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# GPC and PI Controllers Applied to an Aerothermic Process

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*Abstract*: The aerothermic process is a laboratory ventilation and heating system. It is assembled with a heating grate and fan systems, completely associated through the data acquisition system (Humusoft MF624) for real-time control. Its air temperature variable constitutes an element that must be operated for energy saving. In order to keep this variable around a desired value, this article presents an experimental comparison between generalized predictive control (GPC) and integral proportional controller (PI). Both techniques are designed using a model obtained from experimental online data. The effectiveness of two methods is demonstrated by an implementation on an aerothermic process. Experimental results show that the main control objectives, such as set-point tracking and the perturbation rejection, are well achieved. The obtained results in closed loop of the PI controller, are promising in comparison to those the GPC ones.

*Keywords*: Generalized Predictive Control (GPC), proportional integral controller (PI), aerothermic process, and air temperature control.

## 1. Introduction

The control of the heating system is important in numerous industrial areas, including mineral, chemical, and drying systems, as well as agro alimentary production and pharmaceutical units. This type of systems requires a reliable and robust controller taking into account different perturbation that can affect its relevant parameters, and reducing the energy consumption, which is a critical component in the minimization of production costs.

Heating and ventilation systems are widely utilized in industry activities, e.g. pharmaceutical and alimentary production units

Along these lines, in the ongoing years, there are many developing control methodology approaches for regulator's design of heating systems such as the robust PID controller [1]. In this reference, the authors proposed a single input artificial fuzzy controller (SIFLC) approach to minimize the order's calculation time, and they made a comparison between the PID, the conventional FLC, and the SIFLC. Ramzi et al [2] have proposed a Predictive Controller based on the State Space Model (SSMPC) for the control of the aerothermic process; they had controlled both the temperature and air-flow with better performance. a fuzzy immune PID controller and a multi-model predictive control (MMPC) strategy for air-handling and temperature control in ventilating, heating, and air-conditioning systems are also proposed [3]. Other work related to the decentralized PI-D Controller had been developed to control the heating process [4]. Another example is suggested in [5], the authors have concluded that the multi-loop/PID strategy can give proficient results in terms of the control of the air temperature and relative humidity.

The originality of this work is to develop an efficient technique of the control of the outside air temperature of the aerothermic process, which is able to guarantee accurate tracking and to reject the various disturbances affected the system.

In this context, the present article deals with the problem of real-time control of a laboratory aerothermic system. Indeed, the main purpose of this work is to design an efficient controller in terms of set-point tracking and regulation, to meet the requirements mentioned above. Our work also treats the identification and control techniques PI and GPC for monovariable systems and their practical implementation [6]. These two commands exploit a model identified directly from

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the measured physical data in real time. This work studies also the implementation of PI and GPC control techniques on the pilot system.

The manuscript is organized as follows: the description and the identification of the aerothermic process is introduced in Section II. Section III introduces both the development of the polynomial approach predictive control algorithm and integral proportional control. The obtained results are analyzed and then a comparison between the two control strategies is discussed in section IV. Section V, provides a holistic viewpoints of the obtained results and concludes the paper.

