International Journal of Engineering and Advanced Technology Studies
Vol.5, No.2, pp.1-15, September 2017
Published by European Centre for Research Training and Development UK (www.eajournals.org)

DESIGN AND IMPLEMENTATION OF LQG STRATEGIES FOR TEMPERATURE CONTROL UNDER GREENHOUSE

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ABSTRACT: *In order to introduce dynamic model based to climate controlling in real-time an environmental control computer system integration witch electronic communication and software interfaces was developed. This paper presents greenhouses control problem of internal temperature which a solution through an optimal control methodology was introduced. So we begin our study by given a state space model using N4SID numerical algorithms for subspace identification algorithm model that allows estimating KALMAN state and Linear Quadratic LQR gain. This evaluates parameters permits to control the inside temperature in real time by Linear Quadratic Gaussian LQG controller. LQG/LTR-based controllers for a heater and for a ventilator have been presented and the stability of switched system will be approved by a good performances management. This controller will be developed by a blocks of software SIMULINK/MATLAB.*

KEYWORDS: Data Acquisition, Identification, N4SID Algorithm, Kalman Filter, LQG Controller.

INTRODUCTION

Research on greenhouse environment control technology begins earlier, at about 1970. At first, it adopted analog combined meter to collect locale information and display, note and control. By the late 1980, distributed control system appeared. At present, a kind of computer data collection and control system with multi factors is being developed. The automation of greenhouse environment has been more and more necessary to create favorable conditions to improve the development by maintain a reasonable environment in the greenhouse of the plantations and to minimize the prices of production in terms of raw materials and energy consumption is important for the growers.

The study and design of efficient greenhouse environmental controllers require having a prior knowledge of the greenhouse climate [1, 2, 3, 4, 5]. It constitutes a database which must be related to the outside influences of the outside weather conditions (such as solar radiation, outside temperature, wind velocity, etc …), and with the actuating actions performed (ventilation, heating, etc …) [6, 7]. At the present time, few greenhouses are still controlled manually and require the intervention of the grower. A computer system can be used to control the greenhouse climate in order to improve the culture development and to minimize the production costs [8, 9, 10, 11, 12, 13]. The greenhouse environment is automated with several actuators and sensors that are connected to an acquisition card and with a control

ISSN 2053-5783(Print), ISSN 2053-5791(online)

system based on a personal computer. Sensors devices are the basics of climate control because they provide necessary information for optimization. Productivity, repeatability, output signal and usability by growers are the required characteristics of sensors [14, 15].

The automatic study is inevitable, allows controlling a system in a continuous [16], thus to respect a specification (speed, overtaking, stability). Controlling the climatic parameters under greenhouse consists and requires an application of an appropriate method of identification allows giving a very precise approximate model [17, 18, 19]. Then, deducting from those identified parameters, the gains estimated for controlling.

This paper gives the fundamental aspects of the LQG control theory, which can be consulted for more details in [20, 21, 22]. This controller tunes the adaptation parameters using the input-output measurements of the greenhouse [23]. In the LQG case we can use the separation principle, which means that we are able to design the LQG controller in steps. First, the design of the LQR (Linear Quadratic Regulator), and then we have to find a state estimator, an LQE (Linear Quadratic Estimator) applying a modified cost function.

The creation of a favorable environment inside a greenhouse requires modeling and controlling of all relevant variables in the development of the plant notably temperature, and humidity. In our experimental, we restrict our study to control only the temperature because the major factors influencing crop growth is the temperature. Different crop species have different optimum growing temperatures and these optimum temperatures can be different for the root and the shoot environment and for the different growth stages during the life of the crop. If a greenhouse were like a residential or commercial building, controlling the temperature would be much easier since these buildings are insulated so that the impact of outside conditions is significantly reduced. However, greenhouses are designed to allow as much heat as possible to store the growing area. As a result, the insulating properties of the structure are significantly diminished and the growing environment experiences a significant influence from the constantly fluctuating weather conditions. Heater exerts by far the largest impact on the growing environment, resulting in the challenge maintaining the optimum growing temperatures [24].

