Available online at www.sciencedirect.com
ScienceDirect
IFAC PapersOnLine 52-14 (2019) 24–29

A Combined MPC for Milling and Flotation – A Simulation Study

Kevin Brooks*, Merinda Westcott* and Margret Bauer**

**BluESP, 53 Platina St, Randburg, South Africa*
(E-mail: kevin.brooks@bluesp.co.za, merinda.westcott@bluesp.co.za)
***Department of Electrical, Electronic and Computer Engineering,*
University of Pretoria, Lynwood Road, Pretoria, South Africa
(E-mail: margret.bauer@up.ac.za)

Abstract: In the metals and mining industry, an ore-milling step followed by froth flotation is a very common processing route. It is also common that advanced controls of one form or another are installed on these units. It is less common for the advanced controllers to be combined in any formal way. This paper explores the way two typical model predictive control structures could be combined, and what are the benefits of doing so. Use is made of existing linear dynamic models of plants the authors have implemented model predictive control (MPC) on. The results show that the coordinated system can behave differently to the separate controllers, depending on the steady-state optimisation coefficients applied.

Keywords: Identification and Modelling, Advanced Process Control, Model predictive and optimization-based control, Milling, Flotation, Plantwide Control

1. INTRODUCTION

The recovery of metals from mined ores frequently involves the processing steps of milling following by froth flotation. Both milling and flotation are two adjacent of several consecutive steps in ore beneficiation. The remaining processing steps are not considered in this work.

There are different types of mills, classified according to the grinding medium used. Two types commonly utilised are autogenous (AG) mills in which the ore grinds itself, and semi-autogenous (SAG) mills, where size reduction is achieved through the addition of steel balls to the mil.

Flotation in the mining industry is a process for selectively concentrating and separating valuable minerals from gangue minerals in a process slurry. Along with mechanised mining, flotation is widely considered to have been one of the great breakthroughs in the mining industry. The process involves using a collector to render the valuable mineral surface hydrophobic, thus promoting its attachment to injected air bubbles and subsequent recovery in the froth overflow from an agitated tank. The two most important aspects when concentrating the valuable minerals through milling and flotation are the grade produced and the recovery achieved.

The control objectives of the milling circuit are generally stated as to be providing a product of consistent flow, density and particle size distribution. The aim of a flotation circuit is to strike a balance between achieving maximum recovery at economically viable concentrate grades. Recovery is the fraction of valuable metal in the feed reporting to the concentrate, while the grade is the mass fraction of the metal of interest in a particular stream. These variables are controlled through a combination of pulp level manipulation, air injection rates and reagent dosage changes.

There is an extensive literature on the industrial application advanced control on milling circuits. Some examples include Silva and Tapia (2009), Steyn et al. (2010), Karelovic et al. (2013) and Steyn and Sandrock (2013). While there is a large amount of literature on flotation control of simulated systems, there is less published on implementations on industrial scale plants. Some examples include Cortes et al. (2008), who describe the application of MPC for control of froth velocities measured by a camera, a similar approach described by Dawson and Koorts (2014) using fuzzy logic, and Muller et al. (2011), who discuss the use of fuzzy logic for mass pull control, with a higher level MPC for grade and recovery. Brooks and Koorts (2017) describe an MPC flotation scheme using x-ray fluorescence analysers and Brooks and Munalula (2017) use a cascaded MPC scheme involving cameras and online grade measurements.

The interaction of flotation and milling has been considered in improving overall circuit performance through improved control of the milling circuit. Wei and Craig (2009) show a curve relating flotation recovery to the particle size distribution of the flotation feed. Steyn and Sandrock (2013) use this method but note that "a representative model of the primary mill product size to overall plant performance alone is not a trivial task".

The presence of several MPC implementations in connected processes is common in the chemical industry. In distributed MPC, a series of optimisation problems are decomposed into a set of subproblems (Camponogara et al., 2002). The individual MPCs are referred to as 'agents' and can exchange information.

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2019.09.158

Distributed MPC has been app lied to power generation and to the chemical industry (Venkat et al., 2008), however – to the authors' knowledge – not in the minerals processing industry.

