Advanced Control Algorithm: Applications to Industrial Processes

A. Ramdani, S. Grouni, and M. Traïche

Abstract—**As in the most industrial systems, a control of the input of the systems including a classic regulator is a key point. The Proportional-Integral-Derivative controllers are commonly used in many industrial control systems and appeared suitable to stable the control of the majority of real processes. But in some cases like a non-minimum-phase plant or a plant with a dead-time proceed to a thin regulating of coefficients until to get a system respecting the conditions specified. It is possible also to present a problem of overtaking with the increase of the gain or seems impotent for systems having a big delay and the use of sophisticated process controllers is required. Model predictive control is an important branch of automatic control theory, it refers to a class of control algorithms in which a process model is used to predict and optimize the process performance. MPC has been widely applied in industry. Dynamic Matrix Control Algorithm belongs to the family of Model predictive control Algorithms where these algorithms only differ between themselves in the model that represents the process, disruptions and the function of cost. In this paper the study of the Dynamic Matrix Control Algorithm are interested while applying him on processes of water heating and mechanical rotations of steering mirrors in a Light Detection and Ranging system as a second application. The objective of this work consists of solving the problem of prediction of the output and input of the process by fixing a horizon finished N, and while considering the present state like initial state, to optimize a cost function on this interval, while respecting constraints. Therefore, the future reference is known and the system behavior must be predictable by an appropriate model. It results an optimal sequence of N control of it among which alone the first value will be applied effectively. As the time advances, the horizon of prediction slips and a new problem of optimization is to solve while considering the state of the system updating. In summary, every moment, it is necessary to elaborate an optimal control sequence in open loop, refined systematically by the present measure arrival.**

Index Terms—**Dynamic matrix control, predictive control, water heater.**

I. INTRODUCTION

The Dynamic Matrix Control 'DMC', belongs to the family of Model predictive control 'MPC', is an advanced approach command [1] was developed by Cutler and Ramaker Company 'Shell Oil Co' to 1980 [2]. Other methods that have its place in MPC methodology, the commonly used in industry are the algorithm identification-control 'IDCOM' [3]. Quadratic Dynamic Matrix Control (QDMC) [4], Generalized Predictive Control 'GPC' [5], Predictive functional control 'PFC' [6], [7] and Global predictive control (Glob-PC) [8].

To DMC has been widely accepted in the industrial world, mainly petrochemical industries [9]. It is something more than a command and part of its success is due to the application of multivariable systems with support constraints.

In the first part a simplified version of this command is shown in the case where the model is provided as a step response. This formulation is generally chosen because it allows more intuitive understanding of how predictive control operating. Nevertheless similar developments can be conducted to the impulse response model where transfer function leading respectively to the Model Algorithmic Control 'MAC' and generalized predictive control 'GPC'.

II. PROCEDURE ADVANTAGES AND DRAWBACKS OF THE MPC [5], [10]-[12]

MPC can be used either to control a simple plant with little prior knowledge or a more complex plant such as non-minimum phase, open-loop unstable and having variable dead-time. It offers several important advantages, over other methods, amongst which stand out:

- It is particularly attractive to staff with only a limited knowledge of control because the concepts are very intuitive and at the same time the tuning is relatively easy.
- It can be used to control a great variety of processes, from those with relatively simple dynamics to other more complex ones, including systems with long delay times or of non-minimum phase or unstable ones.
- The multivariable case can easily be dealt with.
- It intrinsically has compensation for dead times.
- It introduces feed forward control in a natural way to compensate for measurable disturbances.
- The resulting controller is an easy to implement linear control law.
- Its extension to the treatment of constraints is conceptually simple and these can be systematically included during the design process.
- It is very useful when future references (robotics or batch processes) are known.
- It is a totally open methodology based on certain basic principles which allow for future extensions.

As is logical, however, it also has its drawbacks:

- One of these is that although the resulting control law is easy to implement and requires little computation, its

Manuscript received December 4, 2014; revised March 26, 2015.

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derivation is more complex than that of the classical PID controllers.

- If the process dynamic does not change, the derivation of the controller can be done 'beforehand, but in the adaptive control case all the computation has to be carried out at every sampling time.
- When constraints are considered, the amount of computation required is even higher. Although this, with the computing power available today, is not an essential problem.
- Even so, the greatest drawback is the need for an appropriate model of the process to be available. The design algorithm is based on a prior knowledge of the model and it is independent of it, but it is obvious that the benefits obtained will be affected by the discrepancies existing between the real process and the model used.

III. Applications of Predictive Control

In industries such as oil refineries and petrochemical plants, the predictive control has become the method of choice for difficult control problems, and the study has been done by [13], [14] concluded that the predictive control has proven its performance across many industrial applications. It is still present in most areas, and for different reasons, two industries were the first interested and funded the development of the method.

