

Development and validation of a dynamic model for flotation predictive control incorporating froth physics

Paulina Quintanilla *, Stephen Neethling and Pablo Brito-Parada

Advanced Mineral Processing Research Group **

Department of Earth Science and Engineering, Imperial College London

Part 1

Development and validation of a dynamic model for flotation predictive control incorporating froth physics

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Part 2

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Part 3

Development and validation of a dynamic model for flotation predictive control incorporating froth physics

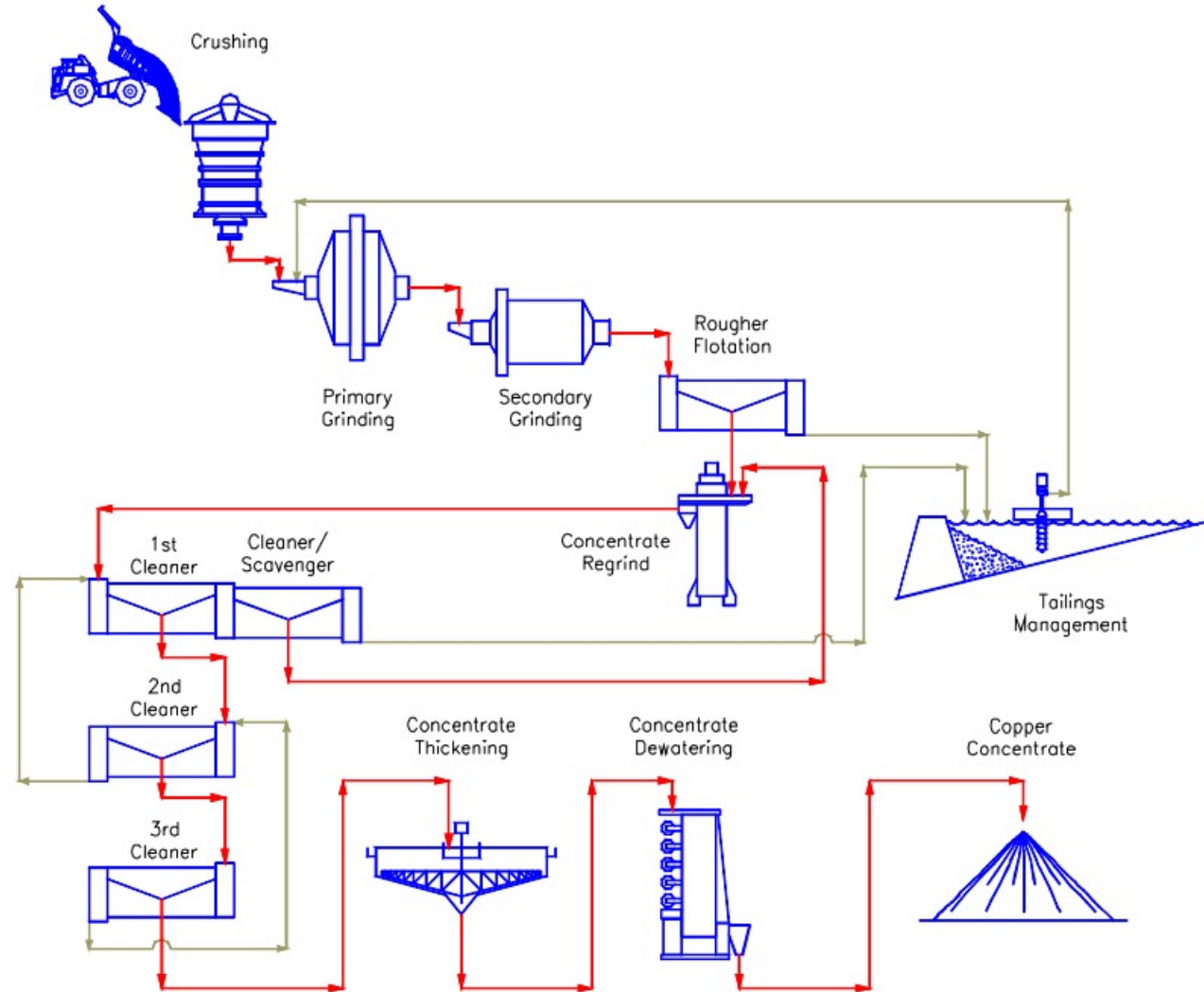
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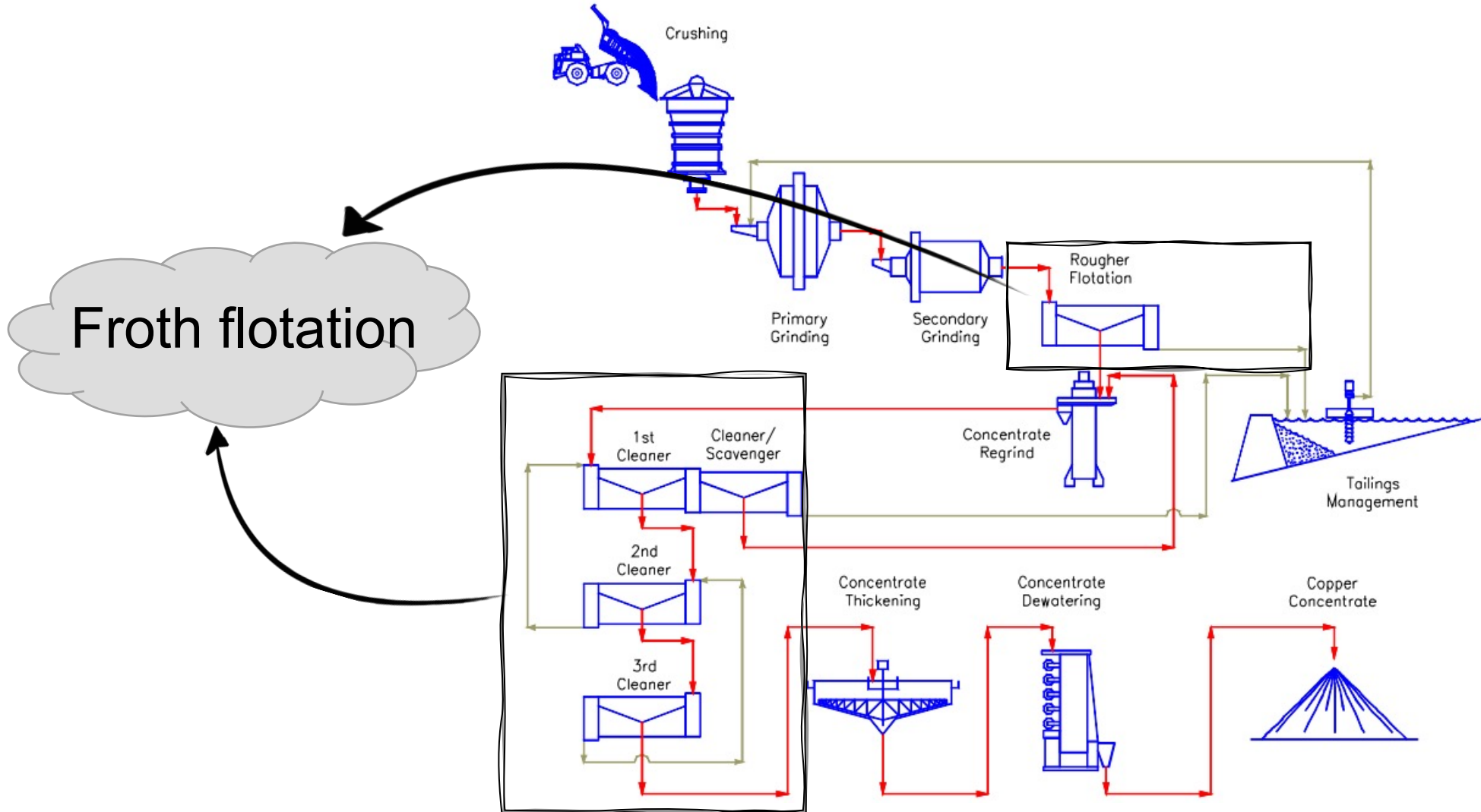
Mineral processing plant flowsheet

Copper process flowsheet example



Mineral processing plant flowsheet

Copper process flowsheet example

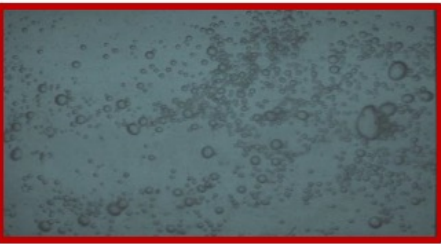


Froth flotation

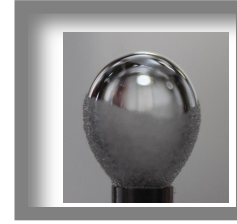
Recovering valuable minerals through bubbles



Froth phase



Pulp phase



Separation of valuable minerals from **waste rock** based on **hydrophobicity**.