The heating requirements of a greenhouse depend on the desired temperature for the plants grown, the location and construction of the greenhouse, and the total outside exposed area of the structure. As much as 25 percent of the daily heat requirement may come from the sun, but a lightly insulated greenhouse structure will need a great deal of heat on a cold winter night. The heating system must be adequate to maintain the desired day or night temperature. The purpose of the heating system is to replace energy lost from the greenhouse when outside temperatures are lower than desired in the greenhouse growing area. Ideally the heating system should have a variable output capable of matching the changing heat load caused by the outside weather conditions. The whole functioning greenhouse system is equivalent to a multi-variable and nonlinear process. It can be summarized in the functional block diagram given in Figure 1 [25].

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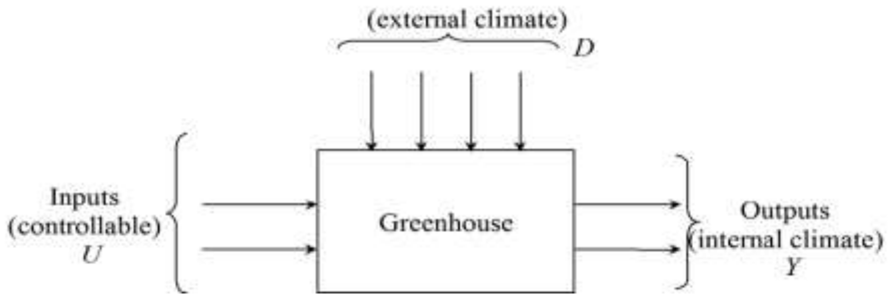

Figure 1. Greenhouse fundamental block diagram

Where generally the actuators such as ventilator, heater have been considered Inputs that permits to control outputs, inside temperature, inside humidity. Since, the external environments were a non-controllable input that plays a role of noise. The application of subspace identification allows estimating the gains of LQG controller and determines the state sequence of the dynamical system directly from input/output observations, without knowing the model. An important achievement of the research in subspace identification was to demonstrate how the Kalman filter states can be obtained directly from input-output data using linear algebra tools (QR and singular value decomposition) without knowing the mathematical model. An important consequence is that, once these states are known, the identification problem becomes a linear least squares problem in the unknown system matrices, and the process and measurement noise covariance matrices follow from the least squares residuals. For more details, the reader can consult [26, 27, 28].

This paper is structured in the following sections:

Section 2 introduces a theoretical model of LQG and his principle. Section 3 describes the greenhouse used and the experiments performed. Section 4 presents the results obtained by LQG controller. Finally, section 5 presents the conclusions derived from these studies.

Principle of LQG command

Subspace based system identification has been recently developed in system identification and has much attention, owing to its computational simplicity and effectiveness in identifying dynamic state space linear systems. The most well-known subspace algorithm is N4SID that is then viewed as the better alternative. Most of a priori parameterizations (a priori knowledge of the order, observability or controllability) needed in a classical identification is not required. Another major advantage is that N4SID is non-iterative with no nonlinear optimization involved. In this work, we will consider the plant state and measurement equations that are determined using N4SID algorithm as follows:

$$A = \begin{cases} x\,(k+1) = A\ x(k) + B\ u(k) + K\ e(k) \\ y\,(k) = C\ x(k) + D\ u(k) + e(k) \end{cases} \qquad (1)$$

Here, x (k) is the state vector, u(k) and y(k) are respectively the measured input and output signals, e(k) is a stochastic processes called measurement and process noise. For simplicity

ISSN 2053-5783(Print), ISSN 2053-5791(online)

one assumes these processes to be white noise (i.e. zero mean, uncorrelated, Gaussian distribution).

Feedback linearization will be used to perform output tracking, whose objective can be described as follows: given a desired output, find a control action u such that the plant follows the desired trajectory with an acceptable accuracy, while all the states and controls remain bounded.

To control temperature under greenhouse, we have recourse to linear-quadratic-Gaussian (LQG) control. It is a modern state-space technique for designing optimal dynamic regulators. It permits trade off a good regulation performance and control effort, and to take into account process disturbances and measurement noise.