Even if predictive control offers many interesting features, historically, only two of these have played a decisive role: the refining and petrochemicals.

IV. Basic Concepts and Objectives of the Predictive Control

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 [15], [16]. And the majority techniques proposed in the literature for several years are as common basis the following ideas:

- Using a model of the system to construct the prediction signals.
- Knowledge of the trajectory to follow.
- Existence of a quadratic criterion.
- Existence of a solver developing real-time optimal / sub-optimal / feasible solution while satisfying the constraints.
- Application of the first element of the command sequence calculated;
- Repeat the procedure to the next sampling period, according to the principle of receding horizon.

The overall objectives of a predictive controller that have been set by [11]:

- Prevent violations of constraints on inputs and outputs.
- Drive output variables to their optimal operating points, while keeping the other outputs within the specified intervals.
- Prevent excessive movement of the input variables.
- Controlling the process variables as possible when a sensor or actuator is not available.

V. Step Response of the Model and Prediction

A. Step Response of the Model

It will be interesting to assume a system SISO Discrete Linear Time Invariant 'LTI' with input $u(t)$ and output $y(t)$ ($t \in Z$). The step response of the system is generated by a unit step (see Fig. 1).

with

$$u(t) = \begin{cases} 0 & \forall\ t < 0 \\ 1 & \forall\ t \geq 0 \end{cases}$$

B. Predicting Output

The model used to predict the dynamic matrix control DMC is the step response model [10], [17]. In the classical approach to predictive modeling various forms of control as the impulse response, transfer function representations and state formalism is used.

Consider the step response of the system described by the expression (Fig. 2).

$$y(t) = \sum_{i=1}^{+\infty} g_i \Delta u(t-i) \quad (1)$$

with $y(t)$ the model output and g_i: the coefficients of the step response

$\Delta u(t\text{-}i)$ is the command increment which:

$$\Delta u(t) = u(t) - u(t-1) \quad (2)$$

The prediction of the system output at $(t+k)$ is given by:

$$\hat{y}(t+k/t) = \sum_{i=1}^{+\infty} g_i \Delta u(t+k-i) + \hat{\eta}(t+k/t)$$

$$\hat{y}(t+k/t) = \sum_{i=1}^{k} g_i \Delta u(t+k-i) + \sum_{i=k+1}^{+\infty} g_i \Delta u(t+k-i) + \hat{\eta}(t+k/t) \quad (3)$$

$\hat{\eta}(t+k/t)$ the predicted disruption in the time $(t+k)$. It is assumed that disruption is constant along the prediction and it equals the difference between the measured output $y_m(t)$ and the model output $y(t)$ given by (1):

$$\hat{\eta}(t+k/t) = \hat{\eta}(t/t) = y_m(t) - y(t) \quad (4)$$

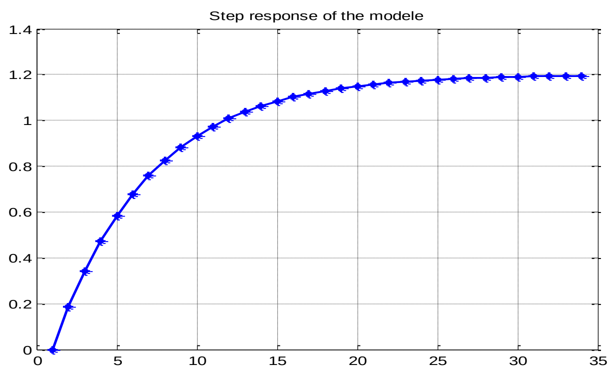


Fig. 1. Step response.

The predicted output can be written as follows:

$$\hat{y}(t+k/t)=\sum_{i=1}^{k}g_i\Delta u(t+k-i)+\sum_{i=k+1}^{+\infty}g_i\Delta u(t+k-i)+ y_m(t)-\sum_{i=1}^{k}g_i\Delta u(t-i) \quad (5)$$

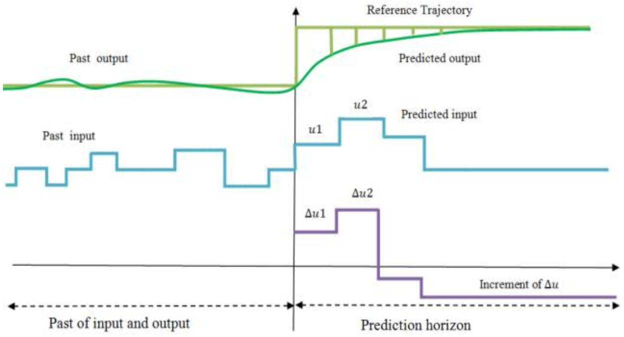


Fig. 2. Prediction of the output of the command on a predefined horizon.