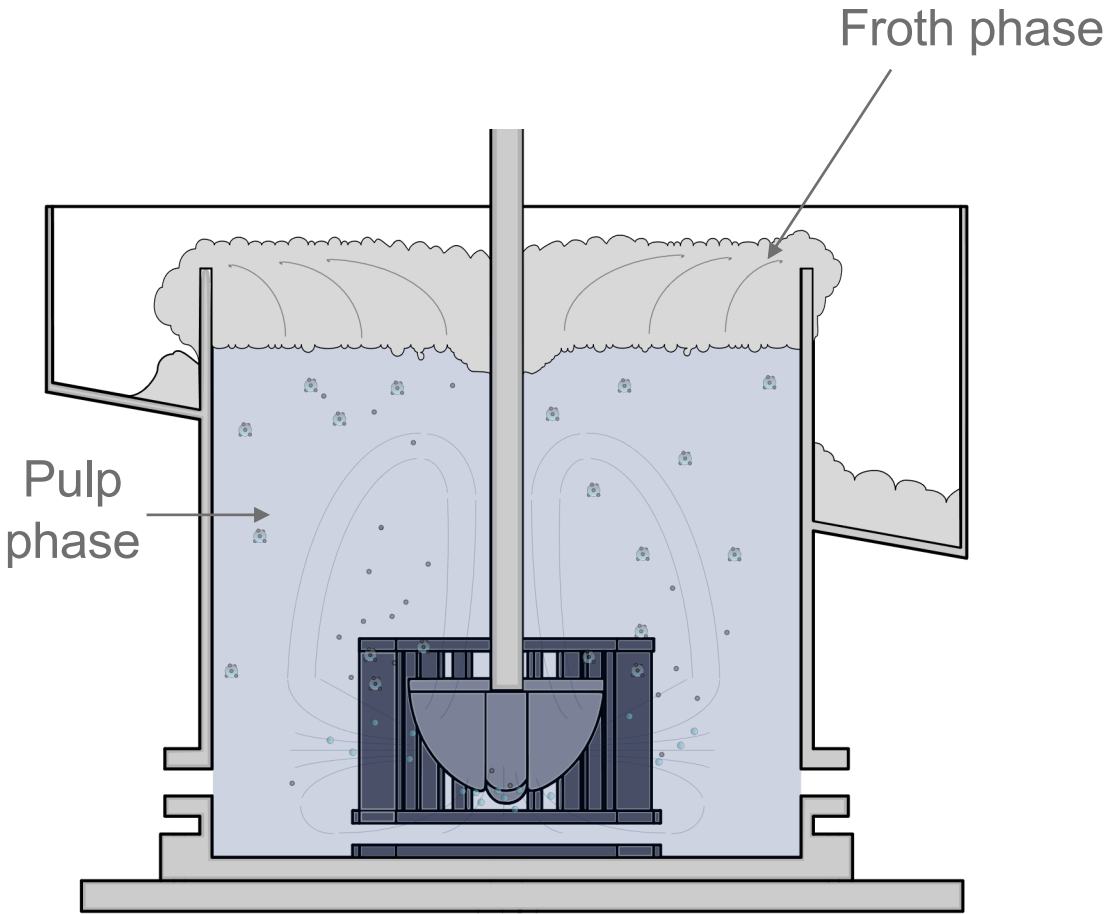
Chemicals and **air** are added into the cell.



Bubble-particles aggregates rise from the **pulp** to the **froth**.

Froth flotation

Operating variables



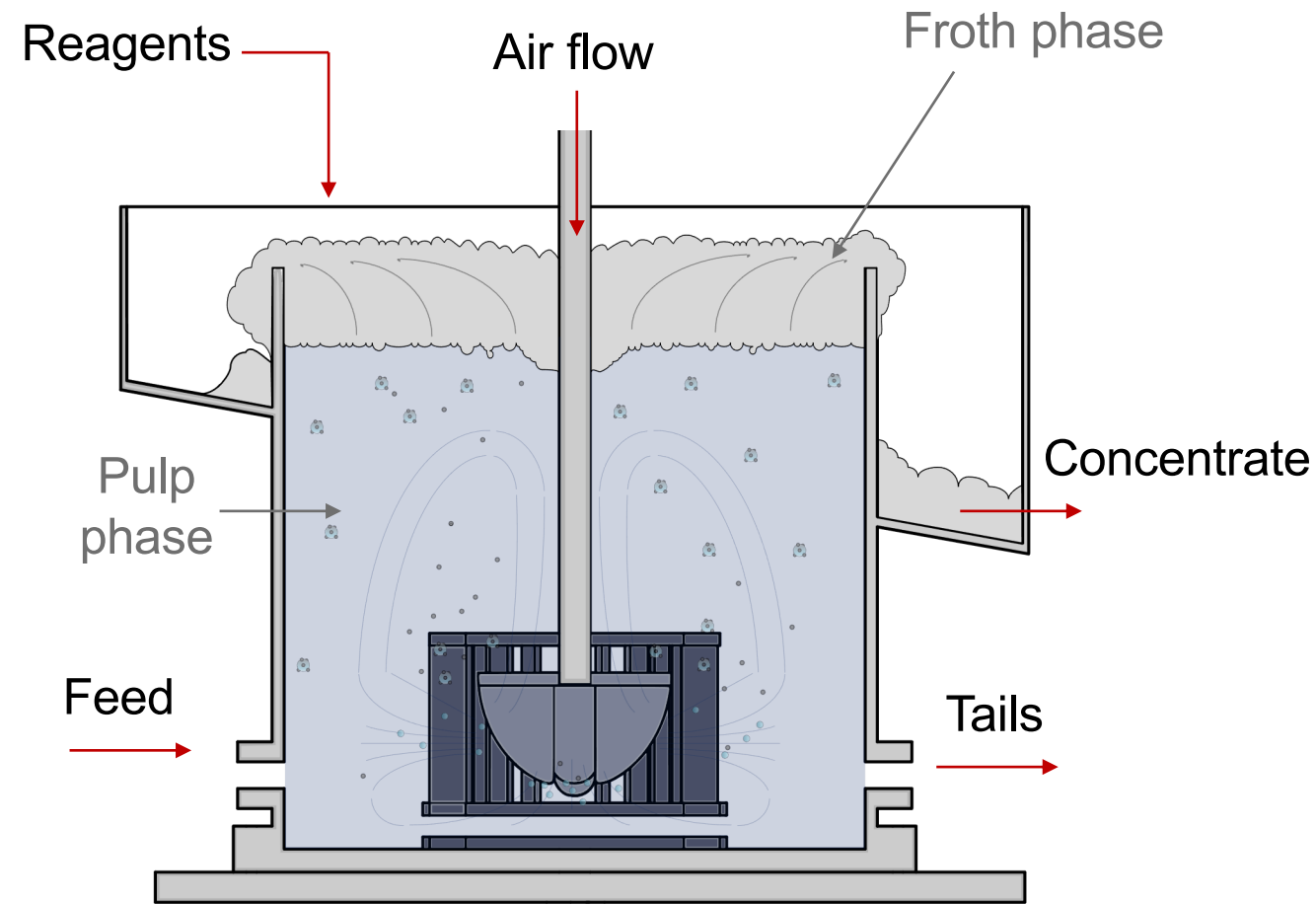
Flotation cell size: 300 m³



Experimental campaign, Riotinto, Seville, Spain.

Froth flotation

Operating variables



Flotation cell size: 300 m³

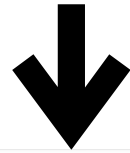


Experimental campaign, Riotinto, Seville, Spain.

Froth flotation

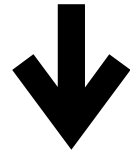
A large-scale process

Small improvements in its efficiency



Great economic and environmental impacts

How?



Optimisation by implementing
advanced controller

Flotation cell size: 300 m³



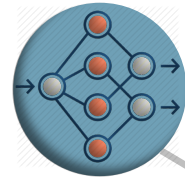
Experimental campaign, Riotinto, Seville, Spain.

Froth flotation

Advanced controllers

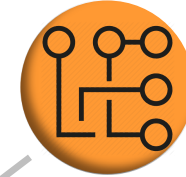
Artificial neural

ANN based controller to reach system's setpoints.



Fuzzy logic

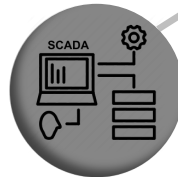
Flotation parameters $\in (0, 1)$
IF-THEN rule based strategy.



Advanced controllers for froth flotation

Supervisory

Interaction with the operator.



Model predictive

Use of an **explicit model** of the process.



Part 2

Development and validation of a dynamic model for flotation predictive control incorporating froth physics

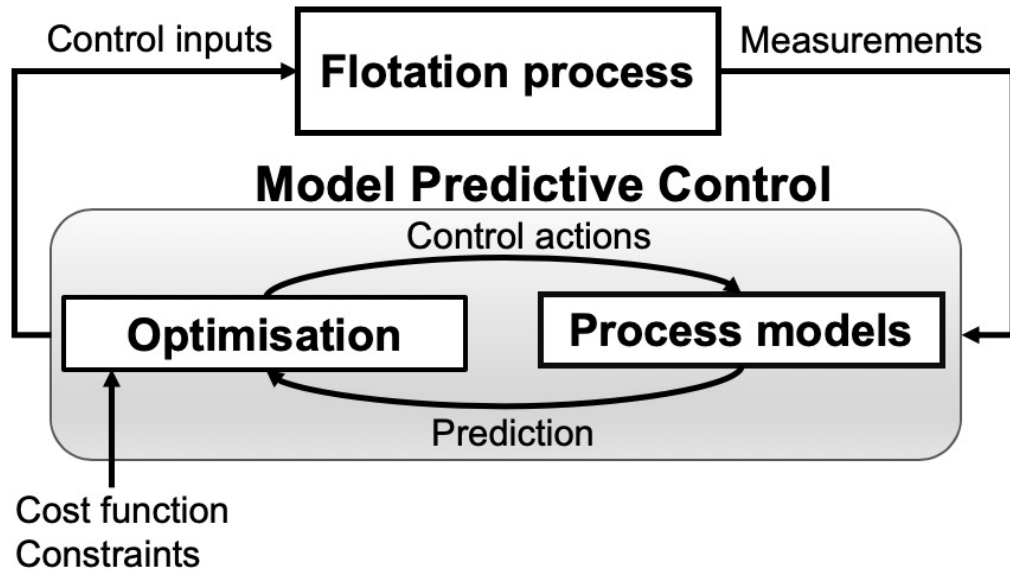
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Model Predictive Control

The concept



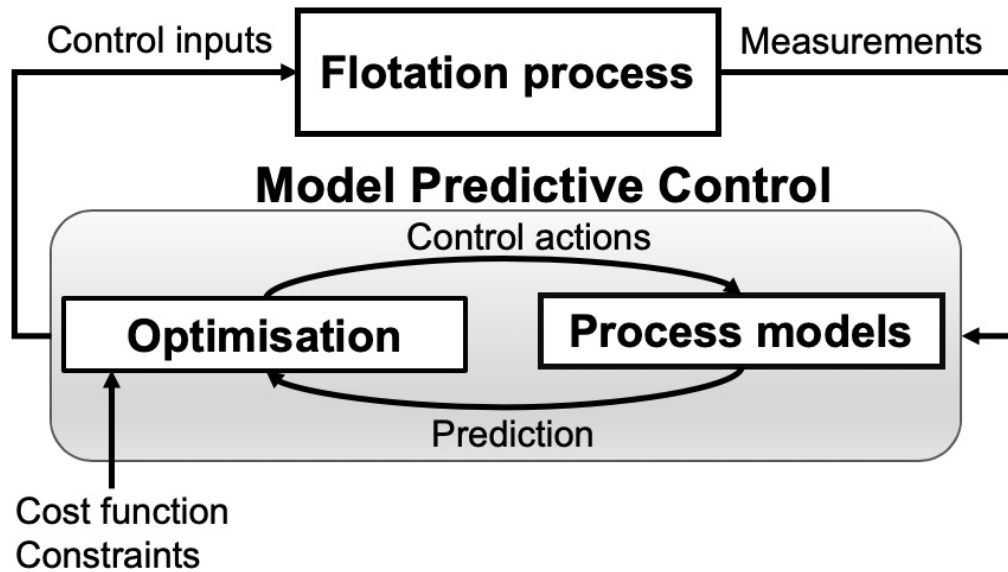
Use a dynamic model of the process to predict its future evolution and choose the best control action

