MODELO OPERACIONAL AND COMPUTATIONAL INTELLIGENCE: A NEW APPROACH TO MINERAL PROCESSING OPTIMIZATION

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MODELO OPERACIONAL AND COMPUTATIONAL INTELLIGENCE: A NEW APPROACH TO MINERAL PROCESSING OPTIMIZATION

Alexis P.Yovanovic [1]
Armando Corrêa de Araujo [2]
Emir Birro de Castro [3]
Daniel Henrique Dominguete Carvalho [4]

(1) Civil - Chemical Engineer, Universidad Católica del Norte, Chile, 1973
OTTIMAH – MODELO OPERACIONAL – Optimization and Control of Mineral Processes
Rua Padre Marinho, 37 – 13º andar, Santa Efigênia CEP 30140-040
Belo Horizonte-MG, Brasil – (55 31) 3241 6295 (55 31) 9235 0374
ayovanovic@modelooperacional.com.br

(2) Mining Engineer, M.Sc, Ph.D.
Associate Professor, Departamento de Engenharia de Minas, Univ. Federal de Minas Gerais, Brasil
Rua Espírito Santo, 35 s. 711B CEP 30160-030
Belo Horizonte-MG, Brasil – (55 31) 3238 1770 armando@demin.ufmg.br

(3) Mining Engineer, M. Sc., Manager of Mineral Processing – Vargem Grande Plant
Minerações Brasileiras Reunidas S.A. – MBR,
Faz. Capitão do Mato, S/N - Mina Capitão do Mato – 34.000-000
Nova Lima -MG, Brasil – (55 31) 3289-9461 (55 31) 9952-8930 emir.birro@caemi.com.br

(4) Electrical Engineer, M. Sc. , Optimization Department, Ottimah Process Improvements Ltda., Brasil
Rua Padre Marinho, 37 – 13º andar, Santa Efigênia CEP 30140-040
Belo Horizonte-MG, Brasil – (55 31) 3241 6295 daniel.dominguete@ottimah.com

ABSTRACT

This work briefly introduces a new phenomenological interpretation of mineral processing unit operations based on the macromolecular mass transfer principle, named as *Modelo Operacional* (operational model). This model considers an analogy between chemical mass transference processes (molecular processes) and operation in mineral processing (based on particle mass transfer). This configures a new macro phenomenological approach for them. From the concepts of the *Modelo Operacional* three mathematical laws are proposed: 1) the macro phenomenological property and its scale up; 2) the continuity equation that represents the mass and metallurgical performance of the circuit as a function of the several stages involved; and 3) the optimization equation that leads to mass movement through the best route. In association with *Ottimah Process Improvements Ltda* (Brasil) a strategy of optimizing control was developed for several mineral processing unit operations that considers in its integrity the utilization of the model here in presented together with the most advanced techniques of artificial intelligence.

A case study in development is presented for the quartz column flotation in an iron ore flotation concentration circuit, utilizing neural nets as support. The phenomenological model elaborated a metallurgical map that indicated on the screen of the software the optimized points for the process. Neural model were used to estimate the movement of mass as a function of several physical variables of the circuit such as the level of opening of column discharge valves and air flow rate admitted into the columns, contributing for the dynamic representation of the plant behavior.

Keywords: Flotation Model, Modelo Operacional, Optimized Control System, Optimization

INTRODUCTION

This work presents the results obtained with the application of a prototype of an original modeling and optimization system tested for the flotation circuit of Vargem Grande iron ore beneficiation plant from Minerações Brasileiras Reunidas (MBR). The developed solution is currently under plant trials. It has as major objective the improvement of mass yield and iron recovery of the flotation circuit through the stabilization of the process and also via the implementation of control measures that promote the optimization of the results and reduction of reagents.

The approach employed for the study presents an interesting differential in comparison to conventional alternatives available in the market for modeling and optimization of industrial processes. The current approach consists of an integration of the benefits arisen from artificial intelligence techniques with the phenomenological basis of the flotation process.

