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A filtered Smith predictor based subspace predictive controller

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Abstract: This paper presents a SPC based in the filtered Smith predictor structure in order to improve the performance of SPC when applied to a stable or integrative dead-time processes. This technique combines the robustness of subspace identification algorithms, the ability of predictive controllers to deal with multi variable processes and operational constraints and robustness of filtered Smith predictor in presence of model uncertainties. The proposed controller is applied in two simulation cases. The first is a boiler temperature control and the second is the control of effluent concentration and temperature in a stirred tank reactor. The obtained results show that the proposed strategy gives good performance when controlling dead-time processes considering estimation errors in dynamics and dead time.

Keywords: subspace predictive control, dead time compensation, filtered Smith predictor, process control

1. INTRODUCTION

The dynamic behavior of many industrial processes can be represented by a differential equations system with dead times. Dead times appear in many processes in industry and they are caused by the transport of mass, energy or information, the accumulation of time lags in a great number of low-order systems connected in series, or the required processing time for sensors. They introduce an additional lag in the system phase, thereby decreasing its phase and gain margin making the control of these systems more difficult (Normey-Rico and Camacho (2007)).

Dead time imposes important constraints in the controllers performance by their effect in the system characteristic equation. Smith's work (Smith (1957)) was a pioneer in this area and their goal was to eliminate the delay from the closed-loop characteristic equation. This control structure became known as the Smith predictor (SP).

Several works have been written proposing modifications to the original structure of the Smith predictor normally denominated as dead-time compensator's (DTC) (Alevisakis and Seborg (1973), Jerome and Ray (1986), Normey-Rico et al. (1997), García and Albertos (2010)). In particular one simple solution is to add a filter in the prediction error of SP scheme, which allows improve the performance when dead-time-estimation errors are considered (Normey-Rico and Camacho (2009)). This structure is called the filtered Smith predictor (FSP).

Another approach to dead-time process control is the use of model predictive control (MPC). Predictive controllers have been widely used in process industries for more than two decades (Camacho and Bordons (2007)). The term predictive control does not designate a specific control strategy but a wide range of control algorithms which make an explicit use of a process model in a cost function minimization to obtain the control signal (Camacho and Bordons (2007)).

Predictive controllers deal intrinsically with dead times, however, as shown in (Normey-Rico and Camacho (2007)), optimal prediction gives low robustness index to MPC. This can be solved by using a different predictor structure, as in the DTC-GPC algorithm, that is an extension of the GPC controller for dead-time process, where the FSP is used to compute the predictions up to the dead time.

In the last decade emerged another class of predictive controllers that consist in a combination of an intermediary result in subspace-based system identification methods and MPC strategies, and is called Subspace Predictive Control (SPC). The SPC uses a subspace linear predictor equation to predict the future value of the system in the MPC implementation. As SPC does not use an explicit model is called data-driven subspace model predictive control (Favoreel and Moor (1998)). This algorithm has the advantage of having the numerical robustness typical of subspace-based methods. There are in literature some results relating the SPC with LQG and GPC strategies and treating all features normally associated with a traditional predictive controller, such as the inclusion of integral action and feedforward compensation for measured disturbances and constraints handling (Hale and Qin (2002), Kadali et al. (2003), Huang and Kadali (2008), Ruscio and Foss (1998)).

The main purpose of this paper is to propose a new structure based on filtered Smith predictor to improve the performance of SPC when applied to a dead-time process. This structure is called Filtered Smith Predictor Subspace Predictive Control (FSP-SPC).

The rest of the paper is organized as follows. In section 2 the SPC theory is revisited. Section 3 is devoted to present the proposed algorithm structure. Simulation case studies are analyzed in section 4, where the proposed strategy is compared with SPC in presence of dynamic and dead-time modeling errors. The paper ends with the conclusions.

