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A data-driven optimal control approach for solution purification process

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ABSTRACT

Solution purification holds a critical position in hydrometallurgy. With its inherent complexity and the mixed raw material supply, solution purification process exhibits various working conditions, and has nonlinear, time-varying dynamics. At current stage, a comprehensive and precise model of a solution purification process is still costly to obtain. More specifically, the model structure could be derived by applying physical and chemical principles, while the accurate model parameters cannot be obtained under certain working conditions due to reasons like insufficient data samples. This, in turn, introduces obstacles in achieving the optimal operation. In order to circumvent the modeling difficulty, this paper proposes a 'Process State Space' descriptive system to re-describe the optimal control problem of solution purification process, accordingly establishes a two-layer receding horizon framework for developing a data-driven optimal control of solution purification process. In the optimal control scheme, on the 'optimization' layer, by utilizing the 'multiple-reactors' characteristic of solution purification process, a 'gradient' optimization strategy is proposed to transform the dosage minimization problem into obtaining the optimal variation gradient of the outlet impurity concentrations along the reactors. On the 'control' layer, a model-free input constrained adaptive dynamic programming algorithm is devised and applied to calculate the optimal dosages for each reactor by learning from the real-time production data. Case studies are performed to illustrate the effectiveness and efficiency of the proposed approach. The results and problems need future research are also discussed.

1. Introduction

Solution purification is a critical step in hydrometallurgical production of high-purity metals. As a widely used industrial technology, hydrometallurgy is referred to extracting pure valuable metals from their concentrate ores by liquid processes which typically include leaching (or roasting and leaching), solution purification and electrowinning (Fig. 1). In the leaching process, the solid concentrate ores are first treated in sulfuric acid solution in order to liberate the valuable metal ions from concentrate ores. Due to the impurity and heterogeneity of the concentrate ores, the other associated metallic ions in the concentrate ores are dissolved into the acid solution simultaneously. Therefore, the resulted leaching solution contains ions of impurity metals harmful to the electrowinning process where the pure valuable metal is recovered [1]. An excessive amount of these impurities would dramatically decrease the current efficiency and downgrade product quality accordingly [2,3]. Thus, a solution purification process, as a link between leaching and electrowinning, is normally requested to replace and remove those impurities using additives, so that the concentrations of these impurities are kept down in acceptable ranges.

The control objective of a solution purification process is to decide the optimal combination of additive dosages to each reactor such that the technical index is met in an economical manner, i.e., the outlet impurity ion concentration is lower than a predefined value, while the additive consumption is minimal. Model is a widely used reference to support the process operations and optimal control [4]. Most existing control methods for solution purification process rely on an accurate process model [5–7]. Knapp et al. [8] and Yu et al. [9] proposed methods for the control of a single reactor that do not depend on the kinetic model, while solution purifica-

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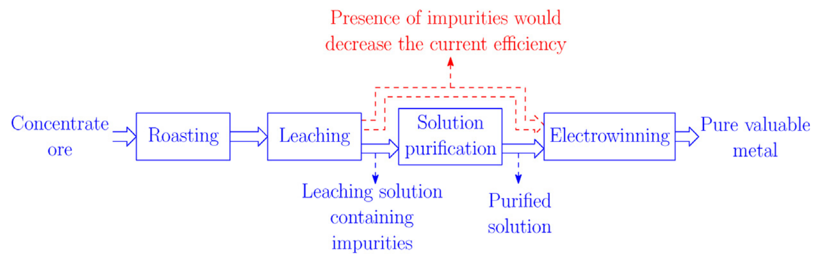

Fig. 1. A typical hydrometallurgical process.

tion process is composed of multiple reactors. In regarding to a solution purification process, the structure of a kinetic model can be derived by applying physical and chemical principles. However, due to reasons such as large modeling cost and insufficient data samples, the accurate value of the model parameters cannot be identified under certain working conditions. To deal with model uncertainty in controlled operation, some other researchers have taken the modeling uncertainties into account in the controller design of solution purification process or processes composed of CSTRs (Continuous Stirred-Tank Reactor). Wu studied the control of an industrial CSTR process by applying a robust model predictive control approach [10]. Hoang et al. developed a nonlinear control law for a large class of CSTRs far from the equilibrium based on Lyapunov method [11]. Sun et al. applied backstepping technique in the design of robust adaptive controller for solution purification process [12]. However, when there exist serious discrepancy between a process and its representative model, the performance of a controller would deteriorate and may cause offsets under steady-state, oscillations and instability of the closed-loop [13]. Therefore, its basic chemical principle (see (1)) could be rough guidance, practical dynamics of a solution purification process is more complex and the optimal operation is more challenging to achieve good quality/quantity of products.

