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Identification and implementation of a Predictive Control in a Thermal System

Identificação e implementação de um Controle Preditivo em um Sistema Térmico

Identificación e implementación de un Control Predictivo en un Sistema Térmico

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Abstract
The present work consists of carrying out the identification and implementation of a predictive controller in a thermal system to follow a didactic design methodology for learning in systems identification, analysis, and controller design. For the identification of the thermal system, the method of least squares was chosen because it allows to obtain a faithful mathematical model that describes the temperature system. The data used in the system identification step are from a didactic industrial plant of a temperature system. From the model obtained for the system in question, the design and implementation of a classic Proportional Integral Derivative (PID) controller and a predictive controller are carried out to verify the behavior of the system against the actions of both controllers. The entire implementation will be carried out in the MATLAB/Simulink computer simulation environment.
Keywords: Thermal system; Systems identification; Predictive control; PID control; Industrial didactic plant.

Resumo
O presente trabalho consiste em realizar a identificação e a implementação de um controlador preditivo em um sistema térmico com objetivo de seguir uma metodologia didática de projeto para o aprendizado em identificação de sistemas, análise e projeto de controladores. Para a identificação do sistema térmico, o método dos mínimos quadrados foi o escolhido por permitir obter um modelo matemático fiel que descreva o sistema de temperatura. Os dados utilizados na etapa de identificação do sistema são de uma planta industrial didática de um sistema de temperatura. A partir do modelo obtido para o sistema em questão, realiza-se o projeto e implementação de um controlador do tipo Proporcional Integral Derivativo (PID) clássico e de um controlador do tipo preditivo com a finalidade de verificar o comportamento do sistema perante as atuações de ambos os controladores. Toda a implementação será realizada no ambiente de simulação computacional MATLAB/Simulink.
Palavras-chave: Sistema térmico; Identificação de sistemas; Controle Preditivo; Controle PID; Planta didática industrial.

Resumen
El presente trabajo consiste en realizar la identificación e implementación de un controlador predictivo en un sistema térmico con el fin de seguir una metodología de diseño didáctico para el aprendizaje en identificación, análisis y diseño de controladores de sistemas. Para la identificación del sistema térmico se optó por el método de mínimos cuadrados porque permite obtener un modelo matemático fiel que describe el sistema de temperatura. Los datos utilizados en la etapa de identificación del sistema son de una planta industrial didáctica de un sistema de temperatura. A partir del modelo obtenido para el sistema en cuestión, se realiza el diseño e implementación de un controlador clásico Proporcional Integral Derivativo (PID) y un controlador predictivo con el fin de verificar el comportamiento

del sistema frente a las acciones de ambos os controladores. Toda la implementación se realizará en el entorno de simulación por ordenador MATLAB/Simulink.

Palabras clave: Sistema térmico; Identificación de sistemas; Control predictivo; Control PID; Planta didáctica industrial.

1. Introduction

Thermal systems in manufacturing processes are quite common industrial applications today. Therefore, it is necessary that engineers who work with this type of process have a greater knowledge of how to manipulate their variables as well as operate them according to a certain imposed dynamics and for the data of this process to be interpreted correctly, it is important that several tests are carried out. Through the tests, it is possible to determine which model will be more faithful to the real system that must be used to represent the operating principle of the plant and which control method will be able to be used in the manipulation of its dynamic behavior (Jaluria, 2007).

Since thermodynamic systems have a slow response, approaching an open loop system, some manipulations for compensation, when subjected to perturbations, cannot be performed and for this reason, the correct tuning of a certain control law is necessary and essential to the process. Another extremely important detail is the definition of the mathematical model that will be used to describe the process plant (Nise, 2022).

There are currently several methods and strategies to model a given dynamic system such as the Smith method, least squares, artificial neural networks, among others (Kaya, 2004; Arnold & King, 2021). In this work, the Least Squares (LQ) method based on the Autoregressive Model with Exogenous Inputs (ARX) will be used (Aguirre, 2004). The choice is given by the fact that even being a simple identification mechanism, the method presents good results when it comes to thermal systems and their non-linear characteristics (Pugliese, et al., 2022).

With the achievement of a mathematical model faithful to the dynamic characteristics of the real system, the objective is to control the system in question, that is, through the synthesis of a controller, send commands to an actuator. Throughout the work, two types of controllers will be designed. At first, the most used controller in the industrial environment, which is the Proportional Integral and Derivative (PID) controller. Such a control strategy presents a simple implementation when compared to modern control strategies (Dorf & Bishop, 2001; Oliveira, et al., 2020). The method for synthesizing the gains of the PID controller will be the Ziegler Nichols open loop (Åström & Hägglund, 2004).

Regarding modern controllers, one of the control strategies that is widely studied in the literature is the predictive control strategy due to its ability to adapt to different types of systems. In this way, the various Model Predictive Control (MPC) algorithms can be applied in numerous areas of industry as well as in different academic research. The applications are the most diverse, as in the health area, cement industries, in robotic manipulation in industrial production or application of manipulators in the military industry. The good performance of the strategy in these applications shows the scope of the predictive controller (Camacho & Alba, 2013; Santos, et al., 2020). After verifying the property of the predictive controller, an extension of the MPC called Dynamic Matrix Control (DMC) will be used in this work (Shridhar & Cooper, 1997).

In this way, the proposal of this work is the identification of a mathematical model that represents an industrial didactic thermal system. In addition, the implementation and comparison in computer simulation of two control strategies for the system will be carried out, the first controller, the classic PID, tuned via open loop Ziegler Nichols method and the second, the predictive controller DMC. All implementations and simulations will be carried out in the MATLAB/Simulink environment.

The work is organized as follows: Section 2 will present the details of the thermal system used in the study and development of the work. Section 3 will describe all the identification of the system and validation of the mathematical model obtained. Section 4 will present the entire theory and design of the control strategies under study. Section 5 will present the results of the controllers' actions. Finally, in Section 6, the conclusions of the work are presented.

