Fuzzy system to increase efficiency in the flotation process in a mining plant

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***Abstract*— The mineral production sector in Brazil has faced fluctuations in demand that have prompted reflection on the processes of internal costs and on improving processes so as to increase efficiency in production processes. What also merits attention is the fact that the ore mined in much of Brazil has ever decreasing levels of iron, which sees to it that the concentration processes become more efficient. In this context, the Flotation circuit of Mineração Usiminas, located in Itatiaiuçu-MG, was chosen for study. The purpose of this study is to use an expert system that, by taking advantage of the experience of engineers and operators, acts on the Set Points of operation in accordance with the results of quality and stability of the process. Knowledge is translated into operating rules which are implemented in fuzzy logic that seek to imitate human logic by acting in a weighted way on the variables. The performance test conducted proves the efficiency of the installed system since the results of mass and metallurgical recovery were satisfactory in addition to which the consumption of reagents was reduced.**

***Keywords*— Expert System. Fuzzy logic. Mining. Flotation**

I. INTRODUCTION

The production of iron ore plays an important role in the economy of Brazil. In the last few years, the mining sector has undergone periods of economic fluctuations, which have led to mining companies having to concern themselves with finding solutions that will increase efficiency in their production processes, maintain quality and reduce costs in different areas of their company. In particular, increasing efficiency while ensuring the quality required in the final product can bring about significant gains to mining plants.

The activity of a mining company can be divided, in a macro way, into three activities, namely: mineral research to find out where the desired material is; mining, by which the mineral asset is extracted in its raw state; and processing, during which ore is treated so that it can be used by industry [1].

The processing of a mineral consists of 3 stages as shown in Fig. 1. The first is comminution, an operation that aims to reduce the size of the ore particles for immediate use or to make them suitable for the later process. The second step is classification, which separates the suitable raw material from that which will return to comminution.

The third stage is concentration, where the separation of the particles according to the mineral species is carried out. Its objective is to reach a concentration of the ore desired that is as rich as possible and a gangue that is as poor as possible [1].

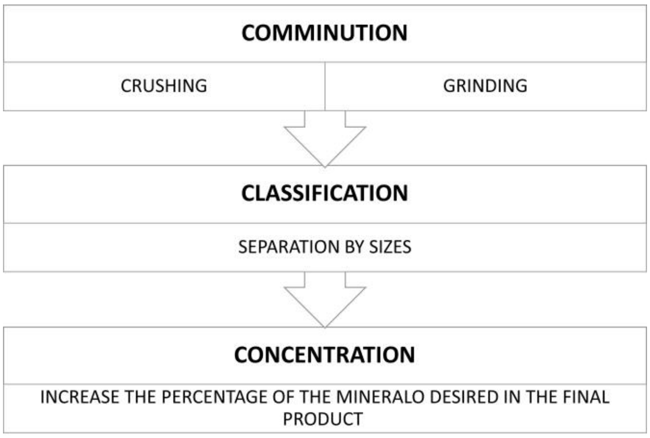

Fig. 1 – Flowchart of how ore is processed

All three stages are semi-automated, accompanied by sample collections, analysis and adjustments by using control and calibration devices. Given the complexity of making proposals for improvements throughout the processing stage, this study is dedicated to presenting a proposal for a fuzzy system for the concentration stage. Flotation is one of the concentration processes that is most used in mining. The purpose of flotation is to derive maximum advantage from ores with very poor mineral levels. A more detailed schema of a flotation process is shown in Fig. 2.

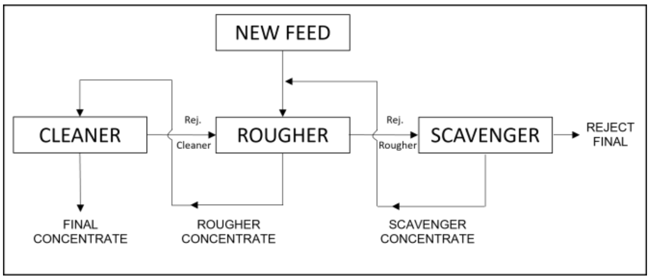

Fig. 2 – Process of Flotation by Froth

The flotation process is based on separating particles from a heterogeneous material by using the principle of “hydrophobicity”. The ore is fed into tank cells and columns, where it comes into contact with air bubbles which are generated mechanically or by means of an injection system. Hydrophobic particles tend to become detached from the liquid medium and to follow the flow of air bubbles that are being discharged at the top of the tanks. By using this principle, the particles of the desired iron ore can be separated from the particles that are of no interest to the product.