2. SUBSPACE PREDICTIVE CONTROL

Subspace Predictive Control (SPC) algorithm consist in a combination of system identification and control strategy development into a single-step implementation. It was conceived as a fusion of an intermediary result in subspace methods in system identification and model-based predictive control algorithm (Mardi (2010)). The SPC algorithm uses subspace predictor equation that predicts the future output of the system in terms of a linear function of past input and output values, future input values, and so-called subspace predictor coefficients. These coefficients are obtained directly from I/O data, often by performing a single QR-factorization step. In this work will be used the subspace linear predictor equation presented in equation (1) and developed by (Favoreel et al. (1999a)), (Favoreel et al. (1999b)) and (Kadali et al. (2003)).

$$\hat{y}_f = L_w w_p + L_u u_f \tag{1}$$

where $\hat{y}_f$ is the future output prediction, w_p is the past input and output, u_f is the future input, and L_w and L_u are the corresponding subspace linear predictor coefficients.

2.1 Predictor as function of Δu_f

According to equation (1), will be defined the following vectors:

$$w_p = w_p^{z^{-1}} + \Delta w_p \tag{2}$$
$$= \begin{bmatrix} y(t-M) \\ y(t-M+1) \\ \vdots \\ y(t-1) \\ u(t-M) \\ u(t-M+1) \\ \vdots \\ u(t-1) \end{bmatrix} + \begin{bmatrix} \Delta y(t-M+1) \\ \Delta y(t-M+2) \\ \vdots \\ \Delta y(t) \\ \Delta u(t-M+1) \\ \Delta u(t-M+2) \\ \vdots \\ \Delta u(t) \end{bmatrix}$$

$$u_f = u_f^{z^{-1}} + \Delta u_f \tag{3}$$
$$= \begin{bmatrix} u(t) \\ u(t+1) \\ \vdots \\ u(t+N_p-1) \end{bmatrix} + \begin{bmatrix} \Delta u(t+1) \\ \Delta u(t+2) \\ \vdots \\ \Delta u(t+N_p) \end{bmatrix}$$

where the superscript z^{-1} for $w_p^{z^{-1}}$ and $u_f^{z^{-1}}$ denotes the value of w_p and u_f at the previous time step $t-1$, N_p is the prediction horizon and M is the order of subspace predictor, and $\Delta = 1-z^{-1}$. In this work was used a discrete time representation of the plant and the controller and was used t to represent the discrete time.
Substituting equations (2), (3) into (1) gives:

$$\hat{y}_f = L_w \Delta w_p + L_u \Delta u_f + L_w w_p^{z^{-1}} + L_u u_f^{z^{-1}} \tag{4}$$

The term $L_w w_p^{z^{-1}} + L_u u_f^{z^{-1}}$ can be written as follows

$$\hat{y}_f^{z^{-1}} = L_w w_p^{z^{-1}} + L_u u_f^{z^{-1}} = \begin{bmatrix} y(t) \\ \hat{y}_f(t+1) \\ \vdots \\ \hat{y}_f(t+N_p-1) \end{bmatrix} \tag{5}$$

where $y(t)$ is the measured output ate instant t. Equation (4) can be rewritten as,

$$\hat{y}_f = L_w \Delta w_p + L_u \Delta u_f + \begin{bmatrix} y(t) \\ \hat{y}_f(t+1) \\ \vdots \\ \hat{y}_f(t+N_p-1) \end{bmatrix} \tag{6}$$

Expanding the predictions for times $t+1$ to $t+N_p$ it is possible to visualize that each prediction depends on the value predicted in the previous time, as shown in equation (7).

