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Advanced Trajectory Tracking Control Applied to Dynamic System with disturbance

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***Abstract*— This paper deals to present an advanced control in predictive control application. This control method is mainly based on the prediction model and the objective function to drive the nearest output possible of the trajectory in the sense of least square within. We are interested in evaluating the performance of these control technique and their applications on dynamic systems**.

Keywords— Generalized Predictive Control; Receding Horizon and CARIMA Model.

I. Introduction

Model Predictive Control (MPC) is an advanced approach command [1], and all commands carries this name, predictive control is the most used in industry, both for the technical qualities and for its performance that permit an ease implementation. Its scope extends to all industries, in particular where PID control is not effective.

Since the 1970, the predictive control has been successfully used in various industrial applications and for many fields of activities. A study on MPC lead by [2, 3] reported that there were over 4500 applications worldwide in 2003, mainly in oil refineries, petrochemical plants, automotive, defense, metallurgy, and other areas. In these industries, MPC has become the method of choice for difficult multivariable control problems that include inequality constraints. The idea of predictive control is already between the lines of the founder of the optimal control with its form of predictive control based on a model using a linear programming approach work [4], [5].

Historically, this idea will be implemented industrially with Richalet in 1978 IDCOM software 'identification-control' [6]. The formalism is then used to consider linear systems such as Finite Impulse Response filters 'FIR'. The costs considered are quadratic; the estimation part is based on a least squares approach. In 1980 appears DMC 'Dynamic Matrix Control' [7]. DMC gets IDCOM many ideas, but the systems are represented by their response to the step. In both approaches, the model was of black box type, objective was to pursue a reference but the constraints were not taken into account. Shortly after, [8] give a detailed description of the algorithm Quadratic Dynamic Matrix Control (QDMC). This formulation as a quadratic problem directly implements the constraints of manipulated variable and output, and appears as the second generation of this variety of command. In 1987 appears Generalized Predictive Control 'GPC', developed by [9]. In 1988, it is possible to consider systems as state model by SMOC (Shell Multivariable Optimizing Control). Predictive functional control 'PFC' developed by Richalet and ADERSA [10, 11]. Global predictive control (GlobPC) is the newest member of the family of predictive controls receding horizon. It is a developed control law in order to increase the flexibility and performance while reducing restrictions and control for multivariable systems [12].

One of the most popular controls is Generalized Predictive Control 'GPC' [13]. The name GPC is used by [9]-as already mentioned-in their formulation proposed for model predictive control. The name GPC has since been widely adopted as a designation of a class of methods of predictive control to adaptive characters.

The principle of predictive control is the creation of an anticipatory effect. The implementation of this command requires:

- The prediction model used is CARIMA. It's an extension of CARMA model, which is incorporated an integral effect to eliminate the system deviation of the effect of constants disturbance.
- Use of the prediction horizon greater than delay.
- Recursively solving DIOPHANTINE equation.
- The introduction of the weighting increments in the test control.
- The choice of the control horizon from which all control increments are taken equal zero.

II. Principles of The GPC Control

Predictive control is repeated at every time resolution of optimal control problem: 'How to get from the current state to a goal of optimally satisfying the constraints [14]. GPC is based on the model of the process used for the purpose of predicting the behavior of the process. The basic idea is shown in Figure (1), the controller predictive calculates the future control sequence which results from the process output. Only the first element of the command sequence is applied, and the remainder rejected as another sequence is ready in the future instants and this principle is known by the receding horizon.

A. Principle of The Receding Horizon

The principle the receding horizon is a completely original procedure distinguishes predictive control from the other control techniques. The idea is to fix a finite horizon N, and considering the current state as the initial state, to optimize a cost function over this interval, while respecting the constraints. This results in an optimal sequence of N orders of which only the first value will be effectively implemented. As time progresses, the prediction horizon slides and a new optimization problem is solved by considering the state of the updated system. In summary, at each step, it is necessary to develop a sequence of optimal open-loop controls, refined systematically by the arrival of these measures (Fig. 1).

B. The Process Model

In predictive controllers, several models of the process can be applied, the implementation of the GPC is made from a model represented in a form of transfer function.

$$y(t) = \frac{B(q^{-1})}{A(q^{-1})}u(t-1) \quad (1)$$

With y (t) process output, u (t) the control system, q^{-1} lag operator.
And defined polynomials such that:

$$\begin{cases} A(q^{-1}) = 1 + a_1 q^{-1} + \cdots + a_n q^{-n} \\ B(q^{-1}) = b_0 + b_1 q^{-1} + \cdots + b_m q^{-m} \end{cases} \quad (2)$$

The prediction can be expressed like:

$$y(t+k/t) = \frac{B(q^{-1})}{A(q^{-1})}u(t+k-1/t) \quad (3)$$

To separate the effect of past and future manipulated variable, a Diophantine equation must be solved.

