Proceedings of the World Congress on Mechanical, Chemical, and Material Engineering (MCM 2015)
Barcelona, Spain – July 20 - 21, 2015
Paper No. 127

Recent Developments in Flotation Column Instrumentation and Control: An Update

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Abstract -For over two decades, LOOP (French acronym for *Process Observation and Optimization Laboratory)* researchers have been working at developing and/or improving specific sensors for flotation columns and their use for automatic control of this process. Several papers have already been published for the mineral processing industrial and scientific community in peer-reviewed journals and conference proceedings, but very few have been presented in European conferences. This paper summarizes the latest milestones completed by the group. On the instrumentation side, developments encompass a more accurate method for measuring electrical conductivity for flotation column sensors, a device for estimating the bias rate, and a better procedure for evaluating bubble size from images taken by bubble viewers. In terms of process control advances, the discussion will focus on results for bubble size control in a two-phase system, and the application of a 2x2 multivariable predictive control to a pilot flotation column running in parallel to industrial columns in a Québec concentrator. Finally, the latest work on two-phase bubble size distribution modeling and control will be summarized.

***Keywords*:** flotation column, bias rate, gas hold-up, bubble size distribution, multivariable predictive control.

1. Introduction

Since the first successful industrial implementation in 1981 (Les Mines Gaspé, Canada), flotation columns have been used in several mineral applications (coal, base metals, phosphates, etc.), mainly in cleaning stages as a result of their froth washing capabilities. Despite their widespread usage, measuring some column-specific variables, and consequently their use for process control, is rather limited. The process efficiency, reflected by the concentrate grade and recovery (primary variables), is dependent on so-called "secondary variables" such as froth depth (H_f), bias rate (J_b), gas hold-up (γ_g) and bubble surface area flux (BASF or S_b). Only the first one is presently monitored in plants, usually through floats coupled to ultrasound, and controlled by manipulating the set-point of the tailing flow rate (or valve position). The gas hold-up is the column volume fraction occupied by bubbles, thus available for particle collection, i.e. directly related to valuable mineral recovery. Even though off-the-shelf sensors are commercially available (O'Keefe et al., 2007; Gomez et al., 2003), it is not monitored on-line in industrial applications and obviously not controlled. The bias rate is defined as the net downward flow of water crossing the interface, and as such it dictates the quality of the column froth cleaning action. Unfortunately, it is not measured either.

BSAF is defined as the rate of bubble surface rising per column unit section. As such, it is the variable most directly associated to the collection process (bubble surface related), and thus to recovery. However, the estimation of a "global" BSAF implies knowing the average bubble diameter ($D_{b,avg}$), a variable which has started being measured off-line only very recently, using the McGill Bubble Viewer (Chen et al., 2001). Amelunxen and Rothman (2009) attempted to use the BSAF for optimizing the recovery. They estimated the $D_{b,avg}$ through a drift-flux analysis (DFA), and used γ_g measurements from a CiDRA™ model GH-100. As mentioned by the authors, this approach though, implies assuming a value for the pulp viscosity. Having a robust on-line $D_{b,avg}$ measurement will certainly encourage the use of BSAF for industrial column control. Nonetheless, the $D_{b,avg}$ is a misleading concept since flotation bubbles are quite different in size; therefore using the actual bubble size distribution (BSD), and/or a sort of 'inferred BSAF distribution', would be more relevant.

Bubble size depends mainly on three factors: gas flow rate (J_g), sparger characteristics (orifice size, porosity, shear water, etc.), and frother type and concentration. Any effort for controlling the bubble size will require manipulating these variables. Whereas J_g and sparger characteristics/settings can presently be adjusted, frother concentration isn't. Some off-line measurement methods have been suggested, but the laboratory procedure introduces long delays incompatible with on-line control. Aiming at an automatic control application, Maldonado et al. (2010a) recently proposed an on-line estimation method, using J_g and γ_g values, from already available commercial sensors.