$$\hat{y}(t+k/t)=\sum_{i=1}^{k}g_i\Delta u(t+k-i)+f_u(t+k) \quad (6)$$

where $f_u(t+k)$ is the free response of the system. This is part of the system that is not dependent on the future control action and can be written as:

$$f_u(t+k)=y_m(t)+\sum_{i=1}^{\infty}(g_{k+i}-g_i)\Delta u(t-i) \quad (7)$$

It is assumed that the process is stable, which is $\lim_{t\to\infty} y(t)$ exists, g_i coefficients of the step response tends to a constant value after N sampling period (see Fig. 2) then it can be consider that $g_{k+1}-g_i\approx 0$ After $i>N$ and thus the free response calculated as follows:

$$f_u(t+k)=y_m(t)+\sum_{i=1}^{N}(g_{k+i}-g_i)\Delta u(t-i) \quad (8)$$

Assuming now that the prediction the output of the system at a future time p is desired, where p is called the prediction horizon, the control horizon m is taken ($m\leq p$) all along this horizon.

$$\hat{y}(t+p/t)=\sum_{i=p-m+1}^{p}g_i\Delta u(t+p-i)+f_u(t+p) \quad (9)$$

with:

$$\hat{y}=\begin{bmatrix}\hat{y}(t+1/t)\\ \hat{y}(t+2/t)\\ \vdots\\ \hat{y}(t+p/t)\end{bmatrix},\ f_u=\begin{bmatrix}f_u(t+1)\\ f_u(t+2)\\ \vdots\\ f_u(t+p)\end{bmatrix}$$

The matrix form of prediction is as followings:

$$\hat{y}=G\,\Delta u+f_u \quad (10)$$

$$\Delta u=\begin{bmatrix}\Delta u(t)\\ \Delta u(t+1)\\ \vdots\\ \Delta u(t+m\text{-}1)\end{bmatrix},u=\begin{bmatrix}u(t)\\ u(t+1)\\ \vdots\\ u(t+m\text{-}1)\end{bmatrix}$$

and the matrix

$$G=\begin{bmatrix}g_1 & 0 & 0 & \cdots & 0\\ g_2 & g_1 & 0 & \cdots & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ g_m & g_{m-1} & g_{m-2} & \cdots & g_1\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ g_p & g_{p-1} & g_{p-2} & \cdots & g_{p-m+1}\end{bmatrix}$$

G is the Dynamic Matrix.

C. Measured Disturbances

Disturbances measured can be added to the prediction equation therefore they can be treated as a system input. Equation (6) may be used to calculate the predicted disturbance.

$$\hat{y}=Pp+f_p \quad (11)$$

where Pp is the measured contribution of the disturbance to the output of the system, P is similar to the G matrix contains the coefficients of the step response matrix of the perturbation model. p is the vector of increment of the disturbance and f_p is part of the response not depend disturbance.

The most general case for the measured and unmeasured disturbances can be continuous the sum of elements: free input response f_u, measured disturbance $Pp+f_p$ and unmeasured disturbance f_n.

$$f=f_u+P_p+f_p+f_n \quad (12)$$

Thus, the prediction can be calculated by the general expression:

$$\hat{y}_G=G\Delta u+f \quad (13)$$

VI. Synthesis of DMC Corrector

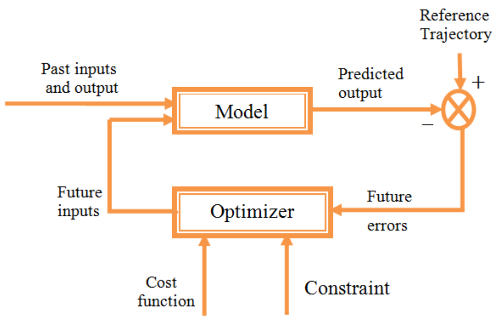


Fig. 3. Basic structure of the command DMC.

The objective of the DMC controller is to drive the closest possible output of the reference in the direction of least square. The manipulated variables are chosen to minimize the quadratic objective.

The two basic loops observed in the Fig. 3 are the model and the optimizer. The model must be able to capture the dynamics of the process, to predict future outputs accurately and its implementation should be easy, the optimizer provide control actions. In the presence of constraint, the solution is obtained through iterative algorithms, more computation time course.

