Decoupling multivariable GPC with reference observation and feed-forward compensation method
Case Study: Neonate incubator

M. A. Zermani [1], E. Feki [2] and A. Mami [3]

[1] Department of Physics, Faculty of Science, Mathematics, Physics and Natural of Tunisia, Tunis, Campus Universities 2092 El Manar,Tunisia

Abstract
In this paper, we focused on a design of an algorithm for decoupling multivariable systems based on generalized predictive control (DGPC). Two techniques are developed and compared for decoupling of TITO (Two-Input, Two-Output) processes. The first method is based on adding compensators between the upper and lower control paths. According to the second method, we use an adaptive error weighting factor in cost function in order to reduce coupling between control loops. The method is applied in simulation to the multivariable control of incubator system.
Keywords: *Incubator Process, Decoupling Predictive Control, Optimal decoupling, Tuning error weighting factor.*

1. Introduction

The progressive technological evolution of servo controlled incubators has created a need constantly to increase the capacity of these incubators to reach and maintain the desired temperature[1][2]. Consequently, the temperature is one of the most important factors that must be maintained with minimal variation to keep constant internal temperature. According to the study conducted in the Center Maternity and Neonatology of Tunisia (CMNT)[3], we noted that the infant is often exposed to disruption because of successive interventions of the medical team, which requires the presence of a controller more efficient. The newest incubators, such as Drager Isolette C2000 [3][4], uses a controller based on Proportional- Integral- Derivative (PID) to control internal temperature and a ON-OFF controller to increases the moisture by vaporization water [1][15]. However, the design of an active humidification system, modeling and implementation of a controller for a multi input multi-output, highly coupled constitute a real scientific challenge[1][15][16][17].. The contribution of this paper focused on the development of a decentralized predictive decoupling controller for heating and humidification systems. Two decoupling methods designed around GPC controller were developed and compared.
The paper is structured as follows: The section 2 is devoted to present decentralized generalized predictive control with constraint. In section 3, we propose the first method of decoupling based on adding compensators between the upper and lower control paths. In second method we develop an adaptive error weighting factor in in order to reduce coupling between control loops. In section 4, computer simulations are conducted shown how the controller parameters of the two predictive control algorithms can be adapted to decrease the coupling effect between controlled variables (temperature and humidity) of incubator system.

2. Decentralized Predictive control

Decentralized control [5][6] is based on several local controllers, instead of a single controller to control a multivariable process (MIMO). Each of these controllers is responsible for controlling a single loop. The decentralized control scheme for a rnultivariable process is illustrated in Fig 1. This decentralized approach provides some advantages, both theoretical and practical very interesting to quote: Structure is easier to achieve (very simple and fast to implement it in industry). This approach is both flexible (the failure of a party system can be treated without affecting the rest, maintenance is also more easily). It is feasible to specify different performance and use of different sampling periods for each particular loop. Removal or addition of a control loop or manual mode setting does not affect the overall stability of system (other loops continue to be compensated). For these reasons, we take into count this structure Fig. 1, for the conception of the decoupling predictive control.

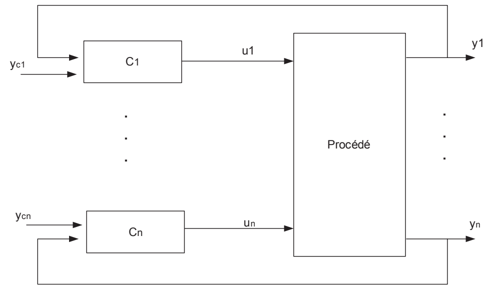

Fig. 1 Structure of decentralized control (or distributed)

2.1 Process model

The synthesis of the generalized predictive controller (GPC) suggested by (Clarke et al, 1987; Clarke, 1988) [7],[8]. This method was used successfully in industrial applications of various forms [9],[10],[11]. The approach of generalized predictive control is based on a dynamic model of type ARIMAX (Auto Regressive Integrated Moving Average with eXternal inputs), given by:

$$A_i(z^{-1})y_i(k) = z^{-d_i} B_i(z^{-1})u_i(k-1) + C_i(z^{-1})\frac{e_i(k)}{\Delta(z^{-1})}. \qquad (1)$$

