International Journal of Signal System Control and Engineering Application 3 (2): 13-27, 2010
ISSN: 1997-5422

Cascade Generalized Predictive Control for Heat Exchanger Process

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Abstract: The Generalized Predictive Controller (GPC) in transfer function representation is proposed for the cascade control task. The recommended cascade GPC (CGPC) applies one predictor and one cost function that results in several advantageous features: The disturbance regulations of the inner and the outer loops can be totally decoupled; the inner disturbance regulation is well damped, the typical overshoot of the traditional cascade control structure is avoided. The investigation is based on simulation experiments of heat exchanger model identified from SISO input and output data.

Key words: CGPC, GPC, HE model, predictive controllers, architecture, heat exchanger

INTRODUCTION

The GPC method was proposed by Clarke *et al.* (1987) and Clarke (1988) and become most popular MPC methods both in industry and academia. It has been successfully implemented in many industrial applications, showing good performance and certain degree of robustness. It can handle many different control problems for a wide range of plants with a reasonable number of designs variables which have to be specified by the user depending upon prior knowledge of the plant and control objectives.

The basics idea of GPC is to calculate a sequence is to calculate a sequence of future control signals in such way that it minimizes a multistage cost function defined over prediction horizon. The index to be implemented is the expectations of a quadratic function measuring the distance between the predicted system output and some reference sequence over the horizons plus a quadratic function measuring control effort.

GPC has many ideas in common with other predictive controllers since, it is based on some differences. As will be seen later, it provides analytical solution (in absence of constraints), it can deal with unstable and nonminimum phase plants and incorporates the concept of control horizons as well as the consideration of weighing of control increments in the cost functions. The general set of choices available for GPC leads to a greater variety of control objective compared to the other approaches, some of which can be considered as subsets or limiting cases of GPC.

MATERIALS AND METHODS

Cascade control: Cascade control is one of the most popular structures for process control (Maffezzoni *et al.*, 1990) as it is a special architecture for dealing with disturbances. The core idea is to feed back an intermediate variable that lies between the disturbance injection point and the controlled process output. The classical cascade control structure is shown in Fig. 1. Where w(t) is the reference signal, u(t) is the control signal and $v_{ref}(t)$ are the intermediate variable and its reference signal, $e_i(t)$ are disturbances and y(t) is the process output.

The control task is to control the y(t) output and to track the w(t) reference signal, meanwhile the process is charged with different disturbances, e_1 and e_2. The cascade structure assumes that there is an intermediate measurable variable in the process thus, the process can be separated into two sub-processes. Compared to a traditional control loop, a second control loop is introduced including only the inner process. The goal of the inner controller (or also called secondary controller) is to attenuate the effect of the inner e_1 disturbance before it significantly affects the process output. This can be realized if high gain can be applied in the secondary controller thus, the secondary loop can quickly regulate the disturbances of the inner loop. The outer controller (or so called primary controller) provides the reference signal for the secondary controller. The cascade structure's main benefits canbe exploited only in certain circumstances (Astrom and Hagglund, 1995):

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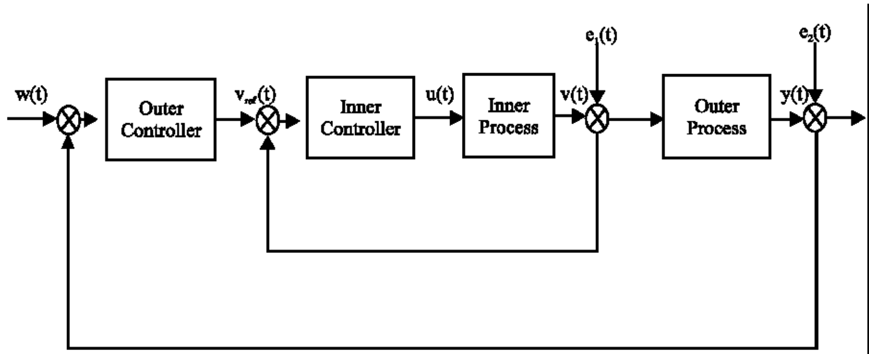

Fig. 1: Cascade control structure

- The inner process has significant nonlinearities that limit the loop performance
- The outer process has significant delay or limits the bandwidth in a basic control structure; the rule of thumb is that the average residence times should have a ratio at least 5
- Essential disturbances act in the inner loop. Even though the cascade control is a traditional method that has been applied for decades, improving the performance of the structure is still a core issue

Some books provide fundamental tuning methods for conventional cascade control systems (Shinskey, 1996; Astrom and Hagglund, 1995; Luyben, 1990). Improvements in the tuning of the traditional PID controller in cascade control scheme have been developed (Lee *et al*., 1998; Huang *et al*., 1998; Tan *et al*., 2000; Soeterboek, 1992; Song *et al*., 2003). Meanwhile new solutions are also presented, Semino and Brambilla (1996), Lestage *et al*. (1999) and Kaya (2001) proposed a cascade control scheme combined with Smith predictor proposed a new two degree of freedom cascade structure that can decouple the tracking and regulation performance and permits the tuning of the robustness of the inner and outer process separately. The robustness of the cascade controller was also given in the research of Maffezzoni *et al*. (1990). Their solution provided an independent design of the cascade control loops and intrinsic avoidance of windup problem. The number of cascade applications in the literature is enormous.

In the following, only a few applications related to the predictive control concept are going to be presented (Maciejowski, 2002; Maciejowski *et al*., 1991; Richalet *et al*., 1976, 1978; Qin and Badgwell, 2003) the application of DMC algorithm in the outer loop of the cascade control of a chlorine producing plant. The DMC gave the set point values for the multivariable compressor control. The good behavior of the proposed control structure was demonstrated on a real-time simulation of the plant. An interesting application of the MUSMAR algorithm for control of a distributed collector solar field was given by Silva *et al*. (1997). The control problem consisted of keeping constant the temperature of the field outlet oil by acting on the circulating oil flow used for heat transfer. In the inner loop, a MUSMAR controller and in the outer loop a PID controller was applied. Difficulties arose from the time varying transport delay of the process. The obtained experiences were generalized to a wide class of industrial processes (Barin, 1989; Camacho and Bordons, 2004; Goodwin *et al*., 2001; Hagglund, 1996) reported a successful application in sludge density control in a sugar factory. In both inner and outer loops GPC, controllers were applied. The study showed the tuning of the controllers regarding the robustness behaviors. The emphasis was put on how simple and powerful the predictive control algorithm was (Shaoyuan *et al*., 2000) applied cascade GPC to a biaxial film production line. In the proposed solution, the traditional control scheme was applied with GPC controllers in the primary and secondary loop as well (Hedjar *et al*., 2000, 2003). Researched the application of the MPC for control of an induction motor. They proposed the application of a nonlinear predictive controller in both the inner and the outer loop.

Cascade generalized predictive controller

Formulation of generalized predictive controller: The cascade generalized predictive controller is derived from the generalized predictive controller. First, the GPC and its main properties are presented to advance the investigation of the properties of the CGPC algorithm.