The fundamental basis of process engineering have been presented by the *Modelo Operacional* [1], which introduces the macro phenomenological property of the flotation process as a ratio between metallurgical recovery and mass concentration ratio of the froth phase through a so called selectivity curve. Mass concentration is a consequence of operational conditions of the flotation circuit and it can be estimated as a function of some process variables such as the opening of discharge valves of flotation columns, air flow rate and others. As the process in question is a multivariable process where an analytical model presents certain difficulties, the estimation of mass concentration was achieved by the application of artificial intelligence techniques.

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As the mass concentration estimation was performed on a continuous basis as a function of process variables, an extension of the concepts of operational model for its application on a real time frame was accomplished, following the flotation process dynamics that can be represented as a point in an operational map, characterized by the metallurgical recovery (R) and by the mass concentration in the process (Rcm). The representation of the operational conditions of the actual plant in the operational map, as a function of the stages involved (2nd law of the *Modelo Operacional*) allows the evaluation of the process recovery as well as indicated the possibilities of the improvement of the results given by the optimized operational points in the operational map.

The solution developed, evaluated as a prototype system as it will be seen the following sections, consists of a support system for the control of the flotation circuit under investigation. This system offers to the operator suggestions and relevant information for the optimization of the supervisory system.

METHODOLOGY

The *Modelo Operacional* establishes an analogy with mass transfer chemical processes suggesting the study of mineral processing processes under the point of view of macromolecular mass transfer processes (particles, grains), the same way molecular mass processes are studied in Chemical Engineering i.e. asking the question how particles would behave if they were molecules? Knowing this condition that normally would tend toward equilibrium or, in the absence of this, would indicate the best path to yield a product; the operator can change the circuit, promoting the mass flow under this important guidance. For this reason the model is called an operational model. The model does not simulate random operational conditions but it defines its optimum path i.e. the model is an optimization model and not a simulation model.

Modelo Operacional **Fundaments**

Actual Phenomenon

Operations take into account, besides the natural phenomenon, subordinate processes of hydraulic classification and macromolecular transport in viscous medium, incorporating the actions of the operator in the optimization routines.

Macromolecular Mass Transfer

Mass transfer is interpreted from a macromolecular standpoint in which grains or particles (from energy application) migrate in observance to analog operations of Chemical Engineering nature.

Continuity Equations

Process description at the stationary state is performed from continuity equations following the major flow and opening traditional black boxes that hide closed circuits and stage wise operations.

Concept of Operational Optimization of the Model

Calculation routines guide operational interventions within the plant to take the process to conditions close to the natural event that would take place on the hypothesis of a conventional molecular chemical process.

This model is macro phenomenological because defines new mechanisms that can be measured to describe the phenomena involved. It is operational because it incorporated the action of the operator within the equations that describe the processes. The model is also optimizing because it determines the optimum conditions for operation and allow that the operator (or the automatic control system) carry continuously the process up to the optimized conditions of each moment, on a real time basis.

- **First Law:** Defines the fundamental phenomenon, the macro phenomenological property and its scale relations for the continuous industrial operation.
- **Second Law:** Mathematical expression that describes the process (complete circuit) in stationary state, called continuity equation.
- **Third Law:** Mathematical equation that indicates the optimum condition for the process, called optimization equation.

Macro phenomenological Property

The first law of the *Modelo Operacional* for the process of mass concentration by froth flotation is used to convert the natural mechanism of capture and flotation into one actual mass concentration action, taking into account that:

$$\mathbf{R} = f\,(\mathbf{Rcm}) \quad (1)$$

R is the metallurgical recovery of the process defined as:

$$\mathbf{R} = [C] / [A] \quad (2)$$

Where [A] and [C] are the distributions of the substance of interest in the feed material and in the concentrate, respectively.