This article investigates the performance of two individual controllers for milling and flotation versus the performance of a combined, large-scale MPC controller for both processes combined.

The paper is structured as follows. Section 2 briefly describes the milling and flotation processes studied here. Section 3 gives the linear process model derived from step responses. Section 4 describes the MPC control strategy both for two individual controllers and for one combined controller, comparing the results of both control strategies. Conclusions are drawn in Section 6.

2. PROCESS DESCRIPTION

The process studied consists of a SAG mill feeding a flotation plant consisting of two rougher cells. Although industrial plants have many more cells, this configuration was chosen for simplicity. The mill is shown in Fig. 1. Run of Mine ore is fed to the mill together with the recycle flow of screen oversize and water. The mill reduces the particle size and the slurry exits the mill into the discharge sump. The screen undersize flows to the surge tank from where it is pumped to the first rougher flotation cell.

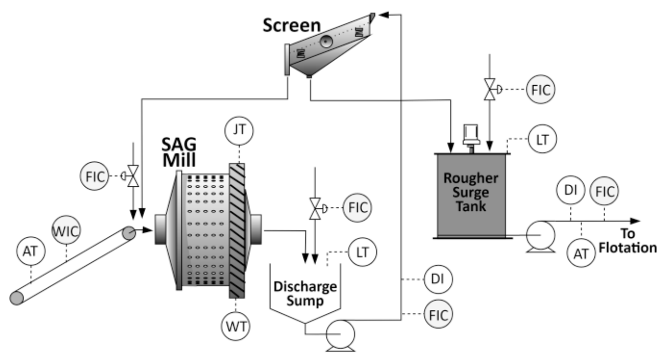

Fig. 1. SAG Mill Showing Base Level Controls

It is assumed that online measurement of the densities and the particle size distribution (PSD) of feed and product are available.

The rougher flotation circuit is shown in Fig. 2. The slurry flows by gravity from Cell 1 to Cell 2. The froth to pulp interface level is controlled in Cell 2, while the air addition rate is controlled to a setpoint in both Flotation cells. A reagent, known as a collector, is added to Cell 1. Composition measurements are available for the feed, concentrate and tails streams.

3. LINEAR MODELS

AspenTech's DMCPlus was used as the MPC engine for this study. This algorithm employs a description of the plant in the form of finite step responses, which are generally obtained

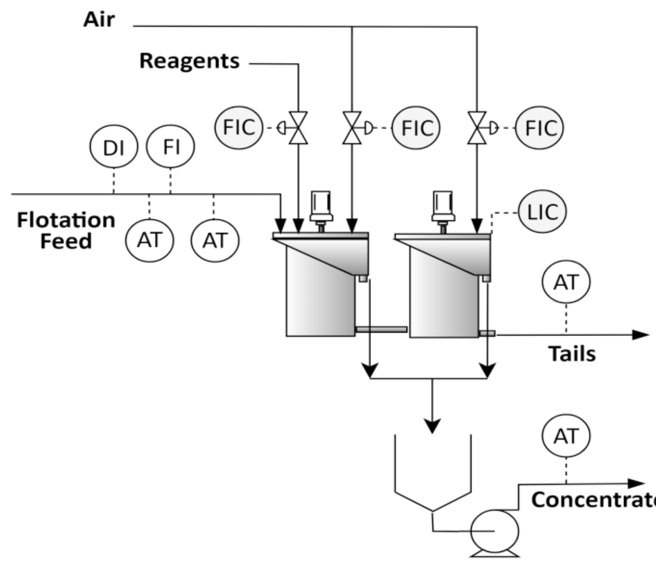

Fig. 2. Rougher Bank Showing Control Loops and Analysers

by plant testing. The models required are represented as unit step responses. The dynamic response of a controlled variable (CV or output) to a unit step in an MV (manipulated variable or input) or FF (feedforward or disturbance variable). The model prediction of an output is then given by (Garcia et al., 1989):

$$y(k) = \sum_{i=1}^{n-1} H_i \Delta u(k-1) + H_n u(k-n) \tag{1}$$

where $y(k)$ is an output at discrete time k, n is the number of truncated coefficients, u is the input and H_i as well as H_n are the step response coefficients. The difference equation for the input is abbreviated as $\Delta u(k) = u(k) - u(k–1)$. The extension of Eq. 1 to the case where there are multiple inputs is straightforward since the assumption of linearity allows for superposition. The step response coefficients, H_i, are obtained by performing a planned experiment. The data of the experiment is used in the fitting routine. In the software used here, either finite impulse response or a subspace technique is used for the fitting (Verhaegen and Dewilde, 1992, Darby et. al., 2009).