So the criterion to be minimized is:

$$J(p_1, p_2, m) = \sum_{j=p_1}^{p_2} \left(\hat{y}(t+j/t) - w(t+j)\right)^2 + \lambda \sum_{j=1}^{m} \left(\Delta u(t+j-1)\right)^2 \tag{14}$$

with Δu $(t+j-1)=0$ For $j \geq m$;

$y(t+j/t)$ predicted output at time $(t+j)$; $w(t+j)$: Reference trajectory at time $(t+j)$; Δu $(t+j-1)$: Increment command at time $(t+j-1)$; λ: weighting coefficient control signal; p_1: minimum prediction horizon, p_2: Maximum prediction horizon, m: Horizon prediction on the command.

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

The criterion previously introduced in analytical form (13) can also be written in matrix form as:

$$J = (\mathrm{G}\,\Delta u + f - w)^T\ (\mathrm{G}\,\Delta u + f - w) + \lambda\ \Delta u^T \Delta u \tag{15}$$

with $w = \left[w(t+1)\ w(t+2)\ ..\ w(t+p_2)\ \right]^T$

The optimum solution is then obtained by derivation of (15) relatively to the control vector increments:

$$J = (\Delta u^T\ G^T + (f-w)^T)\ (G\ \Delta u + (f-w)) + \lambda\ \Delta u^T \Delta u \tag{16}$$

$$J = \Delta u^T\ (G^T G + \lambda I)\,\Delta u + \Delta u^T G^T\ (f-w) + (f-w)^T\ G\Delta u + (f-w)^T\ (f-w) \tag{17}$$

$$\frac{\partial J}{\partial u} = 2\,(G^T G + \lambda I)\Delta u + 2G^T (f-w) \equiv 0 \tag{18}$$

where the optimal solution (with Δu vector of the increment of the future command):

$$\Delta u_{opt} = (G^T G + \lambda I)^{-1}\ G^T\ \ (w - f) \tag{19}$$

Thus only G and f are required to determine the vector of optimal increments to apply , which $\Delta u_{\text{opt}}(t)$ which represents the first element of the vector can be applied to the input of the controlled process ;

$$\Delta u_{opt}(t) = K_1\,(w - f) \tag{20}$$

with K_1 is the first line of the matrix K

$$K = (G^T G + \lambda I)^{-1}\ G^T \tag{21}$$

The sequence of predicted future command will:

$$u(t) = u(t-1) + K_1\,(f - w) \tag{22}$$

In principle of the moving horizon and as in other strategies predictive control, only the first sequence of the command is applied and sent to the process, the calculation is repeated at the next time to have the command u at time t +1.

VII. Steps of Calculating the Predicted Output and the Predicted Command

1) Predicted output:

$$\hat{y}(t+k/t) = \sum_{i=1}^{k} g_i \Delta u(t+k-i) + f_u(t+k) \tag{23}$$

2) A step is applied for the g_i coefficients.
3) Free response:

$$f_u(t+k) = y_m(t) + \sum_{i=1}^{N} (g_{k+i} - g_i)\Delta u(t-i) \tag{24}$$

4) Model (step response)

$$y(t) = \sum_{i=1}^{+\infty} g_i \Delta u(t-i) \tag{25}$$

5) Definition of the prediction horizon p and m
6) Calculation of G and K

$$G = \begin{bmatrix} g_1 & 0 & 0 & \cdots & 0 \\ g_2 & g_1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ g_m & g_{m-1} & g_{m-2} & \cdots & g_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ g_p & g_{p-1} & g_{p-2} & \cdots & g_{p-m+1} \end{bmatrix} \tag{26}$$

$$K = (G^T G + \lambda I)^{-1}\ G^T \tag{27}$$

7) The predicted command:

$$\Delta u_{opt} = K(w - f) \tag{28}$$

8) Previous calculations are repeated at the next sampling time t + 1.

VIII. Simulation and Interpretation of Results

A. Application 1

This application is a part from the system LiDAR [18] (for Light Detection and Ranging) comprises a laser power supply as a source signal and two mirrors to control the direction of the laser beam, two detectors the first one is used for the reference and the second one is for the back scatter signal and to visualize the emitter and received signal a scope is used (see Fig. 4).

The whole system is used as early detector of the forest fire smoke and allows us also to surveillance their assumption. In this part the goal is to make automatic the focalize operation of the laser beam sorted from the supply using a motor step by step (SSM) and direct it to the target to search and detect the fire. Note that the angle $\theta_2 = 2\times\theta_1$ and the angle $\theta_3 = 360^{\circ}$ to sweep azimuthally the area fire.

