minerals

Editorial

Editorial for Special Issue "Design, Modeling, Optimization and Control of Flotation Process"

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Flotation is a significant and widely used processing technique, effectively separating valuable and gangue minerals. Mineral producers have long sought ways to consistently monitor and control the flotation process to ensure optimal conditions for effective mineral separation [1]. However, establishing such a sophisticated control system entails significant financial investments in equipment, resulting in substantial costs. Additionally, ongoing maintenance needs to be performed to uphold the system's high standards, which will incur additional expenses. To address these challenges, predictive models emerge as effective and economically viable solutions to handling the intricacies of the flotation process [2].

In the flotation process, numerous linear and nonlinear relationships exist between the operating parameters, chemical reagents, and minerals [3]. These connections can be evaluated using various experimental and numerical methods. Over recent decades, a variety of intelligent computing and statistical techniques, including machine learning, genetic algorithms (GAs), artificial neural networks (ANNs), fuzzy systems, and image processing, have been employed to predict the flotation process outcome and facilitate the process control [4]. It is worth noting that the crucial role of these techniques in achieving sustainable development across various industrial sectors was recognized more than a decade ago.

The papers featured in this Special Issue of *Minerals*, titled 'Design, Modeling, Optimization, and Control of the Flotation Process', explore innovative approaches for modeling, optimizing, and controlling some flotation processes. These techniques aim to enhance efficiency by maximizing the recovery of valuable minerals, while minimizing energy and reagent consumption in relevant studied flotation processes. The manuscripts published in this issue can be grouped into three broad categories.

The initial category focused on hydrodynamic and kinetic models to examine the attachment of mineral particles to bubbles. The attachment process is intricate, involving multiple physical and chemical interactions, such as adsorption, desorption, and chemical reactions. These mechanisms were numerically represented through a variety of models, employing sets of differential equations that illustrate the concentration of minerals and chemical reagents within the flotation cell as time progresses [5–7].

The second group concentrated on modeling and optimizing the flotation process and developing strategies to enhance our understanding of the effects of gas dispersion and its regulation using dynamic models, multivariable linear models, and image analysis [8,9]. These studies explored the stability of the froth zone under varying flotation conditions and highlighted the significance of the relationship between particle and bubble sizes as critical factors impacting successful collection, froth transport processes, and the flotation rate and efficiency.

The third group of papers in this Special Issue delved into modeling and optimizing the flotation process performance utilizing advanced computational tools and algorithms such as the response surface methodology (RSM), GA, ANN, deep learning, and fuzzy systems [10–14]. Some of the studies published in this Special Issue aimed to address the challenges of recovering target elements more effectively using these methods. Generally, the efficiency of the flotation process is assessed by examining the characteristics of the concentrate, specifically its grade and recovery, which are crucial economic and technical indicators for process management and improvement. Determining these parameters typically involves time-consuming procedures. While the grade can be constantly monitored using an XRF analyzer, recovery is usually determined with mass balancing techniques [15]. However, the online measurement of these parameters using X-ray analyzers, although feasible, requires expensive and complex equipment, along with ongoing maintenance, which justifies the preference for models predicting the key performance indexes derived from secondary variables [16]. Given the nonlinear and intricate nature of the flotation process, coupled with the involvement of numerous variables and a limited understanding of its physicochemical principles, accurately forecasting metallurgical performance parameters presents a significant challenge.

The techniques outlined in the Special Issue have the potential to significantly improve the optimization and control of flotation operation, aiming to maximize the process efficiency. In the near future, with the increasing demand for metals and ongoing research advancements, these innovative computational techniques are expected to become effective solutions for monitoring and controlling the flotation process. We anticipate that this Special Issue will serve as a platform for future multidisciplinary research in modeling, designing, and optimizing the flotation process.

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