

IMPLEMENTATION OF PREDICTIVE MULTIVARIABLE DMC CONTROLLER IN A PILOT PLANT

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Abstract— This study aims to implement the predictive multivariable DMC controller in a real plant and compare it to multi-loop PID. The practical application is made in a pilot plant located in the IFES / Serra, where pressure and level are controlled with pump speed and valve opening. Tuning of the DMC controller is obtained through a simulator based on genetic algorithm. The plant responses to step using multi-loop PID and DMC are compared with and without constraints on valve opening and pump speed. The DMC controller is also tested with output restriction (pressure and level). The didactic interface developed with LabVIEW software is used to interact with MATLAB and CompactRIO controller, allowing the use of MATLAB optimization functions in the implementation of the DMC controller.

Keywords— Predictive DMC controller, didactic interface, pilot plant.

I. INTRODUCTION

According to Aström and Hägglund (2001) around 90% of all controllers used in the industry are PID type and, despite of that, Desborough *et al.* (2001) comment that only 1/3 of the industrial control loops operate properly in automatic mode, 1/3 in manual mode and 1/3 degrades the system performance, instead of improving it. The reasons for that are varied, including the difficult tuning of controllers and lack of qualified teams for the implementation of advanced controls. Thus, implementations of didactic environments to test traditional and advanced control techniques are important, for superior engineer qualification.

Teaching process control requires proper theoretical basis provided in the classroom, as well as experiments that address the use of control techniques currently offered in the market conducted in laboratories equipped with pilot plants having industrial characteristics; see some examples in Gomes and Pinto (2008), Carvalho (2009) and Thomas *et al.* (2010). One of the advanced control techniques that have increasingly been adopted in the industrial sector is the Model Predictive Control (MPC) and, according to Automation Research Corporation (2000), “the predictive control market is growing at the annual rate of 18%”, considering that this control strategy ensures the plant operation at its most profitable level. The study of Qin and Badqwell (2003) shows that most of these applications are concentrated on chemical and oil industries.

Model predictive control was created in the 1970s, with open ended nature, in which different control algorithms have been developed, such as: Dynamic Matrix Control (DMC) (see Cutler and Ramaker, 1979) and Generalized Predictive Control (GPC) (see Clarke *et al.*, 1987), among others. The predictive controller can be used in linear and single- and multivariable processes, with delays and constraints on input and output variables (Camacho and Bordons, 2004).

In this article, the main objective is the implementation of the DMC predictive control algorithm with constraints on manipulated and process variables. The application is made in the multivariable didactic plant in the laboratory of the control and automation engineering course at IFES. A didactic interface, developed at LABVIEW (National Instruments, 2009) is used to interact with MATLAB and CompactRio controller, enabling the use of MATLAB optimization functions to obtain the solution for the DMC algorithm optimization problem. The other objective of this study is to compare the process performance using multivariable DMC controller and multi-loop PID.

This article is organized as follows: Section 2 describes the environment and the controllers, Section 3 presents the tests that compare DMC to PID, with and without constraints. Section 4 brings the conclusion.

II. THE ENVIRONMENT AND THE CONTROLLERS

A. The Plant

Figure 1 and Figure 2 show the instrumentation diagram and a photo of the plant, respectively. The plant has one lower reservoir (T2) and one upper reservoir (T1). The lower reservoir (T2) is made of stainless steel and, using valve HV-04, it is possible to use it as a closed or open reservoir, which will be open in this analysis. Pump B-1 removes the fluid from the bottom of T2 and circulates it through upper control valve FV-02, directing the fluid to upper reservoir T1. Valve FV-01 will be always open, allowing the fluid to return to lower reservoir T2.

For the plant control, CompactRIO 9012 controller of National Instruments (2009) was used, which is an advanced controller that has a data acquisition system designed for high-performance and reliability applications, combining the advantages of computers and rigidity of PLCs. CompactRIO has a real-time processor and a Field-Programmable Gate Array (FPGA) platform. The programming software for this controller is

LabVIEW (Laboratory Virtual Instrument Workbench), which has a graphics programming environment and many resources from the areas of mathematics, instrumentation and automation. Figure 3 shows the controller with its I/O (input/output) boards.