In summary, with the exception of froth depth, continuous monitoring of flotation column variables is so far limited to flow rates (gas, feed, tailings, wash water), i.e. only to available manipulated variables, and grades (generally the concentrate). Process control (generally PID) is also mainly limited to froth level and some flow rates such as wash water (J_{ww}) and air (J_g). Primary variables, concentrate grade and recovery, are targeted through rule-based techniques.

However, the benefits of advanced model-based control and supervision techniques are nowadays well recognized, and this in many industrial fields (Quin and Badgwell, 2003). LOOP researchers have tested a successful application of multivariable predictive control to a pilot-scale flotation column operating with a three-phase (slurry-air) system (Calisaya et al., 2012). Using a modified version of the McGill Bubble Viewer, Maldonado (2008a) measured and modeled the BSD in a two-phase (water-air) system laboratory column. This work led to the automatic control of the Sauter mean bubble size D_{32} (Maldonado et al., 2010b) and the whole BSD (Riquelme et al. 2014b), both in the same two-phase laboratory column.

2. New Instrumentation Developments

2. 1. Conductivity Measurements Using A Field-Programmable Gate Array

As mentioned before, froth depth is successfully measured in industrial columns using a float. For laboratory or pilot-scale units, such as those used by our research group, this option is not possible because of the small cross section of the columns. Instead, froth depth monitoring relies on a semi-analytical procedure based on the electrical conductivity profile across the interface position (Maldonado et al., 2008b). The conductivity is measured by sequentially powering a series of "conductivity cells" (eleven cells 10 cm apart, each one made of two electrodes flush mounted inside the laboratory column) with a high frequency alternating current, to avoid electrolysis and polarization. Both the McGill $\boldsymbol{\gamma_g}$ sensor and the Laval J_b sensor (later on described), also rely on similar conductivity-based techniques.

The main disadvantage of this method is the high load produced in the power supply when all conductivity cells are connected. Moreover, it is sensitive to noise, and the number of output bits of the analog-to-digital converters limits the resolution. This can become a limitation, when the conductivity spans a wide range of operation. Furthermore, since the relationship between the output voltage and conductivity is usually nonlinear, the resolution is related to the changes in the function slope.

To overcome these problems, Riquelme et al. (2014a) used a different approach where each conductivity cell is sequentially connected to a square wave oscillator circuit. Its oscillation frequency becomes a function of the sample conductivity. This strategy reduces the problems related to the noise and DC components, since the square wave frequency can be measured with a digital input. Measurement resolution can be improved by increasing the clock frequency. Since the hardware handles digital signals, data can be transmitted over long distances without degradation. Moreover, the approach allows a wide operational range and only requires a single point for the calibration, which is very convenient in an industrial environment. A Field Programmable Gate Array (FPGA) is used to measure the oscillation period, display the data on a LCD screen, communicate the information to a computer and manage the switching between the various measurement cells.

2. 2. Bias Rate Estimation

At steady-state, bias rate (J_b) can be estimated from a water balance in the lower part of the pulp zone, underneath the feed port. As such, a small value (J_b) is calculated by subtracting two large values affected by measurement errors, propagated and 'amplified', thus limiting the accuracy of the result. Moreover, the calculation assumes steady-state conditions, thus excluding any control application. As a result, the bias rate is simply not measured. Maldonado et al. (2008c) proposed a new approach for a two-phase system, relating J_b to the volumetric fraction of wash water (γ_w) underneath the liquid-froth interface; this latter is estimated through a local conductivity balance below the interface (near the feed port), leading to:

$$\varepsilon_w\,(\%) = 100\left(\frac{k_f - k^*}{k_f - k_w}\right) \qquad \text{where} \qquad k^* = k_i \cdot \left(\frac{k_l}{k_{lg}}\right) \tag{1}$$

k_f , k_w and k^* respectively represent the conductivity of the feed, wash-water streams, and that of the liquid (gas-free) immediately below the interface. The last conductivity value (k^*) is estimated by the right-hand side relation in equation 1, where k_i is the conductivity of the aerated liquid below the interface (measured with a flow cell, e.g. the lowest cell of the level sensor), k_l and k_{lg} are measured by the McGill γ_g sensor located nearby. Using this k_l / k_{lg} ratio, γ_w is computed as:

$$\varepsilon_w\left(\%\right) = \frac{100\left[k_f - k_i\left[0.5\left(\varepsilon_g + 1\right)/\left(1 - \varepsilon_g\right)\right]\right]}{k_f - k_w} \tag{2}$$

