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Predictive Control Algorithm Using Laguerre Functions for Greenhouse Temperature Control

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Abstract

In this paper, a discrete time predictive control (DMPC) algorithm using Laguerre orthonormal functions based model was proposed for controlling the temperature under the greenhouse system. In order to design the controller, a state-space model of the temperature of the system is identified. The observer can be designed using concepts of Kalman filtering, which consider stochastic disturbance in the process and/or measurements. The efficiency of the DMPC method is established, due to a particular choice of the synthesis parameters (the horizon of prediction, the number of Laguerre functions and its scaling factor and the weighting matrices). The proposed algorithm was applied to a scenario consisting of temperature set-point changes. The system response performances of temperature stabilization were acceptable; through a real-time implementation to confirm the capacity of the developed technique for controlling the greenhouse temperature.

Keywords: *Greenhouse Climate Control, Model Predictive Control, Laguerre Orthonormal Functions, Real-Time Control, N4SID Algorithm*

1. Introduction

The research on greenhouse climate control has gained much interest during the last years in the field of agriculture; as it permits the creation of an optimal indoor microclimate for crop development, protecting it from adverse outdoor conditions in order to increase quality and quantity of greenhouse production and also allow us to cultivate certain plants all over the year [1- 2]. Low or high temperature and relative humidity cause many diseases for crops, such as foliar yellowing, stunted growth, poor quality and increased risk of root diseases. For that, this microclimate that is controlled by artificial heating and ventilation actuators in an automatic control system is a necessity to provide the optimal environmental growing conditions for the crops [3- 4]. Therefore, the design and implementation of automation and control techniques for greenhouses systems are of crucial importance.

Recently, computerized controller algorithms have become essential for the greenhouse climate control to decide about heating and ventilation and produce control actions that regulate air temperature inside the greenhouse to overcome the effect of the undesirable climatic conditions. In this respect, many advanced control methods that include fuzzy

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logic controllers [5- 6], feedback controllers [7], and optimal controllers [8- 9] have been proposed in the literature to deal with the temperature under greenhouse control problem.

The model predictive control (MPC) strategy is one of the most popular techniques for the control of dynamical systems, which has attracted much attention as a powerful tool in controlling many industrial process systems [10]. Thanks to its advantages, MPC can be used at different levels of the process control structure and can handle a wide variety of process control constraints. Hence, the MPC is acknowledged as one of the most adopted controller algorithms for industrial process automation [11].

The main procedure in the design of discrete MPC is to model the future control signal trajectory u(k) or its difference Δu(k) by forwarding shift operators. However, the optimal control algorithm aims to minimize a certain cost function as an optimization problem solution. Moreover, the objectives of optimization in greenhouse systems are, generally, the minimization of control effort and energy consumption. Thus, MPC is adapted as a very powerful approach that has proven its capacity to handle the problems of systems automation [12].

A method of designing an MPC using orthonormal functions was proposed with the main advantage of reducing the number of parameters used for the description of the control signal trajectory that makes fewer computations compared to the traditional MPC approach [13-14]. The change of control trajectory is accomplished through adjustment of scaling factor presented in the orthonormal function.

The purpose of this study is to implement a satisfactory real-time MPC controller based on Laguerre function in order to regulate the temperature under an experiment greenhouse system.

2. Material and Methods

2.1. Experimental Setup of the Real-Time Greenhouse System

The experimental greenhouse, where all data were collected, is located at the Electronic Automatic and Biotechnology Laboratory, Faculty of Sciences, Meknes, Morocco. It is a greenhouse chapel, which is covered with a transparent material. The experimentation consists of setting up a station acquisition composed of a set of sensors and electronic devices to complete the acquisition and controlling and monitoring of climatic parameters (temperature, humidity, and CO_2 content). The proposed solution utilizes a data acquisition card type PCI-6024E connected with a personal computer as illustrated in Figure 1. This card will act as an interface between the PC and the different cards conditioning sensors, power card, protection and signalling card [15-16].

