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ENGINEERS TRAINING IN AUTOMATION OF FLOTATION PROCESSES

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Abstract: The wide plant control integration of mining, mineral and metal processes poses many challenges. Testing process monitoring, diagnosis and control strategies for flotation processes is expensive, and usually requires either complex pilot plant facilities or to deal with the hard constraints posed by experimentation in real plants.
One critical aspect to take advantage of the present technological developments is the training of engineers to understand and master when and how some technique may be appropriate to solve a particular problem and to identify the challenges implicitly underlying in its implementation. In this sense the use of hybrid laboratories is presented, where fully instrumented pilot plants are operated under PLC and DCS coupled on-line with phenomenological models, to recreate an environment as close as possible to industry.

Keywords: training, flotation, modeling, automation, process control

1. INTRODUCTION

How to improve the operation of different processes by using several techniques have been proposed in the last decade. Hodouin *et al.* (2001) and Hodouin (2011), for example, recently discussed the state of art and challenges in the mining, minerals and metal processing area. These discussions included data reconciliation, soft sensor and pattern recognition, process modeling, process monitoring, fault detection and isolation, control loop monitoring, control algorithms and supervisory control.

Theoretical advantages of any novel method have to be finally confronted and tested in real plants. However, experimentation on real plants may present several difficulties and usually is of high cost. To avoid risky operating conditions or high losses in products, the input variables can only be changed inside a narrow band. Some confusing results may be obtained when important disturbances cannot always be managed, interrupting and degrading the experiments. On the other hand, to reproduce experimentally a given disturbance may be extremely difficult, as, for example, a change in particle size distribution. In the mineral processing industry, the measurements of important variables, such as a stream grade or particle size, demands large efforts on instrumentation maintenance plans in order to obtain these measurements with the required quality. In summary, data collected following a designed experiment to make good decisions is more difficult and costly to be obtained.

Simulations of the application of novel methods by using a plant model present some known advantages and drawbacks. If a model of a plant were available, the new methodology can be tested under a number of different conditions, at low cost. However, the high cost of producing reliable models for complex process must be considered. Usually, highly non-linear phenomenological models could be built, with the aid of experiments to estimate model parameters. However, in order to reduce the mathematical complexity and thus find a solution, some simplifying assumptions are usually made. Consequently, the value of comparisons of different methods by simulation can be significant degraded, and often cannot replace experimentation in the real world.

On the other hand, pilot plants can reproduce most of the experimental advantages of a real plant. The small plant scale provides a better chance to a wide experimentation, by relaxing at the same time some constraints. However, installations, with large storing facilities and expensive on stream analyzers, are demanded because of the presence of solids in flotation, or expensive organic solvents for copper extraction. The lack of instrumentation and computer platforms may represent a problem difficult to overcome, even when the pilot plant were located nearby a plant. Environmental issues are strongly dependent on plant location and facilities. The flexibility gained for working in a smaller scale is lost when environmental regulations put hard constraints and when the instrumentation investment and maintenance cannot be paid by the generation of products in small scale.

2. A HYBRID APPROACH

Some processes can be represented by differentiating the phenomena in different classes: the hydrodynamics and the change in concentration of one or more species. The hydrodynamics refer to how the different streams are mixed and separated in a process unit. In most cases, the physical properties of each phase, such as viscosity or density, are usually invariant or experiment moderate changes as a function of the concentration of one solute. This can occur due to a chemical reaction, where some species partially disappear to form other species, or due to a selective difusion of some species from one phase to another. In flotation some species are selectively attached to gas bubbles and form a froth phase separated from a pulp phase. In the pulp phase some solid particles remain in the liquid phase and are reported to the tailings. Sometimes, changes in solute concentration may also change transport properties, and this artificial decoupling is not effectively occurring.
More generally speaking, the process behaviour can be separately represented when the process hydrodynamics is not significantly influenced by changes in solute concentration. The experimentation approach in pilot plants can be simplified when this hypothesis is accepted, in twofolds:

(i) Experimentally each fluid (liquid, pulp and gas) may be substituted by low cost and easy manageable fluids, such as water in a liquid phase reaction, water and organic solvent in solvent extraction process or water and air in flotation. The process hydrodynamics will be well characterized by such fluid mixing and separation in a process unit. In this way, experimental work can be carried on under safety and low cost condition.