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In the controllers to be implemented, the process variables (PVs) will be the piping pressure and the level in the upper reservoir, and the manipulated variables (MVs) will be the pump speed and the upper valve opening. The plant model should be known for the development of both DMC and PID controllers (Seborg *et al.*, 2004); for this reason, a pump step was applied,

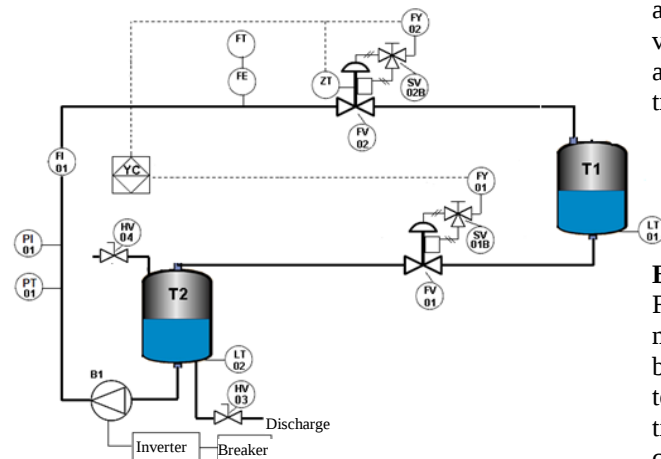


Figure 1. Diagram of the didactic plant



Figure 2. Photo of the didactic plant



Figure 3. CompactRIO controller and its I/O boards

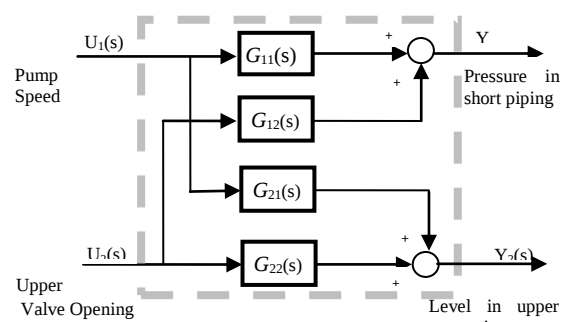


Figure 4. Pressure and level of the plant model.

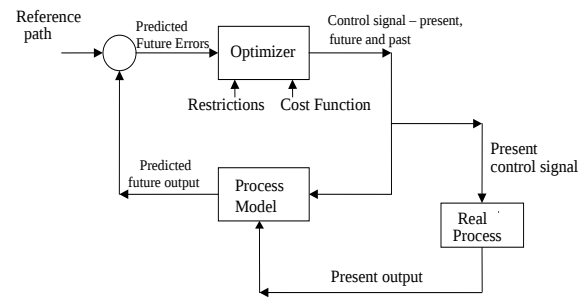


Figure 5. MPC Structure

measuring the step influence on pressure output (G_{11}) and level output (G_{21}). A step was also used in the valve, measuring the step influence on pressure (G_{12}) and level (G_{22}). Figure 4 shows the plant model, and the transfer functions obtained.

$$G_{11} = \frac{1.45e^{-0.1s}}{0.85s + 1} \quad G_{12} = \frac{-0.11e^{-0.1s}}{0.85s + 1}$$

$$G_{21} = \frac{1.18e^{-2s}}{206s + 1} \quad G_{22} = \frac{1.27e^{-1.5s}}{225.5s + 1}$$

B. DMC predictive controller

Figure 5 illustrates the basic structure of MPC. One model is used to predict the future output of the plant, based on the past and present information of the plant, to propose an optimal action of future control. This optimization is calculated by an optimizer, taking into account the cost function and the constraints.

The process model is one of the most important parts, as it should be able to capture the process dynamics, as well as a precise prediction of future output.

The MPC strategy of all controllers that belong to the MPC family has the following characteristics (see Fig. 6):

i) The future output for a certain prediction horizon h_p will be predicted at each instant t , using the process model. This predicted output of k steps ahead from instant t , $\hat{y}_m(t+k/t)$, for $k=1, 2, \dots, h_p$, (where h_p is the prediction horizon), depends on the knowledge of past input and output values and future control signal k steps ahead from instant t , $u_1(t+k)$, $k=0, 1, \dots, h_c-1$, (where h_c is the control horizon, in such way that $h_c \leq h_p$). The predicted output of DMC for a system with 2 inputs and 2 outputs is

$$\hat{y}_m(t+k) = \sum_{l=1}^2 \sum_{i=\max\{1, k-h_c+1\}}^{N_m^1} g_{ml}(i) \Delta u_l(t+k-i),$$

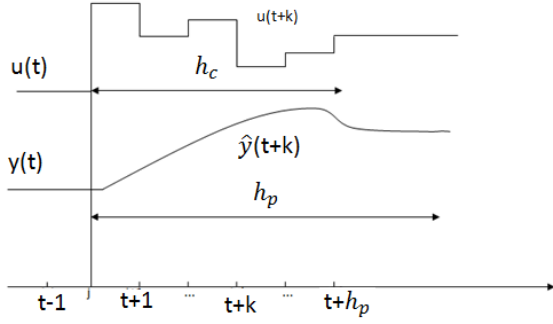


Figure 6. MPC Strategy

where g_{ml} is the step response of output $m=1, 2$ in relation to the input $l=1, 2$; $\Delta u_l(t+k) = u_l(t+k) - u_l(t+k-1)$ is the control signal variation.