## 2. Identification of Aerothermic Process

*A. Aerothermic Process Description*

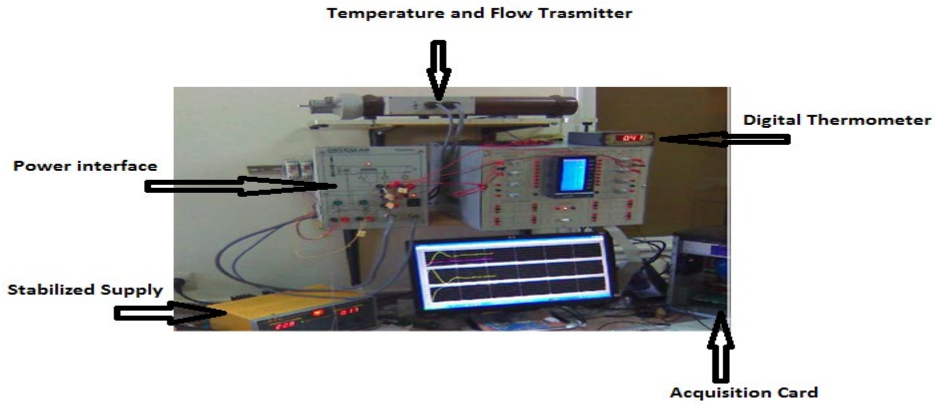


Figure 1. Aerothermic system

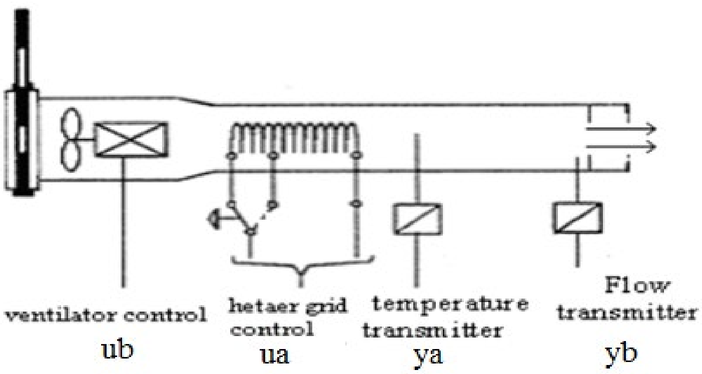


Figure 2. Schematic illustration of Aerothermic process

The pilot scale process [2], [4], is depicted in Figure.1 and shown as a schematic diagram in Figure.2. It is composed with both measuring actuators and transmitters. The two transmitters represent respectively the temperature and the air-flow, varying respectively between 25 and 75°C and between 0 and 50 mmH2O. The two actuators correspond to a heating resistance with a motor and controlled power equipped with a rotating fan with controlled rotation speed. Both actuators and transmitters afford electrical quantities 4 to 20mA. Two kinds of step perturbation are feasible on this system.

*B. Mathematical Model Identification*

In order to select a suitable controller for a given process, it is first necessary to have a knowledge of the properties of the process, i.e. a suitable mathematical description. The search for such a description is called process identification, and it is the first step to be solved by the automation engineer.

To ensure proper identification [7], the input signal of the aerothermic process must be in the form of a pseudo-random binary sequence (SBPA). The choice of this type of signals lies in their wealth of information which can be transmitted to the system so as to excite the entire frequency range where it will be identified. the inputs and outputs signals are shown in respectively in Figure.3 and Figure.4. The sampling interval used in the experiment is Ts=1s. The signals gathered, by means the data acquisition module (Humusoft MF624), are delivered in the interval (0V, 10V) [8], [9], [10].

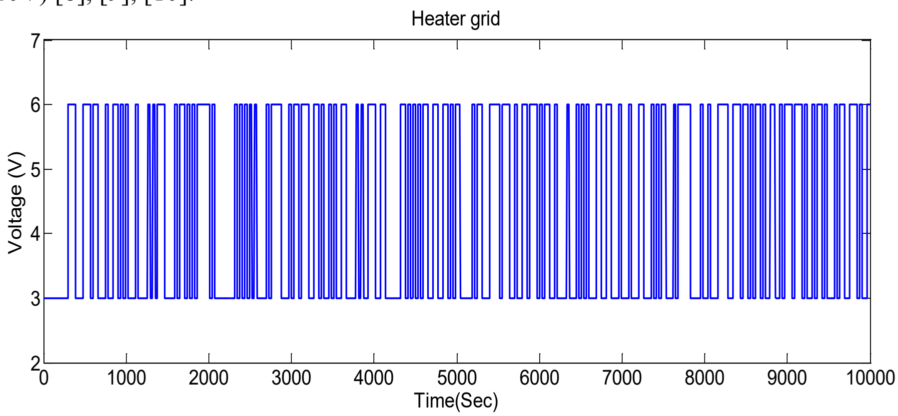


Figure 3. Input signals (pseudo-random bit sequence)

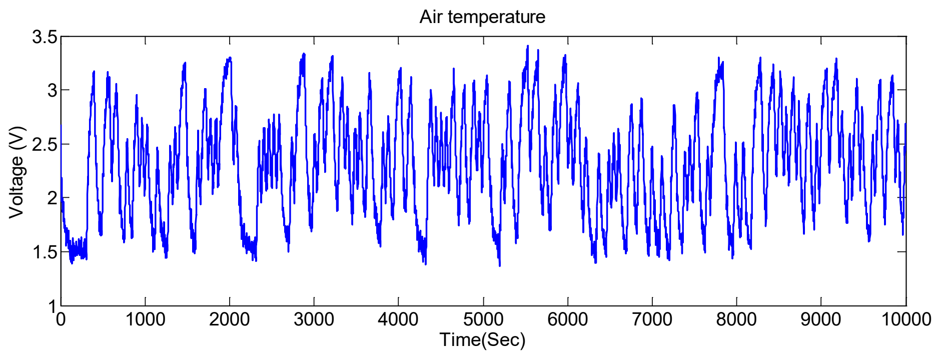


Figure 4. Responses to excitations

- *System identification using the ARX structure*

The identification is an experimental approach based on the input-output of the system to be identified in order to determine the dynamic model of this one. It has four essential steps [7]:

- Acquisition of inputs-outputs under an experimental protocol.
- Estimate the model order.
- Estimate the model parameters.
- Validation of the identified model.

