A Parametric Dynamic Matrix Controller Approach for Nonlinear Chemical Processes

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Abstract: This study presents a Parametric Dynamic Matrix Controller (PDMCr) to handle independently the process gain, time constant and dead time effects over the DMC performance. The controller is complemented with a fuzzy supervisory module that monitors changes on the process nonlinear behavior and keeps updated the embedded process model, saving time by avoiding repeating the open-loop step response identification. The new PDMCr is able to improve regulation and control tasks, even in those cases when the operation point is far from the initial identification point. Three examples are used to assess the PDMCr performance, a linear FOPDT and two nonlinear chemical processes: a mixing tank, and a neutralization reactor. The PDMCr improves the DMC performance, tracking set point and rejecting disturbances with shorter settling times and less overshoot, it remains stable when DMCr oscillates; and show more tolerance to noise than the DMCr, keeping a stable behavior for longer times under noisy input signals. When both performances are comparable, the IAE values for the PDMCr are until 23% lower compared to the DMCr.

Key-Words: Nonlinear DMC, Nonlinear Chemical Processes, Parametric DMC, Tuning parameters, Fuzzy Logic, Supervisor Module

1 Introduction

Dynamic Matrix Control (DMC) was originally developed by Cuttler and Ramaker in 1979 [1]. It was first intended to fulfill requirements of petrochemical and power plants; more than three decades later, it has been successfully applied in chemical, food processing, pulp and paper and aerospace industries [2] [3]. DMC is a Model Predictive Control technique, which decisions are driven by real data of the process dynamics over a future horizon time, this is its key issue [4]. The essence of DMC is to find the optimal control output vector using a least squares solution for the residuals of non-compensated errors coming from the Dynamic Matrix, a linear combination of future outputs and future inputs of the process [2]. It is a Model Based Control (MBC) which success is due to its ability to anticipate and eliminate feed forward and feedback disturbances [4] with a less aggressive output and a more robust response compared to other techniques such as the traditional and universally implemented PID control [5]. As a MBC technique, DMC allows intrinsic dead time compensation [2], and due to its Dynamic Matrix can be easily extended to multivariable cases [4]. Industrial processes are nonlinear by nature and DMC approaches them using a linear step response model. This may result in negative consequences such as very slow to oscillatory responses [6] [7] [8] and in some cases, large Integral Squared Error (ISE) values for set-point tracking due to steady state error [5]. Ill-conditioned matrices are also a problem and lead to poor DMC performances [9].

Currently, many of the DMC improvement alternatives are focused on two points, improvements on how to deal with nonlinearities in MIMO systems with strong variable interactions [10], and improvements on the control parameter tuning for horizon and move suppression factor [11]in order to avoid fluctuation and decrease execution frequency [5].

Proposals to solve the DMC weaknesses can be grouped in two sets: one set is focused on the DMC algorithm reformulation, and the other one is focused on the control parameter tuning. Examples in the first set are McDonald and McAvoy [8], Brengel and Seider [12], Peterson, et. al. [13], Aufderheide and Bequette [14]. Some of these proposals suggest the addition of a disturbance vector to take into account the effect of nonlinearities in the prediction horizon [13], or a multiple model structure: standard DMC plus First Order Plus Dead Time (FOPDT) [14]. McDonald and McAvoy [8] proposed a gain and time scheduling technique to update the DMC algorithm and enhance its control performance. The second set uses the control parameter tuning to improve DMC performance. Recently Jeronimo and Coelho [11] used SISO processes represented by a FOPDT model to propose auto tuning and self-tuning methods based on DMC minimum realization (optimal move suppression factor and optimal horizon) and online minimization of the objective function to reduce set-point tracking error and control ringing.

The work presented here proposes a hybrid approach that includes changes in the standard DMC's control law to isolate the process gain, time constant and dead time effects; and an auto-tuning module. The traditional Dynamic Matrix Controller (DMCr) is transformed into a Parametric Dynamic Matrix Controller (PDMCr). Also an auto tuning technique is suggested to calculate the optimal move suppression factor based on regression analysis using a FOPDT model. The input parameters for tuning come from a fuzzy supervisor module that monitors changes on the process nonlinear behavior, detects them and sends the information to update the PDMCr. The new PDMCr is able to improve regulation and control tasks, even in those cases when the operation point is far from the initial identification point.

The paper is organized as follows: section two shows how to implement a DMCr for a SISO system. Section three describes the proposed PDMCr, and section four presents the fuzzy supervisor model. Section five presents the PDMCr performance in a mixing process and a neutralization reactor compared to the conventional DMCr. The final section shows the noise effect on the PDMCr, and finally conclusions are presented.

2 Conventional DMC Implementation

There are many ways to describe the DMC algorithm; for the purpose of this research, the form suggested by Sanjuan [15] is used. The following discussion describes the DMC implementation for Single-Input-Single-Output (SISO) systems. The process is identified first using a step change in the signal to the valve input (Δm), sampling the sensor signal provides the process response. This data is collected in a sampling vector (S_v) until a new steady state is reached. A sampling time between one tenth and one fifth of the process time constant is usually recommended, resulting in a Sampling Size (SS) between 25 and 50 samples. The length of the sample vector is directly related to the Prediction Horizon (PH), which is the number of future steps where the process output variable will be predicted. Each component of the sampling vector is transformed by subtracting the final steady state. Each element of this new vector is then divided by Δm. The final component of this new vector (A_v) is the process gain K_P. For the DMC algorithm the vector A_v is used to build the dynamic matrix process A

as follows:

$$A = \begin{bmatrix} A_v & 0 & \dots & \dots & 0 \\ K_P & A_v & 0 & \dots & 0 \\ K_P & K_P & A_v & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ K_P & K_P & \dots & \dots & A_v \end{bmatrix}_{PH \times CH} \quad (1)$$

The number of columns of A in Eq.(1) corresponds to the Control Horizon (CH). For industrial applications only 5 or 10 step moves are investigated by the optimizer [13] [16]. The lower CH is, the slower the controller (less aggressive) will be and vice versa. Once CH is chosen, the Prediction Horizon (PH) is defined as:

$$PH = SS + CH - 1 \quad (2)$$

The dynamic matrix control A Eq.(1) is now used to find the control output vector ΔM. This task is done by the minimization of the residuals R from the predicted error vector E using a least square technique.

$$A\Delta M = E + R \quad (3)$$

The controller output ΔM can be calculated from Eq. (4)

$$\Delta M = \left(A^T A\right)^{-1} A^T E \quad (4)$$

Usually a suppression factor λ is used as a tuning parameter to change the aggressiveness of the controller, in that case the control move is expressed as:

$$\Delta M = \left(A^T A + \lambda^2 I\right)^{-1} A^T E \quad (5)$$

Equation (5) is the DMC standard control law proposed by Cutler and Ramaker [1]. This study proposes to isolate the dynamics process characteristics (process gain K_P, time constant τ, delay time t_o) from the A matrix, in order to take direct actions over their specific changes.

