Indonesian Journal of Electrical Engineering and Computer Science
Vol. 11, No. 1, July 2018, pp. 377~385
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v11.i1.pp377-385

Microclimate Control of a Greenhouse by Adaptive Generalized Linear Quadratic Strategy

Mohamed Essahafi[1], Mustapha Ait Lafkih[2]
[1]University of Sultan Moulay Slimane, Morocco
[2]Professor at the Electrical Engineering Department, Faculty of Sciences and Technology, University of Sultan Moulay Slimane, Morocco

Article Info

Article history:

Received Dec 19, 2017
Revised Jan 09, 2018
Accepted Jan 16, 2018

Keywords:

Adaptive control
Greenhouse
Identification
Linear quadratic Gaussian
Multivariable process
Recursive least squares

ABSTRACT

To highlight the conceptual aspects related to the implementation of techniques optimal control in the form state, we present in this paper, the identification and control of the temperature and humidity of the air inside a greenhouse. Using respectively an online identification based on the recursive least squares with forgotten Factor method and the multivariable adaptive linear quadratic Gaussian approach which the advanced technique (LQG) is presented. The design of this controller parameters is based on state models identified directly from measured greenhouse data. Hence the performances of the controller developed are illustrated by different tests and simulations on identified models of a greenhouse. Discussions on the results obtained are then processed in the paper to show the effectiveness of the controller in terms of stability and optimization of the cost of control.

Corresponding Author:

Mohamed Essahafi,
University of Sultan Moulay Slimane, Morocco.
Email: mohamed.essahafi@yahoo.fr

1. INTRODUCTION

A greenhouse is a structure that can be perfectly enclosed to protect plants and to promote the growth of crops (vegetables, flowers, etc.) in creating more favorable climatic conditions than the local climate. It aims to remove food crops from climatic elements for better management of plant needs and to accelerate growth or produce them regardless of the seasons.

The main asset of greenhouses is crop protection. Indeed, the greenhouse effectively protects against changes in climatic conditions, such as cold or hail. By monitoring the temperature, relative humidity, CO2 level. And good aeriation with a combination of a roof vent, front doors and fans [1].

1.1 Background

The greenhouse is a multivariable non-linear system. Thus, with the current control methods used, for the synthesis of the parameters of the dynamic model of the greenhouse, mathematical models likely to represent the greenhouse will be necessary to identify [2].

1.2 The Problem

The problem of optimal control when applied to coupled multivariable systems is the adaptability between its control strategy and the internal model of the controller process, which is generally very time-evolving [3-4].

1.3 Proposed Solution

The linear Gaussian linear method known as LQG will be integrated with an adaptive strategy control using an on-line identification approach. The LQG control is a technique that is widely used and recently implemented in various industrial applications [5]. It makes it possible to calculate the gain of a control by return of state in a particular concern to reduce the white noises. However, the LQG control combines an LQ controller (Linear Quadratic) and a Kalman estimator that can be calculated independently according to the separation principle.

The paper is organized as follows: The first part is devoted to the modeling of the greenhouse and its dynamic behavior using energetic transfers to its indoor climate. In the second part, we present the linear quadratic Gaussian (LQG) optimal control technique. The adaptive control scheme combined with parametric identification of the process is developed in the third part. In the fourth part, we present the results of simulations obtained by the application of the LQG controller on the climate control of the greenhouse. A general conclusion will summarize the work done, as well as the prospects for possible improvements.

2. RESEARCH METHOD

The models based on energy storage elements give qualitatively good results when idealized input signals are applied. The greenhous [6]. is a multi-input and multi-output (MIMO) system which is equipped with several sensors and actuators as show in Figure 1.