When processing a mineral, concentration is essential in order to obtain a product with the mineral levels that the market requires. Considering factors such as the rise in the cost of energy, the reduction in the market values of products derived from mining, ores with ever lower levels of the element of interest, and strict environmental requirements, all this adds to the challenge of seeking greater efficiency for mining processes.

The operation and control of the processes of the ITM Flotation of Mineração Usiminas located in Itatiaiuçu-MG is carried out by a DDCS (Digital Distributed Control System). By using a supervisory system, the operators change the working set point of the variables in accordance with the laboratory results on the quality of the product. These are obtained from samples collected at the exit from the circuit. As a result, there is a delay in defining control actions, which reduces the efficiency of the process.

What is expected from the Flotation process at Mineração Usiminas is to deliver a product with the highest percentage of the desired material content, in this case iron content, and the lowest percentage of possible contaminants, in this case silica. Therefore, the controlled variables are the iron content and the silica content and the manipulated variables are the set points of the layer of froth and the air flow in the tanks and the addition of the amine and starch reagents.

The ITM Flotation plant receives the gangue that has already been processed in other mineral processing plants in order to make it even finer so that it can be properly used in the later process called Flotation, which depends on a grain size below 0.15 mm to reach its maximum yield.

The main objective of this study is to apply computational intelligence tools to create an Expert System using fuzzy logic, based on operating rules that seek to increase the efficiency of the flotation process.

An expert system is a tool used to solve problems by using a knowledge base built on the experience of people who have the technical mastery on a given subject. Fig. 3 summarizes how this concept is constructed.

To develop an ES, operational knowledge of the process where it will be applied must be acquired. Based on such information, a set of rules is created that defines the actions to be taken to achieve the desired result. Once defined, the rules are implemented computationally in computer software and the inference machine controls whether or not the rules acting directly in the process are activated.

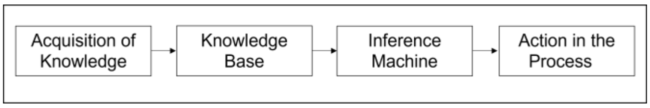

Fig. 3 – Flowchart of an Expert System

Therefore, what must be done is to detail the circuit in focus, to define and list the main variables involved and to describe, together with the engineers and operators, the work rules to be implemented in the advanced control tool that will interface with the conventional control system currently installed.

The article is organized as follows: Section II presents the main related studies, while Section III sets out the theoretical foundation, and in Section IV, the methodology is applied and the results achieved are reported.

II. Related Studies

The studies and definitions of the laws that define the operations contained in a grinding process have been carried out over several decades. In 1951, Bond [2] describes Rittinger's law which states that the area of the new surface produced by fragmentation is directly proportional to the useful work consumed. The second law, known as Kick's Law, says that the work required is proportional to the reduction in volume of the particles involved. For Bond, the results of the two proposed laws so far did not satisfy all the cases found in practice. Thus, he suggested a new study that became known as the “3rd Law of Fragmentation”, the energy consumed to reduce the size of a material is inversely proportional to the square root of its size. Bond proposed an index called WI (Work Index), which is defined as the work needed to reduce the unit of weight (short ton = 907 kg) of the material considered, from a theoretically infinite initial size ($F = \infty$), to a particle size 80% passing through 100 µm. The application of Bond's law in the definition of the energy necessary for the comminution of a certain material has spread and is still applied today in several laboratories.

Austin and Klimpel [3] present a study on the laws of the grinding process and call attention to the most important variables for the ideal operating conditions of the grinder. The objective of their study is to bring into the discussion a more mechanistic approach that involves what happens in the grinder as a whole and not just to address the power required for the comminution of a material. Austin and Klimpel [3] also mention that using computational tools is of great importance for creating and simulating models that precisely define the complete behavior of a grinder.

Walt et al. [4] argued that in the metallurgical industry there are several processes of an ill-defined nature that require a search to be made for new modeling techniques to assist in gaining knowledge about and defining the ideal points of operation. For this reason, neural networks have become an ideal regression tool for modeling ill-defined systems. The authors describe the fundamentals and use an SBNN (Sigmoidal Backpropagation Neural Network) to demonstrate that metallurgical and chemical systems can be modeled satisfactorily without any prior knowledge about the system, as long as sufficient data on the process is accessible.

In [5], the authors reaffirm that if sufficient data is available, SBNNs can be used effectively as a modeling tool for ill-defined situations, such as metallurgical engineering systems. In this study, it was shown how the efficiency of a hydrocyclone classifier can be determined by using an SBNN neural network.