(ii) The solute concentration changes can be obtained from detailed models relating measured operating conditions, such as flow rates, temperatures, pressures and levels, and initial concentration state of the feed. These virtual variables will replace the real variables, overcoming the difficulties found in a real case to use low cost and reliable instrumentation. This kind of models usually is difficult to obtain and remain a problem to be solved.

Therefore, when the pilot plant is operated by using these low cost fluids and a model is available, a hybrid system can be developed. The main hydrodynamic characteristics are still well represented even when the real plant behaviour has been simplified. The target variables of the process operation can now be predicted (not measured), under a wide operating region, by using this kind of models.

Distributed control of local objectives can be administrated by supervisory control strategies based on estimation of the crucial variables. Process monitoring, diagnosis and fault detection, isolation and remediation studies can also be developed under low cost. Figure 1 shows how real and virtual input variables (feed characterization) can be combined with real output variables to feed a plant simulator. The plant simulator produces on-line virtual output variables.

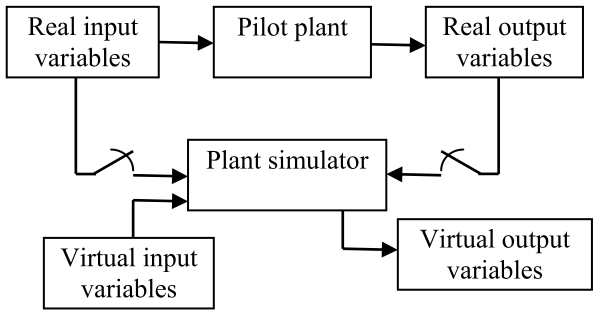

Fig.1 Hybrid system: combining real plant with simulators.

The Process Automation and Supervision Laboratory at Santa Maria University, consists of four pilot plants fully instrumented and controlled: a solvent extraction unit, a continuous stirred tank reactor, a flotation pneumatic cell circuit and a flotation column. In this paper both flotation plants are described. The communication and control platforms are shown in Figure 2.

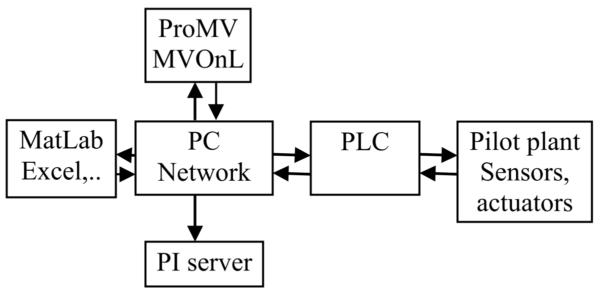

Fig. 2. Communication and control platforms.

Sensors and actuators are communicated to a PLC (Fanuc 90/30 from General Electric (2013)) where calibrations and local control are implemented, and the data is sent to a PC network, that it is used as a DCS platform, running the software Wonderware InTouch ®, from Invensys (2013). Process model predictions are obtained by running software in Matlab ® or Excel Macros ®. All data is displayed at PC stations and historical data files are built in a PI server, from OsiSoft (2013) for further analysis. Operating variables (real and virtual) can also be analyzed off-line by using ProMV software or on-line VOnLine from Prosensus (2013). Supervisory control running on PC network writes DCS set points on PLC.

At the Control Laboratory in Santa Maria University, two flotation pilot plants were built, instrumented and controlled in the mineral processing area: a column and a three mechanical cells circuit. A brief description of both plants and their instrumentation and control systems is as follows.