After separating the past control actions from present and future control actions, we have

$$\hat{y}_m(t+k) = \sum_{l=1}^2 \sum_{i=\max\{1, k-h_c+1\}}^k g_{ml}(i) \Delta u_l(t+k-i) + \sum_{l=1}^2 \sum_{i=k+1}^{N_m^1} g_{ml}(i) \Delta u_l(t+k-i).$$

Let us define $f_{m1}(t+k) = \sum_{l=1}^{N_m^1} g_{ml}(i) \Delta u_l(t+k-i)$ and

$f_{m2}(t+k) = \sum_{l=k+1}^{N_m^2} g_{m2}(i) \Delta u_2(t+k-i)$. The predicted output is

$$\hat{y}_m(t+k) = \underbrace{\sum_{l=1}^2 \sum_{i=\max\{1, k-h_c+1\}}^k g_{ml}(i) \Delta u_l(t+k-i)}_{\text{Forced response.}} + \underbrace{\sum_{l=k+1}^{N_m^2} g_{m2}(i) \Delta u_2(t+k-i)}_{\text{Free response.}} \quad (1)$$

Obtaining using Present and future inputs

Obtaining using Past inputs

Next we will present an expression equivalent to (1) in the matrix form. For this, let us define

$$\hat{Y}_m = \begin{bmatrix} \hat{y}_m(t+1) \\ \hat{y}_m(t+2) \\ \vdots \\ \hat{y}_m(t+h_c) \\ \vdots \\ \hat{y}_m(t+h_p) \end{bmatrix}_{(h_p \times 1)}, \quad \Delta \hat{U}_l = \begin{bmatrix} \Delta u_l(t) \\ \Delta u_l(t+1) \\ \vdots \\ \Delta u_l(t+h_c-1) \end{bmatrix}_{(h_c \times 1)}$$

$$G_{m,l} = \begin{bmatrix} g_{m,l}(1) & 0 & \cdots & 0 \\ g_{m,l}(2) & g_{m,l}(1) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ g_{m,l}(h_c) & g_{m,l}(h_c-1) & \cdots & g_{m,l}(1) \\ \vdots & \vdots & \ddots & \vdots \\ g_{m,l}(h_p) & g_{m,l}(h_p-1) & \cdots & g_{m,l}(h_p-h_c+1) \end{bmatrix}_{(h_p \times h_c)}$$

$$\hat{Y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \end{bmatrix}_{(2h_p \times 1)}, \quad G = \begin{bmatrix} G_{1,1} & G_{1,2} \\ G_{2,1} & G_{2,2} \end{bmatrix}_{(2h_p \times 2h_c)}, \quad \Delta \hat{U} = \begin{bmatrix} \Delta \hat{U}_1 \\ \Delta \hat{U}_2 \end{bmatrix}_{(2h_c \times 1)}$$

$$F_{m,l} = \begin{bmatrix} f_{ml}(t+1) \\ f_{ml}(t+2) \\ \vdots \\ f_{ml}(t+h_p) \end{bmatrix}_{(h_p \times 1)}, \quad F = F_{11} + F_{12}$$

Therefore, the future output can be determined by

$$\hat{Y} = G \Delta \hat{U} + F. \quad (2)$$

ii) The group of future control signals will be calculated through an optimization of a criterion established to keep the process as close as possible to the predicted reference path, $w_m(t+k)$, k steps ahead from instant t , represented by $w_m(t) = y_m(t)$ and

$$w_m(t+k) = w_m(t+k-1)\alpha_m + (1-\alpha_m)r_m(t+k),$$

where $k=1, 2, \dots, h_p$, α_m is a parameter between 0 and 1, $r_m(t+k)$ is the evolution of the future reference and $y_m(t)$ is the real process output. The usually adopted criterion to keep the process as close as possible to the reference path has the form of a quadratic function of the error between the predicted output signal and the predicted reference path. In many cases, the variation of control signal Δu_l is included in the objective function defined in expression (3), to enable the smallest possible variation of control action (Δu_l).