The linear dynamic models for the two plants are shown in the form of unit step responses in Fig. 3 and Fig. 4. The manipulated variables (MVs) and feedforwards (FFs) are down the rows, while the controlled variables (CVs) are across the columns. The SAG mill MVs are the solids feed rate, the inlet water, discharge sump and surge tank water addition, and flows out of the discharge sump and surge tank. The CVs are the load, power, discharge sump and surge tank level, the discharge sump and product densities and the product PSD. The manipulated variables for flotation are the pulp level, the two air flows and reagent addition flowrate. The controlled variables are concentrate and tailings grade, the reagent dosage (amount of reagent per tonne of metal in feed), and the calculated steady-state recovery. The feedforward variables are the feed flow, grade, density and PSD.

The inclusion of calculated dosages as CVs with reagent flows as MVs is unusual but allows the controller to smoothly change reagent flows on changes of total metal feed. This functionality can be included by use of PID control; this method, however, neglects the dynamics associated with rejecting the disturbance.

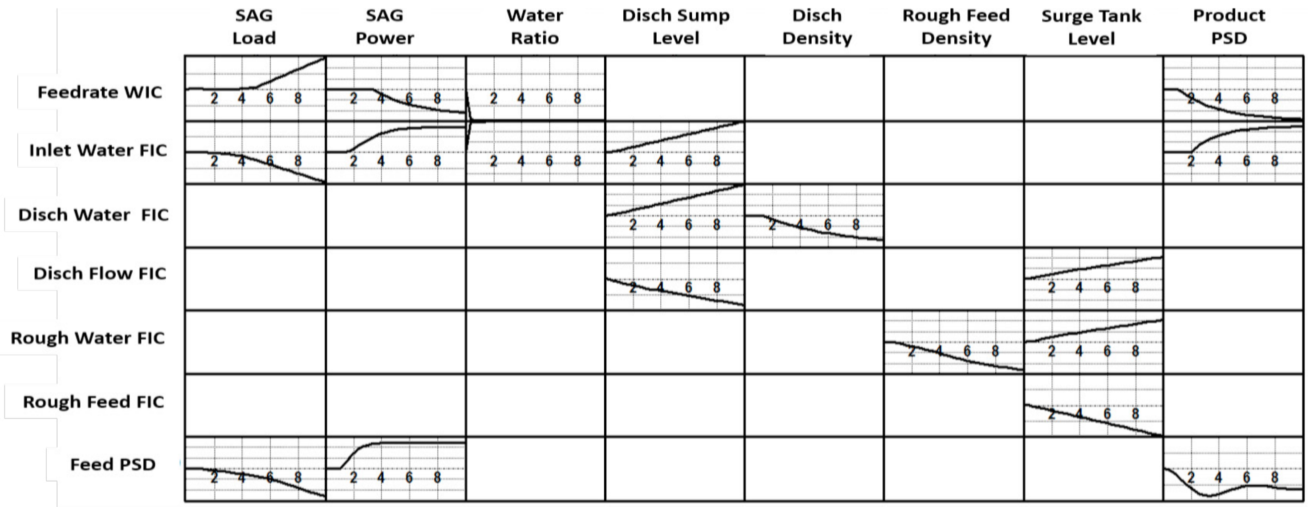

Fig. 3. Unit Step Response Models for the Mill with time scale in minutes

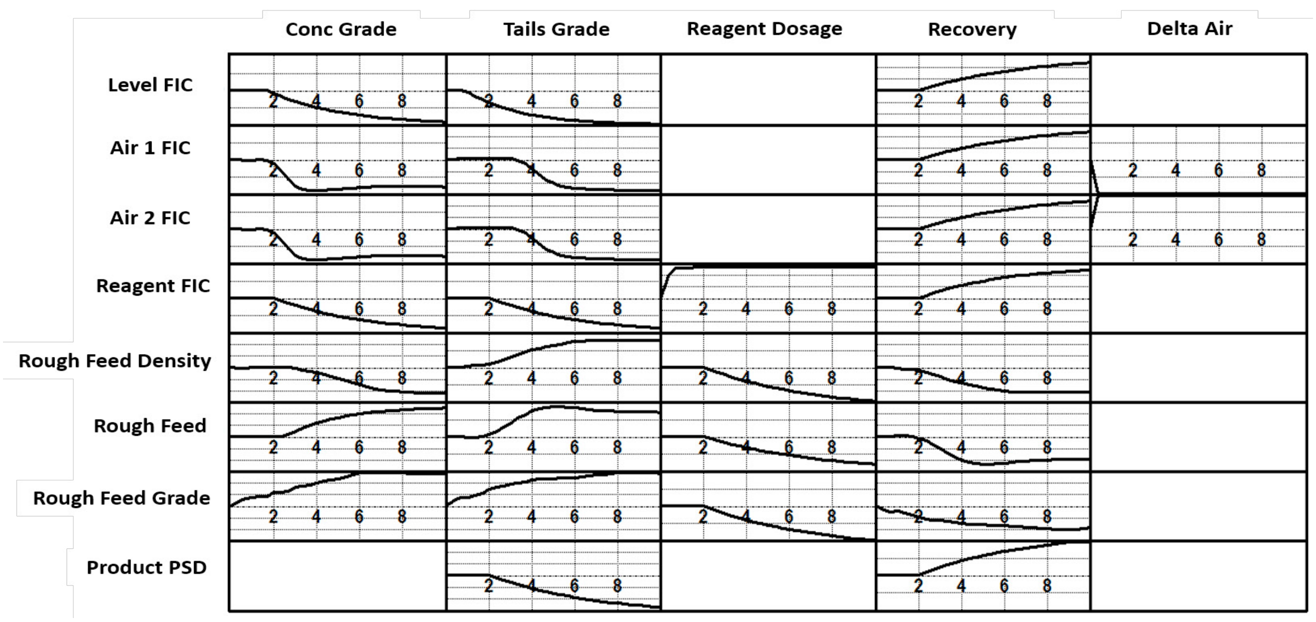

Fig. 4. Unit Step Response Models for Flotation with time scale in minutes.