The predictive control concept: The predictive control is based on the process model applied for the prediction of the process behavior. The basic idea of the predictive control is shown in Fig. 2. The predictive controller

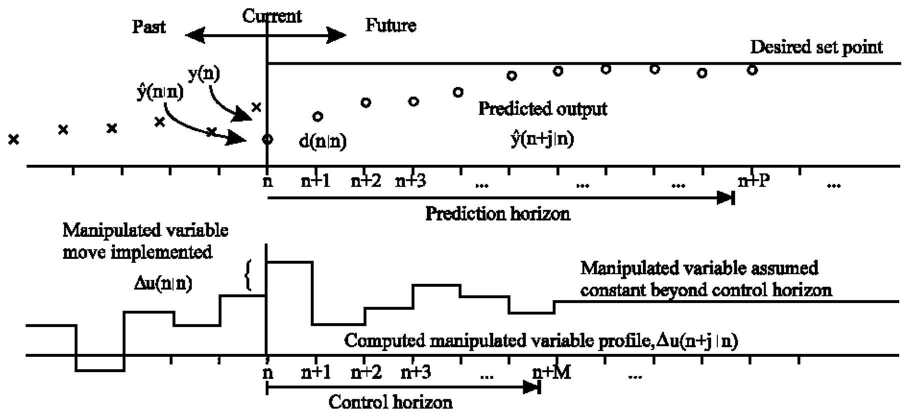

Fig. 2: Moving horizon concept of model predictive control

calculates such future control sequences that result in the process output close to the desired output on the prediction horizon. In the receding Control horizon controller, the whole control sequence is not applied only its first element and the optimization procedure is repeated in the next sampling instant. The controller may have several design parameters. The most important ones are the optimization horizon, the control horizon and the weighting factors. In the cost function, the error between the reference signal and the predicted process output appears on the time range between the minimum (H_m) and the prediction horizon (H_p) and also the control signal values are included according to the control horizon. The optimization horizon shows which future error values should count in the cost function. The control horizon (H_c) value means how many changes in the control signal are allowed in the future.

The process model: In predictive controllers, different process models can be applied. In the following, the most common ones are presented.

Transfer function model: The process output signal is given by:

$$y(t)=\frac{B(z^{-1})}{A(z^{-1})}u(t-1) \tag{1}$$

$$\begin{aligned} A(z^{-1}) &= 1+a_1z^{-1}+a_2z^{-2}+----a_{na}z^{-na} \\ B(z^{-1}) &= b_0+b_1z^{-1}+b_2z^{-2}+----b_{nb}z^{-nb} \end{aligned} \tag{2}$$

The prediction can be expressed as:

$$\hat{y}(t+k/t)=\frac{B(z^{-1})}{A(z^{-1})}u(t+k-1/t) \tag{3}$$

To separate the effects of the past and future inputs a diophantine equation must be solved:

$$\frac{B(z^{-1})}{A(z^{-1})}=E_k(z^{-1})+q^{-k+1}\frac{F_k(z^{-1})}{A(z^{-1})} \tag{4}$$

Replacing it into the prediction follows:

$$\hat{y}(t+k/t)=E_k(z^{-1})U(T+K-1/t)+\frac{F_k(z^{-1})}{A(z^{-1})}u(t) \tag{5}$$

This model is already able to describe unstable processes (i.e., integrative process) and another advantage is the limited number of required parameters. The disadvantage of the model is that a priori knowledge is required about the orders of the A and B polynomials.

Disturbance model: The disturbance model has special importance in the predictive controllers. The most general one is the Controlled Autoregressive and Integrated Moving Average (CARIMA) in which the difference between the measured output and the output calculated by the process model given by:

$$n(t)=\frac{C(z^{-1})}{D(z^{-1})}\xi(t)$$

Where the denominator $D(z^{-1})$ includes the integrator, generally chosen as $(1-z^{-1})\,A(z^{-1})$; $\xi(t)$ is a white noise with mean value of zero and the polynomial C is identified or chosen as a controller parameter. To calculate the predicted error, the following diophantine equation must be solved:

$$\frac{C(z^{-1})}{D(z^{-1})}=E_k(z^{-1})+q^{-k}\frac{F_k(z^{-1})}{D(z^{-1})} \tag{6}$$

The prediction of disturbance:

$$\hat{n}(t+k/t) = \frac{C(z^{-1})}{D(z^{-1})}\xi(t+k/t) = E_k(z^{-1})\xi$$
$$(t+k/t) + \frac{F_k(z^{-1})}{D(z^{-1})}\xi(t) \quad (7)$$

Since, the order of the E_k polynomial is <k and the $\xi(t)$ signal is a white noise with zero mean, the expected value of the first term on the right side is 0. Thus, the prediction of the future disturbance is:

$$\hat{n}(t+k/t) = \frac{F_K(z^{-1})}{D(z^{-1})}\xi(t) \quad (8)$$

The free and forced response: In the GPC, a predictor is required to estimate the future outputs with its disturbances. Combining the process model with the disturbance model, it is possible to derive the predictor to estimate the future values of the output signal based on the information available up to the actual t time instant. Taking the transfer function model and the CARIMA model, the output of the process is given by:

$$\frac{C(z^{-1})}{D(z^{-1})} = E_k(z^{-1}) + q^{-k}\frac{F(z^{-1})}{D(z^{-1})} \quad (9)$$

$$y(t) = \frac{B(z^{-1})}{A(z^{-1})}u(t-1) + \frac{C(z^{-1})}{D(z^{-1})}\xi(t) \quad (10)$$

where, $D(z^{-1}) = (1 - z^{-1})\, A(z^{-1})$ and the delay of the process is included in the B polynomial by zero first coefficients of the polynomial. The k-step ahead output prediction is given by the disturbance term can be separated into available and future information as in the previous section:

$$\hat{y}(t+k/t) = \frac{B(z^{-1})}{A(z^{-1})}u(t+k-1) + \frac{C(z^{-1})}{D(z^{-1})}\xi(t+k/t)$$
$$1 = \frac{E_k(z^{-1})D(z^{-1})}{C(z^{-1})} + q^{-k}\frac{F_k(z^{-1})}{C(z^{-1})} \quad (11)$$

Multiplying Eq. 11 with this expression follows:

$$\hat{y}(t+k/t) = \frac{E_k(z^{-1})D((z^{-1})}{C(z^{-1})}$$
$$\left[\frac{B(z^{-1})}{A(z^{-1})}u(t+k-1) + \frac{C(z^{-1})}{D(z^{-1})}\xi(t+k)\right] + \quad (12)$$
$$\frac{F_k(z^{-1})q^{-k}}{C(z^{-1})}\left[\frac{B(z^{-1})}{A(z^{-1})}u(t+k-1) + \frac{C(z^{-1})}{D(z^{-1})}\xi(t+k)\right]$$

Equivalently:

$$\hat{y}(t+k/t) = \left[\frac{E_k(z^{-1})B(z^{-1})(1-z^{-1})}{C(z^{-1})} u(t+k-1) + E_k(z^{-1})\xi(t+k)\right] +$$
$$\frac{F_k(z^{-1})q^{-k}}{C(z^{-1})}\left[\frac{B(z^{-1})}{A(z^{-1})}u(t-1) + \frac{C(z^{-1})}{D(z^{-1})}\xi(t)\right]$$

Considering that the expected value of the second term of the first row is equal to 0 and the term within the brackets in the second row is equal to the actual process output, the prediction of the process output is given by:

$$\hat{y}(t+k/t) = \frac{E_k(z^{-1})B(z^{-1})}{C(z^{-1})}u(t+k-1) +$$
$$\frac{F_K(z^{-1})}{D(z^{-1})}y(t) \quad (13)$$

The effect of the control signal is included in the first term on the right side. To separate the effect of the past and future control actions, the following diophantine equation must be solved:

$$\frac{E_k(z^{-1})B((z^{-1})}{C(z^{-1})} = G_K(z^{-1}) + q^{-k}\frac{L_k(z^{-1})}{C(z^{-1})} \quad (14)$$

The final form of the predictor is:

$$\hat{y}(t+k/t) = G_k(z^{-1})\Delta u(t+k-1) +$$
$$\frac{L_K(z^{-1})}{C(z^{-1})}\Delta u(t-1) + \frac{F_K(z^{-1})}{C(z^{-1})}y(t) \quad (15)$$

In the predictive control literature, the first term on the right side is called forced response $\hat{y}_{free}$ and the rest is called free response $\hat{y}_{free}$. The free response expresses the prediction of the process outputs based on the past inputs and assumed to keep constant the last control signal.

