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IMPROVEMENT OF THE DECOUPLING EFFECT OF THE PREDICTIVE CONTROLLER GPC AND PFC BY PARAMETER ADAPTATION

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Abstract: Two simple techniques are presented and compared for predictive control of TITO (Two-Input, Two-Output) processes to improve the decoupling effect. These techniques are applied for GPC (Generalized Predictive Control) and PFC (Predictive Functional Control). According to the first technique the controller parameters are tuned in synchronization to a reference signal change. According to the second one the controller parameters are set dependent on the actual control error. The second method makes the synchronization to a reference signal change superfluous and its realization is therefore very easy.

Keywords: Generalized predictive control, predictive functional control, controller parameter adaptation, control error-dependent controller parameters

1. INTRODUCTION

Improvement of the decoupling effect in multivariable processes is an important issue. It is desired that change of one reference signal would affect mainly on the corresponding controlled variable, while the effect on the others with constant reference signal would be reduced, i.e. the control error of the other controlled variables would be minimized (Maurath, Seborg and Mellichamp, 1986). MIMO (Multi-Input, Multi-Output) controllers can handle this problem using manually designed decoupling controllers or MIMO predictive controller which enhances the decoupling automatically.

The question arises how the decoupling can be improved without complicated multivariable controller design. In this paper two different methods are recommended for multivariable control of stable aperiodic processes. The TITO controller is realized by GPC (Generalized predictive control) (Clarke et. al., 1987) and PFC (Predictive Functional Control) (Richalet and O'Donavan, 2009).

The paper is structured as follows. In section 2 the TITO GPC algorithm is shown. In section 3 the TITO PFC algorithm is shown. In section 4 a TITO process is controlled by both predictive control algorithms with fixed controller parameters. In sections 5 and 6 two different methods are shown how the controller parameters of the two predictive control algorithms can be adapted to decrease the coupling effect. The results are summarized in the conclusion.

2. GENERALIZED PREDICTIVE CONTROL

The cost function of a TITO predictive control is:

$$\begin{aligned}J &= \lambda_{y1}\sum_{n_e=n_{e11}}^{n_{e21}}[y_{r1}(k+d_1+1+n_e)-\hat{y}_1(k+d_1+1+n_e\,|\,k)]^2 \\ &+\lambda_{y2}\sum_{n_e=n_{e12}}^{n_{e22}}[y_{r2}(k+d_2+1+n_e)-\hat{y}_2(k+d_2+1+n_e\,|\,k)]^2 \\ &+\lambda_{u1}\sum_{j=0}^{n_{u1}-1}\Delta u_1^2(k+j)+\lambda_{u2}\sum_{j=0}^{n_{u2}-1}\Delta u_2^2(k+j)\Rightarrow \underset{\Delta\mathbf{u}}{MIN}\end{aligned} \tag{1}$$

with the denotations:

- $y_{ri}(k+d_i+1+n_e\,|\,k)$: reference signal of the i-th output n_e steps over the dead time d_i,
- $\hat{y}_i(k+d_i+1+n_e\,|\,k)$: predicted i-th output signal n_e steps over the dead time.

The tuning parameters of the control algorithm in (1) are:

- $n_{e2i}-n_{e1i}+1$: length of the prediction horizon for the i-th output,
- n_{ui}: length of the control horizon of the i-th input,
- λ_{yi}: control error weighting factor of the i-th output,
- λ_{ui}: control increments weighting factor of the i-th input.

The control increments vector in the control horizon from k to $k+n_{ui}-1$ which has to be optimized is:

$$\begin{aligned}\Delta\mathbf{u}_1 &= [\Delta u_1(k\,|\,k)\ \ldots\ \Delta u_1(k+n_{u1}-1\,|\,k)]^T \\ \Delta\mathbf{u}_2 &= [\Delta u_2(k\,|\,k)\ \ldots\ \Delta u_2(k+n_{u2}-1\,|\,k)]^T \\ \Delta\mathbf{u} &= \left[\Delta\mathbf{u}_1^T\ \ \Delta\mathbf{u}_2^T\right]^T\end{aligned} \tag{2}$$

The predicted i-th output vector in the future time domain (prediction horizon) from $k+d_i+1+n_{e1i}$ to $k+d_i+1+n_{e2i}$ can be divided into free and forced responses:

$$\hat{\mathbf{y}}_i = \hat{\mathbf{y}}_{i,free} + \hat{\mathbf{y}}_{i,forc}$$

$$\begin{bmatrix}\hat{y}_i(k+d_i+1+n_{e1i}\,|\,k)\\ \vdots \\ \hat{y}_i(k+d_i+1+n_{e2i}\,|\,k)\end{bmatrix} = \begin{bmatrix}\hat{y}_{i,free}(k+d_i+1+n_{e1i}\,|\,k)\\ \vdots \\ \hat{y}_{i,free}(k+d_i+1+n_{e2i}\,|\,k)\end{bmatrix} + \hat{\mathbf{y}}_{i,forc} \tag{3}$$

