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Development of a GPC-based sliding mode controller

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Abstract

This article presents a sliding mode controller that uses a generalized predictive controller in the reaching mode. The proposed predictive sliding mode controller is developed from a first-order-plus-deadtime model that represents a good approximation to many chemical processes. The predictive sliding mode controller has six tuning parameters and the tuning rules are given in the paper. Four simulation examples show the features of the proposed controller, which overcomes some of the disadvantages of sliding mode control and generalized predictive control strategies.

Keywords: Sliding mode control; Generalized predictive control; First-order-plus-deadtime model

1. Introduction

Industry requires control systems that provide optimal performance and robustness against disturbances or system failures and that are easy to tune by plant operators. Research in this area continues to grow and at present there are various alternatives to the traditional PID controller. Over the last 20 years interest in variable structure controllers (VSCrs), in particular in sliding mode controllers (SMCrs) and in model based predictive controllers (MPCrs), has grown both within the research control community and industry.

Control systems with variable structure are nonlinear systems with a discontinuous part in the control signal. These control strategies switch between two control systems with different closed loop behavior. Even though they were both unstable, when alternated they can produce a stable closed loop behavior. The VSCr was first presented to the scientific Soviet community by Utkin [1] and its principal theoretic support comes from Lyapunov's stability theory. Its greatest advantage is that it is a very robust controller, but it also has some disadvantages. One of these is that it has implementation problems, which are due to the high frequency actuator switching required in order to attain the ideal sliding movement towards the desired closed loop behavior. Furthermore, in spite of the robustness of this controller, when the processes exhibit long deadtimes the controlled system response moves away from optimal performance [2].

There is a huge amount of literature dealing with SMC in continuous time applied to linear systems [1,3] and to nonlinear systems [4,5] and also with uncertainties and delays [6]. The different design methodologies have been widely studied by Itkis [3], Utkin [4], Decarlo et al. [7], Naranjo [8] and Zinober [9]. Also in discrete time by Furuta [10], Sira-Ramírez [11], Chan [12], Yu and Potts [13]

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0019-0578/01/$ - see front matter
PII: S0019-0578(01)00014-3

and Gao [14]. In 1996 Pieper [15] developed an adaptive discrete SMC and Naranjo [16] collected the different methodologies for discrete SMC in 1997. In 1999 Park and Kim [17] developed a hybrid between time delayed control (TDC) and SMC called TDSMC. Research has also been done on fuzzy adaptive SMC [18] and SMC based on modeling with neural networks [19] for nonlinear systems. There is an excellent paper describing the trends in SMC research written by Young et al. in 1999 [20]. Finally, in the context of SMC for nonlinear chemical processes the paper by Camacho et al [2] can be mentioned.

At the end of the 1970s some algorithms appeared that explicitly used a dynamic model of the process to estimate the effect of the future control actions on the process outputs. The control actions were determined by minimizing the error between the future output predicted by the model and the known future reference, subject to operation constraints. Model predictive heuristic control (MPHC) [21,22], later known as model algorithmic control (MAC), and dynamic matrix control (DMC) [23] can be mentioned among the first MPC algorithms. Clarke established the first concepts about Generalized Predictive Control (GPC) [24,25] using CARIMA models. Over the last 15 years GPC has become widely accepted for controlling the processes described. This is because it can deal with MIMO, unstable or non-minimum phase plants. Furthermore, it is able to handle a great variety of control objectives, and thus GPC has been chosen from among all the MPC techniques in order to develop the present controller.

MPC in general and GPC in particular present certain advantages: firstly MPC computes the control signal to obtain optimal performance for a finite horizon. This allows the inclusion of process constraints to generate the control law (Grossner et al [26] and Camacho [27,29]). Furthermore the process dead time is optimally compensated and it is simple to extend the controller to the multivariable case. MPC is particularly useful when future references are known. In spite of these advantages MPC has some limitations. The computational cost can be very high, particularly if a high prediction horizon is chosen and when constraints are present, although a very easily implemented and tuned controller has been obtained by Bordons and Camacho [31] for the case of plants that can be modeled by a first order plus deadtime (FOPDT) model. Since the control law is model dependent, a good model is required to guarantee the success of MPC control strategies. Because of the finite horizon, the stability and robustness of the process is difficult to analyze and guarantee, especially when constraints are present. Some modification of the basic algorithms, based on imposing terminal constraints, terminal regions or a quasi infinite control horizon has been proposed in literature to increase stability of MPC schema.

In brief, the present research work shows an alternative hybrid control structure. It combines the advantages that have made the mentioned SMC and GPC control strategies so popular and overcomes most of their specific disadvantages. The paper is organized as follows: Section 2 is divided into two parts to show the basic concepts of SMC and GPC used in this work. Section 3 shows the proposed controller synthesis, Section 4 is dedicated to simulation results and Section 5 to conclusions.

2. Basic concepts

2.1. Sliding mode control (SMC)

As has been commented in the Introduction, SMC is a particular technique of VSC. The control law is composed of two parts: the sliding mode control law and the reaching mode control law. The first of these is responsible for maintaining the controlled system dynamic on a sliding surface, which represents the desired closed loop behavior. The second control law is designed in order to reach the desired surface.

The first step in SMC is choosing the sliding surface that is usually formulated as a linear function of the system states. The state is composed of the integral tracking error $\int_o^t e(t)\mathrm{d}t$, and its different derivatives. This is known as integral-differential surface [33], and its expression is given by

$$s(t) = \left(\frac{\mathrm{d}}{\mathrm{d}t} + \mu\right)^n \int_0^t e(t)\mathrm{d}t \tag{1}$$

where n is the model process order, and μ is a tuning parameter.

