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Evaluation of Changes in Feed Particle Size within an Economic Model Predictive Control Strategy for Froth Flotation

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Abstract: This study presents the evaluation of the impact of feed particle size on an Economic Model Predictive Control (E-MPC) strategy for a flotation bank. The effect of particle size was assessed under two scenarios: (1) assuming constant floatability with no dependency on particle size, and (2) assuming variable floatability as a function of particle size. The E-MPC strategy uses a dynamic model that includes froth physics, which was previously calibrated and validated using experimental data. Two typical control variables were considered: air flowrate and pulp height setpoints. The proposed objective function depends on three flotation variables: (1) dynamic air recovery, a measurable variable used to quantify froth stability and is directly related to flotation performance, (2) metallurgical recovery at steady-state, and (3) dynamic concentrate grade. A moving horizon estimator (MHE) was implemented to estimate the model states in both scenarios. Simulation results showed that the estimation of metallurgical indicators (concentrate grade and recovery) was significantly affected by changes in the floatability parameter. A poor estimate of floatability is likely to lead to very different results for the control strategy. Future research should focus on estimating and updating the most significant parameters of the dynamic model, such as floatability, with an appropriate sampling time.

Keywords: Economic model predictive control; Floatability; Froth flotation control; Froth phase modelling; Particle size

1. INTRODUCTION

Froth flotation is one of the most important mineral separation processes. Flotation can be affected by a great number of disturbances, including changes in feed flowrate, ore composition, ore liberation, and feed particle size. It is well known that feed particle size has a significant impact on flotation recovery. While several studies showed that there is an optimal range of particle sizes, which usually goes between 20 μm to 150 μm (Gaudin et al., 1942), its independent relationship with operating variables makes the application of advanced control and optimisation very challenging (Norori-McCormac et al., 2017).

Advanced control and optimisation strategies have been the focus of much research in recent years. Model Predictive Control (MPC) is one of the most effective advanced control strategies for enhancing process performance. In contrast to other chemical sectors, however, the mineral processing sector has yet to successfully integrate such advanced strategies. A survey conducted by Olivier and Craig (2017) found that although even small improvements result in significant increases in production due to the large scale of the processes, there is still great scope for advanced control strategies in the mineral processing industry. In particular for froth flotation, the potential of implementing MPC strategies has so far remained untapped, as it is difficult to model this process due to its complex dynamics with inherent instabilities (Quintanilla et al., 2021a).

The use of steady-state models for real-time optimisation (RTO) applications has been reported in the literature, such as the studies proposed by Sbarbaro and del Villar (2010) and Navia et al. (2018). It has been questioned, however, whether a steady-state operation is the best strategy given the time-dependent process economy and the process' inherent nonlinearity (Ellis et al., 2014). As such, Economic Model Predictive Control (E-MPC) has been proposed as a control strategy that considers both closed-loop stability and dynamic economic performance (Diehl et al., 2011) when a dynamic model of the process is available. It must be noted that the term "economic" in E-MPC can directly or indirectly measure process economics. This concept is further explored in Ellis et al. (2014), which presents an example of E-MPC implementation using kinetic models to maximise reactor production.

The main contribution of the present work is to study the effect of changes in feed particle size in a flotation bank within the E-MPC strategy proposed in Quintanilla et al. (2023b). The E-MPC strategy uses a dynamic

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physics-based flotation model, presented in Quintanilla et al. (2021c), and commonly measured flotation variables to maximise mineral recovery in a flotation bank while maintaining a minimum limit of the concentrate grade at 20%. An effective objective function for the optimisation problem is proposed, which was built based on both available online measurements and process economics. A moving horizon estimator strategy (MHE) was also implemented to estimate the states of the model.

2. PROCESS DESCRIPTION

The principle of mineral separation in froth flotation is based on the surface properties of the different mineralogical classes in the feed ore. Chemical reagents and air are added to the process to make the valuable mineral particles hydrophobic, so they attach to the air bubbles, covering them and generating bubble-particle aggregates. The bubble-particle aggregates rise to the top of the cell, forming a froth that overflows as a mineral-rich concentrate, while the gangue (waste rock) remains in a pulp phase, and then leaves from the bottom of the cell as tailings. Efficient separation of valuable minerals from gangue is not possible in a single flotation cell due to the physical nature of the separation, so the cells are connected in series (a flotation bank) to improve overall performance. The main goal of a rougher flotation bank is to recover as much valuable metal as possible while maintaining a desired concentrate grade. The concentrate flowrate is sent to further stages, usually to cleaning cells, where the objective is to increase the concentrate grade.