2. Methodology

Based on the methodological procedures presented by Köche (2016), this research has qualitative and quantitative characteristics. The development and implementation of the system illustrated in this work allows the application of concepts related to system identification and controle theory in disciplines related to industrial control and industrial automation content and programming. For the development of the system, the four steps of the action research method were followed: plan, act, describe, and evaluate. Action research is a structure for conducting applied research-oriented toward making diagnoses, identifying problems, and finding solutions (Tripp, 2005; Pugliese, et al., 2022).

As industrial technology advances, understanding system identification concepts, control theory, and implementation of controllers in industrial processes are of utmost importance for a control and automation engineering student. Thus, education in industrial control and industrial automation has become a significant issue in universities' most diverse interdisciplinary engineering departments (Özerdem, 2016). Didactic benches and laboratory devices are essential tools for teaching, where theoretical content is consolidated with practice, especially in technology-oriented courses (Pinho, et al., 2021).

In this work, the identification of a thermal system and the tuning of two control strategies for the temperature system are carried out to present in a didactic way a methodology to aid in the learning of controller design for industrial dynamic systems. This methodology, in addition to assisting in teaching industrial automation, covers advanced concepts of the current industry, allowing the control of industrial processes through a project methodological structure. The implementation carried out in this work also provides a method to improve learning outcomes. It will enable the development of projects in the laboratory, allowing the student to acquire real-time skills and experiences in engineering education, such as electrical, electronics, mechatronics, and control engineering regarding the contents of identification of systems and implementation of controllers.

2.1 Description of the Didactic Thermal System

The didactic industrial plant used in this work can be seen in Figure 1. Note that the didactic plant consists of 2 tanks, one for storing water at room temperature and the other for the heating process. To simplify the explanation of how they work, they will be named as tanks 1 and 2, respectively. Driven by a frequency inverter, the electric pump transfers water from the storage tank to the process. There are several meters and sensors in the didactic process plant, both for level control and for temperature control. As this work is dedicated to the temperature process, only the actuators and sensors that involve it will be highlighted.

Figure 1 - Industrial didactic plant.

Source: Authors.

For the process of reading the temperature and heating of tank 2, there is internally a PT-100 type sensor and a heating resistor, respectively. Both are connected to a Programmable Logic Controller (PLC), directly or indirectly, that is, with the use or not of a transducer. Thus, all sensor and actuator elements are connected to the PLC through analog or digital inputs and outputs with the main objective of manipulating and monitoring the main variables associated with the thermal process.

Below is a list of the elements associated with the thermal process of the didactic plant as well as some technical characteristics:

a) Programmable Logic Controller: ABB's PM554 controller was used, which has a memory of 128kB, 8 digital inputs, 6 digital outputs and a voltage of 24V DC. For communication, the RS232 serial or TCP/IP protocol is used.
b) Analog expansion module: As the PLC does not have analog inputs and outputs, ABB's AX561 module was used, which has 4 analog inputs and 2 analog outputs, respectively. The module allows to work with 4--20mA and -10 to +10V outputs.
c) Heating resistor: The resistor used is made of stainless steel by the manufacturer Corel. Such a resistor is controlled by means of a static power switch, considering that its current can reach up to 10A.
d) Static power switch: To send a command signal to the resistor, the TH6200A10 switch is used. The switch receives a signal from the 4-20 mA PLC analog output and converts this signal to a 0 to 10 A output.
e) PT-100: Temperature readings come from a 3-wire PT-100. Temperature readings from this sensor can range from -200 to 700 °C. It is located at the bottom of tank 2 and is connected to the temperature transmitter.
f) Temperature transmitter: Responsible for converting the information from the PT-100 to the PLC. ABB's TTH200 is used in the plant.

3. System Identification and Validation

In identifying systems, obtaining a mathematical model capable of faithfully representing the functioning of the real

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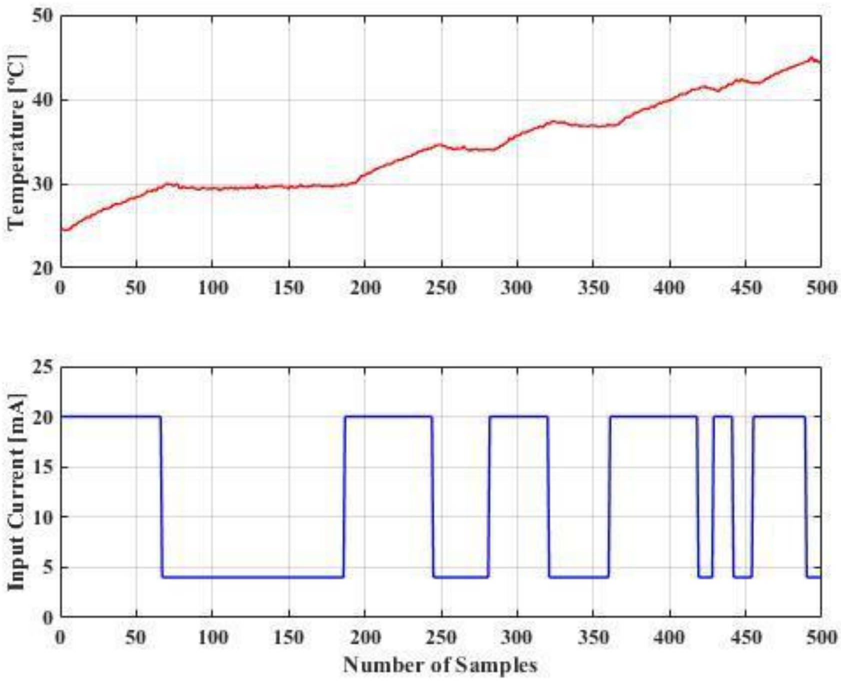
system is essential. Identification methods may vary according to knowledge of the process under study. To obtain a mathematical model that faithfully represents the real system, it is necessary to know the process plant under study and its variables, as this will make it possible to obtain a good model. For the industrial didactic plant used in this work, the representation in black box is the one that will be used to obtain the data.

Black box modeling is used when it is not necessary to have prior knowledge of the system and its variables. Therefore, the mathematical model only describes the relationship between input and output of the process plant. The temperature reading was then performed, and the signal sent to the resistor. The sampling time for reading these data was 4 seconds, in a total of 499 samples. Figure 2 represents the data collected from the system.

Figure 2 - Temperature collected data.



Source: Authors.