Where i is the number system, $y_i(k)$ is the system output, $u_i(k)$ is the system input, $e_i(k)$ is the uncorrelated random sequence, $\Delta(z^{-1}) = 1 - z^{-1}$ corresponds to an integral action. Its presence in the direct channel allows a zero error in steady state value. $A_i(z^{-1})$, $B_i(z^{-1})$ and $C_i(z^{-1})$ are polynomials.

$$\begin{aligned} A_i(z^{-1}) &= 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_{nai} z^{-na_i}, \\ B_i(z^{-1}) &= b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_{nbi} z^{-nb_i}, \\ C_i(z^{-1}) &= 1 + c_1 z^{-1} + c_2 z^{-2} + \cdots + c_{nci} z^{-nci}. \end{aligned} \qquad (2)$$

With $na_i, nb_i\ et\ nc_i$ indicate the respective order of these polynomials.

The generalized predictive control based on the minimization of a quadratic criterion on a sliding horizon, which involves a term related to the difference between the predicted output sequence and the sequence of future control [12].

The criterion is given by:

$$J_i = \lambda_{yi} \sum_{t=N_i}^{HP_i} [y_{C_i}(k+t) - \hat{y}_i(k+t)]^2 + \lambda_{ui} \sum_{t=1}^{N_{c_i}} \Delta u_i^{\,2}(k+t-1) \quad (3)$$

with $\hat{y}_i(k)$ is the output value predicted at time k, $y_{C_i}(k)$ is the set points values at time k, $\Delta u_i(k)$ is the increment of control at time k, N_i is the minimum prediction horizon, HP_i is the maximum prediction horizon, N_{c_i} is the control horizon, λ_{ui} is the control weighting factor and λ_{yi} is the error weighting factor.

2.2 Prediction of the system output:

Consider the output expressed by (1) the output at time instant (k+t) will be:

$$y_i(k+t) = \frac{B_i(z^{-1})}{A_i(z^{-1})} u_i(k+t-d_i-1) + \frac{C_i(z^{-1})}{A_i(z^{-1})\Delta(z^{-1})} e_i(k+t) \qquad (4)$$

By applying the Euclidean algorithm on the second term of (4) we get

$$\frac{C_i(z^{-1})}{A_i(z^{-1})\Delta(z^{-1})} = L_t(z^{-1}) + z^{-t} \frac{G_t(z^{-1})}{A_i(z^{-1})\Delta(z^{-1})} \qquad (5)$$

After using (4) and (5), we assume that the term related to the disturbance is zero, the optimal predictor of the output is:

$$\hat{y}_i(k+t) = \frac{L_t(z^{-1})B_i(z^{-1})\Delta(z^{-1})}{C_i(z^{-1})} u_i(k+t-d_i-1) + \frac{G_t(z^{-1})}{C_i(z^{-1})} y_i(k) \qquad (6)$$

A second Diophantine equation decompose the predictor in two terms: a term based on the current output, old orders, the system output and a second term dependent on future orders.

$$\frac{\sigma_i(z^{-1})}{C_i(z^{-1})} = H_t(z^{-1}) + z^{-t+d_i} \frac{R_t(z^{-1})}{C_i(z^{-1})} \qquad (7)$$

With:

$$\sigma_i(z^{-1}) = L_t(z^{-1})B_i(z^{-1}) \qquad (8)$$

The optimal predictor of the output is:

$$\begin{aligned} \hat{y}_i(k+t) &= H_t(z^{-1})\Delta(z^{-1})u_i(k+t-d_i-1) + \\ &\frac{G_t(z^{-1})}{C_i(z^{-1})} y_i(k) + \frac{R_t(z^{-1})}{C_i(z^{-1})} \Delta(z^{-1})u_i(k-1) \end{aligned} \qquad (9)$$

Where $H_t(z^{-1})$ $G_t(z^{-1})$ $R_t(z^{-1})$ and $L_t(z^{-1})$ are polynomial solutions to the Diophantine equations [13]. The matrix formulation is represented by:

$$\hat{Y}_i = \hat{H}_i \Delta U_i + \hat{G}_i Y_i^* + \hat{R}_i \Delta U_i^* \qquad (10)$$