The E-MPC strategy proposed in this study involves a rougher flotation bank comprising three tanks. This specific number of tanks was selected because the proposed E-MPC strategy will be further assessed in the laboratory-scale flotation bank presented in Quintanilla et al. (2023a).

3. MODEL OVERVIEW

A nonlinear, dynamic physics-based model that includes froth physics was used in this study. The model was developed by Quintanilla et al. (2021c), and calibrated and validated using experimental data, as shown in Quintanilla et al. (2021b). The dynamic model is classified as a DAE (Differential and Algebraic Equations) system. The model has $26 + 5K + 10I$ equations and $29 + 5K + 12I$ variables, where K is the number of bubble size classes, and I is the number of mineralogical classes used. The number of bubble size classes, K, allows better accuracy for estimating the dynamic gas holdup. In this work, a total of 10 bubble size classes (i.e. $K = 10$) were considered, in addition to two mineralogical classes (i.e. $I = 2$): (1) Chalcopyrite as a valuable mineral ($i = 1$), which contains 32.64% of copper, and (2) quartz as gangue ($i = 2$). For a more detailed overview of the dynamic model's equations, variables and parameters, the reader is referred to Tables 5 and 6 in Quintanilla et al. (2021c).

The effect of particle size on flotation performance is considered in the flotation model in various ways:

(1) **Flotation kinetics:** Flotation kinetics is influenced by particle size through the kinetic parameter k_i, which is defined as $k = P_i S_b$. The parameter P_i represents the floatability of the mineralogical class, while S_b is the bubble surface flux. The relationship between particle size and floatability was first established based on empirical data available in the literature. Fig. 1 illustrates this relationship. The kinetic parameter k_i is then used to calculate the mass of solid transfer due to true flotation ($m_{TF_{i,j}}$ for mineralogical class i and cell j, Eq. (51) in Quintanilla et al. (2021c)), which is used to calculate the total grade of the bank ($G_{conc_{bank}}$) and recovery. $G_{conc_{bank}}$ is defined as the sum of the mass of the metal in each flotation cell ($M_{metal_{conc_j}}$) divided by the total mass of solids in the concentrate of each flotation cell ($M_{total_{conc_j}}$). Each of these terms is defined as follows:

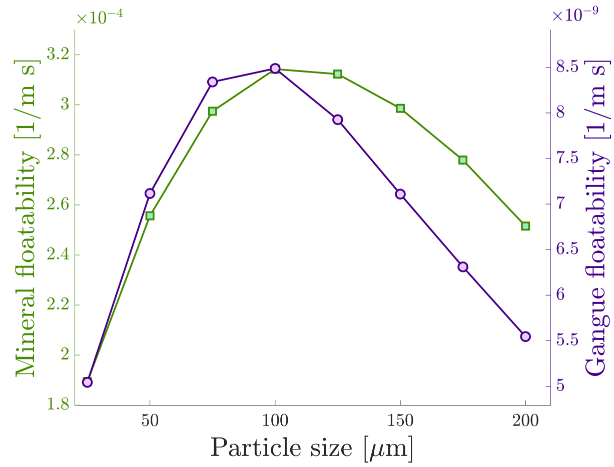

Fig. 1. Floatability for valuable mineral and gangue as a function of particle size (d_p). Data taken from Hu (2014).

$$\mathrm{G}_{conc_{bank}} = \frac{M_{\text{metal conc } j}}{M_{\text{total conc}_j}}, \tag{1}$$

$$M_{\text{metal}_{\text{conc } j}} = \sum_{j=1}^{3} m_{TF_{metal_j}} + m_{ENT_{metal_j}}, \tag{2}$$

$$M_{\text{total}_{\text{conc } j}} = \sum_{i=1}^{2}\sum_{j=1}^{3} m_{TF_{i,j}} + m_{ENT_{i,j}}, \tag{3}$$

where $m_{ENT_{i,j}}$ is the mass transfer of solids due to entrainment ((56) in Quintanilla et al. (2021c)) for mineralogical class i and cell j. The total recovery of the bank (Rec_{bank}) is defined as:

$$Rec_{bank} = \frac{M_{\text{metal}_{\text{conc}_j}}}{M_{\text{metal}_{Feed}}} \tag{4}$$

where $M_{metal_{conc_j}}$ is calculated from Equation 3 and $M_{metal_{Feed}}$ is the amount of metal in the feed ((10) in Quintanilla et al. (2021c)).