The time scales have the units of minutes; the indicated time to steady-state is ten minutes. The responses have been sped up by a factor of 6 for ease of simulation. The actual times to steady-state of the systems are in the region of sixty minutes

4. OPTIMISATION AND THE DMC ALGORITHM

The DMC Plus algorithm has been described by Garcia et al., (1989). The equations will not be repeated here. Suffice it to say that a quadratic program formulation is used to solve for an optimal move plan subject to MV and CV constraints.

Before solving the dynamic optimisation problem, the algorithm checks for steady-state feasibility by solving the optimisation problem:

$$\min \phi = \sum_{i=1}^{n_c} \epsilon_i^2 \, W_i \tag{2}$$

subject to:

$$\hat{y}_{i,ss} \le y_{i,max} + \varepsilon_i \tag{3}$$

$$\hat{y}_{i,ss} \ge y_{i,min} - \varepsilon_i \tag{4}$$

where ϕ is the objective function value, n_c is the number of controlled variables, ε_i are slack variables, W_i are weights, $\hat{y}_{i,ss}$ is the steady-state value of CV i and $y_{i,max}$ and $y_{i,min}$ are the high and low limits on CV i.

In order to facilitate the handling of multiple constraints, a rank can be assigned to each dependent variable. This allows the controller to relax a dependent variable's constraints as described in Eq. 3 and Eq. 4 in order to honour another higher-ranked variable's constraints.

