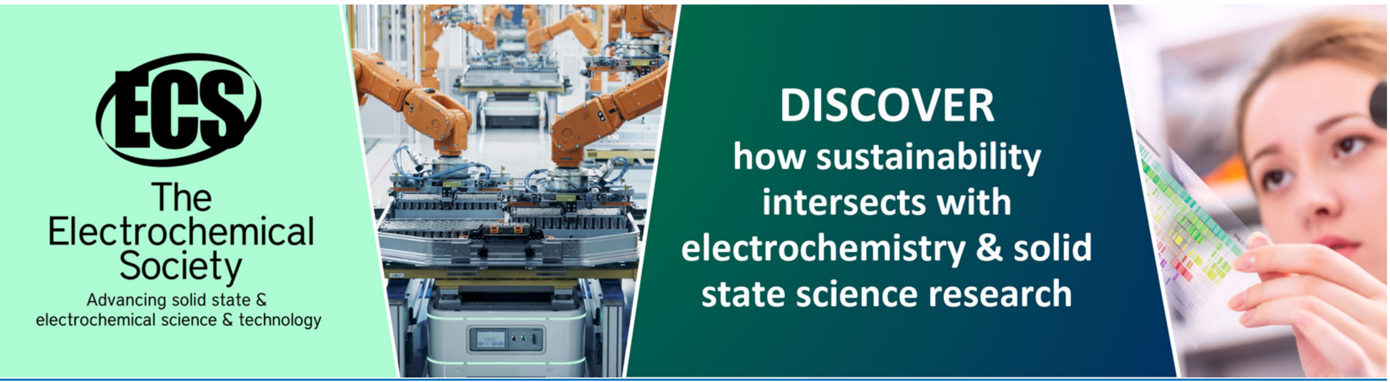
IOP Conference Series: Materials Science and Engineering

PAPER • **OPEN ACCESS**

Characterization of Predictive Control Based on Model (MPC) in Multivariable Process of Milling in a Mineral Concentrator Plant

To cite this article: Juan Tisza and Mario Chauca 2020 *IOP Conf. Ser.: Mater. Sci. Eng.* **852** 012082



Characterization of Predictive Control Based on Model (MPC) in Multivariable Process of Milling in a Mineral Concentrator Plant

Juan Tisza[1], Mario Chauca[2*]

[1]Universidad Nacional de Ingeniería

[2]Universidad Ricardo Palma

*mario.chauca@urp.edu.pe

Abstract. In this article, the simulation level characterization of the predictive control system - based in multivariable model (MPC) is developed, without restrictions in a milling process of a mineral concentrator plant. The multivariability of the process is considered and is evaluated the interaction between the variables. The control strategy that integrates all the control actions is developed, assessing the robustness in the application against disturbances. Generalized predictive control (GPC) is used, presenting the methodology in accordance with the philosophy of predictive control MPC, based on an initial modeling of the process, developed in reference [1]. The case study includes the use of a ball mill in a process of 4 input variables by 4 output (MIMO 4x4), where one of the output variables of greater control is the size of the mineral particles in an iron mine. The results of the control are evaluated observing and discussing the temporal responses in all the variables, the robustness of the control system is evaluated considering the response of the system before the application of multiple disturbances. Results are presented in various simulation scenarios using MATLAB. **Keywords**— Model-based predictive control (MPC), Generalized predictive control (GPC), Multivariate system (MIMO) 4x4, Objective function, Law of control, Disturbances, Robustness.

1. Introduction

In general, the mills and in particular the ball mills are very used for the processing of minerals from a mine, reducing the mineral to very small particles to facilitate the separation of the desired mineral from the raw extracted rock. The particle size obtained after grinding greatly influences the quantity and quality of recovery of the useful mineral.

The grinding circuits represent around 50% of the total investment of the concentrator plant, and consume approximately 10% of the electric power.

To achieve an efficient operation with reduction of production costs, the control system in the milling process must be quite thin and robust in order to obtain a better recovery of the useful mineral. However, the system is complex because it is multivariable and with significant correlations between its process variables, and in practice it is not a linear system, Figure 1 shows a scheme that describes the conventional grinding process, incorporating the MPC control considering 4 control variables and 4 controlled variables.

The problem is to implement a control system that can optimize the process, considering that the system has multiple process variables and considering the interactions and correlations between them, makes it a complex system. It is proposed to solve the problem with a control strategy that has an integrated conception of all the variables within the process and proposes an optimized and robust solution.

The control system MPC-GPC, applied in this study to a MIMO process of 4x4 variables is presented as a solution to the problem raised and figure 1 shows the system with the selected variables.