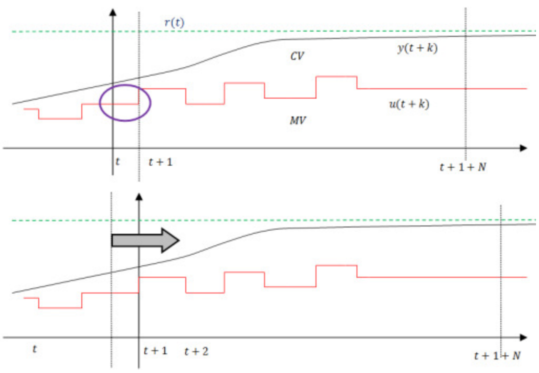


Fig. 1. Principle of the receding horizon

$$\frac{B(q^{-1})}{A(q^{-1})} = E_k(q^{-1}) + q^{-k+1}\frac{F_k(q^{-1})}{A_k(q^{-1})} \quad (4)$$

Replacing in the prediction output, one gets:

$$\hat{y}(t+k/t) = E_k(q^{-1}).u(T+K-1/t) + \frac{F_k(q^{-1})}{A(q^{-1})}u(t) \quad (5)$$

This model is ready to describe an unstable model, and another advantage is that the numbers of parameters required are limited. The disadvantage of this model is that the order of the polynomials A and B must be known a priori.

C. Disturbance Model

The disturbance model has a special importance in predictive controllers. The most general is the CARIMA model (Controlled Autoregressive Moving Average), wherein the difference between the measured output and the output calculated by the model of the process is given by:

$$n(t) = \frac{C(q^{-1})}{D(q^{-1})}\xi(t) \quad (6)$$

Hence the denominator $D(q^{-1})$ includes the integrator usually chosen as $(1-q^{-1})A(q^{-1})$, ξ (t) is white noise with zero mean value, and the polynomial C is identified or selected as a parameter controller. To calculate the predicted error, the following Diophantine equation must be solved:

$$\frac{C(q^{-1})}{D(q^{-1})} = E_k(q^{-1}) + q^{-k}\frac{F_k(q^{-1})}{D(q^{-1})} \quad (7)$$

The predicted disturbance is:

$$\hat{n}\left(t+\frac{k}{t}\right) = \frac{C(q^{-1})}{D(q^{-1})}\xi\left(t+\frac{k}{t}\right) = E_k(q^{-1})\xi\left(t+\frac{k}{t}\right) + \frac{F_k(q^{-1})}{D(q^{-1})}\xi(t) \quad (8)$$

And as the order of polynomials is $E_k < k$ and ξ (t) is white noise, the value expressed in the first term to the right is equal to 0, and the prediction of future disturbance is

$$\hat{n}\left(t+\frac{k}{t}\right) = \frac{F_k(q^{-1})}{D(q^{-1})}\xi(t) \quad (9)$$

III. Development of Predictors

For simplicity in developing $C(z^{-1})$ is selected as equal to 1, the model obtained is:

$$[A(z^{-1})y(t) = B(z^{-1})z^{-d}u(t-1) + \xi(t)/\Delta] \quad (10)$$

To derive the predictor j-step, we consider the identity

$$1 = E_j(z^{-1})\tilde{A}(z^{-1}) + z^{-j}F_j(z^{-1}) \quad (11)$$

With $\tilde{A}(z^{-1}) = \Delta A(z^{-1})$

$E_j(z^{-1})$: is a polynomial of order $(j-1)$, and(z^{-1}) : is a polynomial of order (*na*).

Multiplying the equation (10) by the term $\Delta E(z^{-1})z^{-j}$, one gets:

$$\tilde{A}(z^{-1})E_j(z^{-1})y(t+j) = E_j(z^{-1})B(z^{-1})\Delta u(t+j-d-1)+E_j z^{-1}\xi(t+j) \quad (12)$$

We therefore deduce the output equation y (t + 1)

$$y(t+j) = F_j(z^{-1})y(t) + E_j(z^{-1})B(z^{-1})\Delta u(t+j-d-1)+E_j z^{-1}\xi(t+j) \quad (13)$$

Since $E_j(z^{-1})$ is of degree (j-1) the noise term $E_j(z^{-1})e(t+j)$ of the equation (13) is found to future instants, the best prediction of y (t + j) is as follows:

$$\tilde{y}(t+j/t) = G_j(z^{-1})\,\Delta u(t+j-d-1) + f_j(t+j) \quad (14)$$

With: $\Delta u(t+j-d-1) = u(t+j-d-1) - u(t+j-d-2)$, for $1 \le j \le N_u$

$G_j(z^{-1}) = E_j(z^{-1})B(z^{-1}), f_j(t+j) = F_j(z^{-1})y(t)$, for $j = 1\ldots.N_2$

$F_j(z^{-1}) = f_{j,0} + f_{j,1}z^{-1} + \cdots + f_{j,na}z^{-na}$, $E_j(z^{-1}) = e_{j,0} + e_{j,1}z^{-1} + \cdots + e_{j,j-1}z^{-(j-1)}$

Therefore to long horizon, the prediction is gotten by the recursive calculation of the polynomial$G_j(z^{-1})$ and the function $f_j(t+j)$.

To calculate $G_{j+1}(z^{-1}) = E_{j+1}(z^{-1})B(z^{-1})$ and $f_{j+1}(t+j) = F_{j+1}(t+j)y(t)$, one proceeds the recursion equation Diophantine used previously.