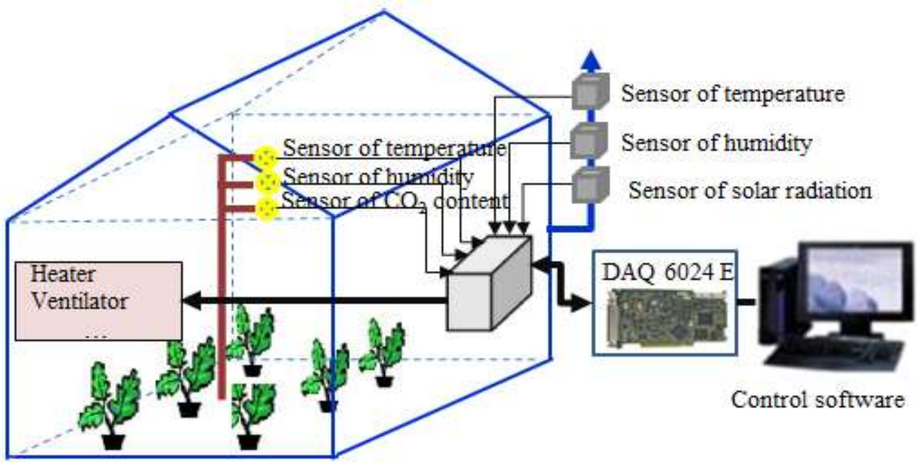

Figure 1. Schematic Block Diagram of Greenhouse Experimental Setup

2.2. DMPC Controller Based on Laguerre Orthonormal Functions

This section provides a brief discussion of the discrete time model predictive control used in this paper. The approach uses orthonormal functions to describe the trajectory of the control variable, and a state space model is used in the design.

We consider a plant with p inputs, q outputs, and n states, the discrete time state space model, describing the process, is given as:

$$\begin{cases} x_m(k+1) = A_m x_m(k) + B_m u(t) \\ y_m(k) = C_m x_m(t) + D_m u_m(k) \end{cases} \tag{1}$$

where $u(k)$ is the input variable, $y_m(k)$ is the process output and $x_m(k)$ is the state vector.

The major principle of the design of discrete-time MPC is constructed upon the optimisation of the future control trajectory, which is the difference of the control signal, $\Delta u(k)$. For that, the model of the process is changed to suit our design purpose in which an integrator is embedded. So, the process described by equation (1) can be expressed in augmented state-space form as [17]:

$$\begin{cases} x(k+1) = Ax(k) + Bu(t) \\ y(k) = Cx(t) \end{cases} \tag{2}$$

where: $A = \begin{bmatrix} A_m & O_{n*q} \\ C_m A_m & I_{q*q} \end{bmatrix}$, $B = \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix}$, $C = \begin{bmatrix} O_{q*n} & I_{q*q} \end{bmatrix}$ are the corresponding augmented matrices and $x(k) = \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix}$ is the augmented state.

In MPC theory, at the sampling instant k_i, the state variable vector $x(k_i)$ provides the current plant information which is available through measurement. The future control trajectory is defined by equation (3) [18]:

$$\Delta U = \begin{bmatrix} \Delta u(k_i) & \Delta u(k_i+1) & \Delta u(k_i+2) & \ldots & \Delta u(k_i+N_c-1) \end{bmatrix} \tag{3}$$

With N_c is the control horizon indicating the number of parameters used to capture the future control trajectory. Having $x(k_i)$, the future state variables are predicted for N_p samples, N_p being the prediction horizon. N_p is also the length of the optimization window. Then, the future state variables are as follows:

$$x(k_i+1|k_i), x(k_i+2|k_i), \ldots, x(k_i+m|k_i), \ldots, x(k_i+N_p|k_i) \tag{4}$$

where $x(k_i+m|k_i)$ is the predicted state variable at k_i+m having current plant information $x(k_i)$.

As in the receding horizon control strategy, the MPC technique takes only the first sample of the sequence of the control signal vector and implements it. Additionally, in the next sample time period, the more recent measurement is used to formulate the state vector for the calculation of the new control signal sequence.

Laguerre functions can approximate the incremental terms contained in ΔU. The discrete-time Laguerre network was generated by the discretization of the continuous-time Laguerre network. The z-transform of the discrete-time Laguerre networks is given as [19]:

$$L_i(z) = \sqrt{1-a^2}\,\frac{(z^{-1}-a)^{i-1}}{(1-az^{-1})^i} \tag{5}$$

where $0 \leq a < 1$ is called scaling factor for Laguerre functions.

Considering $l_i(k)$ the inverse z-transform of $L_k(z, a)$, the set of discrete-time Laguerre functions are given in a vector form as:

$$L(k) = \left[l_1(k) \quad l_2(k) \quad \ldots \quad l_N(k) \right]^T \tag{6}$$

where N is the number of coefficients used.