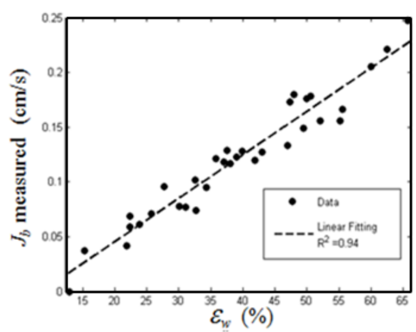

Fig. 1. Relationship between bias rate and volumetric fraction of wash-water

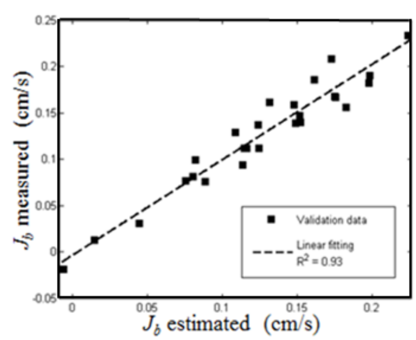

Fig. 2. Bias rate validation (estimated = using the additivity rule)

Figure 1 shows the static relationship between the bias rate measured through the "additivity-rule" (valid only for two-phase steady-state systems), and that obtained with the present method (J_b vs γ_w). Figure 2 depicts the validation of this method using a different set of data.

Esteban-Rojas (2011) extended this approach to estimate $\boldsymbol{\gamma_w}$ in a three-phase system. Considering that the air hold-up is measured sufficiently close to the interface, assuming non-conductive solids, and using the "additivity rule" for a three-phase system, $\boldsymbol{\gamma_w}$ can be estimated from:

$$\varepsilon_w(\%) = \frac{100\left[k_f - k_i\left(0.5\cdot\varepsilon_g + 1\right)\cdot\left(1-\varepsilon_g\right)^{-1}\right]}{k_f - k_w(1-\Phi_s)} \tag{3}$$

where k_f is the conductivity of feed pulp, k_i is the conductivity of pulp-gas mixture underneath the interface, k_w is the conductivity of wash water and Φ_s is the solid concentration (%) in the pulp being fed. This relation was validated as part of the control tests done at a concentrator, as described in section 3.1.

2. 3. Bubble Size Measurement

As previously mentioned, the BSD and BSAF are directly related to the collection process. Therefore, targeting a given recovery value implies monitoring and controlling these variables. The former has lately become possible using the so-called "bubble viewer" for bubble image acquisition and processing. In order to obtain accurate estimates of the BSD, hundreds of pictures must be analyzed. The image processing program commonly used (Circular Shape Detection, CSD) has shown some flaws, as it does not detect large, overlapped, clustered, elliptical or incomplete (at the edge of the frame) bubbles. The image presented in Figure 3 (left) shows examples of "uncounted" bubbles (greyish ones). Vinnett et al. (2012) have suggested an off-line procedure to account for clustered and large bubbles, which obviously is not useful for control purposes. Recently, Riquelme et al. (2013) have proposed an on-line strategy for bubble detection addressing two issues: detecting non-perfectly circular bubbles, and automating the procedure. The technique makes use of the Circular Hough Transform (CHT) to detect any sort of bubbles. Before applying the pre-calibrated CHT-based algorithm, the original image must undergo a series of automated pre-processing steps. To evaluate the proposed method, tests were carried out in a two-phase laboratory flotation column. A set of 25 pictures (bubbles between 1 and 70 pixels) was analyzed using the CSD algorithm, the CHT algorithm and a "manual" bubble count. Figure 3 compares the number of detected bubbles (for a given image) between the CSD and the CHT methods.

