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Predictive Control applied to a mathematical model of a Flotation Column

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***Abstract*—*As the flotation process is multivariable, this work investigates the implementation of a predictive multivariable controller for operation a typical flotation column. This controller was tested using a model with delays of a prototype column mounted on Nuclear Technology Development Center (CDTN). Taking as input signals the flushing wash water, air feeding, and non floated fraction flow rates, the controller determines the froth layer height and air holdup in the recovery zone. This control maintains stability. The operation of the controller is based on the optimization of a cost function. The conducted tests were based on the change of setpoint of the controlled variables. It was intended to analyze the system behavior for different operation conditions, considering the constraints of the process and the response speed.*
Keywords*—*Flotation Column, Multivariable Predictive Control, Mining, Optimization, Restrictions.

I. INTRODUCTION

As one of the most used processes in the mineral industry, flotation makes it possible, economically and with satisfactory yields, to use complex and / or low-grade ores. The floating column is one of the outstanding equipments in this process. The achievement of better concentrates, higher metallurgical yield and lower capital investment justify this importance.

In the control of a flotation column, the main objective is to obtain better recovery rates and concentrate content. Due to the difficulties in online measurements of these variables, it is commonly chosen to control them indirectly through other variables [1].

The control system in the column flotation process must act directly on the manipulated variables, being able to maintain, properly, the controlled variables in their reference values, even in the presence of load disturbances or any other disturbances.

Because the column floating process is multivariate, interactions among variables are inevitable, so manipulation of input variables can affect all output variables.

The proposal of a multivariate control using a predictive controller (MPC), the subject of this work, seems to be very pertinent to the process, since its use is advantageous both in reducing sensitivity to system disturbances and in maintaining stability.

The motivation for the development of a multivariate predictive controller applied to the flotation column comes from the interest in improving the development of this process, knowing that this results in the maximization of the level of production, not impacting the quality of the product. In this case, the result should lead to a decrease in energy costs and chemicals added to the process, maintaining the physical and chemical specifications of the product with the lowest operating cost.

II. METHODS

2.1 Flotation Column

Flotation column is intensively used in the mineral processing industry [2]. The success of column flotation depends on the hydrophobic and hydrophilic nature of particles or it may be imparted using reagent[2].

The classical scheme of a flotation column is shown in Fig. 1. It consists of two main zones: the collection zone (or recovery zone) and the cleaning zone .

2.2 Mathematical model

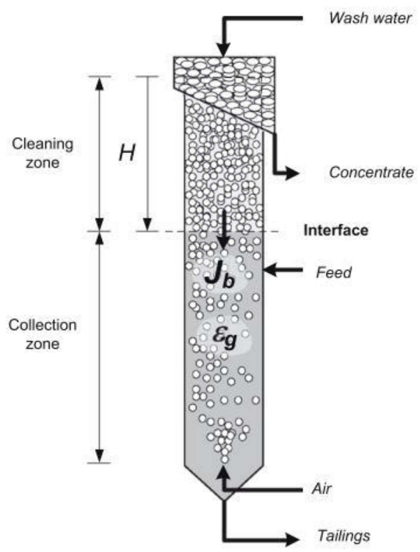

Fig.1:Basic schematic of flotation column [3]

The data used in this work are from a pilot column mounted at the Nuclear Technology Center (CDTN)

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located in Belo Horizonte, Minas Gerais, Brazil. The process variables worked in this plant are:

- Manipulated variables: flushing wash water(U_W), non floated fraction flow rates (U_T)and air feeding (U_g).
- Controlled variables: froth layer height (h) and air holdup in the recovery zone (ϵ_g).

The mathematical model for this pilot column in the biphasic system is developed in [4] being identified in terms of the functions of transfer in continuous time in the transfer matrix of Equation 1:

$$\begin{bmatrix} h(s) \\ \epsilon_g(s) \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} & G_{13} \\ G_{21} & G_{22} & G_{23} \end{bmatrix} \begin{bmatrix} U_W(s) \\ U_g(s) \\ U_T(s) \end{bmatrix} \quad (1)$$