After collecting the test data, it is necessary to obtain the mathematical equation that will describe the behavior of the process. In thermal processes, it is important to highlight the presence of transport delay since the delay has a destabilizing effect on the control loop. Thus, for the identification of the thermal process, the method of least squares will be used as a strategy. By analyzing the collected data, it is possible to approximate the thermal system, which is originally nonlinear, by a first-order system with transport delay (Aguirre, 2004).

The least squares method can be described by equation (1) given by

$$y = \Psi\theta + \xi \ (1)$$

where, y is the estimated system output, Ψ the regression matrix, θ the estimated parameters and ξ the system error. The terms Ψ, θ and ξ are represented, respectively, by

$$\Psi(k-1) = \begin{bmatrix} y(k-1) & u(k-1) \\ \vdots & \vdots \\ y(k-n_y) & u(k-n_u) \end{bmatrix} \ (2)$$

$$\theta = [\Psi^T\Psi]^{-1}\Psi^T y \ (3)$$

$$\xi = y - \Psi\theta \quad (4)$$

Equation (2) refers to the system's regressors matrix, it is defined according to the process plant. As it is a plant with first order characteristics with transport delay, the vector of regressors will have only three regressors. The regressors used to obtain the plant model are represented in equation (5).

$$\begin{bmatrix} \Psi(k_3 - 1) \\ \vdots \\ \Psi(k_n - 1) \end{bmatrix} = \begin{bmatrix} y(k_3 - 1) & u(k_3 - 1) & u(k_3 - 2) \\ \vdots & \vdots & \vdots \\ y(k_n - 1) & u(k_n - 1) & u(k_n - 2) \end{bmatrix} \quad (5)$$

As it is a matrix, the values of k must vary according to the number of samples n. To obtain the model, 373 samples were used. It should be noted that the initial conditions must be null and to obtain the regressors, two constraints must be satisfied (Aguirre, 2004).

i. The variables are taken up to the instant k-1;

ii. The variables are linear in the parameters that make up the θ vector.

The vector of estimated parameters θ is defined in the equation (3), so it is obtained by multiplying the matrix Ψ and the output vector y, resulting in the vector of equation (6).

$$\theta = [0.9993 \quad -0.0008 \quad 0.0060] \quad (6)$$

From the θ vector it is possible to represent the system through equation (7).

$$y(k) = 0.9993y(k-1) - 0.0008u(k-1) + 0.0060 \quad (7)$$

The representation of equation (7) is said to be a difference equation, that is, a model of the system in discrete time. As the predictive controller design requires the system in continuous time, some approximation methods can be used, such as Tustin, zero-order latch, and linear approximation. The three approximation methods were tested, and it was observed that the difference between the values found was minimal. Therefore, the Tustin method was used to approximate the discrete model to the continuous model. After the conversion, the model of equation (8) was obtained in continuous time.

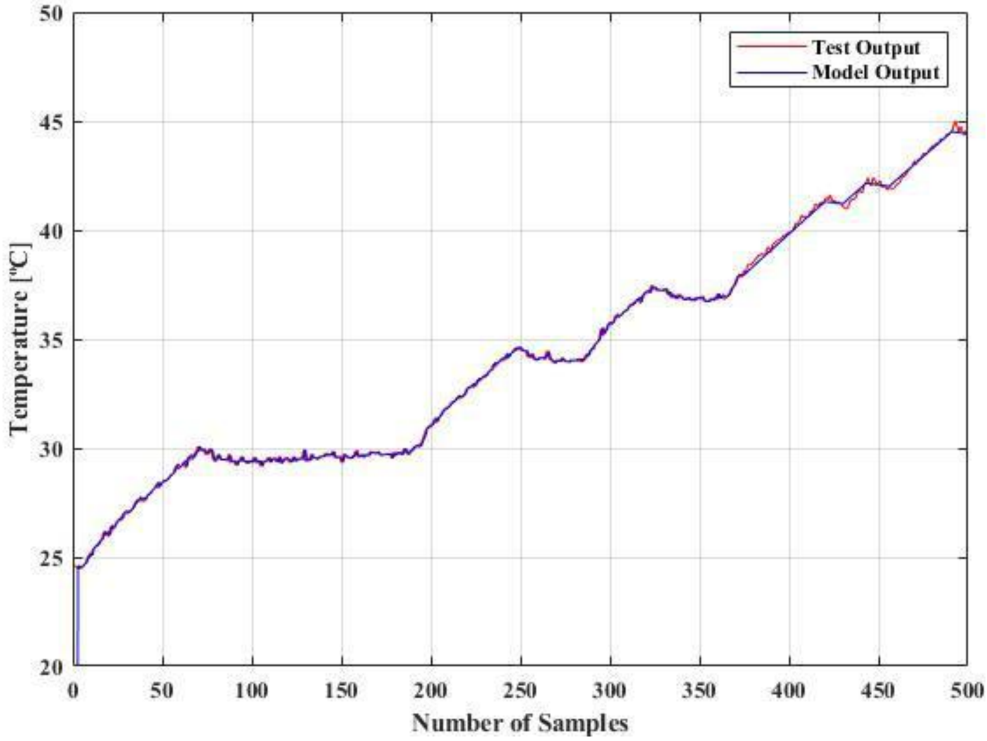
$$\frac{Y(s)}{U(s)} = \frac{(-1.139s + 0.7716)}{569.476s + 1} e^{-2s} \quad (8)$$

After the process identification step, it is possible to obtain the final model that mathematically describes the process according to equation (8). However, it is necessary to verify if the characteristics of the system correspond to the expected. Considering that the mathematical representation of the plant is a fundamental step for the development of a good control strategy, validation methods must be carried out to show the fidelity of the mathematical model obtained.

The first validation test to be performed is the simulation of the model with the real data collected. In practice, it is common to divide the data obtained from the trial into two parts, which are not necessarily equal. One of them for model identification and the second for validation (Aguirre, 2004).

For this work, 499 samples were collected, and approximately 75% of the data were used to obtain the model and the other 25% for its validation.

Figure 3 - Validation of the thermal process model.



Source: Authors.