The predicted forced i-th output vector in (3) is:

$$\hat{\mathbf{y}}_{i,forc} = \sum_{j=1}^{2}\mathbf{H}_{ij}\Delta\mathbf{u}_j \tag{4}$$

where:

$$\mathbf{H}_{ij} = \begin{bmatrix} h_{ij}(n_{e1i}+1) & h_{ij}(n_{e1i}) & \cdots & h_{ij}(n_{e1i}-n_{uj}+2) \\ h_{ij}(n_{e1i}+2) & h_{ij}(n_{e1i}+1) & \cdots & h_{ij}(n_{e1i}-n_{uj}-1) \\ \vdots & \vdots & \vdots & \vdots \\ h_{ij}(n_{e2i}+1) & h_{ij}(n_{e2i}) & \cdots & h_{ij}(n_{e2i}-n_{uj}+2)\end{bmatrix} \tag{5}$$

whereas $\mathbf{H}_{ij}$ is the matrix of step response coefficients of the process model, and $h_{ij}(k) = 0$ if $k < 0$.

For the TITO process, the predicted vectors (in the prediction horizon) of the reference signals, process outputs, free responses and forced responses are respectively:

- $\mathbf{y}_r = \left[\mathbf{y}_{r1}^T, \mathbf{y}_{r2}^T\right]^T$: predicted reference signals,
- $\hat{\mathbf{y}} = [\hat{\mathbf{y}}_1^T, \hat{\mathbf{y}}_2^T]^T$: predicted outputs,
- $\hat{\mathbf{y}}_{free} = [\hat{\mathbf{y}}_{1free}^T, \hat{\mathbf{y}}_{2free}^T]^T$: predicted free responses,
- $\hat{\mathbf{y}}_{forc} = [\hat{\mathbf{y}}_{1forc}^T, \hat{\mathbf{y}}_{2forc}^T]^T$: predicted forced outputs.

The predicted vector of the forced responses is:

$$\hat{\mathbf{y}}_{forc} = \begin{bmatrix} \sum_{j=1}^{2} \mathbf{H}_{1j} \Delta\mathbf{u}_j \\ \sum_{j=1}^{2} \mathbf{H}_{2j} \Delta\mathbf{u}_j \end{bmatrix} = \begin{bmatrix} \mathbf{H}_{11} & \mathbf{H}_{12} \\ \mathbf{H}_{21} & \mathbf{H}_{22} \end{bmatrix} \begin{bmatrix} \Delta\mathbf{u}_1 \\ \Delta\mathbf{u}_2 \end{bmatrix} = \mathbf{H}\Delta\mathbf{u} \tag{6}$$

The cost function (1) becomes:

$$J = \left(\mathbf{y}_r - \hat{\mathbf{y}}\right)^T \mathbf{\Lambda}_y \left(\mathbf{y}_r - \hat{\mathbf{y}}\right) + \Delta\mathbf{u}^T \mathbf{\Lambda}_u \Delta\mathbf{u} \Rightarrow \underset{\Delta\mathbf{u}}{MIN} \tag{7}$$

with the diagonal weighting matrices (for simplicity) of the control errors and the control increments:

$$\mathbf{\Lambda}_y = \mathbf{\Lambda}_y^T = \mathbf{diag}\left\langle \mathbf{\Lambda}_{y1}, \mathbf{\Lambda}_{y2} \right\rangle = \mathbf{diag}\left\langle \lambda_{y1}\mathbf{I}, \lambda_{y2}\mathbf{I} \right\rangle;$$
$$\mathbf{\Lambda}_u = \mathbf{\Lambda}_u^T = \mathbf{diag}\left\langle \mathbf{\Lambda}_{u1}, \mathbf{\Lambda}_{u2} \right\rangle = \mathbf{diag}\left\langle \lambda_{u1}\mathbf{I}, \lambda_{u2}\mathbf{I} \right\rangle$$

and $\mathbf{I}$ is the identity matrix.

Substituting of free and forced responses vectors results in:

$$J = \left(\mathbf{y}_r - \hat{\mathbf{y}}_{free} - \mathbf{H}\Delta\mathbf{u}\right)^T \mathbf{\Lambda}_y \left(\mathbf{y}_r - \hat{\mathbf{y}}_{free} - \mathbf{H}\Delta\mathbf{u}\right) + \Delta\mathbf{u}^T \mathbf{\Lambda}_u \Delta\mathbf{u} \Rightarrow \underset{\Delta\mathbf{u}}{MIN} \tag{8}$$

Unconstrained minimization of the cost function (8) according to the whole sequence of input increments in the control time domain leads to:

$$\frac{dJ(\Delta\mathbf{u})}{d\Delta\mathbf{u}} = -\mathbf{H}^T \left[\mathbf{\Lambda}_y^T + \mathbf{\Lambda}_y\right]\left(\mathbf{y}_r - \hat{\mathbf{y}}_{free} - \mathbf{H}\Delta\mathbf{u}\right) + \left[\mathbf{\Lambda}_u^T + \mathbf{\Lambda}_u\right]\Delta\mathbf{u} = \mathbf{0}$$

which results in

$$\Delta\mathbf{u} = \left[\mathbf{H}^T \mathbf{\Lambda}_y \mathbf{H} + \mathbf{\Lambda}_u\right]^{-1} \mathbf{H}^T \mathbf{\Lambda}_y \left(\mathbf{y}_r - \hat{\mathbf{y}}_{free}\right) \tag{9}$$