3. FLOTATION COLUMN PILOT PLANT

Flotation columns (Finch and Dobby, 1990) have been used world-wide as efficient cleaning stages in a large number of sulfide mineral concentrators. Large variations in metallurgical performance have been observed due to more degrees of freedom in their operating variables, leading to much scope for improving their control than mechanical cells (Bergh and Yianatos, 1993, 2003).

The primary objectives are the concentrate grade and the column recovery, as indices of product quality and process productivity. These variables can be obtained if the grade of each stream is measured with good accuracy and high availability (Bergh and Yianatos, 2003). However, the on-line estimation from on-stream analyzers requires significant amount of work in maintenance and calibration. Therefore, most of the time secondary objectives, such as, feed pH, froth depth, gas flow rate and wash water flow rate are controlled (Bergh and Yianatos, 1993).

Consistent metallurgical benefits can be obtained if basic distributed control systems are implemented to ensure a stable operation of flotation columns. In general, at least froth depth, air flow and wash water rates are measured on line, and tailings, air and wash water flow rates are manipulated. Chemical reagent addition and pH controls are also included in some circuits. A P&ID of the pilot column is shown in Figure 3. The virtual variables are shown in grey boxes.

A hydrodynamics supervisory control coordinates the control of these secondary objectives. The approach of substituting the feed by water and frother represents quite well the column hydrodynamics and avoid working with solids and collectors. The output grades are predicted from operating variables by using a phenomenological model reported in Bergh *et al.* (1998) and it is schematically shown in Figure 4.

4. MECHANICAL CELLS CIRCUIT

Mechanical cells have been used for a long time as efficient rougher and scavenger circuits. Similarly to flotation columns, the primary objectives are the concentrate grade and the column recovery, as indices of product quality and process productivity. However, the quality of these on-line estimations usually requires significant amount of work in maintenance and calibration of on-stream analyzers (Thwaites, 2007). Therefore, most of the time secondary objectives, such as, feed pH, chemical reagent addition, solids percentage, froth depth profile and gas flow rate profile in forced air cells are controlled (Bergh and Yianatos 2011). Consistent metallurgical benefits can be obtained if basic distributed control systems are implemented to ensure a stable operation. In general, at least froth depth profile and air flow rates (in forced air cells) are measured on line, and tailings and air flow rates are manipulated. pH control and chemical reagent addition control are also included in some circuits.