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

$$\frac{\mathrm{d}s(t)}{\mathrm{d}t} = 0 \tag{2}$$

and substituting it in 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. 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 [37] and avoid chattering in the control signal when the surface is (pseudo) reached. This is known in the literature as reaching a pseudo-sliding mode. The expression for the reaching mode control law can then be expressed as:

$$U_{\text{reach}}(t) = K_{\mathrm{D}} \frac{s(t)}{s(t) + \eta} \tag{3}$$

where K_{D} is the tuning parameter responsible for the speed with which the sliding surface is reached, and η is used to reduce the chattering problem. Most processes in industry can be modeled by an FOPDT model described by

$$G(s) = \frac{K}{\tau s + 1} \mathrm{e}^{-t_{\mathrm{o}} s} \tag{4}$$

where K is the process modeled static gain, τ is the time constant or process modeled lag, and t_{o} is the modeled deadtime or delay.

Camacho [30] obtained the following expression to tune K_{D} and η for FOPDT models:

$$K_{\mathrm{D}} = \frac{0.51}{|K|} \left(\frac{\tau}{t_{\mathrm{o}}}\right)^{0.76} \tag{5}$$

$$\eta = 0.68 + 0.12|K|K_{\mathrm{D}} \frac{t_{\mathrm{o}} + \tau}{t_{\mathrm{o}} \tau}. \tag{6}$$

2.2. Generalized predictive control (GPC)

Model predictive control (MPC) does not designate a specific control strategy but a very ample range of control methods, which make an explicit use of a model of the process to obtain the control signal by minimizing an objective function. The ideas appearing in greater or lesser degree in all the predictive control family are basically:

1. explicit use of a model to predict the process output at future time instants (horizon).
2. calculation of a control sequence minimizing an objective function;
3. receding strategy, so that at each instant the horizon is displaced towards the future, which involves the application of the first control signal of the sequence calculated at each step.

One of the most popular MPC methods is generalized predictive control (GPC). The basic idea of GPC is to calculate a sequence of future control signals in such a way that it minimizes a multistage cost function of the form:

$$J(N_1, N_2, N_{\mathrm{u}}) = \sum_{j=N1}^{N2} \delta(j)[w(k+j) - \hat{y}(k+j|k)]^2 + \sum_{j=1}^{Nu} \lambda(j)[\Delta u(k+j-1)]^2 \tag{7}$$

where $y(k+j|t)$ is an optimum j-step ahead prediction of the system output on data up to time t, N_1 and N_2 are the minimum and maximum costing horizons, N_{u} is the control horizon, $\delta(j)$ and $\lambda(j)$ are the weighting sequences (normally chosen as $\delta = 1$ and a constant λ) and $\omega(k+j)$ is the future reference trajectory.

The objective of GPC is to compute the future control sequence $u\ (t),\ u\ (t+1),\ \ldots$ in such a way that the future plant output $y(k+j)$ is driven close to $\omega(k+j)$ by minimizing the quadratic cost function $J\ (N_1, N_2, N_u)$.

Given a process modeled by a discrete transfer function in the backward shift operator z^{-1}:

$$P(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})} z^{-\mathrm{d}} \tag{8}$$

and perturbated by an output additive noise given by

$$\frac{T(z^{-1})}{(1 - z^{-1})A(z^{-1})} n(t) \tag{9}$$

where $n(t)$ is a white noise with zero mean and $T(z^{-1})$ is the noise coloring polynomial which is normally used as a robustifying filter. In the following $T(z^{-1})$ will be considered to be 1. The used cost horizons are $N_1 = \mathrm{d}+1$ and $N_2 = \mathrm{d}+1+N$, being N the prediction horizon. The GPC control law is given by:

$$u(k|k) = u_\mathrm{p} = U(k-1) + k_\mathrm{GPC}\hat{e}_\mathrm{f} \tag{10}$$

where $\hat{e}_\mathrm{f} = [w(k+\mathrm{d}+1) - \hat{y}_\mathrm{f}(k+\mathrm{d}+1|k) \cdots w(k+\mathrm{d}+1) - \hat{y}_\mathrm{f}(k+\mathrm{d}+N|k)]^T$ is a column vector with the predicted error calculated by the free predicted system response (i.e. the response obtained from the model when the control signal in the future is kept constant and equal to $U(k-1)$, and k_GPC is the first row of a matrix of gains K_GPC:

$$K_\mathrm{GPC} = \left(G^T G + \lambda I_{\mathrm{N}\times\mathrm{N}}\right)^{-1} G^T \tag{11}$$

where the square matrix G depends on the process model, and I_NxN is the identity matrix of width N [29]. N_u can be chosen smaller than N (this means considering that $U(k+j) = U(k+N_\mathrm{u})$ for $j = N_\mathrm{u} + 1, \cdots, N$). The computational complexity of Eq. (11) considerably decreases.

3. Synthesis of the predictive sliding mode controller (PSMCr)

Nonlinear high order models describe most processes in industry. Some studies have shown that a simplified model of a nonlinear high order model can be used to design a controller. A FOPDT model is recommended [30,31], it can be used to obtain the controller since this kind of model is easily obtained from the popular reaction curve method. The first step in developing a general SMCr is to choose a sliding surface $s(t)$ [32]. If Eq. (4) is expressed by using a first-order Taylor series instead of the dead time term, a second order system is obtained and we can define a sliding surface as a function of $\int_o^t \mathrm{e}(t)\mathrm{d}t$, presented by [33], and described by

$$s(t) = \frac{\mathrm{de}(t)}{\mathrm{d}t} + \mu_1 \mathrm{e}(t) + \mu_0 \int_0^t \mathrm{e}(t)\mathrm{d}t \tag{12}$$

where $\mathrm{e}(t)$ is the tracking error between the set point and the output measurement and μ_1, μ_0 are tuning parameters. The desired global behavior of the closed loop system for instance stability and tracking performance is represented by $s(t)$. The tuning parameters are chosen by the designer to get the desired performance.