$$\begin{aligned} \hat{y}_f(t+1|t) &= L_w^{(1)} \Delta w_p + L_u^{(1)} \Delta u_f + y(t) \\ \hat{y}_f(t+2|t) &= L_w^{(2)} \Delta w_p + L_u^{(2)} \Delta u_f + \hat{y}_f(t+1) \\ &\vdots \\ \hat{y}_f(t+N_p|t) &= L_w^{(f)} \Delta w_p + L_u^{(f)} \Delta u_f + \hat{y}_f(t+N_p-1) \end{aligned} \tag{7}$$

where the superscripts $^{(1)}$; $^{(2)}$; ... ;$^{(f)}$ in $L_w^{(i)}$ and $L_u^{(i)}$ above denotes the first, second and f-rows in the L_w and L_u matrices respectively.
In MPC is usual to use the control horizon N_c less than the prediction horizon N_p. If $N_c < N_p$ only input values in the first N_c-time steps will affect the output of the system and the future Δu_f vector is truncated to the first N_c-values thus giving us the vector Δu_{N_c}. In the same way the matrix L_u can be truncated to the first N_c-columns, as in the equation (8), in order to remove the unnecessary terms.

$$L_u^{N_c} = L_u \begin{bmatrix} I_{N_c} \\ 0_{1\times N_c} \end{bmatrix} \tag{8}$$

By recursively substituting $\hat{y}(t+1)$, $\hat{y}(t+2)$,...,$\hat{y}(t+N_p-1)$ on the right hand side of equation (7) and setting different control and prediction horizons, the linear subspace predictor can be expressed in terms of Δu_f as follows

$$\hat{y}_f = F_l y(t) + \Gamma_l L_w \Delta w_p + \Gamma_l L_u^{N_c} \Delta u_{N_c} \tag{9}$$

with

$$F_l = \begin{bmatrix} I_l \\ I_l \\ \vdots \\ I_l \end{bmatrix}, \Gamma_l = \begin{bmatrix} I_l & 0 & \cdots & 0 \\ I_l & I_l & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I_l & I_l & \cdots & I_l \end{bmatrix} \tag{10}$$

2.2 Cost function

The cost function used in subspace predictive control can be the same used in traditional MPC and expressed in equation (11), where $r(t+j)$ is the future reference. The only difference between both algorithms is the way to obtain the linear predictor.

$$J = \sum_{j=1}^{N_p} \left[\hat{y}_f(t+j|t) - r(t+j)\right]^2 + \sum_{j=1}^{N_c} \lambda \left[\Delta u(t+j)\right]^2 \tag{11}$$

Using equation (9) and the future references, the cost function can be updated as,

$$J = \left(\Gamma_l L_w \Delta w_p + \Gamma_l L_u^{N_c} \Delta u_{N_c} + F_l y(t) - F_l r(t+1)\right)^T \left(\Gamma_l L_w \Delta w_p + \Gamma_l L_u^{N_c} \Delta u_{N_c} + F_l y(t) - F_l r(t+1)\right) + \Delta u_{N_c}^T \lambda I \Delta u_{N_c} \quad (12)$$

Expanding equation (12) and taking into account only the terms dependent on Δu_{N_c}, the cost function can be written in quadratic form as,

$$J = \frac{1}{2} \Delta u_{N_c}^T H \Delta u_{N_c} + \Delta u_{N_c}^T b_0 \quad (13)$$

with,

$$H = \left(\Gamma_l L_u^{N_c}\right)^T \left(\Gamma_l L_u^{N_c}\right) + \lambda I$$
$$b_0 = \left(\Gamma_l L_u^{N_c}\right)^T \left(\Gamma_l L_w \Delta w_p + F_l \left(y(t) - r(t+1)\right)\right) \quad (14)$$

2.3 Unconstrained SPC

Without constraints the future control actions can be computed as

$$\Delta u_f = -K_{\Delta w_p, N_c} \Delta w_p - K_{e,N_c} \left(y(t) - r(t+1)\right) \quad (15)$$

where $K_{\Delta w_p, N_c}$ and K_{e,N_c} defined as,

$$K_{\Delta w_p, N_c} = \left(\Gamma_l L_u^{N_c}\right)^T \left(\Gamma_l L_u^{N_c}\right) + \lambda I^{-1} \left(\Gamma_l L_u^{N_c}\right)^T \left(\Gamma_l L_w\right)$$
$$K_{e,N_c} = \left(\Gamma_l L_u^{N_c}\right)^T \left(\Gamma_l L_u^{N_c}\right) + \lambda I^{-1} \left(\Gamma_l L_u^{N_c}\right)^T F_l \quad (16)$$