Optimisation problem

$$\begin{aligned} \min_u J &= \int_{t_0}^{t_f} L[x, y, u, w, t] dt \\ \text{s.t. } \frac{dx(t)}{dt} &= f(x, y, u, w, t) \\ h(x, y, u, w, t) &= 0 \\ g(x, y, u, w, t) &\leq 0 \\ x(t_0) &= x_0 \text{ Feedback!} \end{aligned}$$

Model Predictive Control

The concept



Optimisation problem

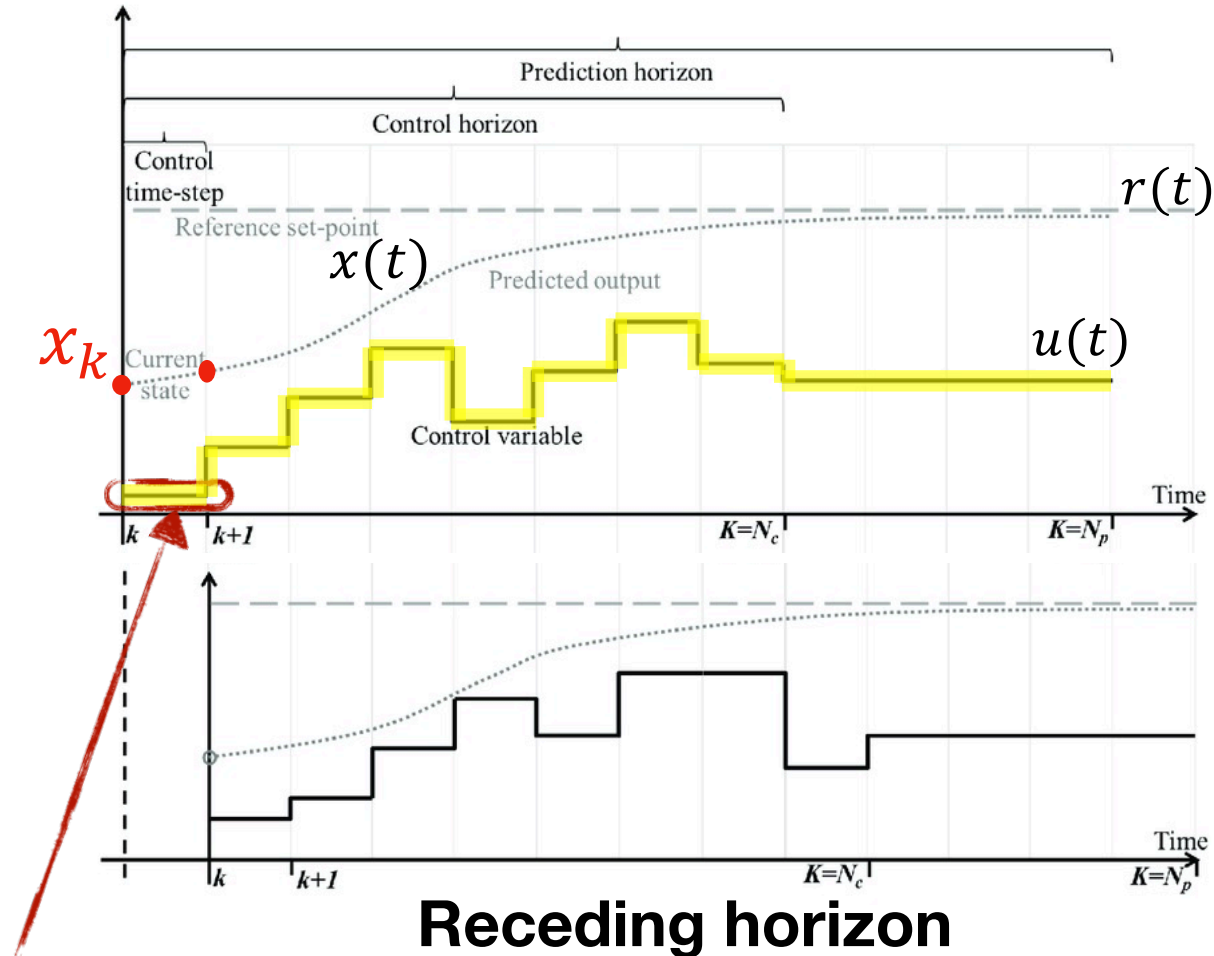
$$\min_u J = \int_{t_0}^{t_f} L[x, y, u, w, t] dt$$

$$\text{s.t. } \frac{dx(t)}{dt} = f(x, y, u, w, t)$$

$$h(x, y, u, w, t) = 0$$

$$g(x, y, u, w, t) \leq 0$$

$$x(t_0) = x_0 \text{ Feedback!}$$

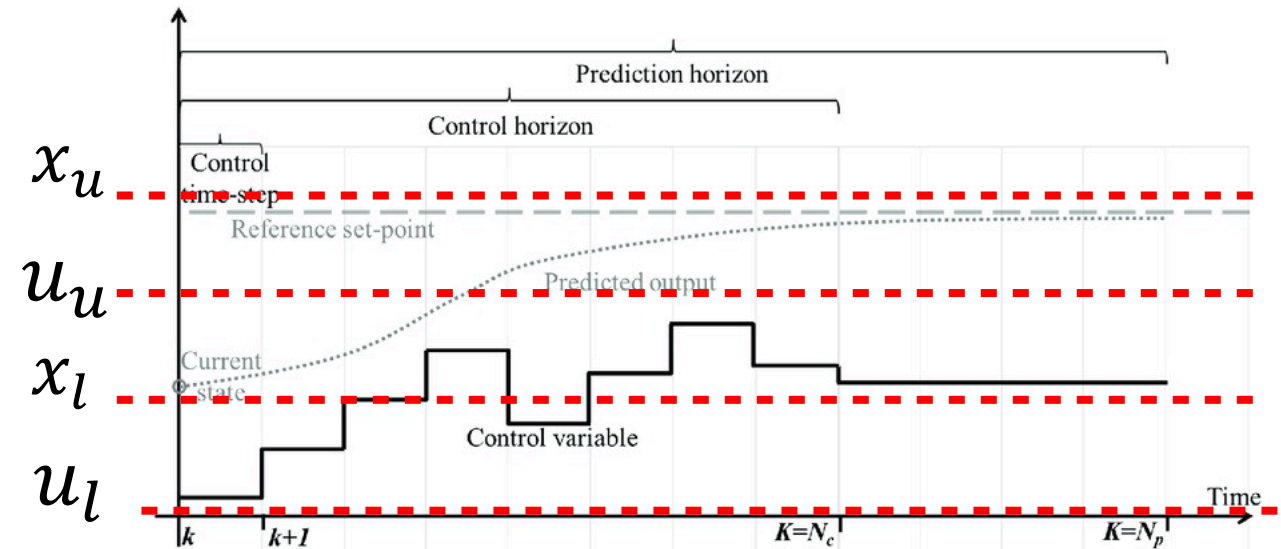
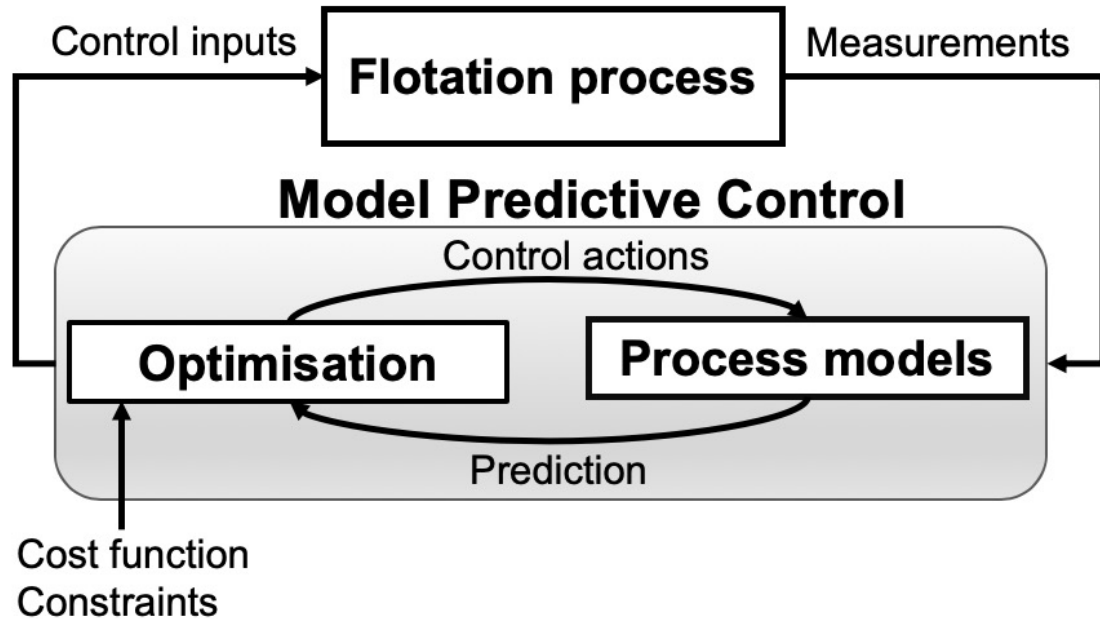


Apply the first optimal move $u(t) = u_0^*$,
throw the rest of the sequence away

At time $t + 1$: obtain new measurements, repeat the optimisation.

