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Controlling the Temperature and Humidity within a Greenhouse by Adaptive Multivariable Generalized Predictive Control

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 # Preparing a PhD thesis in adaptive control at the faculty of Sciences and Technology, University of Sultan MoulaySlimane, [1]mohamed.essahafi@yahoo.fr

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Abstract— **In this paper we presentan application of the adaptive multivariable Generalized Predictive Control (AMGPC) approach with measurable disturbances presence. The (AMGPC) which mixes the method of scheme identification using recursive least-squares with forgotten factor (FFRLS) algorithm and the scheme of generalized predictive response control design, has been presented and efficiently applied. The proposed method was verified by simulation of a microclimate greenhouse inside temperature and humidity control. The achieved results show that the AMGPC with disturbance deliver improved behaviour that standard techniques.**

***Keywords*— adaptive control, generalized predictive control, greenhouse, multivariable process, recursive least-squares, identification algorithm**

I. Introduction

A greenhouse is a remarkably outlined farmstead structure building to give a more controllable microclimate to improved crop production, harvest security, product planting and seeding. Also, the accessible space of area for developing yields has been overall increasing, following to more space of area is dynamically utilized for covering and marketable ventures as a part of this present day period. Therefore, to improve profitability, we must grow crops in optimal environments, by controlling the air temperature, humidity, and CO2 level. All these factors must be considered in the energy balance, because each can influence other.

This study enters in a contribution to the development of the greenhouse driving by using a generalized predictive control (GPC) approach ([1, 2].). Adaptive control can be seen as an automation of plant modeling and controller design in which the dynamical behavior and controller are updated during each sampling period. However, the adaptive GPC, which combines the process of system identification using recursive least-squares (RLS) algorithm described in ([3, 4].). And the process of generalized predictive feedback control design, has been presented and successfully implemented in real time.

This paper is structured in four chapters. After this general introduction, section 2, deals in its first part on the general modelling of the greenhouse, section 3 presents the adaptive multivariable controller combined with GPC strategy. Section 4 illustrate the parametric estimation of the greenhouse environment by the identification method based on the criterion of least squares recursive forgetting factor (FFRLS) asanalysed in ([5].). The last part of this thesis includes the simulation results with an overall conclusion and outlook of the thesis.

II. System Modelling

As shown in Fig. 1.we show the main physical variables cited in ([6].) used for modelling the experimental greenhouse.

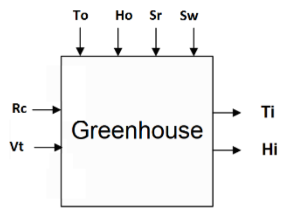

Fig. 1Schematic diagram of controlled greenhouse

With:

Rc: heating energy applied to the plant (KW).

Vt: ventilation angle outside the greenhouse (°degree)

To,Ho: air temperature and relative humidity outside the greenhouse (° C,%).

Sr: Solar radiation (W / m²).

Ti,Hi: air temperature and relative humidity inside the greenhouse(° C,%).

Sw: wind speed outside the greenhouse (km/h).

Assuming that the greenhouse climate can be described by a linear system around an operating point, the differential equations describing the dynamic behaviour of the greenhouse are

$$\frac{dTi}{dt} = (\alpha 1 + \alpha 2.Ov)(Te - Ti) + \alpha 3.Rc + \alpha 4.Sr + \alpha 5 \quad (1)$$

$$\frac{dHi}{dt} = (\beta 2.Vv)(He - Hi) + (\beta 3 + \beta 4.Ry).\Delta Hi + \beta 5 \quad (2)$$

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These differential equations are substituted by discrete model.

$$\begin{bmatrix} Ti(k+1) \\ Hi(k+1) \end{bmatrix} = \begin{bmatrix} a11 & a12 \\ a21 & a22 \end{bmatrix} \begin{bmatrix} Ti(k) \\ Hi(k) \end{bmatrix} + \begin{bmatrix} b11 & b12 \\ b21 & b22 \end{bmatrix} \begin{bmatrix} Rc(k) \\ Vt(k) \end{bmatrix} + \begin{bmatrix} d11 & d12 & d13 & d14 \\ d21 & d22 & d23 & d24 \end{bmatrix} \begin{bmatrix} To(k) \\ Ho(k) \\ Sr(k) \\ Sw(k) \end{bmatrix} \quad (3)$$

