ROBUST CONSTRAINED HORIZON PREDICTIVE CONTROLLER FOR DEAD TIME SYSTEMS

Bismark Claure Torrico, Julio E. Normey-Rico

Depto. de Automação e Sistemas, Universidade Federal de Santa Catarina, Cx.P. 476, 88040-900, Florianópolis, SC, BRASIL. e-mails: bismark,julio@das.ufsc.br

Abstract: This paper presents a constrained horizon predictive controller based on a filtered Smith predictor structure (CHSPPC). The proposed algorithm is particulary appropriate to control dead time systems as it exhibits better robustness than others, specially when errors in the dead time estimation are considered. The tuning of the controller parameters includes a low pass filter that is easy defined to obtain a compromise between performance and robustness. Simulation results show that the proposed control strategy allows better results than other approaches.

Keywords: Model based predictive control, Dead-time Systems, Robustness, Constrained horizon

1. INTRODUCTION

Model predictive controllers MPC have received much attention in recent years and have been successfully used to control several industrial processes. The basic idea of a predictive controller is to compute a sequence of future control signals in such a way that it minimizes a multistage cost function defined over a control horizon. The index to be optimized is normally a quadratic cost considering the distance between the predicted system output and some predicted reference sequence over the control horizon plus a function measuring the control effort over the same horizon (Camacho and Bordons, 1999).

Using these ideas, different algorithms have been proposed in literature, using linear models to compute the predictions (Clarke and Mothadi, 1989; Richalet *et al.*, 1976; Kouvaritakis *et al.*, 1992), and with non-linear ones (Kouvaritakis and Cannon, 2001). Because of the simplicity and the good results obtained in practice, MPC based on linear models have been extensively analyzed. Several studies of the stability and robustness of these algorithms have been presented in recent years. Stability has been addresses using different approaches. A Stable Generalized Predictive controller, that is based on stabilizing the loop before the application of the control strategy, is analyzed in (Kouvaritakis *et al.*, 1992; Rossiter and Kouvaritakis, 1994; Rossiter *et al.*, 1996). Another solution that uses terminal constrains in a generalized predictive approach was presented in (Clarke and Scattolini, 1991; Scokaert and Clarke, 1994). In order to improve the robustness of the MPC when model uncertainties are considered, different strategies have been proposed in the literature. The effects of a prefilter on the robustness of the closed loop system has been analyzed in several papers (Clarke and Mothadi, 1989; Robinson and Clarke, 1991; Kouvaritakis *et al.*, 1992; Yoon and Clarke, 1995; Ansay and Wertz, 1997). The effect of the predictor structure on the robustness of the closed-loop system have been analyzed for the GPC in (Normey-Rico and Camacho, 1999;

Normey-Rico and Camacho, 2000; Núñez-Reyes *et al.*, 2005) specially for dead-time systems. In these papers the robustness of the controller is improved using a filtered Smith predictor structure and assuming that the controller parameters could be tuned so as to obtain nominal closed loop stability.

To complete the analysis of the predictive control of dead-time processes it is necessary to obtain some conditions to guaranty the nominal stability, thus, in this paper the ideas presented in the constrained receding-horizon predictive controller CRHPC (Clarke and Scattolini, 1991) are extended for the Smith predictor generalized predictive controller SPGPC (Normey-Rico and Camacho, 1999). The proposed algorithm allows to obtain a nominal stable closed loop with the same nominal performance as the CRHPC but allowing better robustness when controlling dead-time processes. In this sense the proposed algorithm introduce some advantages if compared to the previous SPGPC and CRHPC.

The paper is organized as follows: Section 2 presents the plant model considerations and a brief revision of the main ideas of the SPGPC and CRHPC. The proposed controller is presented in section 3 showing some of its structure properties. Section 4 compares the robustness and the closed-loop performance of the proposed strategy with the CRHPC. Some simulation results are shown in section 5 and finally the conclusions and perspectives of the work are presented in section 6.