IV. The Free and Forced Response (Resolution of the Diophantiennes Equations)

In the GPC the prediction is required to estimate the future output with its disruptions. Combining the model of the process and the model of disruption, one draws the prediction to estimate the future value of the output based on the available information more the instant of the time present t. taking the model function of transfer and the CARIMA model, the output of the process is given by:

$$\frac{C(q^{-1})}{D(q^{-1})} = E_k(q^{-1}) + q^{-k}\frac{F_k(q^{-1})}{D(q^{-1})} \quad (15)$$

$$y(t) = \frac{B(q^{-1})}{A(q^{-1})}u(t-1) + \frac{C(q^{-1})}{D(q^{-1})}\xi(t) \quad (16)$$

Of where, $D(q^{-1}) = (1-q^{-1})A(q^{-1})$ and the delay of the process is included in the B polynomial by 0 value given to the first coefficient to the polynomial. The prediction can be separate like continuation:

$$\hat{y}(t+k/t) = \frac{B(q^{-1})}{A(q^{-1})}u(t+k-1) + \frac{C(q^{-1})}{D(q^{-1})}\xi\left(t+\frac{k}{t}\right) \quad (17)$$

$$1 = \frac{E_k(q^{-1})D(q^{-1})}{C(q^{-1})} + q^{-k}\frac{F_k(q^{-1})}{C(q^{-1})} \quad (18)$$

Multiplying the equation (17) by (18), one gets:

$$\hat{y}(t+k/t) = \frac{E_k(q^{-1})D(q^{-1})}{C(q^{-1})}\left[\frac{B(q^{-1})}{A(q^{-1})}.u(t+k-1) + \frac{C(q^{-1})}{D(q^{-1})}\xi(t+k/t)\right] + q^{-k}\frac{F_k(q^{-1})}{C(q^{-1})}\left[\frac{B(q^{-1})}{A(q^{-1})}.u(t+k-1) + \frac{C(q^{-1})}{D(q^{-1})}\xi(t+k/t)\right] \quad (19)$$

Which is equivalent to :

$$\hat{y}(t+k/t) = \left[\frac{E_k(q^{-1})B(q^{-1})(1-q^{-1})}{C(q^{-1})}u(t+k-1) + E_k\xi(t+k)\right] + \frac{F_k(q^{-1})}{C(q^{-1})}\left[\frac{B(q^{-1})}{A(q^{-1})}u(t-1) + \frac{C(q^{-1})}{D(q^{-1})}\xi(t)\right] \quad (20)$$

Whereas the value expressed in the second term of the first row is equal to 0 and the term in braces in the second row is equal to the current output of the process, the prediction of the process output is given by:

$$\hat{y}(t+k/t) = \frac{E_k(q^{-1})B(q^{-1})}{C(q^{-1})}u(t+k-1) + \frac{F_k(q^{-1})}{C(q^{-1})}y(t) \quad (21)$$

The effect of the command includes the first term on the right. To separate the effect of the action of past and future command, the following Diophantine equation must be solved.

$$\frac{E_k(q^{-1})B(q^{-1})}{C(q^{-1})} = G_k(q^{-1}) + q^{-1}\frac{L_k(q^{-1})}{C(q^{-1})} \quad (22)$$

The final form of the prediction is:

$$\hat{y}(t+k/t) = G_k(q^{-1})\Delta u(t+k-1) + \frac{L_k(q^{-1})}{C(q^{-1})}\Delta u(t-1) + \frac{F_k(q^{-1})}{C(q^{-1})}y(t) \quad (23)$$

The first term on the right is called the forced response and the rest called the free response. Free response expresses the prediction of process output based on past manipulated variable and assumes constant to keep the last command. Free response also includes disturbances already measured and their effects on future output (expressed in the last term prediction). The forced response is the prediction generated by the current and future command.

The output of the process is influenced by the command u (t) after a period of one sampling d+1. The values, N_1, N_2 and N_u defining the horizon can be defined by: $N_1 = d+1, N_2 = d+N$ and $N_u = N$. For simplicity, we take N_1 =1 and N_2 =N.
From equation (14) we obtained

$$\begin{cases} \tilde{y}\left(t+\frac{d+1}{t}\right) = G_{d+1}(z^{-1})\,\Delta u(t) + f_{d+1}y(t) \\ \tilde{y}\left(t+\frac{d+2}{t}\right) = G_{d+2}(z^{-1})\,\Delta u(t) + f_{d+2}y(t) \\ \vdots \\ \tilde{y}\left(t+\frac{d+N}{t}\right) = G_{d+N}(z^{-1})\,\Delta u(t) + f_{d+N}y(t) \end{cases} \quad (24)$$

The resulting predictive model is expressed as follows Vector writing

$$\tilde{y} = G\Delta u + f \quad (25)$$

The matrix G is lower triangular ($N \times N$)

$$G = \begin{bmatrix} g_0 & 0 & \cdots & 0 \\ g_1 & g_0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ g_{N-1} & g_{N-2} & \cdots & g_0 \end{bmatrix}; \ g_{ij} = g_j \quad \text{for } j = 0,1,\ldots \leq i, \ g_{ij} = 0 \quad \text{for } j > i$$