The objective function in Eq. 2 is minimised subject to the current constraints on the MVs and CVs. If there are slack

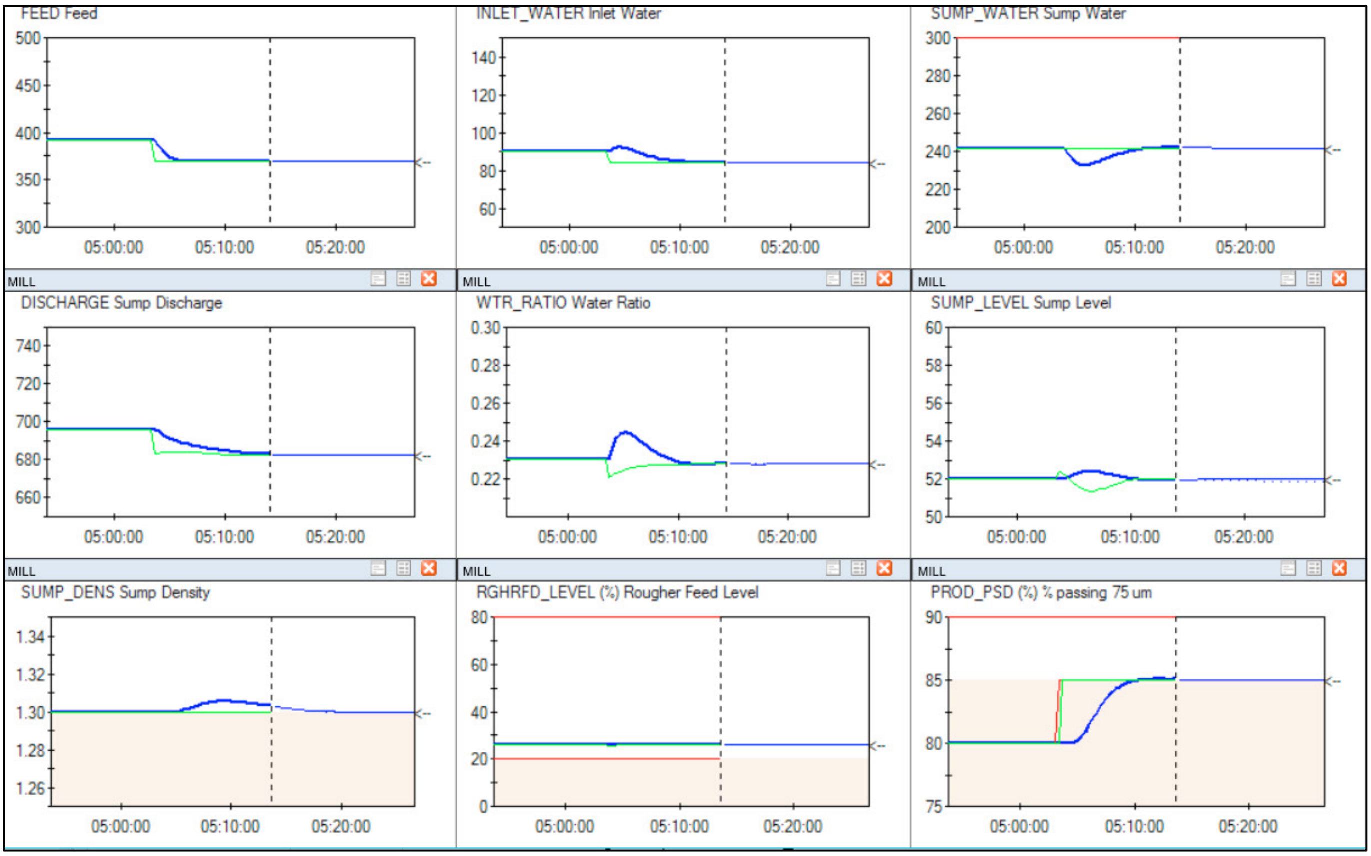

Figure 5. A subset of Mill MPC dynamics in response to a limit change at Product PSD at time 05:04:00 (bottom right subplot).

variables that are non-zero, this implies that the steady-state solution is not feasible. In this case, the CV limits are relaxed until the solution is feasible.