As shown in the previous section, the typical control law in variable structure control is composed of the addition of two parts: a continuous part that controls the system during normal working, and a discontinuous part that changes the structure to obtain the desired behavior when a disturbance misleads the system output. In SMCr, continuous control is obtained using equivalent control procedure [34,35] and works during sliding mode condition, that is to say, when the performance is the desired one. To remain on the sliding surface, the equivalent control law satisfies Eq. (2), thus deriving Eq. (12) and satisfying (2)

$$\frac{\mathrm{d}^2\mathrm{e}(t)}{\mathrm{d}t^2} + \mu_1 \frac{\mathrm{de}(t)}{\mathrm{d}t} + \mu_0 \mathrm{e}(t) = 0 \tag{13}$$

with $\mathrm{e}(t) = R(t) - X(t)$ where $R(t)$ is the set point and $X(t)$ is the output measurement. Then

$$\frac{\mathrm{d}^2 X(t)}{\mathrm{d}t^2} = \frac{\mathrm{d}^2 R(t)}{\mathrm{d}t^2} + \mu_0 \mathrm{e}(t) + \mu_1 \frac{\mathrm{d}(R(t) - X(t))}{\mathrm{d}t} \tag{14}$$

staying (11) in the differential domain and substituting in (12)

$$\left(KU_{\mathrm{eq}}(t)-(\tau+t_{\mathrm{o}})\frac{\mathrm{d}X(t)}{\mathrm{d}t}-X(t)\right)\frac{1}{t_{\mathrm{o}}\tau}=\frac{\mathrm{d}^2R(t)}{\mathrm{d}t^2}+\mu_o\mathrm{e}(t)+\mu_1\frac{\mathrm{d}(R(t)-X(t))}{\mathrm{d}t} \tag{15}$$

Then the equivalent control law stays as

$$U_{\mathrm{eq}}(t)=\frac{t_{\mathrm{o}}\tau}{K}\left[\left(\frac{t_{\mathrm{o}}+\tau}{t_{\mathrm{o}}\tau}-\mu_1\right)\frac{\mathrm{d}X(t)}{\mathrm{d}t}+\frac{1}{t_{\mathrm{o}}\tau}X(t)+\mu_{\mathrm{o}}\mathrm{e}(t)+\frac{\mathrm{d}^2R(t)}{\mathrm{d}t^2}+\mu_1\frac{\mathrm{d}R(t)}{\mathrm{d}t}\right] \tag{16}$$

In [36], it is shown that the derivatives of the reference can be discarded without any effect on the control performance. Thus,

$$U_{\mathrm{eq}}(t)=\frac{t_{\mathrm{o}}\tau}{K}\left[\left(\frac{t_{\mathrm{o}}+\tau}{t_{\mathrm{o}}\tau}-\mu_1\right)\frac{\mathrm{d}X(t)}{\mathrm{d}t}+\frac{1}{t_{\mathrm{o}}\tau}X(t)+\mu_{\mathrm{o}}\mathrm{e}(t)\right] \tag{17}$$

Also in [36], it is justified that the best choice of μ_1 is

$$\mu_1=\frac{t_{\mathrm{o}}+\tau}{t_{\mathrm{o}}\tau} \tag{18}$$

To ensure a critical or overdamped behavior μ_0 must satisfy

$$\mu_0\leqslant\frac{\mu_1^2}{4} \tag{19}$$

Thus, in order to simplify Eq. (16), it can be chosen

$$\mu_{\mathrm{o}}=\frac{1}{t_{\mathrm{o}}\tau} \tag{20}$$

because substituting Eqs. (18) and (20) into Eq. (19) results in $(t_{\mathrm{o}}-\tau)^2\geqslant 0$ and this is always true for any pair (t_{o},τ). Some optimization proofs have been developed to verify that this assumption is one of the best. Thus, in Table 1 and Fig. 1, the ISE index obtained for several μ_0 and four different processes is shown. The ISE in boldprint in Table 1 corresponds to the μ_0 calculated from Eq. (20) for each case. The following set of process models has been used in the simulations of this article:

$$G_1(s)=\frac{\mathrm{e}^{-5s}}{1+s} \tag{21}$$

$$G_2(s)=\frac{\mathrm{e}^{-5s}}{(1+s)^3} \tag{22}$$

$$G_3(s)=\frac{\mathrm{e}^{-5s}}{(1+s)(1+0.5s)(1+0.25s)(1+0.125s)} \tag{23}$$

$$G_4(s)=\frac{-0.4(s-0.5)\mathrm{e}^{-5s}}{(s+1)(s+0.2)} \tag{24}$$

The processes were modeled, as FOPDT models, with $K=1$ and the chosen values of τ and t_{o} were obtained by applying the reaction curve method. The model dead times t_{o} were adjusted to an exact multiple of the sampling time. The sampling times were chosen as one tenth of the time constant τ. These parameters are shown in Table 2.

Table 1
ISE optimization proofs to choose μ_0

μ_0	0.01	0.021	0.045	0.08	0.1	0.134	0.15	0.18	0.2	0.25	0.3
G_1	–	–	–	–	0.268	0.228	0.217	0.205	0.202	0.209	0.246
G_2	–	0.69	0.37	0.28	0.28	0.36	0.47	–	–	–	–
G_3	–	–	–	0.403	0.365	0.343	0.347	0.381	–	–	–
G_4	1.508	0.984	1.646	8.790	–	–	–	–	–	–	–

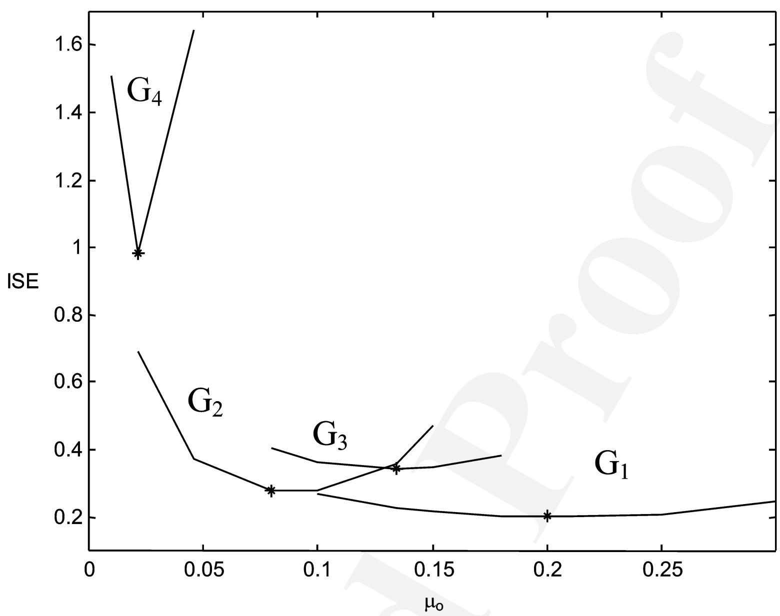

Fig. 1. ISE optimization proofs to choose μ_0.

