

Simulation of Monitoring and Diagnosis of Flotation Columns Operation Using Projection Techniques

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Abstract— On line monitoring and diagnosis systems have become important part of industrial programs leading to improve process operation and therefore product quality over time. Today, great amount of process variables are routinely collected at high frequency by Distributed Control Systems (DCS). Highly correlated process input variables, low signal/noise ratios and missing data are some of the main difficulties found in modelling the process for monitoring and diagnosis purposes. Multivariate statistical projection methods, such as Principal Component Analysis (PCA) have been proposed to effectively deal with these situations. The development of a simulator to illustrate the application of these ideas to a flotation process is discussed here. In this work, the use of these projection tools in the detection of relevant variables presenting measurement problems, and in the identification of the set of variables responsible for driving the process outside its normal operating region, is demonstrated, giving considerable information for the correction of the operating problem.

INTRODUCTION

In the last two decades the use of pneumatic flotation columns became wide-spread throughout the mineral processing industry of metallic, non-metallic and coal ores in the world. Columns out perform conventional mechanical cells in cleaning operations (better product grade) due to their particular froth operation [1]. The classical flotation column design consisting of two principal zones: the collection zone and the froth zone. Following Figure 1, the pulp feed enters near the top of the collection zone. Hence, particles are contacted counter-currently with air bubbles generated near the bottom of the column. Hydrophobic particles collide and adhere to the bubbles, and they move upwards to the pulp/froth interface. The froth zone is a mobile bubble bed, approximately 1m in froth depth, which is contacted counter-currently with wash water (added near the overflow level). Some of the wash water is recovered into the concentrate overflow, the remainder providing a net

downward flow rate called a positive bias. The wash water plays an important role in eliminating fine particles entrainment from the concentrate. However, a significant interaction occurs among operating variables such as froth depth, air and wash water flow rates, as was discussed in previous dynamic model identification work [2]. The air flow rate is one of the most sensitive variables which directly affects the air holdup, mineral recovery and product grade. The column feed characteristics such as flow rate, pH, values grade, solids content, mineralogy, particle size distribution, liberation and reagent concentration (collectors, frothers, etc) are usually determined from previous grinding operations, flotation stages (rougher and scavenger) and conditioning tanks. A complete discussion on mineral processing automation can be found in [3]. More degrees of freedom in operating variables have led to large variations in metallurgical performance and have provided much scope for improving their control. A more complete discussion can be found in [4].

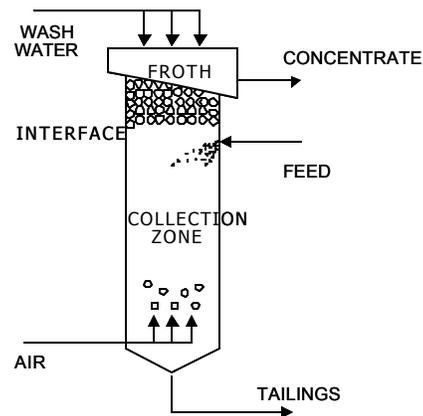


Fig. 1. Flotation column .

I. FLOTATION COLUMN CONTROL

The primary objectives are column recovery and concentrate grade, which represent the indices of process productivity and product quality. The on-line estimation of these indices usually requires a significant amount of work in maintenance and calibration of on-stream analysers, in order

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to maintain good accuracy and high availability. Therefore, a common practice is to control secondary objectives, such as pH at the feed, froth depth, air flow rate and wash water flow rate. These are usually implemented as local controllers or under distributed control systems (DCS). Ideally, when primary objectives are measured, the control strategy is to change the set points of the controllers under DCS, in order to achieve a good process performance. This is usually implemented in the form of expert systems [5]. On line analysers, tailings, feed flow rates and some other measurements are often incorporated into the system when a supervisory control strategy is implemented on top of a distributed control system. A schematic of a control system is shown in Figure 2.