Duarte et al. [6] developed a new multivariable controller with a predictive effect using neural networks. The scheme uses three neural networks that play the role of controller, identifier and predictor respectively. The idea proposed can be used for both linear and non-linear systems and presents more accurate results than control tools that do not consider predictive effects. The model was tested at the Codelco-Andina crushing plant, and the results were similar to those found by the adaptive control techniques already used in the company.

Chelgani et al. [7] used an ANN and regression procedures to predict the recovery of a concentrate for a Quartz Flotation process considering different operational conditions. The dimensionless numbers used in fluid mechanics (Froude, Reynolds and Weber), particle size, air flow rate, bubble diameter and velocity of the rise of bubbles for both methods were considered as input. The linear regression method shows that the relationships between the input variables and the recovery of the concentrate can reach correlation coefficients between 0.54 and 0.87. An RNAFF with a 3-3-3-2 arrangement can achieve a correlation coefficient of 0.98. This shows that the proposed ANN models can be used to determine the most advantageous operating conditions for the recovery of the concentrate expected in the flotation process.

Ahmadzadeh and Lundberg [8] used MLP neural networks to predict the remaining life of the linings of the grinder without having to stop production. The determining variables were defined using the PCA technique, which eliminates variables that are not significant for the process. The results show a remarkably high degree of relationship between the input and output variables. The study carried out is an advance for the maintenance of grinders, as the technique developed avoids production stoppages for inspection and for defining the useful life of the lining of the grinder.

Umucu et al. [9] compared the results of an experimental procedure performed in the laboratory using a kinetic model of a ball grinder with the results achieved by implementing MLP and RNF neural networks to estimate the accumulated weight within a grinder for each range of granulometric distribution required by the process. The networks implemented present satisfactory and accurate results compared to those of a kinetic grinding model.

Dai et al. [10] developed a configuration platform called OSC (Optimal-Setting Control) in order to assist researchers and engineers to design controllers. After creating the controller, the program can be modeled automatically using Petri nets and by doing so the performance of the controller is adjusted and verified. The tool also offers integration with several algorithms based on fuzzy logic and neural networks. The performance of the platform was verified and validated by applying it in a closed grinding circuit.

Abdollahi et al. [11] used an RNA to predict the effects of the process variables on the dissolution of Cu, Mo and Re in the Molybdenite concentrate by using the process of (meseocidophilic (Obs. Essa palavra está certa?) bioleaching. The input variables were the PH, the concentration of solids, the percentage of inoculum and the time in days and as output from the model, the percentage of Cu, Mo and Re recovered was considered. A BPNN was used to model and predict recoveries, trained by 105 data sets. Three arrangements were used for the network. The regression analysis of the models gave correlations of approximately 0.99 which demonstrates that the ANNs can predict recoveries of Cu, Mo and Re.

This paper puts forward a detailed study of the laws that describe the grinding process described in [1], [2] and [3], in order to discover the effects of the input and output variables that are determinants for the process. In [4], the authors emphasize the need to use computational intelligence to model ill-defined processes, which is why we propose a detailed study of the entire process and its unit operations using neural network models as well as those demonstrated in [5] , [6], [7], [8], [9] and [11]. The studies listed here show significant improvements but fail to define a model that satisfactorily represents a mineral process already in operation. In this study, we intend to use neural networks to create a model that understands the operation of a milling plant and therefore can assist the operation in making decisions regarding the variables involved to maintain quality with the lowest possible energy cost.

III. Theoretical Foundation

For a satisfactory evolution of the proposed study, what must be known is what the main characteristics are that describe a foam flotation process.

The concentration itself aims to separate as much as possible the particles of interest from those of no interest in a heterogeneous mineral mixture. In flotation, according to Luz et al. [13] this is done in a suspension in water called pulp that is pumped into tanks where the particles of the material of interest follow a flow opposite to that of the unwanted material.

It is by knowing how this operation takes place that the ideal working conditions can be defined and thus how to use computational resources to implement a system based on fuzzy logic that can perform a more efficient control of the variables involved.

A. *Concepts*

Hydrophobicity is the mineral property that defines the ability of a species to have more affinity with the gaseous medium than with the liquid medium. The opposite property is hydrophilicity which defines the capacity of a species to have more affinity with the liquid medium than with the gaseous medium [14].

The desired minerals have hardly any of these two well-defined properties, which makes it necessary to add substances called reagents that help the species become more hydrophobic or hydrophilic [13].

Fuertenau et al. [14] said that the collector is the substance that can be attached to the surface of a mineral and so can make it more hydrophobic. In this study, the substance is amine. It often happens that the collector gets trapped on the surface of all minerals present in a mixture, which reduces the necessary selectivity, for which there is a depressant, a substance that depresses the collector's action on unwanted particles. The substance that plays this role in the process under study is starch.