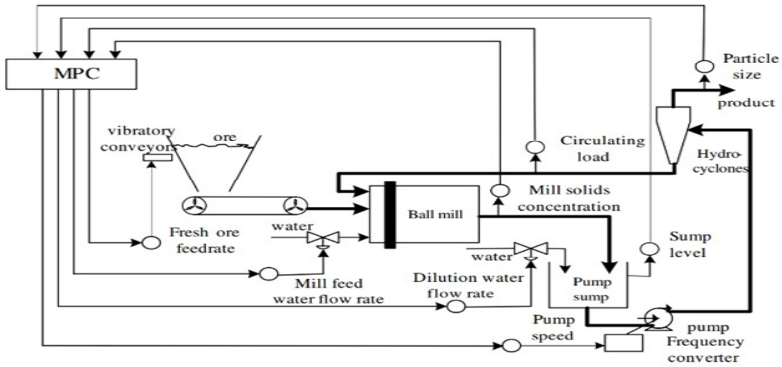


Figure 1. Grinding process with ball mill, with built-in MPC control. (Figure obtained from ref. [1])

The method implemented is based on the theoretical foundations of the control philosophy MPC, which is described in the second section II.
The objective of the work is to validate the proposed solution by applying the control strategy to a conventional grinding plant in the mining industry, in a general manner and without considering specific instrumentation and process constraints for a particular plant. For the purposes of the tests for evaluation purposes, different action scenarios are considered and the system is subjected to multiple disturbances seeking to destabilize and / or degenerate the implemented control system.
In section II, we describe the method briefly and synthetically, presenting significant relationships and equations that support the method used. In section III, the application of the method to the case study is presented. In section IV, the conclusions are presented in section V.

2. Methodology

The methodology of the control strategy is developed and based on the philosophy of predictive control that is synthesized in Figure 2, where we have the model that allows generating the predicted variables (future values) and also based on the Behavior history includes past and present values, this output is compared with the desired references, producing an error that is loaded to controller C, which generates the control actions, after performing an optimization by minimizing the objective function that minimize errors. The control actions are applied simultaneously to the plant and the process model. On the other hand, the measurements of the present are compared with the values generated by the model for the present of the output variables and the comparison of the errors of present values for each of the output variables are identified, these errors are added as disturbances to the other values generated by the model, thus providing us with the complete output that will be compared with the references.
1.-The first step of the method is to determine and identify the input and output variables that we will consider. We select 8 input and output variables for the 4x4 MIMO system, this is presented in table 1.

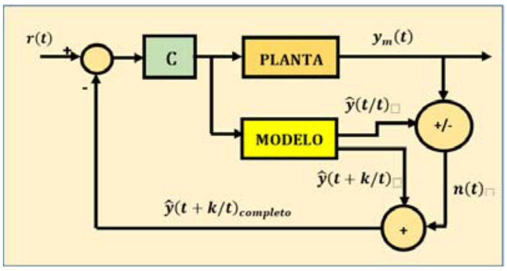


Figure. 2. Basis of the MPC control considering the error in the present value

Table 1. Identification of variables

Input or control variables and Output or controlled variables		
Nº	**Representation**	**Name of the variable**
1	u_1	Regime of entry of fresh mineral to the mill
2	u_2	Income flow of water to the mill
3	u3	Flow of dilution water to the sump
4	u_4	Pump speed
5	y_1	Size of the particle at the exit
6	y_2	Percentage of solids at the exit of the mill
7	y_3	Circulating load in the process
8	y_4	Level in the sump tank

2.-The next step is the modeling of the process that is obtained experimentally in a process of excitation and response to obtain 16 transfer functions in the space of Laplace, which presented in matrix form represent the model that we use in this work, the The procedure for identifying the model is discussed in detail in reference [1].

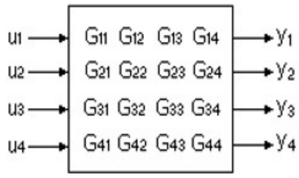


Figure 3. MIMO 4x4 model, with matrix of transfer functions

3.-From the equation of the prediction of future values is developed. Based on the model, we project ourselves into the future in k time intervals

$$y(t) \rightarrow t+k \rightarrow \hat{y}(t+k/t) \tag{1}$$

Where:

$y(t)$ It is the current output

$\hat{y}(t)$ It is the future exit (the prediction)

t It is the current time

$t+k$

It's time in the future

At time t, before an entrance $u(t)$, the plant will give a real output $y_m(t)$ and the model will predict an output $\hat{y}(t/t)$, the prediction equation is presented then assuming, for convenience, $y_o = 0$:

$$\hat{y}(t+k/t) = \sum_{i=1}^{\infty} g_i \Delta u(t+k-i) \tag{2}$$

In this equation, when:

$k-i \geq 0 \rightarrow$ Describe the future.