At time instant k_i, the control signals trajectory $u(k_i), u(k_i+1), u(k_i+2), \ldots, u(k_i+k), \ldots$, is deemed as the impulse response of a stable dynamic system. Hence, a set of Laguerre functions, $l_1(k), l_2(k), \ldots, l_N(k)$ are employed to capture the dynamic response determined from the design process based on the following expression:

$$\Delta u(k + k_i) = \sum_{j=1}^{N} c_j(k_i) l_j(k) \tag{7}$$

where k_i is the initial time of the moving horizon window and k is the future sampling time, N is the number of terms used in the expansion, c_j, $j = 1,2,\ldots, N$, are the coefficients being functions of the initial time of the moving horizon window, k_i.

The control horizon N_c from the classical approach is not involved in the design process anymore. The number of terms N along with the parameter a is used for capturing the trajectory. Equation (11) can also be rewritten as [20]:

$$\Delta u(k + k_i) = L(k)^T \eta \tag{8}$$

where η has N Laguerre coefficients

$$\eta = \left[c_1 \quad c_2 \quad \ldots \quad c_N \right] \tag{9}$$

Therefore, the coefficient vector η is optimized and computed in the design procedure. The task is finding the coefficient vector η to minimize the following cost function [21]:

$$J = \sum_{m=1}^{N_p} x(k_i + m | k_i)^T Q x(k_i + m | k_i) + \eta^T \mathrm{R} \eta \tag{10}$$

Where $Q \geq 0$ and $R>0$ are symmetric positive definite weighting matrices.

So, having optimal parameter vector η, the control law of DMPC based Laguerre functions is given as flowing:

$$\Delta u(k_i) = L(0)^T \eta \tag{11}$$

where:

$$L(0)^T = \left[l_1(0) \quad l_2(0) \quad \ldots \quad l_N(0) \right] \tag{12}$$

For a given N and a:

$$l_1(0) = \sqrt{1 - a^2} \left[1 \quad -a \quad -a^2 \quad \ldots \quad (-1)^{i-1} a^{i-1} \right] \tag{13}$$

2.3. Design of Robust State Observer

A discrete time Kalman observer is utilized to estimate the state variable from the available output. The control law is then computed using the estimated state variables given by the following equation [22]:

$$\hat{x}(k+1) = Ax(k) + Bu(k) + K_{obs}(y(k) - C\hat{x}(k)) \tag{14}$$

where $\hat{x}(k)$ is the current observer state, and K_{obs} is the Kalman observer gain to be determined by solving recursively (for $i = 0, 1, \ldots$) the Discrete-time Algebraic Riccati Equation (DARE) is as follows:

$$P(k+1) = APA^T - APC^T(R + CPC^T)^{-1} CPA^T + Q \tag{15}$$

and:

$$K_{obs}(k) = APC^T (R + CPC^T)^{-1} \tag{16}$$

where R and Q are the matrices to be chosen.

Once designed, the observer can be connected to the rest of the feedback system. The feedback gain K_{mpc} can be broken down as $K_{mpc}= [K_x\ K_y]$, where K_y is the last element of the gain vector K_{mpc}. Moreover, the application of the receding horizon control principle leads to the optimal solution of $\Delta u(k_i)$ at time instant k_i which is a standard state feedback control law with estimated $x(k_i)$ [23]:

$$\Delta u(k_i) = K_y r(k_i) - K_{mpc}\hat{x}(k_i) \tag{17}$$

The DMPC algorithm is employed to control the temperature of the greenhouse system. The general block diagram representing DMPC is illustrated in Figure 2.