The vector of the predicted outputs $\hat{Y}_i$ is the sum of the predicted forced $\hat{H}_i \Delta U_i$ and free responses $\hat{G}_i Y_i^* + \hat{R}_i \Delta U_i^*$

with:

$$\hat{Y}_i = [\hat{y}_i(k+1/k), \hat{y}_i(k+2/k) \cdots \hat{y}_i(k+HP_i/k)]^T, \qquad (11)$$

$$Y_i^* = [y_i^*(k), y_i^*(k-1) \cdots y_i^*(k-na_i)]^T, \qquad (12)$$

$$\Delta U_i = [\Delta u_i(k) \cdots \Delta u_i(k+N_{Ci}-1)]^T, \qquad (13)$$

$$\Delta U_i^* = [\Delta u_i^*(k-1) \cdots \Delta u_i^*(k-nbi-di+1)]^T, \qquad (14)$$

$$\hat{G}_i = [G_{1+d_i}(z^{-1}) \cdots G_{HP_i+d_i}(z^{-1})]^T, \qquad (15)$$

$$\hat{R}_i = [R_{1+d_i}(z^{-1}) \cdots R_{HP_i+d_i}(z^{-1})]^T, \qquad (16)$$

$$\hat{H}_i = \begin{pmatrix} h_0 & 0 & \cdots & 0 \\ h_1 & h_0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ h_{HP_i-di-1} & h_{HP_i-di-2} & \cdots & h_{HP_i-di-N_{Ci}} \end{pmatrix} \qquad (17)$$

Where:

$$y_i^*(k) = \frac{y_i(k)}{C_i(z^{-1})}, \Delta u_i^*(k-1) = \frac{\Delta u_i(k-1)}{C_i(z^{-1})},$$

and $\begin{cases} \mathrm{DIM}(\hat{G}_i) = (\mathrm{HP}_i - \mathrm{d}_i,\ \mathrm{na}_i + \mathrm{d}_i - 1), \\ \mathrm{DIM}(\hat{R}_i) = (\mathrm{HP}_i - \mathrm{d}_i,\ \mathrm{nb}_i + \mathrm{d}_i - 1), \\ \mathrm{DIM}(\hat{H}_i) = (\mathrm{HP}_i - \mathrm{d}_i,\ \mathrm{N}_{Ci}), \end{cases}$

denote the dimension of $\hat{G}_i$, $\hat{R}_i$ and $\hat{H}_i$, respectively.

2.3 Law order

We write the criterion J in matrix form

$$J_i = [\hat{Y}_i(k) - Y_{C_i}(k)]^T \chi_i [\hat{Y}(k) - Y_{C_i}(k)] + \lambda_{ui} \Delta U_i(k)^T \Delta U_i(k) \qquad (18)$$

With:

$$Y_{Ci} = [y_{C_i}(k+d_i) \cdots y_{Ci}(k+HP_i+d_i)] \qquad (19)$$

The optimal vector ΔU_i is:

$$\Delta U_i = (\hat{H}_i^T \chi_i \hat{H}_i + \lambda_{ui} I_{N_{Ci}})^{-1} \hat{H}_i^T \hat{Y}_i^T \qquad (20)$$

The optimal control law is derived from analytical minimization of the previous cost function. Only the first control value is finally applied to the system.

$$u_i(k) = \Delta u_i(k) + u_i(k-1). \qquad (21)$$

Which $\Delta u_i(k)$ is the first element of the vector ΔU_i and I_{N_C} is diagonal matrix of size $N_{Ci} * N_{Ci}$ and χ_i is diagonal matrix of size $HP_i - d_i * HP_i - d_i$

$$I_{N_{Ci}} = \begin{pmatrix} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \end{pmatrix}, \chi_i = \begin{pmatrix} \lambda_{yi} & & 0 \\ & \ddots & \\ 0 & & \lambda_{yi} \end{pmatrix} \qquad (22)$$

2.4 Constraints formulation

Generally, the constraints imposed on the control signal and its increment are described by inequalities forms

$$\begin{aligned} & u_{\min}(k) \le u_i(k) \le u_{\max}(k) \quad \forall k \\ & -su_i \le \Delta u_i(k) \le su_i \end{aligned} \qquad (23)$$