Rcm, or the ratio of mass concentration expresses the proportion of the feed mass and the mass concentrated in a flotation cell (**Rcm** is the inverse of the mass yield):

$$\mathbf{Rcm} = A / C \quad , \quad \mathbf{Yield} = C / A, \% \quad (3)$$

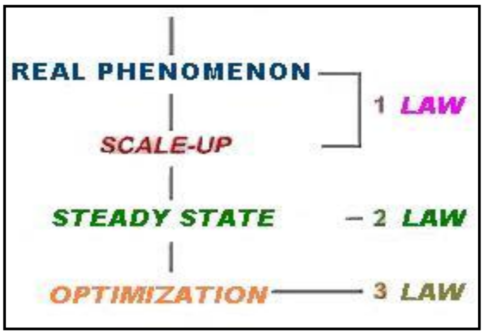

Figure 1 – The structure of the *Modelo Operacional*

Equation (1) will be described as Selectivity Equation or Concentration, and the macroscopic mechanisms used by the *Modelo Operacional* are a consequence of its utilization. This first law is valid for residence time not inferior to the times required for the natural flotation phenomenon to occur. With the help of the 1st Law, metallurgical results can be measured on a same basis (laboratory and plant), allowing for scale-up.

In figure 2 the first law is visually explained. The conversion of the phenomenon of natural flotation into an actual macroscopic operation of concentration takes place. This indicates that the process of mass concentration in a flotation plant depends, fundamentally, on physical actions of the operator.

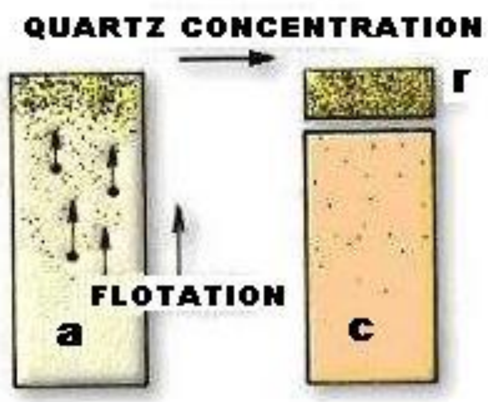

Figure 2 – First Operational Law

APPLICATION: OPTIMIZING CONTROL OF A FLOTATION CIRCUIT

Using the *Modelo Operacional*, an optimizing control system for the flotation circuit number 1 of the Vargem Grande Beneficiation Plant of MBR was developed in association with Ottimah, a Brazilian Computational Intelligence company. The work described herein was started in November of 2005 and in April of the current year a prototype of the optimizer system was tested on an industrial scale.

Technical Description of the Optimizing System

The OPTIMIZER uses the three mathematical laws of the *Modelo Operacional*:

- **1st Law**: The model establishes that quartz metallurgical recovery is a function of ratio of mass concentration in the froth phase. The metallurgical map of the OPTIMIZER is constituted basically by this curve also known as selectivity curve for the separation of quartz from hematite. This curve can be permanently optimized.
- **2nd Law**: The model establishes the material balance of flotation process as a function of the several stages of the circuit. Each arrangement leads to a different selectivity curve, i.e. the metallurgical map is unique for each case. The Optimizer developed for Flotation Plant takes into consideration arrangement options with and without a scavenger stage and separate models and selectivity curves for each situation were developed.
- **3rd Law**: The model shows the path for reaching the maximum selectivity in the process of quartz flotation, based upon actual operational conditions that move toward an equilibrium of mass and grades on the flotation stages involved in the process, fixing the mass movement operation in its optimized condition. This is the optimizing function of the Optimizer that works in order to make process operation as close as possible to the selectivity curve.

In order to allow for a real time approach for the phenomenological model, a model of artificial intelligence based upon neural nets was also developed to predict the mass flows as a function of measurable physical variables of the flotation circuit under study. The system implements an interface with the PIMS system for acquisition of information on the variables required for the prediction of the mass flows.

Neural predictors for mass flow movement

Non linear regression was employed for the creation of predictors for mass flow movements represented by Artificial Neural Nets [2]. From a historic database of the flotation circuit operation the extraction of correlations between operational variable set points and mass flow movements was obtained. These operational variables included feed flow rate and slurry density, flotation column discharge valve openings, dosage of reagents, air flow rate and absolute pressure readings.

Artificial neural nets were conceived in a way to emulate, in a compute, the structure and functionality of a brain. The artificial neurons model, mathematically, a biologic neuron regarding both its structure and functionality. Figure 3 presents an example of a generic neural net.