V. Optimization Criterion and Obtaining Command

Once the predictions, we must find the future control sequence to be applied to the system to achieve the desired along the reference path with a desired optimum method. For this, just minimize a cost function that differs according to the methods but generally this function contains the squared errors between the reference trajectory and predictions on the prediction horizon and the variation of the command.
This cost function is:

$$J(N_1, N_2, N_u) = \sum_{j=N_1}^{N_2} \left(\hat{y}(t+j/t) - w(t+j)\right)^2 + \lambda \sum_{j=1}^{N_u} (\Delta u(t+j-1))^2 \quad (26)$$

With $\hat{y}(t+j/t)$: predicted output at time (t +j), $w(t+j)$: reference trajectory,$\Delta u(t+j-1)$: Increment command at time $(t+j-1)$,λ: Weighting coefficient command signal, N1 and N 2: minimum and Maximum horizon prediction, N_u : Horizon prediction on the command.

Analytical minimization of this function provides the sequence of future command which only the first is actually applied to the system. The procedure is iterated again the next sampling period according to the principle of receding horizon.

The criteria previously introduced under analytic shape (26) can write also under matrix shape as:

$$J = \left(Gu + f - w\right)^T (Gu + f - w) + \lambda u^T u \quad (27)$$

With $w = [w(t+1)\, w(t+2) \ldots w(t+N)]^T$

The optimal solution is gotten then by derivation of (27) in relation to the vector of command increments:

$$J = \left(\tilde{u}^T G^T + (f - w)^T\right) (G\tilde{u} + (f - w)) + \lambda \tilde{u}^T \tilde{u} \quad (28)$$

$$J = \tilde{u}^T (G^T G + \lambda I)\,\tilde{u} + \tilde{u}^T G^T (f - w) + (f - w)^T G\tilde{u} + f - wTf - w \quad (29)$$

$$\frac{\partial J}{\partial \tilde{u}} = 2(G^T G + \lambda I)\,\tilde{u} + 2G^T (f - w) \equiv 0 \quad (30)$$

The optimal solution is:

$$\Delta u_{opt} = (G^T G + \lambda I)^{-1} G^T (f - w) \quad (31)$$

Thus only G and f are necessary to determine the vector of increments optimal to apply, of which $\Delta u_{opt}(t)$that represents the first element of the vector that will be confirmed to apply to the manipulated variable of the controlled process;

$$\Delta u_{opt}(t) = K_1 (f - w) \quad (32)$$

With K1 is the first line of the matrix control K

$$K = (G^T G + \lambda I)^{-1} G^T \quad (33)$$

The sequence of predicted future command will:

$$u(t) = u(t-1) + K_1 (f - w) \quad (34)$$

VI. Choice of Synthesis Parameters [9, 13]

A. *choice of Minimum Horizon of Prediction (P_1)*

If the delay time (d) is exactly known, it is unnecessary to set $\mathbf{p_1}$ less than **d** because it would be unnecessary calculations in the corresponding output that cannot be affected by the first action **u (t)**. If **d** is not known or is variable, $\mathbf{p_1}$ can be set to **1**.

B. *Choosing The Maximum Horizon of Prediction (P_2)*

For a system representative of pure delay on any path we take $\mathbf{p_1}$= 1, the maximum horizon of prediction is chosen so that $\mathbf{p_2} \times \mathbf{T_e}$ is equal to the maximum response time in open loop for each channel. Where $\mathbf{T_e}$ is the sampling time of the controller. It should be noted that more p_2 the greater the computing time is long:

$$\mathrm{OLRT} = \mathrm{p}_2 \times \mathrm{T_e} \Rightarrow \mathrm{p}_{2\max} = \mathrm{OLRT}/\mathrm{T_e} \quad (35)$$

C. Choice of The Control Horizon (m):

For simple process, to take control horizon **m** equal to 1 often gives good results, on the other hand, for complex processes **m** must be equal to at least the number of unstable poles or poorly damped. The control horizon should not in any case have a value greater than the maximum prediction horizon.

D. Choice of Control Weighting λ:

The problem with this parameter is that it determines (with p2) the dynamics of the closed loop system a very precise manner.

Indeed, we can say that more λ is high, more the response time of the system is long, and however, there is no direct relationship between this parameter and the response time. If the value of λ is related to the gain of the system, it remains to extend this finding to the multivariate case where the prediction horizon control m is different from "1" while maintaining good performance robustness. We can also report increasing λ returns to increase the constraint on the command, the case λ = 0 unrealistic returns to put no constraint. Note finally that the matrix λ plays an important role in the packaging of the digital method since it occurs in the matrix $\boldsymbol{G}^{\boldsymbol{T}} \times \boldsymbol{G} + \boldsymbol{\lambda}$ that must be reversed.

VII. Constraints on The Control and Output System

In all predictive control techniques, input variables, states and outputs of a system are often constrained by their field definitions. These constraints are of various kinds: physical limitations of the actuators, specification of product quality, safety requirements and tolerance range for output, etc. For example, in practice, the control signal must satisfy the constraint domain of validity of the actuator.