The free response also includes the already measured disturbances and their effect on the future outputs (expressed in the last term of predictor). The forced response corresponds to the prediction triggered by the actual and future control signal.

The cost function: Different cost functions can be applied in the predictive controllers. In the generalized predictive controller, the following form is usual:

$$J(\Delta u) = \sum_{j=H_m}^{H_p}\rho_1(j)[\hat{y}(t+j/t) - w(t+j)]^2 +$$
$$\sum_{j=1}^{H_c}\rho_2(j)[\Delta u(t+j/t)]^2 \quad (16)$$

where, w is the reference signal. The cost function includes the predicted errors and the control actions. The tuning parameters of the controllers can be properly seen in the cost function: Hm the minimum horizon, specifying the beginning of the horizon in the cost function from which point the output error is taken into account.

Since, the control action affects the process output only after the process delay, the minimum horizon is suggested to be equal or higher than the process delay.

Hp the prediction horizon, specifying the end of the horizon in the cost function in other words the last output error that is taken into account Hc the control horizon, the number of consecutive changes in the control signal ρ_1, ρ_2 the weighting vectors, enabling the weighting of the terms in the cost function also with respect to their appearance in time.

The control algorithm: The analytical minimization of the cost function is possible if no constraints on the control signal are assumed. The cost function is the following:

$$J(\Delta u) = \sum_{j=H_m}^{H_p} \rho_1(j)[\hat{y}(t+j/t) - w(t+j)]^2 + \sum_{j=1}^{H_c} \rho_2(j)[\Delta u(t+j/t)]^2 \quad (17)$$

Introducing the free and forced response notation and organizing the signals into vectormatrix form, the cost function is:

$$J(\Delta u) = (G\Delta u + \hat{y}_{free} - w)^T \Gamma_1 (G\Delta u + \hat{y}_{free} - w) + \Delta u^T \Gamma_2 \Delta u \quad (18)$$

Where;

$$\hat{y}_{free} = m \begin{bmatrix} \hat{y}_{free}(t+H_m) \\ : \\ \hat{y}_{free}(t+k) \\ .. \\ \hat{y}_{free}(t+d+H_p) \end{bmatrix} = \begin{bmatrix} L_{H_m}(z^{-1}) \\ : \\ L_k(z^{-1}) \\ .. \\ L_{H_p}(z^{-1}) \end{bmatrix} \frac{\Delta u(t-1)}{C(z^{-1})} + \begin{bmatrix} F_{H_m}(z^{-1}) \\ : \\ F_k(z^{-1}) \\ .. \\ F_{H_p}(z^{-1}) \end{bmatrix} \frac{y(t)}{C(z^{-1})} \quad \Delta u = \begin{bmatrix} \Delta u(t) \\ \Delta u(t+1) \\ .. \\ \Delta u(t+H_c) \end{bmatrix} \quad w = \begin{bmatrix} w(t+H_m) \\ w(t+k) \\ .. \\ w(t+H_p) \end{bmatrix} \quad (19)$$

$$\Gamma_1 = \mathrm{diag}[\rho_1(H_m), \rho_1(H_m+1), \ldots\ldots, \rho_1(H_p)]$$
$$\Gamma_1 = \mathrm{diag}[\rho_2(1), \rho_2(2), \ldots\ldots, \rho_2(H_c)] \quad (20)$$

and;

$$G = \begin{bmatrix} g_{min} & 0 & 0 \\ g_{min+1} & g_{min} & 0 \\ : & : & : \\ g_{H_p} & g_{H_p-1} & g_{H_p-H_{c+1}} \end{bmatrix} \quad (21)$$

Where;

$$G_k(z^{-1}) = g_0 + g_1(z^{-1}) + \ldots\ldots + g_k q^{-k} \quad (22)$$

These g_i coefficients are the same as the parameters of the step response model. Equation 18 can be written in the following form:

$$J(\Delta u) = \frac{1}{2}\Delta u^T H \Delta u + b^T \Delta u + f_0 \quad (23)$$

Where:

$$H = 2(G^T \Gamma_1 G + \Gamma_2)$$
$$b^T = 2(\hat{y}_{free} - w)^T \Gamma_1 G \quad (24)$$
$$f_0 = (\hat{y}_{free} - w)^T \Gamma_1 (\hat{y}_{free} - w)$$

The minimum of the J cost function assuming the absence of any constraints can be found by making the gradient of J equal to zero which leads to the solution:

$$\Delta u = -H^{-1}b = -(G^T \Gamma_1 G + \Gamma_2)^{-1} G \Gamma_1 (\hat{y}_{free} - w)^T \quad (25)$$

As it was already mentioned, the GPC is a receding horizon controller and thus, the first element of the calculated control signal sequence to be applied on the process. The procedure of minimization of the cost function is repeated in the next sampling instant. The applied control signal is:

$$\Delta u(t) = k(w - \hat{y}_{free}) \quad (26)$$

where, K is the first row of the matrix $(G^T \Gamma_1 G + \Gamma_2)^{-1} G \Gamma_1$. Assuming that the future reference trajectory keeps constant along the prediction horizon (or equivalently it is unknown and therefore, assumed to be constant) the control algorithm is the following:

$$\Delta u(t) = w(t) \sum_{i=H_m}^{H_p} k_i - KL \frac{\Delta u(t-1)}{C(z^{-1})} - KF \frac{y(t)}{C(z^{-1})} \quad (27)$$

Where, k_i coefficients are the elements of the K vector and:

$$L=\begin{bmatrix} L_{H_m}(z^{-1}) \\ L_{H_{m+1}}(z^{-1}) \\ .. \\ L_{H_p}(z^{-1}) \end{bmatrix} \text{and}, f=\begin{bmatrix} F_{H_m}(z^{-1}) \\ : \\ F_k(z^{-1}) \\ .. \\ F_{H_p}(z^{-1}) \end{bmatrix} \quad (28)$$

The derived controller is the GPC. The numerous predictive controllers are the following:

- The application of the CARIMA process model; the use of long-range prediction over a finite horizon
- The weight of the control increments; the application of the control horizon concept

Closed loop relations of the GPC: The derived control algorithm in Eq. 27 can be written in the following form:

$$\Delta u(t)=w(t)\sum_{i=H_m}^{H_p}k_i w(t)-\sum_{i=H_m}^{H_p}k_i L_i\frac{\Delta u(t-1)}{C(z^{-1})}-\sum_{i=H_m}^{H_p}k_i F_i\frac{y(t)}{C(z^{-1})} \quad (29)$$

The GPC controller can be easily transformed into the R-S-T structure by some simple manipulations:

$$\Delta u(t)\left(C(z^{-1})+q^{-1}\sum_{i=H_m}^{H_p}k_i L_i\right)=C(z^{-1})\sum_{i=H_m}^{H_p}k_i w(t)-\sum_{i=H_m}^{H_p}k_i F_i y(t) \quad (30)$$

The R-S-T control law is:

$$\Delta u(t)=S(z^{-1})=w(t)T(z^{-1})-y(t)R(z^{-1}) \quad (31)$$

The R-S-T polynomials: In the following the T polynomial is not:

$$S(z^{-1})=\frac{C(z^{-1})+q^{-1}\sum_{i=H_m}^{H_p}k_i L_i}{\sum_{i=H_m}^{H_p}k_i L_i};$$
$$R(z^{-1})=\frac{\sum_{i=H_m}^{H_p}k_i F_i(z^{-1})}{\sum_{i=H_m}^{H_p}k_i};T(z^{-1})=C(z^{-1}) \quad (32)$$

Distinguished and only the C polynomial notation is going to be applied. The control loop in R-S-T form is shown in Fig. 3. In the following, the R-S-T forms of the controllers are shown to facilitate the derivation of certain properties of the control loops.