$k-i < 0 \rightarrow$ Describe the past

We can present the equation of the current prediction error (perturbation):

$$n(t) = y_m(t) - \hat{y}(t/t) \tag{3}$$

and the future error: $\hat{n}(t+k/t) = n(t)$ (4)

We then obtain the complete prediction model including the disturbances to prevent a cumulative error from occurring: $\hat{y}(t+k/t) = \sum_{i=1}^{k} g_i \Delta u(t+k-i) + y_m(t) + \sum_{i=1}^{N} (g_{j+k} - g_i) \Delta u(t-i)$ (5)

$$\hat{y}(t+k/t) = \sum_{i=1}^{k} g_i \Delta u(t+k-i) + f(t+k) \tag{6}$$

In equation (6) we have the free response (function f) and the forced response in the summation, N is called the prediction horizon and Nu is the control horizon. The prediction equation can be developed and obtain a series of equations, one for each value of k. All of them can be summarized by matrix notation [14]:

$$\begin{bmatrix} \hat{y}(t+1/t) \\ \hat{y}(t+2/t) \\ \vdots \\ \hat{y}(t+N/t) \end{bmatrix} = \begin{bmatrix} g_1 & 0 & \cdots & 0 \\ g_2 & g_1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ g_P & g_{N-1} & \cdots & g_1 \end{bmatrix} \begin{bmatrix} \Delta u(t) \\ \Delta u(t+1) \\ \vdots \\ \Delta u(t+N-1) \end{bmatrix} + \begin{bmatrix} f(t+1) \\ f(t+2) \\ \vdots \\ f(t+N) \end{bmatrix}$$

From where: $\hat{Y} = GU + F$ (7)

Objective Function

The objective function is used to obtain the future inputs, (), as a function of the difference of the future outputs with the reference trajectory and the control effort, both affected by weighting parameters.

It is expressed with the following equation: $J=\sum_{k=1}^{N}\delta(k)[\hat{y}(t+k/t)-W(t+k)]^2+\sum_{k=1}^{N_u}\lambda(k)[\Delta u(t+k-i)]^2$ (8)

Where:

J Is the cost function (objective function)

$\hat{y}(t+k\,t)$ are the prediction outputs

$W(t+k)$ are future references $\hat{y}(t+k\,t)-W(t+k)$ is the error in control

$\delta(k)$ ponder the error by following the reference

$[\Delta u(t+k-i)]^2$ represents the control effort

$\lambda(k)$ ponders the control effort

In matrix form, for each value of k:

$$J=\left(\hat{Y}-W\right)^T\delta\left(\hat{Y}-W\right)+\lambda U^TU \quad (9)$$

$$J=(GU+F-W)^T\delta(GU+F-W)+\lambda U^TU$$

$$\frac{\partial J}{\partial U}=\frac{\partial(GU+F-W)^T\delta(GU+F-W)+\lambda U^TU}{\partial U}=0 \quad (10)$$

Deriving and equating to zero $2(G^T\delta G+\lambda I)U+2(F-W)\delta G=0$ (11)

Clearing the control matrix, U: $U=\left[(G^T\delta G+\lambda I)^{-1}+G^T\delta^T\right](W-F)$ (12)

(W - F) is calculated in each sampling period. The other factors remain constant. Of the matrix U only the first row is interested and it is the control law: $\Delta u = k(w-f)$ (13)

3. Aplication

The application of the control strategy in this work in a specific way is established with the process whose transfer functions are specified in the reference [1]

4. Results and discussion

The results show variations in the references of the output variables 1 and 2 in different cases as in figures 4 and 5, where multiple disturbances are included at different times and we confirm the robustness of the control system because none of the disturbances produces instability nor does it produce deviation of the control that continues working without being altered. On the other hand, the control performance is seen in the other variables, figures 6 and 7, observing that there is interaction in the other variables that in all cases produces variations that are quickly controlled. In all cases the magnitudes of the variables are only referential and are not subject to interpretation as magnitude. Because of the nature of the present study.

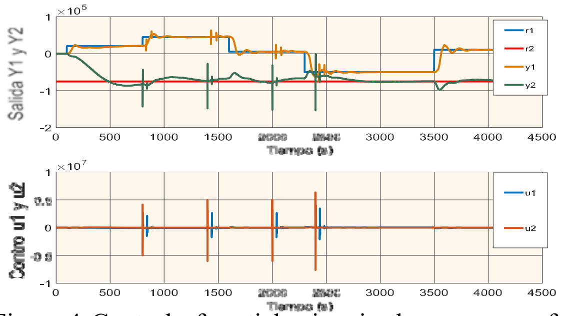


Figure.4 Control of particle size, in the presence of multiple disturbances, effect on variables 1 and 2.