According to the receding horizon technique only the actual control signals will be used and the computation is repeated in the next control step:

$$\Delta\mathbf{u}_{actual}(k) = [\Delta u_1(k), \Delta u_2(k)]^T \tag{10}$$

3. PREDICTIVE FUNCTIONAL CONTROL

The principle of SISO PFC with constant reference signal is that the controlled variable achieves the reference trajectory at the target point using one change in the manipulated variable. The desired change in the controlled variable during the prediction horizon n_p (from the actual time k) is calculated from the change of the reference trajectory and compared to the predicted change of the non-delayed model output to define the required control signal, see Fig. 1.

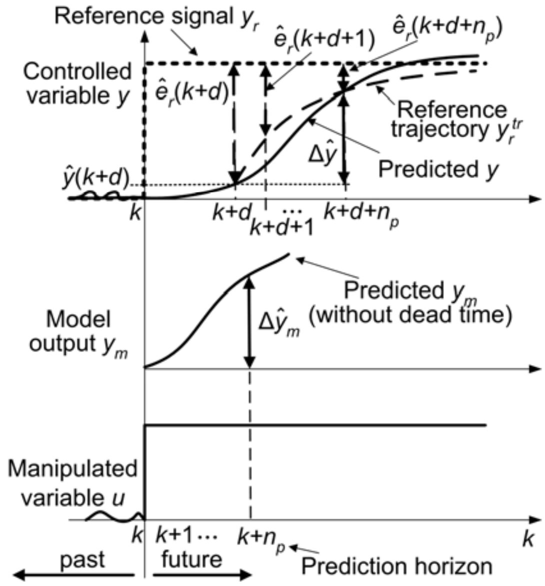


Fig. 1. PFC principle of processes with dead time

The aim of the control equation is:

$$\begin{aligned} &\hat{y}(k+d_m+n_p\,|\,k) - \hat{y}(k+d_m\,|\,k) = \hat{y}_m(k+n_p\,|\,k) - y_m(k) \\ &(1-\lambda_r^{n_p})[y_r - \hat{y}(k+d_m\,|\,k)] = \hat{y}_m(k+n_p\,|\,k) - y_m(k) \end{aligned} \tag{11}$$

with the denotations:

- $\hat{y}(k+d_m+n_p\,|\,k)$: predicted controlled variable n_p steps over the dead time d_m,
- y_r : reference signal (supposed constant in the future),
- $\hat{y}_m(k+n_p\,|\,k)$: predicted non-delayed model output n_p steps over the actual time,
- λ_r : reduction ratio of the bias between the reference signal and its trajectory.

The controller parameters (for sampling time Δt) are:

- $T_c = -3\Delta t / \ln(\lambda_r)$: desired closed loop settling time
- n_p : prediction horizon (≥ 1)

The control equation of PT1 (proportional, 1st-order) process with dead time (chosen for simplicity) is described as:

$$u(k) = k_0[y_r - \hat{y}(k+d_m\,|\,k)] + k_1 y_m(k) \tag{12}$$

where:

$$\hat{y}(k+d_m\,|\,k) = y(k) + [y_m(k) - y_m(k-d_m)] \tag{13}$$

- $k_0 = \dfrac{1-\lambda_r^{n_p}}{K_m[1-(-a_m)^{n_p}]}$, $k_1 = \dfrac{1}{K_m}$: controller coefficients
- a_m: discrete-time model parameter
- K_m: static gain of the model

In case of n-th order aperiodic processes the transfer function of the non-delayed model can be partitioned in parallel connection of n first-order models with the corresponding parameters $K_{i,m}$ and $a_{i,m}$ of i-th sub-model. (If the model has multiple poles then different but very similar poles have to be assigned to each multiple pole.)

The basic algorithm can be easily extended for this case, as well (Khadir and Ringwood, 2008):

$$u(k) = k_0\{y_r - [y(k) + [y_m(k) - y_m(k-d_m)]]\} + \sum_{i=1}^{n} k_i y_{i,m}(k) \tag{14}$$

where:

$$k_0 = \frac{1-\lambda_r^{n_p}}{\sum_{i=1}^{n} K_{i,m}[1-(-a_{i,m})^{n_p}]} \quad ; \quad k_i = \frac{1-(-a_{i,m})^{n_p}}{\sum_{j=1}^{n} K_{j,m}[1-(-a_{j,m})^{n_p}]}$$

and, discrete-time equation of i-th sub-model is:

$$y_{i,m}(k) = -a_{i,m}y_{i,m}(k-1) + K_{i,m}(1+a_{i,m})u(k-1) \tag{15}$$

The algorithm is extended for TITO processes with the following tuning parameters:

- $T_{ci} = -3\Delta t/\ln(\lambda_{ri})$: desired closed loop settling time of the i-th controlled variable,
- n_{pi}: prediction horizon of the i-th controlled variable.

