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Multivariable Parametric Modeling of a Greenhouse by Minimizing the Quadratic Error

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Abstract

This paper concerns the identification of a greenhouse described in a multivariable linear system with two inputs and two outputs (TITO). The method proposed is based on the least squares identification method, without being less efficient, presents an iterative calculation algorithm with a reduced computational cost. Moreover, its recursive character allows it to overcome, with a good initialization, slight variations of parameters, inevitable in a real multivariable process. A comparison with other methods recently proposed in the literature demonstrates the advantage of this method. Simulations obtained will be exposed to showthe effectiveness and application of the method on multivariable systems.

Keywords*: recursive least squares, greenhouse, multivariable process, identification*

1. Introduction

The identification of multivariable systems is a topic of current research but whose industrial applications remain punctual. Until now, the identification of multivariable processes (MIMO) has generally been handled by applying multi-input, single-output (MISO) techniques to each output of the system [1].

Hence, the identification methods are classified into two broad categories: parametric and nonparametric. The non-parametric methods aim at determining models by direct techniques, without establishing a class of models a priori, they are called non-parametric because they do not involve a parameter vector to represent the model as developed in [2].

The objective of parametric identification is to estimate the parameters of a mathematical model, so as to obtain a satisfactory representation of the real system studied; in this kind of identification we also find different techniques.

One of them is called "heuristic identification", it is based on the determination of the parameters of a transfer function by having the step response of the system. Another technique called "linear regression" is used in the simple least squares method. We also find methods based on the output error and the prediction error [3].

2. Background

The use of dynamic system identification techniques is based on a systemic approach to heat transfer [4]. In this approach, modeling a process uses three types of quantities:

a. The inputs of the system (magnitudes exogenous to the system), which are the cause of its dynamic evolution and will be denoted by the « vector U (t) »
b. The outputs of the system, which are the variables through which the system is observed; these are by definition quantities which can be the object of an experimental measurement: «vector Y (t) ».
c. Finally, the state of the system « vector X (t) » which groups together all variables (possibly non-measurable) allowing at a given moment to characterize its dynamic state [5].

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3. The Problem

Recently, many self tuning models have been suggested to describe the dynamic behaviour of the greenhouse. In the reported literature the application of conventional methods requires preliminary knowledge of a model of the process in order to control it optimally in the presence of environmental disturbances. However, in our case, this knowledge is often not available and the process control must be preceded by a preliminary step of identifying the model. This type of approach leads to a two-step realization of the control system (identification of the model and control of the process) [6]. The major disadvantage of this approach is to set the control system according to the model obtained during the identification step; during which the process operating conditions may be different from that corresponding to the effective application of the control [7].

4. Proposed Solution

We have therefore been led to develop models of parametric identification of greenhouse climate which are based on the writing of energy balances at the main components of the greenhouse: walls, indoor air, vegetation, different horizons of the soil. These multivariable models will then be compared to the parametric models obtained by parametric identification based on the quadratic error minimization criterion [8].

This article is structured as follows. Section 5 presents a general greenhouse mlodeling. Section 6 presents the principle of recursive least sqaure algorithm by highlighting our contribution to this paper. Section 7 unveils simulations on the simulink code of the proposed method [9].

5. System Modeling

The descriptive model shown in Figure 1 will be set in parametric identification in real time in order to obtain the dynamic model of the behavior of the greenhouse containing all the parameters to be identified [10].

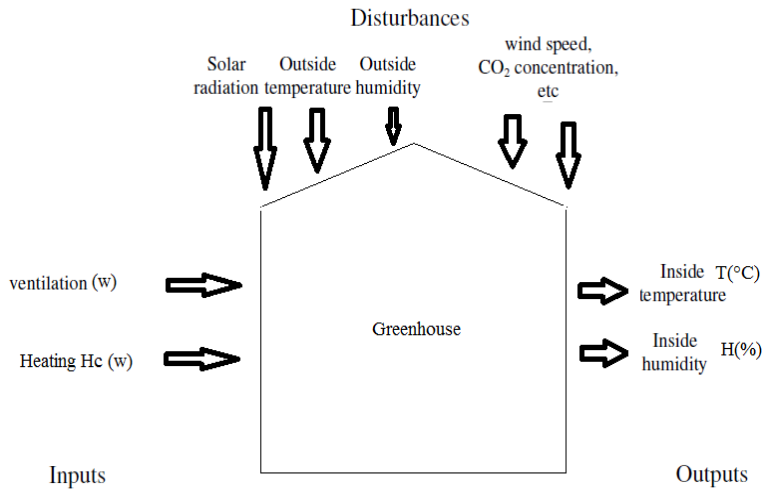

Figure 1. Greenhouse system modeling

The validation of these parameters is done by minimization of quadratic criterionon time horizon which allows this error to be acceptable [11]. by using the RLS identification algorithm applied in multivariable mode, we will be able to concretize the dynamic model of the greenhouse as seen in Figure 2.