2. PLANT MODEL AND CONTROLLER REVISION

The dynamic behavior of many industrial processes near an operating point can be represented by models consisting of a linear differential equation and a dead-time. For control purposes simple models are very important, so in practice low order models coupled with dead-times are extensively used (Astrom and Hagglund, 1995). The importance of this approximation is proved by the fact that the reaction curve method is probably one of the most popular methods used in industry for tuning regulators. Thus, in this paper the model of the plant, for the purpose of tuning the controller, is represented by a transfer function with a dead-time. Thus, the correspondent state space discrete model of the plant is given by a reachable and observable system with a dead-time of d samples and without zeros in $z = 1$.

$$\begin{aligned} x(t+1) &= \hat{\mathbf{A}}x(t) + \hat{\mathbf{B}}u(t-d) \\ y(t) &= \hat{\mathbf{C}}x(t) \end{aligned} \tag{1}$$

To guarantee regulation with zero steady-state error for constant set-points, let the control variable u be the output of the following discrete-time integrator:

$$\begin{aligned} v(t-d+1) &= v(t-d) + \delta u(t-d) \\ u(t-d) &= v(t-d) + \delta u(t-d) \end{aligned} \tag{2}$$

The overall system is then described by:

$$\begin{aligned} \begin{bmatrix} x(t+1) \\ v(t-d+1) \end{bmatrix} &= \mathbf{A} \begin{bmatrix} x(t) \\ v(t-d) \end{bmatrix} + \mathbf{B}\delta u(t) \\ y(t) &= \mathbf{C} \begin{bmatrix} x(t)^T & v(t-d)^T \end{bmatrix} \end{aligned} \tag{3}$$

System (3) admits the input-output representation:

$$A(q^{-1})\Delta(q^{-1})y(t) = q^{-d}B(q^{-1})\delta u(t-1) \tag{4}$$

where q^{-1} is the backward shift operator and:

$$\begin{aligned} A(q^{-1}) &= 1 + a_1q^{-1} + a_2q^{-2} + ... + a_nq^{-n} \\ B(q^{-1}) &= b_0 + b_1q^{-1} + b_2q^{-2} + ... + b_{n-1}q^{-(n-1)} \\ \Delta(q^{-1}) &= 1 - q^{-1} \end{aligned}$$

Moreover the incremental control action $\delta u(t)$ is given by:

$$\delta u(t) = u(t) - u(t-1)) = \Delta(q^{-1})u(t) \tag{5}$$

2.1 The Smith Predictor Generalized Predictive Controller

The Smith Predictor Based Generalized Predictive Control algorithm (Normey-Rico and Camacho, 1999) consists of applying a control sequence that minimizes a multi-stage cost function of the form:

$$\begin{aligned} J = &\sum_{j=N_1}^{N_2} \psi(j)[\hat{y}(t+j \mid t) - w(t+j)]^2 \\ &+ \sum_{j=1}^{N_2-d} \lambda(j)[\delta u(t+j-1)]^2 \end{aligned} \tag{6}$$

where N_1 and N_2 are the minimum and maximum costing horizons, $\psi(j)$ and $\lambda(j)$ are weighting sequences, $w(t+j)$ is a future set-point or reference sequence and $\hat{y}(t+j \mid t)$ is the j-step ahead prediction of the system output on data up to time t. As in Normey-Rico and Camacho (1999) and because of the dead-time of the process the horizons N_1 and N_2 are computed as $N_1 = d+1$ and $N_2 = N + d$. Thus, N is used as a tuning parameter to define the horizons.

The prediction of the output of the plant is computed using the following procedure:

(1) STEP 1: from $t+1$ to $t+d$:

- compute the prediction of the output using the open loop model of the plant given by (1).
- correct each open loop prediction adding the filtered mismatch between the output and the prediction:

$$e(t) = y(t) - \hat{y}(t) \quad (7)$$

$$e_f(t) = F(q^{-1})e(t) \quad (8)$$

$$\hat{y}(t+d-i \mid t) \leftarrow \hat{y}(t+d-i \mid t) + e_f(t-i) \quad (9)$$

where $F(q^{-1})$ is a low pass filter used as a tuning parameter that verifies $F(1) = 1$.

(2) STEP 2: from $t+d+1$ to $t+d+N$ the prediction of the output of the plant is computed using an incremental model of the process (4).

To tune the SPGPC the following two-step procedure can be used:

- Choose the controller parameters N, ψ and λ in order to obtain the desired set-point performance for the nominal plant.
- Estimate the uncertainties of the plant and define F to improve the robustness of the system at the desired frequency region.