Another important substance is the regulator, which is responsible for keeping the pH of the mixture within the range necessary to obtain greater efficiency of the collector [14]. The regulator that will be used is soda.

Regarding the type of material to be floated, there are two concepts that differentiate the process. Direct flotation i.e. when the ore of interest catches the air bubbles and is carried to the top of the columns and is floated while the gangue follows the flow to the bottom of the tank, and reverse flotation i.e. when the rejected material is floated [13].

B. *Flotation Circuit*

The purpose of the flotation process is to separate the desired material from the unwanted material in a given mixture. The principle of this operation depends on the hydrophobicity of each material. This property is what defines the material's capacity to catch air bubbles inside the tanks and go in the opposite direction to the flow of the mixture, and thus is floated and separated [13].

Fig. 4 details the stages of the flotation process, which in this case performs reverse flotation.

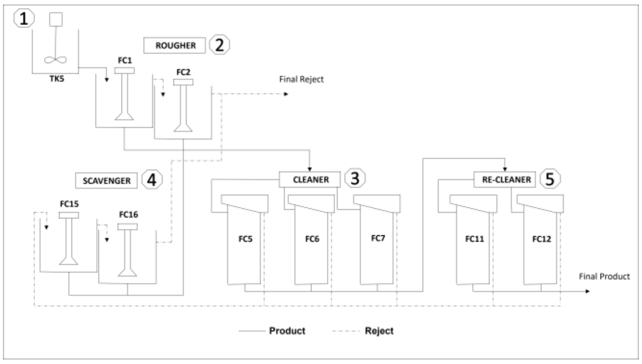

Fig. 4 – Flotation Circuit of Mineração Usiminas

The property of hydrophobicity of the materials to be treated is not always well-defined, so reagents must be added that stimulate and assist in the selectivity of the particle that it is wished to float.

These reagents are added in Step 1, called conditioning so that time is given for the mineral particles and the molecules of reagents to come into contact with each other.

The flotation process itself starts in Step 2, which is called Rougher. This is where the first separation takes place of the material that is low in iron and which is then discarded.

Step 3 called Cleaner receives the product from Rougher and continues to remove the rejected material, further increasing the iron content of the product of interest. Thereafter, the material passes through Re-cleaner 5, where it is again cleaned, and from which the product comes out with an iron content within the one specified.

Scavenger 4 receives the waste from steps 3 and 5 and aims to recover as much as possible of the iron ore that was sent to waste.

C. *Control Theory*

The control systems of mineral processing play an important role in the search for higher quality and to reduce the costs involved.

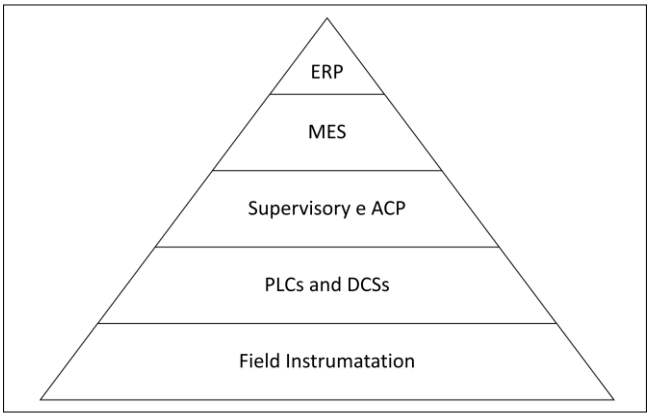

Fig. 5 – Automation and Control System Pyramid

The automation and control systems installed in the mines are made up of field instrumentation, PLCs (Programmable Logic Control) or DCSs (Distributed Control System) of high performance and supervisory that represent the interface of the process with the operator or user of the system. As shown in Fig. 5, they represent levels 1, 2 and 3 of the automation pyramid.

Using supervisory systems, the operator defines the work set-points to achieve the desired results. Despite being efficient, conventional, control strategies end up depending on human action whenever it is necessary to manipulate the variables, which can cause losses and instabilities in the process.

It is in this scenario that the action of advanced process control (APC) strategies emerges. These systems are located at level 3 of the automation pyramid and work together with the supervisory system, thus replacing human action on variables.

In this paper, we shall give further detail on drawing up an advanced control strategy, and on implementing a fuzzy expert system with the objective of taking actions in the process based on the search for a defined quality result.

D. Fuzzy Expert System

Gupta and Nagpal [17] define that the expert system is designed and developed to meet an application that can make a decision based on justified knowledge, which draws on an information base, just like a specialist in a specific area of human knowledge does. Therefore, the objective of an ES is to transfer the skills of an expert to a computer system. Fig. 6 shows the components of a specialist system.