In order to compute the control action for the time $t+1$ only the first value of Δu_{N_c} is used, which corresponds to Δu_{t+1}. Therefore

$$\Delta u_{t+1} = -K_{\Delta w_p} \Delta w_p - K_e \left(y(t) - r(t+1)\right) \quad (17)$$

with,

$$K_{\Delta w_p} = \left[\, 1 \;\; 0_{1\times(M-1)} \,\right] K_{\Delta w_p, N_c}$$
$$K_e = \left[\, 1 \;\; 0_{1\times(M-1)} \,\right] K_{e,N_c} \quad (18)$$

3. FSP-SPC

In (Normey-Rico and Camacho (2007)), was presented a new MPC algorithm based on a combination of a DTC and a GPC (named DTC-GPC). DTC-GPC uses cost function (11) but a different way to compute predictions: (i) the output prediction from $t+1$ to $t+d$ is computed using a filtered Smith predictor (FSP) structure, (ii) the predictions from $t+d+1$ to $t+d+N$ are computed with an incremental model of the plant in equation (19)

$$\Delta A(z^{-1}) y(t) = z^{-d} B(z^{-1}) \Delta u(t-1) \quad (19)$$

as a function of the predictions up to $t = d$. The predictor equation used in the FSP is given by:

$$\hat{y}_f(t+d|t) = \left[G_n(z^{-1}) - P_n(z^{-1}) F_r(z^{-1})\right] u(t) + F_r(z^{-1}) y(t) \quad (20)$$

where $P_n(z^{-1})$ and $G_n(z^{-1})$ are respectively the model with and without dead time and $F_r(z^{-1})$ is the parameter that can be tuned in order to improve the robustness or the disturbance rejection properties of the system, using the same ideas as in the dead-time compensator case (Normey-Rico and Camacho (2007)).

In (Normey-Rico and Camacho (2009)) it is shown that: (i) to avoid the undesirable effect of slow or integrative poles of the plant model in the closed-loop system, F_r should be designed to eliminate these poles from $S(z) = G_n(z) - P_n(z)F_r(z) = G_n(z)[1 - z^{-d} F_r(z)]$; (ii) for steady state conditions $F_r(1) = 1$ and (iii) for robustness F_r should be low pass as F_r appears in the denominator of the robustness index of the FSP controller. Thus, filter poles are used to define a compromise between robustness and disturbance rejection while filter zeros set condition (i). In the simple case of a stable process with no undesirable slow poles, a simple filter can be used: $F_r = (1-\beta)/(1-\beta z^{-1})$ where $\beta \in (0, 1)$ is used to improve robustness (using bigger value of β). In the particular case of an integrative process and a step disturbance, to verify conditions (i) and (iii), $F_r(z^{-1})$ is a second-order filter as

$$F_r(z^{-1}) = \frac{f_{b1} z^{-1} + f_{b0}}{(z-\beta)^2} \quad (21)$$

where $f_{b0} = -d(1-\beta)^2 + (\beta^2 - 1)$ and $f_{b1} = (1-\beta)^2 - f_{b0}$, and β is the tuning parameter used to define the trade-off between robustness and disturbance rejection.

Here, the FSP ideas are used to improve SPC algorithm for dead-time processes. In DTC-GPC algorithm the FSP is implemented based on model transfer function. As the SPC algorithm is model free the inclusion of FSP structure is not direct, as is necessary the prior knowledge of dead-time value. In (Shalchian et al. (2010)) is presented an algorithm based on subspace identification methods to estimate the value of dead time. In this method with only a single Orthogonal-triangular (QR) decomposition procedure, it is possible to extract impulse response for a k horizon from the input-output data. If there are d sample delay on the set of data, the first d elements of the impulse response will be equal to zero. In a noise scenario, these first terms of the impulse sequence are approximately zero. By choosing an appropriate threshold it is then possible to extract the delay value.

