An Approach to Enhance Dynamic Matrix Control Performance.

Oscar Camacho, Edinzo Iglesias, Luís Valverde, Francklin Rivas

Abstract - This paper shows a set of tuning equations, based on the sliding surface response to forecast changes in the parameters of the process, which are used to enhance and to tune the predictive dynamic matrix controller parameters. The controller presents a fixed algorithm and its tuning parameter equations were developed relating the characteristics values of the sliding surface and the characteristic parameters of the first order plus deadtime model. Simulations on a blended tank with variable level that presents non linear behavior are considered.

Key-Words- Dynamic Matrix Controller, Sliding Mode Control, tuning parameters, robustness**.**

I. INTRODUCTION

Time delays or dead times appear commonly in the problem of control of different systems, such as chemical and manufacturing processes. Time delays can be originated by several situations like transportation lags, the effects of recycle loops on systems or by the approximation of higher order systems by lower dimension ones. Also time delay systems can be originated naturally as a consequence of the modeling process, as in the case of chemical processes [1].

Manuscript received February 1, 2008; Revised version received April 18, 2008.

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Several controllers have been developed for stable processes. When the time delay is located at the input (or output) of the system, a commonly used strategy is to eliminate the effect of the delayed signal to obtain a free delay system. This method works only in the case of sufficiently small delay. An alternative approach consists in the approximation of the delay term by the consideration of a Taylor series expansion or the use of Padé approximations via a rational transfer function. In the case of linear systems, the classical strategy is to use the well-known Smith predictor compensator (SPC) [1], which provides a future estimation of the output signal that can be used in the design of a control feedback

The main limitation of the original SPC is related to the class of systems for which it could be used, since it is restricted to stable plants. Later on this research field, Model Predictive Control (MPC) [2] begins at the end of the 70. These kinds of controllers use a dynamical model of the process, to predict the effect of the future controller actions on the system output.

MPC includes a series of algorithms among which the Dynamic Matrix Controller (DMC) is one of the most important ones. DMC were developed for Cutler and Ramaker [3], and it has been used in the industrial world, mainly in the petrochemical industries. DMC is a linear control technique where the process is represented by a first order plus deadtime (FOPDT) model. The model response to an unit step change is used to predict the future response of the dependent variables and formulates a series of control actions for all the independent variables. The actions are selected to minimize the error of the process on the time horizon.

DMC presents some advantages, they can be mentioned as follows: Intuitive and simple tuning, it can be used for systems with complex dynamic, the multivariable case is easily implemented, it is favorable for systems with long delays and the

inclusion of restrictions is simple for controller's design. DMC also presents inconvenience such as the necessity of an appropriate process model.
Sliding Mode Control (SMC) is a type of Variable Structure Control (VSC) that was developed in the Soviet Union [4, 5]. The techniques of SMC have been employees in diverse systems; robustness is one of its principal advantages in the control of non linear and time variant systems and systems with uncertainties. However, also presents disadvantages such as when the delay is too big the performance of the system decreases.

This paper tries to take advantages of both techniques, from the DMC the predictive advantages and from the SMC the robustness attributes.

The paper is divided as follows: Section II presents a brief description of the DMC and a SMC brief summary; section III shows the methodology, section IV presents the results and finally in section V the conclusions are presented.

II. CONTROLLERS.

A. The Parametric DMC

The conventional DMC was designed as a strategy to work with linear systems, or processes with small deviations from its operating point. Unfortunately, the industrial processes are complex with nonlinear characteristics. Several articles report that when the DMC is used in non linear processes the process response can go from very slow to oscillatory [6], [7], [8] and [9]. For this reason, several proposals to modify the algorithm DMC and to improve its performance for non linear processes have been proposed. One of these approaches was developed in 2006 by Iglesias and Smith [10], where they proposed the structure of the Parametric DMC called PDMCr. The new structure was designed to include variable terms whose values can change as necessary adaptation of process variations.