Like pole placement, LQG design requires a state-space model of the plant that we introduce the following assumptions:

(A, C) is observable.

(A, [B K]) is controllable.

The input u and innovation e are jointly stationary and one-way uncorrelated [29].

A full state feedback control law is given by,

$$u(k) = K \quad x(k) \tag{2}$$

The dynamic regulator LQG uses the measurements y to generate a control signal u that regulates y around the zero value by minimizing the cost function,

$$u(k) = \sum_{k=0}^{+\infty} \mathrm{x}^{\mathrm{T}}(\mathrm{k})\ \mathrm{Q}\ \ \mathrm{w}(\mathrm{k}) + \mathrm{u}^{\mathrm{T}}(\mathrm{k})\ \mathrm{R}\ \ \mathrm{u}(\mathrm{k}) \tag{3}$$

Where the nonnegative definite matrix Q, determines the weight placed on each component of state and the nonnegative definite R, determines the weight placed on the control input. The state feedback control law given in (2) is computed through solving of the algebraic Riccatti equation. The implementation of the LQG controller, in real time, is performed using Matlab/Simulink.

Greenhouse Process

The research reported in this paper is focused on modeling and control of temperature under greenhouse by using LQG controller. The greenhouse process automated by this new strategy is located at the Faculty of Sciences, University Moulay Ismail in Meknes (Fig. 2). The dimensions of the greenhouse are 2 m2 surface area, and 2.5 m of average height, covered with a plastic film. The system is based around a microcomputer (PC). In order to control climate under greenhouse, several sensors and actuators were installed and connected to the process through the electronic power interface and card acquisition [14]. Their main features are 16 channels of analog input, two channels of analog output, a 68-pin connector and eight lines of digital I/O. The driving software enables us to maintain the temperature under greenhouse according to the sign of error between the set point and the measured temperature. For that, the heating system engages when the temperature becomes lower than the desired

ISSN 2053-5783(Print), ISSN 2053-5791(online)

temperature. On the other hand, the ventilation system starts when the temperature becomes higher its desired temperature [30].

In order to improve the climate of a culture under greenhouse, tool of supervision to the system was associated and opted for a graphic programming, carried out using Simulink/ Matlab, regrouping the following functionalities: acquirement of sensor data exits, display and treatment of information in real time, orders of actuators and in short a creation of a historic under the shape of a picture database. The driving software permanently compares the sizes measured with the reference range in order to start or stop the appropriate actuators. The communication algorithm was coded in the C language and compiled by the Real Time Workshop to be used within the Simulink environment. The communication with the acquisition card is performed by sending commands formed by character sequences. With these commands, the card can be configured by choice of sampling time and the data retrieved. The aim of this experiment consists of testing the performance of the LQG for future inclusion in the greenhouse environmental control strategy. A supervision tool optimizes the commands sent to actuators, in order to optimize the climate under the greenhouse. Thus, we have developed a graphical interface using LabVIEW software for the local acquisition, monitoring with PC and storage of all data.