The actual codes of the simulations are always implemented as the original algorithm based on Eq. 26 based on Fig. 3 by a couple of manipulations the output can be given by:

$$y(t)=\frac{\frac{C(z^{-1})}{S(z^{1})\Delta}\frac{B(z^{-1})}{A(z^{-1})}z^{-1}}{1+\frac{C(z^{-1})}{S(z^{1})\Delta}\frac{R(z^{-1})}{C(z^{-1})}\frac{B(z^{-1})}{A(z^{-1})}z^{-1}}w(t)+\frac{\frac{C(z^{-1})}{\Delta A(z^{1})}}{1+\frac{C(z^{-1})}{S(z^{1})\Delta}\frac{R(z^{-1})}{C(z^{-1})}\frac{B(z^{-1})}{A(z^{-1})}z^{-1}}\xi(t) \quad (33)$$

or equivalently:

$$y(t)=\frac{C(z^{-1})B(z^{-1})z^{-1}}{S(z^{1})A(z^{-1})+R(z^{-1})B(z^{-1})z^{-1}}w(t)+\frac{C(z^{-1})S(z^{-1})}{S(z^{1})A(z^{-1})+R(z^{-1})B(z^{-1})z^{-1}}\xi(t) \quad (34)$$

Where:

$$\bar{A}(z^{-1})=\Delta A(z^{-1})$$

The characteristic polynomial of the transfer function can be decomposed to obtain the C polynomial as a factor. To find the C polynomial in Eq. 12, the required manipulations are shown in the following. From the first Diophantine equation it follows:

$$\sum_{i=H_m}^{H_p}k_i F_i(z^{-1})=C(z^{-1})\sum_{i=H_m}^{H_p}k_i z^{i}-\bar{A}(z^{-1})\sum_{i=H_m}^{H_p}k_i E_i(z^{-1})z^{i} \quad (35)$$

From the second diophantine Eq. 4, it follows:

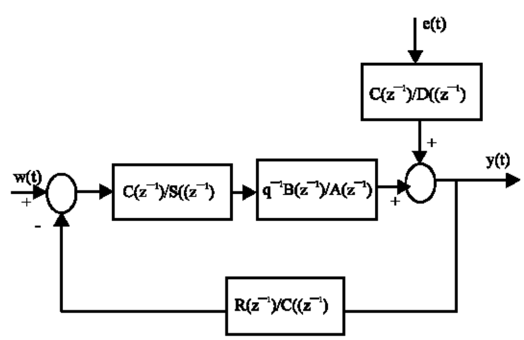

Fig. 3: The R-S-T control structure of the GPC

$$
\begin{aligned}
&B(z^{-1})\sum_{i=H_m}^{Hp} k_i E_i(z^{-1})z^{-i} = \\
&C(z^{-1})\sum_{i=H_m}^{Hp} k_i G_i(z^{-1})z^{i} + \sum_{i=H_m}^{Hp} k_i L_i(z^{-1})z^{i}
\end{aligned}
\tag{36}
$$

Combining these two equations and the definition of the R polynomial:

$$
\begin{aligned}
&BR(z^{-1}) = \frac{C}{\sum_{i=H_m}^{Hp} k_i} \\
&\left[B\sum_{i=H_m}^{Hp} k_i z^{i-1} - \bar{A}\sum_{i=H_m}^{Hp} k_i G_i z^{i-1}\right] - \frac{\sum_{i=H_m}^{Hp} k_i L_i}{\sum_{i=H_m}^{Hp} k_i}
\end{aligned}
\tag{37}
$$

The characteristic polynomial is equal to:

$$
\begin{aligned}
&S\bar{A} + BRz^{-1} = \frac{\bar{A}}{\sum_{i=H_m}^{Hp} k_i}\left[C + z^{-1}\sum_{i=H_m}^{Hp} k_i L_i\right] + \\
&\frac{C}{\sum_{i=H_m}^{Hp} k_i}\left[B\sum_{i=H_m}^{Hp} k_i z^{i-1} - \bar{A}\sum_{i=H_m}^{Hp} k_i G_i z^{i-1}\right] - \frac{\sum_{i=H_m}^{Hp} k_i L_i}{\sum_{i=H_m}^{Hp} k_i}
\end{aligned}
\tag{38}
$$

The second term in the first row and the last term in the second row are the same but shown with different signs. Thus, the characteristic polynomial:

$$
\begin{aligned}
&S\bar{A} + BRz^{-1} = \frac{C}{\sum_{i=H_m}^{Hp} k_i} \\
&\left[B\sum_{i=H_m}^{Hp} k_i z^{i-1} - \bar{A}\sum_{i=H_m}^{Hp} k_i G_i z^{i-1}\right] = CP_c
\end{aligned}
\tag{39}
$$

Recall the Eq. 38 with the elimination of the C polynomial:

$$
y(t) = \frac{Bz^{-1}}{P_c}w(t) + \frac{S}{P_c}\xi(t) \tag{40}
$$

From this expression, one important role of the C polynomial can be clearly seen. The closed loop transfer function between the output and the reference signal (describing the tracking behavior) does not include the C polynomial, thus the stability and the tracking performance is not influenced by the C polynomial. The transfer function between output and the disturbance includes the C polynomial in the S thus, the disturbance regulation depends on the C polynomial. During the derivation of these conclusions, perfect model matching was assumed. If it is not satisfied (the model applied in the controller and the process are not identical) then the shown eliminations can not be performed and the tracking behavior of the GPC will also be influenced by the noise model. In the Eq. 39 and 40, it seems that the roots of the Pc expression give the poles of the closed control loop that must be examined to check the stability of the control loop.

RESULTS AND DISCUSSION

Tuning of the GPC algorithms: The main tuning parameters (as horizons and weighting factors) were already mentioned by the cost function earlier. Now some basic guidelines are given and some simulation (identified heat exchanger model) examples are shown to illustrate the effect of the main parameters.

The minimum horizon is of little amount parameter. Since, the control action affects the process output only after the delay, it is reasonable to choose the minimum horizon higher or equal to the process delay. If the process delay is not known then, the delay can be set to one and the minimum horizon to zero without the loss of stability. The choice of the minimum horizon can be interesting in case of nonminimum phase processes.

The prediction horizon has a remarkable effect on the performance of the controller. In general, the prediction horizon is proposed to set around the settling time of the process but at least equal to the order of the process. If the plant has a nonminimum-phase response (unstable zero in the process transfer function), the prediction horizon has to be long enough that the cost function could include the samples near to the settling time. The control horizon is an essential design parameter. The increasing control horizon parameter results in a more excited control signal and thus a faster response. Over a certain value no further increase can be obtained. The control weighting parameters has the effect of reducing the control activity.

In the case of a stable plant, increasing the weights reduces the effect of the feedback thus, stabilizing the control loop. The drawback of increasing the control weights is to slow down the control loop since, small control actions are resulted. This parameter has special importance if the process output measurement is burdened with serious measurement noise. The cost function includes the vector of the future reference signal. As a consequence, it is possible to prescribe certain tracking behavior. Some parameter settings of the GPC have special importance. Set the control horizon equal to one, the control signal weighting factor equal to zero and suppose a unit step in the reference signal without any disturbance on the process. If the prediction horizon is long enough, the control signal is close to a step and the control performance is similar to the mean-level control. If the process requires even more damping of the control action, the control signal's weighting can be increased. In most of the stable plant cases, the mean-level control is suitable.