(2) **Air recovery:** Feed particle size affects the attachment of particles to bubbles in the pulp, which in turn influences froth stability and flotation performance. Dynamic froth stability can be evaluated by measuring the air recovery (α) in continuous flotation systems. Increasing air flowrate leads to a peak in air recovery, corresponding to optimal flotation performance in terms of mineral recovery. The attachment

of particles to bubbles in the pulp is greatly affected by feed particle size, which in turn affects froth stability, and thus, the froth flotation performance. For continuous flotation systems, dynamic froth stability can be measured using air recovery (α), which is defined as follows:

$$\alpha = \frac{v_f h_{over} l_{lip}}{Q_{air}}, \tag{5}$$

where v_f is the overflowing froth velocity, h_{over} is the froth height over the flotation cell lip, l_{lip} is the lip length, and Q_{air} is the air flowrate. It has been demonstrated that increasing air flowrate leads to a peak in air recovery (PAR), which corresponds to the optimal flotation performance in terms of recovery of minerals to the concentrate (Hadler and Cilliers, 2009). Therefore, air recovery is a variable to be maximised in the objective function, as discussed later in Section 4.

(3) **Entrainment factor:** Predicting the entrainment is key to determining flotation performance and it is crucial to estimate the concentrate grade achieved. The entrainment factor (ENT_i) can be calculated using a simplified phenomenological model as follows:

$$ENT_i \approx \begin{cases} \exp\left(\dfrac{-v_{set,i}^{1.5} h_f}{D_{axial}\sqrt{v_g^*\left(1-\alpha^*\right)}}\right) & \text{if } \alpha < 0.5 \\ \exp\left(\dfrac{-2v_{\text{set},i}^{1.5} h_f}{D_{\text{axial}}\sqrt{v_g^*}}\right) & \text{if } \alpha \geq 0.5 \end{cases} \tag{6}$$

where h_f is froth depth, D_{axial} is the axial dispersion ((58) in Quintanilla et al. (2021c)), v_g^* is the interfacial gas velocity ((37) in Quintanilla et al. (2021c)), and α^* is air recovery ((42) in Quintanilla et al. (2021c)). The term $v_{set,i}$ is the particle settling velocity, which is proportional to the square of the particle size (d_p):

$$v_{set,i} = \frac{g\left(\rho_{\text{solid},i} - \rho_{\text{water}}\right) d_p^2}{18\mu_{\text{pulp}}} \frac{(1-\phi)^{4.65}}{3} \tag{7}$$

$\rho_{solid,i}$ is the density of the solid of mineralogical class i, ρ_{water} is the water density, μ_{pulp} is the pulp density, and ϕ is the volumetric solid fraction.

(4) **Froth recovery:** The fraction of the material entering the froth attached to the bubbles that report to the concentrate, also known as froth recovery ($R_{F,i}$), is dependent on the settling velocity; hence, it is also affected by changes in particle sizes.

$$R_{F,i} = \begin{cases} \left(\dfrac{\alpha^*\left(1-\alpha^*\right) v_g^*}{v_{\text{set },i}}\right)^{\frac{f}{2}} \left(\dfrac{d_{\text{b, int}}}{d_{\text{b, froth}}}\right)^f & \text{if } \alpha < 0.5 \\ \left(\dfrac{v_g^*}{v_{\text{set},i}}\right)^{\frac{f}{2}} \left(\dfrac{d_{\text{b, int}}}{d_{\text{b, froth}}}\right)^f & \text{if } \alpha \geq 0.5 \end{cases} \tag{8}$$

The parameter f is a constant value between 0 and 1 that represents the fraction of material that detaches from bubble surfaces during coalescence. In this study, it was assumed to be 0.5. $d_{b,int}$ is the interfacial bubble size ((38) in Quintanilla et al. (2021c)), and $d_{b,froth}$ is the froth bubble size ((48) in Quintanilla et al. (2021c)). Both entrainment factor and froth recovery allow predicting the metallurgical recovery and concentrate grade by determining the amount of solids transferred from the pulp phase to the froth due to entrainment and true flotation (see Eq. 2).