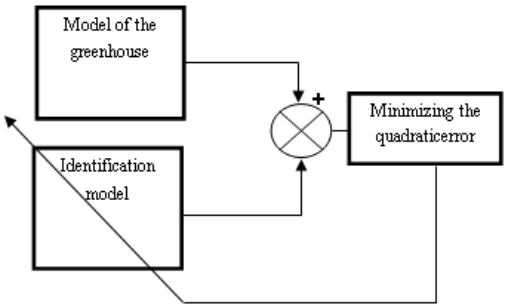

Figure 2. Schematic diagram of controlled greenhouse

To describe the dynamic model of the greenhouse [12-13], we chose the ARMAX [5] representation (recursive exogenous autoregressive moving average) as shown on Figure 3.

$$A(q^{-1}).Y(t) = q^{-d}.B(q^{-1}).U(t) + C(q^{-1})\,w(t) \quad (1)$$

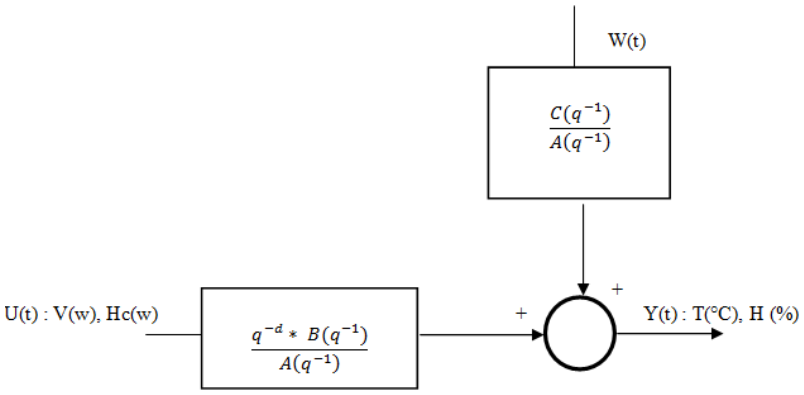

Figure 3. ARMAX structure

To simplify the modeling of the greenhouse [6], we have to limit the order of identification of the polynomials of the ARMAX model to n=2, and we have this:

$$A(q^{-1}) = A_1 q^{-1} + A_2 q^{-1} \quad (2)$$

$$B(q^{-1}) = 1 + B_1 q^{-1} + B_2 q^{-1} \quad (3)$$

$$C(q^{-1}) = 1 + C_1 q^{-1} \quad (4)$$

In the above Equations, *y(t)* represent the greenhouse outputs: the temperature *T°(°C)* and the humidity *H (%)* of the internal climate of the greenhouse. u(t) the greenhouse input: ventilation *V(w)* and heat power *H(w). w(t)* vector-valued zero-mean sequences, with definite power and independent of the inputs of theplant. Moreover$A(q^{-1})$, $B(q^{-1})$and $C(q^{-1})$ are polynomial functions in the backward shift operator (q^{-1}) of order na, nb and nc, respectively.

6. Parametric Identification RLS Method

A general method consists in calculating the quadratic error of the criterion in order to use a generic method of iterative or recursive minimization (see optimization in [14-15]). The criterion is de ned by :

$$Y(k) = \theta^T(k)\,\varphi(k) \quad (5)$$

This predictor does not finish a linear regression because it is looped. It is generally referred to as pseudo-linear regression, and the parameter vector is put in the form:

$$\theta^T(k) = [A_1 A_2 B_0 B_1 B_2 C_1] \quad (6)$$

The vector $\varphi(k)$ contains the measured data of the control and the output of the model of the greenhouse "here temperature and humidity"

$$\varphi(k) = [Y\ U\ W\ ] \quad (7)$$

The method we propose here, [16] although it belongs to the category of "sub-optimal" methods, has the advantage of being simple in terms of both implementation and computational workload, and just as powerful as existing methods. The processing performed on the data will be sequential, ie the set of data to be processed is not supposed to be available at one time; at a moment k, only the history of the measurements *y(k)* constitutes the learning base [17]. Instead of resorting to particulate estimation techniques as in [8] to ensure the calculation of the parameters of the different modes of operation, the approach adopted here is based on recursive least squares.

$$\hat{\theta}(k) = Argmin \sum_{i=1}^{k} (y(k) - \varphi^T(k).\hat{\theta}(k))^2 \quad (8)$$