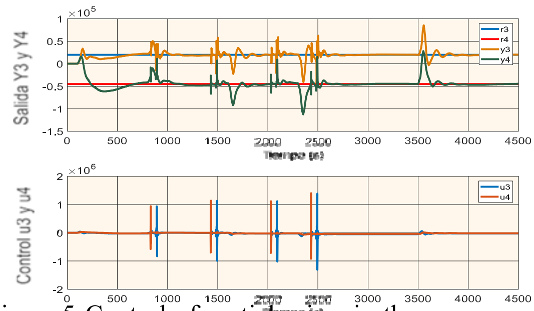


Figure.5 Control of particle size, in the presence of multiple disturbances, effect on variables 3 and 4

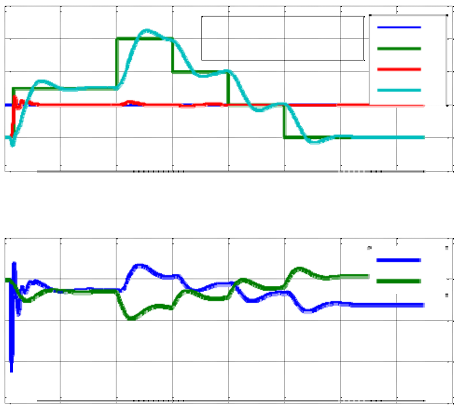


Figure.6 Answers in y1 and y2 before variations in the output variable reference 2.

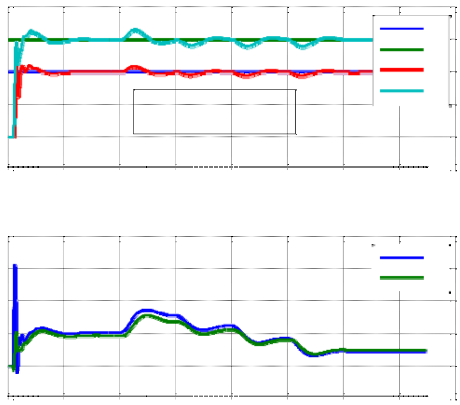


Figure.7. Answers in y3 and y4 before variations in the output variable reference 2.

5. Conclusions

It is concluded that the proposed solution using the MPC-GPC strategy, has a quite good response in general because the control system responds quickly and with a static error close to zero. The strategy generates a robust control system because the multiple disturbances do not affect it.

The solution applied is generic and therefore the conclusions ensure the benefits in the qualitative characteristics of the control strategy and should be tested with the restrictions that are established for each particular case and specific application that is required to implement.

6. References

[1] Chen, X.S., Zhai, J.Y., Li, S.H., Li, Q. (2007). Application of model predictive control in ball mill grinding circuit, Minerals Engineering. Elsevier

[2] Camacho, E., Bordons, C. (2005). Model Predictive Control, in Advance Textbooks in Control and Signal Processing. Segunda edicion. Berlin. Springer Verlag

[3] Forbes, M. G., Patwardhan, R.S., Hamadah, H., Gopaluni, R. B. (2015). Model Predictive Control in Industry: Challenges and Opportunities, (2015), 9th International Symposium on Advanced Control of Chemical Processes, The International Federation of Automatic Control, Whistler, British Columbia, Canada

[4] Botha, S., Craig, I. K., Le Roux, J. D. (2015). Switching cyclones to increase product particle size range for ore milling circuits,(2015),Department of Electrical, Electronic, and Computer Engineering,ELSEVIER,USA

[5] An Overview of Model Predictive Control, K. S. Holkar, K. K. Wagh, Institute of Engineering Education and Research, Nashik, M. S, India, L. M. Waghmare, S. G. Nanded, International Journal of Control and Automation Vol. 3 No. 4, December, 2010

[6] Chen, X.S., Li, Q., Fei, S.M. (2008). Supervisory expert control for ball mill grinding circuits, Expert Systems with Applications 34 (2008) 1877–1885

[7] Chen, X.S., Li, S.H., Zhai, J.Y., Li, Q. (2009). Expert systerm based adaptive dynamic matrix control for ball mill grinding circuit, Expert Systems with Applications 36 (2009).

[8] Chen, X.S., Wang, M.L. (2005). Process control system, Science Press, Beijing,China

[9] Chen, X.S., Wang, L.L., Wang, C.H., Zhang, J.S. (2004). Automatic control system design for ball mill in concentration process, Electrical Automation 26 (4)

[10] Chen, X.S., Zhai, J.Y., Li, S.H., Li, Q. (2007). Application of model predictive control in ball mill grinding circuit, Minerals Engineering. Elsevier