4. CONTROL STRATEGY IMPLEMENTATION

The methodology used for implementing the E-MPC strategy is based on the strategy presented in Quintanilla et al. (2023b). However, the objective function was modified such that it was applicable to a flotation bank, instead of a single flotation cell, as originally formulated in Quintanilla et al. (2023b). The objective function for the flotation bank, J, is then defined as follows:

$$\begin{aligned} J := \sum_{j=1}^{3}\left(\int_{t_0}^{t_{N_p}} \beta_{\alpha_j}\alpha_j(t)dt + \sum_{n=0}^{N_p-1} \mathbf{\Delta u}_{n_j}^T \boldsymbol{\beta}_{\mathbf{u_j}} \mathbf{\Delta u_j}_n\right) \\ +\beta_{\text{Rec}}\,\text{Rec}_{\text{bank}}\left(t_{N_p}\right) - \int_{t_0}^{t_{N_p}} \beta_{G_{conc}} G_{conc_{bank}}(t)dt \\ \text{for j } = 1,2,3, \end{aligned} \tag{9}$$

where α_j is the air recovery (Eq. 5), $G_{conc_{bank}}$ is the total concentrate grade of the flotation bank (Eq. 1), $\text{Rec}_{bank}(t_{N_p})$ is the total recovery of the bank at the end of the prediction horizon N_p (Eq. 4), and $\mathbf{\Delta u}_{n_j}$ is the decision variable vectors of each cell j. As presented in Quintanilla et al. (2023b), each term of the objective function (i.e. air recovery, concentrate grade and metallurgical recovery) was validated through comprehensive sensitivity analyses. Additionally, each of these terms was penalised by a parameter such that $\boldsymbol{\beta}^T := [\beta_{\alpha_j}, \beta_{G_{\text{conc}}}, \beta_{\text{Rec}}, \beta_{u_{1_j}}, \beta_{u_{2_j}}] = [10^8, 10^6, 10^8, 10^6, 10^2]$. The values of these parameters were chosen to lead to the optimal performance of the optimisation solver in terms of convergence time.

The objective function was implemented in a centralised fashion to control all flotation cells simultaneously and find the global optima of the bank. The relationship between each flotation cell j in the centralised strategy is given by:

$$Q_{tailings_{(j-1)}} = Q_{feed_j}. \tag{10}$$

A constraint was enforced in the study to ensure that the total grade in the bank was equal to or greater than 20%. While 20% is a sensible value for rougher cells at an industrial scale, it should be noted that the actual minimum concentrate grade a plant adopts varies depending on its technical and economic requirements. In the Supplementary Material of Quintanilla et al. (2023b), the results demonstrate the capability of the proposed E-MPC to adjust to varying concentrate grade constraints.

Another constraint was imposed on the manipulated variables, specifically the superficial air velocity and h_p setpoints, which were restricted to change no more than 10% of their current value in each iteration.

The control strategy in this study was implemented in MATLAB R2020B using CasADi (Andersson et al., 2019).

CasADi is an open-source software tool that allows large-scale optimisation for DAE systems to be solved. CasADi uses a symbolic framework to obtain the derivatives of the problem using automatic differentiation efficiently.

Since only simulation results are presented in this study, the "measurements" were simulated using the same dynamic model in Quintanilla et al. (2021c), but adding uniformly distributed pseudorandom noise, using the MATLAB function *randi*. Then, the states were estimated using a moving horizon estimator (MHE), as described in Rawlings et al. (2022).

5. RESULTS AND DISCUSSIONS

The changes in particle size were considered measurable disturbances, whose means range between 25 μm to 200 μm, with a frequency of change of 10 minutes. Two Scenarios of floatabilities (P_i) values were evaluated using the same model:

- Scenario 1: Assuming constant floatability (i.e. it does not change with particle size). For chalcopyrite ($i = 1$ in the model), the floatability parameter was 2.4 $\times$ 10^{-4}, and for quartz ($i = 2$ in the model), the floatability parameter was 7.8 $\times$ 10^{-9} ;
- Scenario 2: variable floatability as a function of particle size calculated according to the empirical data depicted in Fig. 1.

The reason for evaluating two different floatability scenarios (constant and particle size dependent) is that this is a difficult parameter to estimate and that it is almost impossible to obtain its value in real-time. Because floatability is linked to the flotation kinetics, entrainment, and froth recovery, it is possible that a poor estimation of this parameter could lead to erroneous results.