3 A New Approach for DMC Structure

As it was previously mentioned, the DMC control law in Eq.(5) is built upon the assumption of a fixed linear process model. This becomes a limitation in some cases where process are highly nonlinear and therefore very sensitive to disturbances. For highly nonlinear processes, a more convenient way to express the DMC control algorithm could be in a parametric form, as a function of the process parameters: gain, time constant and dead time, and the suppression factor λ [17]:

$$\Delta M = f\left(K_P, \tau, t_o, \lambda\right) \quad (6)$$

Once the effect of each process parameter is isolated from the control law, this algorithm can adapt itself to specific changes in the process gain, and/or process time constant, and/or dead time without the need of additional identification steps. All of this keeping the smoothing role of the suppression factor, and the DMC's original advantages such as its ability to handle multivariable cases and processes with high delay times.

The proposal for a new controller algorithm begins with Eq. (1), where the process gain K_P can be factored out as a common term. The A_v can then be expressed as a function of a vector V whose elements varies from 0 to 1 and contains information about the process time constant and the dead time. The dynamic process matrix becomes equal to:

$$A = K_P \begin{bmatrix} V & 0 & \dots & \dots & 0 \\ 1 & V & 0 & \dots & 0 \\ 1 & 1 & V & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 1 & 1 & \dots & \dots & V \end{bmatrix}_{PH \times CH} = K_P U \quad (7)$$

The DMC control law in Eq.(5) is transformed using this new process dynamic matrix Eq.(7) into a new form called *Parametric Dynamic Matrix Control* law (PDMC).

$$\Delta M = \frac{1}{K_P}\left(U^T U + \lambda^2 I\right)^{-1} U^T E \quad (8)$$

Similarly, when the process dead time changes, those changes can be included directly into the matrix U using the vector V.

$$V = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}_{SS \times 1} = \begin{bmatrix} Zu_{n \times 1} \\ Du_{(SS-n) \times 1} \end{bmatrix}_{SS \times 1} \quad (9)$$

In Eq.(9) Zu is a a vector with zeros which dimensions $n \times 1$ are related to the process dead time, because n represents how many sampling periods T_s correspond to it. The vector Du is composed by the remaining no null elements in vector V. A graphical representation is shown in figure 1. If Eq.(9) is used to build the

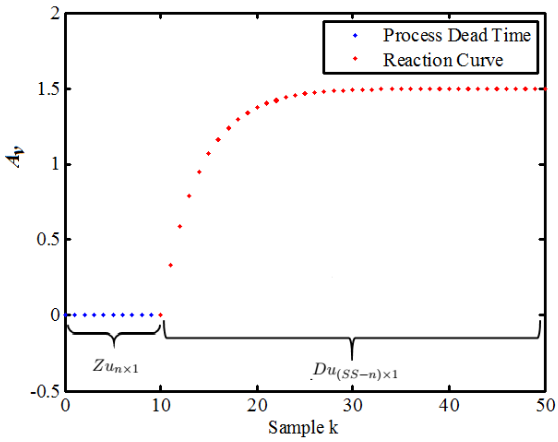

Fig. 1: Discrete Data Contended Inside Vector A_v

process dynamic matrix, this becomes equal to:

$$A = K_P \begin{bmatrix} Zu & 0 & 0 & 0 & \dots & 0 \\ Du & Zu & 0 & 0 & \dots & 0 \\ 1 & Du & Zu & 0 & \dots & 0 \\ 1 & 1 & Du & Zu & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & 1 & 1 & \dots & 1 & Zu \\ 1 & 1 & 1 & \dots & 1 & Du \end{bmatrix}_{PH\times CH} \tag{10}$$

Equation (11) shows that the U matriz is composed of two matrices, the Z and D matrices. The Z matrix is composed by Zu vectors, one in each column of the U matrix; their values are defined by the designer. The D matrix is composed for the remaining elements in the U matrix.

$$A = K_P \begin{bmatrix} Z_{n\times CH} \\ D_{(PH-n)\times CH} \end{bmatrix}_{PH\times CH} \tag{11}$$

To illustrate how these changes will affect the control law, we show here how the term $\left(U^T U\right)^{-1} U^T$ changes if Eq.(11) is included into in the PDMC law Eq.(8) (without the suppression factor to keep it simple):

$$\left(U^T U\right)^{-1} U^T = \left(\left[Z^T_{CH\times n} \ \vdots \ D^T_{CH\times(PH-n)} \right] \begin{bmatrix} Z_{n\times CH} \\ \dots \\ D_{CH\times(PH-n)} \end{bmatrix} \right)^{-1} \times \left[Z^T_{CH\times n} \ \vdots \ D^T_{CH\times(PH-n)} \right] \tag{12}$$

$$\begin{aligned} \left(U^T U\right)^{-1} U^T &= \left(Z^T Z + D^T D\right)^{-1} \left[Z^T \ \vdots \ D^T \right] \\ &= \left[\left(D^T D\right)^{-1} Z^T \ \vdots \ \left(D^T D\right)^{-1} D^T \right] \\ &= \left[Z \ \vdots \ \left(D^T D\right)^{-1} D^T \right] \end{aligned} \tag{13}$$

After some mathematical manipulations and the addition of the suppression factor λ_P the proposed form for the PDMC law Eq.(8) can be written as:

$$\Delta M = \frac{1}{K_P} \left(\left[Z \vdots \left(D^T D\right)^{-1} D^T \right] + \lambda_P^2 I \left[Z^T \vdots D^T \right] \right) E \tag{14}$$