Table 2
Parameters obtained from reaction curve con $K = 1$ for all processes

	G_1	G_2	G_3	G_4
τ	1	2	1.5	6
t_o	5	6	4.95	7.8

Thus the equivalent control law in discrete form from Eqs. (17), (18) and (20) can be expressed by

$$U_{eq}(k) = \frac{R(k)}{K} \tag{25}$$

The next step in SMCr design is finding the part of the control law that changes the structure when the system state is outside the desired surface, this is called the reaching mode. A GPC is used for this purpose to get an optimal predictive gain u_p for the sigmoid-like function, instead of K_D in Eq. (3). Predictive method works on discrete time, so the discrete expression for the system model form Eq. (11) has to be used:

$$G(z^{-1}) = \frac{n_1 z^{-1}}{1 - d_1 z^{-1}} z^{-d} \tag{26}$$

where the discrete parameters are derived from the continuous ones and their expressions are

$$d_1 = e^{-(T_s/\tau)}, n_1 = K(1 - d_1) \text{ and } d = t_o/T_s$$

and the deadtime t_o is computed as an integer, which is a multiple of the sampling time T_s. GPC attempts at minimizing the predicted error $(d + 1)$ sampling instants ahead quite fast, so the sigmoid-like function will work over a predicted surface s_p instead of the current one. The following is the discrete expression for s_p, obtained by discretizing Eq. (12):

$$s_p(k) = \frac{e(k+d+2) - e(k+d+1)}{T_s} + \mu_1 e(k+d+1) + \mu_o \sum_0^k e(k+d+1) \tag{27}$$

Then, from Eqs. (3) and (8) and the latter comments, the reaching control law can be expressed as:

$$U_{reach}(k) = [U(k-1) + k_{GPC}\hat{e}_f] \frac{s_p(k)}{|s_p(k)| + \eta} = u_p \frac{s_p(k)}{|s_p(k)| + \eta} \tag{28}$$

η Can be used to trade off the requirement of maintaining ideal performance with that of ensuring a smooth control action. The prediction (N) and control (N_u) horizons and the control weighting sequence λ, are the tuning parameters, particularly from Eq. (6), which is minimized by the u_p of Eq. (28):

$$J = \sum_{j=d+1}^{N+d+1} [w(k+j) - \hat{y}(k+j|k)]^2 + \sum_{j=1}^{N_u} \lambda [\Delta u(k+j-1)]^2 \tag{29}$$

where $\hat{y}(k+j)$ is the predicted response $(k+j)$ instants ahead.

In fact, what has been done is to replace the traditional constant gain by a predictive gain that gives a smooth and fairly fast approximation to the sliding surface. This can be contrasted in Fig. 2 where the phase planes for the traditional SMCr and the proposed PSMCr are shown. The controlled process is $G_1(s)$ where a step change in the reference of 0.3 is applied in $t=6.1$.

In summary, a control law has been designed with a reaching mode part to obtain the future surface and a part to remain on the current surface. However, it is not enough to make the future surface null in order to really ensure getting the current surface. It is possible for both of them to be different due to a change of reference for example. If it is desirable to maintain the reaching control law signal during delay time, even though s_p has reached a value close to zero, a simple term measuring the difference of the state of the reference between present and future instants should be included. This can be described by

$$W(k+d+1) - R(k) \tag{30}$$

where $W(k+d+1)$ is the future reference $(d+1)$ sampling instants ahead. In the case of their being different it will be guaranteed that the reaching control law still works. When they are equal, u_p will be affected just by the state of s_p. Thus the complete reaching control law is expressed as:

$$U_{reach}(k) = u_p \left[\frac{sp(k)}{|sp(k)| + \eta} + W(k+d+1) - R(k) \right] \tag{31}$$

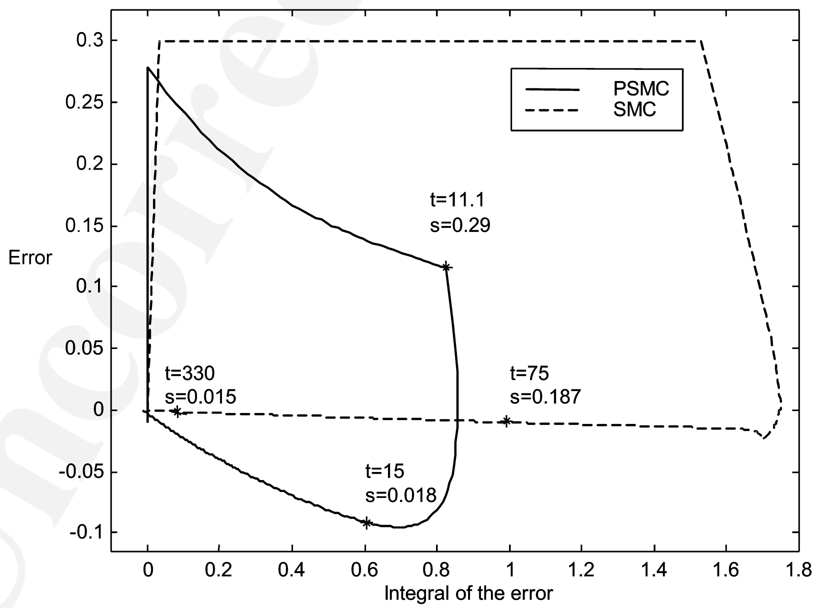

Fig. 2. Phase plane to compare PSMC and SMC performances.