Model Predictive Control

Process constraints



- Receding control horizon
- Use of an explicit model of the process
- **Include process constraints**

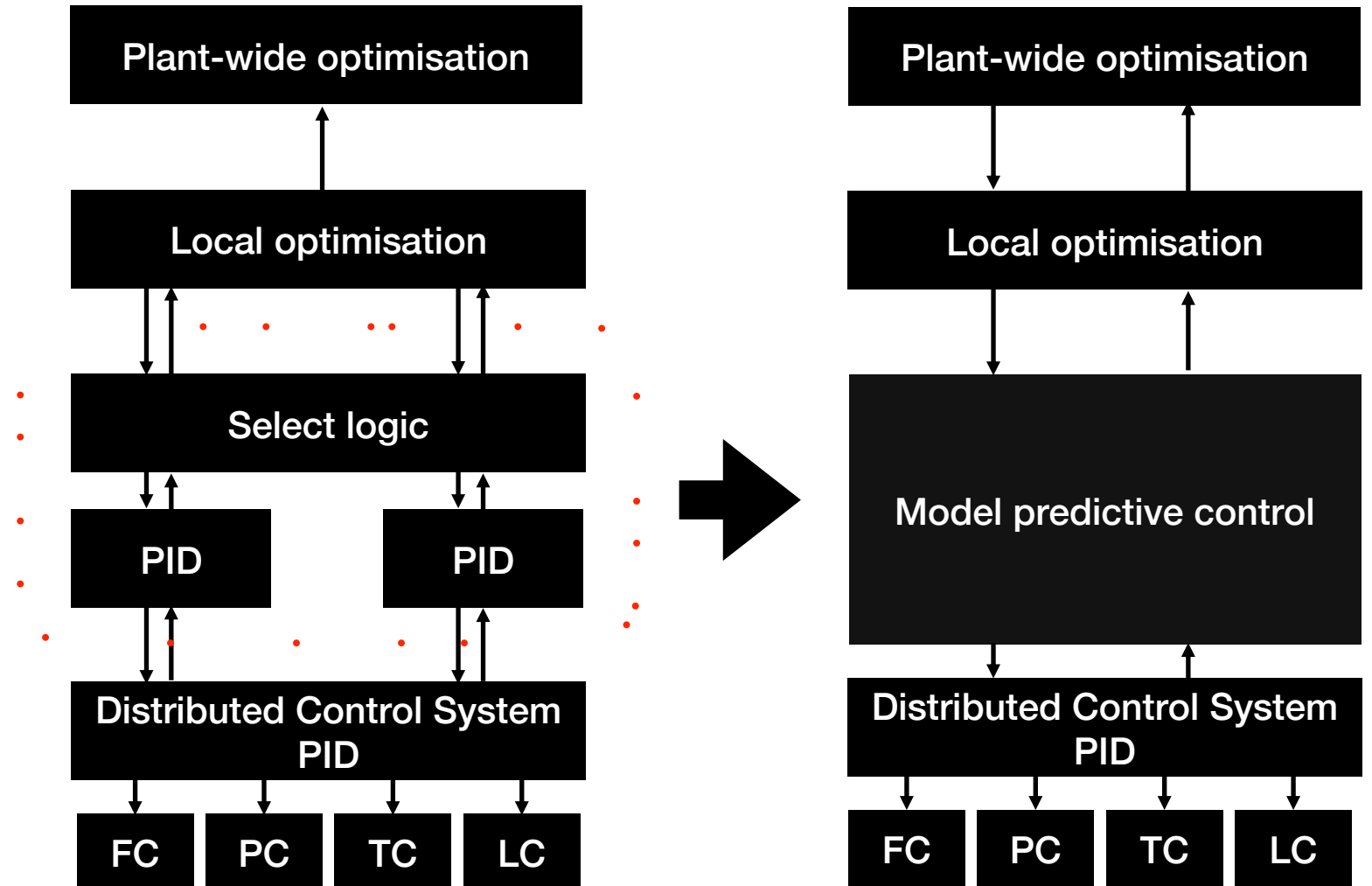
Model Predictive Control

MPC in the operational hierarchy

- Make fine adjustments for local units
- Take each local unit to the optimal condition fast but smoothly without violating the **constraints**

Optimisation layer

- Determine plant-wide the optimal operating condition for the day



Model Predictive Control

Why **modelling** for process control is important?

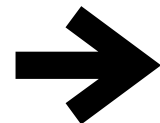
simplified

Use a **dynamic** model of the process to predict its future evolution and choose the best control action

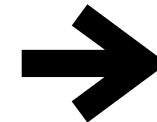
Optimisation problem

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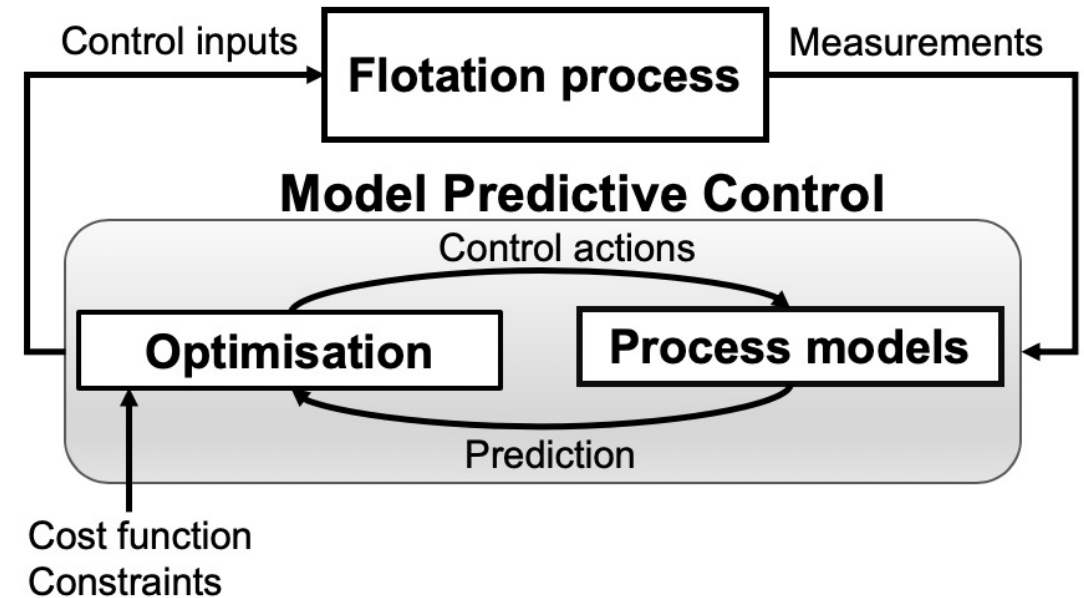
Poor model



Poor prediction



Poor performance



Modelling for flotation control

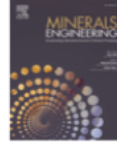
State-of-the-art

Minerals Engineering 162 (2021) 106718

Contents lists available at ScienceDirect

Minerals Engineering

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



Modelling for froth flotation control: A review

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ARTICLE INFO

Keywords:
Froth flotation
Flotation control
Flotation modelling
Model predictive control

ABSTRACT

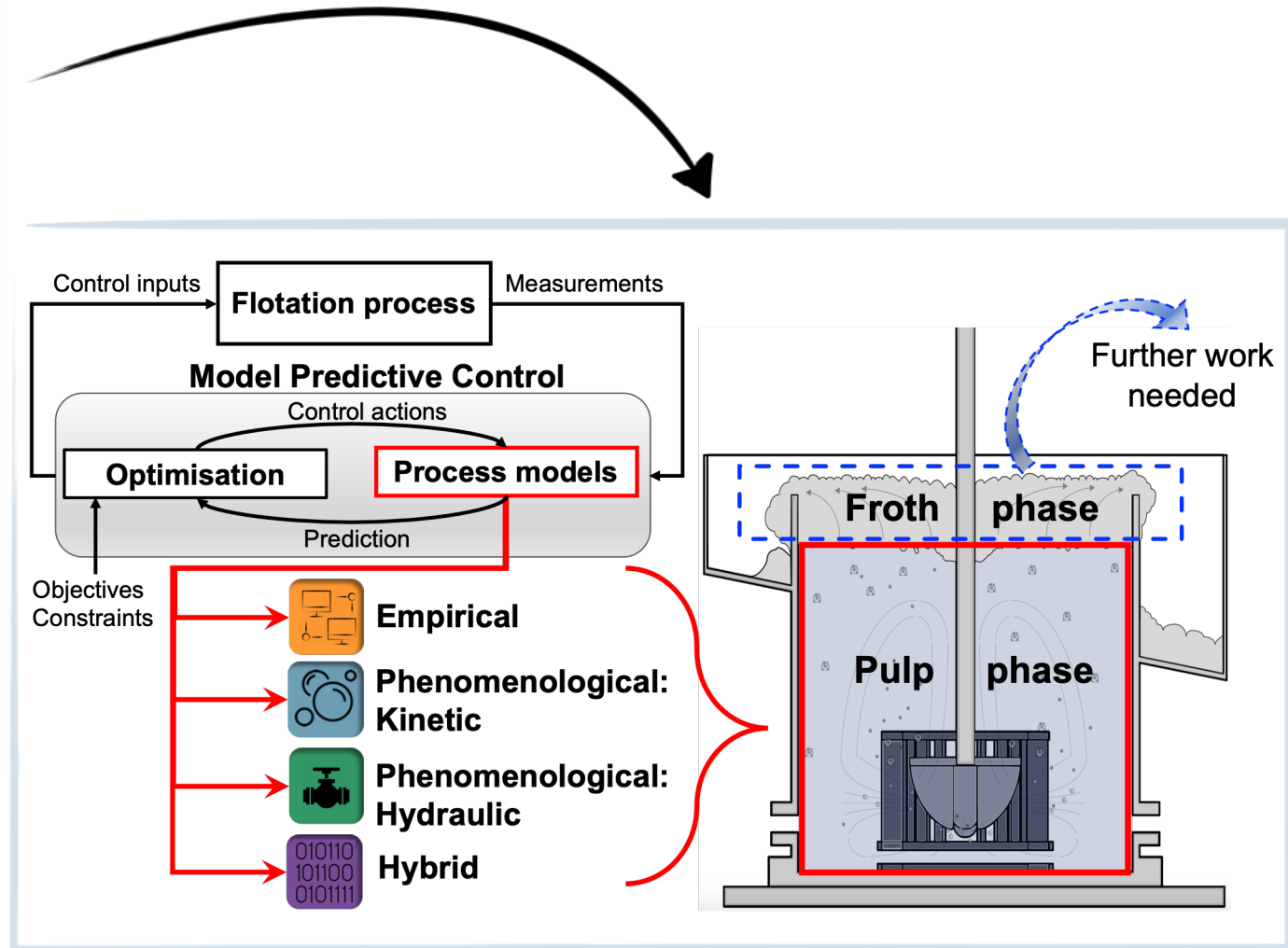
Flotation is a conceptually simple operation; however, as a multiphase process with inherent instability, it exhibits complex dynamics. One of the most efficient ways to increase flotation performance is by implementing advanced controllers, such as Model Predictive Control (MPC). This type of controller is very dependent on the model that represents the dynamics of the process. Although model development is one of the most crucial parts in MPC, flotation models have been mainly developed for simulation purposes (i.e. analysis and design) rather than control purposes. This paper presents a critical literature review on modelling for froth flotation control. Models reviewed have been sub-classified as empirical, phenomenological and hybrid according to their characteristics. In particular, it is highlighted that models have so far primarily focused on the pulp phase, with the froth phase often neglected; when the froth phase is included, kinetics models such as those used for the pulp phase, are commonly used to represent it. Froth physics are, however, dominated by processes such as coalescence, liquid motion and solids motion, which have been previously modelled through complex, steady-state models used for simulation purposes, rather than control purposes. There remains a need to develop appropriate models for the froth phase and more complex models for the pulp phase that can be used as part of MPC strategies. The challenges associated with the development of such models are discussed, with the aim of providing a pathway towards better controlled froth flotation circuits.