B. *Application 2*

The second application, corresponds to a system borrowed from [19], is a liquid vessel and their dynamic are described by first-order model, where the input to the system is the flow rate and the output is the fluid level (see Fig. 5). Assume that a discrete-time first-order transfer function is obtained for a fluid system, leading to the relationship between the input and output:

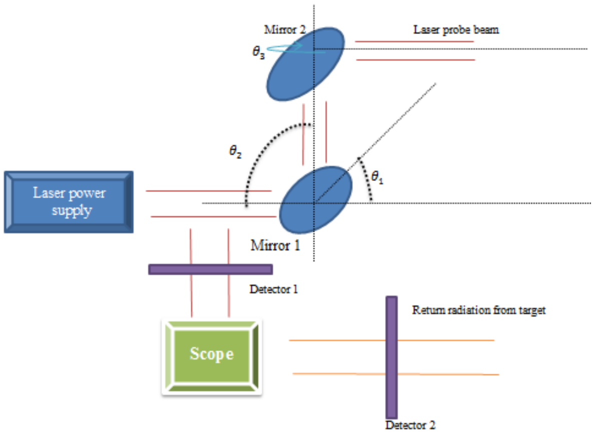


Fig. 4. Synoptic scheme of a LiDAR.

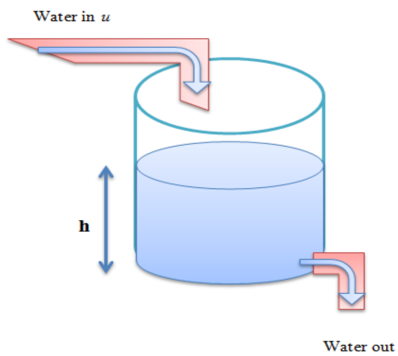
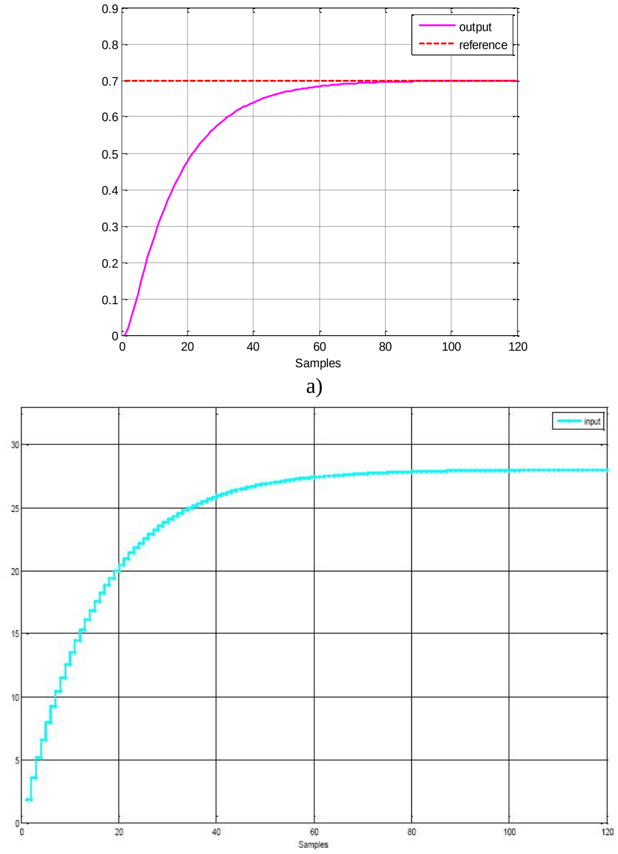


Fig. 5. Schematic diagram for a single tank.

$$Y(z) = \frac{0.01}{z-0.6}U(z) \qquad (29)$$

Design a dynamic matrix control system that will maintain the liquid level at a desired reference position $r(k) = 0.7$ for the first simulation and variable from 0.5 to 1.1 in the succeeding simulation.

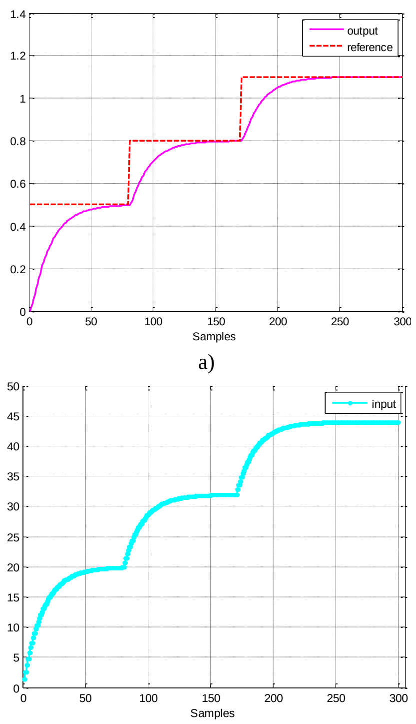
The design parameters for the predictive control system are specified as $m=4$, $p=16$.



a)

b)

Fig. 6. The output a) and the input b) of the system.



a)

b)

Fig. 7. The output a) and the input b) of the system with a variable trajectory.