Table 3
Controllers tuning parameters

	SMCr				GPCr		PSMCr				
	μ_o	μ_1	K_D	η	N:N_u	λ	μ_0	μ_1	η	N:N_u	λ
G_1	0.20	1.2	0.15	0.7	60:5	1	0.20	1.2	0.7	60:5	1
G_2	0.08	0.66	0.22	0.7	60:5	1	0.11	0.66	0.7	60:5	1
G_3	0.13	0.86	0.2	0.7	60:5	1	0.13	0.86	0.7	60:5	1
G_4	0.02	0.29	0.41	0.7	60:5	1	0.02	0.29	0.7	60:5	1

and after adding Eqs. (25), (8) and (28), the discrete PSMCr has the following complete expression

$$U_{\mathrm{PSMC}}(k) = \bar{U} + U_{\mathrm{eq}}(k) + U_{\mathrm{reach}}(k) \tag{32}$$

where $\overline{U}$ is the bias control signal in steady state.

It is necessary to fit six parameters to tune the controller. μ_0 And μ_1 are given by Eqs. (18) and (20). The parameters of the predictive part, the prediction and control horizons (N, N_u) and the control weighting sequence λ, which is usually chosen as a constant, are fitted by taking into account some performance limitations: the computational time for N_u (the greater the N_u the greater the computational time), and the speediness of the response for λ (the greater the λ the slower the response). In this case the GPC parameters were chosen in order to obtain a fast response ($\lambda = 1$, $N_u = 5$, $N = 60$) for reaching the sliding surface. N was considered equal to 60 in order to cover a period of six time constants on the prediction horizon. Finally, η initially tuned with the same optimal Eq. (5) as used by SMC. To obtain fine tuning as higher value of η will be necessary as the process requires greater restrictions in chattering, in spite of slower behavior or it will be more insensitive to model errors in dead time. In other cases when the model errors in the static gain are more critical, the designer should choose a η close to the one produced by (5) to power the reaching control law.

Table 4
ISE performance index for each controller

ISE	G_1	G_2	G_3	G_4
SMC	0.48	0.60	0.55	0.89
GPC	0.03	0.12	Unstable	Unstable
PSMC	0.16	0.31	0.29	0.66

4. Simulation results

In this section, the PSMCr features are shown by some simulation examples. In order to compare the results obtained with PSMC with the results with GPC and SMC, it is first shown how they work with the quite approximated models proposed in Table 2. The controller tuning parameters in Table 3 are obtained from Eqs. (18) and (20) chosen to get good

Table 5
ISE performance indexes with modeling errors

$G_2(s)$	K		τ		t_o	
	+50%	−50%	+50%	−50%	+50%	−50%
SMCr	1.43	4.75	0.69	0.52	0.85	0.37
PSMCr	0.66	0.39	0.45	0.21	0.69	0.16
GPCr	0.57	Unstable	Unstable	Unstable	Unstable	Unstable

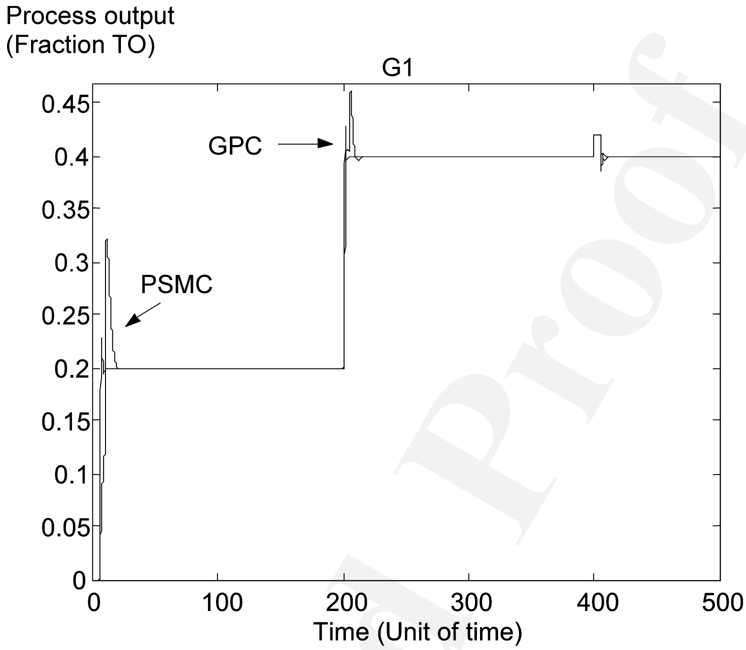

Fig. 3. Comparison between GPC and PSMC using $G_1(s)$.

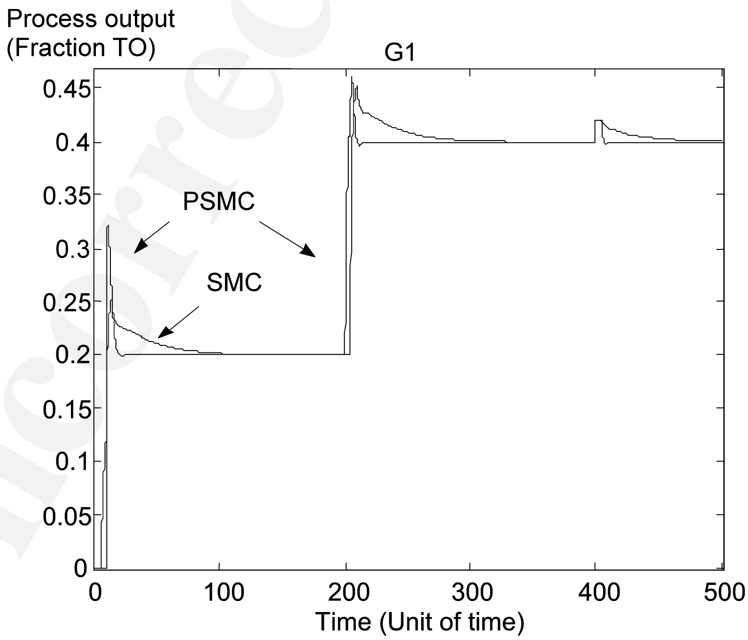

Fig. 4. Comparison between SMC and PSMC using $G_1(s)$.