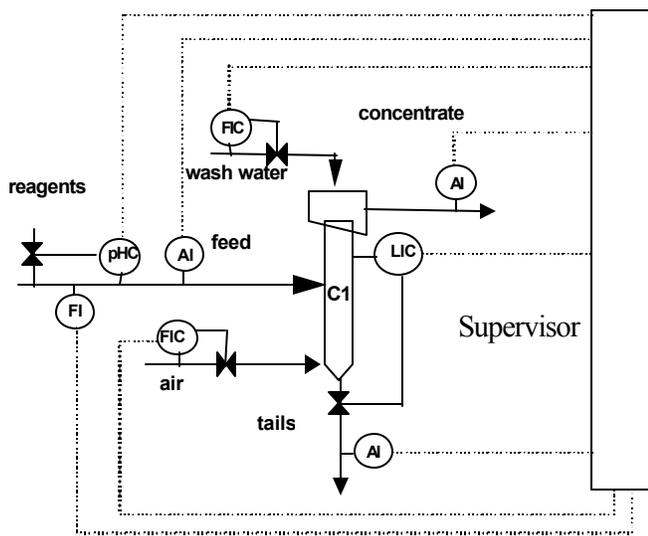


Fig. 2. Typical supervisory control system structure.

II. MULTIVARIATE STATISTICAL TECHNIQUES

The key feature of Principal Component Analysis (PCA) and Projection to Latent Structures/Partial Least Squares (PLS) methods is their ability to mathematically project high dimensional process and quality data into smaller dimensional, summary data sets via the development of linear models. Some of these numerous advantages of PCA and PLS methods have over traditional monitoring and prediction technologies are: provision for data dimension reduction and robustness to highly correlated, noise and missing data [6]. The concept of a latent variable model is that the true dimension of a process is not defined by the number of measured variables, but by the underlying phenomena that drive the process. The latent variables themselves are modeled as mathematical combinations of the measured variables and describe directions of variation in the original data. A latent variable model can contain many fewer dimensions than the original data, it can provide a useful simplification of large data sets, and it can allow better

interpretation of the measured data during analysis. More complete description of PCA and PLS methods, that includes discussion of numerical estimation techniques, are provided in [7] and [8]. Descriptions on the application of these methods for a general class of problems is given by [6]. A particular application to flotation columns can be found in [9] and [10].

Following [11], Principal Components Analysis can be graphically explained in Figure 3. Assume a set of collected data of three variables measured on a process, as shown in this three dimensional plot. It may be that the samples all lie on a plane, enclosed by an ellipse. Some samples vary more along one axis of the ellipse than along the other. The first PC describes the direction of the greatest variation in the data set, which is the major axis of the ellipse. The second PC describes the direction of second greatest variation, which is the minor axis of the ellipse. In this case, a PCA model (the scores and loadings vectors and associated eigenvalues) with two principal components adequately describes all the variation in the measurements.

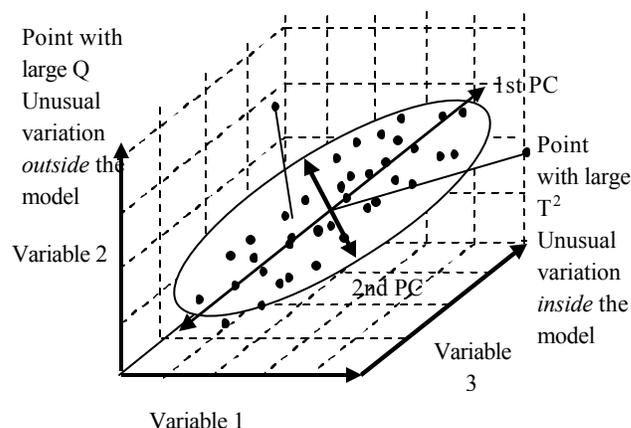


Fig. 3. Data representation by principal components.

