Computers and Chemical Engineering 86 (2016) 62–74

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

Real-time optimization for a laboratory-scale flotation column

Daniel Navia[a,*], Diego Villegas[a], Iván Cornejo[a], César de Prada[b]

[a] Departamento de Ingeniería Química y Ambiental, Universidad Técnica Federico Santa María, San Joaquín, Santiago de Chile, Chile
[b] Systems Engineering and Automatic Control Department, Universidad de Valladolid, P/Prado de la Magdalena S/N, Valladolid, Spain

ARTICLE INFO

Article history:
Received 26 May 2015
Received in revised form
11 November 2015
Accepted 12 December 2015
Available online 31 December 2015

Keywords:
Real-time optimization
Flotation column
Process optimization
Modifier adaptation
Derivative free optimization

ABSTRACT

In this paper, a supervisory layer with real-time optimization (RTO) has been implemented in an experimental laboratory-scale flotation column for copper concentration. A two-stage and modifier adaptation (MA) methodology for RTO has been compared under structural, experimental and dynamic uncertainty. In addition, a gradient-free alternative for MA, called nested modifier optimization, has been proposed and tested. The results show that the KKT updates of the MA approach allow the process optimum to be determined under uncertain scenarios, unlike the two-stage approach. From the perspective of gradient modifiers, the performance of the nested methodology is comparable to the dual approach because previous past values are used to update the modifiers without requiring the gradient estimation step. In addition, the interaction of RTO with the regulatory layer must be considered to propose an optimal implementation.

1. Introduction

The mining industry is the one of the main economic sectors in Chile. In 2013, copper mining constituted 10% of the GDP and 57% of total exports, representing 31% of the global market (Cámara Nacional de Comercio, 2015; Chile, 2013). Most of the copper can be found in sulfide ores, with an average concentration of approximately 0.9% w/w. The forecast of this index shows a continuous decrease, which translates into a reduced competitiveness of the local industry with respect to the rest of the world (Cobre, 2013).

The production of copper from sulfide ores has three main stages: comminution, concentration and refination. In the comminution stage, copper is released from the ore using size reduction methods. Then, copper minerals are separated from the remaining materials (i.e., gangue) in froth flotation circuits because of the selective hydrophobicity produced by chemical reagents (collectors). Finally, the copper concentrate is refined through smelting and electrochemical processes.

This work focuses on the flotation units during the concentration stage. A typical concentration circuit acts as a rougher, scavenger and cleaner. Each role is performed in a set of units, such as mechanical cells, columns and mills. Columnar flotation has been implemented in the cleaning stage at the end of the circuit. The main difference of columnar flotation with respect to other flotation equipment, aside from the shape, is the addition of cleaning water at the top of the column and the use of a bubble generation system (Finch and Dobby, 1990). This increases the degrees of freedom with respect to mechanical cells and allows for a wider control scope (Bergh and Yianatos, 2003). With this in mind, different combinations of the manipulated variables can be expected to improve the metallurgical performance of the column, i.e., recovery and purity. Because these two objectives are in contrast with one another and both affect the efficiency of the upstream processes, the study of systematic methods to optimize the operation of flotation columns is critical to seek out possible improvements.

Bouchard and coworkers (Bouchard et al., 2009) present an extensive review of the modeling, simulation and control of flotation columns. The authors divided the control according to specific tasks and update frequency in three layers, regulatory, intermediate and economic, in the same manner as the hierarchical structure presented by Engell (2007). The regulatory level accounts for the rejection of disturbances of the order of seconds and considers general control elements. The intermediate layer is responsible for maintaining process variables related to metallurgical objectives at given levels. According to Bergh and Yianatos (2011), in the absence of reliable models for flotation processes, methods based in heuristic rules has been proven to be adequate to achieve the goals of this layer (Bergh and Yianatos, 1995; Bergh et al., 1998). Finally, the upper hierarchical layer is responsible for identifying the metallurgical objectives with an economic criterion, looking for improvements with respect to a base case. When an economic

* Corresponding author.
E-mail addresses: daniel.navia@usm.cl (D. Navia), prada@autom.uva.es (C. de Prada).

http://dx.doi.org/10.1016/j.compchemeng.2015.12.006
0098-1354/

optimization is solved at this level, the supervisory control is known as real-time optimization (RTO).