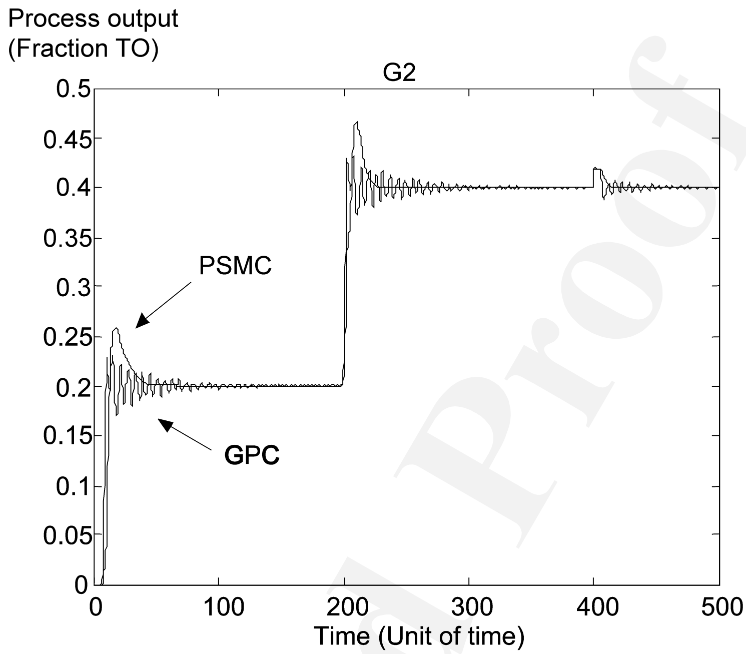

Fig. 5. Comparison between GPC and PSMC using $G_2(s)$.

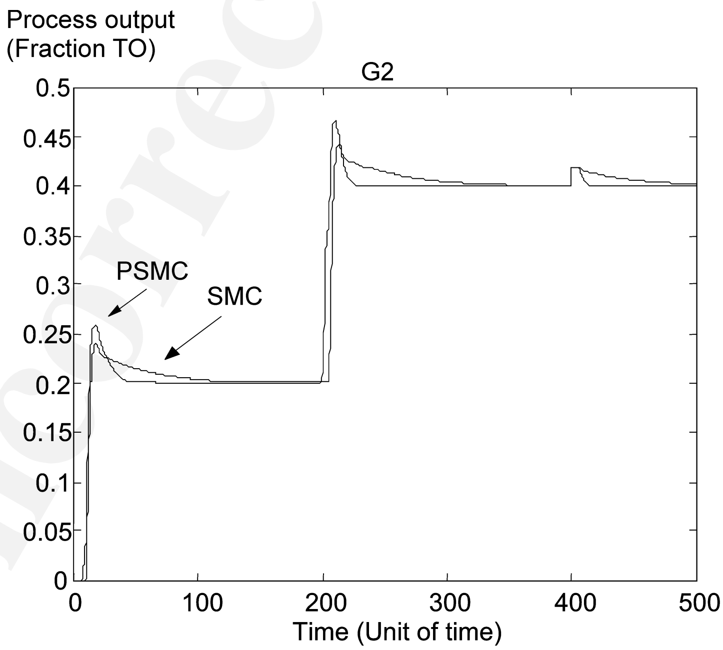

Fig. 6. Comparison between SMC and PSMC using $G_2(s)$.

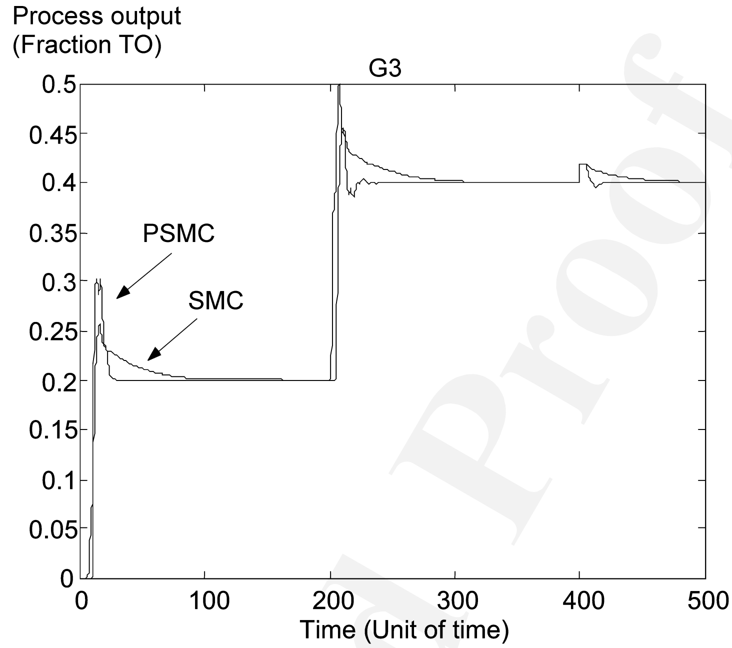

Fig. 7. Comparison between SMC and PSMC using $G_3(s)$.

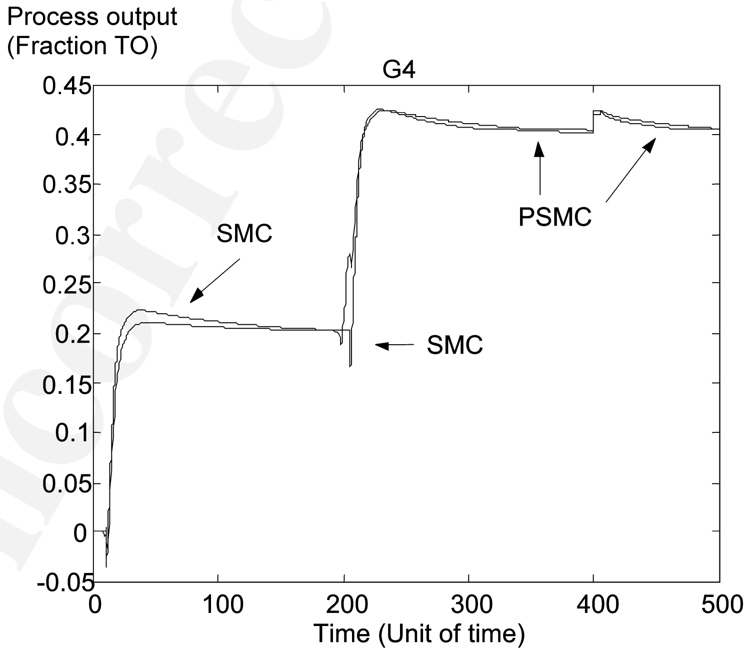

Fig. 8. Comparison between SMC and PSMC using $G_4(s)$.