1. Introduction

Froth flotation is the largest tonnage separation in mineral process-

and the velocity and stability of the froth; and the mineral concentration in the feed, concentrate and the tailings (Laurila et al., 2002). In terms of process control, these variables are classified as manipulated, distur-

<https://doi.org/10.1016/j.mineng.2020.106718>



Part 3

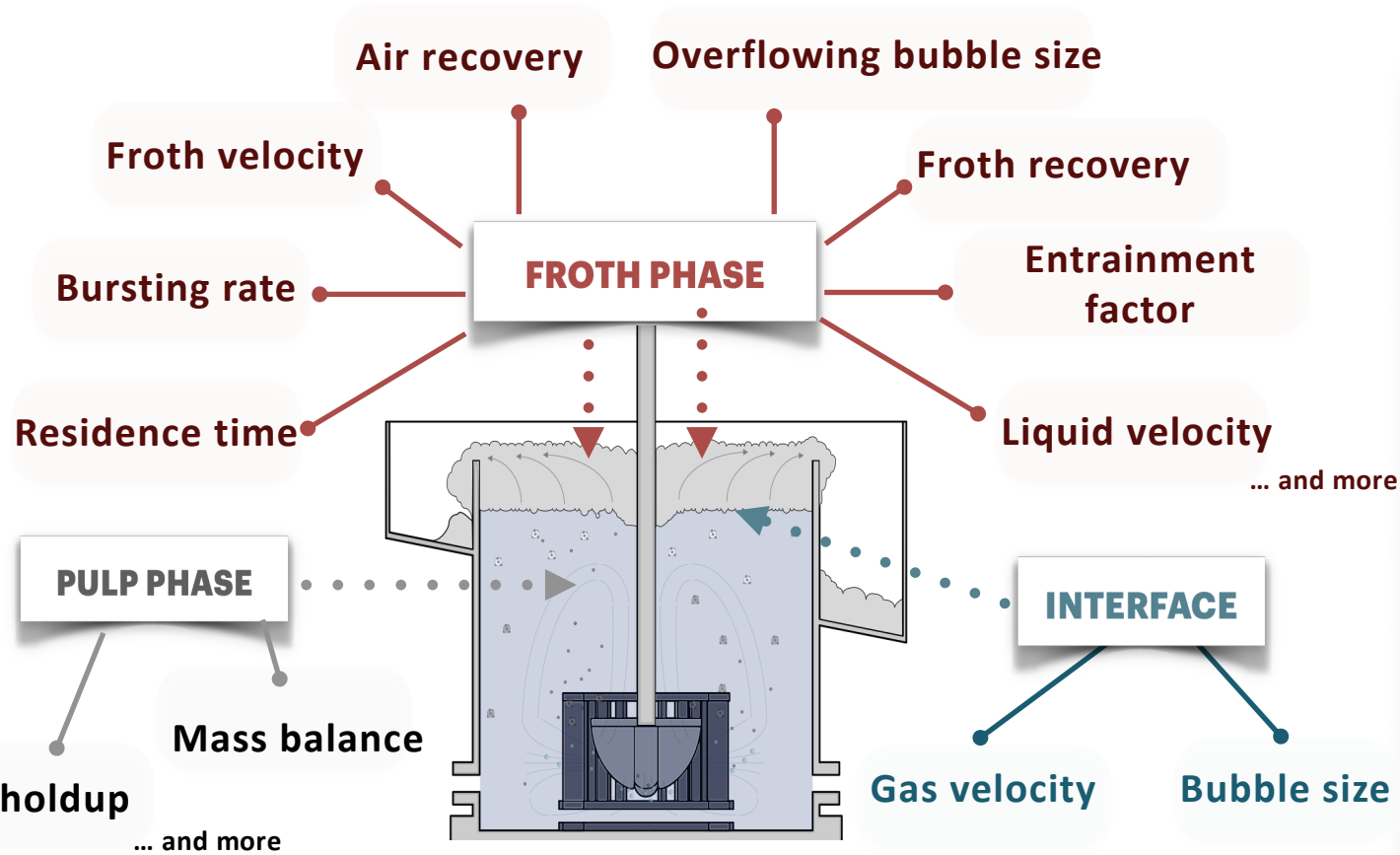
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Dynamic flotation model



Differential and Algebraic Equations (DAE System)

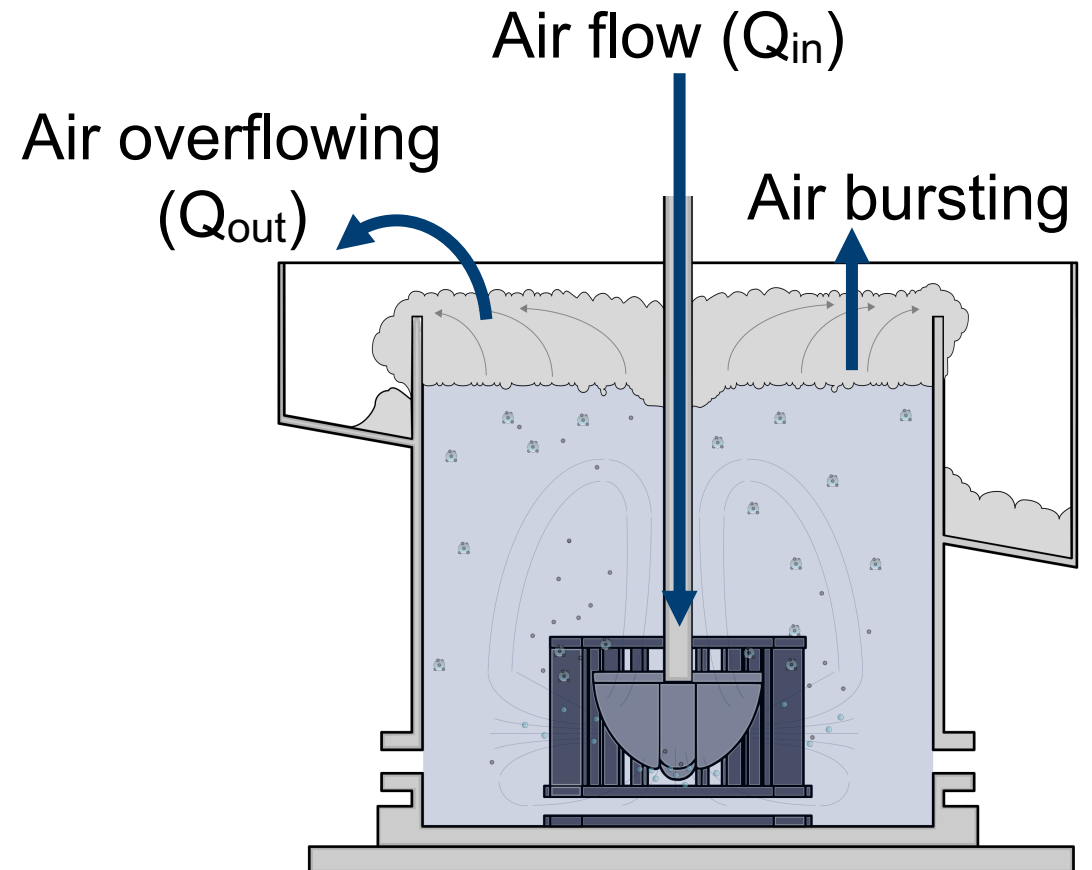
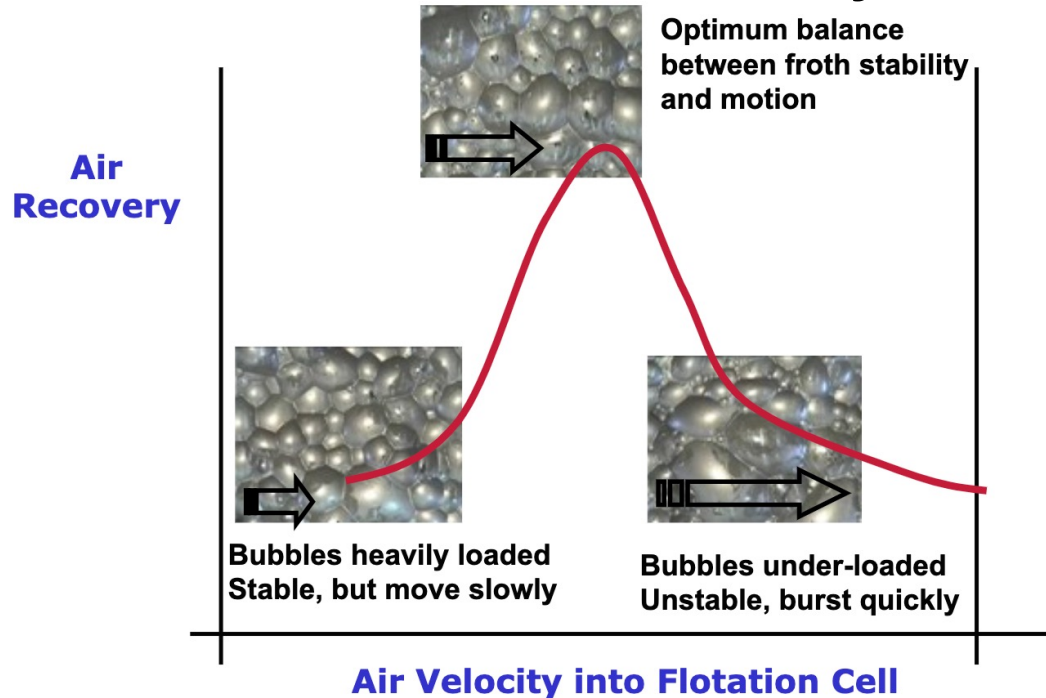