A. Constraints on the amplitude of the control signal

Constraints on the amplitude of the control, fairly frequent in practice, can be expressed by the inequality

$$u_{\min} \le u(t) \le u_{\max} \quad (36)$$

These constraints are satisfied over the whole horizon of prediction, where

$$\mathrm{u(t) = [u(t)u(t+1)...u(t+m-1)]^T} \quad (37)$$

B. Constraints on The Speed of Variation of The Control Signal.

The constraints on the increase of the control signal take a very simple form, and can be expressed by the inequality:

$$\Delta \mathrm{u}_{\min} \le \mathrm{u}(\mathrm{t}) - \mathrm{u}(\mathrm{t}-1) \le \Delta \mathrm{u}_{\max} \quad (38)$$

Or in the vector form on the variations Δu (t)

$$\mathrm{u}_{\min} \le \Delta \mathrm{U}(\mathrm{t}) \le \Delta \mathrm{u}_{\max} \quad (39)$$

C. Constraints on the magnitude of the output

It is very frequent to find as desired specification in the controlled process that their output is around a wanted trajectory, for example, in the case of pursuit of a profile with a certain tolerance. This type of condition can be introduced for the control to forcing the output of the system. It understood at all times in the band constituted by the trajectory more or less tolerance. This type of constraint results in an inequality as:

$$\mathrm{y}(\mathrm{t})_{\min} \le \mathrm{y}(\mathrm{t}) \le \mathrm{y}(\mathrm{t})_{\max} \quad (40)$$

Let

$$\mathrm{y}(\mathrm{t}) = \left[\mathrm{y}(\mathrm{t})\,\mathrm{y}(\mathrm{t}+1)\cdots \mathrm{y}(\mathrm{t}+\mathrm{p})\right]^{\mathrm{T}} \quad (41)$$

Where obviously,

$$\mathrm{y}(\mathrm{t})_{\min} = \left[\mathrm{y}_{\min}(\mathrm{t}+1)\,\mathrm{y}_{\min}(\mathrm{t}+2)...\mathrm{y}_{\min}(\mathrm{t}+\mathrm{p})\right] \quad (42)$$

$$\mathrm{y}(\mathrm{t})_{\max} = \left[\mathrm{y}_{\max}(\mathrm{t}+1)\,\mathrm{y}_{\max}(\mathrm{t}+2)...\mathrm{y}_{\max}(\mathrm{t}+\mathrm{p})\right] \quad (43)$$

Increments relative to the control variable such a constraint can be written:

$$\mathrm{y}(\mathrm{t})_{\min} \le \mathrm{G}\Delta \mathrm{U}(\mathrm{t}) + \mathrm{f}(\mathrm{t}) \le \mathrm{y}(\mathrm{t})_{\max} \quad (44)$$

Where **f** is the output of the free response.

VIII. Simulation Results of a Higher Order Process

Consider the third order process with an integrator

$$\mathrm{w(p)} = \frac{0.25}{(0.2\mathrm{p}+1)^3 \mathrm{p}} \quad (45)$$

Simulation parameters: $T_e = 1$: sampling time; $t_f = 400$ simulation time; $r_P = 0$: the delay; $\mathrm{N}_1 = 1; \mathrm{N}_2 = 30$: Horizon output; $N_u = 2$: command horizon.

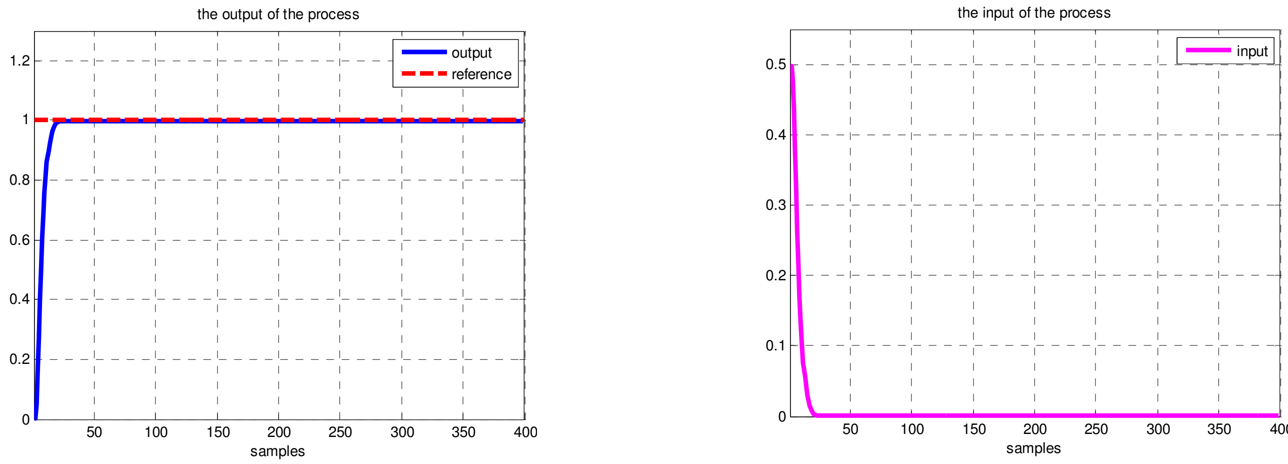
The figures (2 and 3) show the predicted output for constant and variable reference. The constant trajectory is take with a value of r=1. In the variable trajectory r is changed between 1 and 1.5. Use a variable trajectory is for the goal to examine effectiveness to follow; it can be seen that the two cases constant and variable trajectory provide a faster response without oscillation while a variable trajectory gives bigger control action.