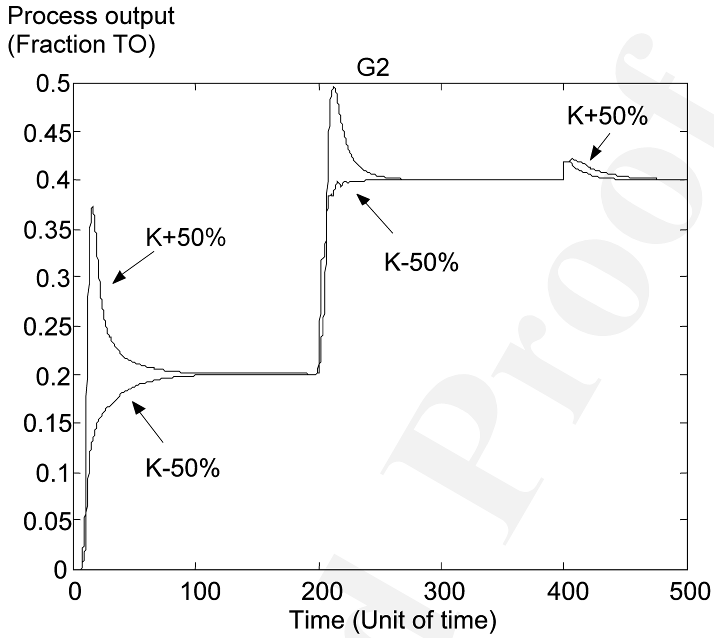

Fig. 9. System step responses with PSMCr when (±50%) modeling errors in static gain, K, were introduced in $G_2(s)$.

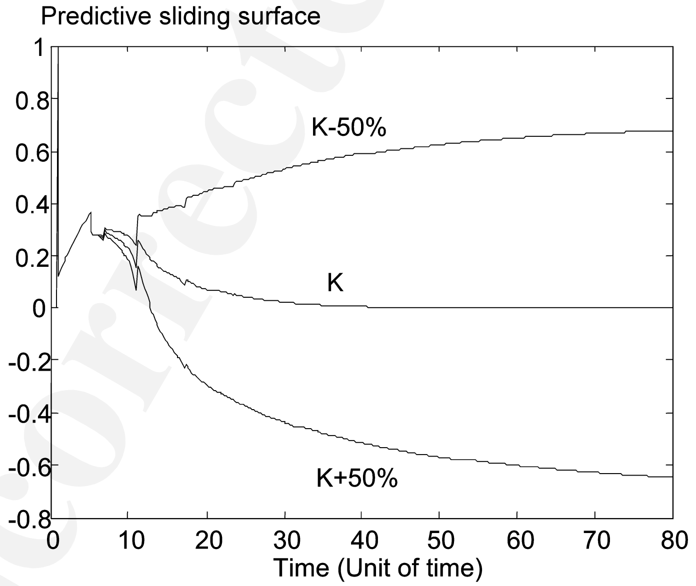

Fig. 10. Predictive sliding surface with PSMCr when (±50%) modeling errors in static gain, K, were introduced in $G_2(s)$.

closed loop dynamics. Notice that by choosing values of λ higher than 1, processes (21)–(24) can be stabilized by GPC, although slower responses are obtained. PSMC works better with small λ, because it has a faster dynamic, and the SMC equivalent law gives the controller robustness.

The ISE index for each experiment with a change of set point and a disturbance of 5% in the

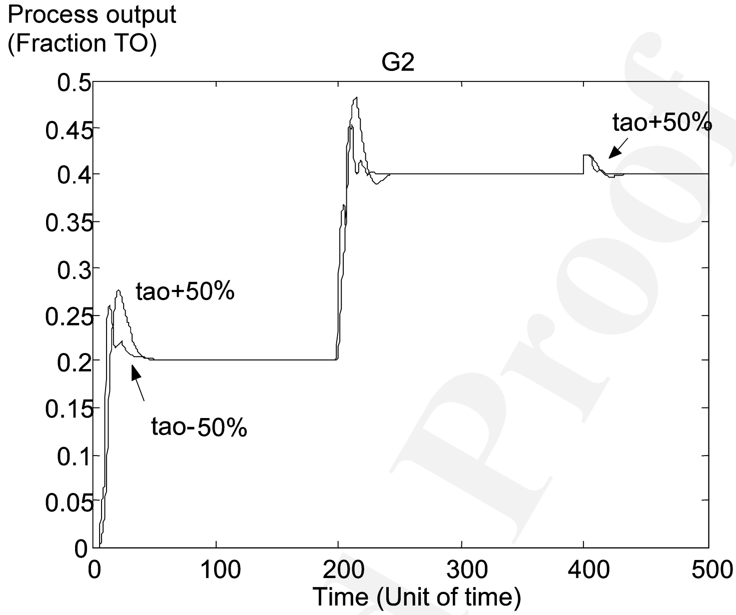

Fig. 11. System step responses when (±50%) modeling errors in time constant, τ, were introduced in $G_2(s)$.