Another way to estimate the dead time is to analyze matrix L_w, where dead-time value is estimated as the number of first zero columns related with input u. This is possible because the free response is computed as $F_l y_t + \Gamma_l L_w \Delta w_p$ according to equation (9). Knowing the delay d it is possible to compute the subspace predictors that represents the response of $P_n(z^{-1})$ and $G_n(z^{-1})$ according to the following steps.

(1) Estimate the dead time value using one of the algorithms mentioned;
(2) To estimate $P_n(z^{-1})$, the number of past data (p) must be greater than d in order to capture the dynamic and the dead time. One idea is to use $p = d + n$, where n is the estimated system order;
(3) To estimate $G_n(z^{-1})$, when computing the I/O matrix, the output data is shifted d steps backwards so as to cancel the delay effect between the input and output.

Equations (23) and (22) describe the P_n and G_n subspace predictors in matrix form.

$$\hat{y}_{P_n} = F_l y(t) + \Gamma_l L_{wP_n} \Delta w_{pP_n} + \Gamma_l L_{uP_n}^{N_c} \Delta u_{P_n N_c} \quad (22)$$

$$\hat{y}_{G_n} = F_l \hat{y}(t+d) + \Gamma_l L_{wG_n} \Delta w_{pG_n} + \Gamma_l L_{uG_n}^{N_c} \Delta u_{G_n N_c} \quad (23)$$

where

$$\hat{y}_{P_n} = \begin{bmatrix} \hat{y}(t+1) \\ \hat{y}(t+2) \\ \vdots \\ \hat{y}(t+N_p) \end{bmatrix}, \Delta w_{pP_n} = \begin{bmatrix} \Delta y(t-M+1) \\ \Delta y(t-M+2) \\ \vdots \\ \Delta y(t) \\ \Delta u(t-M+1) \\ \Delta u(t-M+2) \\ \vdots \\ \Delta u(t) \end{bmatrix},$$

$$\Delta u_{fP_n} = \begin{bmatrix} \Delta u(t+1) \\ \Delta u(t+2) \\ \vdots \\ \Delta u(t+N_p) \end{bmatrix} \quad (24)$$

$$\hat{y}_{G_n} = \begin{bmatrix} \hat{y}(t+d+1) \\ \hat{y}(t+d+2) \\ \vdots \\ \hat{y}(t+N_p) \end{bmatrix}, \Delta u_{fG_n} = \begin{bmatrix} \Delta u(t+1) \\ \Delta u(t+2) \\ \vdots \\ \Delta u(t+N_p) \end{bmatrix},$$

$$\Delta w_{pG_n} = \begin{bmatrix} \Delta y(t-M+d+1) \\ \Delta y(t-M+d+2) \\ \vdots \\ \Delta y(t+d) \\ \Delta u(t-M+1) \\ \Delta u(t-M+2) \\ \vdots \\ \Delta u(t) \end{bmatrix} \quad (25)$$

Only the first line of each predictor and the discrete equation of filter F_r are necessary for FSP implementation. The FSP with subspace predictors approach is showed in equation (26).

$$\hat{y}_{FSP}(t+d) = \hat{y}_{G_n} - \hat{y}_{P_n F_r} + y_{F_r} \quad (26)$$

where $\hat{y}_{P_n F_r}$ is the filtered output of predictor with dead time, $\hat{y}_{G_n}$ is the output of predictor without dead time, y_{F_r} is the filtered plant output and $\hat{y}_{FSP}(t+d)$ is the estimation of plant output at time $t+d$.
Now the future control actions can be computed as

$$\Delta u_f = -K_{\Delta w_p G_n, N_c} \Delta w_p - K_{eG_n, N_c} \left(\hat{y}_f(t+d) - r(t+1) \right) \quad (27)$$

where the gain matrices $K_{\Delta w_p G_n, N_c}$ and K_{eG_n, N_c} are computed using the free-delay system matrices L_{wG_n} and $L_{uG_n}^{N_c}$. The predictions of $\hat{y}_f(t+d)$ is computed using equation (26). This algorithm is called filtered Smith predictor subspace predictive controller (FSP-SPC).