The suppresion factor inside Eq.(14) regulates the controller aggresiveness, and it is calculated as in equation (15).

$$\lambda_P = \frac{\lambda}{K_P} \tag{15}$$

Standard DMC tuning equations for λ [16][3][18] were tested on nonlinear processes in a previous work and gave very aggressive controller responses [19]. For this reason we used the equation proposed by Iglesias [17]:

$$\lambda = 1.631 K_P \left(\frac{t_o}{\tau}\right)^{0.4094} \tag{16}$$

Equation (16) is the final result of a two-stage procedure (factorial experiment plus nonlinear regression analysis) designed to measure the effect of changes in the process variables due to the controller aggresiveness. To measure the controller agresiveness, Iglesias [17] defined a cost function, called Performance Parameter (PP). The cost function combines the Integral of the Absolute Value of the Error (IAE) and the Integral of the Absolute Value of the Change in Manipulated Valve signal (IMV). This cost function is expressed as:

$$PP = \int_0^\infty |e(t)|dt + \Gamma \int_0^\infty |m_{ss} - m(t)|dt \tag{17}$$

The PP depends on process parameters such as K_P, τ, $\frac{t_o}{\tau}$, $\frac{T_s}{\tau}$ and Γ (a weighted parameter in the cost function). A 3^5 factorial experiment was performed to study their effect over PP. Only main effects and second order interactions were considered. The effect of each variable and their possible interactions were tested using the optimal λ values (those that minimize the PP) for each one of the experiments. All experiments were performed on a FOPDT system in SISO control loop under set point changes

$(\pm 10\% TransmitterOutput)$ at different times.
Significant factors $(p < 0.05)$ were the primary variables and their interactions $K_P\tau$, $K_P\frac{t_o}{\tau}$, $\tau\frac{t_o}{\tau}$ and $\frac{t_o}{\tau}\frac{T_s}{\tau}$. The optimal suppression factors (from each one of the signicant variables and their combinations) were fit to different nonlinear tuning equations and the best equation found is presented in Eq.(16) [17] [19].
Once the PDMCr agressiveness was handled, the next step was to find how the changes in the process time constant could be compensated in the PDMC algorithm. Due to the complex dynamic behavior of real processes, there is not an easy way to isolate the information concerning to the process time constant, as it was previously done for the process gain and the dead time. The matrix D in Eq.(14) contains the process dynamic information after the dead time. Therefore, the process time constant is inside this matrix. A nonlinear correction to adjust changes in the process time constant is proposed:

$$D_{adj} = D\left(\frac{1-\exp\dfrac{-k_iT_s}{\tau_{new}}}{1-\exp\dfrac{-k_iT_s}{\tau_{prev}}}\right) \qquad (18)$$

The terms inside Eq.(18) are k_i, the i^{th} term in matrix D row; T_s, the sampling time used to record process data; τ_{new} is the new process time constant; τ_{prev} is the new process time constant. The correction factor is a ratio of two exponential terms with the typical First Order Plus Dead Time (FOPDT) form. The numerator is a function of the new process time constant, whereas the denominator is a function of the previous process time constant value. The exponential form of the time constant correction was chosen based on the good agreement between empirical models and the dynamic behavior of real processes. The effectiveness of our PDMCr is restricted to those processes able to be modeled as FOPDT processes. The idea was to adjust the i^{th} term in the D matrix using its corresponding correction factor as expressed in Eq.(18). The process time constant correction completes the PDMCr, and its control law is then expressed as:

$$\Delta M = \frac{1}{K_P}\left(\left[Z\vdots\left(D_{adj}^TD_{adj}+\lambda_P^2I\right)^{-1}D_{adj}^T\right]\right)_{CH\times PH}\times E \qquad (19)$$

Eq.(19) is the parametric law of the Dynamic Matrix Controller. Its mathematical form offers some advantages when it is neccesary to update the process model after disturbances. If the process gain changes, the change is included into the PDMC model using the factors $\frac{1}{K_P}$ and λ_P. If the process dead time changes, the change is included into the PDMC model, Eq. (14) changing the number of columns n of matrix Z inside the matrix D. If the process time constant τ changes, the D_{adj} matrix is adjusted using the correction factor. All the adjustments can be done with no need to recalculate the Process Dynamic Matrix A. This could save time because the controller algorithm does not need a new identification procedure after disturbances.

4 Definitions of Function Spaces and Notation

To use the PDMCr in an efficient way (adjust the control system to compensate for nonlinearities), it is necessary to detect and quantify changes in process parameters on-line, as soon as they happen, and transfer these changes to the PDMCr and tuning equation. There are several ways to do this, but one of the most reliable procedures is based on the concept of modeling error [20][21]. Modeling error, *em*, is defined as the difference between the actual process output of $c(t)$, and the controller predictive value $c_P(t)$ from the embedded model inside the controller. This concept applies for all MBC controllers.
In a multivariable model there are several ways to determine the modeling errors. For example, *em* can be calculated using the time to reach the steady-state, the ratio of maximum peak to minimum peak, the damping ratio, the decay ratio, etc. In this work 19 different indicators were studied and they are presented in Table 1. These indicators, defined as Modeling Error Indexes (MEI), were statistically related to the changes in the process parameters reported in Table 2. Values for the Modeling Error Indexes were measured from the process response after each one of the changes in Table 2 was applied.
A total of 61236 simulations were performed to evaluate the 19 indexes in Table 1. Just a set of 15 MEIs showed statistically significant correlations with the changes in the process parameters $(p < 0.05)$. Multiple linear regression analyses were applied to these 15 indicators using Equation (20) [17]. Just three of the MEIs, Time for Maximum Peak/τ, Time for Minimum Peak/τ and 10^{th} Correlation Coefficient of modeling error, achieved statistically significant results and showed the maximum changes in their values. The multilinear model coefficients for Eq.(20)

are shown in Table 3.