Where each term is represented by Equations 2, 3, 4,5, 6 and 7:

$$G_{11} = \frac{-0{,}034e^{-10s}}{s} \quad (2)$$

$$G_{12} = \frac{-0{,}015}{s} + \frac{4{,}414e^{-60s}(-681{,}88s+1)}{(80{,}68s+1)(486{,}46s+1)} \quad (3)$$

$$G_{13} = \frac{0{,}016}{s} \quad (4)$$

$$G_{21} = \frac{0{,}18e^{-20s}}{94{,}91s+1} \quad (5)$$

$$G_{22} = \frac{0{,}37e^{-60s}}{48{,}26s+1} \quad (6)$$

$$G_{23} = \frac{0{,}07e^{-20s}}{(38{,}11s+1)} \quad (7)$$

2.3 Predictive Control

The Model Predictive Control (MPC) predictive control strategy can deal with several situations, such as: to be applied to control monovariable (SISO) and multivariable (MIMO) plants, to incorporate a dynamic process model, which allows to consider the future effect of manipulated variables under control, and entry and exit restrictions can be included in the formulation of the control law [5] and [6].

In MPC there is no need for pairing between controlled variables and manipulated variables, i.e., it is not necessary to define which MV will control a specific CV. Therefore, the MPC dispenses this step in the design of the control system which facilitates its implementation and eliminates the possibility of a bad pairing [6].

The MPC control refers to a set of methods that make explicit use of the process model to obtain the control signal from the minimization of a cost function [7]. From the process model, we obtain the future outputs for a prediction horizon N_P. These predicted outputs are calculated at each instant t, using the past values of the inputs, outputs and control signals.

In contrast, future control signals are determined by the optimization criterion in order to minimize the difference between the predicted response of the process and the desired response.

The model was manipulated using the MatLab® S-function level 2 block, applied to the state-space modeled pilot plant written in incremental form.

2.4 Predictive control tuning for the flotation column

For the elaboration of the control system it is necessary to initially define the controlled variables (h e ϵ_g), and the manipulated variables (U_W, U_g e U_T). The next step is the tuning of the parameters: control horizon (N_c), prediction horizon (N_P) and sampling time.

The control and prediction horizons chosen after the control tests were 40 and 30, respectively.

The time worked was 5 seconds according to [4]. The discrete time model was obtained using the ZOH (Zero Order Insurer) discretization method, considering that the control remains constant between the sampling instants.

The MPC algorithm used a quadratic cost function subject to the linear constraints represented in Table 1.

Table 1: Conduit Restrictions

Variable	Minimum Value	Maximum Value
$U_W/U_g/U_T$	0	100%
h	20 cm	140 cm
ϵ_g	0	20%

Control weight was assumed equal to 1 for each input variable. It was found, after testing, that different weights did not show significant variations in the results.

III. RESULTS AND DISCUSSION

In order to evaluate the performance of the system with the proposed predictive controller, tests were carried out by means of simulations of the mathematical model of the pilot plant of the fl otation column with delays.

The tests consisted of verifying the ability of the closed loop system to trace reference signals with satisfactory accommodation time and zero error in steady state. Tests were performed by changing the setpoints of the controlled variables, the sensitivity of the controller and the model were analyzed with the presence of noise in the outputs.

The first test consisted in increasing the desired value of the height of the foam layer (Fig. 2). The time of accommodation of the foam layer height was approximately 1044 seconds, with a highlight of 0.23%. The air holdup time in the collecting zone was 1299 seconds, with a highlight of 0.30%. The flow rates obeyed the actual restrictions imposed on the process, that is, the control signals were between 0 and 100%. The most sensitive variable to this change was U_g.

The test shown in Fig. 3 consisted in varying the reference value of the height of the foam layer from 80 to 90 cm at the instant equal to 2000 seconds and from 90 to

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80 *cm* at the instant equal to 6000 seconds. The air holdup reference value in the collection zone ranged from 19% to 18% at the instant of 4000 seconds and from 18% to 15% at the instant of 10000 seconds.