The control law proposed by Cutler and Ramaker for the conventional DMC is expressed as follows:

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

Where:

A: Is the dynamic matrix

ΔM : Is the output vector

λ : Is the suppression factor

I : Is the identity matrix

In the PDMCr structure, equation (1) can be expressed as function of the characteristic parameters of the process. For the case of an FOPDT model are gain, time constant, dead time besides the suppression factor, therefore, the new model can be represented as follows:

$$\Delta M = f\left(K_p, \tau, t_0, \lambda\right) \cdot E \qquad (2)$$

Equation (2) has the advantage of including the effect of the process parameters in the control law. Therefore, Eq. (2) can be adjusted taking into account changes in process parameters. As mentioned above, this control law was proposed in 2006 by Iglesias and Smith as:

$$\Delta M = \frac{1}{K_p}\left[Z_{CHxn} \;\vdots\; \left[\left(Dadj^T \cdot Dadj + \lambda_P^2 I\right)^{-1} Dadj^T\right]_{CHx(PH-n)}\right] \cdot E$$

(3)

Where

$$Dadj = D \cdot \left(\frac{1-\exp\left(-k_i \cdot Ts/\tau_{nuevo}\right)}{1-\exp\left(-k_i \cdot Ts/\tau_{prev}\right)}\right) \quad (4)$$

Where:

k_i is the i-th term in the D row, Ts is the sampling time, τ_{nuevo} is the new time constant of the process, τ_{prev} is the old time constant D is the transient information after dead time. CH is the control horizon, PH is the prediction horizon, Z is a zeros vector, I is the identity matrix, n represents the periods of sampling.

B. Sliding Mode Control.

Sliding mode control (SMC) [4], [11] is well known for its robustness to modeling errors, insensitivity to parameter variations and disturbances, which are expected in practice. It is the property of the SMC that made it useful for many successful practical applications, [12]. There are two parts in the SMC, namely the reaching part and the sliding mode part. In the reaching stage, the system state is derived onto a specified and user chosen surface, which is called sliding surface, in a finite time. Once in the sliding mode, the system dynamics are strictly determined by the dynamics of the sliding surface and therefore the closed loop system becomes insensitive to parameter changes and disturbances [11]. However, no such insensitivity to parameter variations and disturbances can be possessed during the reaching phase. For that reason, to guarantee a good closed loop system response, the control system should be designed in such a way that the initial reaching phase is as short as possible [11].

To design a SMC controller, the first step is choosing the sliding surface that is usually formulated as a linear function of the system states. The proposed sliding equation is composed of the reference signal, the model output, and the modeling error. Therefore, *s(t)* can be represented

$$S(t) = \mathrm{f}\left(\mathrm{R(t), ym(t), e_m}(t)\right) \tag{5}$$

where *R(t)* is the reference, *ym(t)* is the model output, $e_m(t)$ is the modeling error.

Filippov's construction of the equivalent dynamics is the method normally used to generate the equivalent sliding mode control law [5]. It consists of satisfying the following sliding condition

$$\frac{dS(t)}{dt} = 0 \tag{6}$$

And substituting it into the system dynamic equations, the control law is thereby obtained.

To design the reaching mode control law, the signum function of *s(t)* affected by a constant gain can be used [5,11]. However, this produces the undesirable effect of chattering, normally not tolerated by the actuators. A more appropriate solution is to use the sigmoid-like function, instead of the signum one, to smooth the discontinuity and to obtain a continuous approximation to the surface behavior and avoid chattering [4,5,11] in the control signal when the surface is (pseudo)reached. In a general way, let us propose a general discontinuous control part.

$$U_D(t) = K_D \Psi(t) \tag{7}$$

Where K_D is the tuning parameter responsible for the speed with which the sliding surface is reached, and $\Psi(t)$ is a nonlinear function of *s(t)*.

Then, the complete SMCr can be represented as follows

$$U(t) = \left(\frac{t_0 \tau}{K}\right)\left[\frac{X(t)}{t_0 \tau} + \lambda_0 e(t)\right] + K_D \frac{S(t)}{|S(t)| + \delta}$$

(8a)

with

$$S(t) = sign(K)\left[-\frac{dX(t)}{dt} + \lambda_1 e(t) + \lambda_0 \int_0^t e(t)dt\right]$$

(8b)

Equations 8a and 8b constitute the controller equations to be used. These equations present advantages from process control point of view, first they have a fixed structure depending on the λ's parameters and the characteristic parameters of the FOPDT model, and second the action of the controller is considered in the sliding surface equation, by including the term *sign*(*K*), in Eq. 18b. Note, that *sign*(*K*) only depends on the static gain, therefore it never switches. From an industrial application perspective, Eq. 8b represents a PID algorithm [5].