The total metallurgical recovery of the bank and the concentrate grade are depicted in Fig. 2, for both constant and variable floatability. It can be clearly seen that there is a big difference in recovery and concentrate grade estimation in both scenarios. For scenario 2, the estimation of recovery and grade is always lower. Additionally, it can be observed that the concentrate grade is lower than 20% when feed particle size is below 75 μm. This decrease may be due to the destabilising effect of rupturing the thin films and reduced froth mobility, which makes it more difficult for coarse particles to be entrained and recovered. The maximum metallurgical recovery for scenario 2 was achieved for a particle size of 125 μm. In this case, the concentrate grade was 20 % in all the iterations, except for the first one, which is when the change of particle size is produced.

In Fig. 3, the changes in pulp level and tailings flowrates are shown. It can be observed that the decisions taken by the E-MPC controller are different in both scenarios even though the initial conditions are the same. For example, in scenario 1, the pulp level setpoints change constantly, which may be explained by the fact that concentrate grade in Fig. 2 goes up and down near 20% but not exactly 20%, so the controller tries to adjust both degrees of freedom (air flowrate and pulp level setpoints) in order to avoid constraint violations. It can be also observed that the controller increases the pulp level setpoints when the

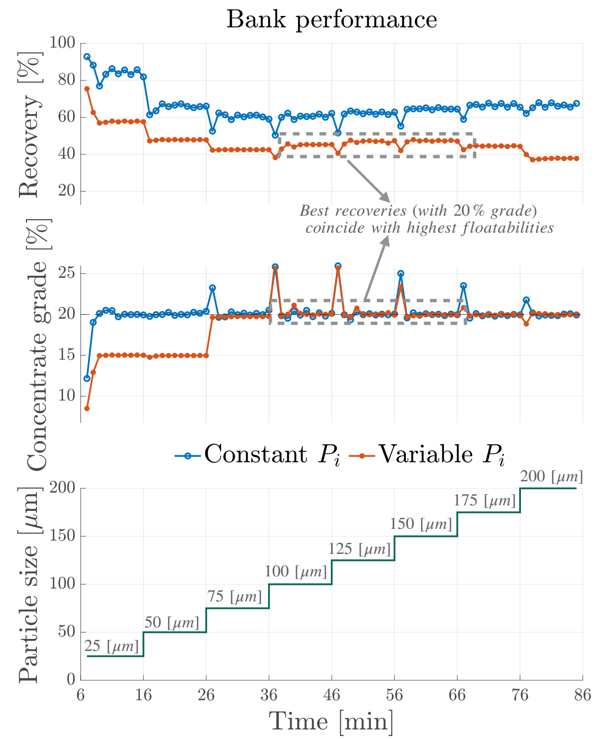

Fig. 2. Metallurgical recovery and concentrate grade of the bank for different particle sizes for Scenario 1 (blue lines, constant P_i) and Scenario 2 (orange lines, P_i as a function of particle size). Note that, for simplification, particle sizes were considered constant in each iteration.

concentrate grade is over 20%. This behaviour is in line with what was expected, as shallower froths would lead to increments in the metallurgical recovery, decreasing the concentrate grade. For particle sizes of 25 μm and 50 μm, the concentrate grade for scenario two was always lower than 20%; therefore, the controller set the pulp levels of all the cells to their lower limit (0.35 m) to increase the concentrate grade. However, since the simulations were run for laboratory-scale dimensions, there was not much range to move pulp level setpoints to achieve higher concentrate grades.

Dynamic air recovery and superficial air velocity (j_g) are depicted in Fig. 4. It must be noted that $j_g = Q_{air}/A_{cell}$, where A_{cell} is the cross-sectional area of the flotation cell. It can be observed from the figure that there is a clear trend of air recovery versus particle size for Scenario 1. On the contrary, the air recovery remains constant in Scenario 2 for all cases when the concentrate grade is below 20%. It is interesting to note that the controller tended to bring both decision variables, air flowrate and pulp level setpoints (see Fig. 3 and 4), to their minimum limits in Scenario 2 when the concentrate grade values were below 20%. It can be also observed in Scenario 2 that there is a peak in air recovery in the three cells when feed particle size 175 μm, with the highest j_g and deepest froth depths (see Fig. 3). This behaviour in the controller raises intriguing questions regarding the nature and extent of how often the significant parameters of the model, such