In this study, the ARX model (Auto Regressive Withe Xogenous Input) is identified. The description of the model behavior is found by connecting its output at a time t denoted by y(t) to the values of the output at previous instants t-1, t-2, denoted y (t-1), y (t-2), .. and the input at a previous instants t-1, t-2, denoted by u (t-1), u (t-2), (Landau et al., 2011, Ljung, 1999). Figure

5 represents the ARX model where “u” is a control input, “e” represent a white noise signal with zero average [10].

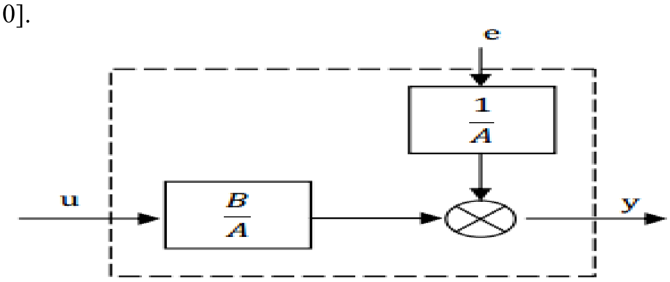

Figure 5. Structure of the ARX model

The following equation describes the identified system:

$$A(q^{-1})y(t) = B(q^{-1})u(t) + e(t) \qquad (1)$$

Where, $A(q^{-1}) = 1 + a_1 q^{-1} + \cdots + a_n q^{-n}$ ; $B(q^{-1}) = b_1 q^{-1} + \cdots + b_n q^{-n}$

In order to select the appropriate ARX model predicting the dynamic behavior of the aerothermic system, several combinations of orders and delays are examined. Using the statistical criteria, a performance comparison of different structures of the ARX model areappliedon the first 5000 measurements and the best structure of the ARX model is obtained for, na = 2, nb = 1, and d = 7. The model parameters obtained are given by the equation (2):

$$\frac{B}{A} = \frac{0.02091q^{-7}}{1-0.5q^{-1}-0.4607q^{-2}} \qquad (2)$$

- *Validation of the identified model*

During this step, model validation is necessary to judge the behavior of the obtained model with the real system. Hence, a validation was applied to the remaining experimental data. Figure. 6 represents the validation results between the measured outputs and estimated model. As shown in this Figure, it can clearly seen that there is a good agreement between the true system output and the identified one.

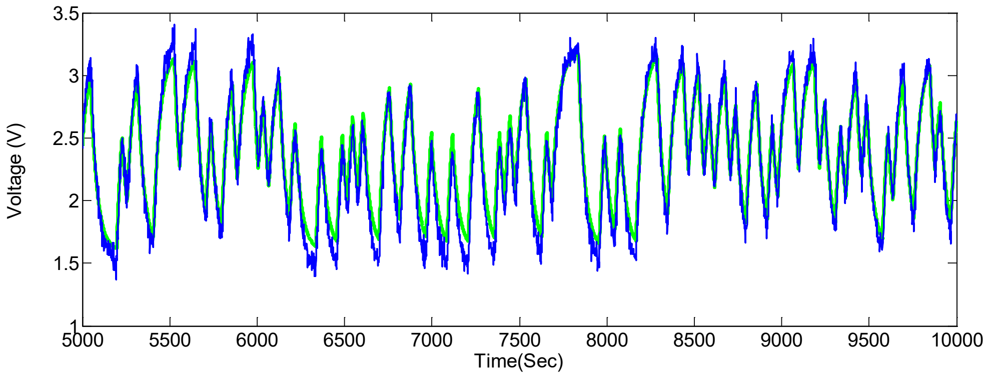

Figure 6. Measured (blue) and estimated (green) outputs aerothermic system

### 3. Implementation of control laws

*A. PI Controller*

The classical regulator PID links directly the control signal u (t) to the difference signal e (t). Its temporal description is shown by the equation [11], [12]:

$$u(t) = K_P e(t) + K_I \int e(t)d(t) \qquad (3)$$

Where e (t) = w (t) - y (t) is the system error (i.e. the difference between the set point value w (t) and the process output y (t)), u(t) is the control variable.

Where $K_p$: is the proportional action and $K_I$ is the integral action.

*B. Generalized Predictive Control Design*

The Generalized predictive control (GPC) method was proposed by Clarke and Mohtadi [13], [14]. It has been effectively implemented in numerous industrial applications. The fundamental thought is to calculate a succession of future control signals so as to limit a multistage cost function characterized over a prediction horizon. The rule of this procedure is to utilize a dynamic model of the process inside the regulator in real time, so as to foresee the future conduct of the cycle. This strategy is based on the following concepts:

- Elaboration of a system model to be controlled in order to predict the output in a future moment from a certain horizon.
- Implementation of a future control sequence, based on a minimization criterion.
- Restoration of the procedure at every cycle and just the principal command is applied to the process.