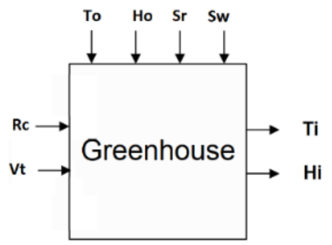

Figure 1. Schematic Diagram of Controlled Greenhouse

In a first approximation the microclimate greenhouse shown on Figure 1 is described by:

$$\begin{bmatrix} Ti(k+1) \\ Hi(k+1) \end{bmatrix} = \mathrm{A}\begin{bmatrix} Ti(k) \\ Hi(k) \end{bmatrix} + B\begin{bmatrix} Hc(k) \\ Vt(k) \end{bmatrix} + D\begin{bmatrix} To(k) \\ Ho(k) \\ Sr(k) \\ Sw(k) \end{bmatrix} \tag{1}$$

$$[Y(k)] = C\begin{bmatrix} Ti(k) \\ Hi(k) \end{bmatrix} \tag{2}$$

with

Rc: heating energy applied to the plant (Kw).
Vt: ventilation angle outside the greenhouse (°C).
To;Ho: air temperature and relative humidity outside the greenhouse (°C, %100).
Sr: Solar radiation (W / m).
Ti;Hi: air temperature and relative humidity inside the greenhouse (°C, %100).
Sw: wind speed outside the greenhouse (m/s).

We consider that the coefficients a_{ij} , $b_{ij}$and d_{ij} are slowly varying in time,then the equations overhead can be written as:

$$\begin{cases} X(k+1) = AX(k) + BU(k) + DNd(k) \\ Y(k) = CX(k) \end{cases} \tag{3}$$

3. LINEAR QUADRATIC GAUSSIAN (LQG) CONTROL

3.1 Design of the Controller

The objective of LQG controller seen in Figure 2 is to generate a suite of commands u which allow the output to follow a desired behavior of the greenhouse determined by the needs of the plant [7-8]. These commands are calculated according to a criterion optimized, from the state space representing the microclimate greenhouse. Consider the following stochastic system:

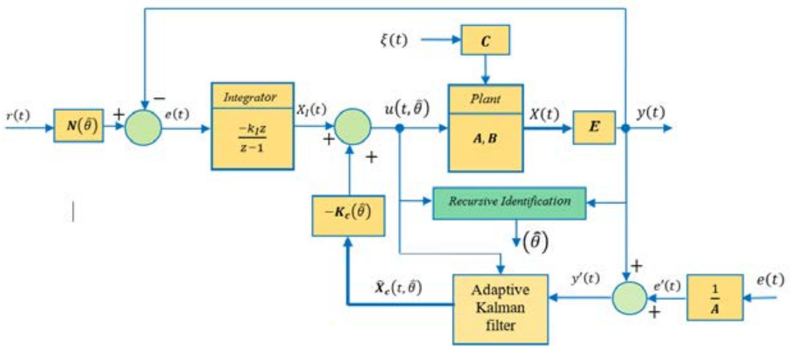

Figure 2. Structure of the LQG Control Method.

$$\begin{cases} \dot{x}\{t) = Ax(t) + Bu(t) + Le(t) \\ y(t) = Cx(t) + Du(t) + Ke(t) \end{cases} \quad (4)$$

where u is the input vector of the process, y is the output, L and K represents Gaussian sequences of zero mean with covariance, and x (k) is the state vector. The objective is to predict, from the initial state, a sequence of inputs u that allows the output y of the process to follow a reference trajectory set by the user. The quadratic cost criterion which we seek to minimise in the LQ problem is given by

$$J = \int_0^{\infty} [x^T(t)\,Qx(t) + u^T(t)Ru(t)]dt \quad (5)$$

Q and R are non-negative definite symmetric matrices, while the state observer is a filter to rebuild the system status from its dynamic model, is usually represented in the form of state space. The output of this filter is a close vector of the system state vector. Consider the following deterministic system (without random noise) [9].