In all cases, obtaining good estimates depends on the choice of an appropriate decision criterion and an appropriate initialization of the parameters [12-13]. Henceeach iteration will be represented by

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)[y(k) - \varphi^T(k).\hat{\theta}(k-1)] \quad (9)$$

$$K(k) = P(k-1)\varphi(k)(1 + \varphi^T(k)P(k-1)\varphi(k))^{-1} \quad (10)$$

$$P(k) = (P(k-1) - K(k)\varphi^T(k)) \quad (11)$$

7. Simulation Results

The excitation input of the greenhouse is chosen as a centered white noise of unit variance; an additive output noise e is also selected white of the same characteristics.The Figures below present the simulation results of the online identification obtained after the calculation iteration of the RLS quadratic algorithm.

The Figures are made for various values of parameters, in order to show the robustness and the time reponse of this method and especially its capacity to operate with very few variations of the internal parameters of the greenhouse. Note that the estimates are relatively close to the true parameters of the greenhouse. They are also quickly calculated by this method. Here to illustrate the method presented above, we give the different initializations of the algorithm of RLS identificationdefined such that:

computing time: 1000; weighting matrix P=106

Also, we consider an example of a greenhouse system of orders na=2 and nb=2 and nc=1;

$$A1 = \begin{pmatrix} -0.1 & 0.2 \\ 0.33 & 0.4 \end{pmatrix} \quad ; \quad A2 = \begin{pmatrix} -0.5 & 0.66 \\ -0.77 & 0.8 \end{pmatrix}$$

$$B0 = \begin{pmatrix} -0.1 & 0.2 \\ -0.3 & 0.4 \end{pmatrix} \quad ; \quad B1 = \begin{pmatrix} 0.5 & -0.6 \\ -0.7 & 0.8 \end{pmatrix} \quad ; \quad B2 = \begin{pmatrix} 0.9 & -0.1 \\ 0.11 & -0.12 \end{pmatrix}$$

$$C0 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

To validate the model, the simulation results of the estimated model with respect to other observations than those used for the estimation phase are shown in Figure 3. The values of the

temperature and humidity inside the greenhouse show that the dominant behavior of the greenhouse is correctly described by the estimated model.

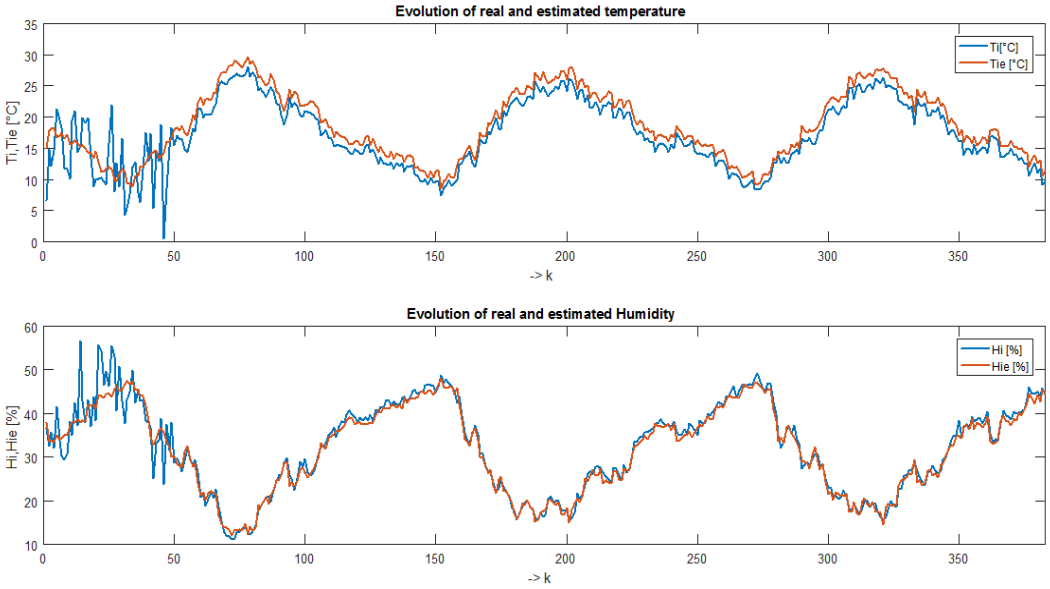

Figure 4. Comparison between measured and estimated output variables

The time-based of the greenhouse parameters is shown in Figures 2 and 3. The parameters values are adjusted with very low values, meanwile the extrnal disturbance are applied, the parameters are again estimated to consider the effect of the new greenhouse state. The curves below make it possible to observe that after 5% of the global time of calculation of the identification, the best results of the values of the parameters of the greenhouse can be obtained.