As noted above, Q is a measure of the variation of the data outside of the principal components defined included in the PCA model. Therefore, Q is a measure of the distance off the plane containing the ellipse. In fact Q is the Euclidean distance of the data point from the plane formed by the 2 PC model. A sample with a large Q is shown on the upper left side of the figure. This sample is out of the plane of the model (although its projection into the model is not unusual). The Q limit defines a distance off the plane that is considered unusual based on the data used to form the PCA model. On the other hand, T^2 is a measure of the distance from the multivariate mean, that is the intersection of the PCs in the figure, to the projection of the sample onto the 2 PCs. The T^2 limit defines an ellipse on the plane within which the data normally project. A sample with a large T^2 value (but small Q) is shown on the upper right side of Figure 3.

Once a PCA model has been built with the normal

operating data, a set of steady state data can be judged to be in each of the following states:

- (i) Normal operation if the new set of data satisfies the Q and T^2 test.
- (ii) Abnormal operation if the T^2 test is failed. If the Q test is passed then the model is adequately representing the process. If the Q test is also failed then either the model is no longer appropriate or a measurement problem occurred.
- (iii) Measurement problem or PCA model representation problem if only T^2 test is satisfied.

In this way a diagnosis of the operation can be accomplished for steady state data. Furthermore, the residuals are informative of the principal process variables affecting the abnormal situation.

III. COLUMN FLOTATION SIMULATION

A. Nonlinear Model from Experimental Data

A flotation column model structure was developed, following [1]. Following Figure 4, first the gas holdup, the bias rate and the kinetic constants for each mineralogic specie are estimated from empirical models, depending on operating variables such as feed flow rate, gas flow rate, wash water flow rate and froth depth. Then, dispersion number, residence times, froth and collection recovery are estimated. Finally concentrate and tailings grades are predicted. The empirical model parameters were fitted using experimental data. More details can be found in [12].

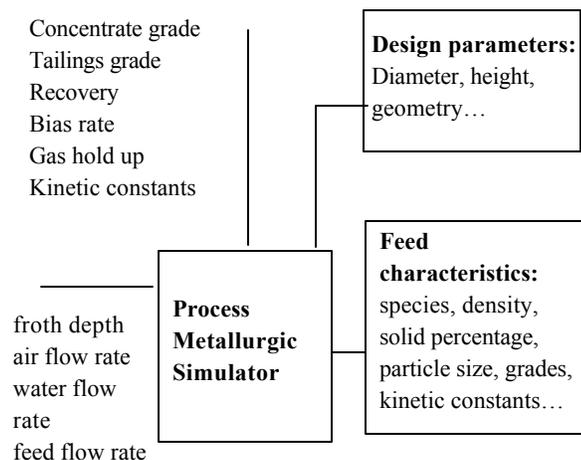


Fig. 4. Flotation column simulator.

Using this steady state non linear multivariate model a set of data was generated for different combinations of input values (32 observations of independent operating variables). These input data was partially taken from an incomplete set of industrial data and a set of generated data. This fact is very important considering that industrial data always show

significant correlation among them. The flow rates are expressed as superficial velocity in (cm/s) to be independent of column geometry (Jf refers to feed, Jg to gas and Jw to wash water). The froth depth (Z) is expressed in centimeters. The copper grade of the feed (Fcu) were not available, then this set of data, was independently generated.

Using the geometry of the pilot column [12], and assuming mineralogical species components of the feed, the model was used to predict a set of dependent variables, for each combination of input variables. Among these are the copper concentrate (ConcCu) and the overall recovery (RecCu), where concentrate grades vary from 31 to 38% in copper and process recovery from 40 to 65%. This data represents a wide range of column operation. More details can be found in [13].