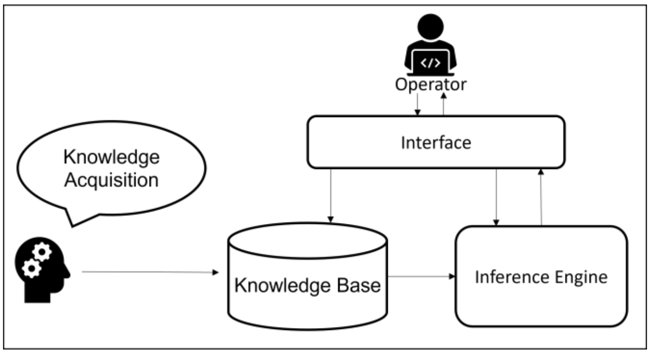

Fig. 6 – Expert System

Knowledge is acquired by studying the process which it is desired to control. In addition, interviews are conducted with engineers, operators and specialists who have experience of operating dynamics.

The knowledge acquired is written in the form of conditional rules that express a conclusion by setting a condition. For example, if the car does not start, then the problem may be to do with the battery.

Once the knowledge base is formed, the rules are implemented in software, thereby translating human language into computational language. The inference engine is responsible for receiving the process data through the interface, applying the knowledge rules and returning the information with the actions to be taken.

To translate the knowledge described by the specialists in computational language, the concept of fuzzy logic was used.

Zadeh [18] conceived this concept in order to translate inaccurate and vague information mathematically. The definition is that variables in fuzzy logic other than discrete logic can be any real number in the range between 0 (false) and 1 (true).

Therefore, non-quantifiable concepts can be measured such as, for example, to evaluate the temperature of coffee, while in the discrete logic the definition would be hot or cold; in diffuse logic we can measure very hot, warm, very cold.

Therefore, fuzzy inference systems can be used to translate human knowledge by creating rules of the type, if x then y. For example, if the flow rate is high and the tank level is very low, then the valve must be tightly closed.

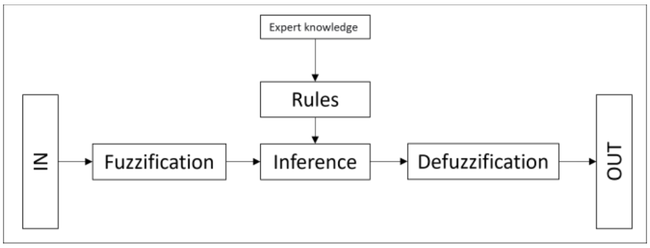

Fig. 7 – Fuzzy Inference System

Fig. 7 explains the flow of a fuzzy inference system, where process variables (input) are transformed into fuzzy sets (fuzzification). Thus, the inference system defines the output set based on the rules and pertinence functions defined by process engineers and operators. After defuzzification, the output can act on the manipulated variables.

IV. Methodology

The methodology applied in the study is summarized in the block diagram of Table 1.

TABLE 1 – The Methodology Applied

Step 1	Survey of related studies; Study of the topic proposed.
Step 2	Survey of theoretical references and detailed study of the processes and tools involved.
Step 3	Definition of the controlled and manipulated variables; Definition of the control rules with the specialists; Implementation of the control in the Software OptProcess ® of CEMI Engenharia.
Step 4	Activation of the Expert System; Conduct of the Performance Test;
Step 5	Analysis and publication of the results.

To implement the Expert System in the flotation process of Mineração Usiminas, the software "OptProcess ©" from the company CEMI Engenharia was used. The tool offers the following modules:

- Tags and Statistics
- Graphs
- Expert
- Fuzzy Logic
- Management

A. Control Strategy

The control strategy was defined together with the technical team of Mineração Usiminas and the controlled variables, manipulated variables and the control rules for implementation were established. Table 2 shows the variables involved in the flotation process.

TABLE 2 – Variables of the Process

Controlled Variables	Silica Content (SiO_2); Iron Content (Fe).
Manipulated Variables	Level of the Froth Layer (%); Air flow (m^3/h); Dosage of Amine (g/t); Dosage of Starch (g/t).

Two control modes were adopted, by content and by velocity.

In content mode, the system will act on the Set Points of the manipulated variables based on the calculation of the error between the Fe content value and SiO2 desired by the operation and the value of the laboratory result.

$$error = SP_{desired} - PV_{result} \quad (1)$$

Thus, the fuzzy inference was performed in relation to the error and the increment value that will act on each manipulated variable according to the error value found in the content. Table 3 shows the fuzzy set used for the increment and Fig. 8 shows the graphical representation of the membership functions used.