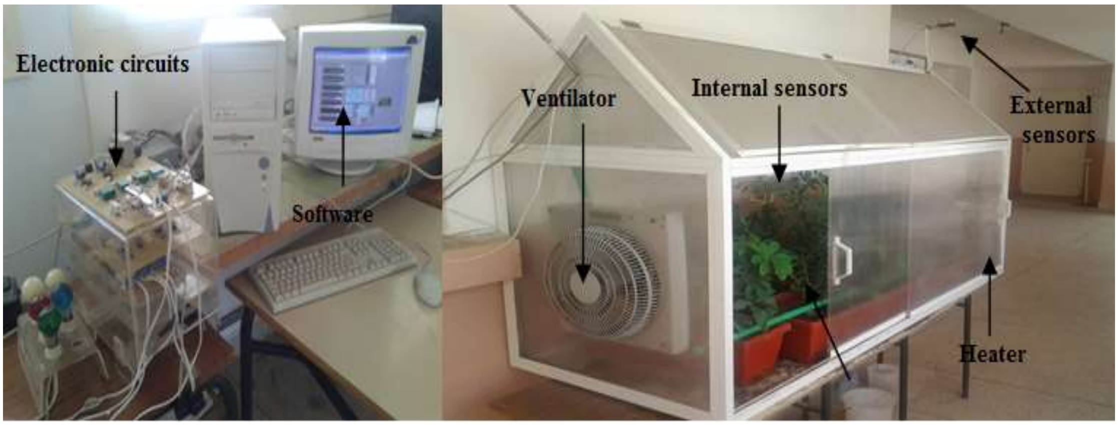

Figure 2. The experimental greenhouse

The greenhouse model

To illustrate some of the constraints and challenges of this benchmark problem, a sample linear quadratic Gaussian (LQG) control design is presented. The first step in this process is focused to identify the relation between measured temperature and inputs sanded to the actuators (Heater and fan) [31]. For modeling temperature under greenhouse in open loop using N4SID algorithms, we have recourse the toolbox GUI of Simulink/Matlab software. In this section are presented the results achieved with the proposed greenhouse climate model realized using the heater and then the fan as input data. The sampling rate used was 5 second. Input-output (black-box) models are often used, due to the difficulties involved in developing physical-chemical (bioprocess) models like greenhouses whose parameters need to be identified each month. The variable to be controlled is indoor temperature, manipulated actuators are heater and fan, measurable disturbances are outside temperature, outside relative

ISSN 2053-5783(Print), ISSN 2053-5791(online)

humidity, and outside CO2. For the simplicity, two days of the July month data are chosen to develop a dynamical state space model of the greenhouse using N4SID algorithms [32], which exhibit robust numerical proprieties and relatively low computation complexity. The model obtained from the identification experiments is in discrete form which then converts to the following structure:

Modeling temperature under greenhouse by a heate

Figure 3 and figure 4 show a plot of the original data from which it is desired to obtain a model using time series analysis.

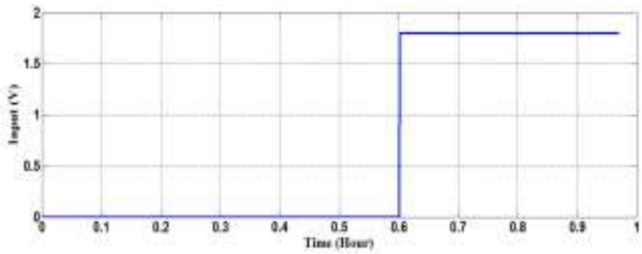

Figure 3. Step of temperature sent in open loop

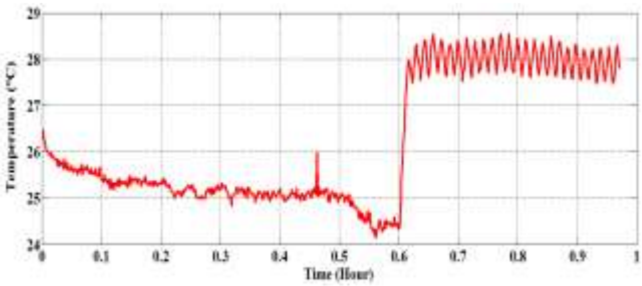

Figure 4. Step response of heating in open loop

To obtain the step response, an input (equal 1.8V) was applied (figure 3). The obtained response (figure 4) varies between 25° C and 28°C. The dynamical state space model of the greenhouse using N4SID algorithms was identified as shown in the following:

$$A = \begin{cases} \mathrm{x}\,(\mathrm{k}+1) = \mathrm{A}\ \mathrm{x}(\mathrm{k}) + \mathrm{B}\ \mathrm{u}(\mathrm{k}) + \mathrm{K}\ \mathrm{e}(\mathrm{k}) \\ \quad \mathrm{y}\,(\mathrm{k}) = \mathrm{C}\ \mathrm{x}(\mathrm{k}) + \mathrm{D}\ \mathrm{u}(\mathrm{k}) + \mathrm{e}(\mathrm{k}) \end{cases} \tag{4}$$