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ \quad y(t) = Cx(t) \end{cases} \quad (6)$$

From which we built the observer following status:

$$\begin{cases} \dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t)4 + Lv(t) \\ \quad \hat{y}(t) = C\hat{x}(t) \\ \quad v(t) = y(t) - \hat{y}(t) \end{cases} \quad (7)$$

The error between the state vectors is written as follows:

$$\begin{cases} e(t) = x(t) - \hat{x}(t) \\ \dot{e}(t) = \dot{x}(t) - \dot{\hat{x}}(t) \end{cases} \quad (8)$$

By replacing the state vectors by their expression of the Equation 7, we get this

$$\dot{e}(t) = Ax(t) + Bu(t) - \left[A\hat{x}(t) + Bu(t) + L\left(y(t) - \hat{y}(t)\right)\right] \quad (9)$$

Then we have

$$\dot{e}(t) = [A - LC]\,e(t) \quad (10)$$

If the eigenvalues of matrix [A – LC] are all in the complex left half-plane, the system is asymptotically stable and the error vector between the state and x the state x̂ tends to zero exponentially [10]. Thus, we can use a state observer and place an order to return state using the observed state such as

$$\begin{cases} \dot{x}\,(t) \;=\; Ax\,(t) \;-\; BK\hat{x}(t) \;+\; w\,(t) \\ \hat{\dot{x}}\;(t) \;=\; A\hat{x}\,(t) \;-\; [BK \;+\; LC]\,\hat{x}\,(t) \;+\; Lv\,(t) \;+\; LCx\,(t) \end{cases} \quad (11)$$

Which can be written as:

$$\dot{x}\,(t) = \;Ax\,(t) - \;BK\,[x\,(t) - \;e\,(t)] + \;w\,(t) \quad (12)$$

$$\dot{e}\,(t) \;=\; [A - LC\,]\,e\,(t) \;+\; w\,(t) - Lv\,(t\,) \quad (13)$$

Or, gathered in the following matrix form:

$$\begin{bmatrix} \dot{x}\,(t) \\ \dot{e}\,(t) \end{bmatrix} = \begin{bmatrix} A - BK & BK \\ 0 & A - LC \end{bmatrix} \begin{bmatrix} x\,(t) \\ e\,(t) \end{bmatrix} + \begin{bmatrix} I & 0 \\ I & -L \end{bmatrix} \begin{bmatrix} w(t) \\ v(t) \end{bmatrix} \quad (14)$$

The quadratic cost criterion objective [11] can be rewritten as

$$J_{LQG} = \mathrm{E}(\int_0^\infty [x^T(t)\,Qx(t) \;+ u^T(t)Ru(t)]dt) \quad (15)$$

Then,

$$J_{LQG} = \mathrm{E}(\int_0^\infty [(\hat{\mathrm{x}} + \hat{\mathrm{e}})^T(t)\,Q(\hat{\mathrm{x}} + \hat{\mathrm{e}})(t) \;+ u^T(t)Ru(t)]dt) \quad (16)$$

We get,

$$J_{LQG} = \int_0^\infty [\hat{\mathrm{x}}^T(t)\,Qx(t) \;+ u^T(t)Ru(t)]dt + 2\int_0^\infty [\hat{\mathrm{x}}^T(t)\,QE(e)]dt + E\int_0^\infty [\hat{\mathrm{e}}^T(t)\,Qe]dt \quad (17)$$

e is a centred random variable, then $E(e) \;=\; 0$, it comes,

$$J_{LQG} = J_{LQ} + E\int_0^\infty [\hat{\mathrm{e}}^T(t)\,Qe]dt \quad (18)$$

With, J_{LQ} is a type of criterion LQ on the observer state vector x̂ of the plant. the observer must be designed so that the quantity $\int_0^\infty [\hat{\mathrm{e}}^T(t)\,Qe]$ is minimal, this observer is called optimal Kalman [12].