$$J(\Delta u) = \sum_{m=1}^2 \sum_{k=1}^{h_p} \delta_m [\hat{y}_m(t+k) - w_m(t+k)]^2 + \sum_{l=1}^2 \sum_{k=1}^{h_c-1} \lambda_l \Delta u_l^2(t+k) \quad (3)$$

where δ_m and λ_l are weights of error and control effort, respectively, which are constants or exponentials usually chosen along the horizon. The matrix form of objective function (3) is

$$J(\Delta U) = (\hat{Y} - W)^T \delta (\hat{Y} - W) + \Delta \hat{U}^T \lambda \Delta \hat{U}$$

where

$$\delta = \begin{bmatrix} \delta_1 & 0 \\ 0 & \delta_2 \end{bmatrix}, \quad \lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}.$$

A sequence of signals $\Delta u_l(t+k)$, $k=0, 1, 2, 3, \dots, (h_c-1)$ that minimize the objective function can be determined explicitly if there are no restrictions. In this case, the solution is

$$\Delta \hat{U} = K(W - F) \quad (4)$$

where K is the first line of matrix $(G^T \delta G + \lambda I)^{-1} G^T$, which is the controller gain. Otherwise, an iterative method for optimization should be used.

iii) The control signal to be applied to instant t , $u(t)$, is sent to the process, while future signals $\Delta u_l(t+k)$, $k=0, 1, 2, 3, \dots, (h_c-1)$ will be rejected. In the following sampling period ($t+1$), signal $y_m(t+1)$ is already known and the calculations of control actions will be made again, just like in the prior step. This method is called receding horizon control.

C. DMC with restriction

Restrictions are always present in any control situation in real life. The operation point that fulfill the global economic objectives of a process is usually at the intersection of restrictions (Garcia *et al.*, 1989). Not consid-

ering the restrictions means forcing the process to operate at a safe distance and, therefore, sub-optimized in relation to the restriction limits, resulting in poor performance of the process. When applying a control system to a certain process, it is desirable to not only keep some variables under control, but also reduce the variability of variables that, the closer they operate to restrictions, the better the process is performing.

In a real process, restrictions to control variation Δu , the excursion of control $u(t)$ and output $y(t)$ are real and present in the entire operation period. Restrictions are the result of equipment limitations in field (such as hydraulic/electric capability to move actuators, stroke limitation of valves, reservoir capability, etc.). In the DMC algorithm, the solution of the problem with constraints is different from expression (4). In this case, the best signal to be applied in the process is calculated using the quadratic programming problem (5).

$$\min_{\Delta u} J(\Delta u) \quad \text{s.t.} \quad S\Delta u \leq c, \quad (5)$$

where the following restrictions have been considered:

i) Variation of control action (Δu)

$$\Delta u_{l\min} \leq \Delta u_i(t+k) \leq \Delta u_{l\max}, k=0,1,\dots,h_c-1 \quad (6)$$

ii) Control signal (u).

$$u_{l\min} \leq u_i(t+k) \leq u_{l\max}, k=0,1,\dots,h_c-1 \quad (7)$$

iii) Predicted output signal ($\hat{y}$)

$$y_{m\min} \leq \hat{y}_m(t+k) \leq y_{m\max}, k=0,1,\dots,h_p \quad (8)$$

To solve the problem defined in (5) from the MATLAB quadprog function, the restrictions above should be dependent on Δu and should be written in the matrix form.

In Camacho and Bordons (2004), restrictions (6), (7) and (8) are placed as illustrated in (5). The vector $\Delta \hat{U}$ is obtained through the optimization function and the first and h_c+1 elements of vector $\Delta \hat{U}$ will be used to obtain the control signals u_1 and u_2 as follows:

$$u_1(t) = \text{the first element of vector } \Delta \hat{U} + u_1(t-1),$$

$$u_2(t) = h_c+1 \text{ element of vector } \Delta \hat{U} + u_2(t-1).$$

The control signals u_1 and u_2 are applied to the process and will place the system outputs closer to the reference in the best way possible, observing the limitations imposed by restrictions.

D. Simulator of DMC and the implementation in the plant

A simulator using LabVIEW was developed to allow easy implementation of DMC control. This simulator was critical in correcting programming errors of DMC algorithms and in tuning tests. The DMC implementation in the plant started only after testing the algorithms in the simulator by replacing the mathematical model of the plant with the real plant. Figure 7 shows the simulated response of the plant.