Where the matrix A, B, K, C and D have the following values

$$A = \begin{bmatrix} 0.99984 & -0.0024597 & 0.0013452 & -0.0025608 \\ 0.00056441 & 0.82753 & 0.55918 & 0.18782 \\ -0.00086584 & -0.481 & 0.81552 & 0.79844 \\ -0.0014404 & 0.0014432 & -0.093753 & 0.75805 \end{bmatrix} \tag{5}$$

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$$B = \begin{bmatrix} 0.00048556 \\ 0.0081055 \\ -0.01809 \\ 0.01891 \end{bmatrix} \tag{6}$$

$$C = \begin{bmatrix} 302.28 & 1.6702 & -0.54188 & 1.0261 & 0.22665 \end{bmatrix} \tag{7}$$

$$D = 0 \tag{8}$$

And the initial condition is,

$$x_0 = \begin{bmatrix} 0.051428 \\ 0.035672 \\ 0.13494 \\ 0.002407 \end{bmatrix} \tag{10}$$

The models performances were evaluated from the time periods used in the identification model and also for validation data, by computing the root-means squared errors. The loss function was equal to 0.0126909 and the Final Prediction Error (FPE) was equal to 0.0132711.

The plots have shown the simulated or predicted outputs of selected models. The models are fed with inputs from the Validation Data set, whose measured output is plotted in red. Then the simulated or predicted model output is shown together with the measured validation data (Figure 5).

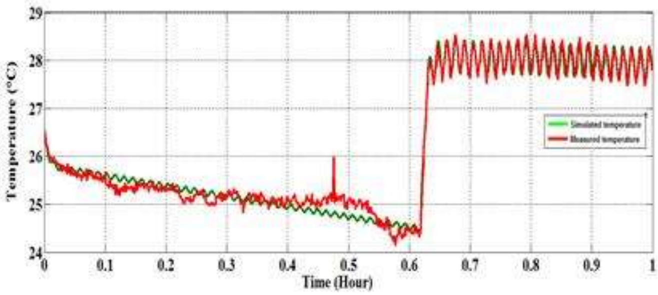

Figure 5. Measured and simulated output

A comparison of the measured and simulated values of inside temperature for the 5 selected days shows that the model had a good ability to simulate the dynamics of this variable. We also take the degree (2) of this model to identify our system.

Note that predicted output pursuit the measured accuracy and the percentage best fit of the output variations reproduced by the model is 82.3 %. The higher number means that the best and the most accurate model has the smallest FPE.

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Modeling temperature under greenhouse by a ventilator

Figure 6 and figure 7 show a plot of the original data from which it is desired to obtain a model using time series analysis. In this case, we excite our system by a step of a ventilator as shown in figure 6 and we measured the obtained step responses as depicted in figure 7.

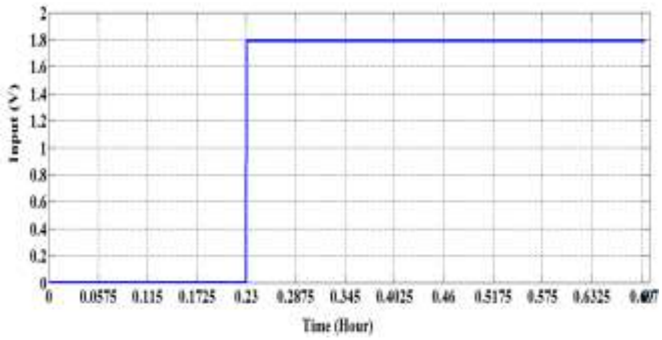

Figure 6. Input step sent in open loop

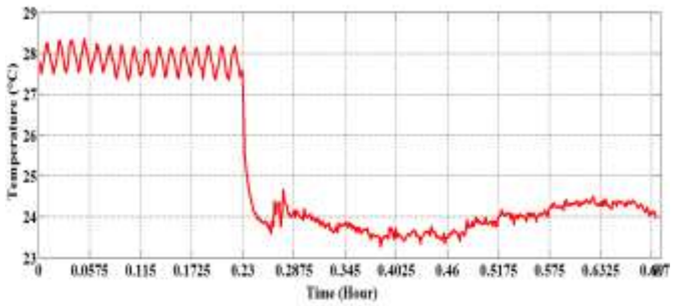

Figure 7. Input step sent in open loop

To obtain the step response, an input (equal 1.8V) was applied (figure 6). The obtained response (figure 7) varies between 28° C and 24°C.