Fig. 6 and Fig. 7 show the responses for $m=4$ and $p=16$ when the reference signal is constant and variable respectively. It is clear that for a constant reference the algorithm have a good performance. If the reference is variable, it is noted that the impact of changes to the output causes a small error in the first time before attain their references with a best behave in term of the tracking error.

C. Application 3

The following example is taken from [10] (a water heating apparatus), the DMC algorithm is applied on the system to control the outlet temperature of the heater.

A furnace is considered, where the cold water is heated by means of fuel gas. The outlet temperature depends on the energy added to the water through the gas burner. Thus the temperature can be controlled by controlling the pump cast into the gas heater.

TABLE I: COEFFICIENTS OF THE STEP RESPONSE OF THE PROCESS

y 1 = 0	y 2 = 0	y3 = 0	y 4 = 0.2713	y 5 = 0.4979	y6 = 0.6871	y 7 = 0.8451	y8 = 0.9770
y 9 = 1.0872	y 10 = 1.1792	y 11 = 1.2561	y 12 = 1.3202	y13 = 1.3738	y14 = 1.4186	y15 = 1.4560	y 16 = 1.4872
y 17 = 1.5132	y18 = 1.5350	y 19 = 1.5532	y 20 = 1.5684	y 21 = 1.5810	y 22 = 1.5916	y23 = 1.6005	y 24 = 1.6079
y 25 = 1.6140	y 26 = 1.6192	y27 = 1.6235	y 28 = 1.6271	y 29 = 1.6301	y 30 = 1.6326		

So, the step response of the system must be obtained for the purpose of control design. The step response is obtained by a unit step signal. The coefficients g_i can directly obtain the response shown in the Fig. 8.

It can be observed that the output stabilizes after 30 periods; in this case the model is given by:

$$y(t) = \sum_{i=1}^{+30} g_i \Delta u(t-i) \tag{30}$$

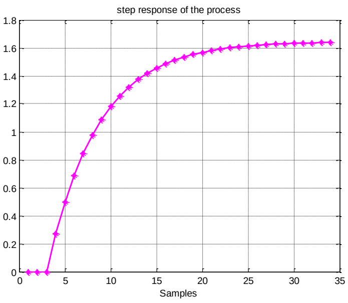


Fig. 8. Step response of the process.

1) Transfer function of the process

The system response is exposed with its transfer function given by:

$$H(z) = \frac{0.2713}{z^3 - 0.8351\, z^2} \tag{31}$$

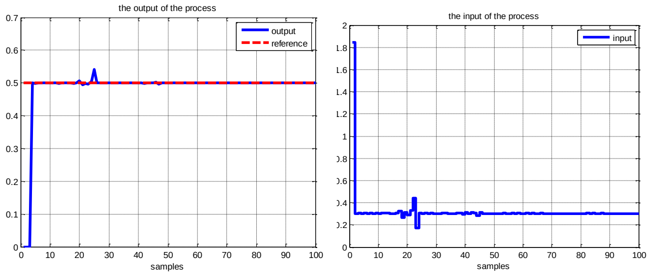
Hence the coefficients g_i are given by the Table I.

In this example, the first three coefficients of the step response hold zero, since the system has a dead time in three sampling period.

For a prediction horizon of 10 and a horizon control equal to 5 and λ = 1. The matrix $\mathbf{K} = (\mathbf{G}^T\mathbf{G} + \lambda\mathbf{I})^{-1}\mathbf{G}^T$ is calculated and thus the control law is given by the multiplication of the first row of the matrix **K** by the difference between the reference trajectory and the free response.

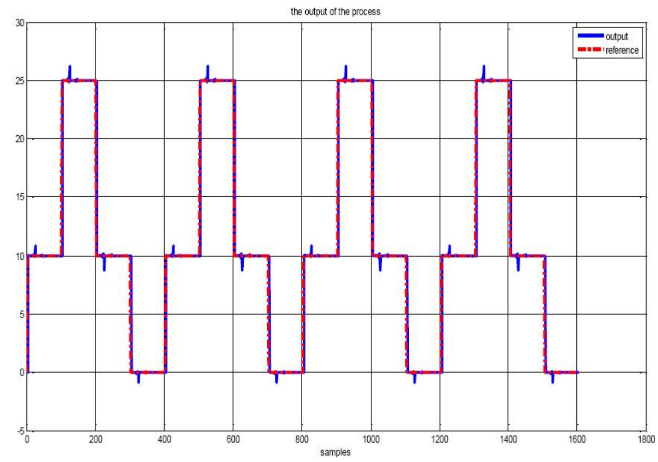
In the meaning of the moving horizon, the first element only of the command is calculated and applied to give the $u(t)$ and at time $t+1$ is repeated all the calculation to obtain $u(t+1)$.