B. PCA Models

Using the nonlinear model predictions a complete set of data was constructed, allowing the exploration of multivariate statistics techniques to obtain PCA models. To obtain such models a research software provided by the McMaster University's Advanced Control Consortium, MACC, was preliminary used. Afterwards, the PLS_Toolbox for Matlab, provided by Eigenvector Research Inc. was used to analyze the data. The first step was to define the set of normal data.

Several PCA models can be obtained according to the number of principal components chosen to explain the variability of the data [13].

For example, a model with 2 PCAs explain 62.5 % of the variability shown in the data. With a 3 PCAs model will increase to 78.2% and with a 4 PCAs model to 89.1%. More PCAs will marginally affect the model representation. In this table the weights on the scaled process variables for each PCA are also given. For example, if a 2 PCAs model is used, all data included in the 95% confidence interval will be considered normal data, as Figure 5 shows. In this case all data except three points, labeled as 18, 20 and 24, are interpreted as normal data.

The application of the Hotelling T^2 and residuals Q test to the same set of data and using a two PCAs models was performed. Most of the data passed both test with exception of points labelled as 20, 28 and 18. The point 24 is just on the border line.

B. Testing new data sets

Once the PCA model has been built, new sets of steady state data can be tested in order to identify an abnormal situation.

After proper scaling and PCAs calculations, the Hotelling T^2 and residuals Q test are applied. From the 32 sets of data, 15 points were chosen, labelled with the numbers 1, 2, 3, 7, 8, 9, 16, 17, 21, 22, 23, 29, 30, 31 and 32, in Figure 5. For each

operating condition, data with errors in minus 50% to plus 50% for feed grade were tested for models with two to four PCAs. For example, for positive errors of 20% (deviation from true value) a 2 PCA model will not detect a single case, but a 3 PCA model will detect at least 27% of the cases, and a 3 PCA model will detect at least 40% of the total cases. Therefore when the number of PCAs in the model increases a great fraction of the measurement error will be detected. The only drawback of increasing the number of PCA in a model is that the graphical analysis becomes more complex, because of large dimensionality.

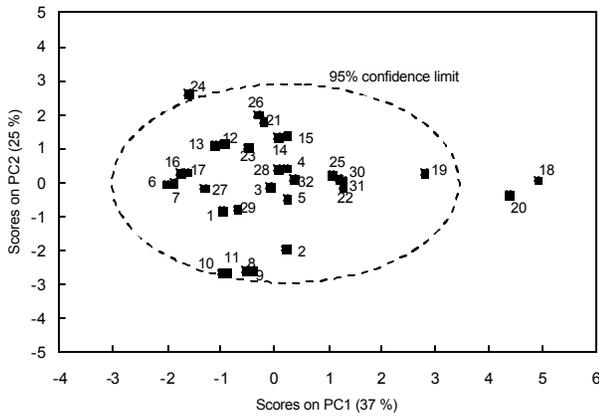


Fig. 5. A two PCs model representing a normal set of data.

Similar results can be found if the same set of data is corrupted by measurement errors in other process variable. The sensitivity of the test will depend on the importance of the variable in the model. For example, if one considers errors in the wash water flow rate, even with a 4 PCA model, measurement errors should be greater than 100% to detect only one over ten abnormal situations.

Sometimes the measurements present small errors, however some process variables or combination of them produce results considered outside the normal area. If an abnormal operating case is detected, then the next step is to identify the variables that causes the problem, in order to start a remediation procedure. To study this kind of problems a normal point of operation is deviated modifying one process variable. For example, the gas velocity is increased from 1.65 to 2.3 (cm/s) in the set of data shown under label 16 in Figure 5. Using the nonlinear steady state model it is predicted that the recovery is going up from 55.6 to 69.9 % and that the concentrate grade is going down from 31.6 to 30.1 %. This new operating point data is scaled and the PCAs are calculated. After that, the Hostelling T^2 and residuals Q test are implemented. The new point lies outside the confidence region of the normal space for the 4 PCA. Furthermore, the new point failed the Q test for each of the four PCA, while failed the T^2 test for PCA number 1, 2 and 4. The contribution of each process variable to fail the T^2 test is