The DMC control was installed in the pilot plant as indicated in Figure 8. The DMC algorithm and data record routine was programmed in the computer from the LabVIEW software. This algorithm calls some routine developed through MATLAB commands, since LabVIEW access the MATLAB functions easily.

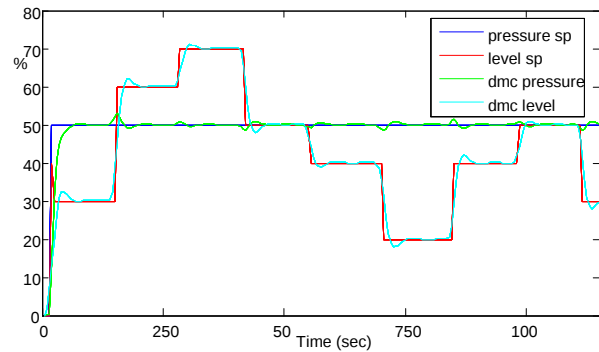


Figure 7. Response of DMC simulator to level set point variation.

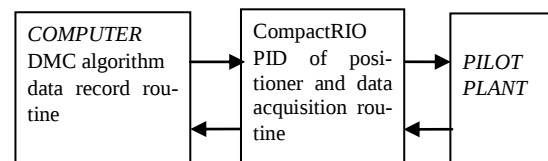


Figure 8. Block diagram of DMC implementation

The DMC algorithm calculates the manipulated variables (valve opening and pump speed, see Fig. 4) and sends them to CompactRIO. The valve opening is the PID set point of the valve positioner. In CompactRIO, the PID output of the valve positioner and the pump speed are converted from percentage (%) to current (ma) in the data acquisition routine to be sent to the plant actuators, i.e. the valve and the pump.

The 4-20ma signals coming from the pressure and level transmitters of the plant (see Fig. 4) are transformed to tension before entering the CompactRIO. After that, they are filtrated and converted to percentage (%) through a data acquisition routine and sent to the computer.

The LabVIEW was installed in the computer and in the CompactRIO. Figure 9 shows the interconnection between the computer and CompactRIO using Ethernet cable and the internal protocol of the labVIEW. It also shows the connection between CompactRIO and the 4-20 ma instrumentation signals of the ditactic plant.

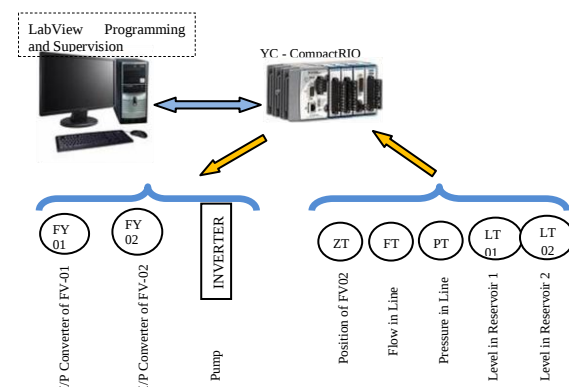


Figure 9. Interconnection between computer-CompacRIO and CompacRIO-instrumentation

The DMC controller tuning was performed by selecting parameters h_c , h_p and to each output of parameters α , δ and λ .

For tuning selection, the application that uses the genetic algorithm (GA) developed in Almeida *et al.* (2009) was used, plus the experience acquired while using the plant. This algorithm works as follows. First, the process model should be inserted and after that the parameters required for the GA execution are defined, i.e. size of population (M), number of generations (G), crossover rate and mutation rate, type of fitness function and selection criterion). After that, M individuals will be randomly created by the GA, and each individual will have the format $[h_c, h_p, \alpha_1, \alpha_2, \delta_1, \delta_2, \lambda_1, \lambda_2]$. Then, these individuals will be placed into the DMC algorithm, which should provide each individual with a fitness value, which, in this case, will be the IAE performance index.

The GA will separate the best and the worst individuals, according to the value presented by the fitness function of each individual. After that, the GA will perform the species evolution through genetic operations of crossover and mutation, and the best individuals will have a lower probability of having descendants in future generations. It should be noted that this study used the technique of elitism, parallel to roulette wheel selection, ensuring that results will never be worse than the results of the prior generation, as this technique guarantees that the best individuals will be copied to the following generation.

The GA will execute a loop of G generations, and, at the end of such loop, the best individual will be obtained, and its elements will be the DMC tuning parameters.