In addition to follow trajectory, a controller should be capable of rejecting unexpected disturbance that cause the process to deviate from the desired operating conditions. The figures (4 and 5) show a simulation under disturbance with constant and variable trajectory where a disturbance occurs from [(t=70 to t=110 and t=270 to t=310) and (t=70 to t= 90 and t=270 to t=290)] for constant variable trajectory respectively. The apparition of the effect of the disturbance on the output is shown in the figure (4.a and 5.a) is countered by the input until the output comes back to its reference.

Figure (6) clearly shows the effect of the prediction horizon, the response is faster for a short horizon and becomes a little slow with the prediction horizon increase. This depends on the manipulated variable, the highest peak resulting by the greatest prediction horizon.

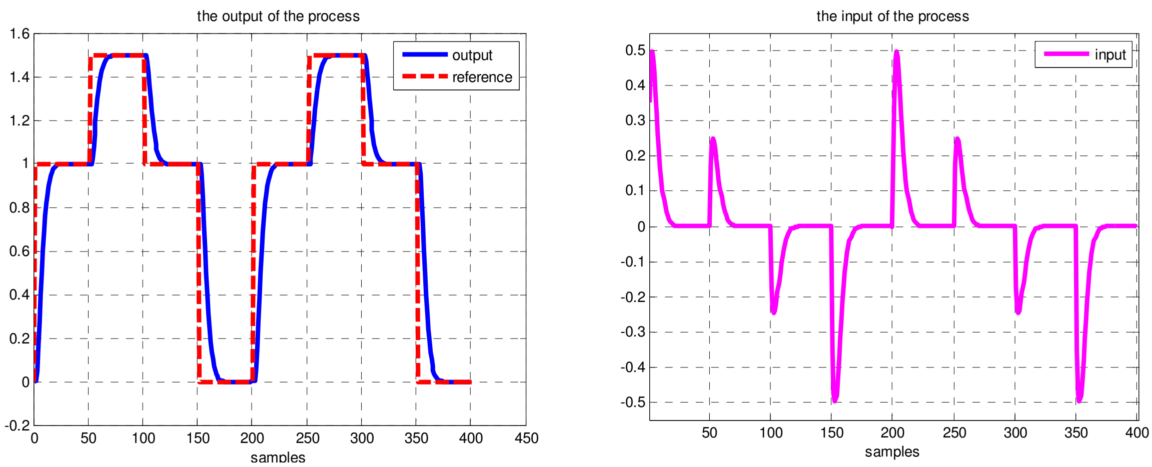
And for the purpose of knowing the effect of the control horizon on the output and manipulated variable, another simulation is made and the figure (7) obtained shows this effect. The better result was with m=2, of where less this value (m=1) increases the RTCL and more of this value can cause an overtaking.

The last simulation illustrates the effectiveness of the tuning of the control weighting factor when λ is increased (Figure 8). The first set point change is made with a value of λ=0. In the second change λ is changed to 0.5 and the last change is for λ=1. The output of the process become more sluggish with a small value of λ (Figure 9-a)and the input become strenuous while a big value of λ gives a faster response with a slight oscillation (Figure 9-b) and less vigorous input.



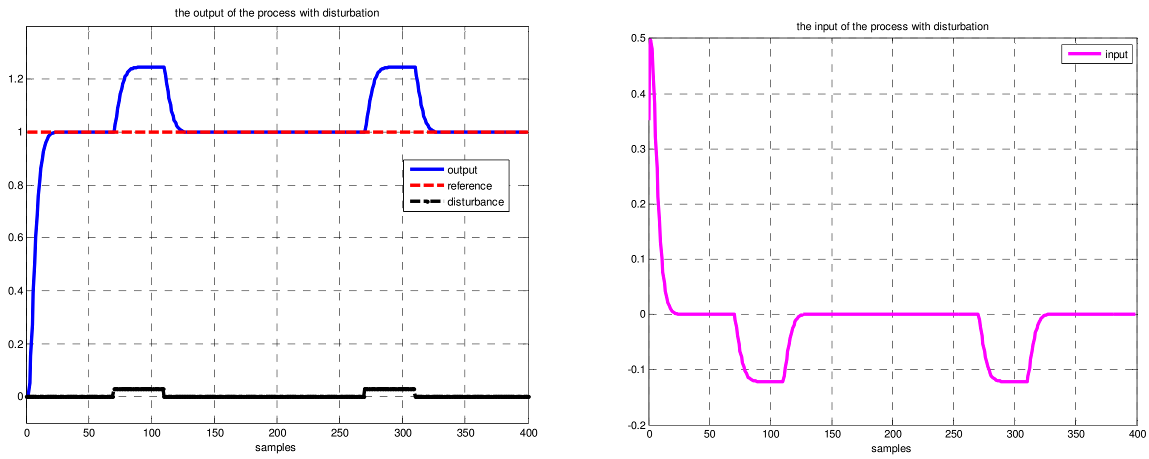
a) b)

