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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, $Q_j\ (t_\mathrm{m})$ (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, $Q_j\ (t_\mathrm{d})$ (where j = 1, 2, …, J, and t_d is the daily time scale), according to the monthly global production indices, $Q_j\ (t_\mathrm{m})$. Finally, the technical department decomposes the daily global production indices, $Q_j\ (t_\mathrm{d})$, into the operational indices, $r^*_{i,j}\ (t_\mathrm{h})$ (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

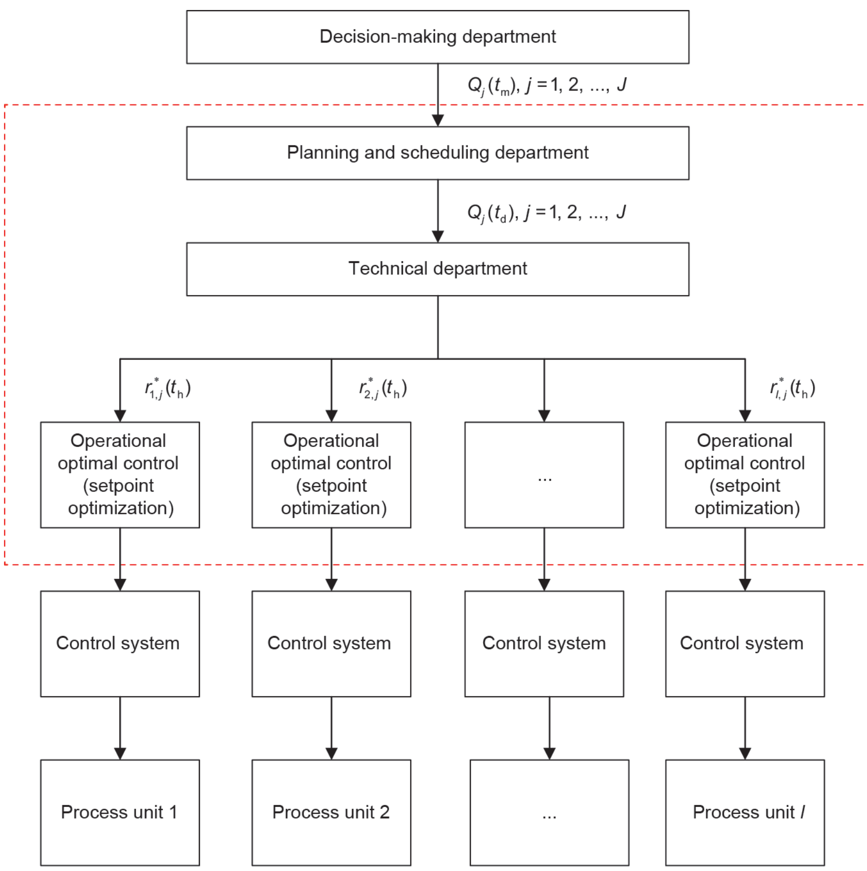

Fig. 1. Problem description of the multiple-layer optimization of mineral processing.