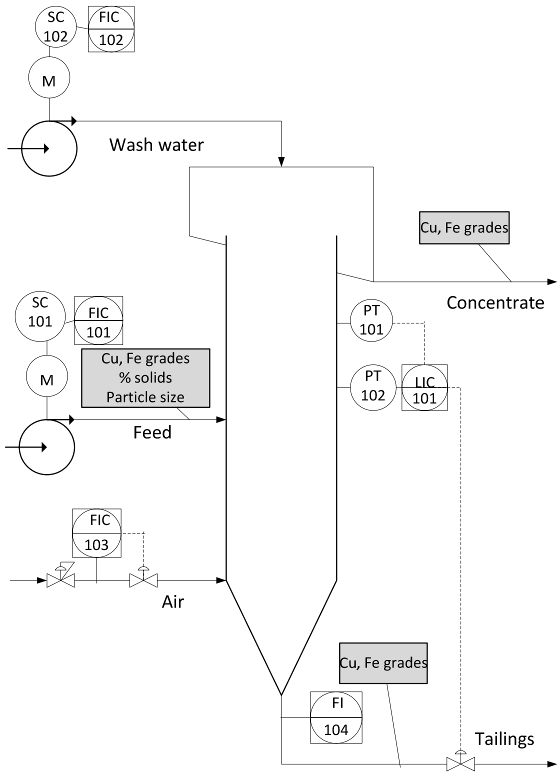

Fig. 3 P&ID of flotation column pilot plant

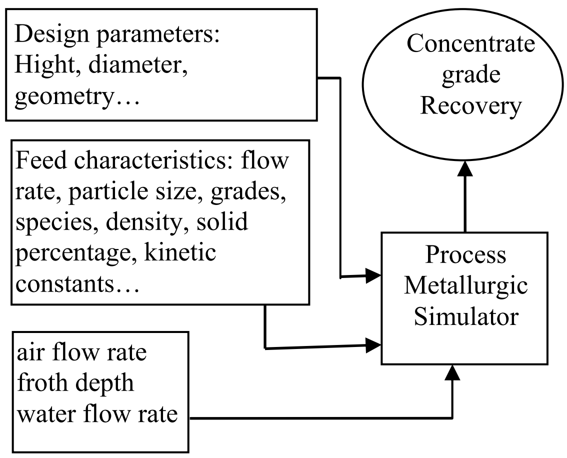

Fig. 4 Metallurgical model of a flotation column.

A P&ID of the pilot cell circuit is shown in Figure 5. The virtual variables are shown in grey boxes. A hydrodynamics supervisory control coordinates the control of these secondary objectives. The approach is similar as the one used in the pilot flotation column. To predict output grades from operating variables a phenomenological model, reported in Bergh and Yianatos (2013), was used. Figure 6 shows the necessary information to build this kind of model.

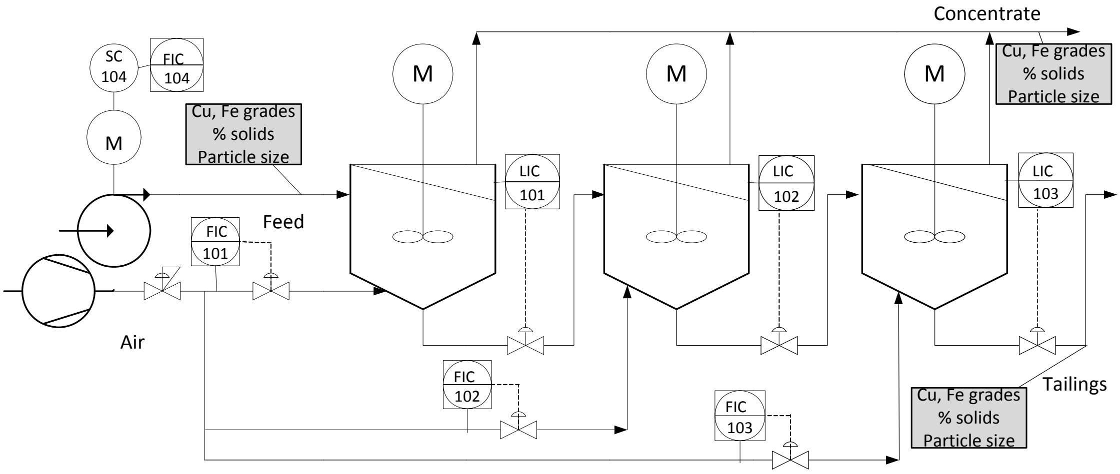

Fig. 5 P&ID of three cells flotation circuit.

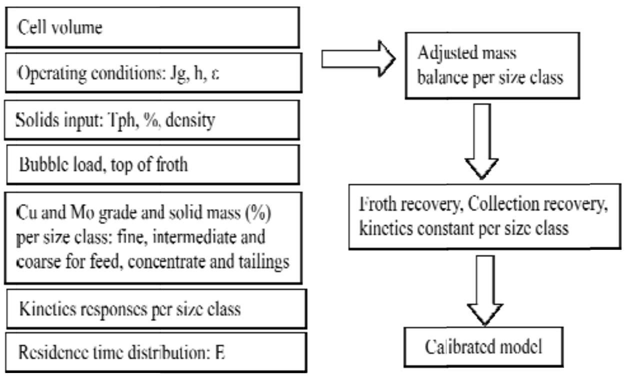

Fig. 6 Experimental data needed to fit model parameters for each cell.