shown in the left hand plot of Figure 6. The abnormal operating point is due to a positive large deviation of the gas velocity (Jg), and in minor way to positive deviation of the wash water flow rate (Jw) and to negative deviation of the froth depth (Hf), resulting in a large positive deviation of the process recovery and a moderate decrement of the concentrate grade. Therefore, this information is suggesting that a reduction of gas flow rate and a combination of increasing the froth depth and decreasing the wash water flow rate will come back the process to its normal operating region. In fact, doing that the pint will be that shown in Figure 5 under the label “29”, that is well inside the normal region.

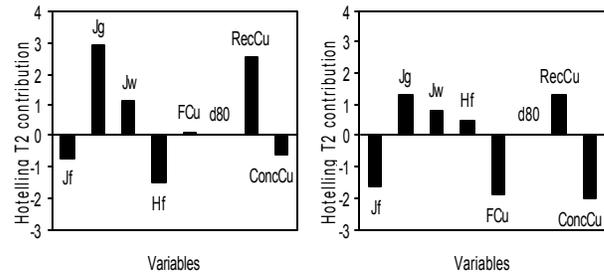


Fig. 6. Contributions of each variable to fail the T^2 test.

In the right hand plot of Figure 6 a second set of data failing to pass the T^2 and Q test was found. In this case a too low concentrate grade and a high recovery is the abnormal situation. The main contribution to these deviations are a too low feed flow rate and too low feed grade. Usually both variables cannot be changed because are the result of grinding and rougher operations, then this undesirable condition has to be remediate by mainly decreasing the gas flow rate.

IV. COLUMN FLOTATION MONITORING

A computer program application was developed in a Microsoft Excel plataform to simulate the column flotation monitoring. Figure 7 shows schematically the architecture of the program.

For a set of input operating variables (Jg, Jw, Hf, Jf, Fcu, d80) the flotation column simulator predicts the output variables (ConcCu and RecCu). With both set of variables and the PCA model, the Q and T^2 quantities are calculated and compared to the 95% confidence limits. Using this information the operator identifies one out of three situations: normal operation (both test passed), abnormal operation (T^2 test failed) and measurement errors (Q test failed). If the operations is abnormal the operator choose one input operating variable, according to the contribution of each variable to fail the test. If the operation detects a measurement error, the contribution of each variable to fail

the test is used to select the variable to check and calibrate. Once the operator changed one variable, a new set of input data is generated and a new cycle starts.

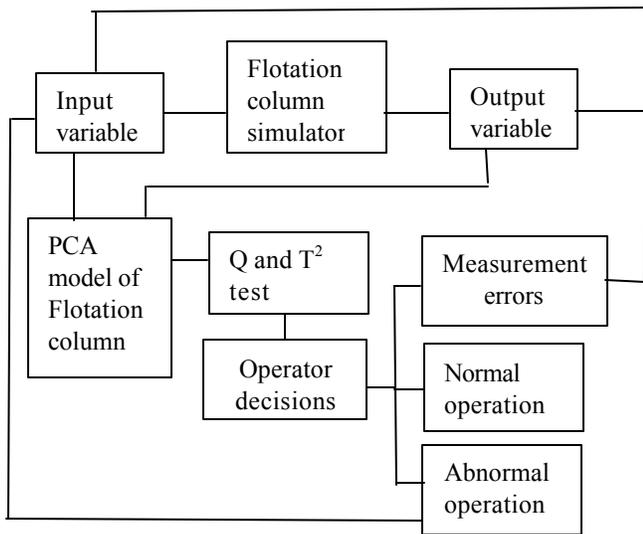


Fig. 7. Schematic architecture of application programs.