The discrete dead time of i-th output signal is supposed as:

$d_{im} = \max(d_{i1m}, d_{i2m})$

where d_{ijm} is the discrete dead time of the model with j-th input signal and i-th output signal.

Thus, these relations can be defined:

$$y_{im}(k-d_{im}) = y_{i1m}(k-d_{i1m}) + y_{i2m}(k-d_{i2m}) \tag{16}$$

whereas y_{ijm} is the non-delayed model output, and $y_{ijm}(k-d_{ijm})$ should represents $y_{ij}(k)$, thus:

$$y_{im}(k-d_{im}) \cong y_{i1}(k) + y_{i2}(k) = y_i(k)$$
$$\hat{y}_{im}(k|k) \cong \hat{y}_i(k+d_{im}|k)$$

$$\hat{y}_{im}(k|k) = \hat{y}_{i1m}(k-d_{i1m}+d_{im}|k) + \hat{y}_{i2m}(k-d_{i2m}+d_{im}|k) \tag{17}$$

$$\hat{y}_i(k+d_{im}|k) \cong y_i(k) + [\hat{y}_{im}(k|k) - y_{im}(k-d_{im})] \tag{18}$$

From (18), the predicted increment of i-th controlled variable n_{pj} step ahead the instant $k+d_{im}$ is defined as:

$$\begin{aligned}&\hat{y}_i(k+d_{im}+n_{pi}|k) - \hat{y}_i(k+d_{im}|k)\\ &= (1-\lambda_{ri}^{n_{pj}})[y_{ri} - y_i(k) - \hat{y}_{im}(k|k) + y_{im}(k-d_{im})]\end{aligned} \tag{19}$$

The predicted increment of i-th process model output n_{pj} step ahead the current k is defined based on (17) as:

$$\begin{aligned}&\hat{y}_{im}(k+n_{pi}|k) - \hat{y}_{im}(k|k)\\ &= \hat{y}_{i1m}(k-d_{i1m}+d_{im}+n_{pi}|k) - \hat{y}_{i1m}(k-d_{i1m}+d_{im}|k)\\ &+ \hat{y}_{i2m}(k-d_{i2m}+d_{im}+n_{pi}|k) - \hat{y}_{i2m}(k-d_{i2m}+d_{im}|k)\end{aligned} \tag{20}$$

This equation in (20) can be reformulated using free and forced responses:

$$\begin{aligned}\hat{y}_{im}(k+n_{pi}|k) - \hat{y}_{im}(k|k) = {}& \hat{y}_{ifree}(k+n_{pi}|k) - \hat{y}_{ifree}(k|k)\\ &+\hat{y}_{i1forc}(k-d_{i1m}+d_{im}+n_{pi}|k)\\ &-\hat{y}_{i1forc}(k-d_{i1m}+d_{im}|k)\\ &+\hat{y}_{i2forc}(k-d_{i2m}+d_{im}+n_{pi}|k)\\ &-\hat{y}_{i2forc}(k-d_{i2m}+d_{im}|k)\end{aligned} \tag{21}$$

whereas:

$$\hat{y}_{ifree}(k|k) = \hat{y}_{i1free}(k-d_{i1m}+d_{im}|k) + \hat{y}_{i2free}(k-d_{i2m}+d_{im}|k)$$

$$\begin{aligned}\hat{y}_{ifree}(k+n_{pi}|k) = {}& \hat{y}_{i1free}(k-d_{i1m}+d_{im}+n_{pi}|k)\\ &+\hat{y}_{i2free}(k-d_{i2m}+d_{im}+n_{pi}|k)\end{aligned}$$

Based on (19) and (21), PFC goal leads to these two control equations (for i=1 and 2):

$$\begin{aligned}&(1-\lambda_{ri}^{n_{pi}})[y_{ri} - y_i(k) - \hat{y}_{ifree}(k|k) + y_{im}(k-d_{im})]\\ &+\hat{y}_{ifree}(k|k) - \hat{y}_{ifree}(k+n_{pi}|k) =\\ &\qquad \hat{y}_{i1forc}(k-d_{i1m}+d_{im}+n_{pi}|k)\\ &\qquad -\lambda_{ri}^{n_{pi}}\hat{y}_{i1forc}(k-d_{i1m}+d_{im}|k)\\ &\qquad +\hat{y}_{i2forc}(k-d_{i2m}+d_{im}+n_{pi}|k)\\ &\qquad -\lambda_{ri}^{n_{pi}}\hat{y}_{i2forc}(k-d_{i2m}+d_{im}|k)\end{aligned} \tag{22}$$

The free and forced responses of the process model with j-th input signal and i-th output signal (which is partitioned in parallel connection of n_{ij} first-order sub-models) are:

$$\hat{y}_{ij,free}(k+n|k) = \sum_{r=1}^{n_{ij}} (-a_{ijm,r})^n y_{ijm,r}(k),$$

$$\hat{y}_{ij,forc}(k+n|k) = u_j(k)\sum_{r=1}^{n_{ij}} K_{ijm,r}[1-(-a_{ijm,r})^n].$$