The previous procedure can be used when some information about the plant uncertainties is known and the set of control specifications is defined in an unconstrained solution. In these cases the tuning of the filter must be carried out in order to attempt a compromise between robustness and disturbance rejection because increasing the low pass characteristics of filter F improves the robustness and deteriorates the closed loop disturbance response (Normey-Rico and Camacho, 1999). This intuitive rule also works in practice, when information about plant uncertainties is poor and/or constrained optimization is used.

It is also important to note that in the SPGPC the filtering only affects the computation of the free response of the algorithm and does not change the optimization procedure. As has been demonstrated in some experimental tests with real processes, a first order filter is normally enough to obtain a robust controller (Núñez-Reyes *et al.*, 2005).

2.2 The CRHPC

The constrained receding-horizon predictive control is intended for demanding control applications where the conventional predictive control designs can fail. The idea behind CRHPC is to optimize a quadratic function over a costing horizon (6) subject to the following set of M future equality constraints:

$$\begin{array}{l} \hat{y}(t+N_2+j) = w(t+N_2) \\ \delta u(t+N_2-d+j) = 0 \end{array} \quad j = 1, ..., M \quad (10)$$

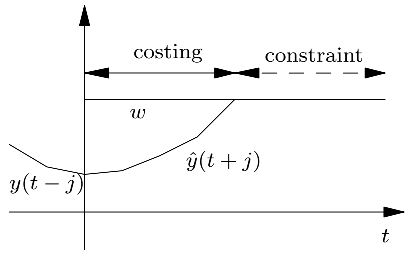

Fig. 1. Constrained receding horizon predictive control.

Using this set of terminal constrains it is possible to obtain a stable nominal closed loop system. This important property is stated as follows (Clarke and Scattolini, 1991):

If:

- $\mathbf{A}$ is nonsingular,
- $\psi(j) = \bar{\psi} \geq 0, \lambda(j) = \bar{\lambda} > 0 \ \forall j = 1, ..., N,$
- $N \geq n + 2$; $m = n + 1$,

then, the closed-loop system is asymptotically stable.

This property is also valid for the case of dead-time systems, since the dead-time is considered in the choice of the horizons of the cost function (6) and thus, it does not affect the imposed conditions. That is, a properly choice of the horizons guaranties that the CRHPC can be used to obtain a stable closed loop system when controlling dead-time processes.

3. THE PROPOSED CONTROLLER

The proposed controller uses the ideas of the SPGPC and CRHPC to obtain a stable closed loop system with better robustness characteristics than previous algorithms. To study the characteristics of the control law the following procedure is used.

Consider first that the values $\hat{y}(t+d|t), ..., \hat{y}(t+d-n-1|t)$ are obtained using the Smith predictor procedure explained in step 1 of section 2.1. Using this data, the prediction of the output of the plant $\hat{y}(t+d+j|t)$ can be computed recursively applying the incremental model of the process (4). Thus, for $j = 1, 2, ..., N, ..., N+M$, follows:

$$\hat{\mathbf{y}} = \mathbf{G}\mathbf{u} + \mathbf{H}\mathbf{u_1} + \mathbf{S}\mathbf{y_1} \quad (11)$$

$$\hat{\bar{\mathbf{y}}} = \bar{\mathbf{G}}\mathbf{u} + \bar{\mathbf{H}}\mathbf{u_1} + \bar{\mathbf{S}}\mathbf{y_1} \quad (12)$$

where:

$\hat{\mathbf{y}} = [\hat{y}(t+d+1|t), ..., \hat{y}(t+d+N|t)]^T$,

$\hat{\bar{\mathbf{y}}} = [\hat{y}(t+d+N+1|t), ..., \hat{y}(t+d+N+M|t)]^T$,

$\mathbf{u} = [\delta u(t), ..., \delta u(t+N)]^T,$

$\mathbf{u_1} = [\delta u(t-1), ..., \delta u(t-(n-1))]^T,$

$\mathbf{y_1} = [\hat{y}(t+d|t), ..., \hat{y}(t+d-n|t)]^T.$

$\mathbf{G}$, $\bar{\mathbf{G}}$, $\mathbf{H}$, $\mathbf{S}$, $\bar{\mathbf{H}}$ and $\bar{\mathbf{S}}$ are constant matrices of dimension $N \times N$, $N \times N$ $N \times n-1$, $N \times n{+}1$, $M \times n-1$ and $M \times n{+}1$, respectively.