3.2. Formulation of the Discrete LQG Controller

The system is described by the following discrete equation:

$$\begin{cases} \dot{x}\{\mathrm{k}) \;=\; Ax\,(\mathrm{k}) \;+\; Bu\,(\mathrm{k}) \;+\; Le\,(\mathrm{k}) \\ y\,(\mathrm{k}) \;=\; Cx\,(\mathrm{k}) \;+\; Du\,(\mathrm{k}) \;+\; Ke\,(\mathrm{k}) \end{cases} \quad (19)$$

The structure of the control u is conditioned by using the criterion appeared in the equation 16.

$$J = \lim_{N\to\infty} \frac{1}{N} \sum_{k=0}^{N} \big(y(k) - y_r(k)\big)^2 + \lambda u(k)^2$$

(20)

With N, the horizon of LQG control yr is as set point desired signal , and λ is the weighting factor for modulating the u input sequences [13]. Hence the optimal control minimise this criterion is

$$u(k) = -Lx(k) + r(k) \quad (21)$$

With,

$$L\,(k) = \;\big((\lambda \;+\; B^T R\,(k)B)^{-1} B^T V\,(k)\big) \quad (22)$$

$$V\,(k)\;=\;(A\;-\;BL\,(k))^{T}\;-\;Cy_{r}(k) \tag{23}$$

$$R\,(k)\;=\;A^{T}R\,(k\;-1)\,A-A^{T}R\,(k\;-\;1)\,B\,(\lambda\;+\;B^{T}R(k\;-\;1)\,A+C^{T}C) \tag{24}$$

With R(0) > 0 . The solution of algebraic Riccati equation, its existence depends to two conditions:
- The pair (A, B) is to be stabilisable. This condition ensures the stability of the LQG control.
- The pair (C, A) should be observable. This condition ensures the stability of the estimator.

$$x\,(k\;+\;1)\;=\;Ax\,(k)\;+\;Bu\,(k)\;+\;K\,(k)\,(y\,(k)-\;Cx(k)) \tag{25}$$

The current state estimate $x\,(k)$ directly computed the equation above, With K (k) is the gain of the Kalman filter adaptive algorithm. The stationary model previously used do not take into account the nonlinearities. This model often underestimates the order process. In addition, the structure of the process varies slowly over time (growth of the vegetation, walls aging). Therefore, we propose to use an adaptive model.

3.3. Parametric Identification Method

The adaptive form of the control algorithm [14-15]. described above consists of using the estimate of the plant model parameters instead of the unidentified real values in the control law. To estimate the parameters of the model described above, the recursive least square (FFRLS) algorithm with forgotten factor has been used [16]. This method uses the model given in equation

$$Y(k)\;=\theta^{T}(k)\varphi(k) \tag{26}$$

Where θ is the vector of the unknown parameters defined as

$$\theta^{T}(k)=[a_{11}(k),\dots,d_{24}(k)] \tag{27}$$

In Equation 26, φ(k) is a regression vector partly consisting of measured input/output variables and is defined as

$$\varphi(k)=[Ti\;Hi\;Rc\;Vt\;To\;Ho\;Sr\;Sw\,] \tag{28}$$

In case the parameters of the model change slowly, we use the method of recursive least squares with exponential forgetting factor. and then try to calculate the parameters that minimize a weighted criterion by a power of a coefficient λ [17]:

$$\hat{\theta}(k)=Arg\;min\sum_{i=1}^{k}\lambda^{k-i}\,(y(k)-\varphi^{T}\,(k).\hat{\theta}(k))^{2} \tag{29}$$

Thus the oldest residues are less important. And by a short demonstration, the following identification algorithm is given [18-19]:

$$\hat{\theta}(k)=\hat{\theta}(k-1)+K(k)[y(k)-\varphi^{T}\,(k).\hat{\theta}(k-1)] \tag{30}$$

$$K(k)=\;P(k-1)\varphi(k)(\lambda+\varphi^{T}\,(k)P(k-1)\varphi(k))^{-1} \tag{31}$$

$$P(k)=\frac{1}{\lambda}(P(k-1)-K(k)\varphi^{T}\,(k)) \tag{32}$$

For, the gain matrix P(t) will not converge to zero as time goes to infinity, hence the algorithm will be able to update the parameters when the system is time varying. In practice, is a design parameter a low value of gives a fast tracking of time varying parameters but a high noise sensitivity [20]. Otherwise, one will choose $\lambda(k)<\;1$ (typically between 0.98 and 0.995. The value of λ depends on the dynamics of changing parameters of the system.