4. SIMULATION RESULTS

This section presents two simulation examples. In the first example the proposed controller is applied to a SISO boiler temperature control system. In the second one the FSP-SPC is used to control a MIMO stirred tank reactor. In both cases the controller performance against dead time and dynamics uncertainties is analyzed. The performance of the proposed controller is compared with SPC. Both process models were extracted from (Camacho and Bordons (2007)) and (Normey-Rico and Camacho (2007)).

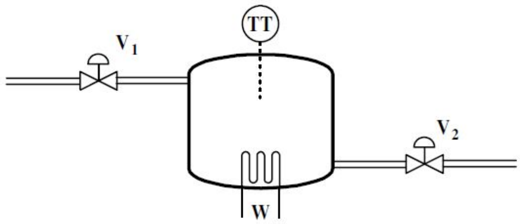

Fig. 1. Boiler Temperature Control System

Table 1. Parameters of FSP-SPC SISO

Parameter	Value
n	2
M	n+d
N_p	200
Nc	25
λ	10

4.1 Example 1 - Boiler

The transfer function between the temperature (T) and the power (W) in the boiler showed in Fig. 1, is presented in equation (28). This model was obtained assuming variations around the operating point $T = 50^0C$ and $W = 50\%$. The time constants are expressed in seconds.

$$P(s) = \frac{e^{-6s}}{s(s+1)} \quad (28)$$

The sampling period is chosen as $Ts = 0.1s$. The tuning parameters used in identification and control steps are presented in table 1.

Figure 2 compares the closed-loop behavior of the plant using both FSP-SPC and SPC. In this simulation was used the filter in equation (21) with $\beta = 0.94$ and no uncertainties were considered. Input and output disturbances were applied at times $80s$ and $110s$ respectively. The input disturbance can be interpreted as a reduction in the boiler feed flow rate and was simulated with a -3% opening in the valve V_1 at time $85s$, output disturbance represents an increase in consumption and was simulated through an 5% opening in the valve V_2 at time $110s$. As it is possible to see FSP-SPC had better performance in reference tracking and output disturbance rejection and SPC rejects faster the input disturbance.

In order to introduce modeling errors equation (29) was used to simulate the process maintaining the same controllers. As can be seen in figure (3), in this case the SPC failed to control the system losing stability while FSP-SPC gives a smooth response. This behavior is due to the robustness added by using the FSP to compute the predictions up to $t+d$.

$$P(s) = \frac{e^{-5.3s}}{s(s+1)(0.5s+1)(0.2s+1)(0.1s+1)} \quad (29)$$

To attenuate the oscillations in the closed-loop response the filter tuning parameter was set to $\beta = 0.98$. The result