Should the minimisation of Eq. 2 prove that all the slack variable values are zero, then there exist one or more feasible steady-state solutions. In this case, the following economic optimisation is solved:

$$\min J = \sum_{i=1}^{N_i} c_i \,\Delta u_{i,ss} + \sum_{j=1}^{N_j} c_j \left|\Delta u_{j,ss}\right| \qquad (5)$$

where J is the objective function value, N_i is the number of MVs that have economic directions, N_j is the number of MVs whose movement is to be minimised and c_i and c_j are cost factors.

The $\Delta u_{i,ss}$ and $\Delta u_{j,ss}$ are the changes in the values of the MVs at the present time to those at steady-state. These are the variables chosen to minimise Eq. 5 subject to the current MV and CV constraints. The steady-state values of the MVs are imposed on the dynamic solution at the end of the control horizon.

4.1 TWO MODEL PREDICTIVE CONTROLLERS

The model matrices as derived through the step responses in Fig. 3 and Fig. 4 were used to implement model predictive control on each unit separately. For this study, the plant and the controller have identical models i.e. no plant model mismatch is included.

The mill controller is configured to maximise the feed subject to the current constraints on densities and the particle size distribution (PSD) of the product. The controller includes three CVs that have integrating models; the load, sump level and rougher feed level. The first of these is configured to control to a value since tight control of load improves grinding performance. The latter two are configured to use as much as possible of the surge capacity. This assists in smoothing the flows out; this is advantageous in stabilising the flotation feed.

The flotation controller has the control objectives to control the overall reagent dosage in a range while maintaining concentrate and tail grade between limits. The optimisation objective of the controller is to maximise recovery.

The two individual controllers give good results in controlling the plants in the specified ranges and reacting to disturbances. The results of increasing the PSD limit percentage is shown in Fig. 5. This can be seen in the red lower curve of PROD_PSD, the PSD after milling, which is changed from 80% to 85%. The MPC reacts smoothly and in a coordinated fashion. Despite the objective to maximise feed, the MPC reduces feed as this is the only method to ensure the finer grind. The vertical dashed line represents current time; the plots extend two times to steady-state in the past, and one in the future.

The flotation controller manages the competing objective of grade and recovery well. This can be seen in Fig. 6 where the MPC responds to an increase in the recovery low limit of one percent. Control is smooth; the increased recovery is achieved at the cost of the use of extra reagent. In this formulation, the effect of the mill parameters on the flotation bank is modelled by including variables feed flow, density, grade and PSD as feed-forward variables in the flotation controller. This approach does not leverage the information on future predictions of CVs and MVs that are available from the mill controller.

The two separate controllers are sub-optimal in the sense that the flotation controller cannot affect the variables that are fed to it. For instance, if the economics are such that increased recovery requires a finer feed, this change would have to be made by a human rather than the system. For these reasons combining of the two MPCs is investigated.

Fig. 6. Flotation MPC: Change in Recovery Low Limit at 04:38

4.2 THE COMBINED CONTROLLER

The aim of combining the two MPCs is to achieve tighter control, particularly in the reaction of the flotation circuit to upstream disturbances. In addition, it is hoped that a superior operating point will be achieved. Fig. 7. outlines the signals that link the behaviour of the two systems.

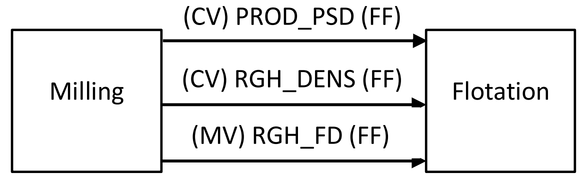

Fig. 7. Linking of milling and flotation through CVs (outputs) and MVs to feed forwards.

To combine the controllers some thought must be given to the resulting models and how they should be formulated. If an MV in an upstream controller is repeated as a feed-forward in a downstream controller then this is straightforward. The replacement of the feed-forward by a manipulated variable and its associated move-plan yields an immediate predictive advantage.