The deadbeat response can also be implemented in GPC. By setting the control and the prediction horizon to be higher than the order of the process and the control weighting factor equal to zero, the realized controller results in deadbeat control. In this case, the process output reaches the reference signal within the possible minimum instants.

Example 1: The effects of the tuning parameters on HE model, the HE model identified for set of inputs and outputs when step input applied across control valve over 1000 samples the data is recorded and model is identified using regression analysis. To show the effect of the main tuning parameters, a series of simulations are presented. The process to be controlled is the following transfer function:

$$G(s) = \frac{0.9789e^{-2.75s}}{4.7362s+1} \tag{41}$$

Thus, the time constant of the process is T, 4.7 sec; the damping factor is 0.65 and the resulting settling time (2%) is $T_{settling}$ = 30 sec. Hence in the future if it is not indicated otherwise, the sampling time is 1 sec and the weighting factor of the predicted errors is one. The minimum horizon is set to be equal to the process delay and the control signal weighting is zero.

In the first simulation the control horizon is equal to one; the prediction horizon is changed to demonstrate the it's effect. The different tracking performances and the corresponding control signals are shown in Fig. 4 and 5, respectively. Figure 4 and 5 clearly show the effect of the prediction horizon.

The shorter the horizon, the faster the response and the control signal is more excited. As it is expected, the long prediction horizon results in performance that is close to the mean level control.

The control signal is almost a step and the tracking behavior tends to the step response with unit gain as the prediction horizon increases. In the next simulation, the control horizon was changing meanwhile the prediction horizon was fixed to 23 steps. The results are shown in

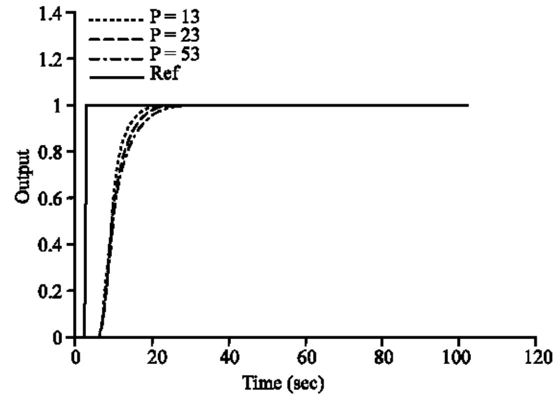

Fig. 4: The effect of the prediction horizon

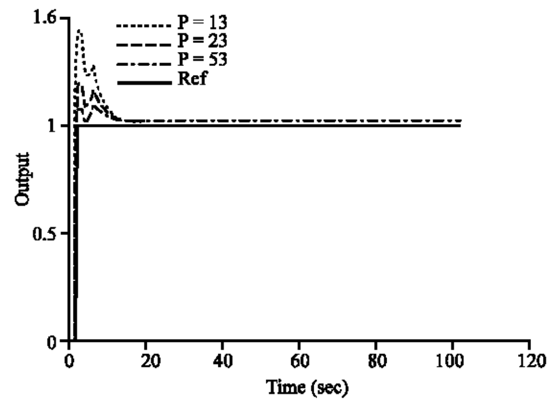

Fig. 5: The effect of the prediction hoizon

Fig. 6 and 7. It shows the effect of the control horizon well: the settling time of the control loop decreased remarkably by increasing the control horizon. From the close to mean level control (Hc = 1) with the increasing control horizon value the dead-beat response (Hc = 3) is reached. Evidently, the >3 control horizon value can not result in any further acceleration in the control loop.

The corresponding control signals reflect the great influence of the parameter. The higher control horizon value results in a more excited control signal. In Fig. 7, the control signal axis is truncated, the peaks of the control signals are approximately 1, 14 and 54, respectively.

In the next set of simulations the prediction horizon is equal to 23 steps and the control horizon is equal to 2 with the control weighting factor being changed from 0-100 (The control weighting factors are assumed to be constant along the time in the prediction). The simulation results are shown in Fig. 8 and 9. For better orientation about the weighting factor values, the elements of the G^T G matrix are within the range 12-15 in Eq. 21. The Fig. 8 shows how the increasing weighting factor slows down

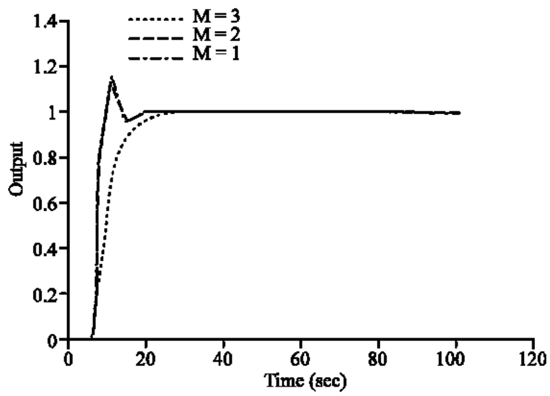

Fig. 6: The effect of the control hoizon

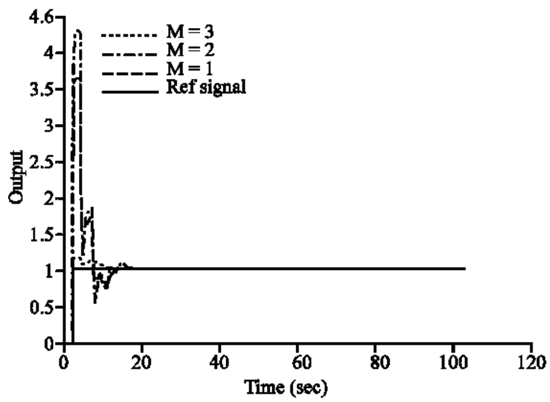

Fig. 7: The effect of the prediction hoizon. The control signal and time axis are truncated

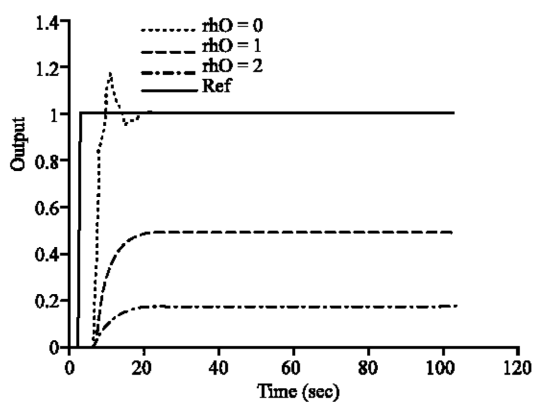

Fig. 8: The effect of the control weighting factor

the control loops by the smoother control signal. As a consequence of the smaller control increments, the overshoot also increased by the increased control weightings.