Where $u_{\min}$, $u_{\max}$ and su_i are respectively lower threshold, the upper threshold and derivative threshold of the control inputs. On the horizon controller HC_i can be written:

$$\begin{aligned} & -su_i \le \Delta u_i(k) \le su_i, \\ & -su_i \le \Delta u_i(k+1) \le su_i, \\ & \quad \vdots \\ & -su_i \le \Delta u_i(k+HC_i-1) \le su_i, \end{aligned} \qquad (24)$$

Or in the condensed form:

$$\begin{bmatrix} I \\ -I \end{bmatrix} \Delta U_i \ge \begin{bmatrix} -\beta_1 \\ -\beta_1 \end{bmatrix}, \qquad (25)$$

With I is identity matrix of dimension (HCi, HCi), ΔU_i and β_1 are two vectors with the same dimensions HCi :

$$\begin{aligned} & \beta_1^T = [su_i \cdots\cdots su_i], \\ & \Delta U_i^T = [\Delta u_i(k), \cdots\cdots, \Delta u_i(k+HC_i-1)] \end{aligned} \qquad (26)$$

On the same horizon control we obtained:

$$u_{min} - u_i(k-1) \le \Delta u_i(k) \le u_{max} - u_i(k-1),$$
$$u_{min} - u_i(k-1) \le \Delta u_i(k) + \Delta u_i(k+1) \le u_{max} - u_i(k-1), \quad (27)$$
$$\vdots$$
$$u_{min} - u_i(k-1) \le \Delta u_i(k) + \cdots \Delta u_i(k+HC_i-1) \le u_{max} - u_i(k-1),$$

Or in the condensed form:

$$\begin{bmatrix} W \\ -W \end{bmatrix} \Delta U_i \ge \begin{bmatrix} \beta_2(k-1) \\ -\beta_3(k-1) \end{bmatrix}, \quad (28)$$

With β_2^T et β_3^T are two vectors with the same dimensions HCi:

$$\beta_2^T(k-1) = \left[\left[u_{min} - u_i(k-1)\right] \cdots \cdot \left[u_{min} - u_i(k-1)\right]\right],$$
$$\beta_3^T(k-1) = \left[\left[u_{max} - u_i(k-1)\right], \cdots \cdot, \left[u_{max} - u_i(k-1)\right]\right]. \quad (29)$$

And W is a matrix of dimension (HCi, HCi).

$$W = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & \cdots & 1 \end{bmatrix} \quad (30)$$

We can rewrite the two inequalities (3.25) and (3.28)

$$\begin{bmatrix} I \\ -I \\ W \\ -W \end{bmatrix} \Delta U_i \ge \begin{bmatrix} -\beta_1 \\ -\beta_1 \\ \beta_2(k-1) \\ -\beta_3(k-1) \end{bmatrix},$$
(31)

The problem of minimization of the criterion J with constraints is writing:

$$\min_{\Delta U_i} J_i = [\hat{Y}_i(k) - Y_{C_i}(k)]^T \chi_i [\hat{Y}_i(k) - Y_{C_i}(k)] + \lambda_{ui} \Delta U_i(k)^T \Delta U_i(k) \quad (32)$$

$$\psi \Delta U_i \ge \phi(k), \quad (33)$$

With:

$$\psi^T = \left[I, \ -I, \ W^T, \ -W^T\right]$$
$$\phi^T(k) = \left[-\beta_1^T, \ -\beta_1^T, \ \beta_2^T(k-1), \ -\beta_3^T(k-1)\right] \quad (34)$$

The minimization of this criterion cannot be performed analytically. The synthesis of the control law amounts to solving an optimization problem of a quadratic criterion under constraints like inequalities. During the simulations proposed subsequently, the determination of the optimal control sequence is done using the function "fmincon" of Matlab™.