To complete the SMCr, it is necessary to have a set of tuning equations. For the tuning equations as first estimates, using the Nelder-Mead searching algorithm [5], the following equations were obtained [5].

- For the continuous part of the controller and the sliding surface

$$\lambda_1 = \frac{t_0 + \tau}{t_0 \tau} \quad [=] \quad [\text{time}]^{-1} \tag{9a}$$

$$\lambda_0 = \frac{1}{4}\left(\frac{t_0 + \tau}{t_0 \tau}\right)^2 \quad [=] \quad [\text{time}]^{-2} \tag{9b}$$

- For the discontinuous part of the controller

$$K_D = \frac{0.51}{|K|}\left(\frac{\tau}{t_0}\right)^{0.76} \quad [=] \quad [\text{fraction CO}] \tag{9c}$$

$$\delta = 0.68 + 0.12|K|K_D \lambda_1 [=] \quad [\text{fraction TO/time}]$$

(9d)

Eqs. 9c and 9d are used when the signals from the transmitter and controller are in fractions (0 to 1). Sometimes, the control systems work in percentages that are; the signals are in % (0 to 100) of range. In these cases the values of K_D and δ are multiplied by 100.

III. METHODOLOGY.

To develop the new tuning equations a factorial experiment was designed, and an analysis of variance (ANOVA) was performed to determine the variables that have a significant effect on the optimal suppression factor λ. The experiment consisted in modeling a general process as a first-order-plus dead time (FOPDT) and determine, using constrained optimization, the best λ value to minimize a cost function. The FOPDT model contains three parameters, process gain, *Kp*, time constant, τ, and dead time t_o.

Therefore, the proposed tuning equations set, were obtained from experiments based on FOPDT models, where each one of the parameters were varied in 10%, 30%, 50% as are shown in Table 1. A total of 3^6 simulations were performed.

Table1. Models used for the experiment

Kp	τ	t_0/τ	ΔKp		
			10%	30%	50%
0.5	5	0.5	0.05	0.15	0.25
1.5	10	1.0	0.15	0.45	0.75
2.5	15	1.5	0.25	0.75	1.25
Kp	τ	t_0/τ	$\Delta\tau$		
0.5	1.5	2.5	0.5	1.5	2.5
1.0	3.0	5.0	1.0	3.0	5.0
1.5	4.5	7.5	1.5	4.5	7.5
Kp	τ	t_0/τ	$\Delta t_0/\tau$		
0.05	0.15	0.25	0.05	0.15	0.25
0.10	0.30	0.50	0.10	0.30	0.50
0.15	0.45	0.75	0.15	0.45	0.75

The purpose of this conducted test is to observe if changes in the process parameters can induce changes in the sliding surface. Fig. 1 shows one of the tests.

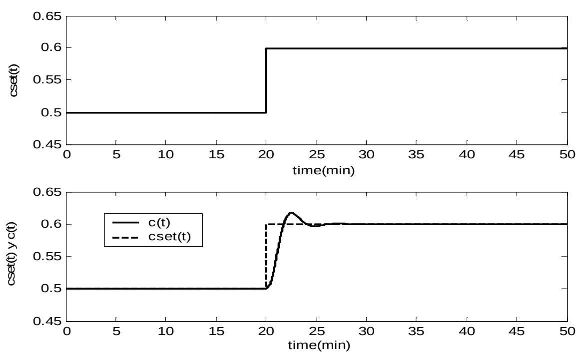

Figure 1. A test used in the experiment

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A. Obtaining the Characteristic Values of the Sliding Surface response.

Using the values presented in Table 1, all simulations were carried out. From the simulations, it was observed that the *S*(t) characteristic values response affected by changes in the process parameters are: minimum time, maximum time, minimum pick, maximum pick and the period (see Fig. 2).