$$MEI = \beta_1 + \beta_2\tau + \beta_3\frac{t_o}{\tau} + \beta_4\Delta K_P + \beta_5\Delta\tau + \beta_6\Delta t_o + \quad (20)$$

$$\beta_7\tau\frac{t_o}{\tau} + \beta_8\tau\Delta K_P + \beta_9\tau\Delta\tau + \beta_{10}\tau t_o$$

The optimal MEI were included in a Fuzzy Inference System (FIS) to create a Supervisor Module for predicting on-line changes in process parameters and readjusting the process model, as well as the suppression factor in the PDMCr. The Supervisor Module was designed to work only when a set point change is detected. This design could seem peculiar because set points are commonly constant. However the idea behind this design is to use the set point change as a tool to test the system for changes in process parameters that could cause controller aging. From a practical point of view this mean that when a plant operator detects an inadequate control loop response rejecting disturbances, the operator would perform a set point change in one direction and later the same change in the opposite direction to return back to the initial conditions. In this way the supervisor has two opportunities to evaluate the process parameter and adjust the PDMCr to the new conditions.

The supervisor records the *em* values until the system reaches the new set point. The data is used to determine the Time for Maximum Peak/τ (MEI_1), Time for Minimum Peak/τ (MEI_2) and 10^{th} Correlation Coefficient of modeling error (MEI_3). These values are then used to determine the changes in the process parameters ΔK_P, $\Delta\tau$ and Δt_o by the optimization of the cost function *CF* shown in Equation (21),

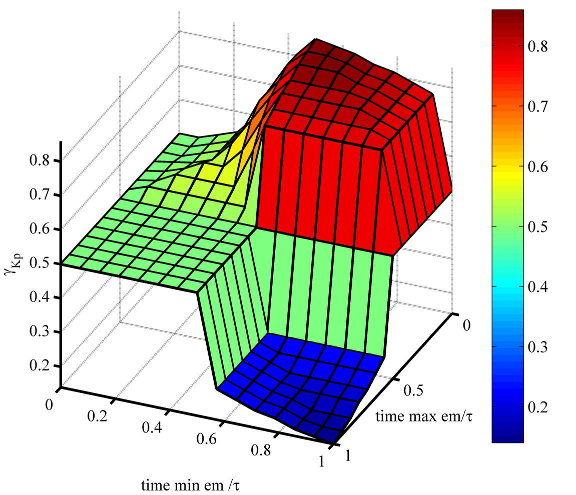

Fig. 2: Nonlinear relationship among two of the MEIs and $\gamma_{\Delta K_P}$

Table 1: Modeling Error Indexes used to predict Process Parameters Changes

Modeling Error Indicator	Calculation Form
2nd , 6th and 10th Correlation Coefficient	$r_k = \frac{\sum_{i=i}^{N-k}(Y_i-\bar{Y})(Y_{i+k}-\bar{Y})}{\sum_{i=1}^{N}(Y_i-\bar{Y})^2}$
Maximum *em*/ $\Delta Cset$	$\frac{Max(em)}{\Delta Cset}$
Maximum *em*/Minimum *em*	$\frac{Max(em)}{Min(em)}$
Minimum *em*/ $\Delta Cset$	$\frac{Min(em)}{\Delta Cset}$
T	$2(time\|_{Maximum(em)} - time\|_{Minimum(em)})$
Ω	$\frac{2\pi}{T}$
Time for Maximum *em*/ τ	$\frac{time\|_{Maximum(em)}}{\tau}$
Time for Minimum *em*/ τ	$\frac{time\|_{Minimum(em)}}{\tau}$
Stabilization time between $\pm 0.1\% TO/\tau$	$\frac{time\|_{\|em\| \leq 0.1\%}}{\tau}$
Difference time for Maximum and time for Minimum/ τ	$\frac{time\|_{Maximum(em)} - time\|_{Minimum(em)}}{\tau}$
Ratio Absolute Minimum/Abs Maximum	$\frac{\|Min(em)\|}{\|Max(em)\|}$
Maximum peak/ $\Delta Cset$	$\frac{\|Max(em)\|}{\Delta Cset}$
Minimum peak/ $\Delta Cset$	$\frac{\|Min(em)\|}{\Delta Cset}$
Time for Maximum Peak/ τ	$\frac{time\|_{\|Max(em)\|}}{\tau}$
Time for Minimum Peak/ τ	$\frac{time\|_{\|Min(em)\|}}{\tau}$
Decay ratio	$\frac{\text{second peak}(em)}{\text{first peak}(em)}$
Damping ratio	$\frac{\log\left(\frac{\text{second peak}(em)}{\text{first peak}(em)}\right)}{\sqrt{4\pi^2 + \log\left(\frac{\text{second peak}(em)}{\text{first peak}(em)}\right)^2}}$
Ratio Minimum *em*/ Maximum *em*	$\frac{Min(em)}{Max(em)}$
Time between peaks/ τ	$\frac{time\|_{\text{second peak}(em)} - time\|_{\text{first peak}(em)}}{\tau}$

Table 2: Factors and Levels Used to Record Modeling Error and Develop the Regression Equations

$\Delta C_{set}\,(\%TO)$	$K_P\left(\frac{\%TO}{\%CO}\right)$	τ	$\frac{t_o}{\tau}$	ΔK_P	$\Delta\tau$	Δt_o
-15	0.5	1	0.2	-40	-40	-15
-7.5	1.5	3	0.6	-30	-30	-10
7.5	2.5	5	1	-20	-20	-5
15				-10	-10	0
				0	0	5
				10	10	10
				20	20	15
				30	30	
				40	40	

Table 3: Parameters for Regression Equations Used in Supervisor Module

β	Time for Maximum Peak/ τ	Time for Minimum Peak/ τ	10^{th} Corr. Coeff. of *em*
β_1	12.5494	7.96350	-0.64086
β_2	-2.3297	-1.20200	-0.00542
β_3	0.789060	5.31050	0.26446
β_4	0.003125	0.19760	0.01052
β_5	-0.003750	-0.03070	0.00154
β_6	-0.033750	0.14062	0.05056
β_7	0.210940	0.18164	0.08960
β_8	0.210940	0.00546	0.000924
β_9	-0.0003125	-0.04484	0.000354
β_{10}	0.037500	-0.00312	-0.00409

where F_1, F_2 and F_3 are the appropriate regression equations corresponding to each MEI. All of them have the same form that Equation (20) with the parameters defined on Table 3. The results for ΔK_P, $\Delta\tau$ and Δt_o are expressed as a percentage of change in the respective parameter. Then, the new process parameters are estimated using the following expressions, where γ is a correction factor with value between 0 and 1.