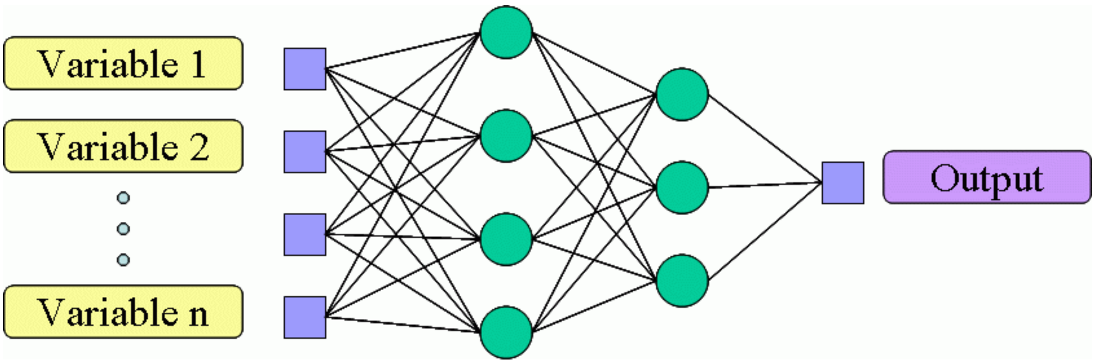

Figure 3 – Example of a generic neural net

The major force of the structure of an artificial neural net resides on its ability to adapt and learn. These features allow neural nets to deal with imprecise data and undefined situations. It permits the solution of practical problems without the requirement of rule lists or precise models. Artificial neural nets are ideal for application in multivariable and complex systems. The learning capability should be initially performed on an off-line mode in order to teach the neural net a basic knowledge about the system. On-line training is possible during the presentation to the system of new examples on a real time basis. It is also desirable that the system to be up-to-date from time to time. Each option depends on the response time of a given plant, costs and implementation conditions.

Neural net parameters are defined through the learning process and should be exposed to a set of training standards. Analyses of the response from the neural net are used to make corrections on the parameters once this type of system is suited to be adapted and it is not pre-programmed. During the training period, artificial neural nets extract statistical information from training sampling campaigns allowing for the creation of new knowledge. In this particular case, the new knowledge base is represented by the real time information of the Rcm value of the flotation circuit.

Figures 4a and 4b depict the result of estimated of Rcm based upon bi-hourly samples used in this study. The model obtained an absolute average error 0f 0.787 and a correlation coefficient of 0.728, i.e. the model created can represent 72% of the variations of Rcm values in the actual system. This level of correlation should be construed as very good as the process is complex and several external noise sources can impact the data acquisition process.

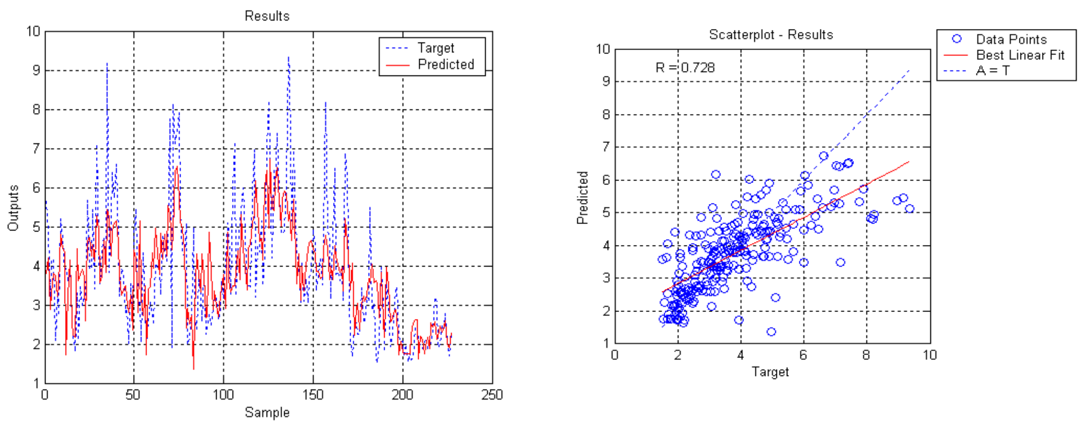

Figure 4 – Example of Rcm estimates based upon process data.