The program inputs are:

- The PCA model (number and composition of principal components, and Q and T² residual test limits)
- A set of operational data in steady state

The program shows a window with the information of the last operating points checked. An example is shown in Figures 8 and 9. The operating point 2 failed the Q test and passed the T² test. Looking at Figure 10, the operator found that the main contributor was the froth depth measurement. After calibration the true value was found to be 120 and not 140 (cm). This is shown in Figure 12.

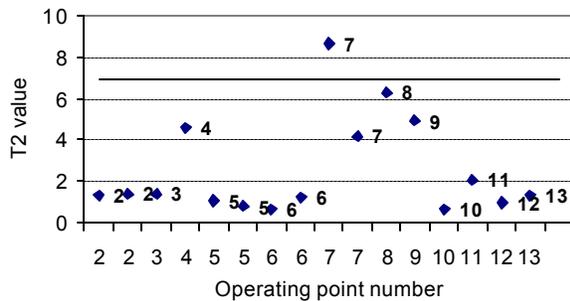


Fig. 9. results for T² test.

The nexts operating point, labelled as second 2, 3 and 4 passed both test. Point 5 failed the Q test and passed the T² test. Examining Figure 10, the operator found that the main contributor was the feed flow rate measurement. After calibration the true value was changed from 2.24 to 1.90, as it is shown in Figure 13. After that, the next point is normal. Point 6 again failed only the Q test, and the measurement problem was due to the feed flow rate measurement and again it was properly fixed.

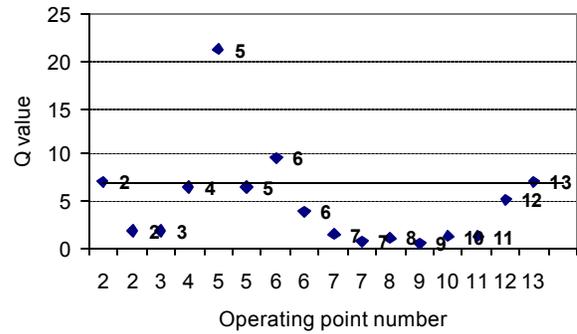


Fig. 8 Results for Q test.

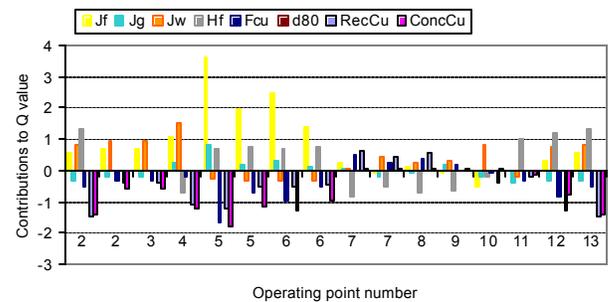


Fig. 10. Variable contributions to Q value.

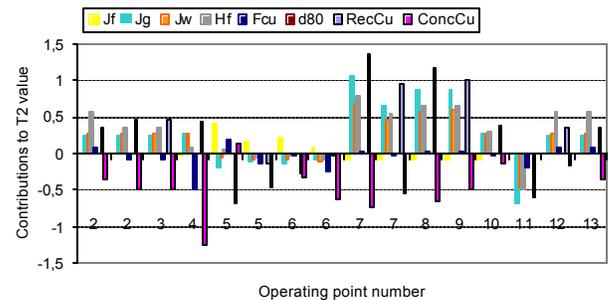


Fig. 11. Variable contributions to T² value.

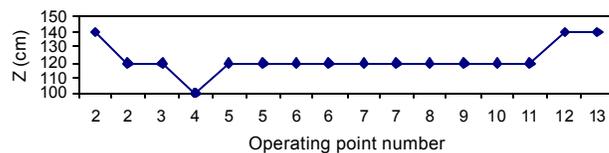


Fig. 12. Froth depth measurements.