Dynamic flotation model

Air recovery

$$\text{Air recovery: } \alpha = \frac{Q_{air,out}}{Q_{air,in}} = \frac{v_f L_{lip} h_{froth}}{Q_{air,in}}$$

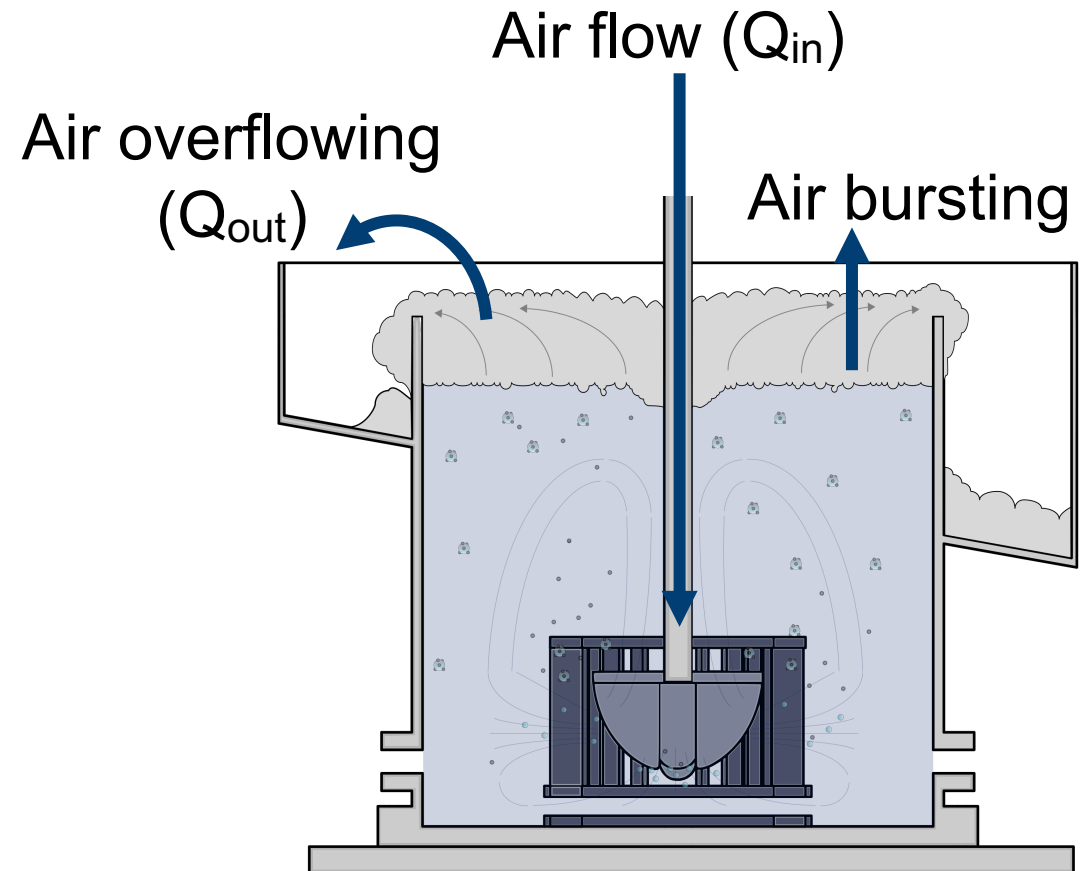
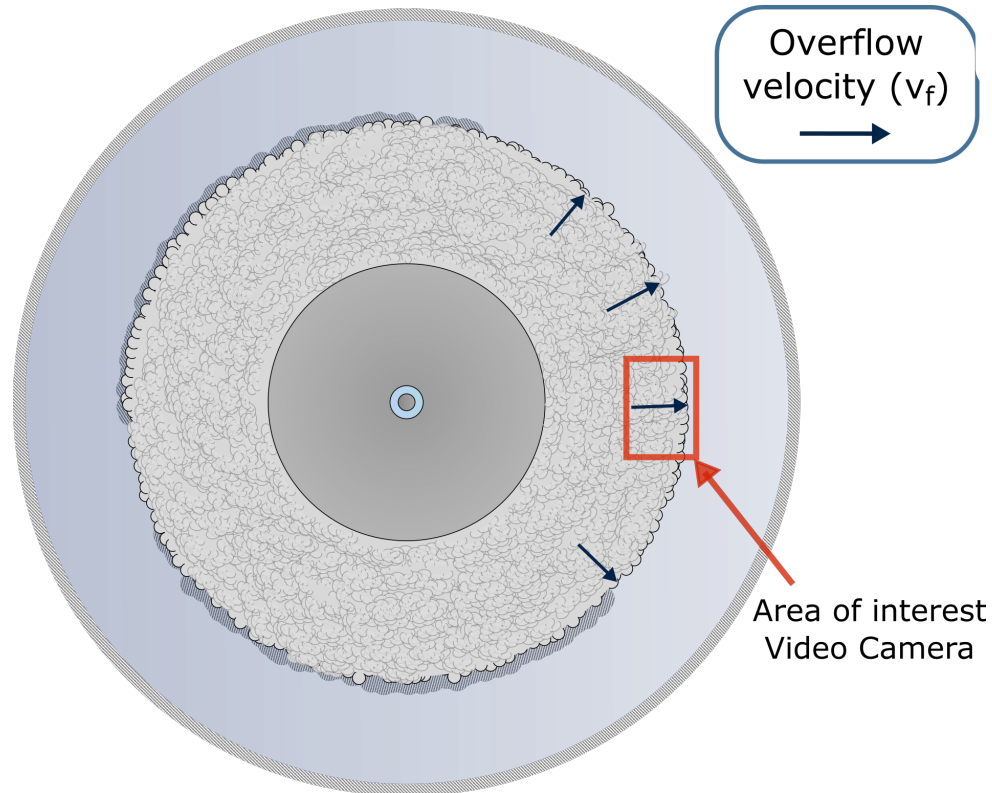
Peak Air Recovery



Dynamic flotation model

Air recovery measurement

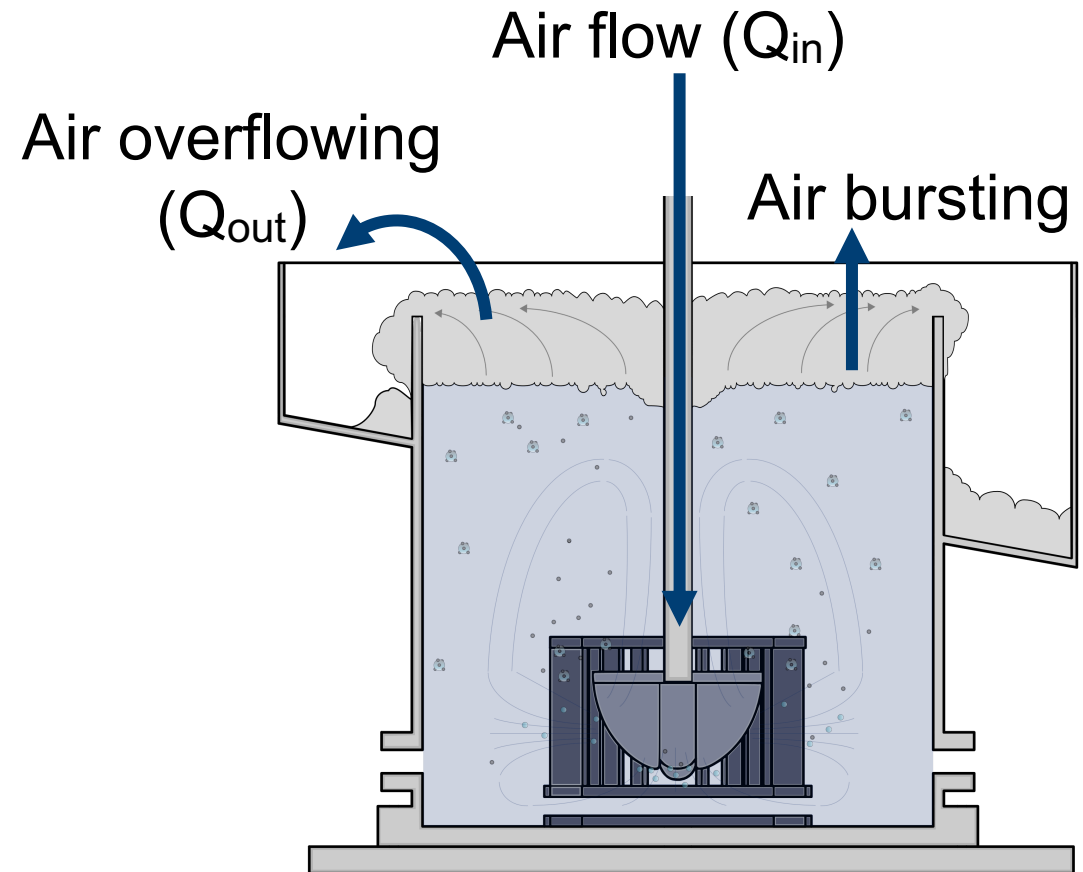
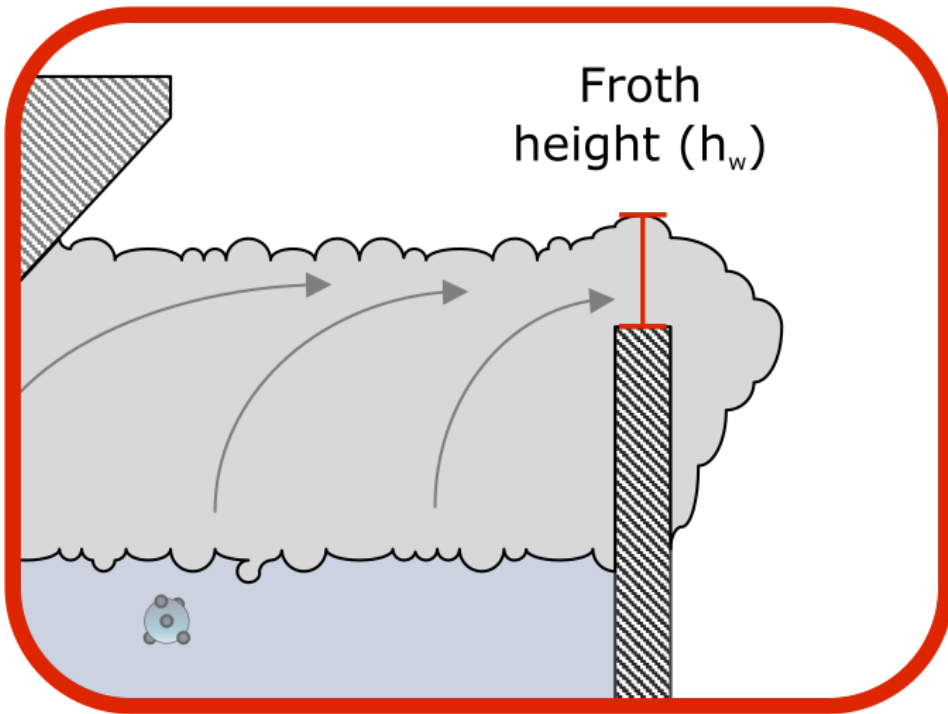
$$\alpha = \frac{v_f L_{lip} h_{froth}}{Q_{air,in}}$$