The cascade GPC algorithm: The basic idea of the cascade control structure was discussed in the introduction. A special cascade structure is introduced. In spite of the traditional, two controllers of the cascade structure only one controller is proposed as shown in Fig. 10. This realizes the same performance as in the traditional cascade structure. The control algorithm is based on the GPC algorithm but the original predictor is replaced by the special cascade predictor. Also, the cost function is unchanged. The predictor covers the whole process. It predicts the process output based on the measured process outputs y(t) on the measured intermediate variable v(t) and the past control signals $\Delta u(t-1)$. The applied process models are ARIMAX models. The model of the inner process:

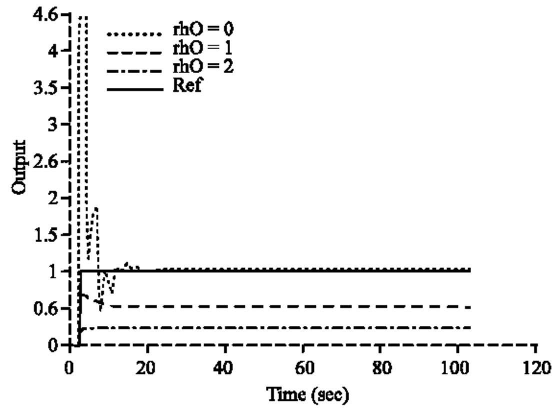

Fig. 9: The effect of the control weighting factor

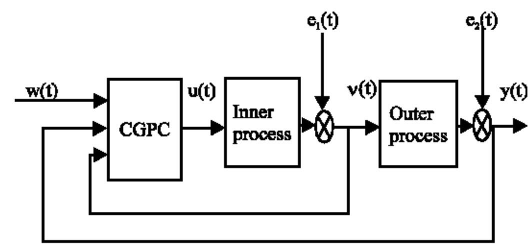

Fig. 10: Cascade generalized predictive controller

$$v(t) = \frac{B_1(z^{-1})}{A_1(z^{-1})}u(t-1) + \frac{C_1(z^{-1})}{D_1(z^{-1})}\xi(t) \qquad (42)$$

Where;

$$D_1(z^{-1}) = A_1(z^{-1})(1-z^{-1})$$

$$y(t) = \frac{B_2(z^{-1})}{A_2(z^{-1})}v(t-1) + \frac{C_2(z^{-1})}{D_2(z^{-1})}\xi_2(t) \qquad (43)$$

Where;

$$D_2(z^{-1}) = A_2(z^{-1})(1-z^{-1})$$

The k-step ahead predictor is derived throughout similar steps as in the case of the original GPC algorithm. The k-step ahead prediction of the process output:

$$\hat{y}(t+k/t)=\frac{B_2(z^{-1})}{A_2(z^{-1})}v(t+k-1)+\frac{C_2(z^{-1})}{D_2(z^{-1})}\xi_2(t+k) \quad (44)$$

The 1st diophantine equation:

$$\frac{C_2(z^{-1})}{D_2(z^{-1})}=F_{2K}(z^{-1})+\frac{G_{2K}(z^{-1})}{D_2(z^{-1})}z^{-k} \quad (45)$$

After substituting the equation:

$$\hat{y}(t+k/t)=\frac{B_2(z^{-1})D_2(z^{-1})F_{2k}(z^{-1})}{A_2(z^{-1})}v(t+k-1)+\frac{G_{2K}(z^{-1})}{A_2(z^{-1})C_2(z^{-1})}\left[\frac{B_2(z^{-1})}{A_2(z^{-1})}v(t-1)+\frac{C_2(z^{-1})}{D_2(z^{-1})}\xi_2(t)\right]F_{2k}(z^{-1})\xi_2(t+k) \quad (46)$$

Rearranging the equation and considering that the expected value of the last term is equal to zero:

$$\hat{y}(t+k/t)=\frac{B_2(z^{-1})}{C_2(z^{-1})}v(t+k-1)+\frac{G_{2K}(z^{-1})}{C_2(z^{-1})}y(t) \quad (47)$$

Where:

$$B'_{2k}(z^{-1})=\frac{B_2(z^{-1})D_2(z^{-1})F_{2k}(z^{-1})}{A_2(z^{-1})}$$
$$v(t+k-1)=B_2(z^{-1})F_{2k}(z^{-1})(1-z^{-1}) \quad (48)$$

The 2nd diophantine equation:

$$\frac{B'_{2k}(z^{-1})}{C_2(z^{-1})}=F_{2K}(z^{-1})+z^{-k+1}\frac{G'_{2K}(z^{-1})}{C_2(z^{-1})} \quad (49)$$

Substituting to the prediction equation:

$$\hat{y}(t+k/t)=F'_{2k}(z^{-1})v(t+k-1)+\frac{G'_{2K}(z^{-1})}{C_2(z^{-1})}v(t)+\frac{G_{2K}(z^{-1})}{C_2(z^{-1})}y(t) \quad (50)$$

Replacing v with the model of the inner process:

$$\hat{y}(t+k/t)=F'_{2k}(z^{-1})\left[\frac{B_1(z^{-1})}{A_1(z^{-1})}u(t+k-2)+\frac{C_1(z^{-1})}{D_1(z^{-1})}\xi(t+k-1)\right]+\frac{G'_{2K}(z^{-1})}{C_2(z^{-1})}v(t)+\frac{G_{2K}(z^{-1})}{C_2(z^{-1})}y(t) \quad (51)$$

The 3rd diophantine equation:

$$\frac{F_{2k}(z^{-1})C_1(z^{-1})}{D_1(z^{-1})}=F_{1k}(z^{-1})+\frac{G_{1K}(z^{-1})}{D_1(z^{-1})}z^{-k+1} \quad (52)$$

After substituting the equation:

$$\hat{y}(t+k/t)=\left[\begin{array}{l}\frac{B_1(z^{-1})D_1(z^{-1})F_{1K}(z^{-1})}{A_1(z^{-1})C_1(z^{-1})}u(t+k-2)+\\ \frac{G_{1K}(z^{-1})}{C_1(z^{-1})}v(t)+F_{1k}(z^{-1})\xi_1(t+k-1)+\\ \frac{G_{2K}(z^{-1})}{C_2(z^{-1})}v(t)+\frac{G_{2K}(z^{-1})}{C_2(z^{-1})}y(t)\end{array}\right]$$

After additional rearrangements and considering zero mean value for the future disturbance:

$$\hat{y}(t+k/t)=\frac{B_1(z^{-1})F_{1K}(z^{-1})}{C_1(z^{-1})}u(t+k-2)+\left[\frac{G_{1K}(z^{-1})}{C_1(z^{-1})}+\frac{G'_{2K}(z^{-1})}{C_1(z^{-1})}\right]v(t)+\frac{G_{2K}(z^{-1})}{C_2(z^{-1})}y(t) \quad (53)$$

$$\hat{y}(t+k/t)=\frac{B'_1(z^{-1})}{C_1(z^{-1})}u(t+k-2)+\left[\frac{G_{1K}(z^{-1})}{C_1(z^{-1})}+\frac{G'_{2K}(z^{-1})}{C_1(z^{-1})}\right]v(t)+\frac{G_{2K}(z^{-1})}{C_2(z^{-1})}y(t) \quad (54)$$

Where;

$$B_1(z^{-1})=B_1(z^{-1})F_{1K}(z^{-1})$$

The 4th diophantine equation:

$$\frac{B'_{1k}(z^{-1})C_1(z^{-1})}{C_1(z^{-1})}=F'_{1k}(z^{-1})+\frac{G_{1K}(z^{-1})}{C_1(z^{-1})}z^{-k+1}$$

Substituting it to get the final expression of the k step prediction:

$$\hat{y}(t+k/t) = F_{1k}(z^{-1})\Delta u(t+k-2) + \frac{G'_{1K}(z^{-1})}{C_1(z^{-1})}\Delta u(t-1) + \begin{bmatrix} \frac{G_{1K}(z^{-1})}{C_1(z^{-1})} + \\ \frac{G'_{2K}(z^{-1})}{C_1(z^{-1})} \end{bmatrix} v(t) + \frac{G_{2K}(z^{-1})}{C_2(z^{-1})} y(t) \quad (55)$$

The final expression of the cascade predictor contains one extra term of the v(k) compared to the predictor of the original GPC controller.