Figure 3 shows the actual output of the temperature system in blue and its estimated output in red. It can be observed that from sample number 370 onwards, the estimated output is slightly different from the actual output. This is since the data used from sample number 370 are validation data and are used to prove that the model can be considered a possible faithful representation of the process.

Another proposed method is the root mean square error (RMSE), which relates the output of the real data to the output of the model. This index compares the model predictions with the system time average. In this method, values smaller than one unit indicate a better performance in relation to the considered standard predictor (Aguirre, 2004). Equation (9) presents the calculation for the mean square error.

$$RMSE = \frac{\sqrt{\sum_{k=1}^{N}(y(k) - y_e(k))^2}}{\sqrt{\sum_{k=1}^{N}(y(k) - y_m(k))^2}} \quad (9)$$

From equation (9), y(k) is the measured signal, ye is the free simulation of the signal, and ym is the average value of the measured signal. The mean square error found for the thermal system data using the calculation presented by equation (9) is 0.0225. In this way, it is possible to certify that the mathematical model presented by equation (8) is faithful and can be used as a good representation for the thermal system under study.

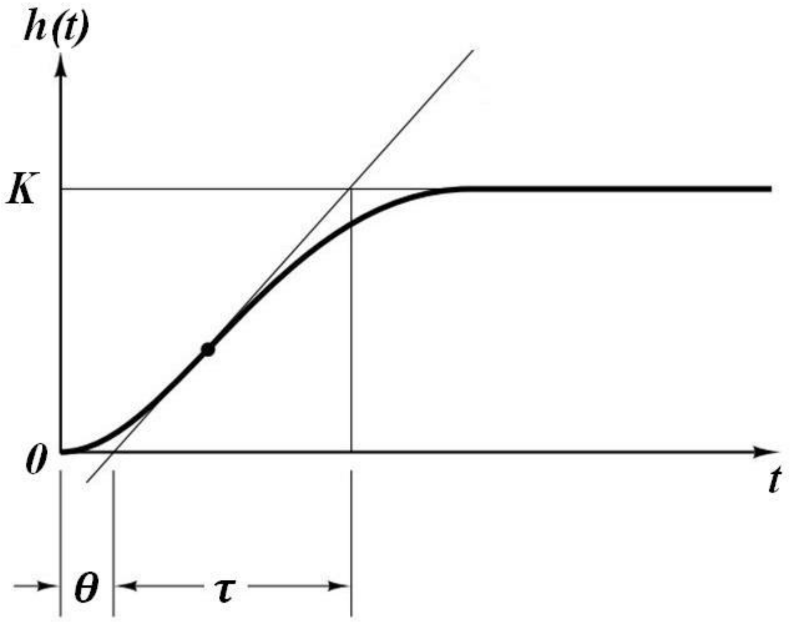
4. Control Strategies

4.1 PID Control

The first controller to be presented will be the PID controller. As it is one of the most used control methods at an industrial level, PID presents viable solutions, without the need for a lot of computational expense or more complex calculations to be tuned and implemented.

To calculate the PID controller gains, the open-loop Ziegler-Nichols method will be used (Ogata, 2011). For this, an open-loop unit step must be applied to the system, following the model presented in Figure 4.

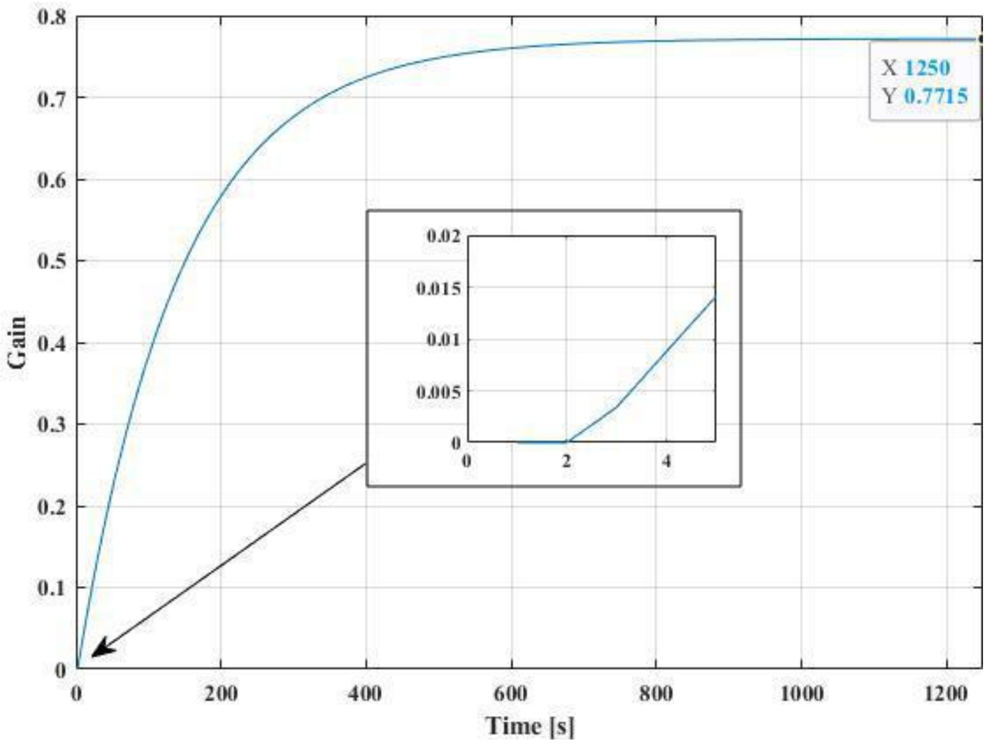
Figure 4 - Open loop response model.



Source: Authors.

In view of the model, the system response to the step was obtained as can be seen in Figure 5.

Figure 5 - Unit step response.



Source: Authors.

After applying the step, one should obtain a first-order transfer function in the pattern of equation (10).

$$G(s) = \frac{Ke^{-\theta s}}{\tau s + 1} \quad (10)$$

From equation (10), K is the steady-state system gain, θ is the transport delay, and τ is the process plant time constant. From this information, it is possible through Table 1 to calculate the estimated gains of the PID controller through the open loop Ziegler Nichols method (Ogata, 2011).

Table 1 - PID Controller Gains.