The Fig. 9 shows the predicted output with pure delay is good without overshoot and the predicted input in these cases. Fig. 10 uses a new trajectory of reference to examine effectiveness to follow; it shows the excellent behavior where the output follows the reference without error of position and with a slight oscillation, but the input seems to be vigorous.

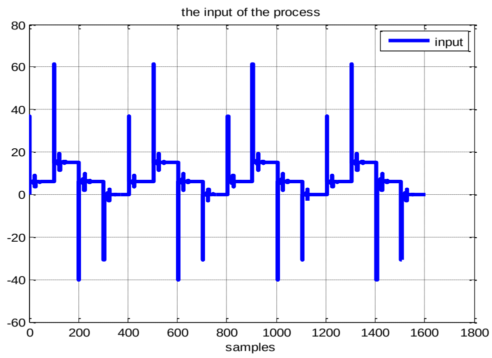


a) b)

Fig. 9. Predicted output a) and predicted input b) of the process.



a)



b)

Fig.10. Predicted output a) and predicted input b) of the process for a new trajectory.

Fig. 11 and Fig. 12 show the influence of the control weighting parameters for different values of λ and α. The temperature change in the system output and the factor λ is included between 0 and 2 for α=0 in the first set point change. Later the value of α is changed to 0.8 for the same values of λ (0, 1 and 2).

The response of the system is found faster for a small value of α with a slight oscillation, however small value of λ gives bigger control actions and the combination (λ = 0 and α=0) provides the best results (Fig. 11. a)).

2) Study of the influence parameters of the weighting on the output and input of the process

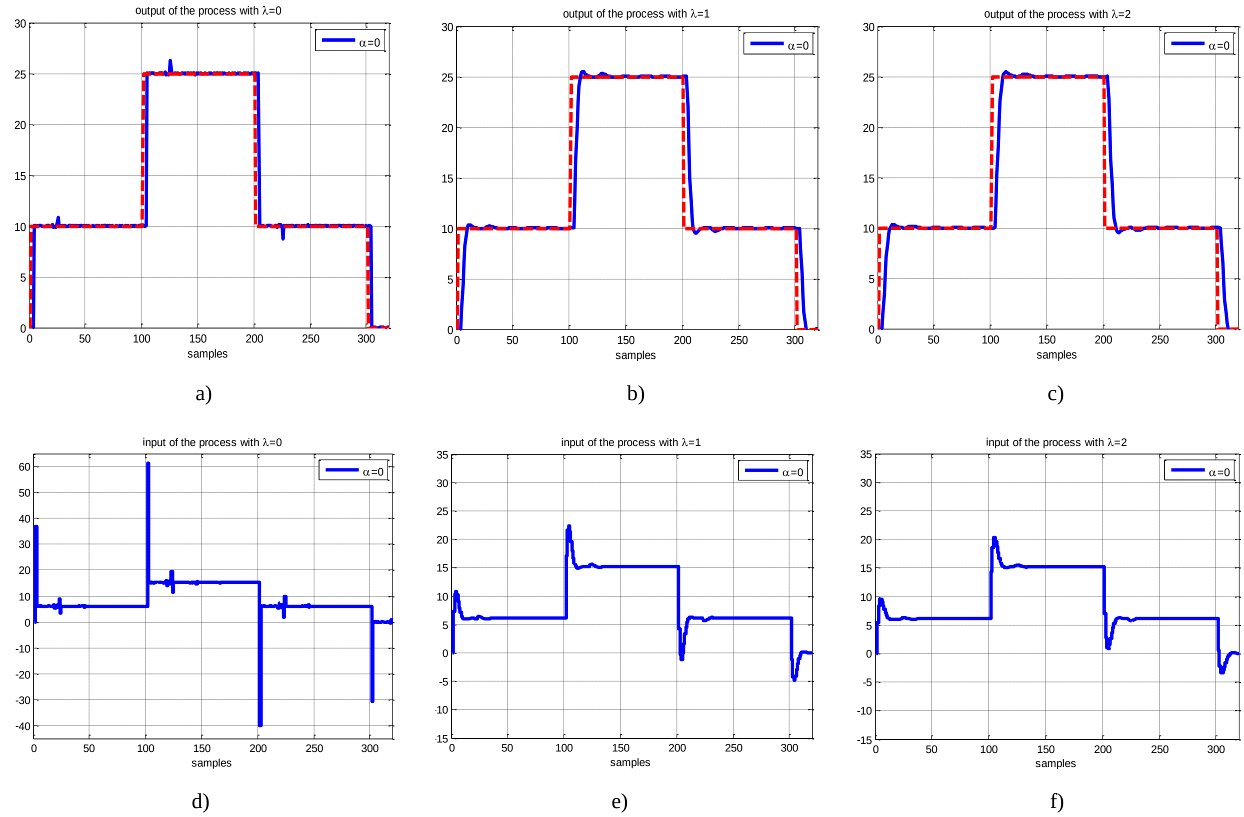


Fig. 11. Influence of the of the weighting factors ($\lambda \in$ [0 to 2] and α=0) on the process output (a, b and c) and on the process input (d, e and f).