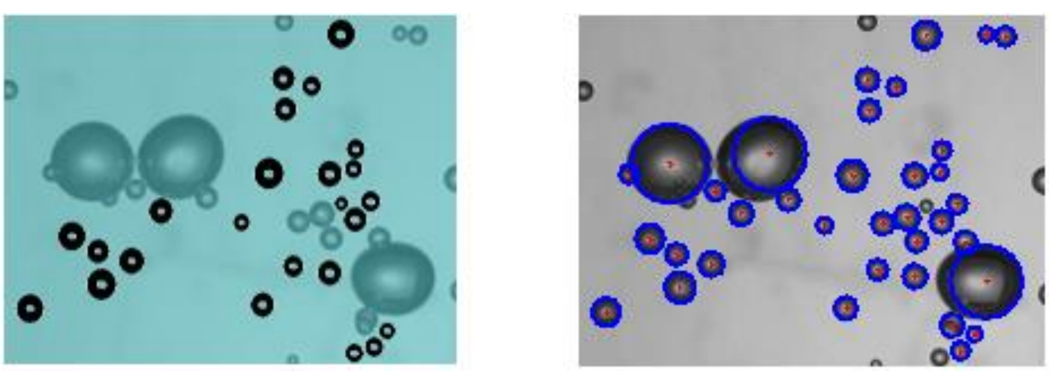

Fig. 3. Comparison between detection algorithms (left: circular detection; right: CHT based method)

Although not so clear in a black-and-white reproduction, the CSD method missed all large and small attached bubbles (greyish bubbles), whereas the CHT-based algorithm detects them all. The reference manual count allowed identifying a total of 537 bubbles whereas the CHT-based and CSD method algorithms respectively reported 525 and 377 bubbles. It is clear that (a) the cumulative function obtained with both the CHT-based algorithm and the manual count are similar, and (b) the precision of the CSD method decreases for bubbles larger than 30 pixels in diameter (larger bubbles) thus introducing biases.

3. New Process Control Developments

3. 1. Multivariable Predictive Control Of H_f, J_b And γ_G

A hierarchical framework is generally recommended for adequate process control. The resulting stack of ‘control layers’ are often depicted in a triangular structure. From the base to the top, the four layers are: instrumentation, regulatory control, advanced process control and real-time optimization. Regulatory control consists of local SISO (single input – ingle output) control loops (PID) providing a steady operation for the flotation column inputs: feed (whenever possible), gas and wash water flow rates. It is also assumed that the feed has been correctly conditioned ensuring adequate pH and reagent concentration. The advanced control layer aims at maintaining the process (secondary) variables, such as the froth depth, bias rate, froth parameters, gas hold-up or bubble surface area flux, at their own set point, hopefully related to the metallurgical objectives (recovery and grade). Real-time optimization (RTO) allows managing on-line the set points of secondary variables, leading, through a mathematical routine, to optimal metallurgical indices.

Maldonado and LOOP co-workers (2009) showed the potential of this control philosophy (Figure 4). The experimental set-up consisted in a Plexiglas column of 7.5 m height and 5 cm diameter, using conductivity-based sensors for measurement of H_f , $\boldsymbol{\gamma_w}$ and $\boldsymbol{\gamma_g}$, peristaltic pumps for handling the various streams, and ad-hoc flow meters for gas, water and pulp streams. Wash-water and air flow rates were managed by PI controllers implemented in a Moore Micro 353© controller. Graphical interfaces and data acquisition were performed by a HMI/SCADA software iFIX©, operating under a Windows©. An Opto 22© I/O system was used to centralize sensor and actuator signals. The control algorithms were implemented in MatLab©, all signals being sampled every two seconds. The considered secondary variables were the froth depth, bias rate (or $\boldsymbol{\gamma_w}$), and gas hold-up.

A 2x2 model-based predictive controller (MPC) (manipulating the wash-water and gas flow rates) supervised $\boldsymbol{\gamma_w}$ and $\boldsymbol{\gamma_g}$, and complemented the standard PI used for froth depth control manipulating the tailings flow rate. Like for industrial applications, froth depth control essentially aimed at maintaining a stable operation. The multivariable controller added a very interesting feature: it was designed to optimize indirectly the grade and recovery, via the gas hold-up and bias rate set-points. More precisely, the strategy consisted in selecting a set point exceeding the normal physical values for $\boldsymbol{\gamma_g}$, while simultaneously satisfying operational constraints, such as ensuring a positive J_b to prevent gangue entrainment. This was equivalent to maximizing the BSAF available for particle collection, thus maximizing recovery, and avoiding deterioration of the concentrate grade.