RTO consists of solving a model-based optimization to find new improved operating points. A steady-state model of the process is required for this purpose. With respect to the availability of reliable models of flotation columns, both Bouchard and coworkers (Bouchard et al., 2009) and Yianatos (Yianatos, 2007) state that there are several open issues in the complete characterization of the mineral recovery in the column. Nevertheless, the RTO methodology accounts for the inherent uncertainty between the real system (called "the process" in this paper) and the model implemented in the optimization (or simply "the model") using the measurements obtained from the data acquisition system.

In this work, RTO has been implemented in a laboratory-scale flotation column to study the capability of finding optimal operating points in the presence of modeling mismatch. The experimental set-up follows the hybrid approach proposed by Bergh (2012) and Bergh and Yianatos (2014).

Two methods have been tested and compared for the RTO layer: classic two-stage RTO and the modifier adaptation (MA) methodology. In addition, a different approach based on solving a nested optimization problem has been presented and implemented (Navia et al., 2013, 2014a). The main contributions of this work are: (1) the use of an experimental system to study the performance of RTO for an industry-relevant process (Bunin et al., 2012; Marchetti et al., 2009; Zhang et al., 2015) and (2) the implementation of the nested modifier adaptation (NMA) as a gradient-free alternative for the original MA method in a laboratory-scale system.

The remainder of this paper is organized as follows. Section 2 presents an overview of the RTO methods applied in this work. Section 3 describes the experimental set-up and the model of the process. Section 4 describes the optimization of the flotation column. Section 5 presents the experimental results of the RTO layer. Finally, section 6 provides some concluding remarks.

2. Real-time optimization

The objective of a supervisory layer is finding the optimal decision variables $\boldsymbol{u} \in \mathbb{R}^{n_u}$, that minimize the objective function of a process $\phi_P : \mathbb{R}^{n_u} \to \mathbb{R}$ subject to given constraints $\boldsymbol{G_P} : \mathbb{R}^{n_u} \to \mathbb{R}^{n_G}$. Problem (1) summarizes this problem, where subscript P represents a quantity measured or estimated from the process. In problem (1), constraints related to bounds of the decision variables are included in $\boldsymbol{G_P}$.

$$\begin{aligned} &\min_{\boldsymbol{u}} \phi_P(\boldsymbol{u}) \\ &\text{s.t. :} \\ &\boldsymbol{G_P}(\boldsymbol{u}) \leq \boldsymbol{0} \end{aligned} \tag{1}$$

Because it is not possible to know the precise representation of the real system, problem (1) is solved using an approximate model of the process as shown in problem (2), where $\boldsymbol{\theta} \in \mathbb{R}^{n_\theta}$ are the parameters of the available model.

$$\begin{aligned} &\min_{u} \phi(\boldsymbol{u}, \boldsymbol{\theta}) \\ &\text{s.t. :} \\ &\boldsymbol{G}(\boldsymbol{u}, \boldsymbol{\theta}) \leq \boldsymbol{0} \end{aligned} \tag{2}$$

2.1. Two-stage RTO

Bamberger and Isermann (1978) proposed a two-stage algorithm to cope with the uncertainty related to the model. The first step consists of solving a parameter estimation problem to calculate the value of $\boldsymbol{\theta}$ in the actual operating point $\boldsymbol{u}_k^\star$ from problem (3). $\boldsymbol{y_P}$ are the measurements of the process, $\boldsymbol{y}(\boldsymbol{u}_k^\star, \boldsymbol{\theta})$ are the predictions of the model, $\boldsymbol{h}(\boldsymbol{u}_k^\star, \boldsymbol{\theta})$ is the mapping of $\boldsymbol{y}(\cdot)$ and $\boldsymbol{D} \in \boldsymbol{S}_+$ a square matrix.

$$\begin{aligned} &\min_{\boldsymbol{\theta}} [\boldsymbol{y_P}(\boldsymbol{u}_k^\star) - \boldsymbol{y}(\boldsymbol{u}_k^\star, \boldsymbol{\theta})]^T \boldsymbol{D} [\boldsymbol{y_P}(\boldsymbol{u}_k^\star) - \boldsymbol{y}(\boldsymbol{u}_k^\star, \boldsymbol{\theta})] \\ &\text{s.t. :} \\ &\boldsymbol{y}(\boldsymbol{u}_k^\star, \boldsymbol{\theta}) = \boldsymbol{h}(\boldsymbol{u}_k^\star, \boldsymbol{\theta}) \end{aligned} \tag{3}$$

With the updated parameters $\boldsymbol{\theta}_k^\star$, the economic optimization of problem (2) is solved and a new stationary point $\boldsymbol{u}_{k+1}^\star$ is calculated. The new operating point is then applied to the process in an iterative scheme.