TABLE 3 – Increment by Fe Content in the Concentrate

Fuzzy Set - Increment by Fe Content in the Concentrate		
Linguistic value	**Pertinence function**	**Interval**
Very Negative	Triangular	-1.5, -1, - 0.5
Negative	Triangular	-1, -0.5. 0
Null	Triangular	-0.5,0, 0.5
Positive	Triangular	0, 0.5, 1
Very Positive	Triangular	0.5, 1, 1.5

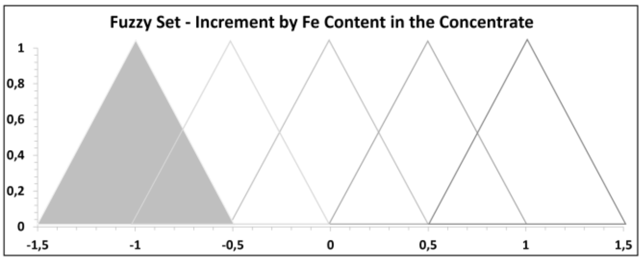

Fig. 8 – Fuzzy Inference Increment by content

Table 4 shows the fuzzy set used to determine the linguistic value referring to the error found between set point and process value and Fig. 9 shows the graphical representation of the membership functions used.

TABLE 4 – Fuzzy Set SP-PV Error by Fe Content in the Concentrate

Fuzzy Set SP-PV Error by Fe Content in the Concentrate		
Linguistic value	**Pertinence function**	**Interval**
Very Low	Zeta	-0.3, 0
Low	Delta	-0.3, 0, 0.3
Normal	Delta	-0.5,0, 0.5
High	Delta	0.5. 1, 1.5
Very High	Sigmoidal	1, 1.5

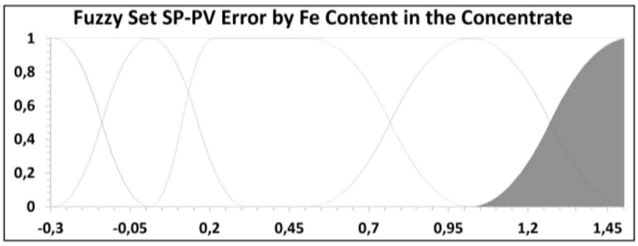

Fig. 9 – Fuzzy Inference SP-PV Error by content

It is observed that in content control, the system classifies the intensity of the error calculated and, by using logic, determines the increment or decrement value that must be modified in the SP of the foam level, air flow and amine and starch dosage.

As to controlling velocity, the objective is to keep the columns and cells floating in as stable a way as possible. Based on the operating conditions, the system defines an ideal value for the velocity of flotation and compares the calculated SP with the actual value of velocity. This is measured by using the OptVision Froth system illustrated in Fig. 10, which by means of image analysis can measure the velocity at which the air bubbles move.

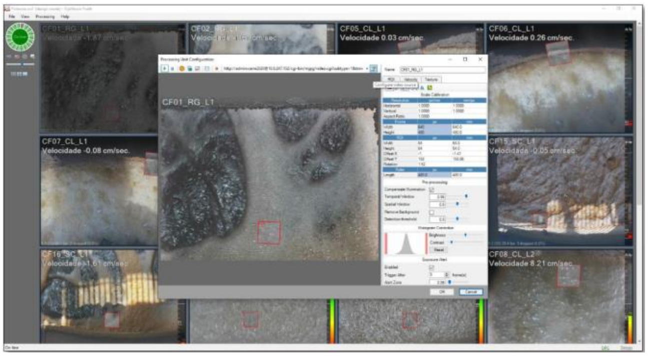

Fig. 10 – OptVision Froth System

Therefore, fuzzy inference was also performed for variable error of velocity and for the increment to be performed in the SP in accordance with the error found. Table 5 shows the fuzzy set used for the increment by velocity of the froth and Fig. 11 shows the graphical representation of the membership functions used.

TABLE 5 – Increment by Velocity of the Froth

Fuzzy Set - Increment by Velocity of the Froth		
Linguistic value	**Pertinence function**	**Interval**
Very Negative	Triangular	-1.5, -1, - 0.5
Negative	Triangular	-1, -0.5, 0
Null	Triangular	-0.5,0, 0.5
Positive	Triangular	0, 0.5, 1
Very Positive	Triangular	0.5, 1, 1.5

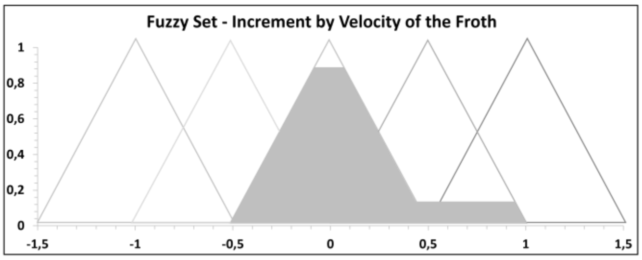

Fig. 11 – Fuzzy Inference Increment by velocity

Table 6 shows the fuzzy set used to determine the linguistic value referring to the error found between set point and process value by velocity of the froth and Fig. 12 shows the graphical representation of the membership functions used.