3. Decoupling Control Design for TITO System

3.1 Optimal decoupling control

The system design of GPC decoupling control based on ideal decoupler is presented in Fig. 2

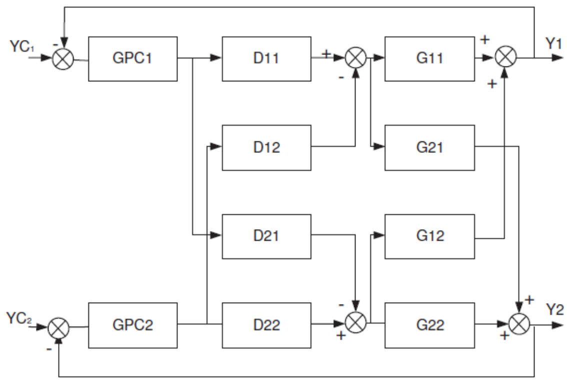

Fig . 2 Configuration of GPC decoupling control system.

D12, D21 and D22 are the decoupling compensation segment.

The advantage of using a decoupling controller over a multivariable GPC is that decoupling and tuning are separate tasks. The decoupling methods use usually in the multivariable coupled process includes diagonal matrix method, unit matrix method and feed-forward compensation method. In this work we interested to the diagonal matrix method to decouple the incubator system. In Fig. 2 G is dynamic transfer function and D is the decoupling matrix. To simplify decoupling process D11= D22=1.

The transfer functions are:

$$\begin{bmatrix} Y_1(k) \\ Y_2(k) \end{bmatrix} = \begin{bmatrix} G_{11}(z)+G_{12}(z).D_{21}(z) & G_{12}(z)+G_{11}(z).D_{12}(z) \\ G_{21}(z)+G_{22}(z).D_{21}(z) & G_{22}(z)+G_{21}(z).D_{12}(z) \end{bmatrix} \begin{bmatrix} U_1(k) \\ U_2(k) \end{bmatrix} \quad (35)$$

The decoupling conditions are obviously:

$$\begin{cases} G_{12} + G_{11} D_{12} = 0 \\ G_{21} + G_{22} D_{21} = 0 \end{cases} \quad (36)$$

The designed decoupling compensation in Fig. 6 is designed as:

$$\begin{cases} D_{11} = 1 \\ D_{22} = 1 \\ D_{21} = \dfrac{-G_{21}}{G_{22}} \\ D_{12} = \dfrac{-G_{12}}{G_{11}} \end{cases} \quad (37)$$

The decoupling dynamic transfer function is:

$$G_d(z) = \begin{bmatrix} \dfrac{G_{12}(z)}{G_{11}(z)} & 0 \\ 0 & \dfrac{G_{21}(z)}{G_{22}(z)} \end{bmatrix} \quad (38)$$

However, these controllers cannot fully solve problems with strong interactions among control loops. Adding interaction compensators to controllers can improve control [6], but in some systems, because of improper delay structure or model mismatch, interaction compensators are not applicable.

3.2 Decoupling by tuning weighting factor based on error observation

To overcome the drawback of the previous method we present a new approach to decoupling the structure of the decoupling control which is also described in the figure 3.

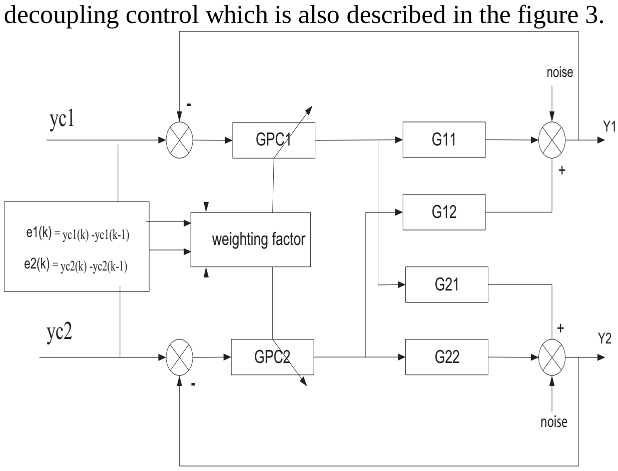

Fig. 3 Control structure of generalized predictive control with weighting factor adjusting.

The main idea of decoupling controller is the following [14]: when some reference changes its value (for example: set-point of y1) controller firstly increases only λ_{y2} in the second loop, and then calculate optimal control vector (32) and (33).