The case is more complicated if a CV in an upstream controller is used as a feed-forward in a downstream controller. One method would be to re-visit the data originally used for model development and attempt to derive the models of the effect of mill inputs on flotation outputs. This approach has some difficulties, since

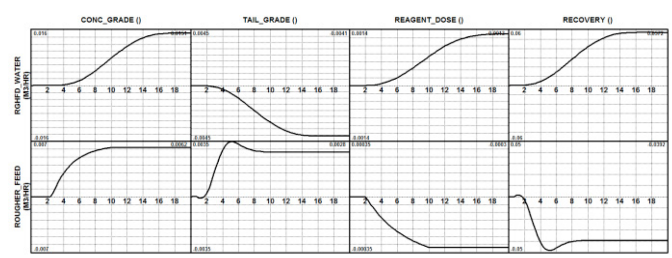

Fig. 8. Convoluted Models for Grades, Dosage and Recovery versus Mill MVs

identifying the effects in the face of other disturbances as well as the relatively long settling times can be challenging.

It is possible to derive the required models by mathematical manipulation. In this case, the models of the downstream controller are found by convolution of the upstream CV model with the downstream CV models that depend on the feed-forward:

$$C(j,k) = \sum_p \sum_q A_U(p,q) A_D(j-p+1, k-q+1) \qquad (6)$$

where A_U is the matrix of the upstream (milling) and A_D the matrix of the downstream system (flotation).

As an example, the rougher feed density and product PSD are CVs in the mill controller and a feed-forward in the flotation controller, while the rougher feed flow is an MV in the mill controller. On combining the matrices, models are formed for the grades, reagent dosage and recovery versus these three mill MVs.

The time to steady state of the convoluted model is double that of the individual models. This reflects the fact that two systems that operate in series have been connected from a modelling point of view. This longer time to steady state can have implications for the control of the system. In principle, the convolution of Eq. 6 removes the intermediate variables from the matrix altogether. The variable can be retained in the matrix if desired, but care must then be taken not to over specify the problem.

The results of a change in the feed PSD for the combined controller are shown in Fig. 9. In this case, the controller recognises that there will be a drop in recovery and increases the air to the flotation cells.