TABLE 6 – Fuzzy Set SP-PV Error by Velocity of the Froth

Fuzzy Set SP-PV Error by Velocity of the Froth		
Linguistic value	**Pertinence function**	**Interval**
Rapid Decrease	Zeta	-1, - 0.5
Decreasing	Delta	-1, -0.5, 0
Stable	Delta	-0.5,0.0, 0.5
Increasing	Delta	0, 0.5. 1
Rapid Increase	Sigmoidal	0.5, 1

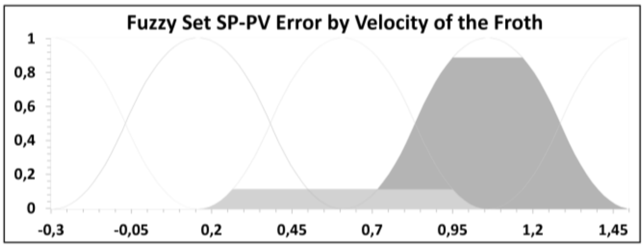

Fig. 12 – Fuzzy Inference SP-PV Error by velocity

From these inferences, the increments to be sent to the set points of the froth level, air flow and amine dosage are calculated in order to achieve the stability of the flotation.

B. Analysis of Results

After coding the expert system, the next step is to conduct the performance test, which aims to compare the results of the operation with the deactivated system and with the activated system.

The period defined for the test was from 03/11/2020 to 24/11/2020. During this period, the days between the active system and the deactivated system were alternated, as shown in Table 7.

TABLE 7 – Period Performance Test

	Period Performance Test - November/2020
Days Active System	3, 4, 9, 10, 11, 12, 13, 14, 15, 19, 20, 21, 22, 23, 24
Days Desactive System	5, 6, 7, 8, 16, 17, 18

During the test period, a database was generated for which the values of the Fe and SiO2 content were measured in the circuit feed, in the Rougher gangue, in the Scavenger gangue and in the final concentrate at the circuit exit, in order to obtain the values of mass recovery and metallurgical recovery in both operating scenarios.

Table 8 shows the result of the measurements during the test period.

TABLE 8 – Operational Data Performance Test

Day	Status Expert System	RM Flot. Calc. (%)	Rmet Flot. Calc. (%)	%Fe feed Flot. Average	%Fe rej. RO Average	%Fe rej. SC Average	%Fe rej. Global calc. Average	%Fe rej.con, Flot. Average	%SiO2 Conc. Flot. Average
03/nov	On	55.80	81.28	44.58	18.01	35.57	18.88	64.94	2.83
04/nov	On	55.77	83.92	42.92	14.71	32.63	15.61	64.58	3.32
05/nov	Off	57.17	80.76	45.73	20.03	30.26	20.54	64.60	2.81
06/nov	Off	55.36	81.09	44.22	17.38	44.51	18.73	64.77	2.39
07/nov	Off	66.74	89.55	48.04	14.16	31.98	15.10	64.45	3.14
08/nov	Off	65.30	89.37	46.49	13.43	29.71	14.24	63.62	3.93
09/nov	On	60.40	87.10	44.05	13.67	27.39	14.35	63.52	3.10
10/nov	On	60.17	88.32	42.92	12.02	23.52	12.59	62.99	4.09
11/nov	On	57.28	85.58	42.52	13.18	30.52	14.35	63.53	3.70
12/nov	On	62.98	89.62	44.89	13.80	38.43	12.59	63.87	2.92
13/nov	On	61.29	88.61	44.35	12.35	26.40	13.05	64.12	3.00
14/nov	On	58.08	87.29	42.59	12.47	21.35	12.91	64.01	3.93
15/nov	On	57.96	85.69	43.24	14.20	24.53	14.72	63.93	3.66
16/nov	Off	59.07	86.09	44.39	14.55	25.36	15.09	64.70	2.90
17/nov	Off	51.55	82.70	40.28	13.77	26.17	14.39	64.62	2.86
18/nov	Off	60.98	88.47	44.40	12.47	25.49	13.12	64.43	2.92
19/nov	On	61.70	87.25	45.99	14.62	28.56	15.32	65.02	2.88
20/nov	On	61.89	87.45	45.47	14.53	23.47	14.98	64.25	3.88
21/nov	On	69.96	91.11	49.99	13.60	37.66	14.80	65.10	2.91
22/nov	On	71.54	92.86	50.23	11.62	31.28	12.60	65.20	2.89
23/nov	On	57.75	86.73	43.07	12.83	26.83	13.53	64.68	3.41
24/nov	On	49.13	81.69	38.77	12.92	33.65	13.95	64.46	3.46

On comparing the average daily values of the days on which the system was active with the days off, notice that the Fe content in the concentrate is slightly higher on the days when the system is off.