The control algorithm: Based on the derived cascade predictor, the control algorithm is given in a similar way than in the case of the original GPC. The only difference is that the formula of the free response that is extended with the terms including the effect of the intermediate variable:

$$\hat{y}_{free} = \begin{bmatrix} G'_{1,H_m}(z^{-1}) \\ : \\ G'_{1,H_p}(z^{-1}) \end{bmatrix} \frac{\Delta u(t-1)}{C_1(z^{-1})} + \begin{bmatrix} G'_{1,H_m}(z^{-1}) \\ : \\ G'_{1,H_p}(z^{-1}) \end{bmatrix} \frac{v(t)}{C_1(z^{-1})} + \begin{bmatrix} G_{2,H_m}(z^{-1}) \\ : \\ G_{2,H_p}(z^{-1}) \end{bmatrix} \frac{v(t)}{C_2(z^{-1})} + \begin{bmatrix} G_{2,H_m}(z^{-1}) \\ : \\ G'_{2,H_p}(z^{-1}) \end{bmatrix} \frac{y(t)}{C_2(z^{-1})} \quad (56)$$

The cost function is exactly the same as in the case of the original GPC algorithm (Eq. 6) thus, the analytical solution leads to:

$$\Delta u = -H^{-1}b = -(F^T\Gamma_1 F + \Gamma_2)F\Gamma_1(\hat{y}_{free} - w)^T \quad (57)$$

Where;

$$F = \begin{bmatrix} f_0 & 0 & 0 \\ f_0 & f_1 & 0 \\ : & : & : \\ f_{H_p} & f_{H_{p-1}} & f_{H_p-H_c+1} \end{bmatrix} \quad (58)$$

And:

$$F_{1k}'(z^{-1}) = f_0 + f_1(z^{-1}) + ... + f_1(z^{-k})$$

The applied control signal according to the receding horizon concept is:

$$\Delta u = K(w - \hat{y}_{free}) \quad (59)$$

where, K is again the first row of the matrix:

$$(G^T\Gamma_1 G + \Gamma_2)^{-1}G^T \quad (60)$$

Assuming that the future reference trajectory keeps constant along the prediction horizon, the control algorithm is given by:

$$\Delta u(t) = w(t)\sum_{i=H_m}^{H_p} k_i w(t) - \sum_{i=H_m}^{H_p} k_i G'_{1i}\frac{\Delta u(t-1)}{C_1} - \sum_{i=H_m}^{H_p} k_i G_{1i}\frac{v(t)}{C_1} - \sum_{i=H_m}^{H_p} k_i G'_{2i}\frac{v(t)}{C_2} - \sum_{i=H_m}^{H_p} k_i G_{2i}\frac{y(t)}{C_2} \quad (61)$$

or equivalently:

$$\Delta u(t) = \left(C_1 + z^{-1}\sum_{i=H_m}^{H_p} k_i G'_{1i}\right) = C_1\sum_{i=H_m}^{H_p} k_i w(t) - \sum_{i=H_m}^{H_p} k_i G_{1i} v(t) - \sum_{i=H_m}^{H_p} k_i G'_{2i}\frac{C_1}{C_2}v(t) - \sum_{i=H_m}^{H_p} k_i G_{2i}\frac{C_1}{C_2}y(t) \quad (62)$$

From this Eq. 62, the R-S-T kind polynomials can be seen:

$$S(z^{-1}) = \frac{C_1 + z^{-1}\sum_{i=H_m}^{H_p} k_i G'_{1i}}{\sum_{i=H_m}^{H_p} k_i}; R_1(z^{-1}) = \frac{\sum_{i=H_m}^{H_p} k_i G_{1i}}{\sum_{i=H_m}^{H_p} k_i}; R_2(z^{-1}) = \frac{\sum_{i=H_m}^{H_p} k_i G'_{2i}}{\sum_{i=H_m}^{H_p} k_i}; R_3(z^{-1}) = \frac{\sum_{i=H_m}^{H_p} k_i G_{2i}}{\sum_{i=H_m}^{H_p} k_i} \quad (63)$$

The structure of the control loop is given in Fig. 11. In the derivation of the predictor both the inner and the outer sub-processes are modeled with ARIMAX models. As a consequence an error free disturbance regulation is expected from the controller.

In Fig. 11, the integrator can be well observed in the inner loop. To obtain error free regulation, an integrator should appear in the outer loop as well. Therefore, the closed loop transfer function of the inner loop (without the outer feedback) should contain an integrator. The closed loop transfer function of the inner loop can be expressed as follow:

$$Y_{1'CL} = \frac{\frac{B_1(z^{-1})}{\bar{A}_1}\frac{C_1}{S}}{1 + \frac{B_1(z^{-1})}{\bar{A}_1}\frac{C_1}{S}\left[\frac{R_1}{C_1} + \frac{R_2}{C_2}\right] +} = \frac{z^{-1}B_1C_1}{\bar{A}_1C_2S + z^{-1}B_1(C_2R_1 + C_1R_2} \quad (64)$$

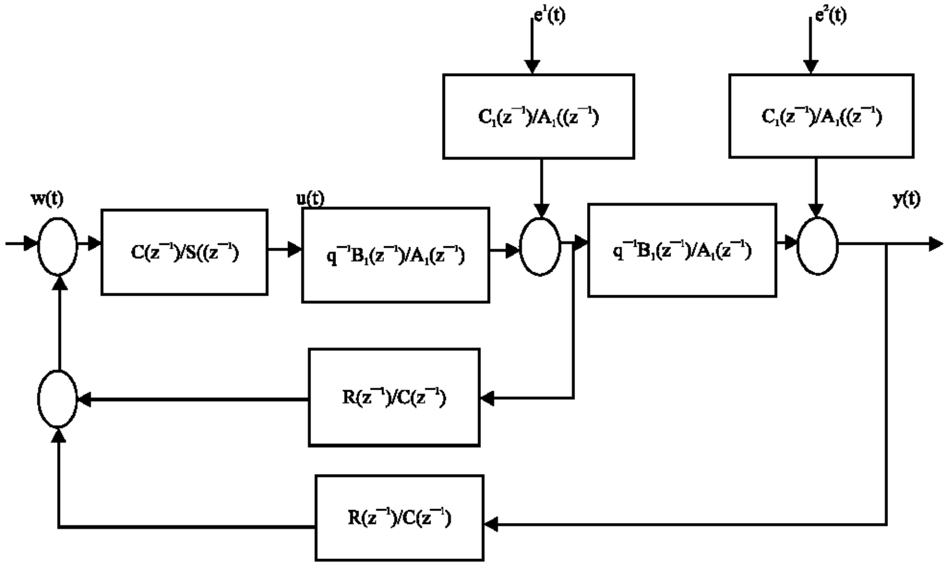

Fig. 11: The control structure of the cascade generalized predictive controller

Recalling that $\bar{A}_1 = \Delta A_1$, the first term of the denominator includes the $1-z^{-1}$ term. From the 3rd Diophantine Eq. 64:

$$\sum_{i=H_m}^{H_p} k_i G_{1i} = C_1 \sum_{i=H_m}^{H_p} k_i F'_{2i} z^{i-1} - \bar{A}_1 \sum_{i=H_m}^{H_p} k_i F_{1i} z^{i-1} \quad (65)$$

From the 2nd Diophantine equation. Combining these expressions we get:

$$C_2 \sum_{i=H_m}^{H_p} k_i F'_{2i} z^{i-1} = \Delta B_2 \sum_{i=H_m}^{H_p} k_i F_{2i} z^{i-1} - \sum_{i=H_m}^{H_p} k_i G'_{2i} \quad (66)$$