The performance index (6) and the constraints (10) can be written as:

$$J = [\hat{\mathbf{y}} - \mathbf{w}]^T \mathbf{Q}_\psi [\hat{\mathbf{y}} - \mathbf{w}] + \mathbf{u}^T \mathbf{Q}_\lambda \mathbf{u} \quad (13)$$

$$\bar{\mathbf{G}}\mathbf{u} + \bar{\mathbf{H}}\mathbf{u_1} + \bar{\mathbf{S}}\mathbf{y_1} = \bar{\mathbf{w}}, \quad (14)$$

where $\mathbf{Q}_\psi$ and $\mathbf{Q}_\lambda$ are the weighting matrices.

By the use of Lagrange multipliers, the minimum of (13) with constraints (14) is obtained by setting:

$$\begin{aligned} \mathbf{u} &= \mathbf{K_1}[\mathbf{w} - \mathbf{f}] + \mathbf{K_2}[\bar{\mathbf{w}} - \bar{\mathbf{f}}] \\ \mathbf{K_1} &= \mathbf{M}\{\mathbf{I} - \bar{\mathbf{G}}^\mathbf{T}[\bar{\mathbf{G}}\mathbf{M}\bar{\mathbf{G}}^\mathbf{T}]^{-1}\bar{\mathbf{G}}\mathbf{M}\}\mathbf{G}^\mathbf{T}\mathbf{Q}_\psi \\ \mathbf{K_2} &= \mathbf{M}\bar{\mathbf{G}}^\mathbf{T}[\bar{\mathbf{G}}\mathbf{M}\bar{\mathbf{G}}^\mathbf{T}]^{-1}, \end{aligned} \quad (15)$$

where: $\mathbf{M} = [\mathbf{G^T}\mathbf{Q}_\psi\mathbf{G} + \mathbf{Q}_\lambda]^{-1}$, $\mathbf{f} = \mathbf{H}\mathbf{u_1} + \mathbf{S}\mathbf{y_1}$ and $\bar{\mathbf{f}} = \bar{\mathbf{H}}\mathbf{u_1} + \bar{\mathbf{S}}\mathbf{y_1}$. The terms $\mathbf{f}$ and $\bar{\mathbf{f}}$ are in the past and correspond to the free response of the system, that is, the output that would be obtained if the control signal is kept constant.

According to a receding horizon strategy, eqn. (15) is to be evaluated at any sampling time, while only the first element $\delta u(t)$ of the vector $\mathbf{u}$ is effectively used to compute the control signal $u(t)$. Thus, the control increment $\delta u(t)$ can be written as

$$\delta u(t) = \mathbf{q}[\mathbf{w} - \mathbf{f}] + \bar{\mathbf{q}}[\bar{\mathbf{w}} - \bar{\mathbf{f}}]$$

where $\mathbf{q} = [q_1, ..., q_N]$ and $\bar{\mathbf{q}} = [\bar{q}_1, ..., \bar{q}_M]$ are the first row of the matrix that multiplies $[\mathbf{w} - \mathbf{f}]$ and $[\bar{\mathbf{w}} - \bar{\mathbf{f}}]$ respectively in (15). The control law also can take the form

$$\delta u(t) = \mathbf{q}\mathbf{w} + \bar{\mathbf{q}}\bar{\mathbf{w}} + [\mathbf{q}\mathbf{H} + \bar{\mathbf{q}}\bar{\mathbf{H}}]\mathbf{u_1} + [\mathbf{q}\mathbf{S} + \bar{\mathbf{q}}\bar{\mathbf{S}}]\mathbf{y_1}$$

where $[\mathbf{q}\mathbf{H} + \bar{\mathbf{q}}\bar{\mathbf{H}}] = [e_1, e_2, ..., e_{n-1}]$ and $[\mathbf{q}\mathbf{S} + \bar{\mathbf{q}}\bar{\mathbf{S}}] = [c_1, c_2, ..., c_{n+1}]$. The coefficients q_i, $\bar{q}_i$, e_i and c_i are functions of a_i, b_i, N, M, $\psi(i)$ and $\lambda(i)$.

The control scheme proposed is shown in Fig. 2. The controller coefficients (q_i, $\bar{q}_i$, e_i, c_i) are computed for each choice of N, $\psi(i)$ and $\lambda(i)$.