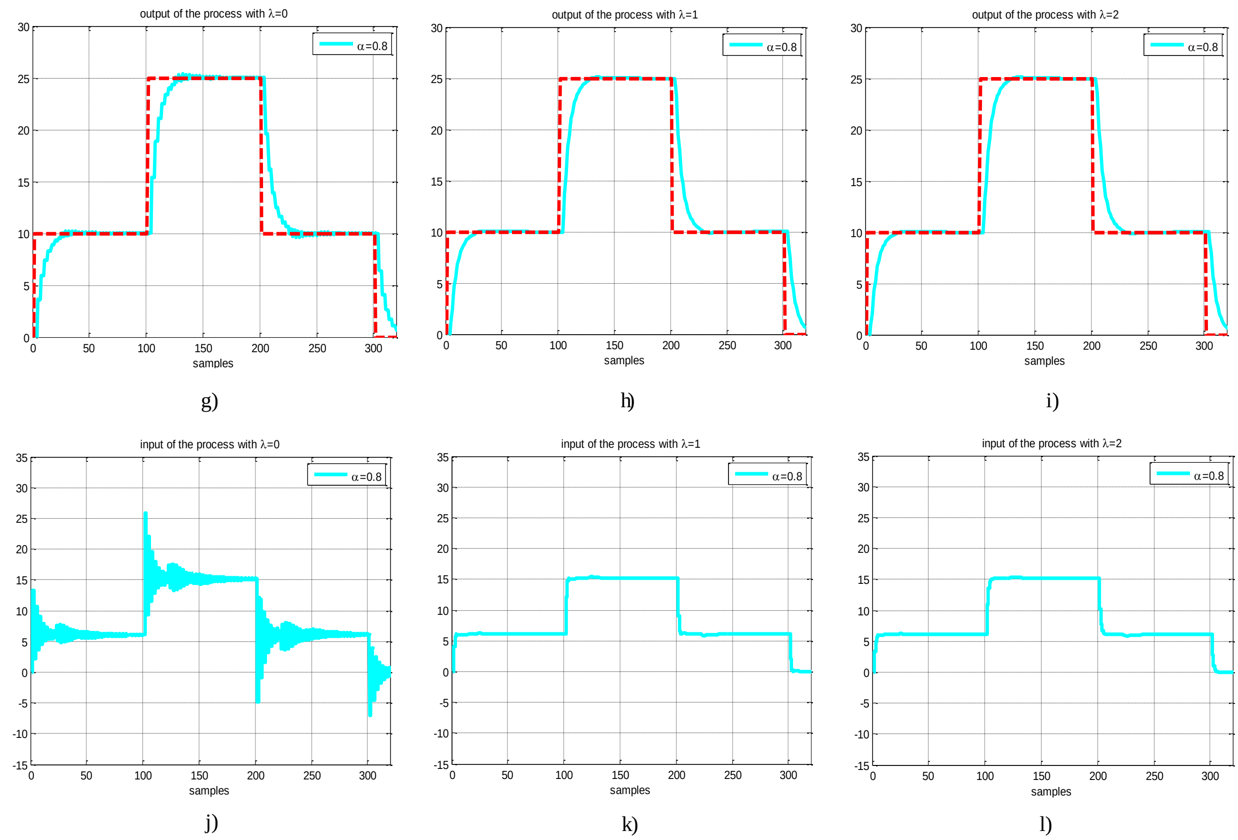


Fig. 12. Influence of the of the weighting factors ($\lambda \in$ [0 to 2] and α=0.8) on the process output (g, h and i) and on the process input (j, k and l).

IX. Conclusion

This study develops the theoretical of the algorithm of Dynamic Matrix Control 'DMC' that uses the step response. The key concept of predictive control is the creation of an anticipatory effect, so we use it to explicit knowledge on the evolution of the trajectory to be followed in the future. A simulation study shows that the DMC controller shows its robust performance in their applications with good to follow of reference even the trajectory is variable. An extension of the designed algorithm, over the disturbance and under constraint, will directed by the following research.

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