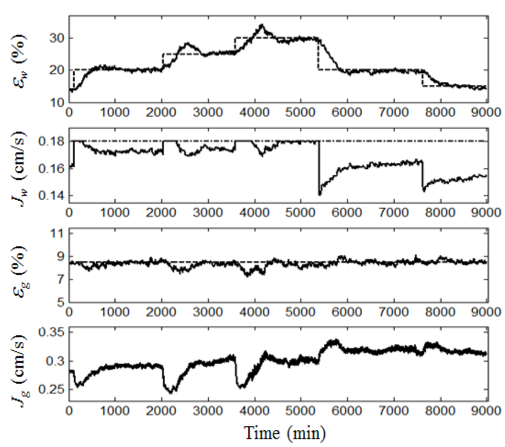

Fig. 4. Control system performance under active constraints on bias rate (lower bound) and wash-water flow rate (upper bound)

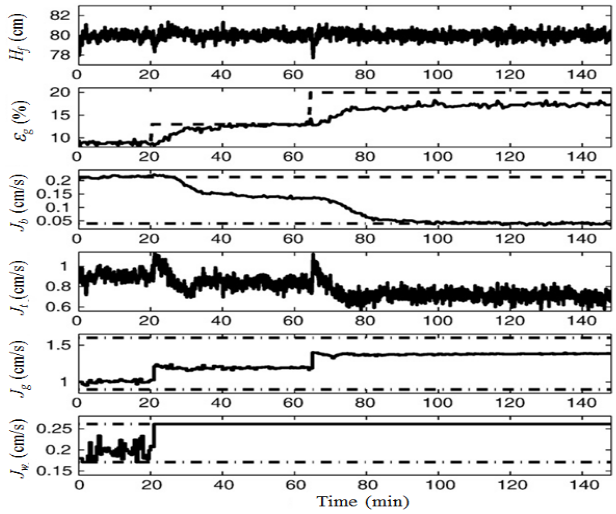

Fig. 5. Control strategy assessment at the AEM-Laronde plant; manipulated ⁄ controlled variable (-), set-point (- -), constraint (- .)

Experimental work undertaken with a two-phase system showed the feasibility of such approach, i.e. requesting a high gas hold-up set point, to optimize the flotation column operation, while respecting the constraints on the bias rate (Figure 4). In particular, the bias rate lower-limit imposed an upper bound on the required superficial gas velocity to prevent concentrate grade deterioration due to hydraulic gangue entrainment (Maldonado et al., 2009). The same control strategy was also successfully implemented at the Agnico-Eagle Mines, Cu-Zn Laronde concentrator in Abitibi (Québec) using a similar experimental set-up, but with a 15 cm diameter column (Calisaya et al., 2012). The column was continuously fed with a slurry flow diverted from the third cleaner column feed (copper circuit). This campaign aimed at validating for a three-phase system the various conductivity-based sensors and the proposed control strategy. In addition, samples of feed, concentrate, and tailings were collected when the column was at steady-state to evaluate the metallurgical performance indices under different operating (controlled) conditions. Results similar to those shown in the previous case study were obtained. Figure 5 shows the long-term behaviour of the control system under set-point changes and disturbances.

3. 2. Mean Bubble Size Control

This work explored the possibility of controlling the Sauter mean diameter as a first step towards the control of bubble surface area flux (Maldonado et al.,2010b). A frit-and-sleeve sparger (Kracht et al,2008) was implemented to have an extra degree-of-freedom, through the flow rate of shear water (J_{ls}) injected through the sparger gap used to modify the bubble size. The D_{32} was calculated on-line from the measured BSD (image processing). A Gaussian mixture model was proposed. Minimizing the log-likelihood of the data points and using a gradient descent method allowed determining the model parameters. Lastly, an internal model controller (IMC) based on a Wiener model manipulated the shear water superficial velocity set-point to supervise the D_{32}. To evaluate the performance of the control system, the laboratory column (5 cm diameter) was first filled with a solution containing 10 ppm Dow-froth 250. Then, changes on superficial gas velocity and frother concentration were implemented to simulate disturbances affecting the D_{32} control loop.