Integration

Given the information is obtained in real time, the phenomenological model performs mass and metallurgical balances of the circuit and guide the operational actions toward the optimized conditions determined by the model. This interpretation is represented by a metallurgical map, based upon the selectivity curve for the circuit in which three operational pairs of points (R, Rcm) are shown for the quartz flotation process: one is from the prior bi-hourly assay (actual values, from chemical assays), the optimized point for the current period and the dynamic point for real time operation. The combination of process engineering (Modelo Operacional) and computational intelligence (neural nets) allowed the creation of the present integrated solution of optimizing control, customized for each client.

Figure 5 presents the screen of the optimizer interface with the plant operators. The optimum points to be reached are presented in the operational map (selectivity curve) as seen in Figure 6, as well as the current operational point and the representation of the last bi-hourly assay.

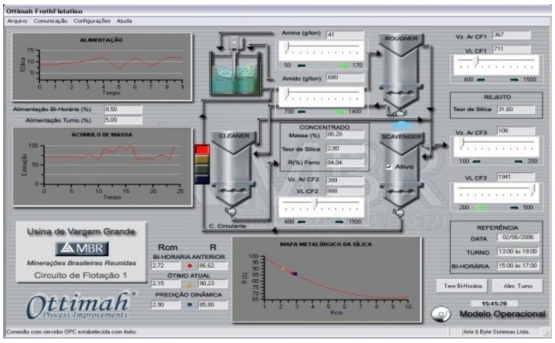

Figure 5 – Optimizer Screen

The difference of the position of the operational point and of the optimum point of operation for the operation in question is used to generate operational suggestions in such a way the actual system closes in to the optimized condition of the period under evaluation. These suggestions are represented by alterations of the dosage of reagents and discharge valve set points among others.

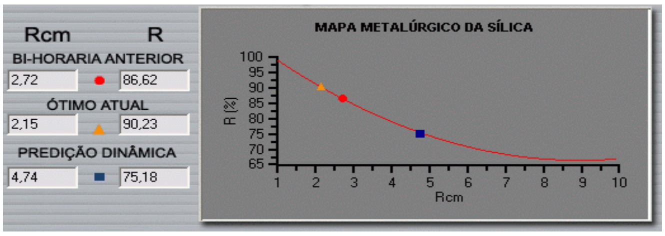

Figure 6 – Metallurgical map of the operation of the flotation circuit.

The metallurgical map employed in the system is composed by the Average Selectivity Curve for the separation of quartz (silica) from hematite, according to the 1st Law of the Operational Model [1], for the circuit in question. This curve can be further optimized through laboratory tests, layout adjustments and operational stability. The optimum operational point is given dynamically as a function of the target silica grade of the concentrate (1.5%) and of the feed silica grade, also estimated by the optimizing system. Besides promoting the optimization of the metallurgical results via operational suggestions, the system has been built with other functions relevant to the trend to lead the process to a stable state by following mass accumulation within the circuit and an estimation of the feed silica grade. Modeling of the flotation process allows for the creation of an on-line balance of metallurgical results, representing an estimation of silica grades on tailings and concentrates streams as well as mass yield and iron recovery values.

RESULTS AND DISCUSSION

During the days of April 18 and 19 of 2006 the optimization system Developer was employed to follow the operation of the flotation circuit number 1 at Vargem Grande Plant. The circuit was operated for 4 shifts (12 bi-hourly assays) with the assistance of the system. The application of the system took place in one isolated shift and on other three continuous shifts. The results of the test on circuit number 1 were compared to the results of circuit number 2 that also was operated with the same feed but without the help of the optimization system. Both circuits have the same configuration layout, like the illustration on Figure 7 below.

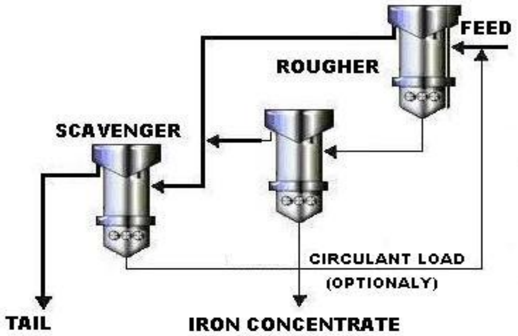

Figure 7 – Vargem Grande Flotation Circuit

Comparisons were also made within circuit number 1 itself when it was operated without the help of the optimization system. The circuit operated with the assistance of the optimization system presented considerable improvements. Tests results are summarized in Table 1. Shaded data and bold font correspond to operation with the support of the Optimizing System.