In the case of generalized predictive control (GPC), the algorithm uses the CARIMA (Controlled Auto Regressive Integrated Moving Average) prediction model given by the following equation [12]:

$$A(q^{-1})y(t) = q^{-d}B(q^{-1}).u(t-1) + \frac{c(q^{-1})}{\Delta(q^{-1})}e(t) \tag{4}$$

Where, y (t) is the output of the system, u (t) is the command; e (t) is a random sequence independent of the Gaussian white noise and $\Delta(q^{-1}) = 1 - q^{-1}$ is the difference operator.

A (q-1), B (q-1) and C (q-1) are q-1 polynomials respectively of degree na, nb and nc and defined by:

$$A(q^{-1}) = 1 + a_1(q^{-1}) + \ldots + a_{na}(q^{-na})$$
$$B(q^{-1}) = b_0 + b_1(q^{-1}) + \cdots + b_{nb}(q^{-nb})$$
$$C(q^{-1}) = 1 + c_1(q^{-1}) + \cdots + c_{nc}(q^{-nc})$$

To build the command, the GPC must implement a minimization criterion J. It's composed of the quadratic sum of the output prediction error and the control increment.

$$J = \sum_{j=hm}^{hp}[y(t+1) - w(t+1)]^2 + \lambda \sum_{j=1}^{hc}[\Delta u(t+j-1)]^2 \tag{5}$$

Where, hm and hp represent respectively the minimum and maximum prediction horizon, hc is the prediction horizon on the command, λ is the weighting on the command. y(t + j) and w(t + j) are respectively the predicted output and the future one-step set-point.

Generalized Predictive Control (GPC) uses the notion of optimal predictor, which aims to anticipate the behavior of the process on j-step in the future on a finite horizon. In the following, we consider the case where C = 1 to simplify the computation of the control law, without loss of major generality.

To calculate the predictor $\hat{y}(t+j)$ at j-step of y (t+j), we consider the polynomial equation, called the Diophantine equation: [6].

$$A(q^{-1})\Delta(q^{-1})E_j(q^{-1}) + q^{-j}F_j(q^{-1}) = 1 \tag{6}$$

Where: $E_j = E_{j.0} + E_{j.1}q^{-1} + \cdots + E_{j.j-1}q^{-(j-1)}$; $F_j = F_{j.0} + F_{j.1}q^{-1} + \cdots + F_{j.na}q^{-na}$

By putting, $\widetilde{A}(q^{-1}) = \Delta(q^{-1})A(q^{-1})$ the relation (6) becomes:

$$1 = E_j\widetilde{A}(q^{-1}) + q^{-j}F_j \tag{7}$$

To obtain the quantity y (t + j), equation (4) is multiplied by the quantity $E(q^{-1})\Delta(q^{-1})q^j$ in this case we have:

$$y(t+j) = B(q^{-1})E_J\Delta u(t+j-d-1) + E_je(t+j) + F_jy(t) \tag{8}$$

By putting: $G_i(q^{-1}) = B(q^{-1})E_j(q^{-1})$

Equation (8) becomes:

$$y(t+j) = G_i(q^{-1})\Delta u(t+j-d-1) + F_jy(t) \tag{9}$$

In this case, $E_j e(t+j) = 0$ because the predictor of any random variable is zero.
We have:

$$\begin{bmatrix} y(t+1) \\ y(t+2) \\ y(t+3) \\ \vdots \\ y(t+hp) \end{bmatrix} = \begin{bmatrix} G'_{1,0} & 0 & 0 & ..0 \\ G'_{2,0} & G'_{2,1} & 0 & ..0 \\ G'_{3,0} & G'_{3,1} & G'_{3,0} & ..0 \\ G'_{hp,hp-1} & G'_{hp,hp-2} & .. & G'_{hp,0} \end{bmatrix} \begin{bmatrix} \Delta u(t) \\ \Delta u(t+1) \\ \Delta u(t+2) \\ \vdots \\ \Delta u(t+hp-1) \end{bmatrix} + \begin{bmatrix} f(t+1) \\ f(t+2) \\ f(t+3) \\ \vdots \\ f(t+hp) \end{bmatrix}$$

This equation can be written in the following reduced matrix form:

$$Y = G'.\Delta U + F \tag{10}$$

It is used when calculating the optimal control law minimizing the criterion J.