In order to realize the optimal control when the model parameters are unknown, this work is conducted to design a model-free optimal control framework for solution purification process. The optimal control problem of solution purification is first formulated. The difficulties in the modeling and control of solution purification process are analyzed. Based on the analysis, a 'Process state space' descriptive system is proposed to re-describe the optimal control problem of solution purification process. The equivalence between the conventional 'state space model'+'model based control' and 'process state space description'+'model-free control' is discussed. The model-free feature of adaptive dynamic programming (ADP) is utilized to circumvent the modeling obstacle. ADP updates the controller iteratively, through excitation and reinforcement learning, to obtain an admissible controller sequence which starting from an initial admissible controller and gradually converges to the optimal controller with guaranteed stability [14]. Due to its ability in handling systems with unknown dynamics, ADP is attracting attention from the process control community [15][16]. Then, within the 'Process state space' framework, a data-driven approximated optimal control approach is proposed that decomposes and approximates the original optimal control problem on the 'optimization' and 'control' layers. On the 'optimization' layer, a 'gradient' optimization strategy is designed using the 'multiple-reactors' characteristic of solution purification process. The 'gradient' optimization strategy transforms the dosage minimization problem into obtaining the optimal decline gradient of the outlet impurity ion concentrations along the reactors. On the 'control' layer, the optimal additive dosage controller based on ADP is derived to track the optimal setting values. The two-layer control strategy operates in a receding horizon manner to account for the variation of process dynamics and inlet conditions. The constraints on the additive dosages of each reactor are also integrated in the controller design.

The rest of this paper proceeds as follows. Section 2 introduces the solution purification process,formulates the optimal control problem of the solution purification process, and analyses the challenging issues in the modeling and optimal control of the solution purification process. Section 3 proposes a 'Process State Space' framework to extend the traditional 'State Space' description. Then proposes a new two-layer approximated receding horizon optimal control by reformulating original optimal control problem to fit the new control requests. Section 4 takes up a case study to demonstrate the feasibility and effectiveness/efficiency of the developed procedure, which could be an example for potential applications. Section 5 presents concluding remarks and some interesting research topics found through this study.

2. Process description and problem formulation

This section gives further technical description of the solution purification process to provide a basis for formulating the optimal control.

2.1. Process description

A solution purification process consists of several impurity removal processes or units connected in serial, each of which is designed to remove a particular type of impurity. As shown in Fig. 2, an impurity removal process usually contains $N \quad (N \in \mathbb{N}_+)$ continuous stirred tank reactors and a thickener. Without loss of generality, the principle of impurity removal is to use additive, which is usually the powder of valuable metal, to replace the impurity ions in the leaching solution under specific reaction conditions (e.g., temperature 65–75 °C, pH 4.5–5.5) and, in some cases, the assistance of catalyst (e.g., antimony trioxide). The replacement reactions taking place in each reactor can be expressed as:

$$a\mathrm{A} + b\mathrm{B}^{m+} = a\mathrm{A}^{n+} + b\mathrm{B} \qquad (1)$$

where A is the often costly additive, B is the impurity metal, $a, b, m, n \in \mathbb{N}_+$ and $bm = an$ [17]. After retention in the consecutive reactors, the solution enters the thickener where the solid-liquid separation takes place. The solid resultant, which could be used as crystal nucleus for cementation, is deposited and recycled to promote impurity removal. The purified solution overflows. It is then filtered and delivered to the subsequent process.

2.2. Nominal kinetic model

Assume the solution in the reactor is perfectly mixed, the reaction rate and the solution temperature are uniform throughout the reactor. Then, the nominal kinetic model of the impurity removal process is [18]:

$$\frac{dc_i}{dt} = \frac{f_{i-1}}{V} c_{i-1} - \frac{f_i}{V} c_i - r_i c_i \qquad (2)$$