The solutions of these equations (22) in the two manipulated variables $u_i \equiv u_i(k)$; i=1,2 are calculated (if they are unique) in every control step using the same algorithm. Otherwise when the solutions are not unique (one equation of two variables which has infinite solutions) the tuning parameters can be changed in order to get a unique solution of the control equations, or the solution with minimum increments can be defined by solving this criteria function:

$$J = [u_1 - u_1(k-1)]^2 + [u_2 - u_2(k-1)]^2 \Rightarrow \underset{u_1,u_2}{MIN} \tag{23}$$

$$\frac{dJ}{du_1} = [u_1 - u_1(k-1)] + [u_2 - u_2(k-1)]\frac{du_2}{du_1} = 0 \tag{24}$$

whereas u_2 and $\frac{du_2}{du_1}$ are defined from one of the two equivalent linear equations (22) of the variables u_1 and u_2.

4. DECOUPLING PREDICTIVE CONTROL OF A TITO PROCESS

In order to illustrate the problem of coupling a TITO process is considered with set of the sampling time Δt=0.1 min. The sub-processes are aperiodic with different static gains K_{ij}, time constants T_{ij}, and dead times T_{dij}. All processes have some (n_{ij}) equal time constants:

- P_{11}: K_{11}=1.5, T_{11}=1.0 min, n_{11}=2, T_{d11}=0.1 min
- P_{12}: K_{12}=0.5, T_{12}=0.5 min, n_{12}=4, T_{d12}=0.5 min
- P_{21}: K_{21}=0.75, T_{21}=0.5 min, n_{21}=3, T_{d21}=0.8 min
- P_{22}: K_{22}=1.0, T_{22}=2.0 min, n_{22}=1, T_{d22}=0.2 min

The step responses of the processes were shown in Fig. 2.

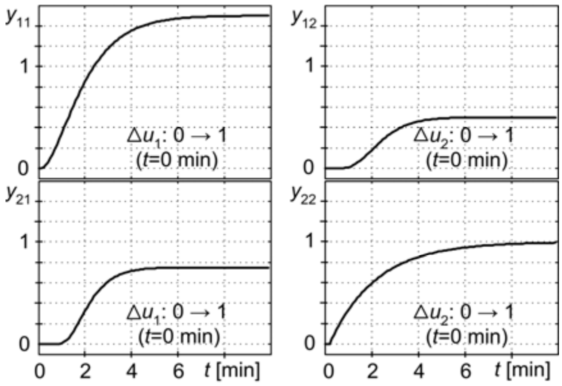


Fig. 2. Step responses of the TITO sub-processes

TITO predictive control was used; see the scheme in Fig. 3.

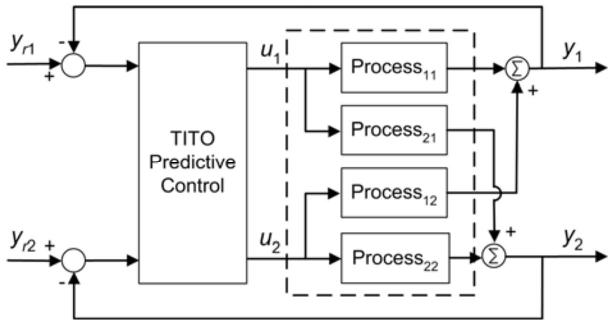


Fig. 3. TITO predictive control scheme

The control scenario was:

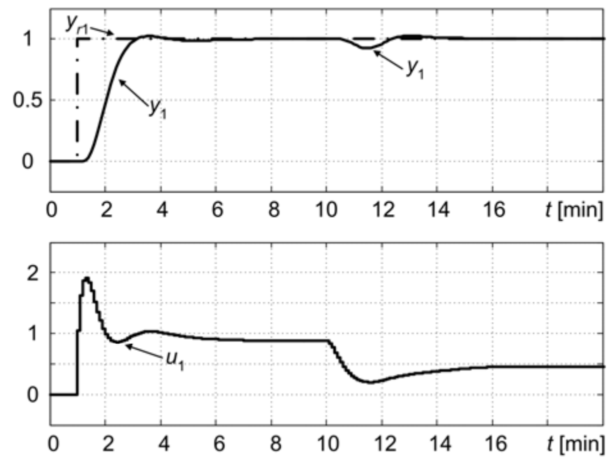
- at t=1 min stepwise increase of the reference signal of y_1 from 0 to 1,
- at t=10 min stepwise increase of the reference signal of y_2 from 0 to 1.