	K_p	K_i	K_d
P	τ/θ	0	0
PI	0.9τ/θ	0.3/θ	0
PID	1.2τ/θ	0.5/θ	0.5θ

Source: Authors.

With the help of Table 1, it is possible to tune the gains that will be used for the controller implementation. Equation (11) presents the transfer function of the PID controller.

$$C(s) = K_p + \frac{K_i}{s} + K_d s \quad (11)$$

Thus, to calculate the gains of the PID controller, the values of K = 0.7715, θ = 2 samples and τ = 150 samples were considered to represent the thermal system represented by equation (10). Therefore, from Table 1, the PID controller gains calculated were $K_p = 90$, Ki = 0.25 and $K_d = 1$.

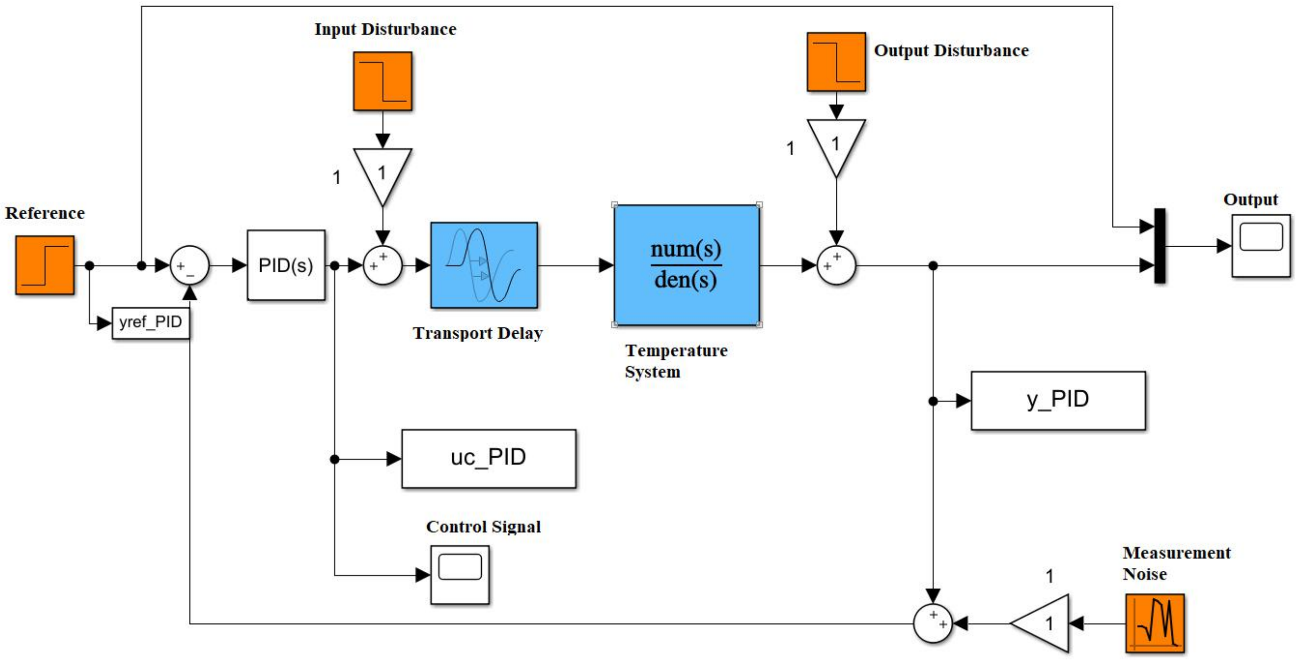
After tuning the controller, to implement the control law (u) in the PLC PM554, the parameters K_p, T_N (integration rate) and T_V (derivative gain time) must respect equation (12). Where $T_N = K_p/K_i$ and $T_V = K_pK_d$.

$$u(t) = K_p\left(e(t) + \frac{1}{T_N}\int e(t)dt + T_V\frac{de(t)}{dt}\right) \quad (12)$$

From equation (12), e(t) is the error between the input reference imposed on the system and the output measured by the sensor.

Figure 10 presents the block diagram developed to simulate the control system containing the process plant represented by the mathematical model obtained, the controller and some disturbances that must be considered to verify in simulation the performance of the PID controller in the rejection of disturbances. The internal parameters in the PID controller block and in the PID heating dynamics were previously determined.

Figure 6 - PID control loop.



Source: Authors.

The transfer function that represents the closed loop system is given by equation (13).

$$T(s) = \frac{0.002s^3 + 0.1786s^2 - 0.1214s - 0.000339}{0.002s^3 - 0.8214s^2 - 0.1232s - 0.000339} \; (13)$$

4.2 DMC Predictive Control

The second method to be analyzed is the predictive controller. This controller has been studied more and more in industrial applications because it has a systematic treatment of restrictions, which allows the operation of the plant at its optimal point, leading to a shorter production time and thus saving raw material in the process. It also has good application in multiple input and output systems and in transport delay systems (Qin & Badgwell, 2003).

The idea about the predictive controller is to look for a sequence of the input process that produces an optimal response from it following some criteria. Therefore, no specific controller structure is chosen. Instead of choosing the structure, an optimizer looks for the best actuation signal sequence, aiming to decrease a cost function. To reduce the complexity of the problem, the sequence of the actuation signal can be defined according to the control horizon (Nelles, 2020).

It is worth mentioning that the optimization in a finite horizon does not imply stability and the chosen cost function is not always the correct one. Stability-assured MPC algorithms are most useful in cases where systems have dynamics with unstable or non-minimum phase plants (Santos, 2011).