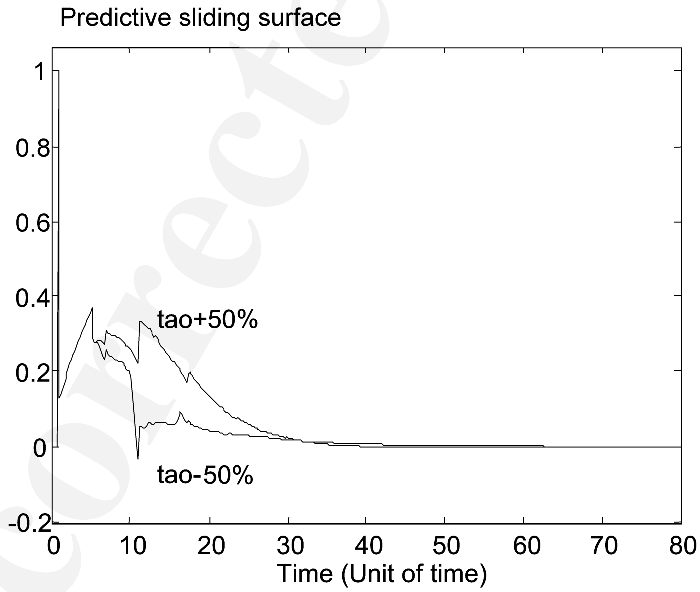

Fig. 12. Predictive sliding surface outputs when (±50%) modeling errors in time constant, τ, were introduced in $G_2(s)$.

output signal is shown in Table 4. It can be seen that GPCr has the best behavior when the model is identical to the process [case $G_1(s)$, (see Fig. 3). If the model substantially differs from the plant the closed loop becomes unstable unless the parameter λ is considerably increased.

Figs. 3–8 show that PSMC has the best behavior using the FOPDT models (Table 2) for controlling

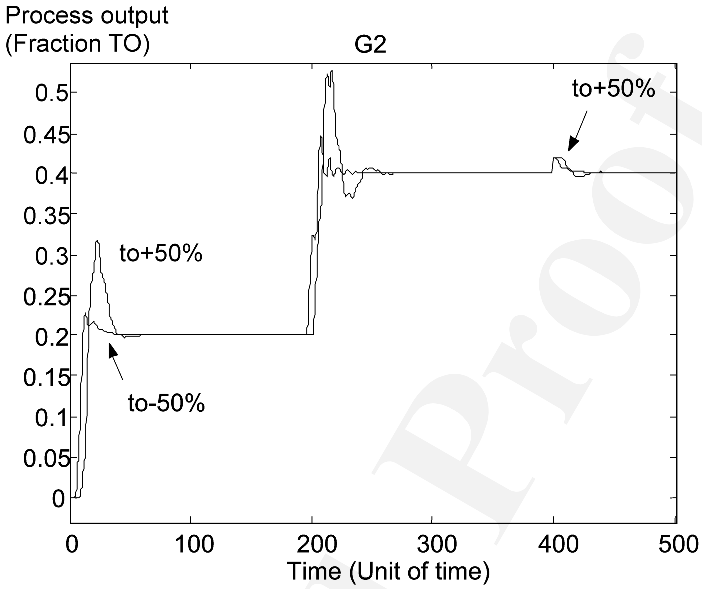

Fig. 13. System step responses when (±50%) modeling errors in deadtime, t_0, were introduced in $G_2(s)$.

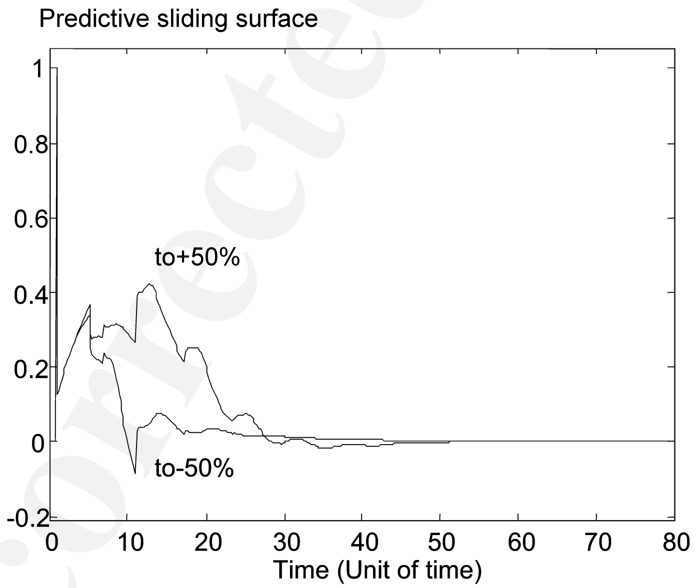

Fig. 14. Sliding surface outputs when (50%) modeling errors in deadtime, t_0, were introduced in $G_2(s)$.

the plants described by Eqs. (21)–(24). Notice that only in the case of $G_1(s)$ the plant is equal to the model.

In the previous tests, although there were modeling errors [except for $G_1(s)$], the models were very good approximations to illustrate how the controllers behave when higher modeling errors occur (50% in K, τ and t_o). The ISE indexes for the process $G_2(s)$ are shown in Table 5. GPCr gets an unstable closed loop (although more robust GPCs could have been obtained by increasing the weighting factor). The SMCr gets the slowest response, even though the closed loop continues to be stable. The PSMCr has both controller advantages and it considerably decreases their disadvantages.

Figs. 9–14 show the responses with modeling errors and the evolution of the predictive sliding surface when the system is controlled with PSMCr. It can be seen that it is a very robust controller and that it is quite insensitive especially to errors in K, τ and t_o. The computational cost for the PSMCr is practically the same as that required by the GPCr, so it is particularly interesting for slow processes such as chemical ones.

5. Conclusions

The use of a GPC-based gain in the reaching mode control law considerably improves the performance of the SMCr. Furthermore, PSMCr is a robust controller, which is able to handle large modeling errors while maintaining fast response characteristics. GPCr has to be detuned to get similar robustness characteristics. Another PSMCr characteristic is that it can easily be implemented using DCS. There is no chattering problem if parameter η is properly fitted and the response is quite fast, compared to SMCr performance. The extension of this technique to nonlinear systems is straightforward.

6. Uncited reference

[28]

Acknowledgements

M.P.P. wishes to thank Universidad de Los Andes, Escuela de Ingenieria Electrica, LABIDAI and Postgrado en Automatizacion e Instrumentacion, Merida 5101, Venezuela, for the support given to accomplish this research.

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