Where:

$$Y = \begin{bmatrix} y(t+1) \\ y(t+2) \\ y(t+3) \\ . \\ . \\ . \\ y(t+h_p) \end{bmatrix}; G = \begin{bmatrix} G_{1,0} & 0 & 0 & ..0 \\ G_{2,1} & G_{2,0} & 0 & ..0 \\ G_{3,2} & G_{3,1} & G_{3,0} & ..0 \\ G_{hp,hp-1} & G_{hp,hp-2} & .. & G_{hp,0} \end{bmatrix} \Delta U = \begin{bmatrix} \Delta u(t) \\ \Delta u(t+1) \\ \Delta u(t+2) \\ . \\ . \\ \Delta u(t+hp-1) \end{bmatrix}; \ F = \begin{bmatrix} f(t+1) \\ f(t+2) \\ f(t+3) \\ . \\ . \\ f(t+hp) \end{bmatrix}$$

We first admit that the control horizon hc is equal to the prediction horizon hp. The criterion j can be written in matrix form:

$$J = [Y - W]^T [Y - W] + \lambda \Delta U^T \Delta U \tag{11}$$

Where Y and ΔU are defined in equation (10).
The purpose of the control law (GPC) is to minimize the criterion J given by equation (5). It is achieved by the minimization of the criterion in matrix form:

$$\frac{\partial j}{\partial \Delta U} = 0 \tag{12}$$

The vector minimizing the criterion J, which satisfy the equation (12), is found such that:

$$\Delta U_{opt} = (G'^T G' + \lambda I)^{-1} G'^T (W - F) \tag{13}$$

In our case, only the first command is actually applied, then we have:

$$U_{opt} = U(t-1) + (G'^T G' + \lambda I)^{-1} G'^T (W - F) \tag{14}$$

*C. Pi Controller Implementation*

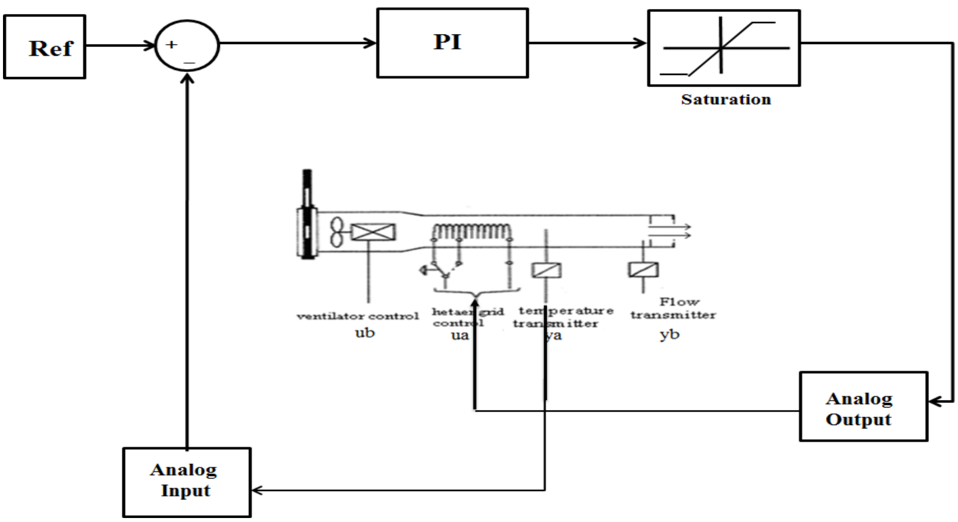


Figure 7. Control diagram of the PI real-time implementation.

The aim of this part is to regulate the air temperature of the aerothermic process, by acting on the electrical power provided to the heater grid. Before proceeding to the real-time application, simulations are performed so as to determine and test the efficiency of the regulator parameters. Figure. 7 represents the block diagram of the PI controller [15], [16].

Figure. 8 represents the behavior of the control and the measured output in real time during four different experiments.

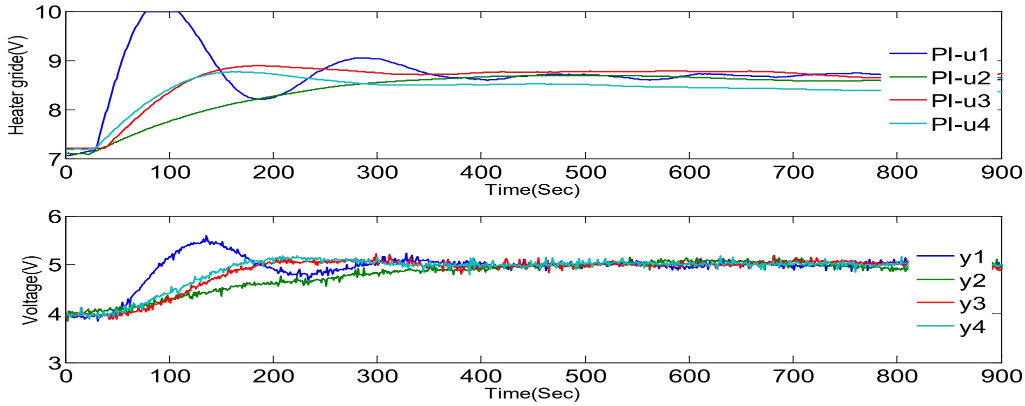


Figure 8. Evolution of the PI command and the response of the system in real time.