4. SIMULATION RESULTS

The objective of this study is to show how adaptive LQG implementation can cope with Multivariable systems. The LQG design is applied to the microclimate greenhouse plant with changes in external disturbances. The Simulation of the plant with the proposed adaptive control scheme are implemented in real time process simulation with the measured weather values of the air temperature and relative humidity and other disturbances (solar radiation, wind speed, external temperature and relative humidity) a Gaussian noise with constant variance is added to disturbances inputs of a greenhouse. From the measured input output signals, the identified model of the microclimate greenhouse that give the best behavior discrete model is:

$$A = \begin{bmatrix} 0.4752 & 0.0878 \\ 0.7879 & 0.5004 \end{bmatrix} \quad B = \begin{bmatrix} 0.1765 & 0.0165 \\ 0.1084 & 0.0704 \end{bmatrix}$$

$$D = \begin{bmatrix} 0.3450 & -0.0385 & 0.0138 & 0.2012 \\ -0.7095 & 0.3639 & -0.0081 & 0.2765 \end{bmatrix}$$

Where the sample time is T = 5 seconds, the reference to be track is chosen as a square wave. After several checks, the recursive identification is made via the FFRLS algorithm with the flowing consideration as stated in [21]

- forgetting factors are $\lambda = 0.97$
- the initial adaptation gain of $P(0) = 10^4 I$
- the initial parameter value is $\theta^T = [0.01, 0.01, 0.01]$.
- the following weighting matrices for the Kalman filter Q = [100 0; 0 50]; R = [10 0; 0 15],

The implementation of the adaptive FFRLS algorithm and the LQG multivariable control for monitoring the temperature and humidity inside the greenhouse, using the MATLAB programming code, gave us the following results. The outputs predicted by the adaptive identification method rigorously converge with the outputs of the model simulating the thermal behavior of the greenhouse, as can be seen from Figure 3.

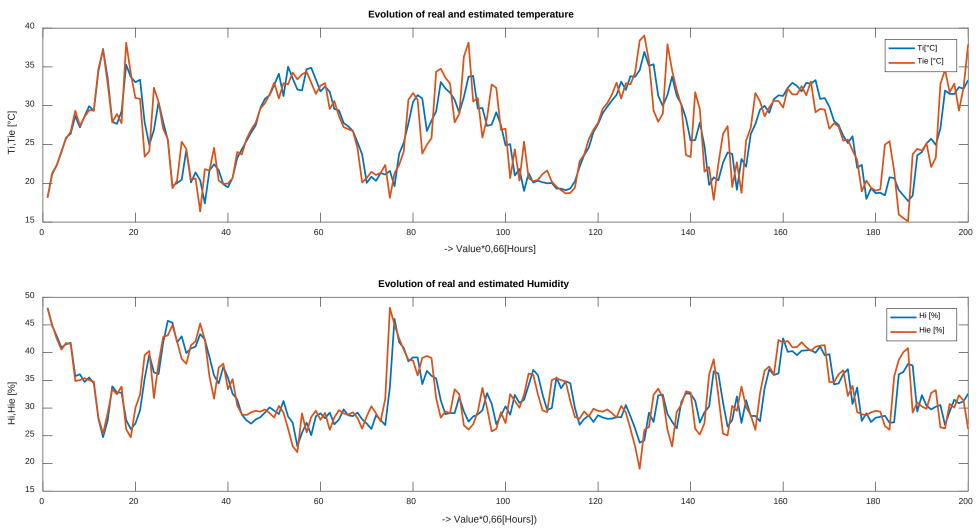

Figure 3. Measured and Simulated Responses of the Greenhouse Air Temperature and Relative Humidity

Time-based Evolution of the Adjustable Parameters of the microclimate green house shown in Figure 4. The Figure 4 has allowed us to highlight that:

Firstly, the recursive FFRLS algorithm for estimating the observation vector based on the square error update produces more reliable estimates of the greenhouse parameters in the presence of the other disturbances.