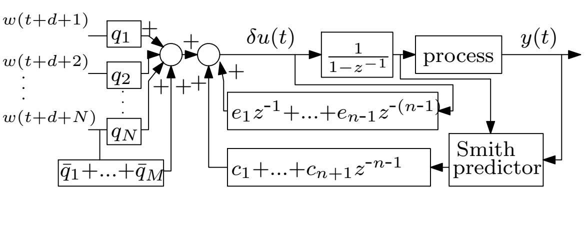

Fig. 2. Control scheme for CHSPPC.

Note that the CHSPPC uses two different models of the plant and disturbances. The coefficients of the control law are computed using an incremental model as in the CRHPC in order to maintain its nominal stability properties. On the other hand the robustness qualities of the SPGPC are obtained because a Smith predictor structure is used to compute the predicted values of the output of the plant from $t{+}1$ to $t{+}d$. To analyze the robustness an equivalent 2DOF structure of the controller can be used, as the one shown in Figure 3. In the diagram $C(z)$ and $W(z)$ are given by:

$$C(z) = \frac{c_1 + c_2 z^{-1} + ... + c_{n+1} z^{-n}}{(1 - z^{-1})(1 - e_1 z^{-1} - ... - e_{n-1} z^{-n-1})} \quad (16)$$

$$W(z) = \frac{\bar{q}_1 + ... + \bar{q}_M + q_N + ... + q_1 z^{-N}}{c_1 + c_2 z^{-1} + ... + c_{n+1} z^{-n}} \quad (17)$$

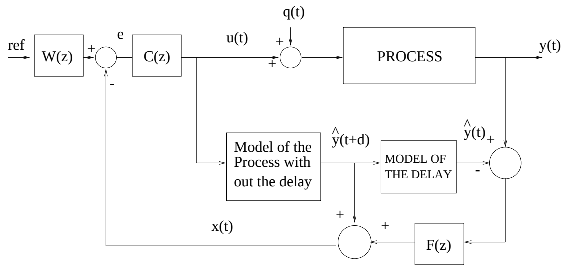

Fig. 3. Structure of the CHSPPC.

4. ROBUSTNESS ANALYSIS

The study of the robustness of the CHSPPC is made using the block diagram of Figure 3. In order to simplify the notation the polynomial dependence in z^{-1} will be omitted in the following. The plant will be represented by a transfer function P and unstructured uncertainties will be considered. It will be assumed from now on that the behavior of the process is described by a family of linear models. Thus, the real plant P will be in a vicinity of the nominal plant P_n, that is: $P = P_n(1 + \delta P)$. If d is the dead-time of the plant it is possible to write, in a discrete representation: $P = Gz^{-d}$ and for the nominal case $P_n = G_n z^{-d_n}$. Thus G represents the plant without the dead-time and G_n is its nominal value.

The tuning of the CHSPPC, originating the cascade controller C and the reference filter W in Figure 3, is made in order to obtain nominal closed loop stability and also to attempt a desired set-point nominal performance. The norm-bound uncertainty region for δP is computed in order to maintain closed-loop stability (Morari and Zafiriou, 1989). The uncertainty norm-boundary is defined by the following expression:

$$| \delta P(e^{j\omega}) | \leq R_b(\omega) = \frac{| 1 + C(e^{j\omega})G_n(e^{j\omega}) |}{| C(e^{j\omega})G_n(e^{j\omega})F(e^{j\omega}) |} \quad (18)$$

$$\forall \omega \in (0, \pi)$$

The last expression shows that the robust stability boundary ($R_b(w)$) is no dead-time dependent, that is the tuning of the robustness properties of the controller could be done independently of the value of the nominal dead-time.

As can be seen, the filter F can be used to improve the robustness of the system at the desired frequency region. As the disturbance rejection performance of the system is affected by the use of the filter, its tuning must be done for a compromise between robustness and disturbance rejection. For a good disturbance rejection performance $\mid u(w)/q(w) \mid$ must be close to one for $\omega < \omega_0$, where ω_0 defines the desired bandwidth of the closed-loop.

As $R_b(w) = \frac{1}{|u(w)/q(w)|}$ the higher disturbance rejection performance gives lower robustness.

As, in general, the model uncertainties are dominant at high frequencies, F must be chosen in order to increase the value of $R_b(w)$ at those frequencies, but maintaining the unitary gain of $u(w)/q(w)$ for the frequencies above ω_0. Thus, F is a low pass filter with the steady-state condition $F(1) = 1$. Note that the compromise between robustness and disturbance rejection does not allow to attempt an arbitrary set of closed loop specifications.