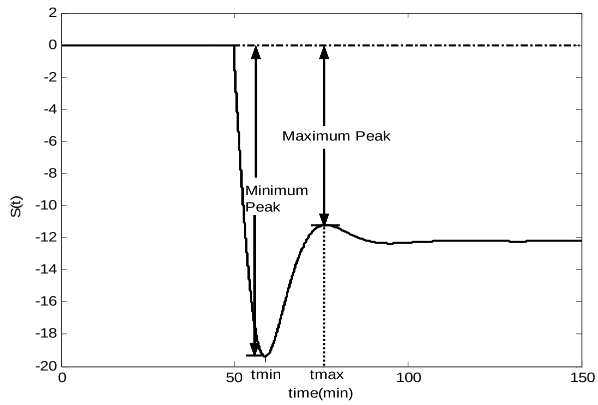

Figure 2. Characteristic values of the sliding surface response

B. Analysis of Variance.

Once completed the 729 simulations, taking into account the characteristic values of the sliding surface response as the output and as independent variables the FOPDT characteristics parameters a variance analysis (ANOVA) were prepared.

The variance analysis and the regression techniques are used to find out the non linear models that relate the sliding surface response characteristics and the FOPDT process parameters.

Table 2. ANOVA considering the minimum pick.

Source	Sum Sq	d.f	Mean Sq.	F	Prob>F
Kp	0.00579	2	0.0029	33.34	0
τ	0.00499	1	0.00499	57.39	0
t_0/τ	0.00263	2	0.00132	15.13	0
ΔKp	0.00294	5	0.00059	6.76	0
$\Delta\tau$	0.00195	6	0.00032	3.73	0.0025

$\Delta t_0/\tau$	0.00132	7	0.00019	2.17	0.0453
Error	0.00713	82	0.00009		
Total	0.10155	107			

Table 3. ANOVA considering the maximum pick

Source	Sum Sq	d.f	Mean Sq.	F	Prob>F
Kp	1582	2	791	41.47	0
τ	4437	1	4436.95	232.63	0
t_0/τ	293.2	2	146.62	7.69	0.0009
ΔKp	1062.9	5	212.59	11.15	0
$\Delta\tau$	331.7	6	55.28	2.9	0.013
$\Delta t_0/\tau$	1130.4	7	161.49	8.47	0
Error	1564	82	19.07		
Total	55956.7	107			

Table 4. ANOVA considering the minimum time

Source	Sum Sq	d.f	Mean Sq.	F	Prob >F
Kp	317.2	2	158.623	40.99	0
τ	781.6	1	781.647	202.01	0
t_0/τ	82.1	2	41.03	10.6	0.0001
ΔKp	92.5	5	18.494	4.78	0.0007
$\Delta\tau$	121.2	6	20.205	5.22	0.0001
$\Delta t_0/\tau$	478.7	7	68.391	17.67	0
Error	317.3	82	3.869		
Total	10991.6	107			

Table 5. ANOVA considering the period

Source	Sum Sq	d.f	Mean Sq.	F	Prob> F
Kp	482.6	2	241.28	25.45	0
τ	1494	1	1494.02	157.61	0
t_0/τ	74.5	2	37.26	3.93	0.0234
ΔKp	659	5	131.8	13.9	0
$\Delta\tau$	461.8	6	76.96	8.12	0
$\Delta t_0/\tau$	380.8	7	54.4	5.74	0
Error	777.3	82	9.48		
Total	19238.9	107			

To observe that values are significant on each output variable a limit is chosen for the value of P in the statistical F. this limit should be smaller than 0.05.

C. *Models of S (t)*

In the design of the different models were realized non linear regressions to adjust the parameters of the surface as a function of the changes in the process. Each pattern represents to an output variable of the sliding surface. To verify the good adjustment R^2 is used to measure the global quality of the pattern. Therefore, the models obtained are:

Y_1: Model that considers the minimum peak

$$\begin{aligned} Y_1 = &-0.12361 + 0.05242\, x_1 + 0.062124\, x_3 + 0.030563\, x_4 \\ &- 0.0050835 x_5 - 0.093941 x_6 - 0.035098 (x_1 \cdot x_3) \\ &- 0.077549 (x_1 \cdot x_4) + 0.00016054 (x_1 \cdot x_5) \\ &+ 0.011387 (x_1 \cdot x_6) - 0.010125 (x_3 \cdot x_4) \\ &+ 0.0011869 (x_3 \cdot x_5) + 0.087821 (x_3 \cdot x_6) \\ &+ 0.023212 (x_4 \cdot x_5) + 0.027632 (x_4 \cdot x_6) \\ &- 0.0076065 (x_5 \cdot x_6) - 0.0026925 (x_1^2) \\ &- 0.0071276 (x_3^2) + 0.03492 (x_4^2) \\ &+ 0.00062833 (x_5^2) - 0.021659 (x_6^2) \end{aligned} \tag{10}$$

Y_2: Model that takes into account the minimum time

$$
\begin{aligned}
Y_2 = {} & 54.127 + 12.104 \cdot x_1 - 18.51 \cdot x_3 - 1.4772 \cdot x_4 \\
& - 0.64188 \cdot x_5 - 8.4622 \cdot x_6 + 1.783 \cdot (x_1 \cdot x_3) \\
& - 22.511 \cdot (x_1 \cdot x_4) + 0.079645 \cdot (x_1 \cdot x_5) \\
& + 4.3791 \cdot (x_1 \cdot x_6) + 10.11 \cdot (x_3 \cdot x_4) - 0.85161 \cdot (x_3 \cdot x_5) \quad (11) \\
& + 16.291 \cdot (x_3 \cdot x_6) + 2.0966 \cdot (x_4 \cdot x_5) + 3.2492 \cdot (x_4 \cdot x_6) \\
& - 0.6627 \cdot (x_5 \cdot x_6) - 0.32554 \cdot (x_1^2) - 11.749 \cdot (x_3^2) \\
& + 27.163 \cdot (x_4^2) + 0.36453 \cdot (x_5^2) - 5.8308 \cdot (x_6^2)
\end{aligned}
$$

Y_3: Model that takes into account the period

$$
\begin{aligned}
Y_3 = {} & 7.8002 + 1.7345 \cdot x_2 - 8.155 \cdot x_3 - 22.957 \cdot x_4 \\
& + 3.4038 \cdot x_5 - 29.598 \cdot x_6 - 1.8113 \cdot (x_2 \cdot x_3) \\
& - 1.2534 \cdot (x_2 \cdot x_4) + 0.21358 \cdot (x_2 \cdot x_5) \\
& + 3.6559 \cdot (x_2 \cdot x_6) + 13.709 \cdot (x_3 \cdot x_4) - 0.48949 \cdot (x_3 \cdot x_5) \quad (12) \\
& + 38.242 \cdot (x_3 \cdot x_6) + 1.0353 \cdot (x_4 \cdot x_5) - 8.9074 \cdot (x_4 \cdot x_6) \\
& - 0.083948 \cdot (x_5 \cdot x_6) + 0.11496 \cdot (x_2^2) + 8.5389 \cdot (x_3^2) \\
& + 15.8 \cdot (x_4^2) - 0.64706 \cdot (x_5^2) - 35.765 \cdot (x_6^2)
\end{aligned}
$$

Where:

x_1 **:** is the process gain.

x_2 **:** is the time constant

x_3 **:** is the controllability relationship

x_4 **:** is the gain variation (ΔK_p)

x_5 **:** is the constant time variation $(\Delta\tau)$

x_6 **:** is the controllability relationship variation $\Delta(t_0/\tau)$

IV. SIMULATION RESULTS

In this section a mixing tank [5], Fig. 3, is used to compare the proposed controller against the SMC and the DMC.

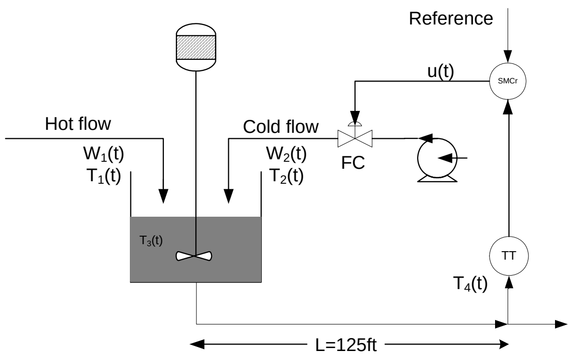

Figure 3. Mixing tank

In Table 6 can be observed the characteristic FOPDT model parameters, they are used to tune the controllers. They are obtained by identification [1].