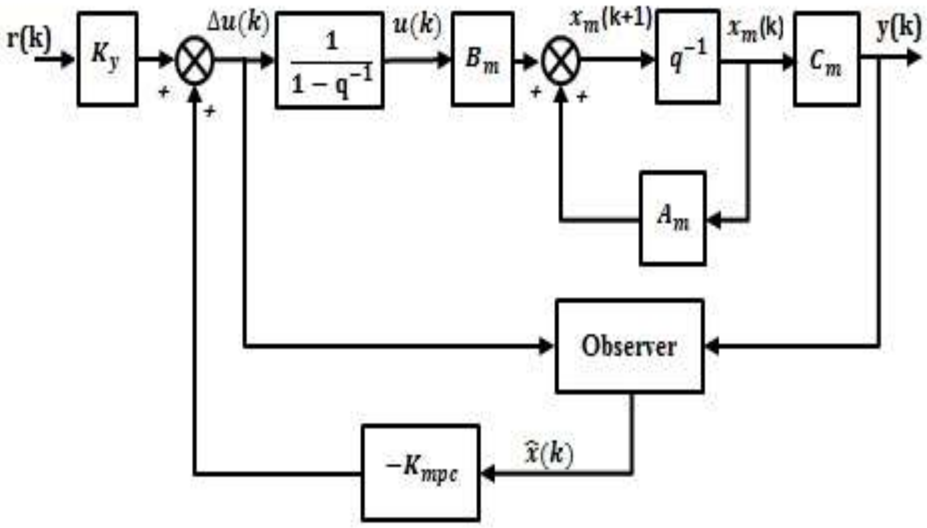

Figure 2. Block Diagram of DMPC with Observer

For that, the design parameters are computed based on expressions of the ones in the equations above. The sampling time is 5s.

3. Results and Discussion

The proposed control strategy has been applied to a greenhouse system. The case studied involving internal temperature regulation by artificial heating and ventilation systems.

The DMPC algorithm is a model-based approach. Therefore, the plant model has to be obtained first for the controller design and tuning purposes. For that, the plant model is estimated using experimental data and the N4SID algorithm to identify the plant model in discrete-time state space form.

The discrete time state space model, describing the behaviour of the temperature under the greenhouse process, can be defined by the two state-space formulations:

$$A_h = \begin{bmatrix} 0,9857 & -0,0045 & -0,0098 & 0,0038 \\ -0.0085 & 0.3432 & 0.4633 & -0.2103 \\ -0.0049 & -0.3721 & 0.3029 & 0.9904 \\ -0.0075 & 0.4488 & -0.5505 & 0.4634 \end{bmatrix}$$

$$A_v = \begin{bmatrix} 0,9781 & -0.0131 & 0.0038 & -0.0079 \\ -0.0338 & 0.2228 & -0.7703 & -0.3369 \\ 0.0154 & 0.6282 & 0.5894 & -0.3753 \\ -0.0129 & 0.2600 & -0.1921 & -0.4710 \end{bmatrix}$$

$$B_h = \begin{bmatrix} 0.0026 & -0.0203 & 0.0378 & -0.0205 \end{bmatrix}^T$$

$$B_v = \begin{bmatrix} 0.0050 & 0.0791 & -0.0425 & -0.0701 \end{bmatrix}^T$$

$$C_h = \begin{bmatrix} 79.8331 & -1.3419 & 0.6145 & -0.9920 \end{bmatrix}$$

$$C_v = \begin{bmatrix} 27.0430 & 1.1485 & -0.2143 & 1.1356 \end{bmatrix}$$

The index '*h*' and '*v*' of the matrices refer respectively to the heater and ventilator actuators as the considered system inputs. The system described by these matrices is stable, observable and controllable.

In order to design the DMPC controller with the Kalman observer based on the identified plant model, the scaling factor and the number of terms used in the Laguerre functions to capture the control signal are chosen respectively to be: $a = \begin{bmatrix} 0.95 & 0.95 \end{bmatrix}$ and $N = \begin{bmatrix} 3 & 3 \end{bmatrix}$, the prediction horizon parameter is chosen to be $N_p = 10$ and the weighting matrices Q and R are chosen respectively to be $Q=C^TC$ and $R=0.1I$ where I is the identity matrix.

The Kalman observer gain is given by the following result:

$$K_{obs_h} = \begin{bmatrix} 0.0126 & 0.0011 & 0.0012 & 0.0001 & 1.9876 \end{bmatrix}^T$$

$$K_{obs_v} = \begin{bmatrix} 0.0361 & 0.0012 & -0.0013 & 0.0004 & 1.9782 \end{bmatrix}^T$$

The constraints are specified as $0 \le u(k) \le 5$ for both control signals of heater and ventilator.

Hence, by using equation (12), the feedback gain vector is obtained via the computation of predictive control which is as follows:

$$K_{mpc_h} = \begin{bmatrix} 403.2858 & 3.4375 & -1.4521 & -3.3642 & 1.2491 \end{bmatrix}$$

$$K_{mpc_v} = \begin{bmatrix} 77.2706 & -2.5371 & -2.7797 & 2.0224 & 1.8471 \end{bmatrix}$$

The block diagram representing DMPC algorithm (Figure 3) is implemented in Matlab/Simulink environment, in order to test the performance of this controller, to regulate in real time the temperature under the greenhouse system. To determine when to cool/heat we apply to actuators (ventilator and heater) according to the sign of the difference between the set point and the measured temperature.