Fig. 2 Predicted output (a) and predicted input (b)



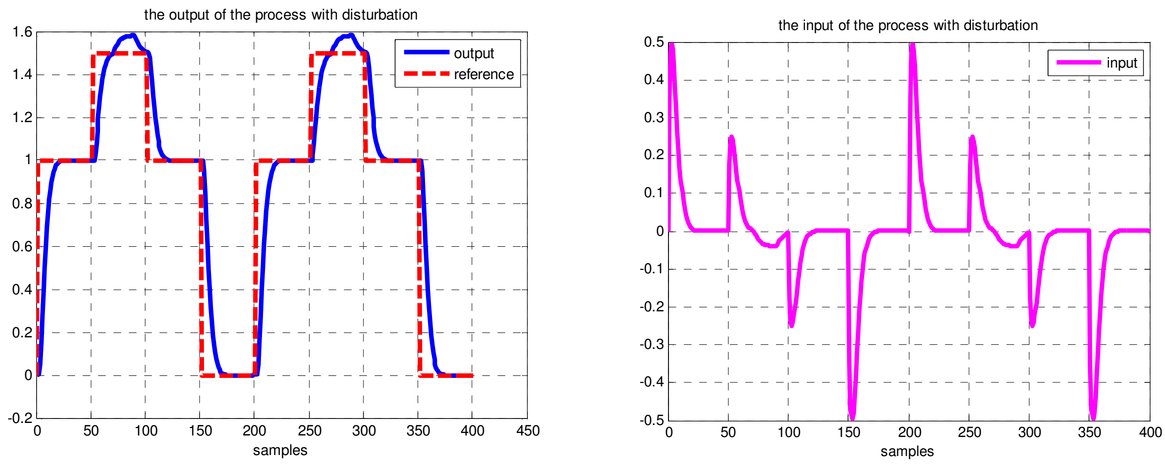
a) b)

Fig. 3 Predicted output (a) and predicted input (b) with variable reference



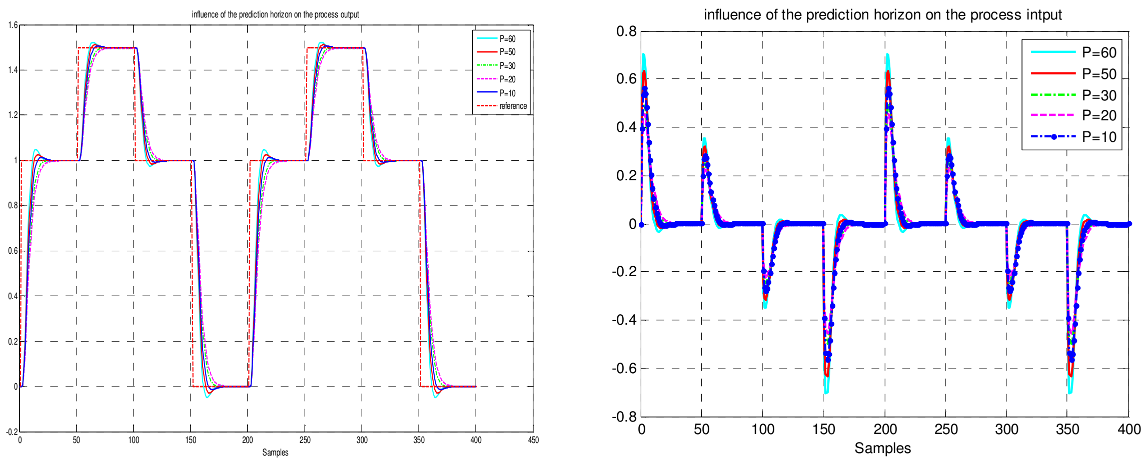
a) b)

Fig. 4 Predicted output (a) and predicted input (b) with disturbance for constant reference



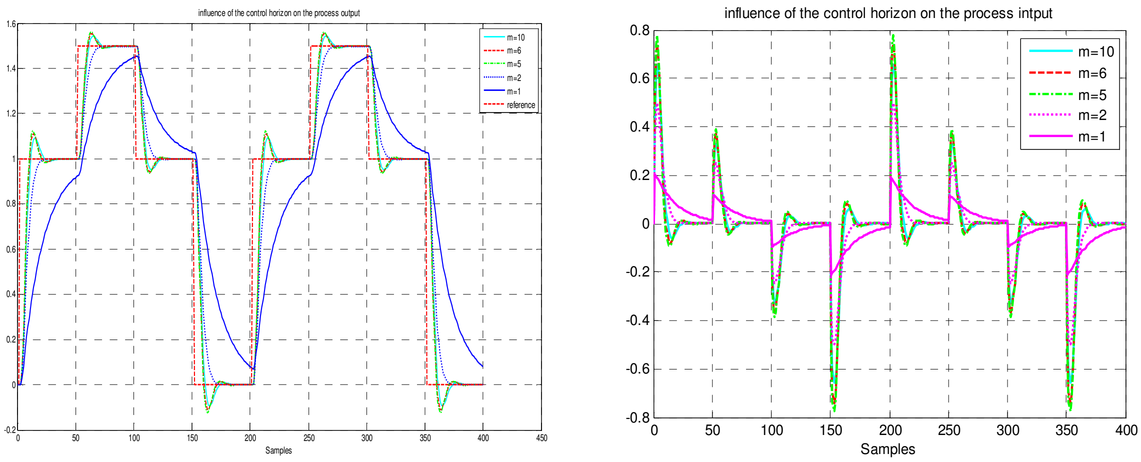
a) b)