Table 6. FOPDT characteristic parameters.

Parameter	Value
K_P	-0.78503 Fraction TO/Fraction CO
τ	2.0906 min
t_0	3.5663 min

Figure 4 shows how the process response is affected when the three controllers are used. As can be observed the proposed approach presents a better performance than the other two, the DMC presents a oscillatory response and the SMC is overdamped.

Figure 5 plots other simulation. In this figure the proposed approach acquires the advantages of the original schemes, therefore same results as was shown in Figure 3 are obtained.

The previous two charts have shown the advantages of this mixed scheme. The simulation results are also compared in a quantitative way using the performance indexes, the next part illustrates the results.

A. Performance.

Table 7 shows two performance indexes for the different controllers used in this work. IAE and ISE are used as the performance indexes.

Table 7. Performance Indexes

Index	SMC	DMC	DMC+SMC
IAE	31.8981	75.1856	23.3072
ISE	1.5875	4.8948	1.1888

As can be observed in Table 7, both indexes show than the proposed approach, DMC+SMC, presents smaller indexes values than the others two

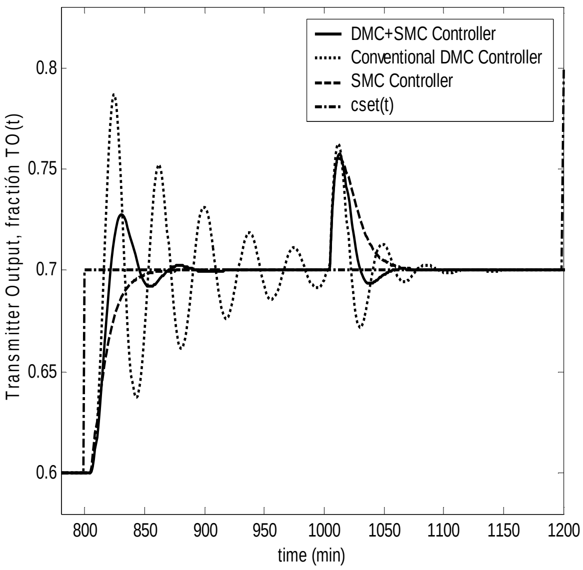

Figure 4. Comparison among the different approaches

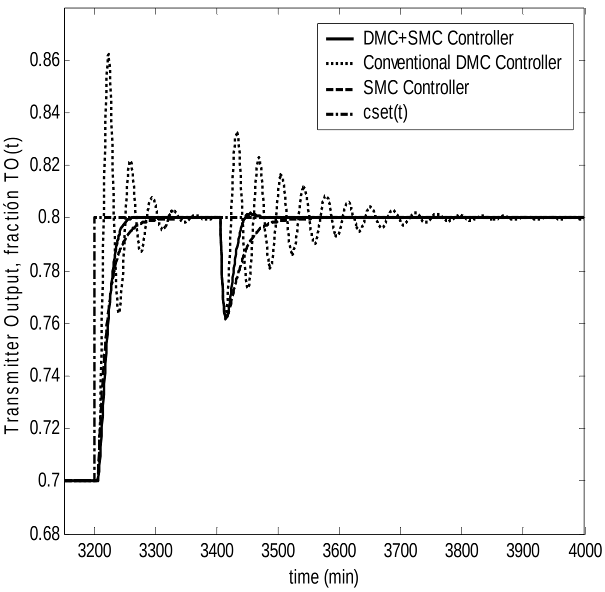

Figure 5. Comparison among the different approaches,

V. CONCLUSIONS

In this work a system of tuning equations has been designed based on the response of the sliding surface. The equations were used to improve the performance of the proposed approach. The results showed in all the cases improvements in the performance indexes with respect to the SMC and the DMC. In spite of robustness indexes were not presented in this paper, the results shown that the proposed approach is less oscillatory than the DMC and faster than the SMC.

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