The dynamical state space model of the greenhouse using N4SID algorithms was identified as shown in the following:

$$A=\begin{cases} \mathrm{x}\,(\mathrm{k}+1)=\mathrm{A}\;\mathrm{x}(\mathrm{k})+\mathrm{B}\;\mathrm{u}(\mathrm{k})+\mathrm{K}\;\mathrm{e}(\mathrm{k}) \\ \mathrm{y}\,(\mathrm{k})=\mathrm{C}\;\mathrm{x}(\mathrm{k})+\mathrm{D}\;\mathrm{u}(\mathrm{k})+\mathrm{e}(\mathrm{k}) \end{cases} \qquad (10)$$

Where the matrices A, B, L, C:

$$A=\begin{bmatrix} 0.99989 & -0.0021414 & -0.0012177 & 0.0026137 & -0.00069348 \\ 0.0045568 & 0.79653 & -0.58085 & -0.10064 & -0.046899 \\ 0.020534 & 0.56154 & 0.82143 & -0.13009 & -0.001645 \\ -0.0028103 & 0.03654 & 0.095927 & 0.74385 & -0.15118 \\ 0.012247 & -0.023363 & 0.010444 & -0.036148 & 0.14281 \end{bmatrix} \qquad (11)$$

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$$B = \begin{bmatrix} -0.0017805 \\ -0.10422 \\ 0.026982 \\ -0.1888 \\ -0.55212 \end{bmatrix} \quad (12)$$

$$C = \begin{bmatrix} 302.28 & 1.6702 & -0.54188 & 1.0261 & 0.22665 \end{bmatrix} \quad (13)$$

$$D = 0 \quad (14)$$

$$L = \begin{bmatrix} 0.0010795 \\ 0.038214 \\ -0.077391 \\ 0.0019768 \\ -0.00047126 \end{bmatrix} \quad (15)$$

And the initial state was,

$$x_0 = \begin{bmatrix} 0.092158 \\ 0.0024717 \\ 0.12765 \\ 0.013206 \\ -0.01589 \end{bmatrix} \quad (16)$$

The models performances were evaluated from the time periods used in the model identification model and also for validation data, by computing the root-means squared errors. The loss function was equal to 0.0126909 and the FPE was equal to 0.0132711.

The models are fed with inputs from the Validation Data set, whose measured output is plotted in red. Then the simulated or predicted model output is shown together with the measured validation data (Figure 6).

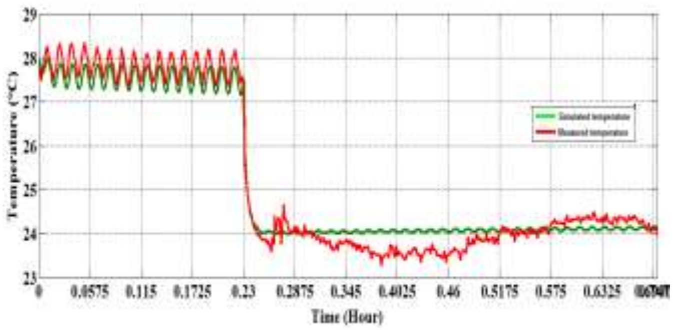

Figure 8. Measured and simulated inside temperature

Note also that the predicted output pursuit accuracy's measured output and the percentage of the output variations that is reproduced by the model is Best fit set to 82.3 %. The higher number means the better model is and the most accurate model has the smallest FPE.

ISSN 2053-5783(Print), ISSN 2053-5791(online)

RESULTS AND DISCUSSION

The principle scheme of the Linear Quadratic Gaussian (LQG) described in the previous section can be summarized as follows:

Step 1: Determine the state space given by (4) and (11).

Step 2: Estimate the state vector {x (t)} using the LQG the adaptive observer.

Step 3: Solve the Riccati Equation.

Step 4: Calculate the control signal

Step 5: Validate the correct working of the control.

Repeat steps 1-5 at each sampling period.