On the other hand, on the days that the system remained active, there are lower levels of Fe in the gangue, which indicates that less product is thrown away. Another important result is the indicators of mass and metallurgical recovery, which show that even with lower levels of Fe in the feed on days of active system the circuit had a good recovery.

TABLE 9 – Operational Data Performance Test

Expert System	RM	Rmet
Off	59.45	85.43
On	60.11	86.96
Difference (pp)	0,66	1.53

The result shown in Table 9 shows that considering the quality of the material in the feed of the circuit, the performance of the process with the active expert system is superior in mass and metallurgical recovery.

The graphs represented in Fig.'s 13 and 14 show the behavior of the mass and metallurgical recoveries, respectively, during the period evaluated. Note that while the system remained connected, beyond there being the best result of the average recovery values, there was also a reduction in variability, which demonstrates that the process is more stable.

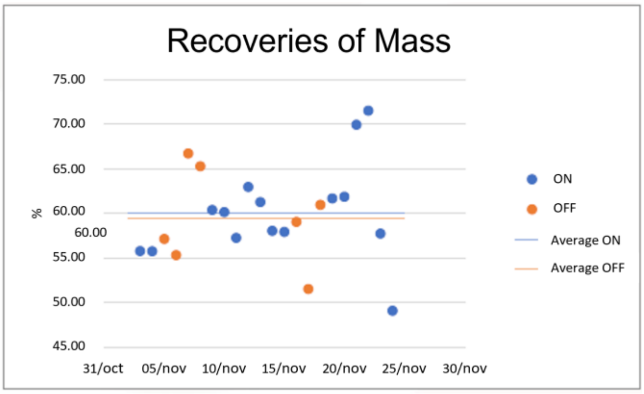

Fig. 13 – Variability in Mass Recovery

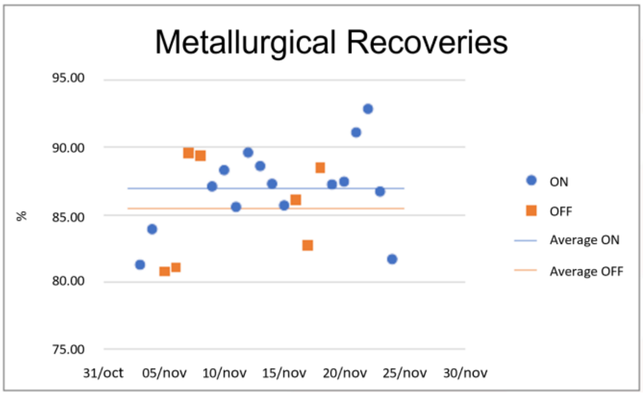

Fig. 14 – Variability in Metallurgical Recovery

Another result evaluated was the consumption of the starch and amine reagents in the period. There was a reduction of both in the period in which the ES was in operation. This implies a significant reduction in operational costs for the process since the purchase price of the reagents is high. Fig. 20 shows the result achieved.

TABLE 10 – Result of the consumption of reagent

Expert System	Amine (g/t)	Rmet (g/t)
Off	58.90	673.73
On	56.72	86.96
Difference (pp)	-2.19	-15.23

V. Conclusion

After evaluating the results, it was concluded that the expert system that had been implemented had reached the objective. During the period that the system remained active, there was a clear gain in mass and metallurgical recovery, in addition to there having been an increase in operational stability.

Another important factor was the reduction in the consumption of amine and starch, which represents a reduction in the cost of production per ton since they are consumables which are expensive.

The use of computational intelligence tools can contribute significantly to increasing the efficiency of industrial processes.

It is known that the performance of the expert system installed at Mineração Usiminas can be further improved. Evaluating it after it has been in operation for longer will allow fine adjustments to be made to the control strategy.

Another important factor is to provide the results of the chemical analysis more frequently, which will imply that actions will be more precise.

Based on the results achieved, there remains the motivation to implement the tool in other stages of the process, and thus to be able to maximize the operating result as a whole.

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