Secondly, this method using the recursive technique with a forgetting factor has a fast convergence dynamic that makes it easily applicable on changing systems. The recursive least squares with forgotten factor method presented in this paper gives unbiased estimates only for ARMAX models. On the other hand, this method, does not use any information a priori on the measurement noise, and we have tested that if the noise is not zero average value. the estimation of the parameters is biased.

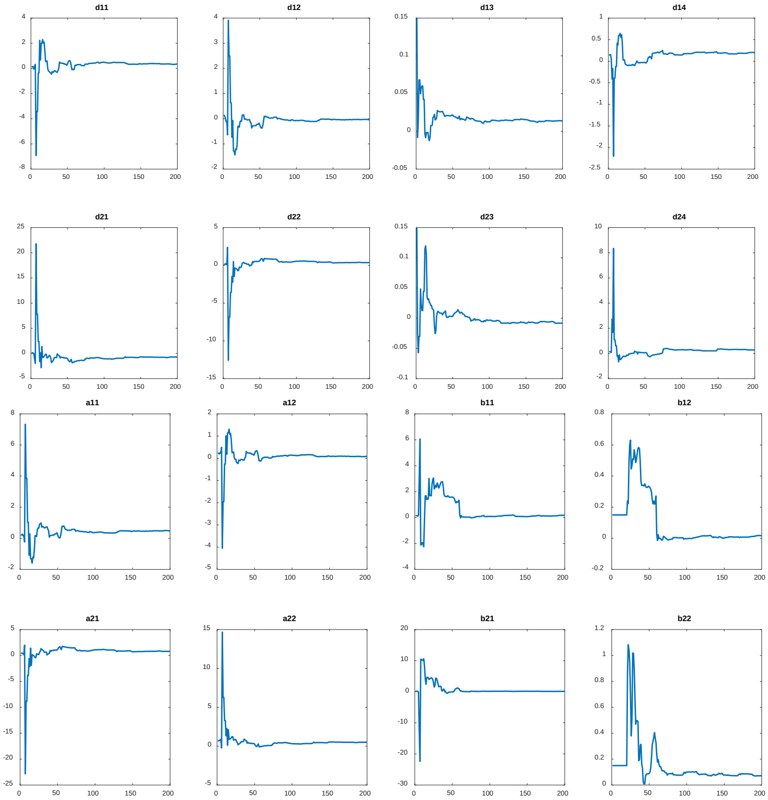

Figure 4. Time-based Evolution of the Adjustable Parameters of the Microclimate Green House (see online version for colours)

To illustrate the applicability and efficiency of LQG control technique on the greenhouse process. Figure 5 show the real-time behavior of temperature T(°C) and humidity H(°C) respectively. These results once again confirm the robustness of the LQG control to be able to cancel almost completely the effect of the strong disturbances added to the thermal process of the greenhouse compared to the standard monovariable control.