$$\begin{aligned} CF = & |MEI_1calc - F_1(\beta, \Delta K_P, \Delta\tau\Delta t_o)| \\ & + |MEI_2calc - F_2(\beta, \Delta K_P, \Delta\tau\Delta t_o)| \\ & + |MEI_3calc - F_3(\beta, \Delta K_P, \Delta\tau\Delta t_o)| \end{aligned} \quad (21)$$

$$K_{Padj} = K_P\left(1 + \frac{\gamma_{\Delta K_P}\Delta K_P}{100}\right) \quad (22)$$

$$\tau_{adj} = \tau\left(1 + \frac{\gamma_{\Delta\tau}\Delta\tau}{100}\right) \quad (23)$$

$$t_{oadj} = t_o\left(1 + \frac{\gamma_{\Delta to}\Delta t_o}{100}\right) \quad (24)$$

There is an uncertainty in the β values due to the inevitable failures in the goodness of fit. The idea behind the γ factor is improving the process parameter prediction using Fuzzy Rules. These rules take advantage of the experience gained by the authors as control engineers, after running more than 60000 simulations for different process changes. Every MEI value is fuzzified using three membership functions: Zero (Z), Small (S) and Large (L). Once the fuzzy rules are evaluated for each input, the Fuzzy inference system gives a set of fuzzy values as a result. For example, if the Time for Maximum Peak/τ is Large, the Time for Minimum Peak/τ is Large and the 10^{th} Correlation Coefficient of modeling error is small, then the $\gamma_{\Delta Kp}$ is small. The final defuzzification operation to transform fuzzy values of γ into crisp values is performed using the centroid method [17].

Figure 2 shows the kind of nonlinear relationship among MEIs and $\gamma_{\Delta Kp}$ that can be obtained evaluating the fuzzy rules. It would be very complex to express mathematically the relationship among the variables, but using 12 Fuzzy Logic rules is easy to do so. Once the initial process parameters are corrected based on the information provided by the modeling error, the adjusted process parameters are sent to the PDMCr to adjust the control law and determine the best tuning parameter. Figure 3 shows a schematic representation of the proposed approach.

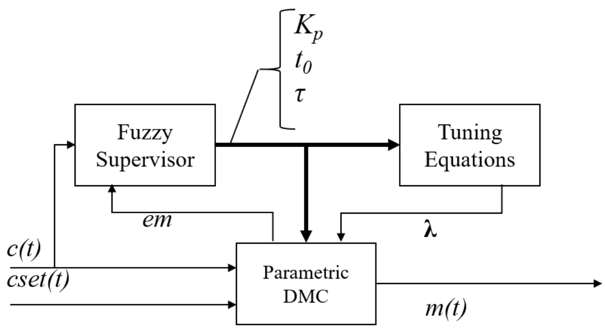

Fig. 3: Schematic representation of the Parametric DMC

5 Simulation Results

The process model uncertainty is one the most important limitations of all MPCrs, including those based on the DMC algorithm. Controllers work as well as the model fits the real process behavior. If non-representative data from the process dynamic is fed to the controller at the identification stage, there will surely be time, resources and money losses involved on its industrial implementation [2]. Once the controllers have been implemented, their embedded model cannot be adjusted and validated to varying process conditions, and therefore suffer significant deterioration, leading controllers to unsuccessful performances [2].

A set of tests were performed to evaluate the PDMCr. The first test was designed to use a known FOPDT system as the process in the control loop. A sequential set of set point changes were induced to the control loop at different times. Simultaneously, the process parameters were modified by $+25\%$, in order to emulate the nonlinear behavior of the process. A disturbance was fed to the process at $400s$. Figure 4 shows the results when standard DMCr and PDMCr were used. The standard DMCr could not compensate for the changes in FOPDT parameters and became oscillatory. The PDMCr using the Fuzzy Supervisor Module detected and estimated the process parameters changes,then compensated for them, allowing a stable process control. Figure 5 shows the comparison of process parameters estimation performed by the Fuzzy Supervisor Module during the test presented in Figure 4. The figure 5 shows that the parameters are updated after every set point change is detected.The time to update the process parameter varies and it depends how long takes to the modeling error to settle down. The process parameters predicted by the Fuzzy Supervisor are accurate enough to guide the PDMCr and adapt its response to the changing process condition.

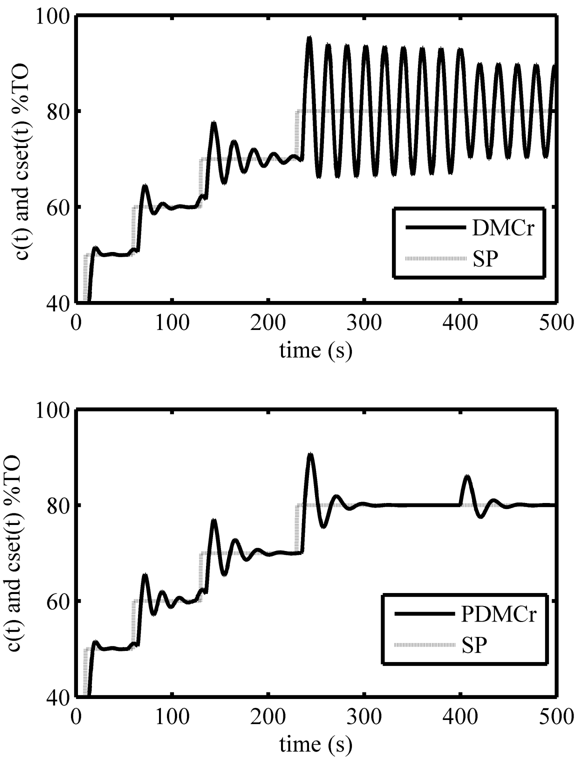

Fig. 4: Comparison of standard DMCr and PDMCr performances applied to a FOPDT process model