These properties of the CHSPPC suggest the following two-step procedure for tuning the controller:

- choose the controller parameters N, ψ and λ in order to obtain nominal stability and also a desired set-point performance for the nominal plant.
- estimate the uncertainties of the plant and compute the norm bound uncertainty using $F = 1$, G_n and the cascade controller C shown in Figure 3.
- compute the filter F in order to obtain robust stability and the higher bandwidth for the disturbance rejection performance.

This procedure uses the advantages of the SPGPC and CRHPC and cope with the draw backs of both the algorithms. It must be noted that the original CRHPC algorithm does not allow, at least using a simple procedure, to introduce a filter in the predictor structure in order to improve the robustness. On the other hand, the original SPGPC does not allow to obtain nominal stability of the closed loop. Therefore the proposed algorithm presents some advantages if compared to the previous controllers.

5. SIMULATION RESULTS

To illustrate the properties of the proposed CHSPPC, and to compare it with the CRHPC, some simulation examples are presented.

Example 1: The real process is represented by:

$$P(s) = \frac{e^{-5s}}{(s+1)(0.5s+1)(0.2s+1)(0.1s+1)} \quad (19)$$

For the predictor model of the controller a simple second order model is used:

$$P(z) = \frac{0.15z + 0.09}{z^2 - 0.97z + 0.22} z^{-10}$$

To obtain nominal closed loop stability and a step following with small overshoot the tuning is defined by $N = 10$, $M = 3$, $\lambda = 25$ and a sampling time $T = 0.5s$. The closed loop behavior of both control systems, is shown in Fig. 4. The nominal performance is observed from $t = 0$ to $t = 100$ where a step change in the set point is introduced in $t = 0$ and in $t = 25$. Also a 50% step disturbance is added at the input and at the output of the plant in $t = 50s$ and $t = 90s$ respectively. To test the robustness a 20% dead time estimator error is introduced at $t = 105s$ and a new change in the set point is applied at $t = 110s$. As can be observed, both systems have the same behavior for step tracking and disturbance rejection in the nominal case, but when dead time estimation error are considered only the CHSPPC has a stable closed loop response.

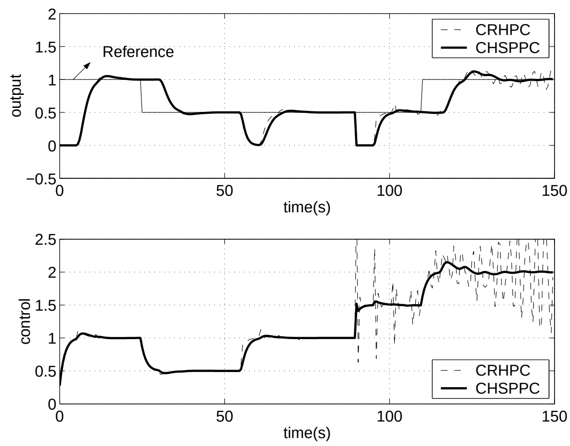

Fig. 4. Example 1.

Example 2: To illustrate the advantages of the use of the robustness filter in the proposed controller the following case is analyzed (Clarke and Scattolini, 1991):

$$(1 - 1.5q^{-1} + 0.7q^{-2})y(t) = (-q^{-1} + 2q^{-2})u(t-4) \quad (20)$$

Note that this model has a zero outside the unitary circle and also a dead-time. As in the previous example, to obtain nominal closed loop stability and a step following with small overshoot the tuning is defined by $N = 8$, $M = 3$, $\lambda = 10$.

The nominal performance of the CRHPC and CHSPPC is compared using the same set point as in example 1 from $t = 0$ to $t = 125$. Also a 5% step disturbance is added at the input of the plant in $t = 50s$ and a 10% step disturbance is added at the output of the plant in $t = 90s$. Until $t = 100s$ the nominal model is used and from $t = 100s$ to the end 25% dead time uncertainties are considered (1 sample). In this situation and with the tuned parameters both closed loop systems became unstable (the simulations of this case are not shown). Thus maintaining the same tuning parameters the robustness of the CHSPPC is increased using the filter $F(z) = \frac{0.15z}{z-0.85}$. The same simulation test is repeated as can be seen in Figure 5. From $t = 0s$ to $t = 100s$ the same results are obtained but from $t = 100s$ to $t = 125s$ only the proposed controller stabilizes the closed loop system. This tuning procedure can be also done on-line in practice, as the filter has only one tuning parameter that can be easily set.