2.2. Modifier adaptation

The physical dependencies of the process are typically not completely represented by the model. Hence, the uncertainty of the model is not only parametric but also structural. In this case, the two-step algorithm will not necessarily converge to the process optimum. With this in mind, several approaches based in the correction of the curvature of the objective function and the inequality constraints have been proposed (Gao and Engell, 2005; Roberts, 1979; Tatjewski, 2002). In these works, the necessary conditions of optimality (NCO) of problem (2), are modified to match the NCO of problem (1). This method is called the MA methodology and was presented by Chachuat et al. (2009) and formalized by Marchetti et al. (2009) and Marchetti (2013). The main concept of the MA method is replacing the model-based optimization with problem (4).

$$\begin{aligned} &\min_{u} \phi_M := \phi(\boldsymbol{u}, \boldsymbol{\theta}) + \boldsymbol{\lambda}_k^{\boldsymbol{\phi}^T} (\boldsymbol{u} - \boldsymbol{u}_k^\star) \\ &\text{s.t. :} \\ &\boldsymbol{G_M} := \boldsymbol{G}(\boldsymbol{u}, \boldsymbol{\theta}) + \boldsymbol{\varepsilon_k} + \boldsymbol{\lambda}_k^{\boldsymbol{G}^T} (\boldsymbol{u} - \boldsymbol{u}_k^\star) \leq \boldsymbol{0} \end{aligned} \tag{4}$$

In problem (4), the modifiers $\boldsymbol{\lambda}_k^{\phi} \in \mathbb{R}^{n_u}$, $\boldsymbol{\lambda}_k^{\boldsymbol{G}} \in \mathbb{R}^{n_G \times n_u}$ and $\boldsymbol{\varepsilon}_k \in \mathbb{R}^{n_G}$ are estimated from the process in the actual operating point using Eq. (5).

$$\begin{aligned} \boldsymbol{\varepsilon_k} &:= \boldsymbol{G_P}(\boldsymbol{u}_k^\star) - \boldsymbol{G}(\boldsymbol{u}_k^\star, \boldsymbol{\theta}) \\ \boldsymbol{\lambda}_k^{\boldsymbol{G}^T} &:= \nabla_{\boldsymbol{u}} \boldsymbol{G_P}(\boldsymbol{u}_k^\star) - \nabla_{\boldsymbol{u}} \boldsymbol{G}(\boldsymbol{u}_k^\star, \boldsymbol{\theta}) \\ \boldsymbol{\lambda}_k^{\boldsymbol{\phi}^T} &:= \nabla_{\boldsymbol{u}} \boldsymbol{\phi_P}(\boldsymbol{u}_k^\star) - \nabla_{\boldsymbol{u}} \boldsymbol{\phi}(\boldsymbol{u}_k^\star, \boldsymbol{\theta}) \end{aligned} \tag{5}$$

Problem (4) is solved iteratively, implementing its outcomes, i.e., $\boldsymbol{u}_{k+1}^\star$, to the process and updating the modifiers once that the steady state is reached, as shown in Fig. 1.

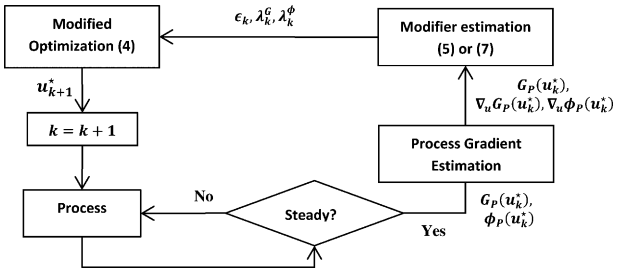

Fig. 1. Iterative implementation of the MA methodology.