Fig. 5 Predicted output (a) and predicted input (b) with disturbance for variable reference



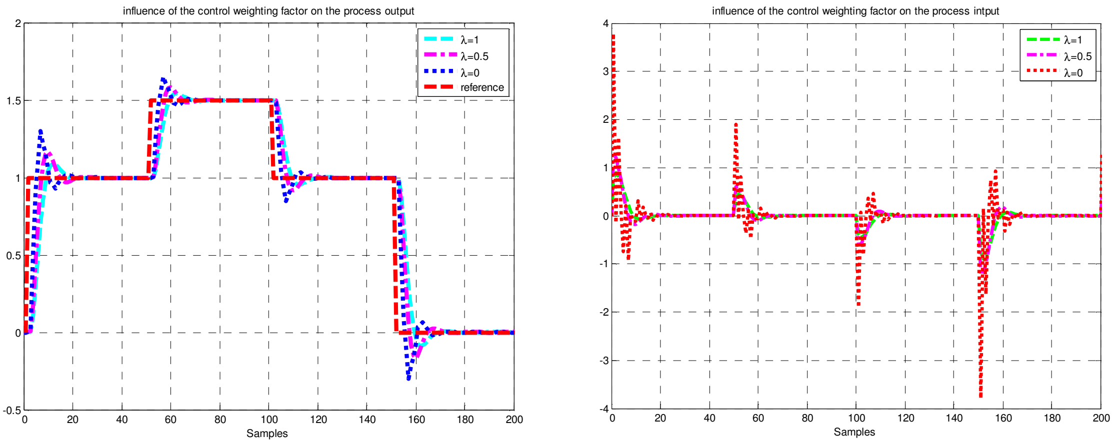
a) b)

Fig. 6 Influence of the prediction horizon on the process output (a) and on the process input (b)



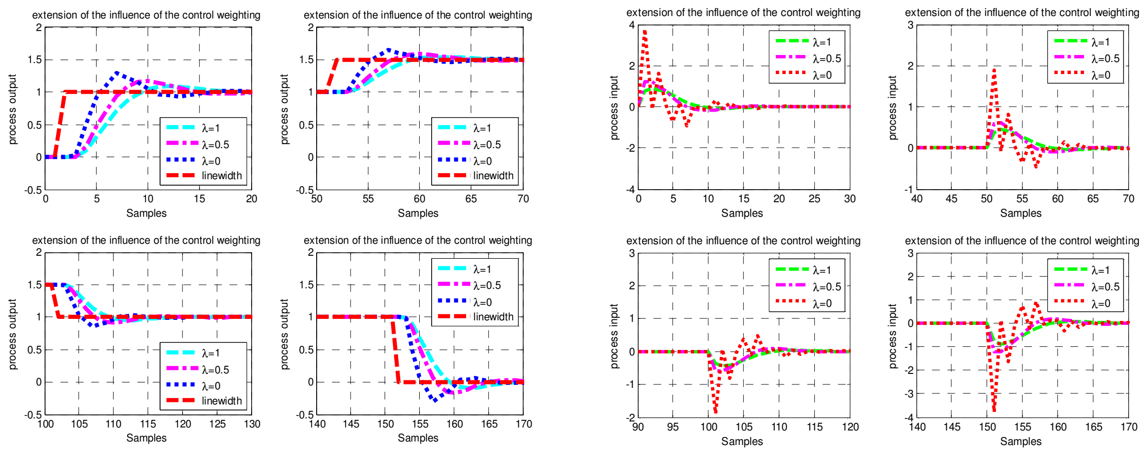
a) b)

Fig. 7 Influence of the control horizon on the process output (a) and on the process input (b)



a) b)

Fig. 8 Influence of the control weighting factor on the process output (a) and on the process input (b)



a) b)

Fig. 9 Extension of the influence of the control weighting on the process output (a) and on the process input (b)

IX. Discussion and Conclusions

The simulation results have shown the effectiveness of the algorithms GPC in terms of the speed of disturbance rejection and minimizing the error between the predicted output and the reference trajectory in the goal to get best performances. The results were simulated with the software Matlab/Simulink. Several parameters are exercised of which are taken in accounts disturbance on the system. Granting to results of simulation, the GPC is efficient. The choice of the prediction horizon, the control horizon, the control weighting factor and the I/O compromise are depended on each other. The performances of the GPC are clearly demonstrated in our illustrative application and of the algorithms GPC is considered very valuable.

X. References

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