In this way, let the cost function be given by

$$J(\hat{y}, \Delta\hat{u}) = (\hat{y} - r)^T(\hat{y} - r) + \rho\Delta\hat{u}^T\Delta\hat{u} \; (14)$$

where, G represents the system response to the unit step as shown in Figure 9 and is described by equation

$$G = \begin{bmatrix} g(1) & 0 & & \dots & 0 \\ g(2) & g(1) & & \dots & 0 \\ \vdots & \vdots & \ddots & & \vdots \\ g(N) & g(N-1) & \dots & & g(N-M+1) \end{bmatrix} \; (16)$$

where N is the prediction horizon defined by the integer closest to equation (17), M is the control horizon given by the integer closest to equation (18).

$$N = \frac{5\tau + \theta}{T} + 1 \approx 51 \ (17)$$

$$M = \frac{\tau + \theta}{T} + 1 \approx 11 \ (18)$$

The sampling period (T) for the predictive controller is given by

$$T = \max(0{,}1\tau, 0{,}5\theta) = 15. \ (19)$$

As seen, theta is the transport delay (2 samples) and tau is the time constant of the thermal system, that is, the time for it to reach 63% of the final value in steady state (150 samples). Then the plant free response (f) is obtained by calculating the equations

$$f(k+i|k) = y(k) + \sum_{n=1}^{N_s-1} [g(n+1) - g(n)]\Delta u(k-n) \ \ (20)$$

and

$$f = \begin{bmatrix} f(k+1|k) \\ f(k+2|k) \\ \vdots \\ f(k+N_s|k) \end{bmatrix} (21)$$

where N_s is the number of samples of the step response that was 1250. Thus, the control increment is calculated, given by the equation

$$\Delta u(k) = K_{MPC}(r - f) \ (22)$$

where K_{MPC} is obtained through the equation

$$K_{MPC} = [1 \quad 0 \quad \ldots \quad 0](G^T G + \rho I_M)^{-1} G^T \ \ (23)$$

Subsequently, the calculation of the control that will be applied to the plant is performed and is given by equation (24).

$$u(k) = u(k-1) + \Delta u(k) \ \ (24)$$

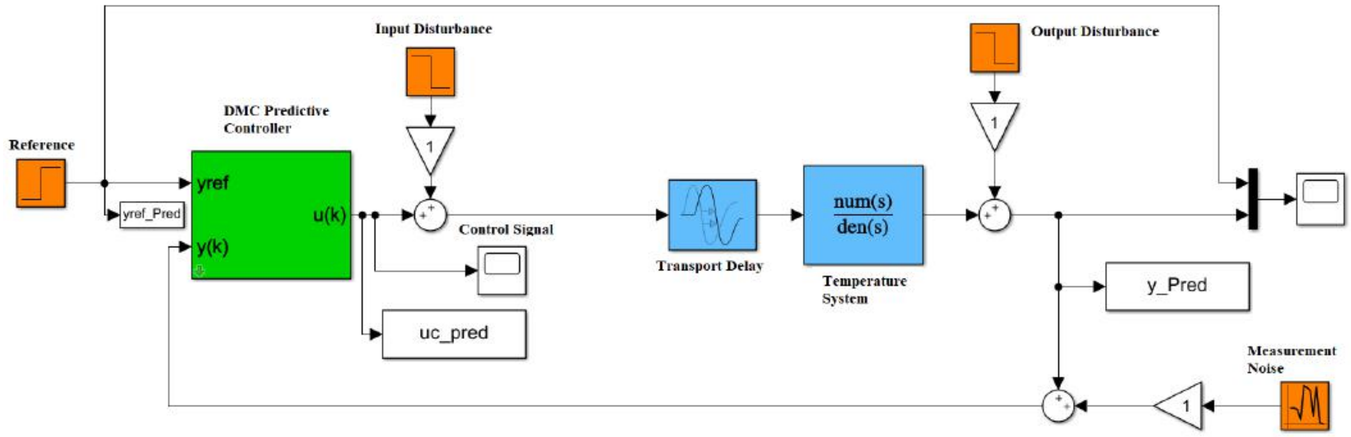
Finally, the value of the control weight (ρ) is chosen so that the first and second parts of equation (14) have the same magnitude. Therefore, its value is given by the equation

$$\rho = g_{ss}^2 + \sum_{i=1}^{N} \left[\frac{g(i)}{g_{ss}} - 1\right]^2 = 22{,}234 \ \ (25)$$

where g_{ss} = 0,7715 is the steady-state gain. All the values described above were obtained through a code developed in the Matlab environment.

From the calculation of the initialization parameters of the predictive controller, a block diagram was developed in the Simulink environment (Figure 7) to simulate the operation of the plant under the actuation of the predictive control.

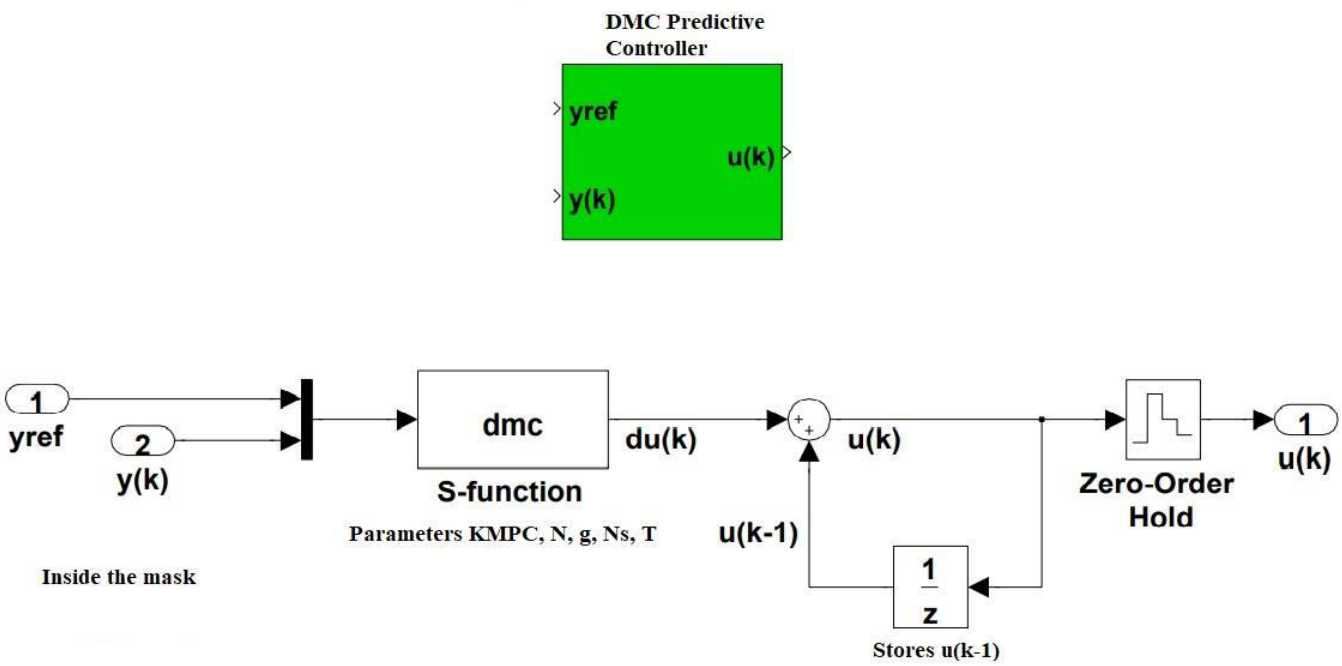
Figure 7 - Predictive control loop.