The experimental evolution has been carried out according to the following experimental planning:

The sampling period is T=5s.

The plant model is estimated as the structure given in (4) and (11) that the order of a process is set to 4.

The controller LQG design needs the user interface to be well structured. The control system in Figure 9 is devised into three subsystems, the design plant, the state feedback controller and the observer. In the state feedback object, a state feedback controller can be designed and the system is analyzed with state feedback only. When using pole placement, the poles can be graphically moved to the desired location on the complex plane. Real poles remain on the real axis until two real poles are moved to the same location.

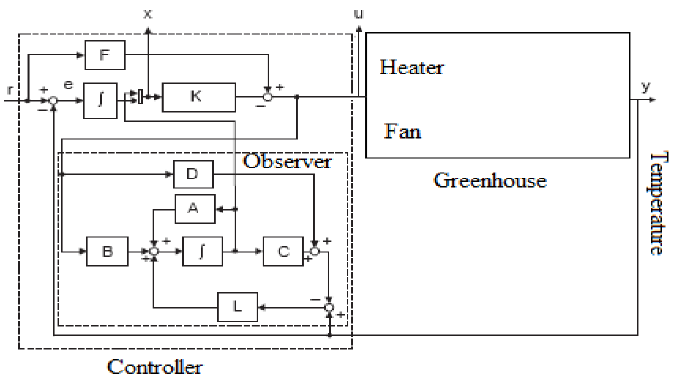

Figure 9. Essential subsystems of LQG controller

To be able to test the algorithm described above, an accurate validated model is needed. Therefore, the first experimental tests were dedicated to the validation of the model, to obtain the most real possible behavior of the greenhouse. In order to control the temperature under greenhouse, we choose the matrices L, W and V for estimating LQG parameters that computed according to the state space equations (4) and (11).

ISSN 2053-5783(Print), ISSN 2053-5791(online)

International Journal of Engineering and Advanced Technology Studies
Vol.5, No.2, pp.1-15, September 2017
Published by European Centre for Research Training and Development UK (www.eajournals.org)

In order to test the performance of the controller, we excite the system by several steps of temperature for measuring in real time temperature response under greenhouse. In the first, we use the value of set-point equal to the 20°C and then we grow and decrease the step of reference trajectory in order to test performance of the LQG Controller. To act on the greenhouse temperature, we used the actuators which are controlled according to the sign of the difference between the set-point and the measured temperature. The set points chosen were between 20 °C and 24 °C until 24 h. These set points are programming to vary each one hour and we maintain it constant as 20 °C until 20 h as depicted figure 10 and figure 11 and we obtain the following real-system behavior.