III. Generalized predictive control

Let the controlled process to be an m-input, n-output linear system which can be described by a discrete CARIMA model. (Controlled Auto-Regressive Integrated Moving Average) process model as described in([7].)

$$A(q^{-1}).y(t) = B(q^{-1}).\Delta u(t) + D(q^{-1})dp(t) \quad (4)$$

Where

$y(t)$is the measured system output,

$u(t)$is the system input,

$dp(t)$is the disturbance measurement.

t is the discrete time iteration expressed as an integer multiple of the sampling interval.

$\Delta = 1 - q^{-1}$is the delay operator.

$A(q^{-1})$and$B(q^{-1})$are polynomial matrices in the backward shift operator q^{-1} such that $B(0) = 0$ and $A(0) = I$, with I being the m × m identity matrix.

$D(q^{-1})$is a disturbance parameter matrix.

the system model can be described as

$$y(t) = \sum_{i=1}^{na} -a_i y(t-i) + \sum_{i=1}^{nb} -b_i u(t-i) + \sum_{i=1}^{nd} -d_i dp(t-i) \quad (5)$$

This predictor of the output y is particularly simple to calculate because it defines a linear regression which is usually written as:

$$\hat{y}(k) = \varphi^T(k).\hat{\theta}(k) \quad (6)$$

The vector $\hat{\theta}(k)$ contains the parameters of the greenhouse that we must predict, And the variable, φ is called the regression variable.

With

$$\varphi^T(k-1) = [-y(k-1), \dots, -y(k-na)), -u(k-nb, \dots, -uk - nb, \dots, dp(k-nd)] \quad (7)$$

$$\hat{\theta}(k) = [\hat{A}_1(k), \dots, \hat{B}_{nb}(k) \dots \hat{D}_{nb}(k)] \quad (8)$$

Since the parameters of the model change slowly, we use the method of recursive least squares with exponential Forgetting factor. From equation (6) we try to minimize the following criterion

$$\hat{\theta}(k) = Argmin \sum_{i=1}^{k} \lambda^{k-i} (y(k) - \varphi^T(k).\hat{\theta}(k))^2 \quad (9)$$

The model parameters can be recursively estimated using the FFRLS algorithm as

$$\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)[y(k) - \varphi^T(k).\hat{\theta}(k-1)] \quad (10)$$

Where the correcting factor, $K(k)$ is

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

And

$$P(k) = \frac{1}{\lambda}(P(k-1) - K(k)\varphi^T(k)) \quad (12)$$

Consider the cost function as proposed by Clarke (1987) of the following form:

$$J = \sum_{N1}^{N2} (w(k+j) - \hat{y}(k+j))^2 + \lambda \sum_{1}^{Nu} (\Delta u(k+j-1))^2$$

Where:

$\Delta u(k+j-1)$: weighted sequence of the future control input increments obtained from the minimization of the finite horizon quadratic criterion.

N1, N2: minimum and maximum prediction horizons for the scalar output yj.

Nu: is the control horizon over all future inputs uj,

λ: weighting factor of the control increment.

$w(t+j)$: Future set-point sequence applied at time t+j.

$y(t+j)$: Output predicted at time t+j.

$\Delta u(t+j-1)$: Increments of command on channel i at time t + j-1.

Where the Diophantine equation is used

$$I_m = E_j A\Delta + q^{-j} F_j \quad (13)$$

Let $Ei, Fj$the unique pair solution of Diophantine equation

$$E_j = E_0^j + E_1^j q^{-1} + \dots + E_{j-1}^j q^{-j+1} \quad (14)$$

$$F_j = F_0^j + F_1^j q^{-1} + \dots + F_{na}^j q^{-na} \quad (15)$$

Using the solution of the first Diophantine equation, in equation (13) leads to

$$y(k+j) = F_j y(k) + E_j B\Delta u(k+j-1) + E_j e(k+j) \quad (16)$$

The optimum prediction at time $y(k+j)$,

$$\hat{y}(k+j) = F_j y(k) + E_j B\Delta u(k+j-1) \quad (17)$$

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The term E may be separated by a second Diophantine equation in G_j and H_j as follows:

$$E_j B = G_j + q^{-j} H_j \quad (18)$$

$$G_j = G_0^j + G_1^j q^{-1} + .. + G_{j-1}^j q^{-j+1} \quad (19)$$

$$H_j = H_0^j + H_1^j q^{-1} + .. + H_{nh}^j q^{-na} \quad (20)$$

The matrices G and H are polynomials of dimension m × m;we get

$$\hat{y}(k+j) = G_j \Delta u(k+j-1) + H_j \Delta u(k-1) + F_j y(k) \quad (21)$$

And which considers the following quantities:

$$Fc = \begin{bmatrix} H_{N_1}\Delta u(k-1) + F_{N_1} y(k) \\ H_{N_1+1}\Delta u(k-1) + F_{N_1+1} y(k) \\ \\ H_{N_2}\Delta u(k-1) + F_{N_2} y(k) \end{bmatrix} \quad (22)$$

For $j = N_1 \ldots N_2$ we have,

$$\hat{y}(k+j) = \begin{bmatrix} \hat{y}_1(k+j) \\ \hat{y}_2(k+j) \\ \\ \hat{y}_m(k+N_2) \end{bmatrix} \quad (23)$$

With

$$\widetilde{U} = \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \\ \Delta u(k+N_u-1) \end{bmatrix} \quad (24)$$

We can then write the equation (20) for$N_1 < j < N_2$, in the form:

$$\hat{Y} = G\widetilde{U} + Fc \quad (25)$$

With $G \epsilon \mathbb{R}^{m(N_2-N_1+1)\times mN_u}$

$$G = \begin{bmatrix} G_{N_1-1} & \Lambda & G_0 & \Lambda & \Lambda & 0 \\ G_{N_1} & G_{N_1-1} & \Lambda & G_0 & \Lambda & 0 \\ M & M & 0 & 0 & 0 & M \\ G_{N_u-1} & G_{N_u-2} & G_{N_u-3} & \Lambda & \Lambda & G_0 \\ M & M & M & M & M & M \\ G_{N_2-1} & G_{N_2-2} & G_{N_2-3} & \Lambda & G_{N_2-N_u+1} & G_{N_2-N_u} \end{bmatrix}$$

The system output prediction sequence, $\hat{Y}$ given by equation (21) can be used in the cost function, which subsequently yields

$$J = (\hat{Y} - W)^T (\hat{Y} - W) + \widetilde{U}^T \Lambda \widetilde{U} \quad (26)$$

With

$$\Lambda = \begin{bmatrix} \begin{bmatrix} \lambda_1 & . & . & 0 \\ . & . & . & . \\ . & . & . & . \\ 0 & . & . & \lambda_m \end{bmatrix}_1 & 0 \\ 0 & \begin{bmatrix} \lambda_1 & . & . & 0 \\ . & . & . & . \\ . & . & . & . \\ 0 & . & . & \lambda_m \end{bmatrix}_{N_u} \end{bmatrix} \quad (27)$$

And the optimal control([8].)applied to the system at time t is:

$$u_{opt}(k) = u(k-1) + \Delta u_{opt}(k) \quad (28)$$

With

$$\Delta u_{opt}(k) = M_1(W - Fc) \quad (29)$$

$M_1 \epsilon \mathbb{R}^{m\times m(N_2-N_1+1)}$ represents the first m rows of the matrix M.

IV. Results and discussions

In this section, the performance of the adaptive controller associated with the GPC controller is applied to control the microclimate of a greenhouse with the presence of external disturbance inputs([9].). The following tests represent variations of humidity and temperature set points in the greenhouse process. In over-all, each trial track can be separated into three sequential phases. Through the first, start-up phase the system plant is achieving steady state around the operation points. The second one is a suitably chosen identifying phase using acquired data, which gives us an initial estimation of CARIMA model parameters. The third phase finally displays the results of the adjusted multivariable adaptive GPC controller.

Several of real-time tests had been simulated in order to choice parameters that would offer the desired controller performance([10, 11].). As a final point, the succeeding values of design parameters were set: sampling times T = 1.5 s, horizons $N1$ =1, $N2$ = 15, Nu = 3, dead time d = 1, and weights [$\lambda 1$, $\lambda 2$] = [0.95, 0.9].