Dynamic flotation model

Air recovery measurement

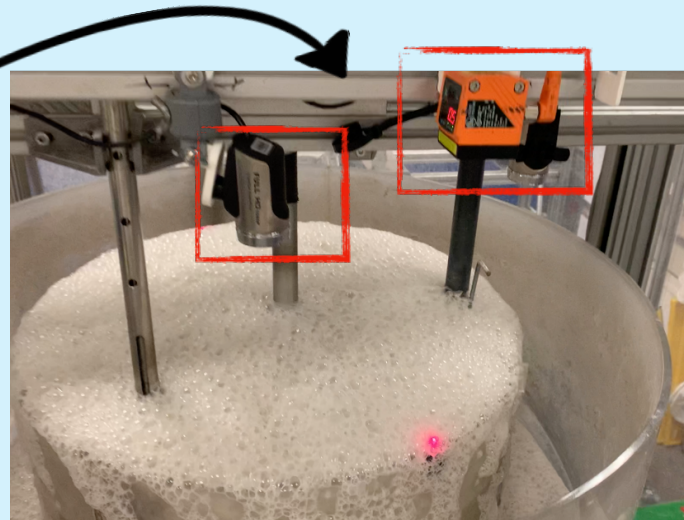
$$\alpha = \frac{v_f L_{lip} h_{froth}}{Q_{air,in}}$$



Model validation

Experiments

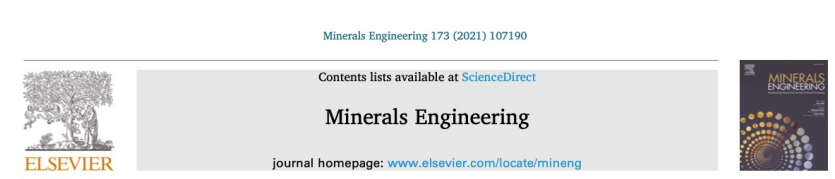
EXPERIMENTAL RIG



MEASUREMENTS

- ✓ Air recovery
- ✓ Pulp height
- ✓ Air and tailings flowrates
- ✓ Overflowing froth velocity
- ✓ Pulp bubble size distribution

87-litre laboratory-scale flotation tank at Imperial College London



A dynamic flotation model for predictive control incorporating froth physics. Part II: Model calibration and validation

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^b Departamento de Ingeniería Química y Ambiental, Universidad Técnica Federico Santa María, Campus San Joaquín, Santiago, Chile

ARTICLE INFO

Keywords:
Froth flotation
Flotation control
Flotation modelling
Model calibration
Model validation
Model predictive control

ABSTRACT

Modelling for flotation control purposes is the key stage of the implementation of model-based predicted controllers. In Part I of this paper, we introduced a dynamic model of the flotation process, suitable for control purposes, along with sensitivity analysis of the fitting parameters and simulations of important control variables. Our proposed model is the first of its kind as it includes key froth physics aspects. The importance of including froth physics is that it improves the estimation of the amount of material (valuables and entrained gangue) in the concentrate, which can be used in control strategies as a proxy to estimate grade and recovery.

In Part II of this series, experimental data were used to estimate the fitting parameters and validate the model. The model calibration was performed to estimate a set of model parameters that provide a good description of the process behaviour. The model calibration was conducted by comparing model predictions with actual measurements of variables of interest. Model validation was then performed to ensure that the calibrated model properly evaluates all the variables and conditions that can affect model results. The validation also allowed further assessing the model's predictive capabilities.

For model calibration and validation purposes, experiments were carried out in an 87-litre laboratory scale flotation tank. The experiments were designed as a randomised 3² full factorial design, manipulating the superficial gas velocity and tailings valve position. All experiments were conducted in a 3-phase system (solid-liquid-gas) to ensure that the results obtained, as well as the behaviour of the flotation operation, are as similar as possible to those found in industrial flotation cells.

In total, six fitting parameters from the model were calibrated: two terms from the equation for overflowing bubble size; three parameters from the bursting rate equation; and the number of pulp bubble size classes. After the model calibration, simulations were performed to validate the predictions of the model against experimental data. The validation results revealed good agreement between experimental data and model predictions of important flotation variables, such as pulp level, air recovery, and overflowing froth velocity. The high accuracy of the predictions suggests that the model can be successfully implemented in predictive control strategies.

1. Introduction

Model Predictive Control (MPC) is attracting widespread interest in fields such as mineral processing. One of the main aspects of MPC is the availability of a dynamic model of the process that is accurate enough – yet simplified – to make predictions on important variables. However,

inherent instability.

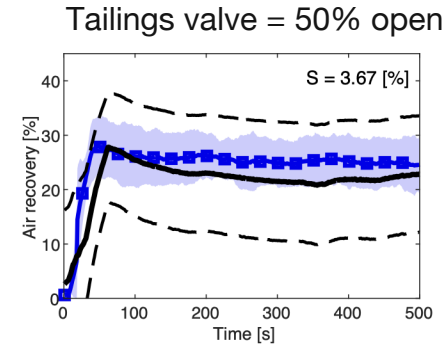
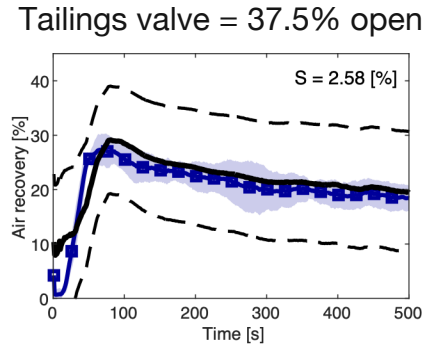
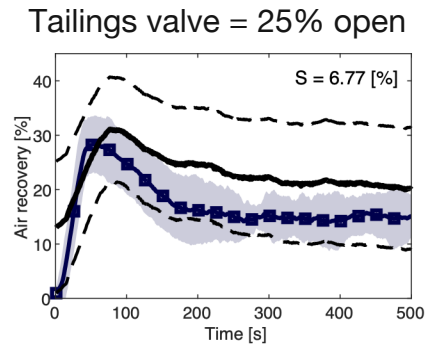
Despite the importance of the froth phase in the overall performance of a flotation cell, only few studies have included it in their models for predictive control, such as those found in Bascur (1982), Zaragoza and Herbst (1989), Putz and Cipriano (2015), Tian et al. (2018). A deeper discussion of these studies is found in Part I of this paper, while an

<https://doi.org/10.1016/j.mineng.2021.107190>

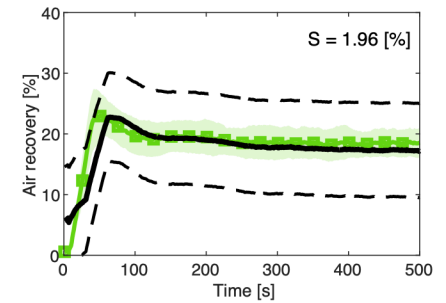
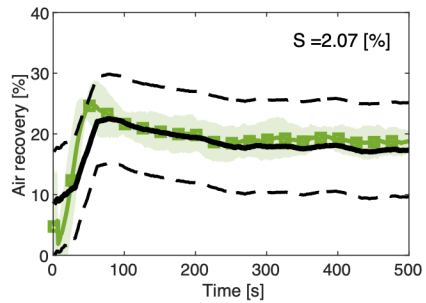
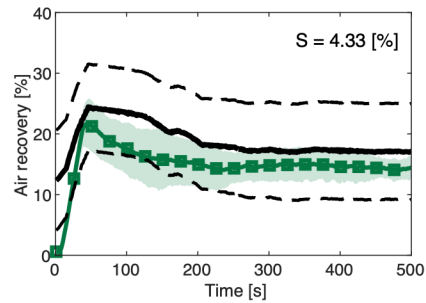
Model validation results

Air recovery

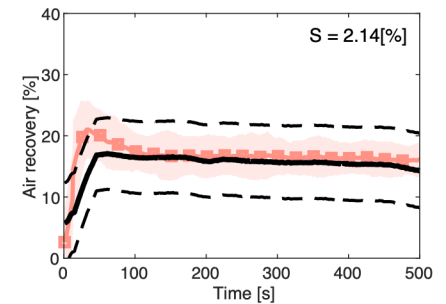
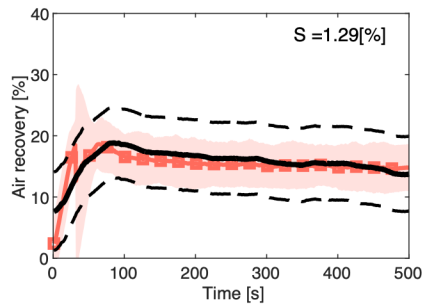
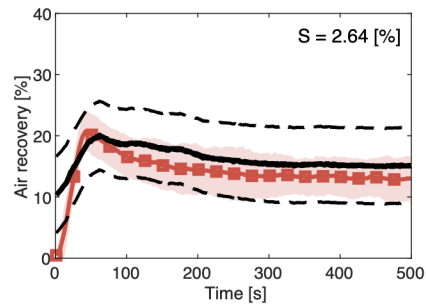
$j_g = 0.5 \text{ [cm s}^{-1}\text{]}$