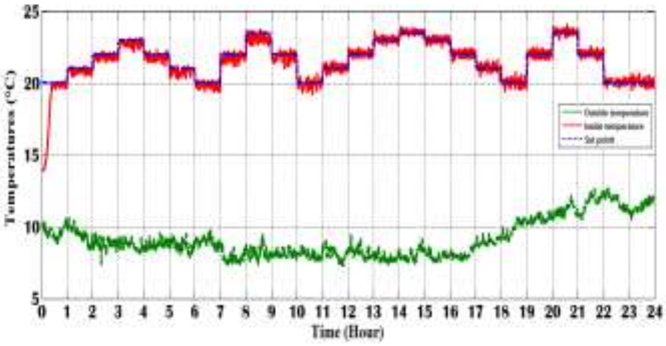

Figure 10. Several steps for regulating temperature

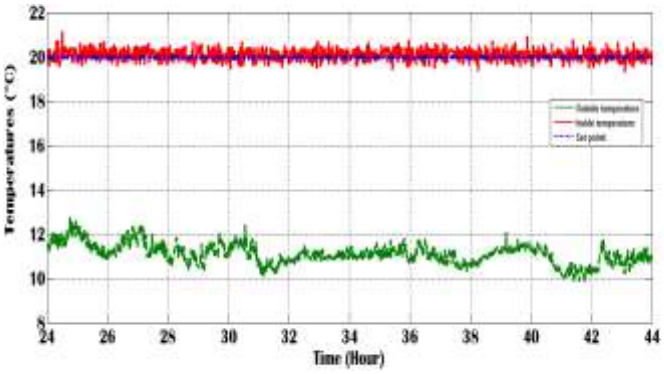

Figure 11. Regulation of temperature in 20 °C

From figure 10 and 11 showed above, it can be noticed that the response speed and the set-point tracking accuracy in greenhouse temperature control are very important. We observed that the inside temperature follows correctly the set-point independently of changes in outside temperature which varies between 20 °C and 24 °C. Both the Figures 12 and 13 shows the evolution of command send to actuators (Heater and fan) according to the error of set point compared with measured internal temperature. The obtained results present a perfect tracking and the effect of perturbation results to the external condition climate was rejected thanks to Kalman filtering.

ISSN 2053-5783(Print), ISSN 2053-5791(online)

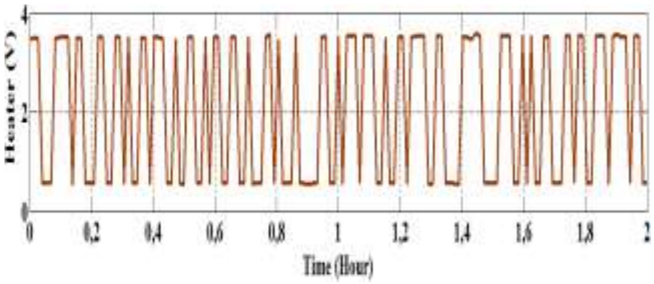

Figure 12. Heater command

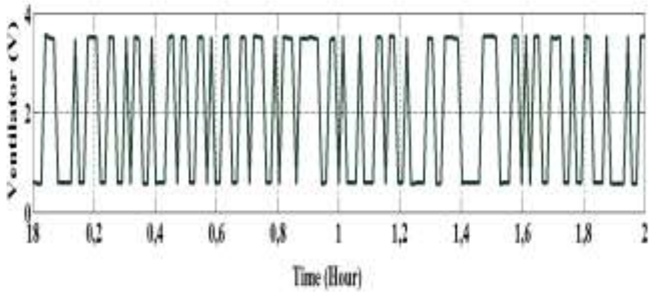

Figure 13. Ventilator command

It is observed that the number of changes in the control signals is small. This fact is a key issue in the actuator life time, especially in greenhouses where the ventilation and heating systems are composed by mechanical actuators.

The LQG controller has been discretized and implemented. The resulting controller was tested on the real time. State feedback controllers are discretized and implemented in modal form. Integrators are equipped with anti-windup.

The LQG controller has been discretized and implemented. The resulting controller was tested on the real time. State feedback controllers are discretized and implemented in modal form. Integrators are equipped with anti-windup strategies and actuator saturation is taken into consideration. Effects of controller discretization signal quantization and saturation can be investigated. Real-time charts allow comparison measured and predicted data, providing useful information about observer design and quality of the plant model. Since system identification, controller test and controller operation are done with the greenhouse plant, suitable safety measures have to be integrated. A card NI6024E based device allows data acquisition for simple analog input, encoder readings with interpolation or even resolver signals. This can be, for example, simple limit switches combined with model based overload protection for user electronic circuits.

The experimental data indicate that the adaptive control system effectively achieves the control objective. The regulation of temperature under greenhouse was maintained within acceptable limits (Figure 10 and Figure 11). The smooth tracking of heater and fan was achieved by the control law.

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CONCLUSIONS

Control and satisfactory performances are important concepts for this system. By using state space model, N4SID algorithm is specified to study control objects. The internal state of the plant has been defined by the internal temperature. This state was correlated and strongly sensitive to the external meteorological conditions to the greenhouse. For control purpose, we make use of a simplified model whose validation was carried out, and then we have elaborated a robust control based on LQG approach permitting to assure the closed-loop stability and to maintain the variations of internal temperature. The information of data acquisition was collected by software interfaces.

Acknowledgments

This work was supported by the Moroccan-French partnership “Partenariat Hubert Curien Volubilis (programme MA/09/211)” and by “Moulay Ismaïl University” under project: “Appui à la Recherche”.

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