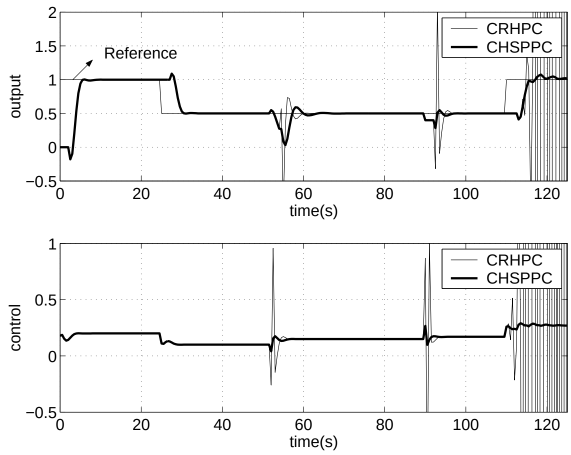

Fig. 5. Example 2.

6. CONCLUSIONS

This paper has shown how to improve the robustness of a constrained horizon predictive controller maintaining the nominal closed loop stability properties when controlling dead-time systems. The proposed controller, based on a different predictor structure, allows to obtain a good compromise between robustness and performance and uses very simple tuning procedure. Comparative simulation results showed the advantages of the proposed algorithm.

REFERENCES

Ansay, P. and V. Wertz (1997). Model uncertainties in gpc: a systematic two-step design. In: *Proc. of the ECC 97*. Bruxelles.

Astrom, K.J. and T. Hagglund (1995). PID *Controllers: Theory, Design and Tuning*. Instrument Society of America.

Camacho, E.F. and C. Bordons (1999). *Model Predictive Control*. Springer Verlag.

Clarke, D.W. and C. Mothadi (1989). Properties of generalized predictive control. *Automatica* **25**(6), 859–875.

Clarke, D.W. and R. Scattolini (1991). Constrained receding-horizon predictive control. *IEE Proceedings-D* **138**(4), 347–354.

Kouvaritakis, B. and M. Cannon (2001). *Nonlinear predictive control: theory and practice*. IEE Control Series.

Kouvaritakis, B., J.A. Rossiter and A.O.T. Chang (1992). Stable generalized predictive control. *IEE-D*. **139**, 349–362.

Morari, M. and E. Zafiriou (1989). *Robust Process Control*. Prentice Hall.

Núñez-Reyes, Amparo, Julio E. Normey-Rico, Carlos Bordons and Eduardo F. Camacho (2005). A smith predictive based mpc in a solar air conditioning plant. *Journal of Process Control* **15**(1), 1–10.

Normey-Rico, J.E. and E.F. Camacho (1999). Robustness effects of a prefilter in smith predictor based generalised predictive controller. *IEE Proceedings, Control Theory and Applications* **146**(2), 179–185.

Normey-Rico, J.E. and E.F. Camacho (2000). Multivariable generalised predictive controller based on the smith predictor. *IEE Proceedings, Control Therory and Applications* **147**(5), 538–546.

Richalet, J., A. Rault, J.L.Testud and J. Papon (1976). Algorithm control for industrial processes. In: *Proc. 4th IFAC Symp. on Identification and System Parameter Estimation*. Tbilisi, URSS.

Robinson, T. and D. Clarke (1991). Robustness effects of a prefilter in receding-horizon predictive control. *IEE-D* **138**, 2–8.

Rossiter, A., J.R. Gossner and B. Kouvaritakis (1996). Infinite horizon stable predictive control. *IEEE Transactions on Automatic Control* **40**(10), 1522–1527.

Rossiter, J.A. and B. Kouvaritakis (1994). *Advances in Model-Based Predictive Control. Chapter: Advances in Generalized and Constrained Predictive Control*. Oxford University Press.

Scokaert, P. and D.W. Clarke (1994). *Advances in Model-Based Predictive Control. Chapter: Stability and Feasibility in Constrained Predictive Control*. Oxford University Press.

Yoon, T. and D. Clarke (1995). Observer design in receding-horizon control. *Int. Journal of Control* **2**, 171–191.