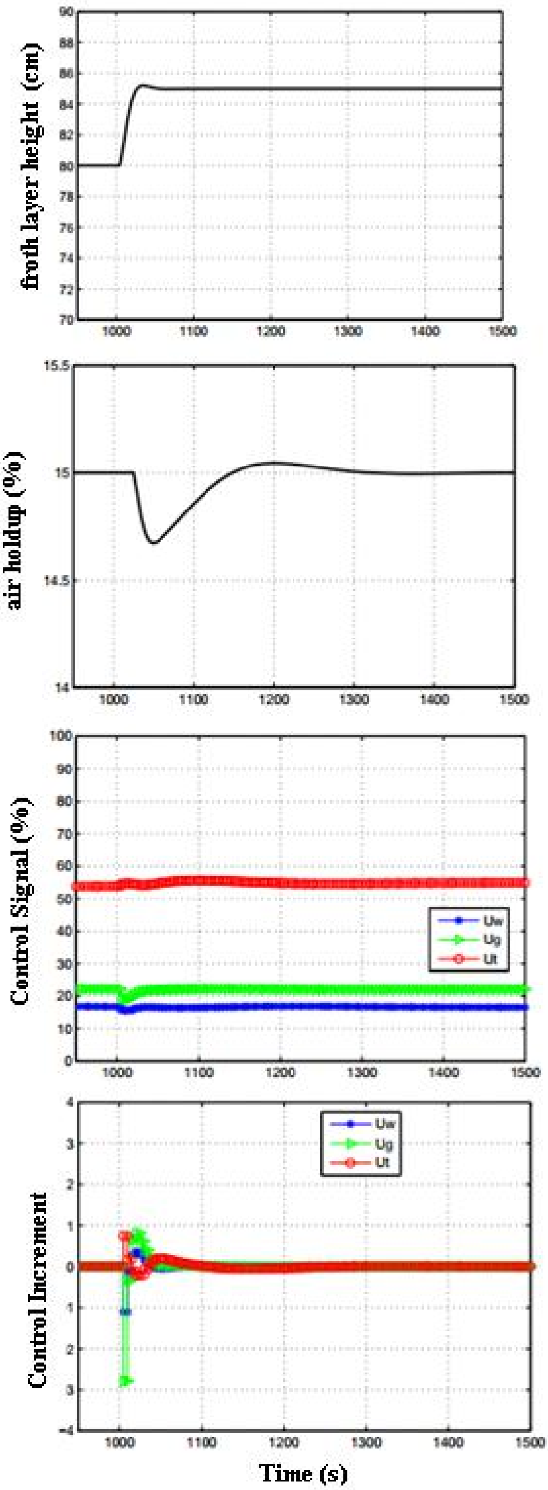

Fig 2: Behavior of the system with the change of setpoint at the froth layer height

For the test analyzed, the height of the foam layer ranged from 79.34 to 94.95 *cm*. The air holdup in the collection zone ranged from 17.86% to 19.70%. The manipulated variables varied between: U_W from 0% to 27,50%; U_g from 7,25% to 35,71% and U_T from 61,57% to 100%. Table 2 shows some points of each variable throughout this experiment. The results showed that all operating restrictions were met.

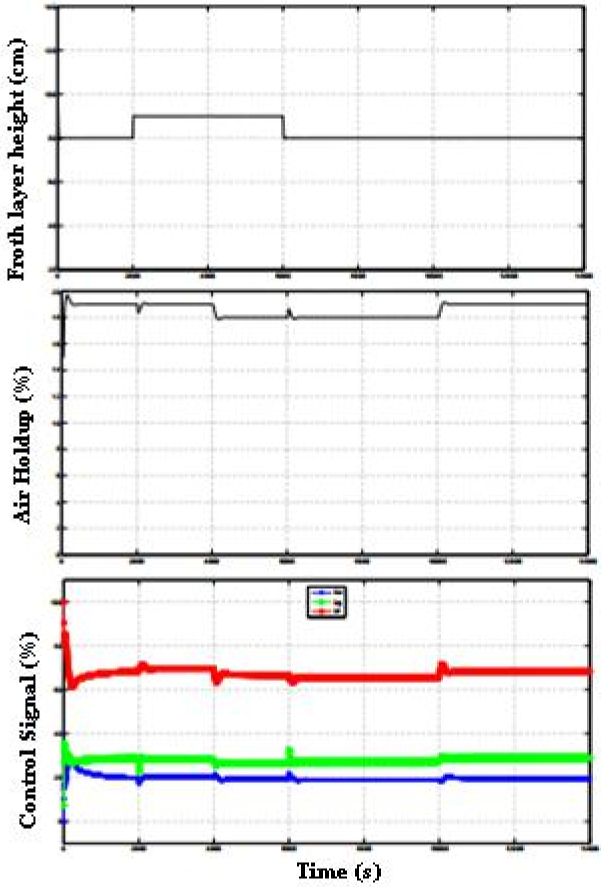

Fig 3: Monitoring of operating restrictions of the pilot column

Table 1:Values of the Variables throughout the experiment

time (s)	0	2000	4000	6000	10000
h(cm)	80	80	90	90	80
ϵ_g (%)	18	19	19	18	18
U_W (%)	0	19,74	20,26	19,62	18,87
U_g (%)	7,25	28,81	28,33	26,51	27,08
U_T (%)	100	68,28	69,60	66,60	65,48

