indices online and in two different time scales. The learning loops are based on the actor-critic architecture [24].

3.3. Optimal operational control/setpoint optimization

Setpoints are the final decisions obtained by further decomposition of the operational indices. In general, setpoint optimization should be based on the characteristics of the unit process [31]. For example, a hybrid intelligent-control method for a shaft furnace-roasting process is proposed [32], which can control the operational indices within the desired range by an online adjustment of the setpoints of the control loops. Another example of setpoint optimization is an intelligence-based supervisory control strategy for a grinding system [33], in which a control loop setpoint optimization module, an artificial neural-network-based soft-sensor module, a fuzzy logic-based dynamic adjustor, and an expert-based overload diagnosis and adjustment module are integrated to perform the control tasks. For more setpoint optimization approaches, refer to the surveys in Refs. [31,34].

4. Conclusions and further work

Complex industrial processes contain multiple unit processes, and the process is often under uncertainty. This requires the optimization of plant-wide global production indices for the whole production line that characterize the overall plant performance. For this reason, this paper reviews a set of decision-making methods that focus on the optimization of the global production indices of complex industrial processes.

For future progress, it will be important to integrate each department's decision-making regarding planning and scheduling, the optimization of operational indices, and process optimization and control, in order to realize the essential global production indices, as presented in Ref. [12]. In addition, the demonstrated effectiveness and universality of the data-driven hybrid intelligent optimization structure, as proposed in Ref. [21], indicate that efforts should be made to improve the performance of each module of the structure.

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Compliance with ethics guidelines

Jinliang Ding, Cuie Yang, and Tianyou Chai declare that they have no conflict of interest or financial conflicts to disclose.

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