4.1 GPC of TITO process

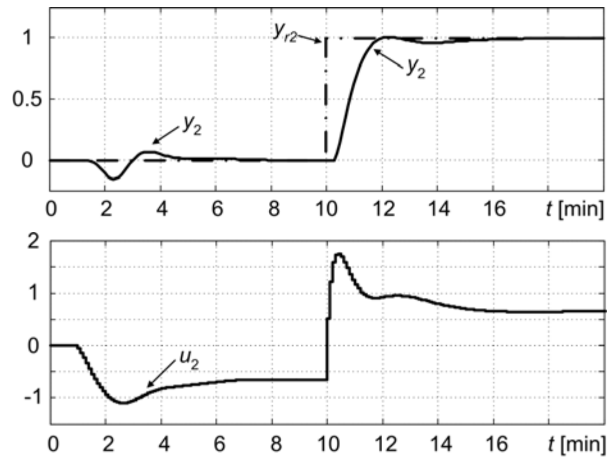
GPC of TITO process is shown in Fig. 4 with the following controller parameters:

- start of control error horizons: n_{e11}=n_{e12}=0
- end of control error horizons: n_{e21}=40 and n_{e22}=30
- length of control horizons: n_{u1}=n_{u2}=3
- weighting factors of the control errors λ_{y1}=λ_{y2}=1
- weighting factors of the control increments λ_{u1}=λ_{u2}=0.5

The control of the reference signal changes is fast and aperiodic. The maximal control error of the controlled variable y_1 is about 6.5% (related to the changes of the reference signal y_{r2}), and is about 16.5% maximal control error of the controlled variable y_2 (related to the changes of the reference signal y_{r1}).



a) GPC of output y_1



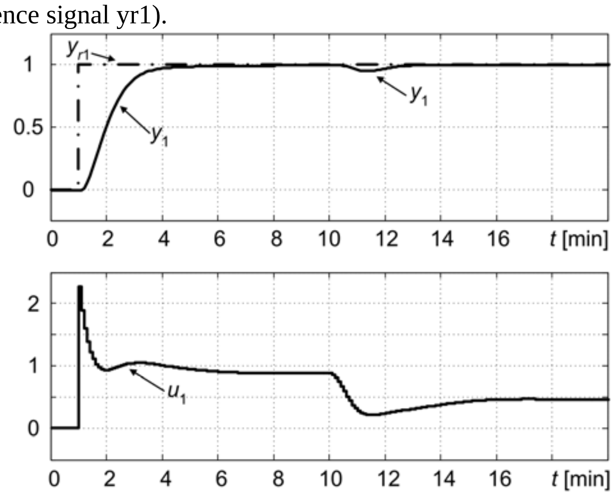
b) GPC of output y_2

Fig. 4. GPC of TITO process

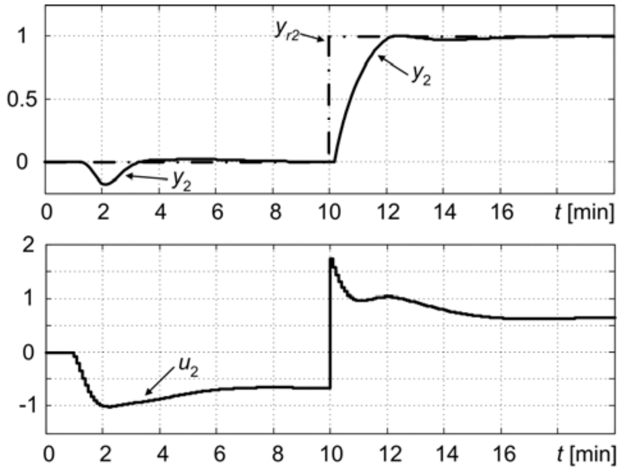
4.2 PFC of TITO process

PFC of TITO process is shown in Fig. 5 with the following controller parameters: settling times T_{c1} = 2 min. and T_{c2} = 1.5 min. and prediction horizons n_{p1} = n_{p2} = 3.

The control of the reference signal changes is fast and aperiodic. The maximal control error of the controlled variable y1 is about 5.2% (related to the changes of the reference signal yr2), and is about 22% maximal control error of the controlled variable y2 (related to the changes of the reference signal yr1).



a) PFC of output y_1



b) PFC of output y_2

Fig. 5. PFC of TITO process

Fig. 4 and 5 shows that the rising times and the maximal control error related to the coupling effect are similar with GPC and PFC for this set of controller parameters, although PFC has a smaller number of the controller parameters and less calculations than GPC. The manipulated variables of the process with GPC and PFC have a similar shape Also.

5. REFERENCE SIGNAL CHANGE-DEPENDENT ADAPTION OF THE CONTROLLER PARAMETER

The time point of the reference signal change in known sometimes by the technology in advance. Otherwise it can be detected with methods of signal analysis.