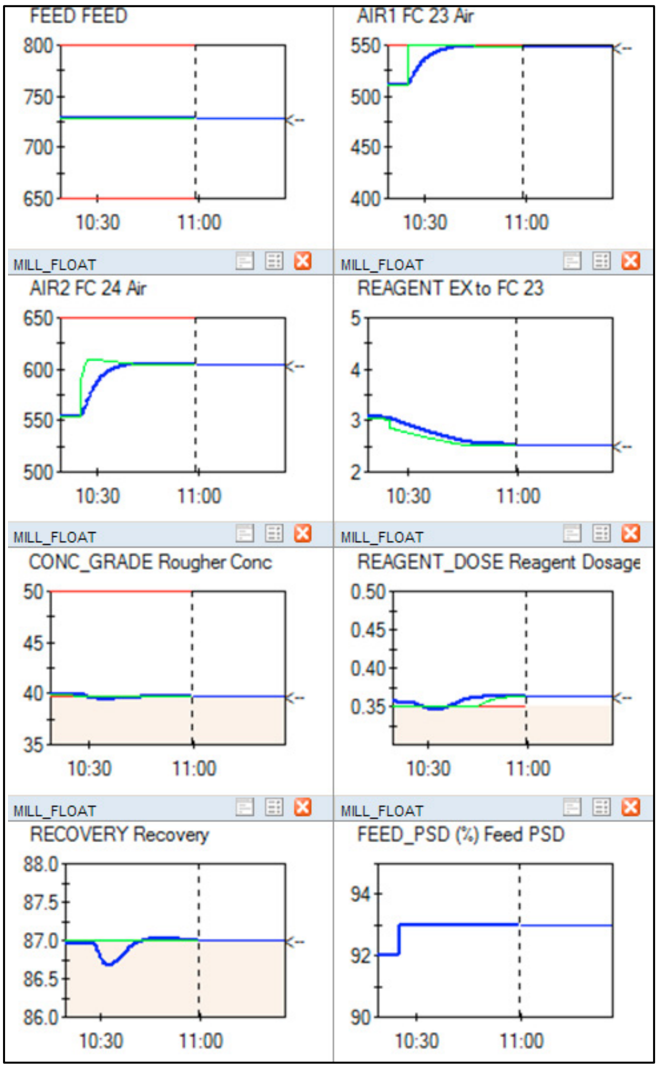

Fig. 9. Combined MPC: Increase in feed PSD at 10.22

5. CONCLUSION

MPC on the commonly found mineral processing operations of milling and flotation is now an industrial reality. This work demonstrates that by careful consideration of common variables, these MPCs may be combined in a mathematically rigorous manner. The resulting larger controller displays more co-ordinated behaviour and can adjust milling circuit parameters to meet flotation circuit requirements.

The combined controller presented here has the potential to improve overall circuit performance beyond that achieved by two local MPCs. The size of the application is not unusually large when measured against applications in the petrochemical industry.

The approach is by no means limited to the unit operations considered. As the use of MPC becomes more commonplace is the mineral processing industry, larger controllers will evolve with improved optimisation scope.

REFERENCES

Bergh, L. G., & Yianatos, J. B. (2011). The long way toward multivariate predictive control of flotation processes. *Journal of Process Control*, **21(2),** 226-234.

Brooks, K.S. and Koorts, R., 2017. Model Predictive Control of a Zinc Flotation Bank Using Online X-ray Fluorescence Analysers. IFAC-PapersOnLine, 50(1), pp.10214-10219.

Brooks, K. and Munalula, W., 2017. Flotation Velocity and Grade Control Using Cascaded Model Predictive Controllers. IFAC-PapersOnLine, 50(2), pp.25-30.

Camponogara, E., Jia, D., Krogh, B. H., & Talukdar, S. (2002). Distributed model predictive control. *IEEE control systems magazine*, **22**(1), 44-52.

Cortés, G., Verdugo, M., Fuenzalida, R., Cerda, J., & Cubillos, E. (2008). Rougher flotation multivariable predictive control: concentrator A-1 division Codelco Norte. *Proceedings of the V International Mineral Processing Seminar* **1(6)** 316-325.

Darby, M.L., Harmse, M. and Nikolaou, M., 2009. MPC: Current practice and challenges. IFAC Proceedings Volumes, 42(11), pp.86-98.

Dawson, P. and Koorts, R., 2014. Flotation Control Incorporating Fuzzy Logic and Image Analysis. IFAC Proceedings Volumes, 47(3), pp.352-357.

Garcia, C.E., Prett, D.M. and Morari, M (1989). Model Predictive Control: Theory and Practice – A Survey. *Automatica* **25(3),** 335-348.

Karelovic, P., Razzetto, R. and Cipriano, A., 2013. Evaluation of MPC strategies for mineral grinding. IFAC Proceedings Volumes, 46(16), pp.230-235.

Silva, D.A. and Tapia, L.A., 2009. Experiences and lessons with advanced control systems for the SAG mill control in Minera Los Pelambres. IFAC Proceedings Volumes, 42(23), pp.25-30.

Steyn, C.W., Brooks, K.S., De Villiers, P.G.R., Muller, D. and Humphries, G., 2010. A Holistic Approach to Control and Optimization of an Industrial R Ball Milling Circuit. IFAC Proceedings Volumes, 43(9), pp.137-141.

Steyn, C.W. and Sandrock, C., 2013. Benefits of optimisation and model predictive control on a fully autogenous mill with variable speed. Minerals Engineering, 53, pp.113-123.

Venkat, A. N., Hiskens, I. A., Rawlings, J. B., & Wright, S. J. (2008). Distributed MPC strategies with application to power system automatic generation control. *IEEE transactions on control systems technology*, **16**(6), 1192-1206.

Verhaegen, M. and Dewilde, P., 1992. Subspace model identification part 2. Analysis of the elementary output-error state-space model identification algorithm. International journal of control, 56(5), pp.1211-1241.

Wei, D. and Craig, I.K., 2009. Economic performance assessment of two ROM ore milling circuit controllers. Minerals Engineering, 22(9-10), pp.826-839.