The experiment of Fig. 4 consists of the introduction of a Gaussian noise of variance 0,1 at the outputs of the system. The test relies on changing the value in the reference signal in the air holdup in the collection zone from 15% to 18%. The variation occurs at the instant 1002 seconds. The setpoint of the height of the foam layer remained constant at 79 *cm* throughout the experiment.

It is observed that even with the presence of noisy signals, the MPC controller maintained the stability of the system and followed the desired performance criteria.

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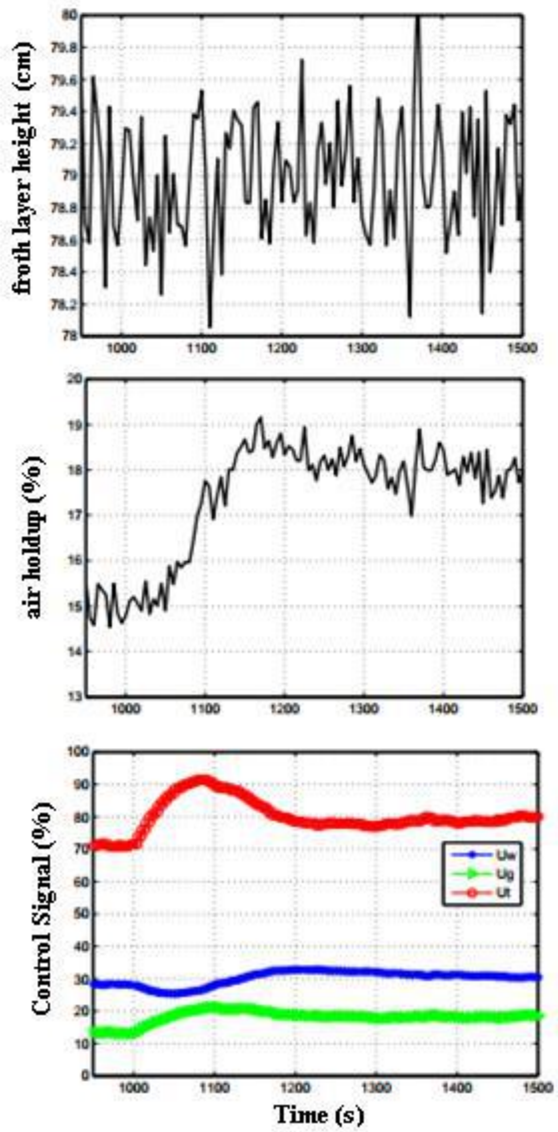

Fig 4: Robustness analysis

The objective of this experiment (Fig. 5) is to analyze the effect that parametric variation has on the implemented controller. In the test, 20% increase in the percentage value gain was obtained for the speed of the non-flotation pump, the air holdup in the collection zone, and the controller with the same parameters of the previous tests remained. The test consists in increasing the desired height of the foam layer from 80 to 85 *cm* at a time equal to 1002 seconds. The air holdup setpoint in the collection zone remained constant at 15%.