We write the criterion J of each controller:
GPC1:

$$J_1 = \lambda_{y1} \sum_{j=N_1}^{HP_1} [y_{C_1}(k+t) - \hat{y}_1(k+t)]^2 + \lambda_{u1} \sum_{j=1}^{N_C} \Delta u_1^2(k+t-1), \quad (39)$$

GPC2:

$$J_2 = \lambda_{y2} \sum_{j=N_2}^{HP_2} [y_{C_2}(k+t) - \hat{y}_2(k+t)]^2 + \lambda_{u2} \sum_{j=1}^{N_C} \Delta u_2^2(k+t-1) \quad (40)$$

This control vector would minimize output deviation caused by reference changes. Values λ_{yi} are evaluated from equation:

$$\lambda_{yi} = 1 + \sum_{j=1}^{m} \frac{K_{ri}}{M(q^{-1})} \Delta y_{Cj}(k) \quad (41)$$

K_{ri} : maximum error weight in j loop,
Δy_{Cj} : reference change on j input,
$M(q^{-1})$: Polynomial of q^{-1} defined by designer.

4. Application to an incubator system

4.1 Modeling

The incubator system include an AC-powered heater, a fan to circulate the warmed air, a container for water to add humidity and access ports for nursing care. With the technology available currently, incubators use microprocessor-based control systems to create and maintain the ideal microclimate for the preterm neonate.

In this work, we recovered an incubator (Drager Isolette C2000)[15][4] from Maternal and Neonatal Unit of Rabta-Tunisia. After that, we replaced the passive humidifier by an external block based on a ultrasonic nebulizer which is an instrument for converting a liquid into a fine spray[15][3][2].

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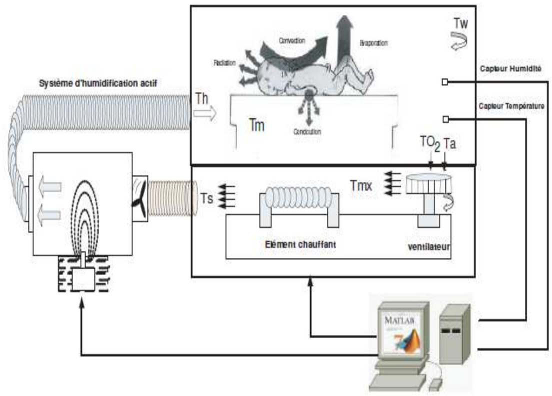

Fig. 4 Schematic of the incubator process with experimental arrangement for active humidification to control temperature and Humidity.

An experimental method is proposed for modeling of the TITO system. The incubator system has two inputs and two outputs.

The inputs to the system are:

U1: control signal applied to the heater,

U2: control signal applied to the nebulizer.

The outputs are:

Y1: temperature value output signal,

Y2: humidity level output signal.

The transfer function matrix of the incubator system can be expressed as follow:

$$\begin{bmatrix} Y_1(k) \\ Y_2(k) \end{bmatrix} = \begin{bmatrix} G_{11}(z) & G_{12}(z) \\ G_{21}(z) & G_{22}(z) \end{bmatrix} \begin{bmatrix} U_1(k) \\ U_2(k) \end{bmatrix} + \begin{bmatrix} C_1(z) & 0 \\ 0 & C_2(z) \end{bmatrix} \begin{bmatrix} e_1(k) \\ e_2(k) \end{bmatrix} \quad (42)$$

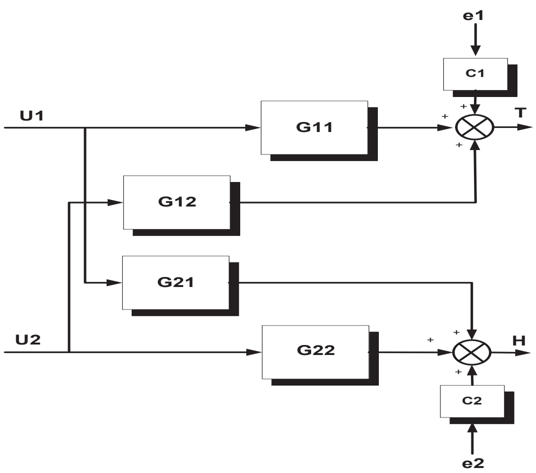

Figure 5. Input-output model of incubator system.