As observed in the Figure. 8, it is clearly observed that the output $y_3$ does not present an overtaking. It has a fast behavior compared to the other outputs. These parameters are given as follows:

Kp = 0.015 Ki = 0.02

*D. GPC Controller Implementation*

The synthesis of the optimal GPC controller parameters is an essential step for a more efficient control of the aerothermic process. For a wise choice of these parameters, we follow the same available recommendations that are based on the identified model. In order to confirm the parameters of the GPC controller, simulations are performed. The results achieved are encouraging and make it possible to implement the GPC command in real time on the studied process. The following Figure. 9 represents the block diagram of the GPC controller used in the experimentation. The parameters calculated for the GPC controller are given as follows:
hp = 26; hm = 7 ; hc = 1 ; $\lambda$ = 1.

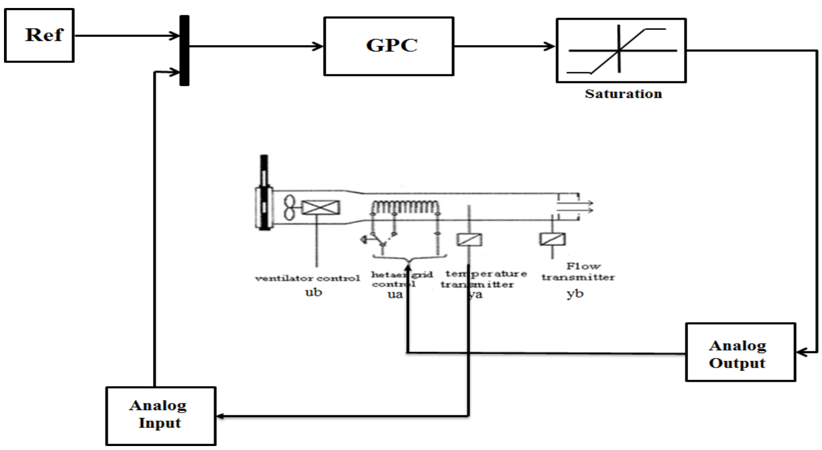


Figure 9. Control diagram of the GPC real-time implementation.

After implementing the GPC controller strategy to the aerothermic process, we have obtained results as shown in Figure. 10.

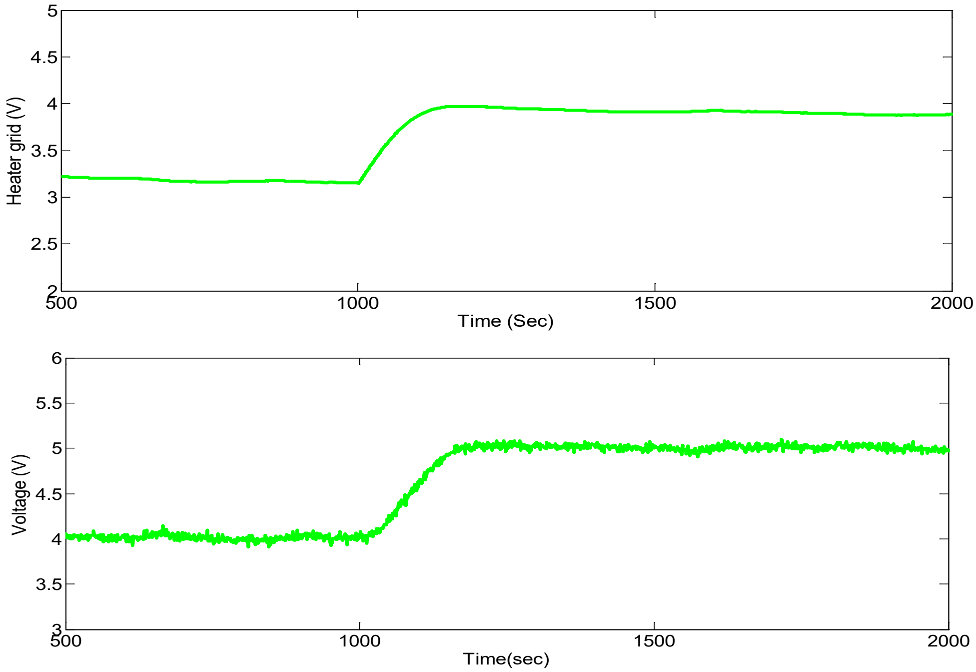


Figure 10. Evolution of the GPC command and the response of the process in real time

The obtained results show that the performance of the system in the terms of set-point tracking, rapidity and regulation are successfully tested.