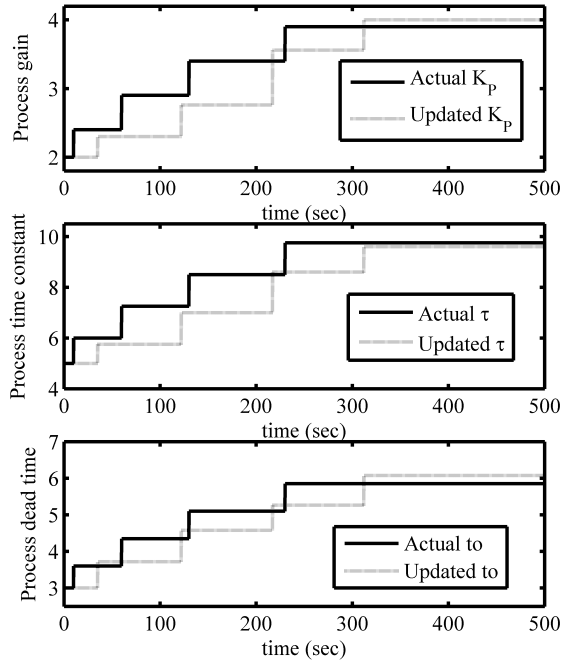

Fig. 5: Comparison among actual process parameters and estimated parameters by the Fuzzy Supervisor Module applied to a FOPDT process model

As a second test, the PDMCr and standard DMCr were incorporated to control the mixing process described by Iglesias et. al.[19][22][23] (see Figure 6). Figure 7 shows the comparison when facing consecutive set point changes. Figure 7 shows that every time the set point was decreased by 5%, the standard DMCr became more and more oscillatory until finally reached a completely oscillatory behavior. This was a consequence of the nonlinear characteristic in the mixing process. On the contrary, the PDMCr showed a smooth response and it was able to track the set point changes during the test. It also rejected a cold temperature increment used as disturbance at time $700s$. Every time a set point change was detected by the Fuzzy Supervisor, the model parameters were estimated and adjusted to adapt the controller to the new process conditions. When the disturbances affected the process, the PDMC tracked the set point

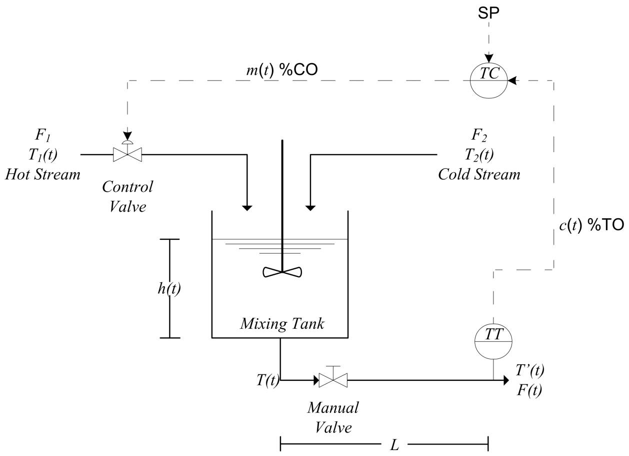

Fig. 6: Schematic representation of a mixing tank

avoiding large deviation. The two controllers were

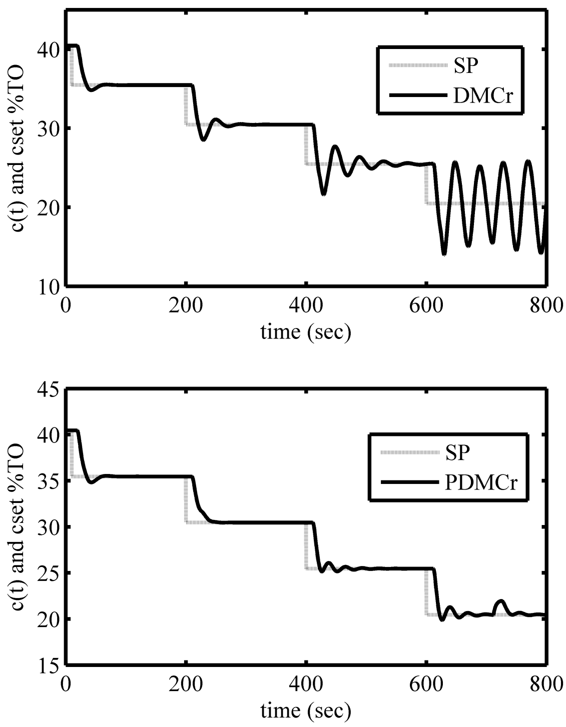

Fig. 7: Performance comparison between the DMCr and the PDMCr for the mixing tank process

also tested using the neutralization reactor described by Iglesias et. al.[19] (Fig. 8). A series of consecutive set point changes were induced, and a reduction of 15% in acid stream concentration was used as disturbance; figure 9 shows the results. PDMCr tracked the set point with less overshoot that the standard DMCr, for both set point changes and disturbance rejection. The IAE values were 4284 for standard DMCr and