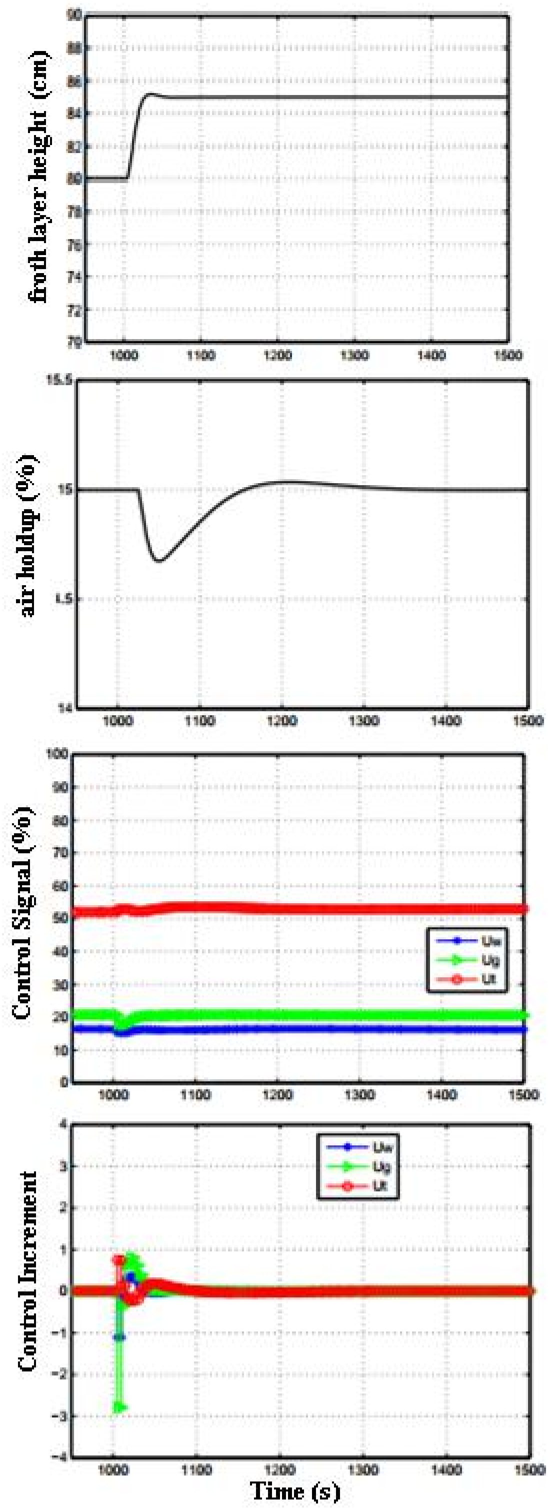

Fig 5: Sensitivity analysis with change in the gain of the U_T manipulated variable of the air holdup in the recovery zone

IV. CONCLUSION

The predictive controller was implemented using the S-function level 2 block on the MatLab® platform with the aid of Simulink®. An analysis was also made of the behavior of the system for various operating conditions, considering the points of operation of the actuators and the speed of response.

The most arduous step of the work was the adjustment of configurable parameters, such as input and output weights and control and prediction horizons. There is no unified and well-defined strategy for choosing these parameters. A bad adjustment of them makes control of the process impossible.

The proposed MPC technique was applied to the state space process model and optimized system control by minimizing a quadratic cost function. This function weighted the mean square error of the controlled variable and the control effort, finding the appropriate control signal.

This controller is designed to control the height of the foam layer and air holdup of the floating column by manipulating control signals from the wash water inlet valve, air inlet valve and pump speed of the non-floated material. This means that the studied system used a multivariable mathematical model with 3 inputs and 2 outputs.

The height of the foam layer is one of the most important parameters to be controlled, and it has been observed that its stability is strongly linked to the air flow at the base of the column.

This structure presented the capacity to deal with the constraints imposed on the float column, respecting the minimum and maximum values of its manipulated and controlled variables. For manipulated variables, the actuators should be in the range of 0 to 100%, the holdup should be 0 to 20% and finally, the height of the foam layer should respect its minimum value of 20 *cm* and maximum of 120 *cm*.

The experiments performed meet the control requirements: transient performance requirements such as stability, low response time and adequate damping, and performance requirements in steady state, such as low or zero reference errors. The predictive controller implemented was able to stabilize the system and maintain at zero the error between the permanent system output and the reference signal, even when changes occurred in the setpoints of the foam layer height and air holdup in the collection zone, and with the variation of process inputs.

The MPC was able to maintain the stability of the system and follow the reference of the controlled variables even with the addition of Gaussian noise in the outputs of the system and changes in the mathematical model. That is, these variations did not affect the performance of the controller implemented here. The tests also allowed to observe a satisfactory accommodation time when compared to other controls already implemented. That is, for a variation of the height of the foam layer from 80 to 85 *cm*, the time required for accommodation was 42 seconds. For air holdup variation in the collection zone from 15% to 18%, it took 283 seconds. It is observed that, although the air holdup needs a longer time to reach the permanent regime, its projection is smaller than the height of the foam layer.

By analyzing the system responses with the closed loop predictive controller, it is possible to consider that the methodology applied to the design is adequate for the column floating process. The results showed that the implemented controller followed the response tendency of the robust controller.

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