## 4. Results and discussions

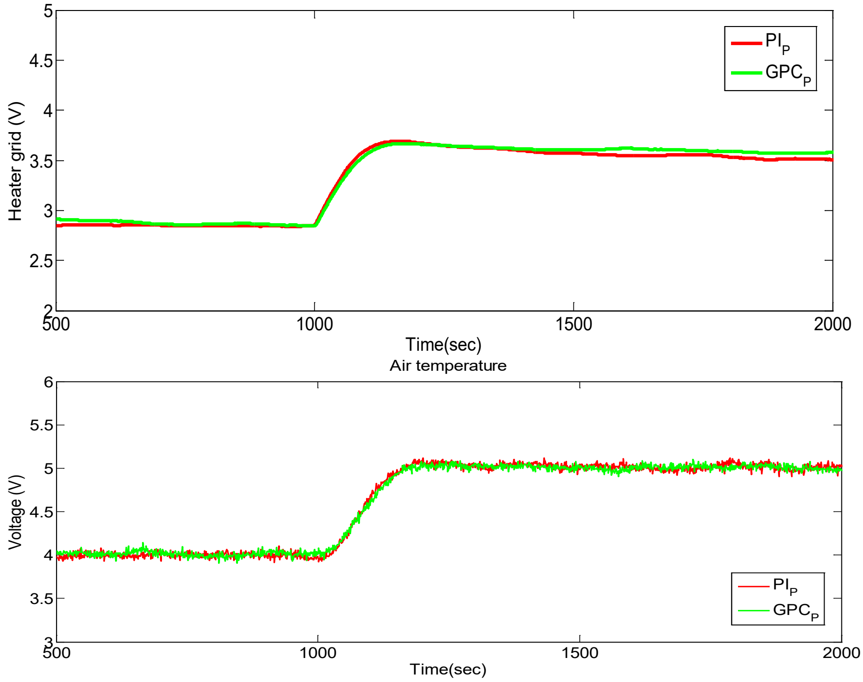


Figure 11. The two actual process outputs controlled by GPC and PI

In this work, the selected parameters of the PI and GPC controllers show a good convergence to set-point value as illustrated in Figure. 8 and Figure. 10. In order to show the advantage of these two commands, the aerothermic process temperature is controlled in real time by the two controllers PI and GPC. The results obtained are given in Figure.11. As can be seen from Figure. 11, the output controlled by the GPC and PI techniques displays good monitoring and control performance.

The robustness of the two controllers is tested by injecting the perturbation in step form at the output. The obtained results are depicted in Figure.12 and Figure.13. As shown in these Figures, the behavior of the output controlled by PI and GPC gives a better performance versus the injected perturbation during the experiment. These results confirm the robustness of these two control techniques to cancel, the injected perturbation effect.