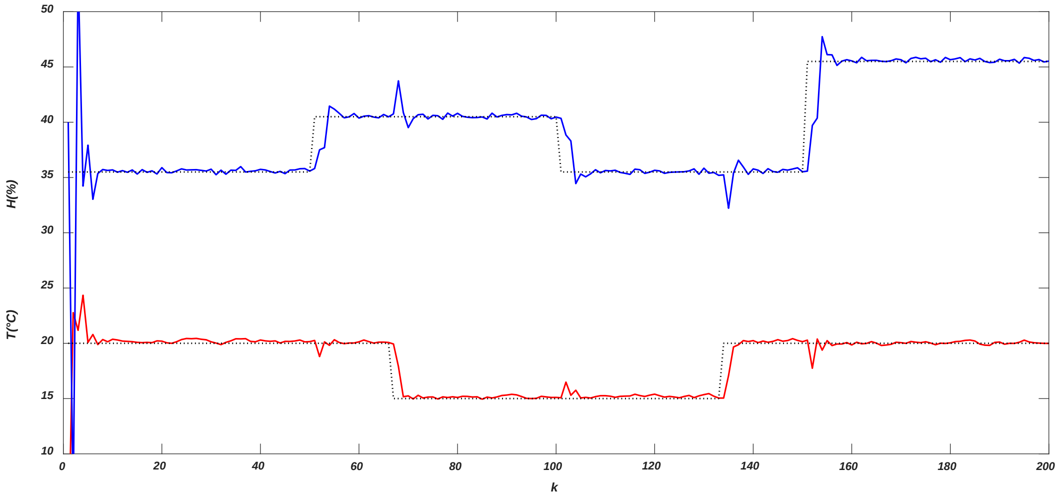

Figure 5. Responses of Greenhouse Air Temperatures and Relative Humidity using the Adaptive LQG Controller

With the observation of the Figure 6 , we note that in spite of the presence of the coupling between the variables of the greenhouse, the change of setpoint carried out in real time on both the temperature (high) and the second output which is the humidity of the air (bottom) has less impact on both outputs. The commands applied to the system are given in Figure 6. A s in simulation mode, the influence of the multivariable coupling is clearly felt on the first heating control at the time of the change of the set point applied to the second air humidity output H (%). The first control reacts so that the temperature of the air T (° C) is not disturbed by the change in behavior of the greenhouse that affects humidity H (%).

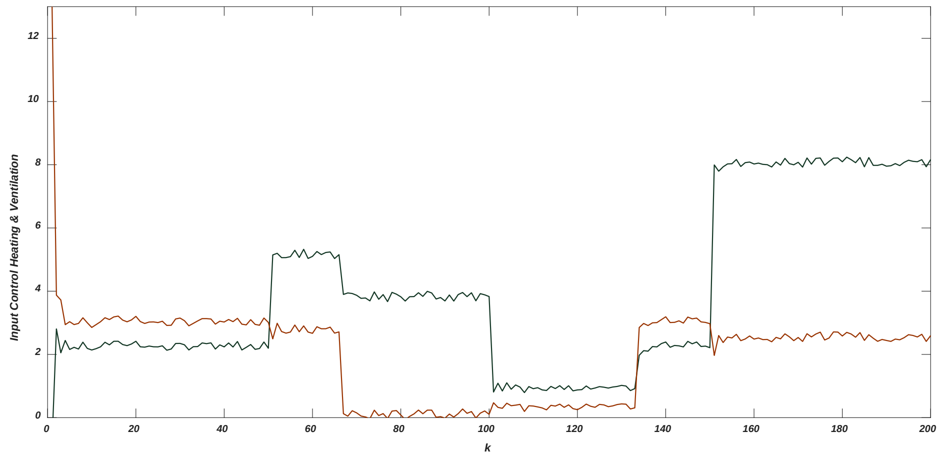

Figure 6. The Input Control of the Greenhouse with the Adaptive Multivariable LQG Controller

5. CONCLUSION

In this paper, a multivariable adaptive LQG controller combined with the FFRLS parameter estimation method was applied to driving the microclimate greenhouse air temperature and relative humidity with external disturbances. The simulation results show that the proposed scheme is able to sufficiently control the plant, and conserves a high level of performances, in terms of pursuing, response time and disturbance rejection.

REFERENCES

[1] Revathi S, Radhakrishnan T K and Sivakumaran N, "Climate control in greenhouse using intelligent control algorithms," *2017 American Control Conference (ACC)*, Seattle, WA, 2017, pp. 887-892.

[2] L. Meihui, D. Shangfeng, C. Lijun and H. Yaofeng, "Greenhouse multi-variables control by using feedback linearization decoupling method," *2017 Chinese Automation Congress (CAC)*, Jinan, China, 2017, pp. 604-608.

[3] Q. Gao, X. Gao and X. Chen, *"Analysis of current situation and existing problems in greenhouse environment control," Proceeding of the 11th World Congress on Intelligent Control and Automation*, Shenyang, 2014, pp. 4516-4520.

[4] E. J. van Henten and J. Bontsema, "Singular perturbation methods applied to a variational problem in greenhouse climate control," *Proceedings of the 31st IEEE Conference on Decision and Control*, Tucson, AZ, 1992, pp. 3068-3069 vol.4.