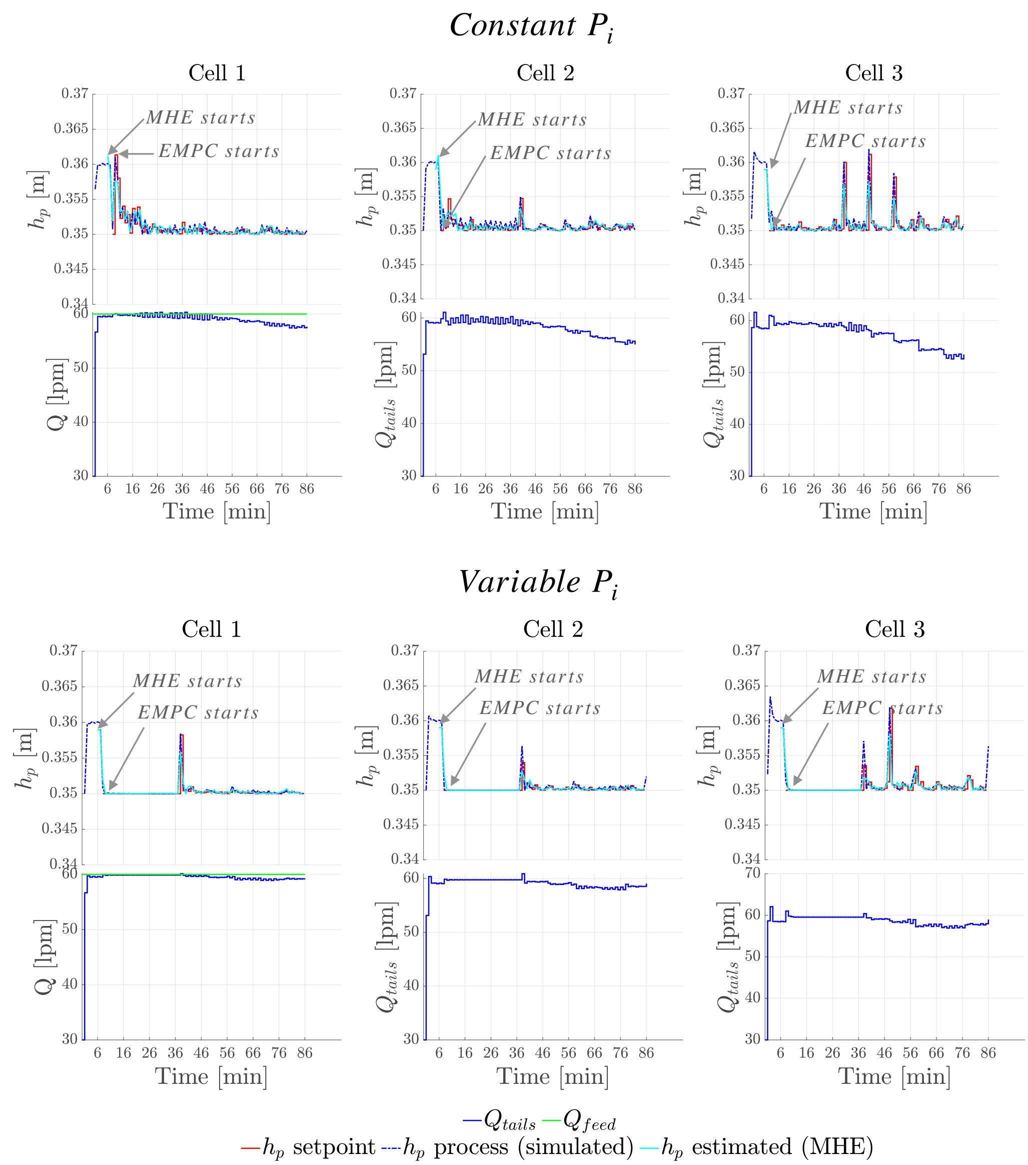

Fig. 3. Pulp level (h_p) control for each flotation cell in the bank, for Scenario 1 (constant P_i) and Scenario 2 (P_i as a function of particle size). The blue lines are the process values (simulated), the red lines are the pulp level setpoints, and the cyan lines are the pulp level estimated using moving horizon estimator (MHE).

as floatability, should be updated when implementing an advanced controller at an industrial scale.