Figure 6 shows the controlled variable, D_{32}, and the inner loop manipulated variable, J_{ls}. Good tracking performances can be achieved when the pump speed was not saturated. More details about the tests and their results are provided in the reference (Maldonado et al., 2010b). Figure 7 shows the trends for both the gas hold-up and bubble surface area flux for test conditions shown in Figure 6. A significant correlation can be seen between gas hold-up and bubble surface flux, initially suggesting that both variables carry similar information and consequently either variable could be used for control purposes.

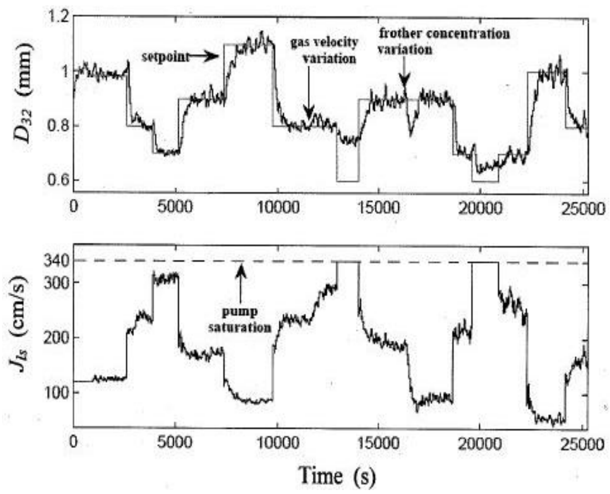

Fig. 6. Average bubble diameter (D_{32}) control: tracking and regulation performances

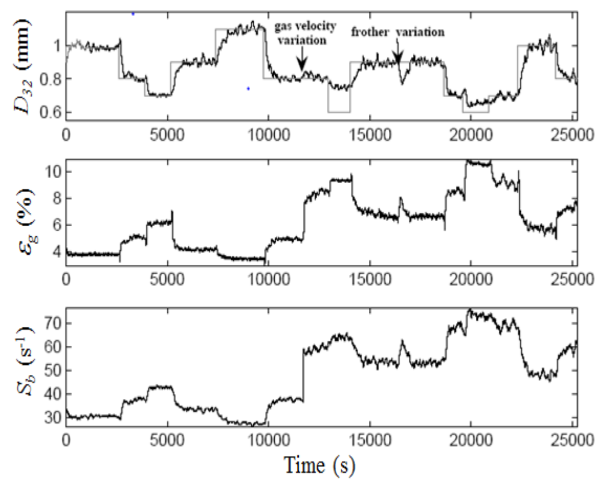

Fig. 7. Average bubble diameter (D_{32}) control: relationship between D_{32}, γ_g and BSAF

One potential problem with controlling the BSD via its mean value (in this case, the D_{32}) is that all the available information regarding the shape of the bubble size distribution, such as multi-modal and tailing behaviour, is completely lost in this averaging exercise. In fact, it is possible to generate very different bubble size distributions having the same D_{32}. Therefore, using the latter for control purposes will be appropriate only for unimodal narrow BSD. Finally, frother concentration was considered in this study as an unknown disturbance. Since it has a strong effect on the bubble size, its use as a manipulated variable deserves to be explored.

3. 3. Modelling And Control Of Bubble Size Distribution

The objective of this work is to control the bubble size distribution since controlling D_{32} may lead to various BSD and thus potentially very different flotation performances.

The automated CHT-based algorithm allowed monitoring the BSD from which a Wiener model (dynamic model with nonlinear gains) is estimated. The outputs of the Wiener model are the mean and standard deviation of the distribution while the inputs are the gas and shearing water (frit-and-sleeve sparger) flow rate set-points. Based on the Wiener model, a constrained nonlinear model predictive controller is designed to control the mean and standard deviation of the distribution.