In order to evaluate the proposed control approach, the experimental results are illustrated in Figure 3, Figure 4 and Figure 5. In Figure 3, we present the setpoint, the internal and external temperature in an interval of 24 hours of the experiment duration. It can be seen that the inside temperature follows, within a reasonable error, the set-point independently from the changes of the external temperature which varies between 7 ℃ and 15 ℃.

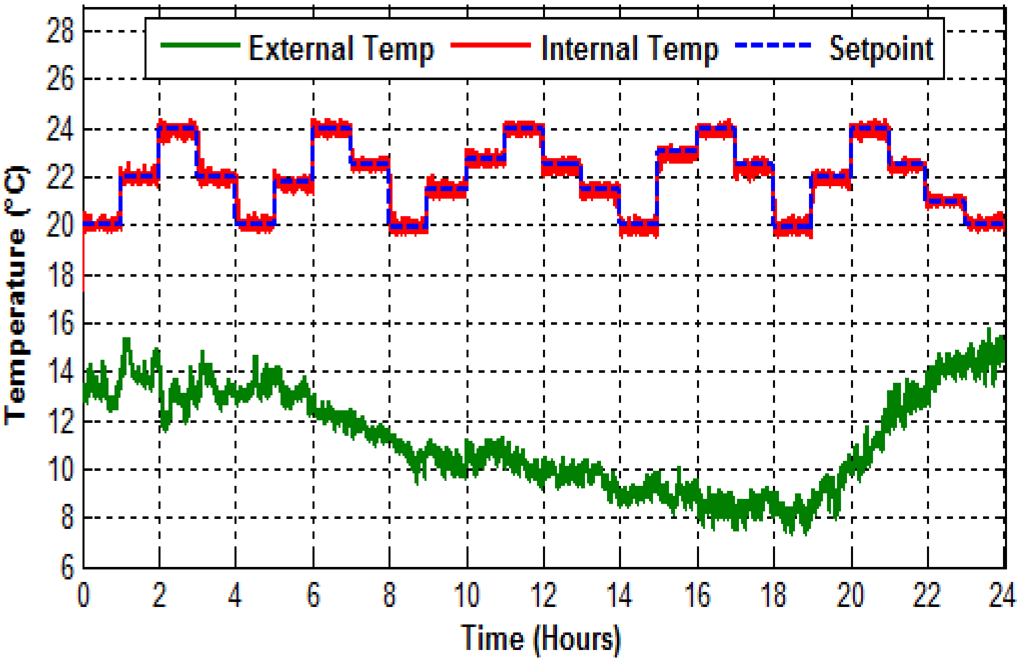

Figure 3. Evolution of the Setpoint, Internal and External Temperature during 24 h

Moreover, through zooming in Figure 3, one can notice in Figure 4 that the response of the system tracks, with acceptable accuracy, the desired temperature setpoint signal. Indeed, the controller proves a good performance in set-point changes tracking within a reasonable range of error, ensuring fast rise time and quick settling time in step changes, with no occurrence of overshoot and maintaining the desired setpoint with no steady state error.