6. CONCLUSIONS

This study investigated the effect of particle size by evaluating two possible scenarios: (1) assuming constant floatability, and (2) assuming variable floatability that is dependent on particle size.

The selected decision variables (manipulated variables) were air flowrate and pulp level setpoints. The objective function considered air recovery as a measure of froth stability, metallurgical recovery, and concentrate grade. The final goal was to maximise the metallurgical recovery of the flotation bank by maximising air recovery (which can be measured online) and maintaining the concentrate grade at a minimum value of 20%.

The results showed that changes in the floatability parameter significantly affect the predictions of the metallurgical indicators: concentrate grade and recovery. The two scenarios evaluated in this study also showed that the controller takes different decisions in the manipulated variables to maximise the objective function, based on the prediction of the model, which is different due to floatability being, in fact, a parameter with high sensitivity in the dynamic model. Therefore, the findings suggest that the control strategy could lead to very different results if the floatability is poorly estimated. Further work should thus focus on developing a more sophisticated tool to update key parameters of the model by using, for example, reinforcement learning.

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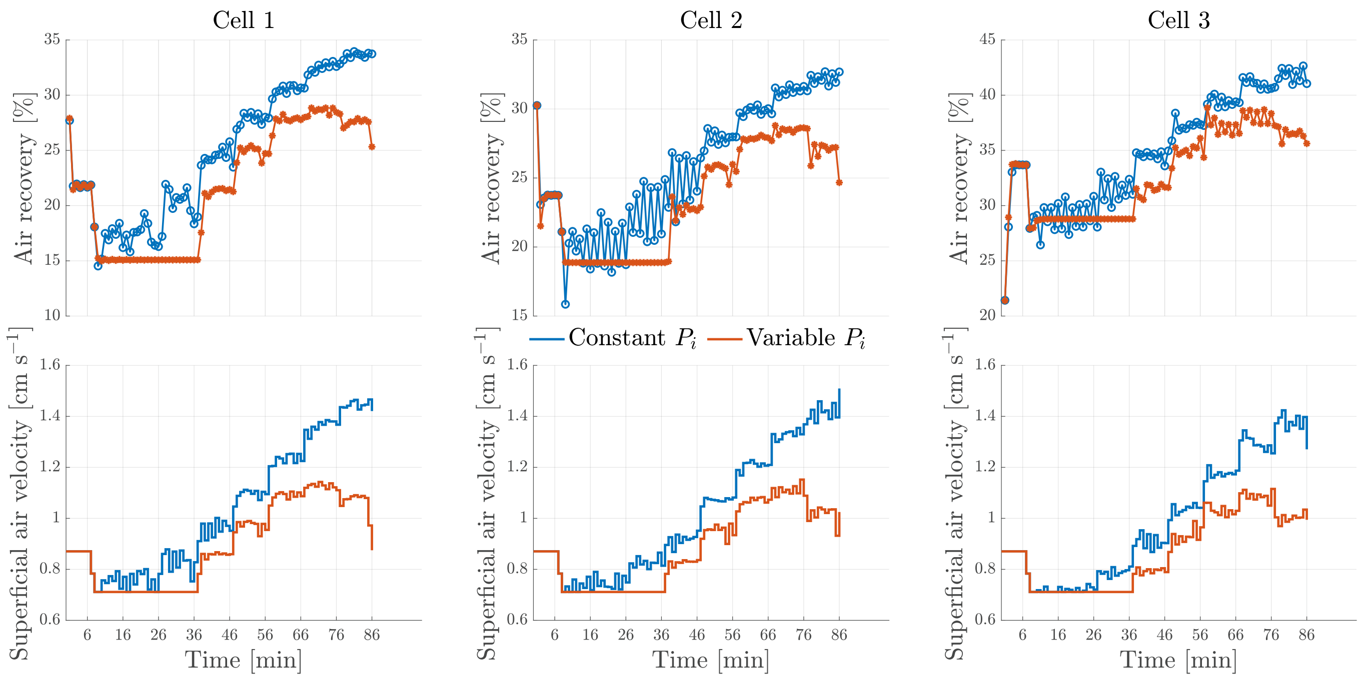

Fig. 4. Air recoveries for each flotation cell in the bank and their superficial air velocity (j_g) for Scenario 1 (blue lines, constant P_i) and Scenario 2 (orange lines, P_i as a function of particle size).

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