This control algorithm was tested on a two-phase pilot column. Results show that the proposed approach leads to good control performances, as depicted in Figure 8, confirming the possibility to use this strategy to optimize the valuable mineral recovery by adequately selecting the BSD for a given particle size distribution.

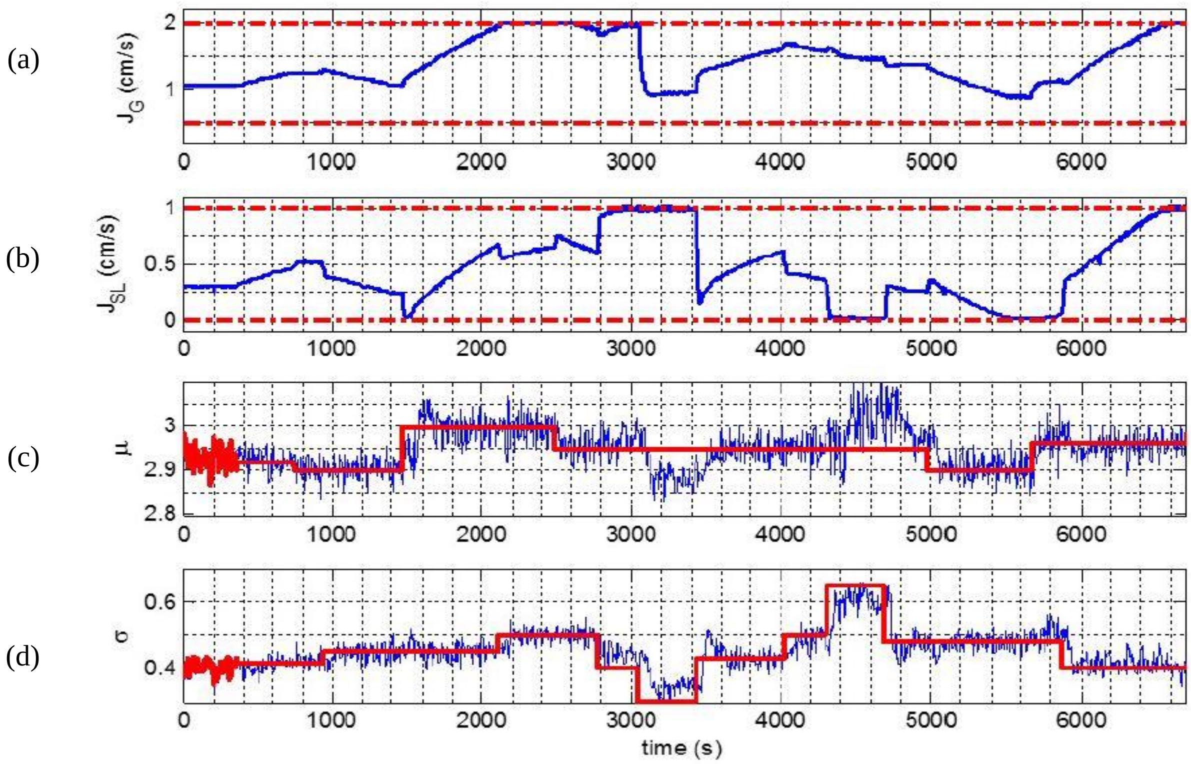

Fig. 8. a) Gas flow rate set-point and its constraints; b) Shearing-water flow rate set-point and its constraints; c) BSD mean and set-point; d) BSD standard deviation and set-point (red lines indicate the constraints or the set-point value)

4. Conclusion

The work summarized in this paper and references herein, shows that adequate sensors and/or methods exist for monitoring and control the most important variables of flotation column operation. In particular, the averaged D_b (e.g. D_{32}) can be estimated <u>on-line</u> and used for control purposes, via BSAF or gas hold-up. The on-line evaluation and modeling of bubble size distributions, in two-phase systems, have been proven feasible and could be employed for process control as is, or through a sort of 'inferred BSAF distribution'. Model-based control of "traditional" secondary column variables has been accomplished in an industrial environment, and could be implemented in industrial columns using available commercial sensors. Model-based control of the bubble D_{32}, calculated from BSD measurements, was also achieved with excellent results in a two-phase laboratory column.