G11 is a transfer function showing the relation between input U1 and output y11. Likewise, G12 is the transfer function that shows the effect of input U2 to output y12, G21 indicates the effect of input U1 to y21; G22 indicates the effect of input U2 to output y22.

The transfer functions of the various subsystems are described as follow:

$$y_{ij}(k) = \frac{z^{-dij} B_{ij}(z^{-1})}{A_{ij}(z^{-1})} U_i(k-1) \quad (43)$$

$$\begin{aligned} Y_1(k) &= y_{11}(k) + y_{12}(k) + C_1 e_1(k) \\ Y_2(k) &= y_{22}(k) + y_{21}(k) + C_2 e_2(k) \end{aligned} \quad (44)$$

Where i and j are the level indices i, j = {1, 2} and A_{ij} , B_{ij} and C_{ij} are polynomials:

$$\begin{aligned} A_{ij}(z^{-1}) &= 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_{na} z^{-na} \\ B_{ij}(z^{-1}) &= b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_{nb} z^{-nb} \\ C_i(z^{-1}) &= 1 + c_1 z^{-1} + c_2 z^{-2} + \cdots + c_{nc} z^{-nc} \end{aligned} \quad (45)$$

We present the multivariable system as matrix form:

$$G(z) = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} = \begin{bmatrix} z^{-d11} \frac{B_{11}(z^{-1})}{A_{11}(z^{-1})} & z^{-d12} \frac{B_{12}(z^{-1})}{A_{11}(z^{-1})} \\ z^{-d21} \frac{B_{21}(z^{-1})}{A_{21}(z^{-1})} & z^{-d22} \frac{B_{22}(z^{-1})}{A_{22}(z^{-1})} \end{bmatrix} \quad (46)$$

$$= \begin{bmatrix} \frac{z^{-10}(5.9746\text{e-}004+5.9412\text{e-}004z^{-1})}{1\text{-} 0.3467z^{-1}\text{-}0.6463z^{-2}} & 0 \\ \frac{z^{-32}(1.3698\text{e-}004\text{-}4.1930\text{e-}004z^{-1})}{1-0.28321z^{-1}-0.7133z^{-2}} & \frac{z^{-3}(0.00203+0.00088z^{-1})}{1-0.5091z^{-1}-0.4262z^{-2}} \end{bmatrix}.$$

The temperature variation is almost not related to the change in moisture level (G12=0), and this weak relation can be modeled as a disturbance to the system. The other components are simply modeled with a second order system with a time varying delay.

4.2 Computer simulations of optimal and weighting factor decoupling of incubator system

The principal parameters are set as follows; the prediction horizon is $HP_1 = HP_2 = 20$, the control horizon is $N_{C1} = N_{C2} = 1$, the weighting factors of the control increments are $\lambda_{u1} = 0.0026$, $\lambda_{u2} = 0.6273$ and the error weighting factor is $\lambda_{y1} = \lambda_{y2} = 1$. The coupling effect was suppressed by adding interaction compensators to controllers. In the following simulation plots the ranges of the control signal applied to the heater and to the nebulizer were scaled to 0 to 100 %. The multivariable control was simulated with constraints and at sampling time T=20 seconds.

Chosen constraints $\begin{matrix} 0\% \le U_1 \le 100\% \\ 0\% \le U_2 \le 100\% \end{matrix}$

To overcome the drawback of the previous method we present the simulation result of decoupling by tuning weighting factor which λ_{y2} is evaluated from equation (41)

With :

$$M(q^{-1}) = 1 - 0.989q^{-1}, \quad Kr_2 = 5$$

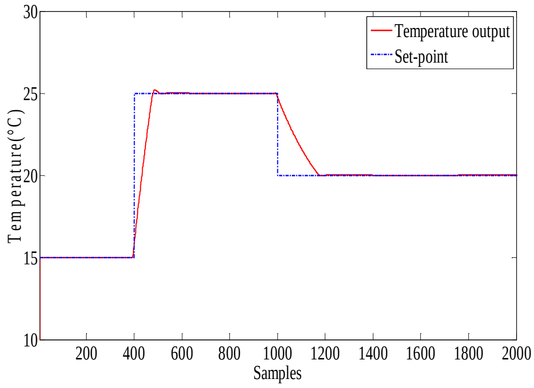

Fig. 6 Simulation result of set-point tracking temperature for predictive decoupling control.