The 2nd term is equal to the $C_1 R_2$ expression:

$$C_2R_1 + C_1R_2 = C_1 \Delta B_2 \frac{\sum_{i=H_m}^{H_p} k_i F_{2i} z^{i-1}}{\sum_{i=H_m}^{H_p} k_i} - C_2 \bar{A}_1 \frac{\sum_{i=H_m}^{H_p} k_i F_{1i} z^{i-1}}{\sum_{i=H_m}^{H_p} k_i}$$
$$= \Delta \left(C_1 B_2 \frac{\sum_{i=H_m}^{H_p} k_i F_{2i} z^{i-1}}{\sum_{i=H_m}^{H_p} k_i} - C_2 A_1 \frac{\sum_{i=H_m}^{H_p} k_i F_{1i} z^{i-1}}{\sum_{i=H_m}^{H_p} k_i} \right) \quad (67)$$

$$C_2 R_1 = C_2 \frac{\sum_{i=H_m}^{H_p} k_i G_{1i}}{\sum_{i=H_m}^{H_p} k_i} = C_1 \frac{\Delta B_2 \sum_{i=H_m}^{H_p} k_i F_{2i} z^{i-1}}{\sum_{i=H_m}^{H_p} k_i} -$$

$$C_1 \frac{\sum_{i=H_m}^{H_p} k_i G'_{2i}}{\sum_{i=H_m}^{H_p} k_i} - C_2 \bar{A}_1 \frac{\sum_{i=H_m}^{H_p} k_i F_{1i} q^{i-1}}{\sum_{i=H_m}^{H_p} k_i} \quad (68)$$

This expression means that the closed loop transfer function of the inner loop contains an integrative effect, and thus, facilitates the error free regulation of the disturbances arising in the outer loop as well.

Example 2: Comparison of a simple GPC and the CGPC for HE model: This example illustrates the advantage of the cascade structure: a process is controlled by an original GPC and by a cascade GPC (Fig. 12). The CGPC is going to be compared to cascade loop containing two GPCs. The inner and outer process model identified for HE process are. The inner process is:

$$G_1(s) = \frac{0.9789 e^{-2..75s}}{4.7362s + 1} \quad (69)$$

The outer process is:

$$G(s) = \frac{0.9818 e^{-2.533s}}{6.1941s + 1} \quad (70)$$

These processes are going to be applied in the following to test and compare the cascade structures. The ratio of the average residence times (corresponding to the 2% error) is about six therefore, it can be considered as a

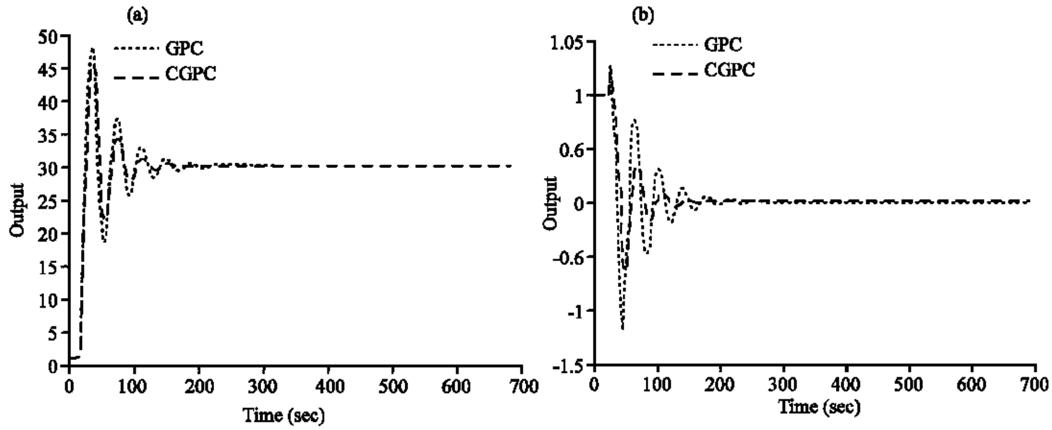

Fig. 12: The tracking and regulation behavior of the CGPC and the original GPC

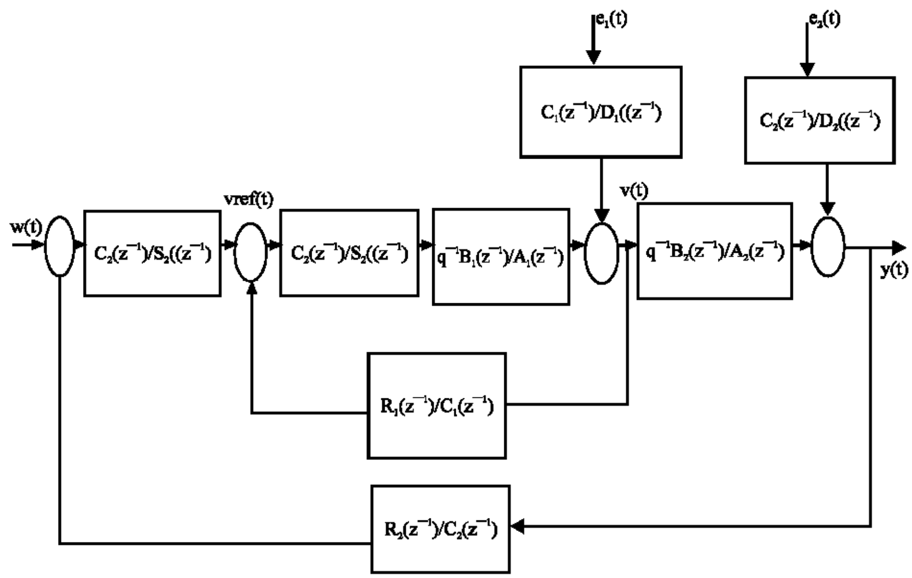

Fig. 13: The structure of the cascade control loop including 2 GPCs

typical process where cascade control is relevant. The parameters of the controllers are: $H_p = 40$; $H_c = 2$; the control weighting factor is 0. In the CGPC, the C_1 polynomial is equal to the denominator of the inner process; the C_2 is equal to the denominator of the outer process. The C polynomial of the GPC algorithm was equal to the convolution of the C_1 and C_2 polynomials. In the simulation, there was an inner (e_1) and an outer disturbance (e_2) at 200 and 600 sec, respectively both are step kind with amplitude 0.5. The outer process outputs (primary outputs) of the control loops are shown in Fig. 13. It clearly shows the difference and the similarities of the control loops. The tracking behaviors and the outer output disturbance (e_2) regulations are identical in both cases since, the controller parameters are identical. This implies that all the good properties of the GPC are kept in the CGPC. The main difference is in the intermediate disturbance regulation. The CGPC acts much earlier to regulate this disturbance because its prediction is based on the intermediate variable as well. This behavior is specific to the cascade structures. Both controllers could regulate the disturbances without error. Thus, the CGPC controller is also able to regulate perfectly. This result was expected based on the derivation since, ARIMAX models were applied for both the inner and the outer processes. It is important to distinguish the CGPC controller and the GPC controller extended with feedforward action. In the CGPC control loop, the disturbance is not measured only its effect on the intermediate variable. Meanwhile in the disturbance feedforward compensation, the disturbance signal is measured. As a consequence in the CGPC, all the disturbances affecting the inner variable are regulated not only the measured disturbance as it is in the feedforward compensation.

CONCLUSION

This study simulates the effect of cascaded GPC and GPC control algorithms on a model of heat exchanger process in terms of servo and regulatory performance with inner loop disturbance (d_1) and outer loop disturbance (d_2). After their implementation in the HE process their step response was simulated using the Matlab/Simulink™ software and compared with the conventional GPC controller, tuned by various practical scenarios. Such scenarios include the implementation of input constraints or disturbances. According to the simulations results, cascaded GPC control algorithms perform satisfactory step behavior with good set point tracking and smooth steady state approach. They also sustain their robustness and performance during the introduction of input constraints or measured disturbances. Surprisingly, the step response of the conventional GPC controller wasn't as optimal as it has been expected as its overshoot exceeds any typical specification limits.

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