Acknowledgements

The authors acknowledge the contributions of the various graduate students who completed the experimental work and co-authored the referred papers. The financial support of NSERC, COREM, AEM-Division Laronde and Xstrata-Ni (Strahcona) was fundamental to the success of these projects.

References

Amelunxen, P.A., & Rothman, P. (2009). The Online Determination Of Bubble Surface Area Flux Using The Cidra GH-100 Sonar Gas Holdup Meter. *IFAC MMM2009*.

Calisaya, D.E., Riquelme, A., Desbiens, A., Poulin, É., & del Villar, R. (2012). Constrained Multivariable Control Of A Pilot Flotation Column. *Proceedings 44th CMP Conf.*, 169-181.

Chen, F., Gomez, C.O., & Finch, J.A. (2001). Technical Note: Bubble Size Measurement In Flotation Machines. *Minerals Engineering,* 14(4), 427-432.

Esteban-Rojas, R.M. (2011). Validation Industrielle De La Mesure Du Différentiel D'eau Dans Une Colonne De Flottation (M.Sc. Thesis). Université Laval, Québec, Canada.

Gomez, C.O., Cortés-López, F., & Finch, J.A. (2003). Industrial Testing Of A Gas Hold-Up Sensor For Flotation Systems. *Minerals Engineering,* 16, 493-501.

Kracht, W., Gomez, C.O. & Finch, J.A., (2012). (2008). Controlling Bubble Size Using A Frit-And-Sleeve Sparger. *Minerals Engineering*, 21, 660-663.

Maldonado, M., Desbiens, A., delVillar, R., Girgin, H., & Gomez, C.O. (2008a). On-Line Estimation Of BSD Using Gaussian Mixture Models. *5th Int. Mineral Processing Seminar*, *Procemin,* 389-398.

Maldonado, M., Desbiens, A., & del Villar, R. (2008b). An Update On The Estimation Of The Froth Depth Using Conductivity Measurements. *Minerals Engineering*, 21, 935-939.

Maldonado, M., Desbiens, A., del Villar, R., & Chirinos, J. (2008c). On-Line Bias Estimation Using Conductivity Measurements. *Minerals Engineering,* 21, 851-855.

Maldonado, M., Desbiens, A., del Villar, R. (2009). Potential Use Of Model Predictive Control For Optimizing The Column Flotation Process. *Int. Journal of Mineral Processing,* 93, 26-33.

Maldonado, M., Desbiens, A., del Villar, R., Aguilera, R. (2010a). On-Line Estimation Of Frother Concen-Tration For Flotation Processes. *Canadian Metallurgical Quarterly,* 49(4), 435-446.

Maldonado, M., Desbiens, A., Poulin, É., del Villar, R., & Riquelme, A. (2010b). Control Of Bubble Size In A Laboratory Flotation Column. *Proc. of Copper 2010 Vol.7*, 2829-2844.

O'Keefe, C., Viega, J., & Fernald, M. (2007). Application Of Passive Sonar Technology To Mineral Processing And Oil Sand Applications. *Proceed. 39th CMP Conference,* 429-457.

Quin, S.J., & Badgwell, T.A. (2003). A Survey Of Industrial Model Predictive Control Technology. *Control Engineering Practice*, 11, 733-764.

Riquelme, A., Bouchard, J., Desbiens, A., & del Villar, R. (2013). Bubble Detection In Flotation Columns Based On Circular Hough Transform. *World Mining Congress*.

Riquelme, A., Desbiens, A., del Villar, R., & Maldonado, M. (2014a). A Device For Measuring Conductivity Of Dispersions. *Measurements,* 53, 49-55.

Riquelme, A., Desbiens, A., del Villar, R., Maldonado, M. (2014b). Non-Linear Bubble Size Distribution Modeling In A Flotation Column. *Submitted to International Journal of Mineral Processing.*

Vinnett, L., Contreras, F., & Yianatos, J. (2012). Gas Dispersion Pattern In Mechanical Flotation Cells. *Minerals Engineering,* 26, 80-85.