[5] David Greenwood; Michael J. Grimble, "Multivariable LQG optimal control — Restricted structure control for benchmarking and tuning", *European Control Conference (ECC)*, 2003 Print ISBN:978-3-9524173-7-9 .

[6] D. Lauri, J. V. Salcedo, S. Garcia-Nieto and M. Martinez, "Model predictive control relevant identification: multiple input multiple output against multiple input single output," in *IET Control Theory & Applications*, vol. 4, no. 9, pp. 1756-1766, September 2010.

[7] X. Blasco, M. Martnez, J. M. Herrero, C. Ramos, J. Sanchis, "Model-based predictive control of greenhouse climate for reducing energy and water consumption", *Computers and Electronics in Agriculture*, vol. 55, Jan 2007.

[8] Grimble M. J. 2000 "Restricted Structure LQG Optimal Control for Continuous Systems" *IEE Proc. Control Theory Applications*, Vol 147 No2 (185-195) March.

[9] Muhammad Ali Raza Anjum, "Adaptive System Identification using Markov Chain Monte Carlo." *TELKOMNIKA Indonesian Journal of Electrical Engineering Vol*. 13, No. 1, January 2015, pp. 124

[10] R. Garrido-Moctezuma, D. A. Suárez and R. Lozano, "Adaptive LQG control of positive real systems," *European Control Conference (ECC)*, Brussels, 1997, pp. 144-149.

[11] Grimble M. J, “Restricted structure controller performance assessment and benchmarkin”. *American Control Conference*, 2001, 2718-2723.

[12] Laroussi Oueslati « Commande multivariable d'une serre agricole par minimisation d'un critere quadratique » Phd thesis University of Toulon, 1990.

[13] Mustapha Ait Lafkih, Zohra Zidane, Mohamed Ramzi “Design of Linear Quadratic Gaussian Controller for Sample Power System” *International Journal of Emerging Technology and Advanced Engineering*, Issue 3, March 2013.

[14] M. Outanoute , A. Lachhab, “Synthesis of an Optimal Dynamic Regulator Based on Linear Quadratic Gaussian (LQG) for the Control of the Relative Humidity Under Experimental Greenhouse”. *International Journal of Electrical and Computer Engineering (IJECE)* Vol. 6, No. 5, October 2016.

[15] Tang Minan, Wang Xiaoming, Cao Jie , Li Ying, “Model Reference Adaptive Control Based on Lyapunov Stability Theory”, *TELKOMNIKA Indonesian Journal of Electrical Engineering*, Vol.12, No.3, March 2014, pp. 1812.

[16] Grimble M. J. and M. A. Johnson, “Optimal Control and Stochastic Estimation”, *John Wiley and Sons Chichester UK* Volume 1 and 2. 1988.

[17] Zhiyong Zhang, Dongjian He1, “Adaptive Tracking Control Algorithm for Picking Wheel Robot” *TELKOMNIKA, Vol.10, No.8, December 2012, pp. 2131~2138*

[18] M. Prandini and M. C. Campi, "A self-optimizing adaptive LQG control scheme for input-output systems," *Proceedings of the 39th IEEE Conference on Decision and Control* (Cat. No.00CH37187), Sydney, NSW, 2000, pp. 1110-1115 vol.2 doi: 10.1109/CDC.2000.912001

[19] S.M.Veres, J.P.Norton, “Predictive self-tuning control by parameter bounding and worst-case design”, *Automatica*, Volume 29, Issue 4, July 1993, Pages 911-928.

[20] H.T.Banks,ed., “Control and Estimation in Distributed Parameter Systems“(SIAM, Philadelphia, 1992).

[21] M. Prandini and M. C. Campi, "*A self-optimizing adaptive LQG control scheme for input-output systems*," *Proceedings of the 39th IEEE Conference on Decision and Control* (Cat. No.00CH37187), Sydney, NSW, 2000, pp. 1110-1115 vol.2 doi: 10.1109/CDC.2000.912001