Point 7 failed only the T² test. Examining Figure 11, the operator found that the main contributor to the abnormal operation was the gas flow rate. He decided to reduce it from 2.0 to 1.8 (cm/s), regarding that process recovery was too high and concentrate grade was too low. The change can be observed in Figure 14. The effect of increasing the concentrate grade is shown in Figure 15, while the decrement in recovery is shown in Figure 16. The next operating points was found to be normal. Figures 17 and 18 show the other operating variables.

The application was constructed to resemble as close as possible the real monitoring of a plant in order to opportunely detect abnormal operations, and to help finding the necessary action to come back to a normal operation. Usually this kind of application form part of a supervisory control systems, where the plant simulator is the process itself.

This application is useful to show people in industry the principles and application of multivariate statistics methods, and in particular the use of PCA models in monitoring a plant, and how to use the processed data to remedy the operating problem when it is detected.

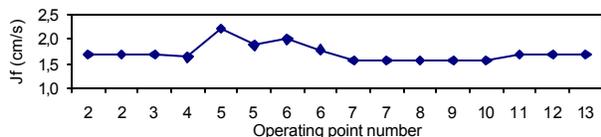


Fig. 13. Feed flow rate measurements.

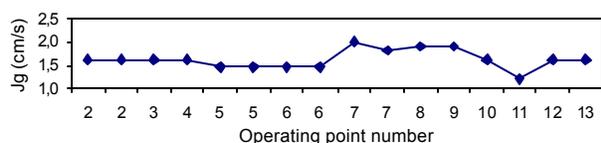


Fig. 14. Gas flowrate measurements.

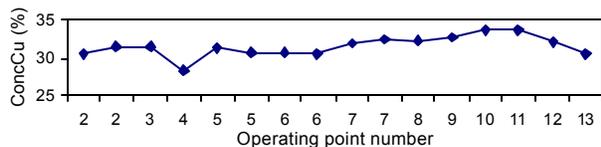


Fig. 15. Concentrate copper grade measurements.

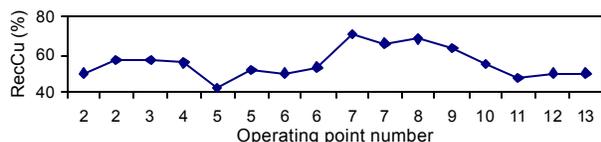


Fig. 16. Process copper recovery estimations.

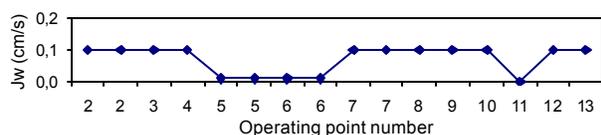


Fig. 17. Wash water flowrate measurements.

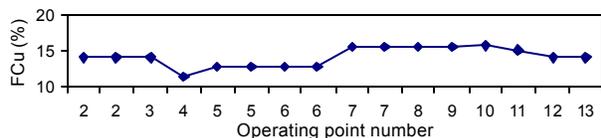


Fig. 18. Feed copper grade measurements.

V. CONCLUSIONS

The quality of flotation column control is strongly depending on the accuracy of key measurements as feed, concentrate and tailings grades, and also on operating

variables such as gas and wash water flow rate, and froth depth. Thus methods leading to detect and isolate measurement errors are very important and difficult to implement. PCA models based on normal steady state data can provide an excellent opportunity to aid in the solution of this complex problem. Even when all available measurements were accurate enough, flotation in columns is a very complex process making difficult the choice of how to remedy an abnormal operation, specially when the deviation is not caused by a single outrange input variable. This combination of correlated inputs put to much trouble in selecting the best decision. PCA models based on steady state data can help not only to detect abnormal operations but also to identify the main variables that are provoking the problem, suggesting in this way how to remedy the operation and go back to a normal operation. One advantage is that this monitoring tool can work on-line and therefore can be a part of a more complex supervisory control scheme. However, one limitation is that this method is applicable to analyze steady state data.

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