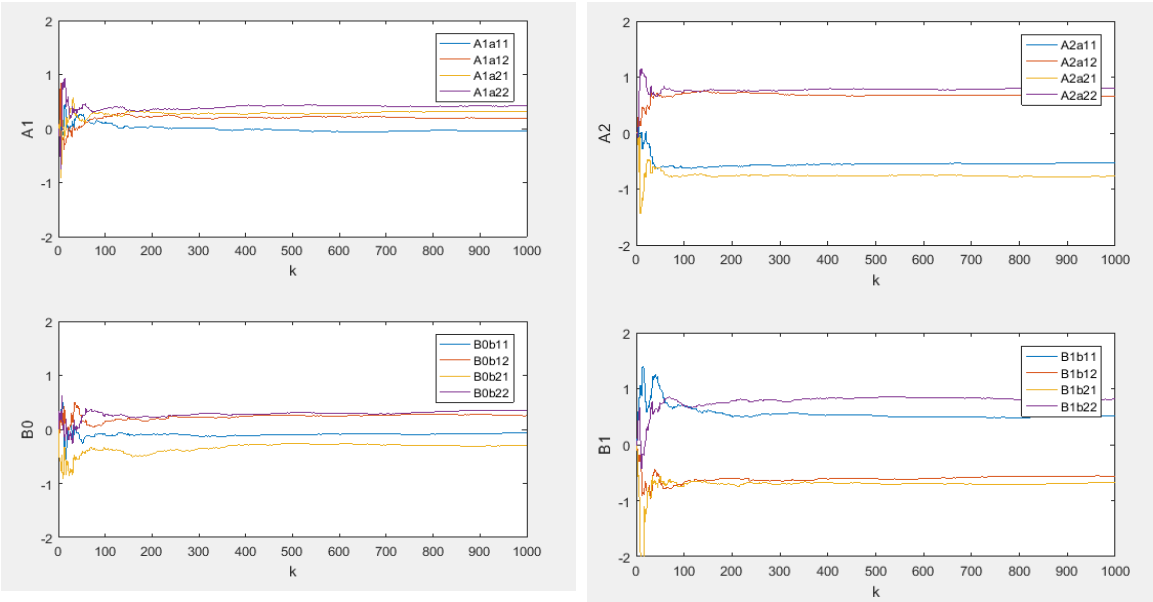

Figure 5. Evolution of the estimate of the dyanamic parameters of the greenhouse A1, A2, B0 and B1

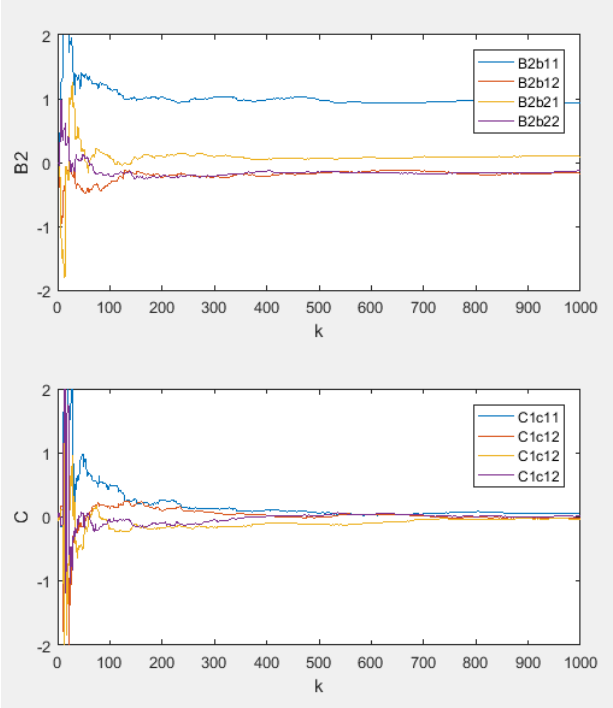

Figure 6. Evolution of the estimate of the dyanamic parameters of the greenhouse B2 and C1

8. Conclusion

In this paper, We have suggested a multivariable method for the recursive identification of systems with evolving coupled variables. The approach proposed here for the identification of a greenhouse is built around an idea which consists in coupling the tasks of identification and estimation of the parameters. by minimizing the qaudratic error between measurement and real-time estimation of measured outputs.Compared with single-variable methods, it has been shown that for equivalent performance, our method has the advantage of being inexpensive in terms of computing loads.Our next work will extend to the recursive identification of the multivariable greenhouse, subject to more advanced controls that can be adaptive.

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