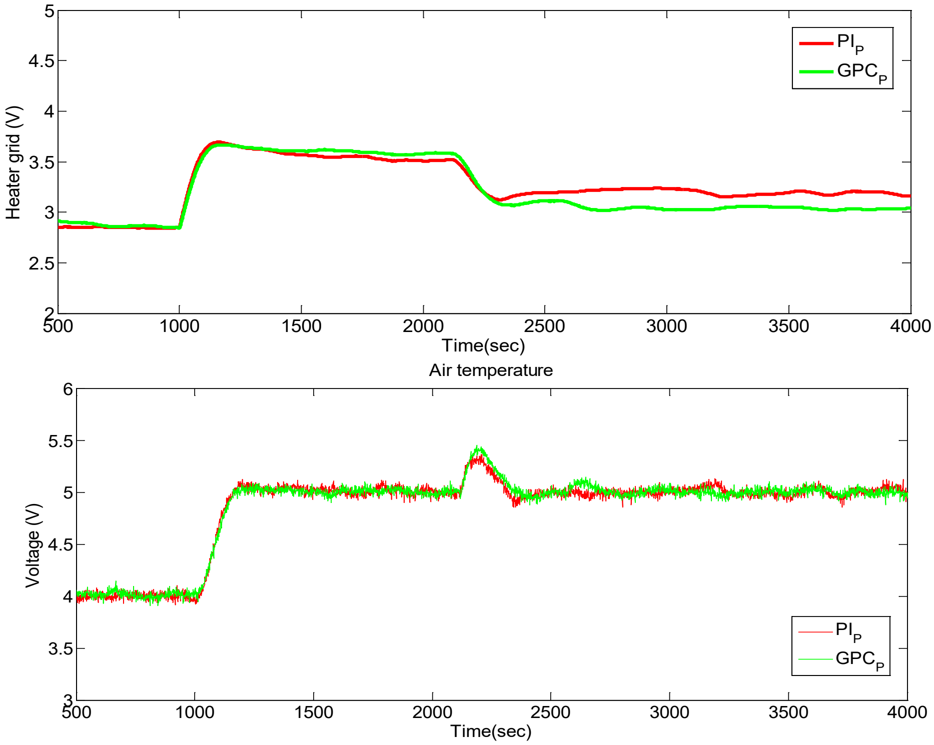


Figure 12. Air temperature and Heater grid control responses in closed-loop for the GPC and PI controllers.

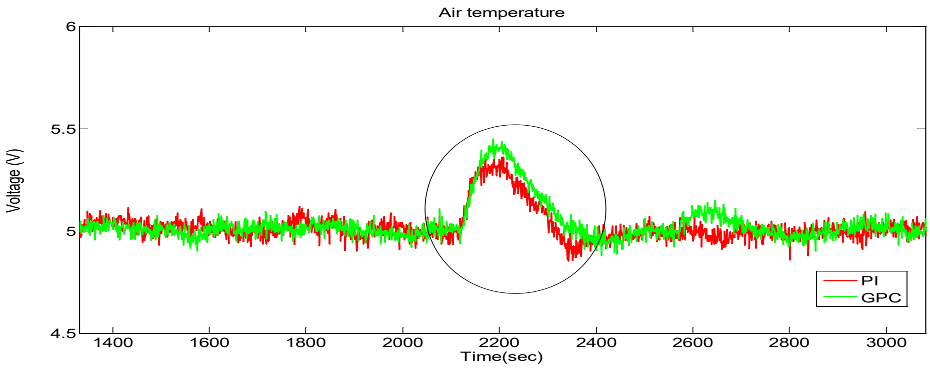


Figure 13. Zoomed view of the steady state.

Table 1 represents the statistical comparison of the variation recorded during the transient and steady phases of the response of the two controllers.

Table 1. Comparison between the variance of the command and the output of the two controllers

| Iterations (Sec) | GPC | | PI | |
|---|---|---|---|---|
| | Var ($U_{GPC}$) | Var ($Y_{GPC}$) | Var ($U_{PI}$) | Var ($Y_{PI}$) |
| 1000-1350 | 0.0467 | 0.1264 | 0.0430 | 0.1399 |
| 1350- 2000 | $2.8231e^{-4}$ | $8.5734e^{-4}$ | $8.2742e^{-4}$ | 0.0013 |

It is clearly observed from the table 1, that during the transient phase (1000-1350 iterations) and the permanent phase (1350-2000 iterations), the variance of the GPC command (Var($U_{GPC}$)) and the PI command (Var($U_{PI}$)) do not present a significant difference in their statistical values. During these two phases, the variance of the output controlled by GPC Var ($Y_{GPC}$) has a small value compared to that of PI controller Var($Y_{PI}$).
Table 2 summarizes the comparison of the performances indices (settling time, rise time, overshoot) and the Root Mean Square (RMS) of the responses obtained by PI and GPC controllers.

Table 2. Numerical performances of the closed loop response.

| Controller | Rise time (min) | Overshoot (%) | Settling time (min) | RMS (V) |
|---|---|---|---|---|
| PI | 1.1 | 1.052 | 4.87 | 5.504 |
| GPC | 1.56 | 0.947 | 5.56 | 5.523 |

As observed in table 2, the PI controller exhibits an RMS (Root Mean Square) estimated at 5.504 V and a rise time evaluated at 1.1 minutes that is lower than that of the GPC controller. In addition, the overshoot obtained with the PI and GPC does not show any significant difference. One can notice that the high value of the stabilization time produced in the experiments of the GPC controller raises the necessary time to reach the desired reference value and to reject the disturbances Figure.13.

## 5. Conclusion

In this research work, we focused on PI and GPC identification and control techniques for mono-variable process and their practical implementation. These two commands use a model identified directly from the physical data measured in real time. The pilot scale process is used for the implementation of these two techniques. The simulation results on the identified model of this process are promising. In practical, both commands have been applied to control the laboratory process temperature in real time. The results confirmed the effectiveness in set-point tracking and regulation. The behavior of the output controlled by the PI and GPC controllers indicates very similar results. However, the standard control PI reacts quickly to cancel the effect of the perturbation effect. This is an advantage for the PI control which also allows combining the simplicity of use, and maintenance.

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