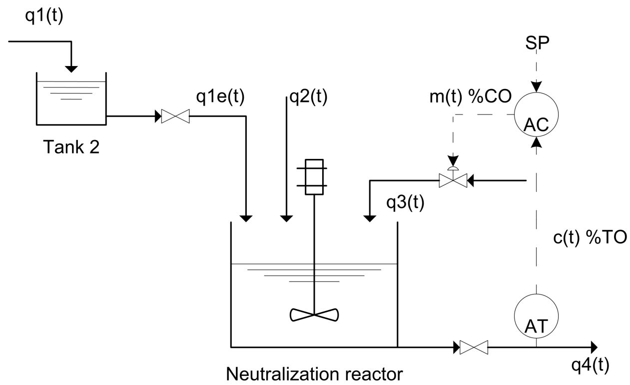

Fig. 8: Schematic Representation for a neutralization reactor

3214 for PDMCr, a difference of about 23%. Figure

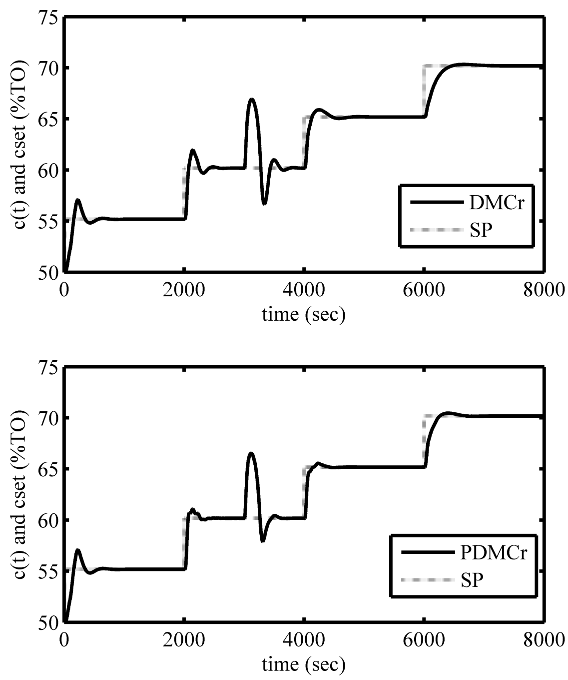

Fig. 9: Performance comparison between standard DMCr and PDMCr for the neutralization reactor

10 shows another test performed using the neutralization reactor. Initially a reduction on acid stream affects the process as disturbance; later, two consecutive set point changes in opposite directions (reaching the initial value again), are induced into the control loop, to allow the PDMCr estimate and update the process parameters (Fig. 10 a.). Later two consecutives changes in acid stream affect again to the process. Figure 10 shows that PDMCr tracked set point with less deviation than the standard DMCr. The total IAE values were 8080 for standard DMCr and 6717

for PDMCr; a reduction about 17%. The last two disturbances were compensated in less time and with less overshoot when PDMCr was used. This test could represent the way the control engineer should use the consecutive set point changes to allow the PDMCr adapt to varying operating conditions.

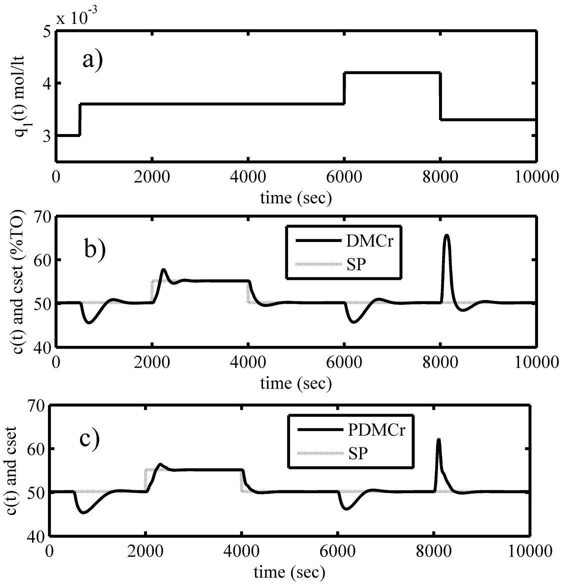

Fig. 10: Neutralization reactor test for disturbances Rejection: a.Changes induced on the acid stream b.DMCr response c.PDMCr response

6 Effect of noise

To test the effect of noise on the DMCr and PDMCr performance, the mixing process describe in Fig.6 was modified to include a noisy signal in cold stream $F2$. The noise used had an ARMA$(1,1)$ structure: $Zn = \phi_1 Zn - 1 + a_n - \theta_1 an - 1$, $(\phi_1 = 0.6, \theta_1 = 0.3)$. Two different values of variance were used to generate the noise: $\sigma_2 a = 0.02$ y $\sigma_2 a = 0.03$. Figure11 shows cold stream signal affected by the noise. Figure 12 shows the effect of noise on the DMCr and PDMCr performances. The same test shown in Figure 7 is now used with the noisy cold water flow shown in Figure 11. Figures 12(a) and (b) compare standard DMCr and PDMCr when noise has a variance equal to 0.02, whereas Figures 12(c) and (d) show the same test but this time with variance 0.03. The test shows that the PDMCr was sensitive to the presence of noise as it was expected for controllers of a discrete nature. A slight variation on noise variance could cause oscillatory behavior on the PDMCr, see Figure 12(d). However, compared with the standard DMCr,

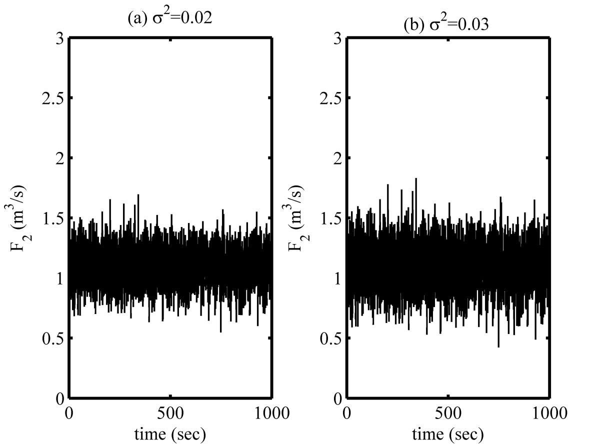

Fig. 11: Cold Stream $F2$ Affected by Noise With Structure ARMA$(1,1)$

the PDMCr showed more tolerance to the noise presence, and kept a stable behavior for longer times.