Source: Authors.

It is possible to observe that the control loop in Figure 7 has the DMC predictive controller block. It is responsible for comparing the reference signal with the estimated output signal and returning the command to the actuator. Figure 8 presents the block in more detail. In conjunction with the block, a code was developed in the Matlab environment to perform the control increment (Camacho & Alba, 2013; de Moraes, et al., 2013).

Figure 8 - Detailed Predictive Controller Block.



Source: Authors.

5. Results

To perform the conversion of the control signal obtained in the simulation to the plant actuator, some approximations were used. The first important approximation was the PT-100 reading, represented by the equation

$$T = 0{,}0046Q_{w0} - 3{,}0925 \quad (26)$$

where T is the temperature read by the PT-100 and Q_{w0} is the value read from the analog input, ranging between 642 and 22411. In addition to the reading information, the control signal approximation calculation for the static power switch (C) is seen by the equation (27).

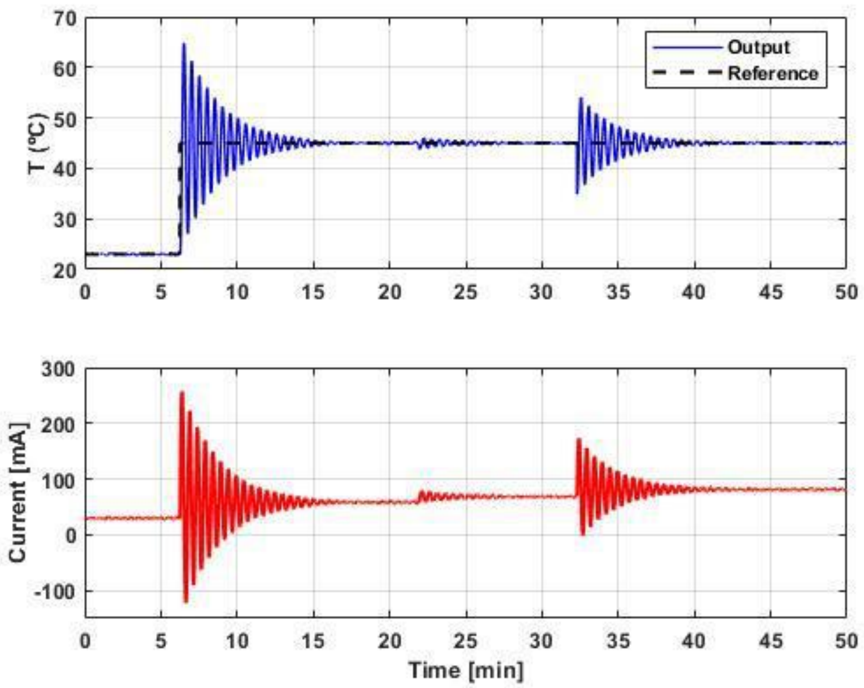
$$C = \frac{u_c - 20}{16} \quad (27)$$

From equations (26) and (27) it is possible to implement in the actuator the appropriate control signal (u_c) to converge the plant output to the desired reference. It is worth noting that the data obtained in the approximation of equation (27) are values derived from simulation in a computational environment, so it would be necessary to carry out some practical tests in the process plant to obtain the correct value of the signal.

After adjustments and theoretical analysis of the controllers, a computer simulation was carried out through the Simulink environment with the objective of presenting the response of the controllers' performance on the thermal system under certain conditions. With the system at room temperature, in approximately 6 minutes, a step was applied to a temperature of 45 ºC. After the applied step, two perturbations are inserted in the system. The first being a disturbance of 10 mA at the entrance of the process plant simulating a small failure of the actuator and the second being a disturbance of -10 ºC at the output of the process plant simulating a drop in temperature inside the tank 2. The first disturbance is performed in approximately 22 minutes and the second disturbance is performed in approximately 33 minutes.

At first, the PID controller designed by Ziegler Nichols open loop method was tested and implemented in the Simulink environment. Figure 9 presents the system output response and the control signal to the applied step and disturbances inserted in the system.

Figure 9 - PID controller response.

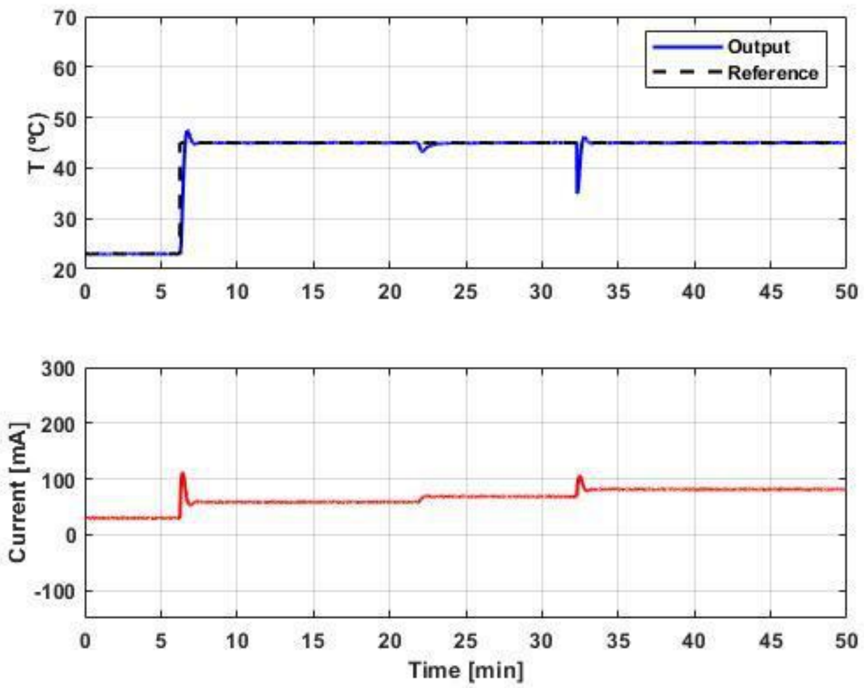


Source: Authors.