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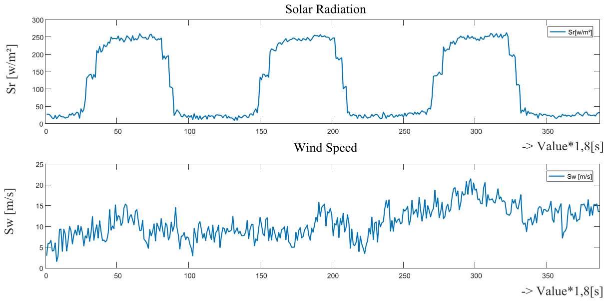

Fig. 2Measurement data respectively for solar radiation and speed wind

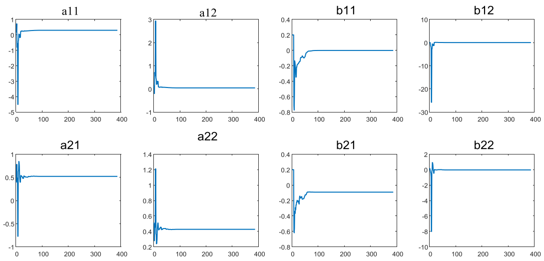

Fig. 3 The online estimation of the greenhouse's parameters

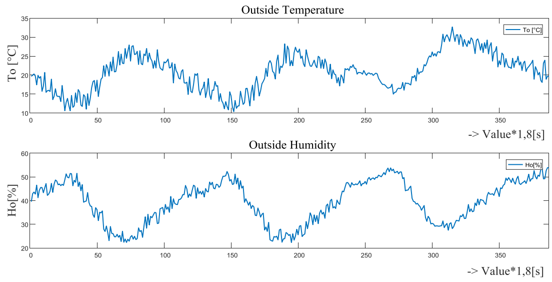

Fig. 4 Measurement data respectively for Outside Air Temperature and relative Humidity

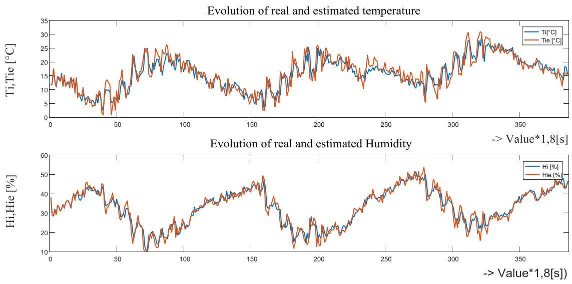

Fig. 5 Measured and simulated responses of the greenhouse air temperature and relative humidity

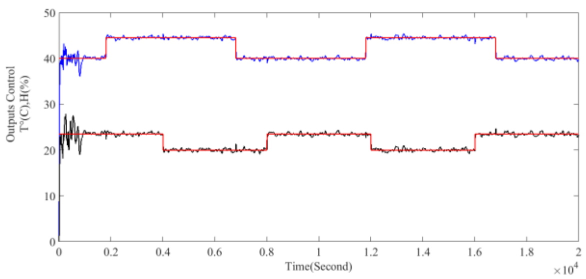

Fig. 6Responses of greenhouse air temperatures and relative humidity using the ALQG controller.

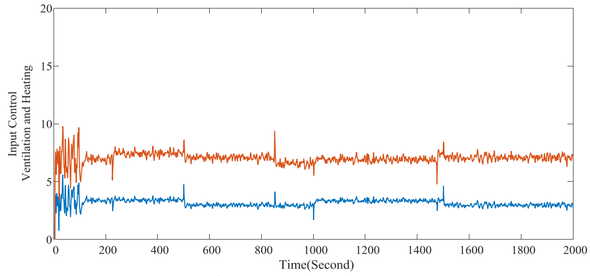

Fig. 7The input control of the greenhouse with the AMGPC controller.

V. CONCLUSION

In this paper, an adaptive multivariable controller joined with GPC control scheme with measurable disturbances has been presented. The results simulations described in this work show that we have developed the useful aspects of the proposed control algorithm through a case study concerning air temperature and relative humidity control within a microclimate greenhouse. Moreover, the AMGPC technique will be implemented and tested not only for greenhouse temperature and humidity control, but also for air CO2 concentration control.

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