Table 1 – Specific results of the evaluation test.

Date and time	Feed (%SiO_2)	Concentrate %SiO_2		Tailings %SiO_2 CIRC. 1	CONCENTRATE CIRC. 1	
		CIRC. 1	CIRC. 2 (*)		% MASS	R(%) Iron
18/04/06						
01 - 07 AM	7.10	3.30	3.26	16.68	69.72	72.57
7AM – 1PM	**5.55**	**2.09**	3.63	**19.08**	**79.63**	**82.51**
1– 7PM	5.89	2.63	3.78	11.40	62,83	65.23
7PM – 1AM	**7.34**	**2.01**	3.26	**20.19**	**71.51**	**75.06**
19/04/06						
01 - 07 AM	**10.65**	**2.12**	3.15	**19.91**	**52.06**	**57.26**
7AM – 1PM	**8.10**	**1.60**	2.68	**16.56**	**56.56**	**60.55**

(*) Circuit 2 does not allow for sampling of tailings stream.

On Figure 8 the selectivity curve is depicted and the 6 operational points (R, Rcm) are presented, representing the 6 shifts of testing as per Table 2. One can note in Figure 8 the Optimizer leads the process to a quick stability region (points close to the selectivity curve). After reaching stability the system maintained the circuit in operation close to the optimized operational point of this selectivity curve, enhancing selectivity and warranting stability to the process. Initially the plant operated on point 1 when the Optimizer use was started. This led to operation at point 2, in a region close to the selectivity curve.

Table 2 – Operational points of the test shifts.

N°	Date and time	Shift Operational Point		
		R	**Rcm**	**%SiO_2 conc.**
1	18.04.06 – 1-7 AM (*)	66.68	3.52	3.30
2	**18.04.06 – 7AM – 1 PM**	**69.96**	**4.91**	**2.09**
3	18.04.06 – 1-7PM (*)	71.95	2.69	2.63
4	**18.04.06 – 7PM-1AM**	**80.64**	**3.41**	**2.01**
5	**19.04.06 – 1AM-7PM**	**89.64**	**2.09**	**2.12**
6	**19.04.06 – 7AM-1PM**	**88.83**	**2.30**	**1.60**

(*) Shifts operated without the Optimizer System Application.

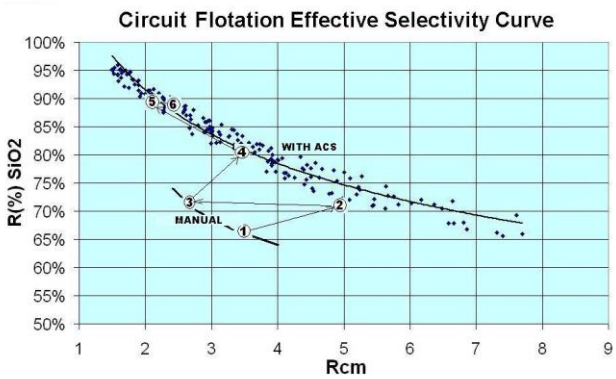

Figure 8 – Representation of the Evaluation test of the Metallurgical Map of the Operation

Point 2 did not reach in its totality equilibrium once the first bi-hourly assay still operated under the conditions of the former regimen. On the third shift plant operators decided to retake conventional operational criteria and opted to speed up circuit 1, increasing dosages of starch (depressant), taking Rcm from 4.91 to 2.69 which means to move froth mass from 21.3% to 37.17% in order to try to attain the specified silica level of the concentrate. As it can be seen in Figure 5, the process departed from the selectivity curve, silica grade increased and iron recovery was reduced by almost 17% in the shift (see table 1). The optimizer operation was retaken on shift 4 when the system performed a smoothing mode (Rcm from 2.69 to 3.41) and quickly directed the operation back to the selectivity curve, as illustrated by point 4 in Figure 7. Concentrate silica grade was consequently reduced to 2.01%.