The DMC algorithm follows the logic presented in the flow diagram illustrated in Figure 10.

First the discrete model of the plant is identified. Using the model, the best tuning of DMC is obtained using the genetic algorithm (GA). Then the model and the tuning parameters are inserted in the DMC algorithm, which calculates the matrix G . After that the program starts a loop and calculates the reference prediction (W), the free response (F) and, using the quadprog function plus previously defined restrictions, it calculates $\Delta \hat{U}$, which is used to obtain the signals of controls u_1 and u_2 to be applied in the plant.

E. PID controller

Two structures with multi-loop PID control have been developed. One conventional structure and one using a cascade control.

The classic parallel PID with anti-windup was implemented, see details in Pereira *et al.* (2011), to be used in controllers whose output (u) is

$$u(t) = k_c \left(e(t) + \frac{1}{T_i} \int e(t) dt + T_d \frac{de(t)}{dt} \right)$$

The conventional PID control implemented has a pressure loop and a level loop, as illustrated in Figure 11.

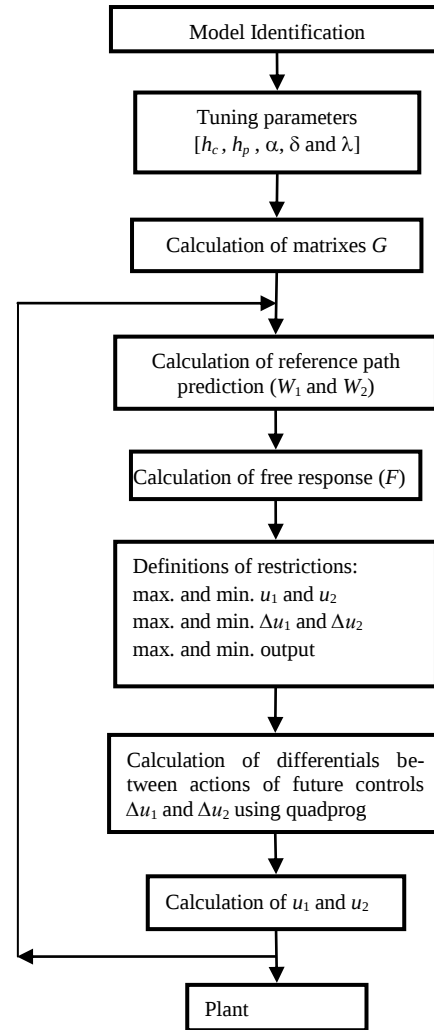


Figure 10. Flow diagram of DMC algorithm

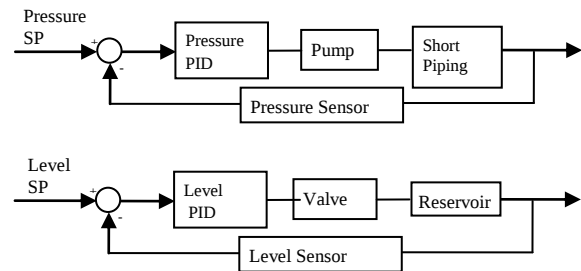


Figure 11. Configuration of conventional PID controller

In the cascade PID control, the pressure loop is identical to the pressure loop of the conventional PID, and the level loop has a cascade flow controller with the level controller, as illustrated in Figure 12.

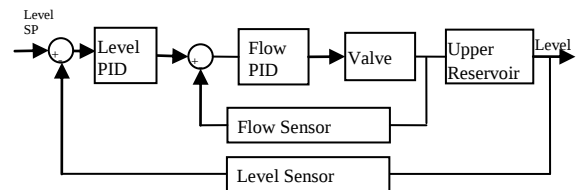


Figure 12. PID level loop with a cascade

In this study, the method used in PID tuning was the minimization of integral of the absolute value of the error (IAE), and the parameters were selected using the tables presented in Seborg *et al.* (2004). The PID controllers were implemented in the CompactRIO controller, and the controlled variables (level, flow and pressure) are sent to the computer in real time to be recorded in the data record routine.

III. COMPARISONS BETWEEN CONTROLLERS

A. Comparison without restrictions

For the comparison, the plant response to each type of controller will be presented and then its data will be tabulated for analysis.

Figure 13 shows the real pressure and level responses to variations of level SP, with constant pressure SP, using the multi-variable DMC control without restrictions.

Figure 14 shows the real pressure and level responses to variations of pressure SP, with constant level SP, using the DMC controller without restrictions.