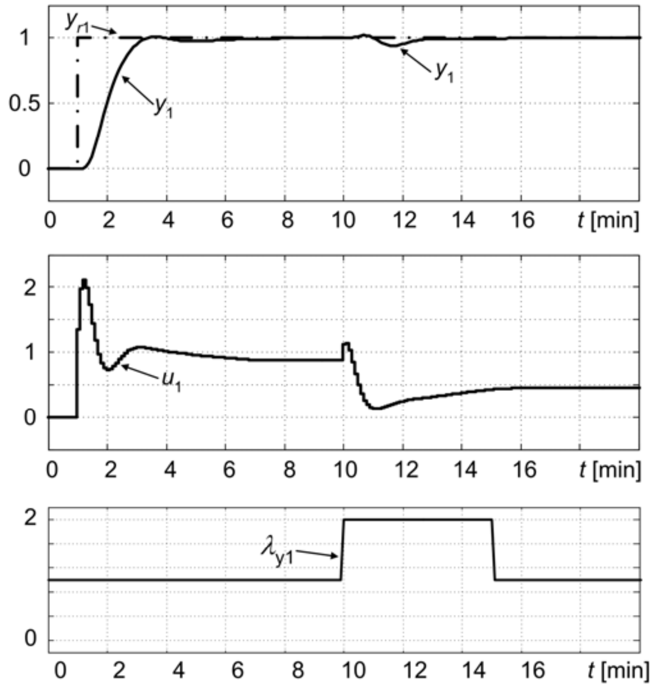
5.1 Reference signal change-dependent adaptation of GPC parameters

The control equation of GPC shows that the increasing of the control error weighting factor of one controlled variable shall reduce the control error in that variable. Therefore increasing of the control error weighting factor of the controlled variable whose reference signal was kept constant reduces the control error in this variable.

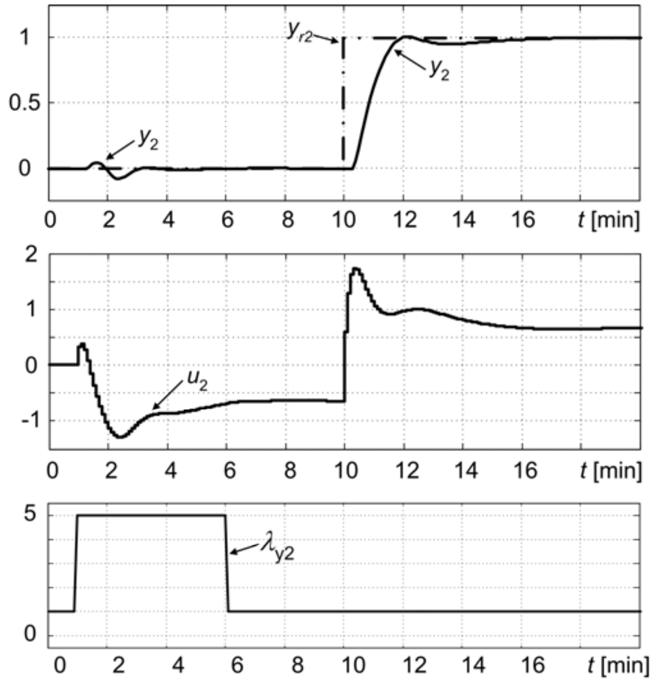
This technique is illustrated in Fig. 6 for reference signal changes. The weighting factors of both control errors were changed stepwise from $\lambda_{y1}=\lambda_{y2}=1$ to $\lambda_{y1}=2$ and $\lambda_{y2}=5$ for that variable whose reference signal was kept constant in the moment of the other reference signal change. The duration of the weighting factors change was 5 min which is about 2 min longer than the settling time of the controlled process.

The plots show that the two controlled variables are better decoupled. The maximal control error of the controlled variable y_1 is about 5.6% (related to the changes of the reference signal y_{r2}), and is about 8% maximal control error of the controlled variable y_2 (related to the changes of the reference signal y_{r1}).

The critical point of the manual controller parameters adaptation is the detection of the reference signal change. Nevertheless a method which does not care about the time point of the reference signal change would be preferable.