Following the suggestions of the optimizer system with respect to the gradational increase of feed % silica, a drastic reduction of Rcm is offered (Rcm from 3.41 to 2.09), to manipulate almost 50% of tailings (shift 5). With these measures taken within the selectivity curve, metallurgical results were stable and the drastic increase in silica feed grade (from 7% to almost 12%) was smoothed up without compromising the concentrate grade (2.12% silica). The process carried on to shift 6 with an Rcm of 2.3 and as a result a grade of 1.6% silica in the concentrate. From the test results several potential improvements can be forecast if the circuit is operated with the application of the tested optimizer system.

Stability

Table 3 depicts the variation of silica grade for the final concentrate obtained from the two flotation circuits in operation. A reduction of variability can be noted for circuit number 1 in which the Optimizer System was operated in comparison to circuit number 2 that operated only on a manual basis.

Table 3 – SiO_2 grade in concentrates as per bi-hourly assays

CIRCUIT	Minimum	Mean	Maximum
CIRCUIT 2	1.32	3.30	4.00
CIRCUIT 1	**0.93**	**1.98**	**2.53**

Disturbance Prediction

The system allows following the variation of silica feed grade, for each bi-hourly interval, which constitutes a significant advantage to the current system, which operates only taking into account the global average value of a past shift, known at each 6 hour interval but with a delay of an extra hour. On the first shift of April 19^{th}, for instance, an abrupt increase in silica feed grade took place, increasing its value from 7.3% to more than 12% in the last bi-hourly assay (value later confirmed by the shift average of 10.70%). Circuit 1, guided by the optimizer system, followed this variation closely. Conversely, circuit 2 could only count on the past shift information of 7.34% silica. Other disturbances also took place during operation. Noteworthy were two complete plant shut downs, three partial feed interruptions for decreased feed density values, three stops on the reagent feeding system, change of reagent addition mode and clogging of one of the flotation columns. Besides all of these events, the optimizer kept circuit 1 within stable operation limits.

Real Time Balance

Real time appraisal of mass and metallurgical balances constitutes an invaluable tool for plant operators, allowing for quick decision making and sensitivity analyses of process regarding several measures that could have been taken and their responses in the circuit.

Speed of Response

The optimizer system developed has shown that the operator can be informed in a few minutes about the position of the operational points, inclusively at retaking periods after sudden circuit shut downs. One or two bi-hourly assays are required to stabilize the system and to present meaningful results, allowing for operational in adverse conditions.

Reagent Consumption

The optimizer suggests to the operator the optimum dosage of reagents at each instant aiming at not only on reagent reduction but also on improved selectivity. Laboratory studies should be performed to supplement the operator with new information to further optimize reagent consumption.

Metallurgical Performance

As a consequence of the benefits already discussed, the plant operator could be oriented to explore the maximum performance allowed by the process. Figures 9 and 10, for instance, show average selectivity and metallurgical recovery of the circuit 1 of this plant for the periods spanning from July to December of 2005 and from January to March of 2006.

Operational improvement in both cases can be estimated by observing the theoretical values of mass yield and iron recovery if the circuit were to be operated fully on optimized conditions allowed by the plant, in other words, with the average selectivity curve of each period. Data presented as actual production values, obtained by the endeavor of the technical team at the plant, depicting a significantly enhanced operation in 2006 in comparison to 2005. One of the merits of the optimizing system is to find out the potentialities, in their diverse ways, and tale the process to these optimized conditions based on phenomenological fundaments in real time and to keep the operation in these (optimized) set points.

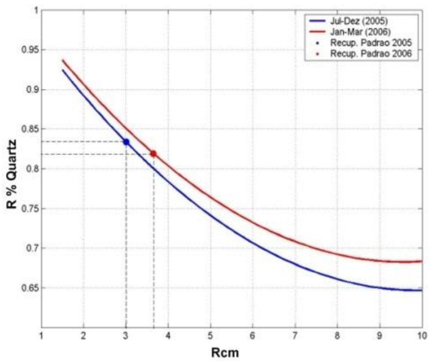

Figure 9 – Selectivity curves

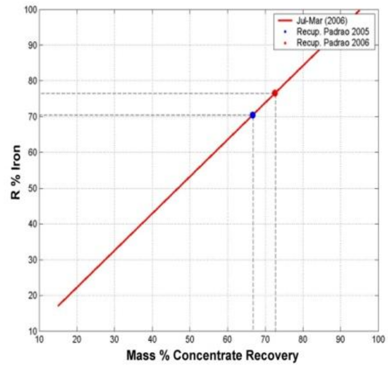

Figure 10 – Concentrate recovery

The calculation that should be performed for a correct evaluation is the following:

- To establish equivalent conditions of feed and product quality for all conditions evaluated. In this case an average feed grade of 6 % SiO_2 and a concentrate grade of 1.5% SiO_2.
- To verify, within its respective selectivity curve of each period evaluated, which pair of values (R_o, Rcm_o) concurs the previous requisites. This pair of values corresponds to the point of optimum operation for each situation:

$$\mathbf{c} = 1.5 = [6.0\ (1 - \mathbf{R_o})] / [1 - (1/\mathbf{Rcm_o})]$$

- Once the value $\mathbf{Rcm_o}$ is obtained, it possible to then determine the mass yield for the concentrate ($\mathbf{M} = 100 - (100 / \mathbf{Rcm_o})$) for each condition.
- On the relation between iron recovery and mass yield (Figure 10), it is observed that a good linear approximation is reached when all data points have approximately 1.5% silica in the concentrate. These values can then be compared in one single basis for evaluation.

Hence, great potentialities of even larger gains in iron recovery exist if the selectivity of the process is enhanced and, with the help of the optimizer system, the circuit be operated most of time within the selectivity curve. The use of this system during an extended period of time could corroborate these preliminary conclusions and quantify the effective gains that are indicated to be very significant. Figure 11 depicts the general selectivity of the plant based upon data for the second semester of 2005. Operation instability is norm for the lack of an optimizer system as the one presented herein.

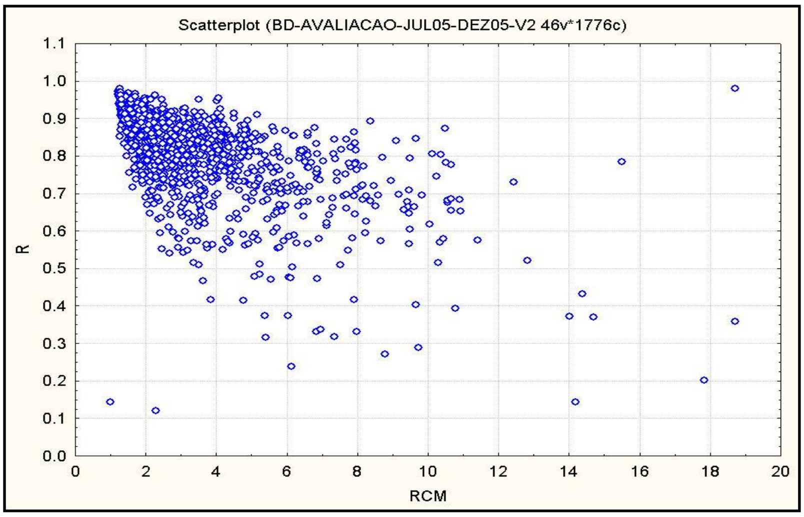

Figure 11 – Operational variability of flotation circuit number 1.

CONCLUSIONS

A new methodology for the optimizing control of a flotation process was presented, based on a prototype industrial plant trial. The benefits achievable by the optimization system on the flotation circuit number 1 were relevant. The originality of the system and the use of the most modern technologies of computational intelligence and process engineering should be emphasized. In summary, the use of the current optimizing tool allows one to:

1. Know, define, implement and work taking into consideration the effective selectivity curve of the circuit, establishing a bridge of support with the laboratory (to test new reagents, different ores, etc.).
2. Operate correctly the circuit on the basis of information acquired on real time, allowing for the prediction of disturbances with greater response speed from the circuit, better stability and with integration with other plant areas (feed variation, for instance), with the laboratory and taking into account different configurations of the circuit stages.
3. Stable and optimized operation allows the maintenance of the operational points for the maximum time possible within the selectivity curve with its derived benefits.

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