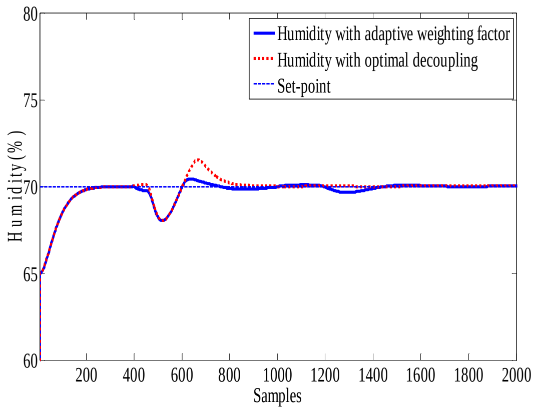

Fig. 7 Compared result of set-point tracking humidity with tuning weight factor by reference change and by adding interaction compensators .

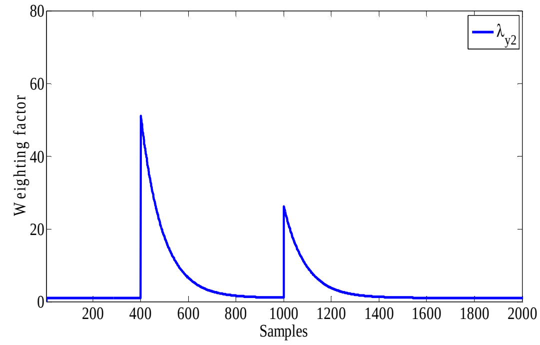

Fig. 8 Evolution of the weighting factor synchronized with change set point.

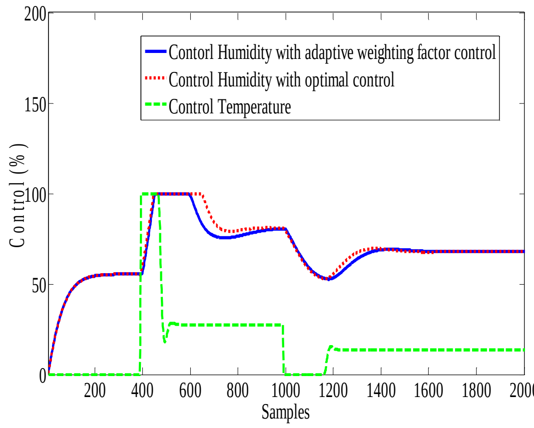

Fig. 9 Simulation results of temperature and humidity control with decoupling in incubator system

The simulation was done by using decentralized generalized predictive control with constrain. Two techniques are presented and compared for predictive control of TITO (Two-Input, Two-Output) processes. The first method is based on adding compensators between the upper and lower control paths. The second method based on synchronization of the weighting factor with a reference signal change. Described model has strong interaction between input U1 and output Y2, so the analyses has been done by changing temperature's reference and observing output signals of the humidity with two decoupling approaches. After stationary had been reached, mentioned reference increased from initial temperature to 25°C and decreases to 20°C that is seen in Fig. 6. In Fig. 7 comparing the simulation result of set-point tracking humidity for predictive control with two decoupling method proposed, it can be noticed that decoupling by adjustment weighting factor has succeeded to reduce interactions in the control loop better than the decoupling

by compensation block. In Fig 8, we present the evolution of the weighting factor which is synchronized with reference change. Fig. 9 illustrates the simulation results of temperature and humidity control with two decoupling method in incubator system.
Proposed concept of tuning weighting allows to simple decoupling controller and it is applicable to all multivariable controllers based on some cost function minimization.

5. Conclusions

In this paper, we have developed a multivariable control algorithm based on decoupled predictive control, which takes into account natural constraints on the actors (the heater and nebulizer). Simulations results have been demonstrated that decoupling by tuning weighting factor with synchronization in set-point change is simpler for implementation than decoupling by adding interaction compensators.
Main advantage of the weight decoupling method is its simplicity and computational burden, which makes it more suitable as adaptive controller for complex system than others decoupling method.

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