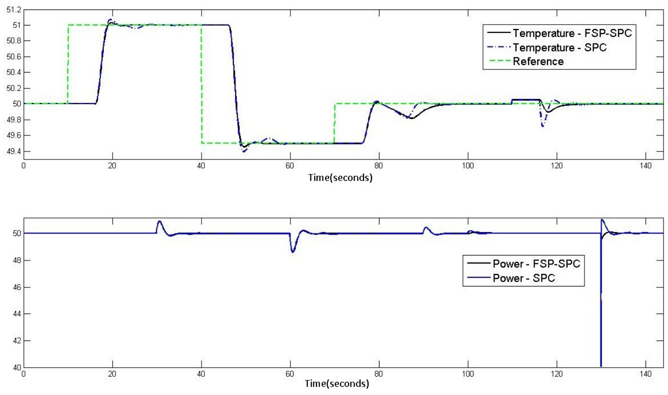

Fig. 2. Boiler temperature control without modeling errors

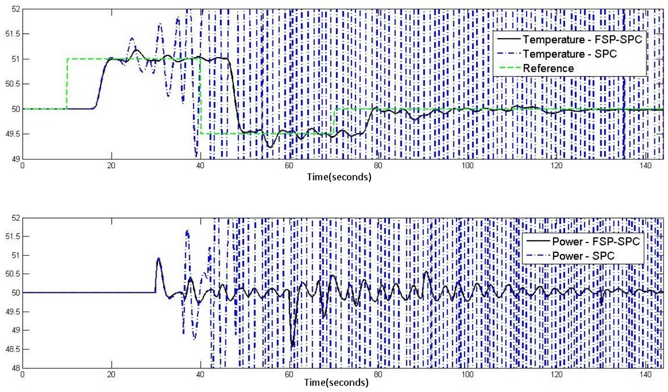

Fig. 3. Boiler temperature control with modeling errors and $\beta = 0.94$

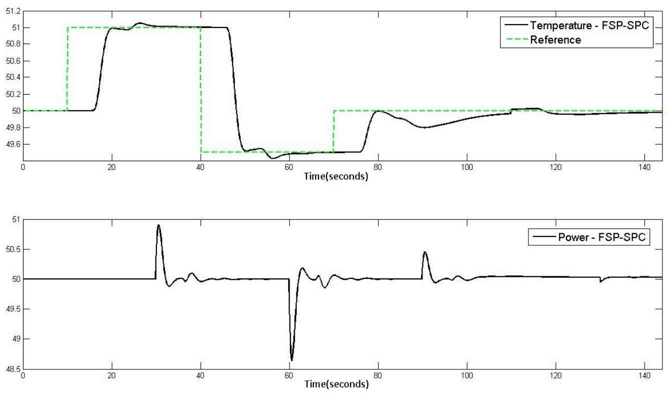

Fig. 4. Boiler temperature control with modeling errors and $\beta = 0.98$

is shown in Fig. 4 where it can be seen that the price to pay is a slower response.

4.2 Example 2 - Stirred Tank Reactor

To illustrate the application of the FSP-SPC to a MIMO system a stirred tank reactor is used in this example. The small signal model of stirred tank reactor in Fig. 5 is described by the transfer matrix in equation (30). The time constants are expressed in minutes.

$$\begin{bmatrix} Y_1(s) \\ Y_2(s) \end{bmatrix} = \begin{bmatrix} \dfrac{e^{-0.24s}}{0.7s+1} & \dfrac{5e^{-0.24s}}{0.3s+1} \\ \dfrac{e^{-0.09s}}{0.5s+1} & \dfrac{2e^{-0.09s}}{0.4s+1} \end{bmatrix} \begin{bmatrix} U_1(s) \\ U_2(s) \end{bmatrix} \qquad (30)$$

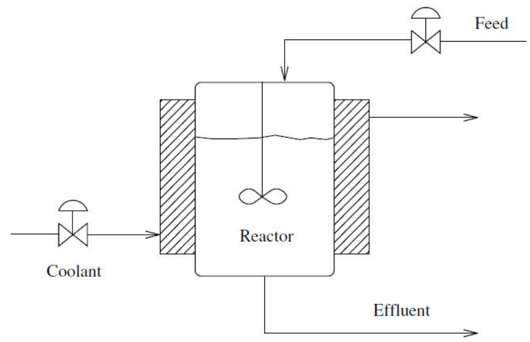

Fig. 5. Stirred Tank Reactor

where the manipulated variables $U_1(s)$ and $U_2(s)$ are the feed flow rate and the flow of coolant in the jacket, respectively. The controlled variables $Y_1(s)$ and $Y_2(s)$ are the effluent concentration and the reactor temperature, respectively. The sampling time used in this example is $Ts = 0.03min$. The dead times in this case are caused by measurement effects and are equal for all the $g_{ij}(s)$ of each row. The dead time in the output temperature $y_2(t)$ is caused by the time necessary to transport the fluid to the sensor. The dead time in the concentration $y_1(t)$ is caused by the transportation effect and the time required by the analyzer. This model was obtained assuming variations around the operating point $Y1 = 7,12kgmol/m^3$, $Y2 = 34^0C$,$U1 = 25m^3/h$ and $U2 = 2,7m^3/h$. Both controllers were implemented for the MIMO case in accordance with the considerations presented in (Mardi (2010) and Normey-Rico and Camacho (2007)). The tuning parameters used in identification and control steps are presented in table 2.