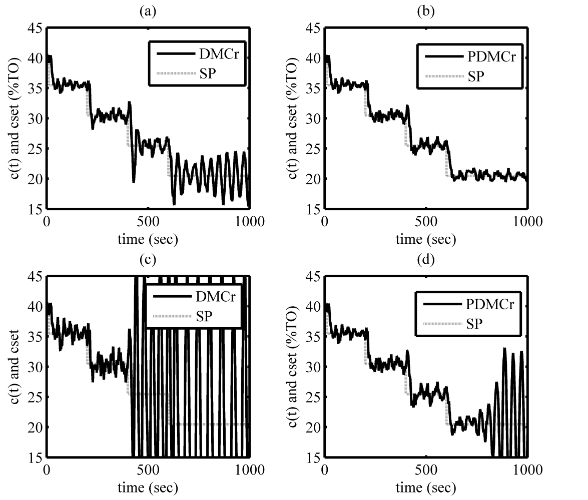

Fig. 12: Noise Effect on DMCr and PDMCr performance when applied to the mixing tank

7 Conclusion

The proposed PDMCr was tested under noisy input signals and varying process dynamics, common characteristics of real industrial processes. The PDMCr was able to overcome problems with a better performance that the standard DMCr, controlling nonlinear processes. The PDMCr also showed more tolerance to continuous noisy input signals, keeping a stable behavior for longer times as compared to the DMCr.
The PDMCr tracked set point changes with less deviation compared to the standard DMCr, and compensated disturbances in less time and with less over-

shoot. The PDMCr kept its stability under conditions where the DMCr was completely unstable. When both performances were similar to each other, the IAE values for PDMCr were up to 23% lower than for the DMCr.
The PDMCr-Fuzzy Supervisor Module set presented in this study exerted a continuous supervisory role on the process model in order to avoid its aging. The supervisory module kept the model updated using only three MEI values coming from closed-loop set point change responses. This was an advantage compared to the conventional procedures, because it was not necessary to do a new open-loop step-response model identification. This could save time and effort during its implementation.
Future studies should be focused on the adaptation and implementation of the PDMCr to control MIMO systems.

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References

[1] C. Cutler and B. Ramaker, Dynamic Matrix Control- A Computer Control Algorithm, in *Proceedings of the 86th National Meeting of the American Institute of Chemical Engineering*, 1979, pp. WP5–B.

[2] S. Qin and T. A. Badgwell, A survey of industrial model predictive control technology, *Control. Eng. Pract.* 11, 7, 2003 , pp. 733 – 764.

[3] R. Shridhar and D. J. Cooper, A Tuning Strategy for Unconstrained SISO Model Predictive Control, *Ind. Chem. Eng. Res.* 36, 3, 1997 , pp. 729–746.

[4] A. Yousef Ali, Neural Network Predictive Control based power system stabilizer, *J. Eng. Sci.* 39, 6, 2011 , pp. 1431–1447.

[5] F. Islam Khan and M. Shoukat Choudhury, Comparative Study of Different Supervisory Control Structures, in *Proceedings of the 5th International Symposium on Advanced Control of Industrial Processes (ADCONIP 2014)*, 2014, pp. 455–460.

[6] C. M. Chang, S. J. Wang and S. W. Yu, Improved DMC design for nonlinear process control, *AIChE Journal* 38, 4, 1992 , pp. 607–610.

[7] A. Georgiou, C. Georgakis and W. L. Luyben, Nonlinear dynamic matrix control for high-purity distillation columns, *AIChE J.* 34, 8, 1988 , pp. 1287–1298.

[8] K. McDonald and T. McAvoy, Application of Dynamic Matrix Control to Moderate and High-Purity Distillation Towers, *Ind. Eng. Chem. Res.* 26, 5, 1987 , pp. 1011–1018.

[9] B. S. Dayal and J. F. MacGregor, Recursive exponentially weighted PLS and its applications to adaptive control and prediction, *J. Process Control* 7, 3, 1997 , pp. 169 – 179.

[10] P. Lundstrom, J. Lee, M. Morari and S. Skogestad, Limitations of dynamic matrix control, *Comput. Chem. Eng.* 19, 4, 1995 , pp. 409 – 421.

[11] D. Jeronimo and A. Coehlo, Minimum Realization Tuning Strategy for Dynamic Matrix Control, in *Preprints of the 19th World Congress The International Federation of Automatic Control*, 2014, pp. 1314–1319.

[12] D. D. Brengel and W. Seider, A Multi-Step Nonlinear Predictive Controller - An Introduction, in *American Control Conference, 1989*, 1989, pp. 1100–1101.

[13] T. Peterson, E. Hernández, Y. Arkun and F. Schork, A nonlinear DMC algorithm and its application to a semibatch polymerization reactor, *Chem. Eng. Sci.* 47, 4, 1992 , pp. 737 – 753.

[14] B. Aufderheide and B. W. Bequette, Extension of dynamic matrix control to multiple models, *Comput. Chem. Eng.* 27, 8–9, 2003 , pp. 1079–1096, in 2nd Pan American Workshop in Process Systems Engineering.

[15] M. Sanjuan, Control Dinámico Matricial: Fundamentos y Aplicaciones, *Rev. Ing. Des.* 1, 3-4, 1999 , pp. 85–92.

[16] R. Shridhar and D. J. Cooper, Selection of the Move Suppression Coefficients in Tuning Dynamic Matrix Control, in *Proceedings of the American Control Conference*, 1997, pp. 729–733.

[17] E. Iglesias, *Using Fuzzy Logic to Enhance Control Performance of Sliding Mode Control and Dynamic Matrix Control*, Doctoral Dissertation, University of South Florida, Tampa, FL, USA, 2006.

[18] D. Dougherty and D. J. Cooper, Tuning Guidelines of a Dynamic Matrix Controller for Integrating (Non-Self-Regulating) Processes, *Ind. Chem. Eng. Res.* 42, 8, 2003 , pp. 1739–1752.

[19] E. Iglesias, M. Sanjuan and C. Smith, Tuning Equation for Dynamic Matrix Control in SISO Loops, *Rev. Ing. Des.* 19, 1-2, 2006 , pp. 88–100.

[20] J. Barreto and M. Laborde, *Controlador DMC Escalable para procesos SISO de Ganancia No Lineal*, Thesis for Bachellor Degree, Universidad del Norte,Barranquilla, Colombia, 2003.

[21] Y. García, *Fuzzy IMC for Nonlinear Processes*, Doctoral Dissertation, University of South Florida, Tampa, FL, USA, 2006.

[22] E. Iglesias, Y. García, M. Sanjuan and O. Camacho, Fuzzy Surfaced-Based Sliding Mode Control, *ISA T.* 43, 2007 , pp. 73–83.

[23] O. Camacho, E. Iglesias, L. Valverde and F. Rivas, An approach to Enhance Dynamic Matrix Control Performance, *Int. J. Math. Comput. Sim.* 2, 1, 2008 , pp. 81–88.