Figure 15 shows the plant responses in a closed loop to variations of level SP for the conventional PID control and cascade PID, both without restrictions, which did not show any significant variation in pressure in both PIDs, except in instances with set point changes

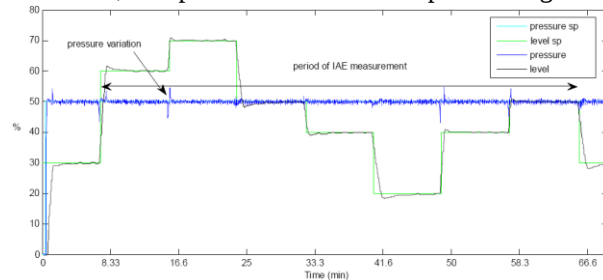


Figure 13. Response to different level set points using DMC

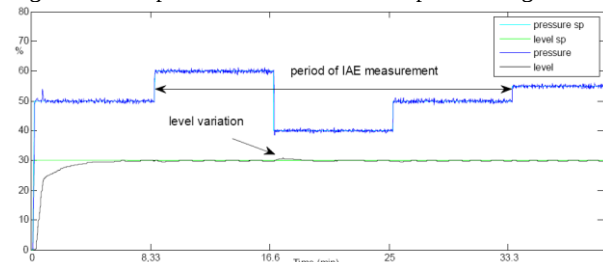


Figure 14. Response to different pressure SPs using DMC

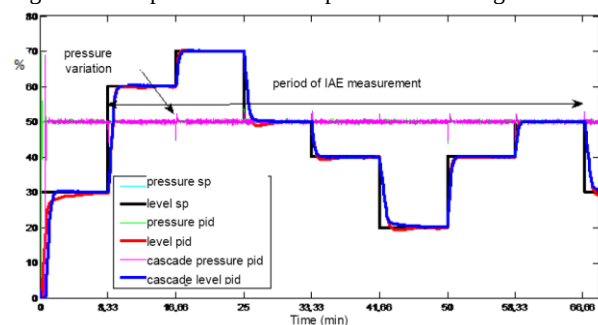


Figure 15. Real responses to variations of level SP without restrictions

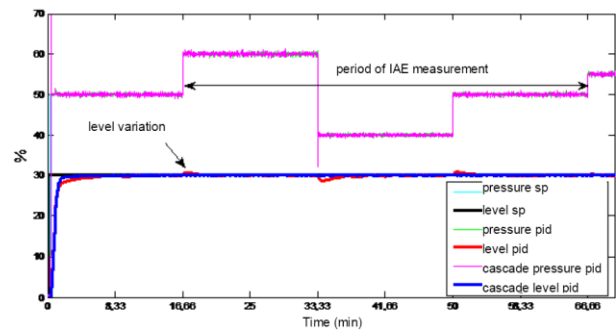


Figure 16. Responses to variations of pressure SP without restrictions

Table 1. Performance of loops in the pilot plant, with different controllers, without restrictions, for variations of level sp and constant pressure sp.

Variations of Level SP	DMC	Conventional PID	Cascade PID
IAE_{Level}	0.69	1	1.02
$IAE_{Pressure}$	0.36	0.23	0.26

Table 2. Performance of loops in the pilot plant with different controllers, without restrictions, for variations of pressure sp and constant level sp.

Variations of Pressure SP	DMC	Conventional PID	Cascade PID
IAE_{Level}	0.07	0.19	0.02
$IAE_{Pressure}$	0.19	0.23	0.25

Figure 16 shows the plant responses in a closed loop to variations of pressure SP, both also without restrictions, and the pressure set points were achieved satisfactorily in both PIDs. It also shows that the variations of pressure set points caused greater level changes with the conventional PID than with the cascade PID, which can be confirmed by the level IAE index, which was 0.19% with the conventional PID and 0.04% with the cascade PID.

Table 1 shows the results of tests with variations of level SP, keeping constant pressure SP. These data indicate that the best level performance was obtained with the DMC, considering that the pressure performance was very similar in all three cases, with the conventional PID producing the best result.

Table 2 shows the results of tests with variations of pressure SP, keeping constant level SP. For this test, the best pressure performance was achieved with the DMC, considering that the best level performance was obtained with the cascade PID.

Finally, considering the sum of level and pressure IAE values as the plant performance score for all cases, the best result was obtained using the DMC predictive controller.