Table 2. Parameters of FSP-SPC MIMO

Parameter	Value
n	[4; 5]
p	$[n_1 + d_1; n_2 + d_2]$
N_p	[20; 20]
N_c	[10; 10]
R	[1; 1]
Q	[1; 1]
β	[0,98; 0,96]

Initially were used the same values for the nominal and real dead-times. The dead times for each output are $d_1 = 8$ and $d_2 = 3$. Were simulated input disturbances in the inlet temperature and concentration. The disturbances are assumed as steps of 10% at time $10min$ and 5% at time $15min$ respectively. Figure 6 shows control experiment and it is possible to see that both controllers had good response in reference tracking and SPC reject faster the disturbances.

In order to simulate a modeling error the real dead-times were changed to $d_1 = 12$ and $d_2 = 7$. The result is shown in Fig. 7. As in the first example SPC was not able to control the process and loose the stability. However the FSP-SPC controlled satisfactorily the reactor performing the reference tracking and disturbance rejection in presence of great dead-time uncertainties in both controlled variables.

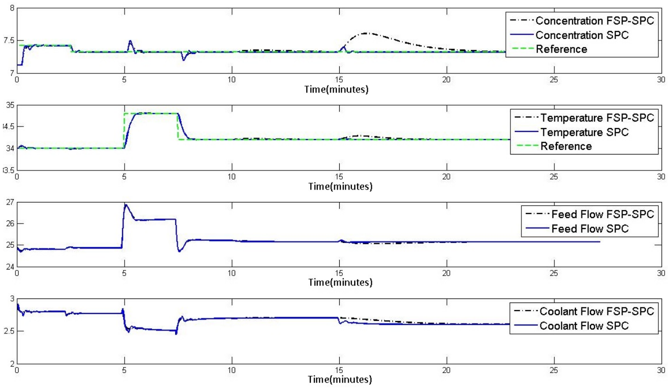

Fig. 6. Reactor control without modeling errors

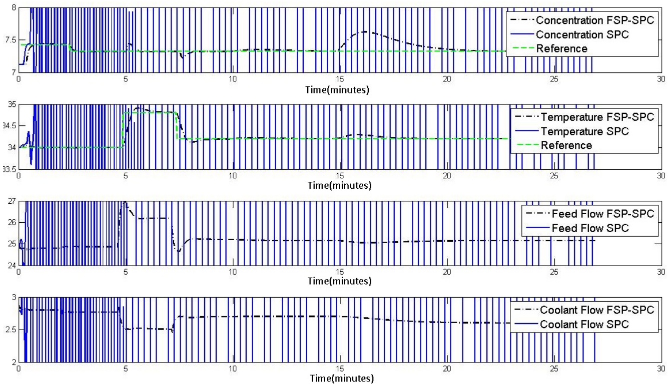

Fig. 7. Reactor control with modeling errors

5. CONCLUSION

In this work a filtered Smith predictor based subspace predictive controller is proposed. The characteristics of the proposed scheme are: (i) the use of model free FSP to compute prediction up to time $t + d$; (ii) improve performance and robustness of SPC algorithm when applied to dead-time process ; (iii) deal with estimation errors in dynamics and dead time. According to the obtained simulation results one can conclude that the use of the proposed strategy allow for better transient response when estimation errors are considered in the predictor. Other robust approaches, as for example min-max MPC, could be applied to this problem, however the use of the predictor filter is simpler and can be tuned manually in practical applications (Normey-Rico and Camacho (2007)). The proposed method also gives good results for non minimum phase systems, however the case of unstable processes is under study. The use of the proposed controller in real practice can be considered promissory. Future work includes studies with controlled variables corrupted by noise, the add of operations constraints and tests in complete phenomenological models.

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