5. EXPERIMENTAL RESULTS

5.1 Process Monitoring and Diagnosis

1800 sets of data corresponding to a normal condition of 16 variables were used to build a PCA (Principal Component Analysis) model (Kourti and MacGregor, 1995; MacGregor et al., 2007). The variables included were: the measured gas hold up (E), froth depth (Z), low and high pressure (PL, PH), mA signals to tailings (PT) and air (PA) control valves, bias (Jb), air (Jg), wash water (Jw) and feed (Jf) flow rates, the defined virtual variables: feed particle size d_{80} (D), Cu grade (FCG) and solid percentage (S), and the predicted variables: Cu concentrate grade (CCG) and process recovery (R). At least 92 % of the variance in the centered and scaled pretreated data was explained by a model with 6 latent variables. For monitoring the process the Hotelling T^2 limit was found to be 12.6, while the PSE (prediction square errors) limit was 3.81 (Bergh and Yianatos, 2011).

Experiments were carried on to detect when an abnormal operating condition is met., One can see from Figure 7 that most of the time the PSE test is satisfied, while T^2 test is failed at intervals 130-200, 300-430 and 480-560. On these periods, the concentrate grade is too low and recovery is high or recovery is low and concentrate grade is too high, then an abnormal operation has been detected.

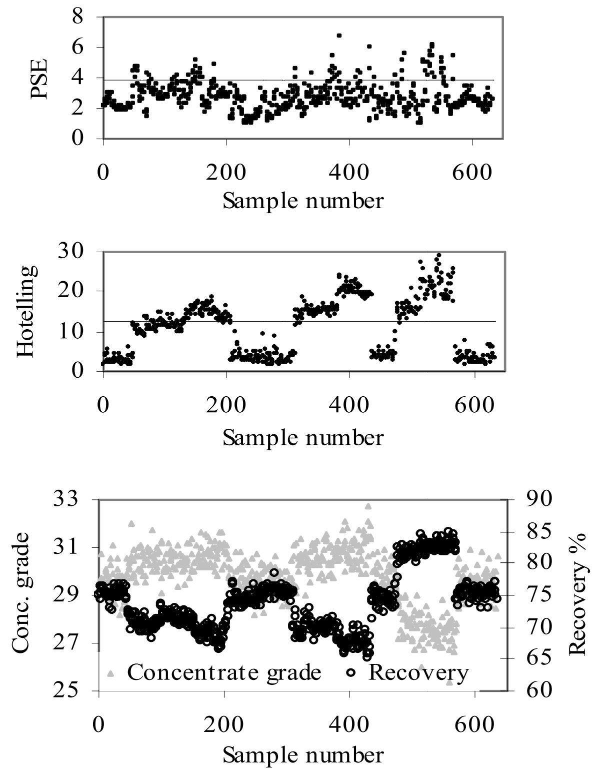

Fig. 7 Operating condition test.

Figure 8 shows the contribution to the T^2 residuals for sample 512, in order to identify which variables are causing this problem. Froth depth and the high and low dp/cells presented the main contributions, showing that the problem is due to a low froth depth, causing high recovery and low concentrate grade.

Another interesting case is when only the PSE test fails, indicating that a measuring device must be recalibrated or replaced. The sensibility of this test was measured in percentage of error necessary to detect the failure. Errors less than 7% on Dp/cells, 15% on flow meters, 5% on pressure to control valves and 10% on virtual measurements of concentrate grade were detected for different operating conditions. The virtual measurement error of copper concentrate grade is shown in Figure 9.

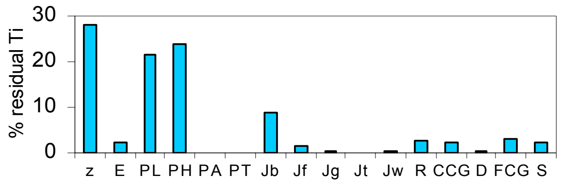

Fig. 8 Contributions to abnormal operation.