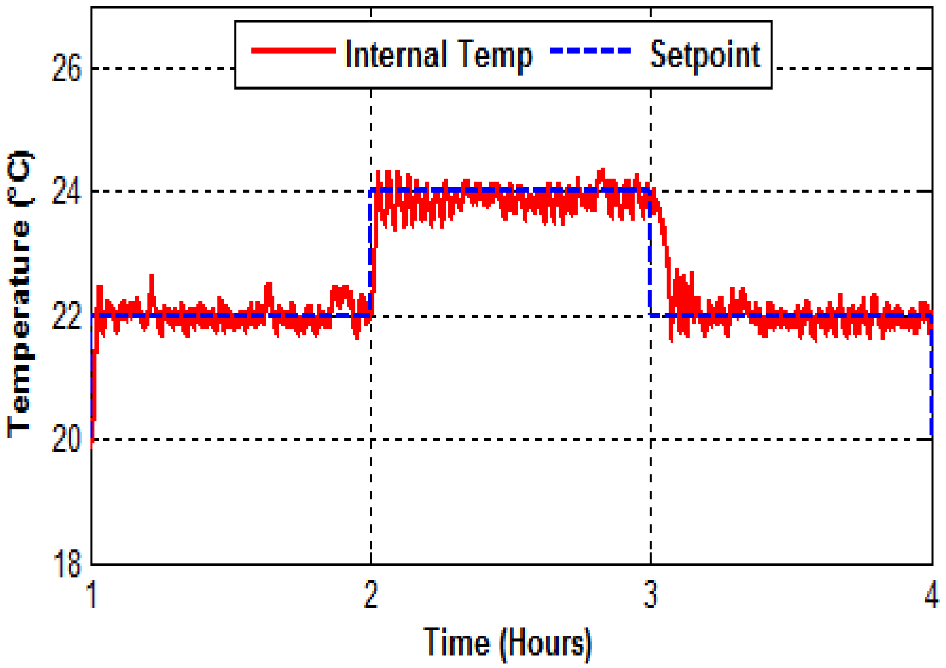

Figure 4. Evolution of the Setpoint and Internal Temperature during [1, 4] h

Figure 5 depicts the corresponding control actions behaviour of the two actuators used to act on the greenhouse system.

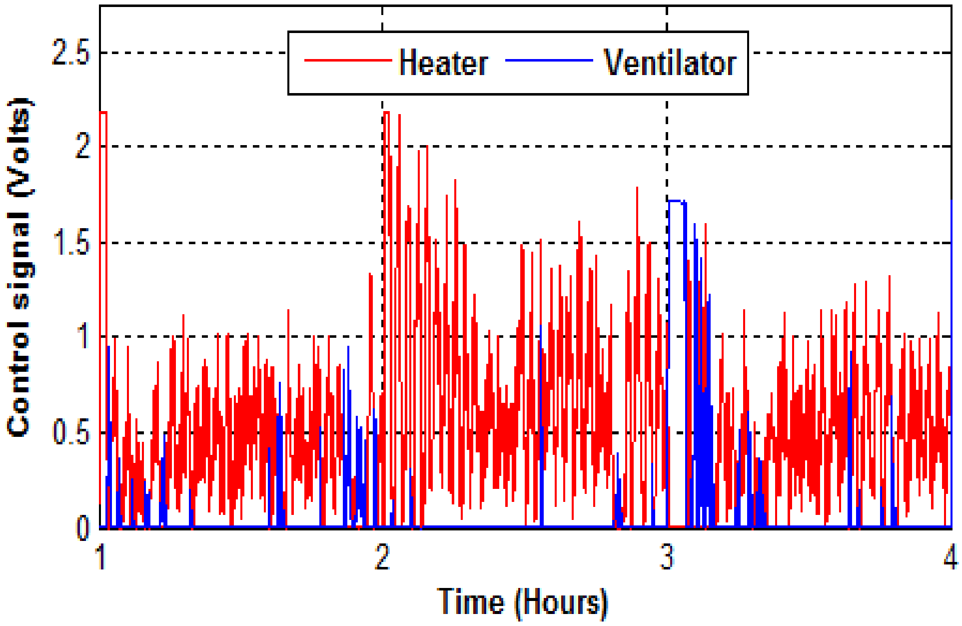

Figure 5. Control Actions Behaviour of Heating and Fan Actuators during [1, 4] h

From the insight into the behaviour profile of the two actuators, it can be seen that the controller had a good performance, the maximum value of the applied control signals does not exceed 2.5 Volts and stops at several moments which reduce the load of actuators. Apart from saving power, this will prolong the life of the actuators, especially in greenhouses where the fan and heating systems are composed of mechanical actuators. Hence, that justifies the benefits of the constraint on the magnitude of the control signals sent to the actuators related to the integrator effect of the MPC algorithm in the implementation of predictive control. Also, the benefit of limiting the voltage consumption of the actuators permits us to obtain a good performance, thus, there is no saturation of used actuators.

Compared to our previous investigations [24] and the existing ones [25], we have found that this tested strategy overcame successfully the known shortcomings in terms of power consumption.

Regarding the strategy of predictive control by using the Laguerre functions to capture the control trajectory in the control law, Figure 3, Figure 4 and Figure 5 prove that it was successful. Thus, it is feasible to maintain the greenhouse at the desired temperature with minimal power consumption, which reduces the energy costs of the greenhouse system.

4. Conclusion

This paper presents the implementation of the discrete model predictive control algorithm with Laguerre orthonormal functions which have been employed in order to verify its performance of controlling in real time the temperature under the greenhouse. The proposed controller uses orthonormal functions to describe the trajectory of the control variable. The design of this algorithm is based on a discrete time state space model which is identified through the N4SID identification tool. In addition, an observer based on the Kalman filter is used to estimate the greenhouse temperature state variable. By selecting appropriate values of scaling factor a, the number of terms used in the

Laguerre functions N and the prediction horizon parameter N_p, the control experiments were accomplished successfully for tracking the temperature set point changes and the attained performances were satisfactory.

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