From Figure 9, the tracking was kept for the step response and the controller performed the rejection of the disturbances imposed on both the input and the output of the system. However, it is also noted that the dynamic response of the PID controller is too oscillatory, with high overshoot and high accommodation time for the thermal system under study. In addition, it is possible to observe that the control signal has negative values, which can damage the actuator element because as the resistor does not have cooling characteristics and, when implemented, the sensor present in the reading of the system data can perform the reading of erroneous data, that do not match what would be happening in the real system.

Similarly, the DMC predictive controller was also tested and implemented in the Simulink environment. Figure 10 shows the response of the system output and the control signal to the applied step and disturbances inserted in the system.

Figure 10 - Predictive controller response.

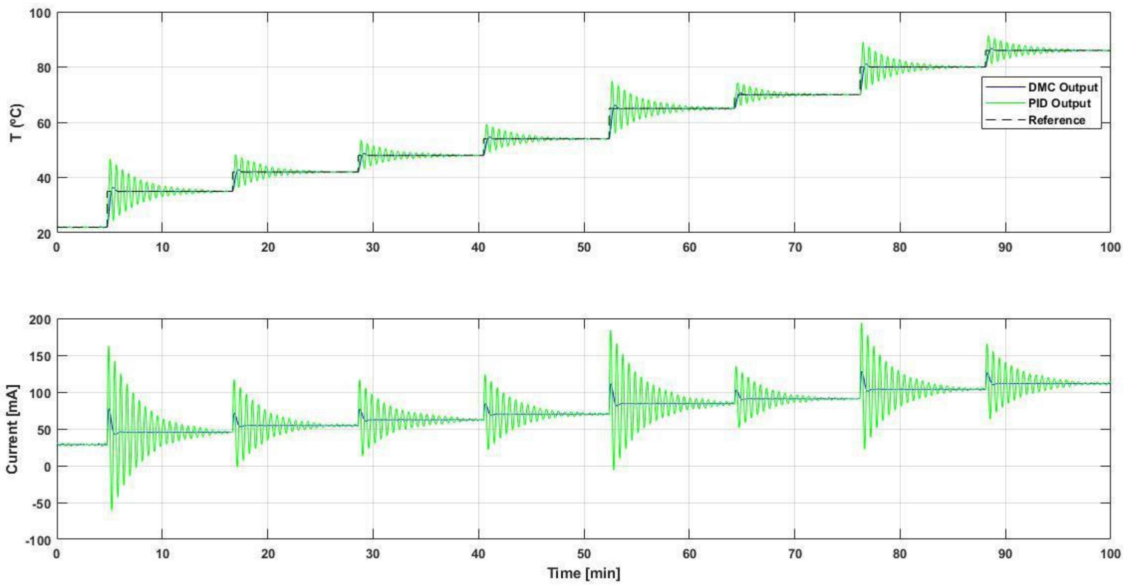


Source: Authors.

From Figure 10, the tracking was also maintained for the step response and the designed predictive controller also performed the rejection of disturbances imposed on both the input and output of the system. It is noteworthy that compared to the PID controller implemented previously, the dynamic response of the predictive controller shows little oscillation, with much lower overshoot and a shorter settling time for the thermal system under study. In addition, it is possible to observe that the control signal does not present negative values, being safer for the actuator element of the system and guaranteeing that the sensor will perform correct data reading and that in fact show what would be happening in the real system.

Finally, a last simulation condition to compare the control strategies developed in this work was performed. From the ambient temperature, 8 steps were applied at different moments of time to verify the performance of the controllers in a range of actuator heating operation. Figure 11 presents the response of the system output and the control signal to the imposed impositions.

Figure 11 - Controllers' response to the application of different steps.



Source: Authors.

From Figure 11 for the reference changes imposed on the thermal system, both controllers kept tracking the system, but the PID controller presented greater oscillations, overshoot and settling time when compared to the predictive controller. In addition, it is again possible to notice that the performance of the PID controller presented negative values, which may cause damage to the process actuator as already described. On the other hand, the performance of the predictive controller has always remained positive, even with the imposed reference variations. Thus, it is evident that the predictive controller is more effective for thermal systems with transport delay when compared to empirical and conventional tuning techniques for PID controllers. Another highlight is that the fact that the dynamic response of the PID controller presents a high overshoot and settling time, which makes its application for certain actuators unfeasible.

6. Conclusion

Because it is a project that involves computer simulation, it is necessary that the data obtained in the practical test are reliable. In this way, the instrumentation must be as adequate as possible and must guarantee a good acquisition so that the data obtained allow the identification of the mathematical equation that describes the real physical system with certain fidelity.

Obtaining a model of the process plant and carrying out the validation is a crucial and extremely important step in the project so that the development of a good controller can be carried out. In the case of systems with transport delay, the representation must still be more reliable, due to its instability character. The least squares method that was applied in this work proved to be a good tool for the identification of dynamic systems with transport delay.

The choice of method for tuning the PID controller gains was not the best for the process under study since it does not consider the transport delay of the plant model throughout the application of the method. There are other methods of tuning PID controllers but the Ziegler Nichols approach in open loop was chosen due to its wide applicability in industrial systems.

The DMC predictive controller, being a modern control technique, is still widely studied in the industrial scope. It was possible to observe that its application in thermodynamic systems such as the one proposed in this work has a good performance regarding the dynamic response and performance of the control signal. It is worth mentioning that the work was carried out only in a simulation environment, requiring its real implementation for its effective validation.

For future work, it is of great value to carry out tests on thermal systems with real transport delay to validate the predictive control used in simulation in this work. Also noteworthy is the possibility of implementing and comparing different optimization strategies for tuning the predictive controller.

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