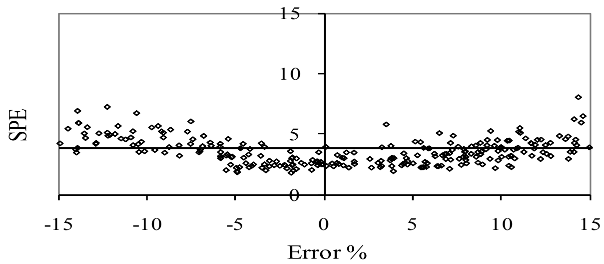

Fig. 9 Failure detection on concentrate grade.

5.2 Modeling and Distributed Control

Laboratory, pilot and industrial scale experiments have been done over many years to better understand the flotation phenomena and to build phenomenological models. Dynamic models were discussed in Bergh and Yianatos (1994), hierarchical control aspects in Bergh et al. (1995), and contributions to mixing characterization in Yianatos et al. (2005), estimation of kinetics parameters in Yianatos et al. (2010a), Yianatos (2007), froth modeling in Yianatos et al. (2010b and 2012), Yianatos and Contreras (2010), Leiva et al. (2010, 2012), Vinnett et al. (2012), Contreras et al. (2013), Liu and MacGregor (2008).

5.3 Supervisory Control

Expert-fuzzy systems to keep concentrate grade in a narrow band and copper recovery over a minimum value were the control objectives in a flotation column. The available resources were the froth depth, air flow rate and wash water flow rate set points. When column capacity was reached feed flow rate set point was decreased (Bergh and Yianatos, 1999). Fuzzy system was based on actual and past Cu grade errors, by using triangular membership functions (Soto, 2013). Similarly in the cells circuit, the control objectives were to maximize the Cu recovery while keeping the concentrate grade in an acceptable band (to be determined by the cleaning circuit actual capacity). These are classical objectives for rougher and scavenger circuits. In this case froth depth and air flow rate profiles are adjusted (Bergh and Yianatos, 2013; Duran, 2014) to keep the process on targets.

5.4 Soft Sensors

Using the hybrid systems, the available real and virtual variables were collected in the pilot plant for a set of steady state operations. PLS models (MacGregor et al. 2007) have been built to predict on-line Cu concentrate and tailings grades (Nakagawa and Bergh, 2008).

5.5 On-line Steady State Test

Since supervisory control often is running when a steady state condition is met and in practice a plant is never in steady state, algorithm proposed by Cao and Rinehardt (1995) has been implemented on-line. This application is very useful to collect the proper data to build models.

5.6 Formal Programs

In the Chemical Engineering Program students learn the control fundamentals and use the Lab to master conventional modeling techniques and PID control. Some students can follow a Research Lab in advanced process control topics and learn in a Process Control Seminar how to configure a PLC, a DCS software and in general how to use the complete hybrid systems to experiment with the kind of applications discussed before. Students following the Master Program learn identification and discrete control techniques in Application of Computer Control. This activity is both theoretical and practical, using the Lab facilities. In the course Advanced Statistics they learn the theory and practice of multivariate statistics methods, such as PCA models for diagnosis and fault detection and PLS modeling for soft sensors. Finally, a thesis that has been developed either in the Lab or in industry completes the training program.

CONCLUSIONS

Low cost, as well as safe and wide range experimentation in pilot plants is possible when on-line process measurements are combined with variables predicted by models. When the phenomena of changing the concentration of some species can be decoupled from process hydrodynamics, considerable simplification for experimentation can be achieved. Experiments describing the real process hydrodynamics can be performed using low cost materials, such as water and air. Reliable information on key unmeasured variables can be obtained from these simpler phenomenological models.

These hybrid units can be used to train engineers in testing the advantages and drawbacks of novel approaches related to process monitoring, diagnosis, fault detection and isolation, virtual sensors and supervisory control of complex processes as flotation, in a quasi industrial environment.

In a near future, more tests on novel strategies can be performed giving considerable insight on process performances under real experimentation.

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