B. Comparison using restrictions

Tests were conducted in the pilot plant using PIC and DMC controllers with restrictions. Each test has four periods, defined as T1, T2, T3 and T4. In T1, the plant response without restrictions will be presented, in T2 the restriction limits the maximum pump speed to 75%, in T3 the maximum valve opening is also limited to 75%, and in T4 previously defined restrictions are ap-

plied simultaneously. In the DMC, the restrictions are part of the algorithm itself, while in the PID the restrictions were inserted limiting the MV when the limits are exceeded.

Figure 17 shows the test of level variation with restrictions applied to the conventional PID. In T2, pressure and level set points were achieved, but reduced pressure was observed during ramp up time. In T3, pressure did not change, but the permanent regimen of level was not achieved, showing that the valve restriction had a strong impact on the plant response. In T4, pressure was not changed either, and with simultaneous restrictions to pump speed and valve opening, the level set point did not achieve the regimen in this period.

Figure 18 shows the test of level variation with restrictions, using the DMC controller. In T2, the pressure and level set points were achieved, but reduced pressure was observed during ramp up time. In T3, the pressure and level set points were achieved. In T4, with the simultaneous restrictions on pump and valve, the pressure and level set points were also achieved, with pressure change during level increase.

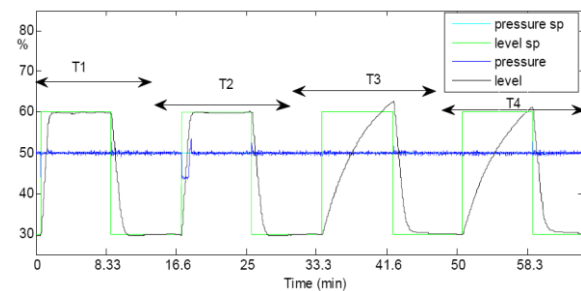


Figure 17. Level response using PID with restrictions

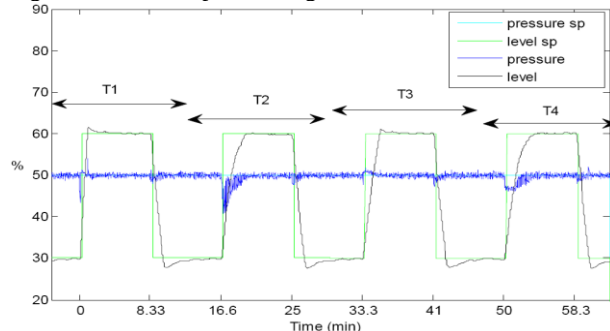


Figure 18. Level response using DMC with restrictions at the input

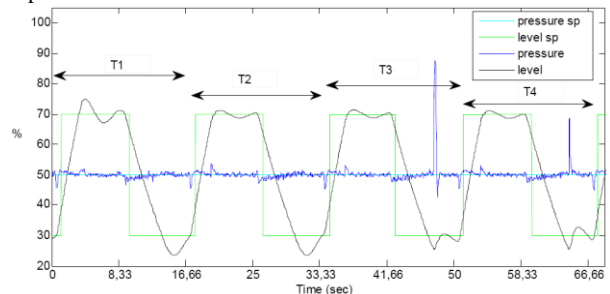


Figure 19. Response of level and pressure using DMC with restrictions at the output

It should be noted that, with the DMC, it is possible to insert restrictions at the process output; in this case,

for level and pressure. A test was conducted to show this resource, illustrated in Figure 19. In T1, no restriction was applied, in T2 the maximum output restriction (72%) was active and limited the level satisfactorily. In T3, the restrictions of maximum level (72 %) and minimum level (26%) were applied simultaneously. In this case, the maximum and minimum levels were not exceeded, but, to make it feasible, a pressure increase occurred when the level value reached its minimum value. In T3, besides the restrictions of maximum and minimum level, the maximum pressure restriction (55%) was applied, which limited the pressure, but exceeded 5%, as it was not feasible to limit pressure to 55%.

IV. CONCLUSIONS

The results of tests with multivariable DMC and multi-loop PID controllers implemented in the plant were compared. The plant performance score using the multivariable DMC controller was better than that obtained using the PID. The plant responses, with the same restrictions using PID and DMC, indicate better results with the DMC, as this controller considers the restrictions within its algorithm.

As indicated in the test, when using the DMC, it is possible to apply restrictions also at the process output, which enables easy and safe operation within the physical boundary of the plant.

Considering the DMC tuning complexity, the simulator development had a critical participation in tuning and it enabled easy correction of algorithm programming errors. This DMC simulator and the controllers implemented can be used as excellent didactic tools for teaching purposes in the control area.

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