$j_g = 0.7 \text{ [cm s}^{-1}\text{]}$



$j_g = 0.9 \text{ [cm s}^{-1}\text{]}$

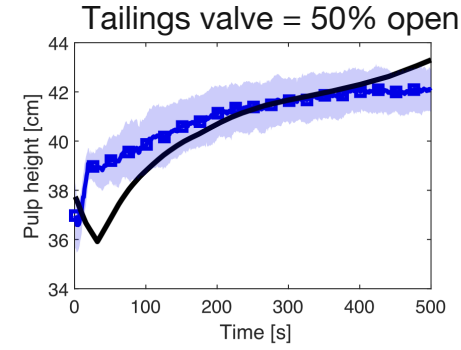
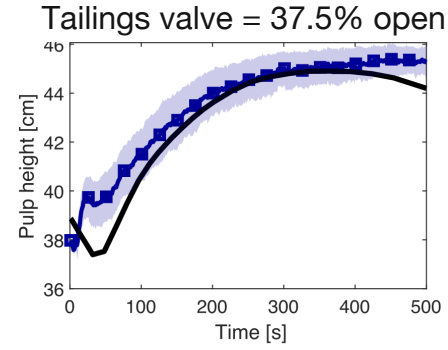
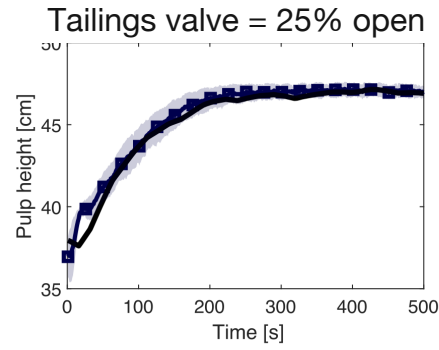


— Model prediction —■— Experimental
- - - 95% Prediction Interval ■ 95% Confidence Interval

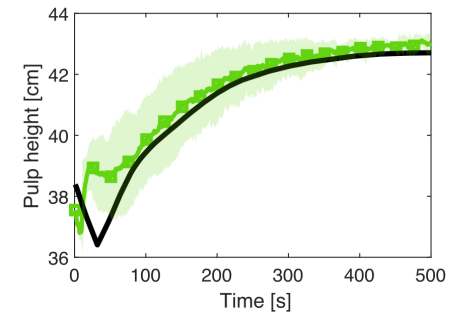
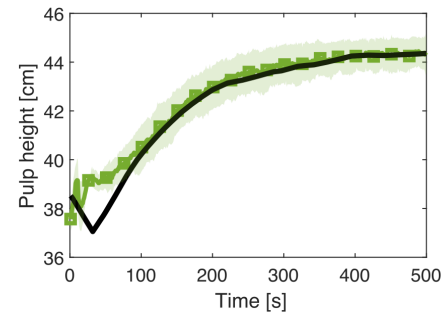
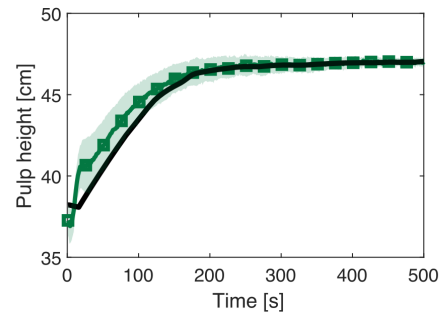
Model validation results

Pulp height

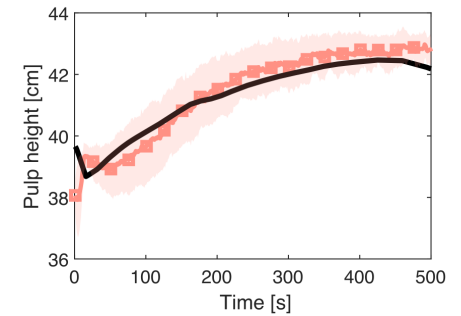
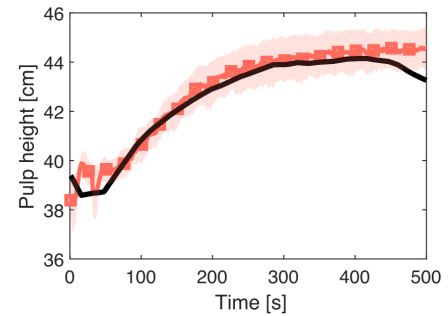
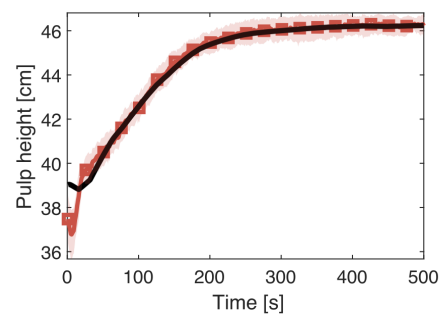
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$j_g = 0.7 \text{ [cm s}^{-1}\text{]}$



$j_g = 0.9 \text{ [cm s}^{-1}\text{]}$

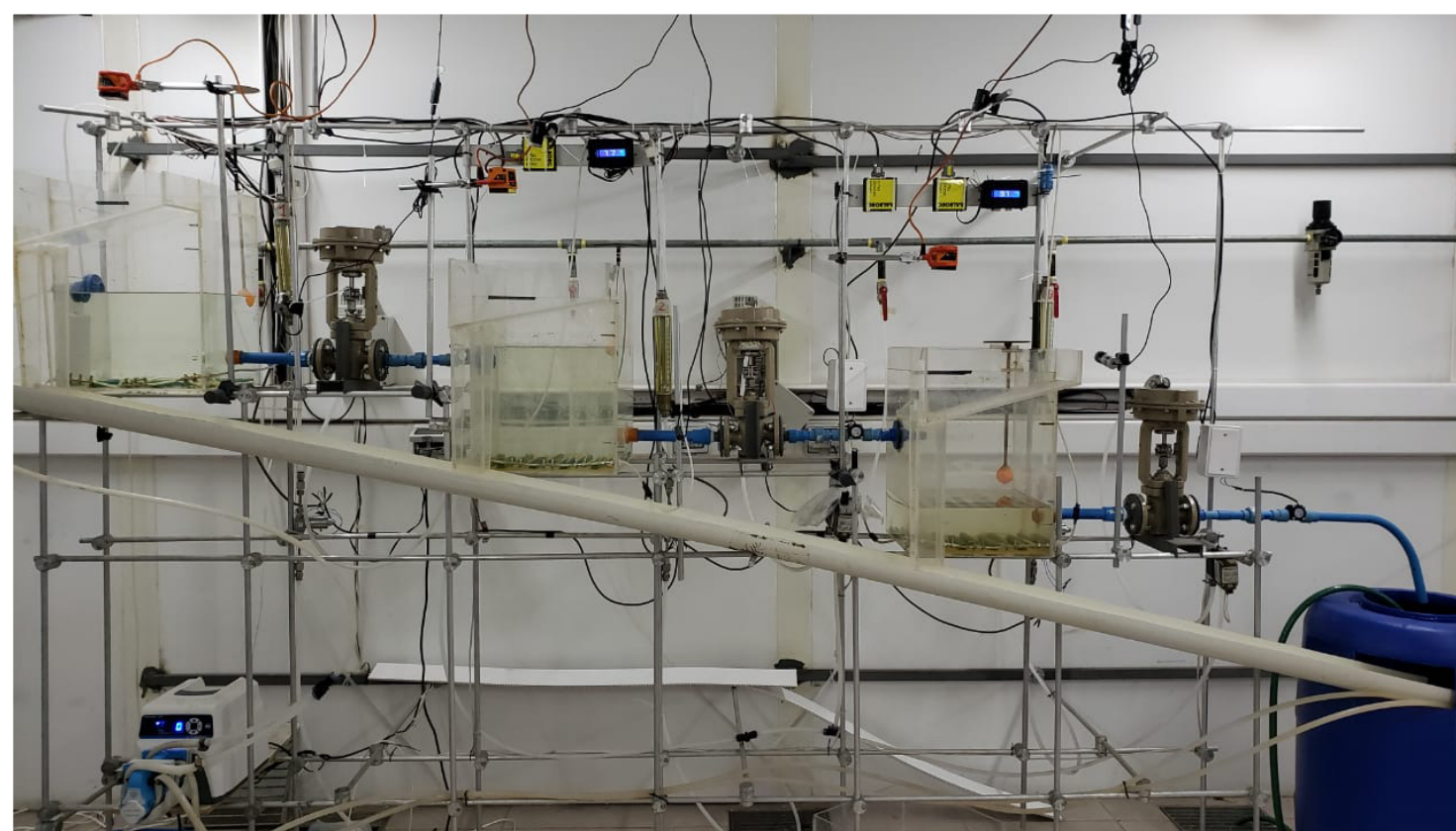


— Model prediction ■ Experimental 95% Confidence Interval

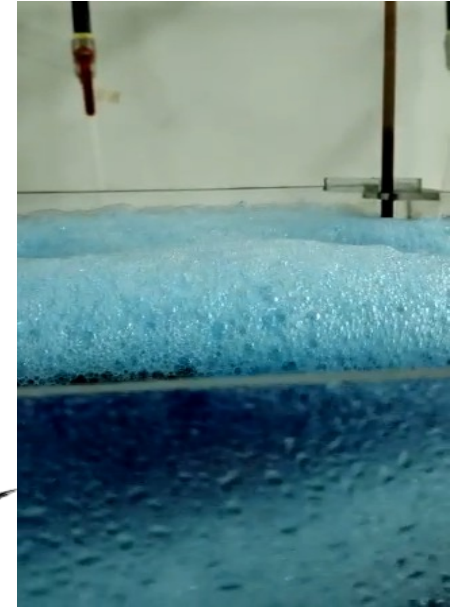
Model Predictive Control

Laboratory-scale implementation

EXPERIMENTAL RIG



40-litre laboratory-scale flotation tanks at USM (Chile)



Bubbles in slow motion!



Final remarks



Development of a new flotation dynamic model for predictive control, focused on the **froth phase**.

Air recovery for
flotation control



Model validation revealed **high predictive capability** of critical variables.



2 degrees of freedom for control: Air and tailings flowrates.



Fully **remote control implementation** in Chile from the UK.



Acknowledgments



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