a) GPC of output y_1



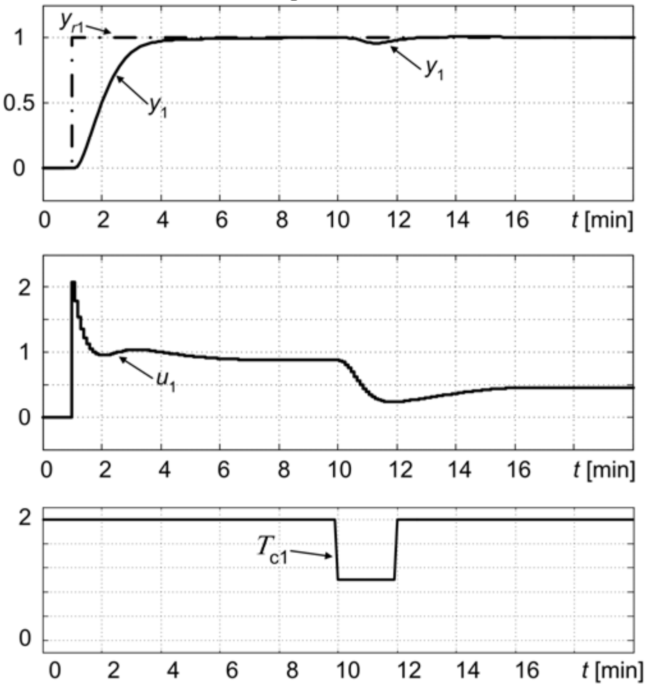
b) GPC of output y_2

Fig. 6. TITO GPC with reference signals changes-dependent adaptation of λ_y

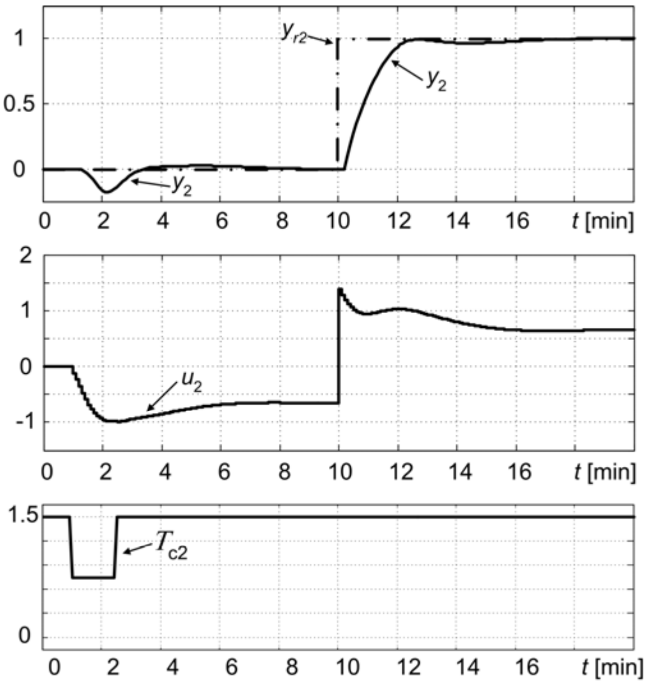
5.2. Reference signal change-dependent adaptation of PFC parameters

The main controller parameter with PFC is the settling time T_c. The decoupling ability with a TITO process can be improved by tuning the settling times (T_{c1} and T_{c2}). Decreasing of the desired settling time of the controlled variable whose reference signal was kept constant accelerates the control and hence reduces the control error in this controlled variable.

Fig. 7 illustrates this case for reference signal changes. The desired settling time of the first controlled variable was changed stepwise from T_{c1}=2 min to T_{c1}=1 min and the desired settling time of second controlled variable was changed stepwise from T_{c2}=1.5 min to T_{c2}=0.75 min. The desired settling times were changed for that controlled variable whose reference signal was not changed in the moment of the change of the other reference signal. The duration of the changes were equal to the desired settling times for both. The maximal control error is about 4% (related to the changes of y_{r2}) in the controlled variable y_1, and about 18% (related to the changes of y_{r1}) in the controlled variable y_2. The plots show that the two processes are fast and better decoupled than with constant settling times but worse than with GPC in Fig. 6.



a) PFC of output y_1



b) PFC of output y_2

Fig. 7. TITO PFC with reference signals changes- dependent adaptation of T_c

6. CONTROL ERROR-DEPENDENT ADAPTATION OF THE CONTROLLER PARAMETERS

The synchronisation at the reference signal change can be performed automatically if the highlighted controller parameters were decentralized functions of the control errors.

6.1 Control error-dependent adaptation of GPC parameters

The control error of the controlled variable whose reference signal was changed increases faster than the control error of the other variable whose reference signal was kept constant. Consequently, if the control error weighting factors are set inverse proportional to the control error for both controlled variables then the weighting factor of the controlled variable whose reference signal was kept constant will be higher than the weighting factor of the controlled variable whose reference signal was changed.

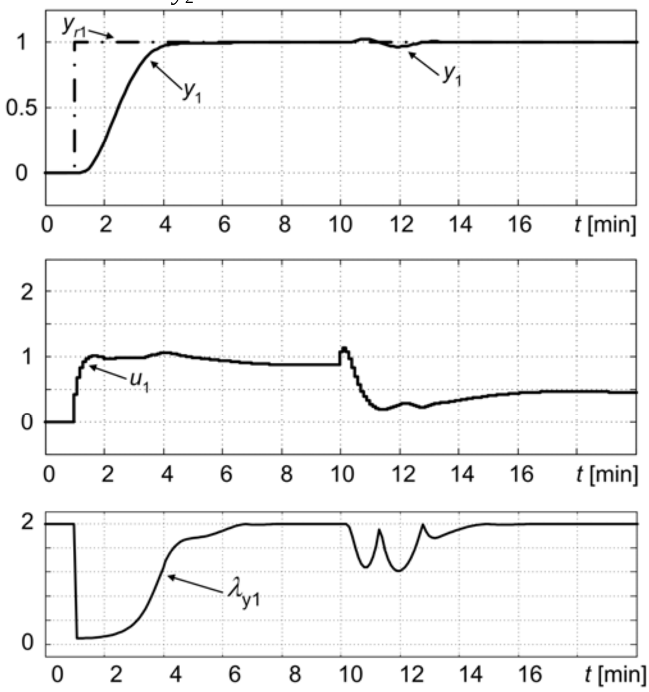
The following dependence of the weighting factors on the control error were supported (Schmitz, et. al., 2007):

$$\lambda_{yi} = \frac{\lambda_{yi,\max}}{\left(1+\left|e_i(k)\right|\cdot\lambda_{yi,damp}\right)}$$

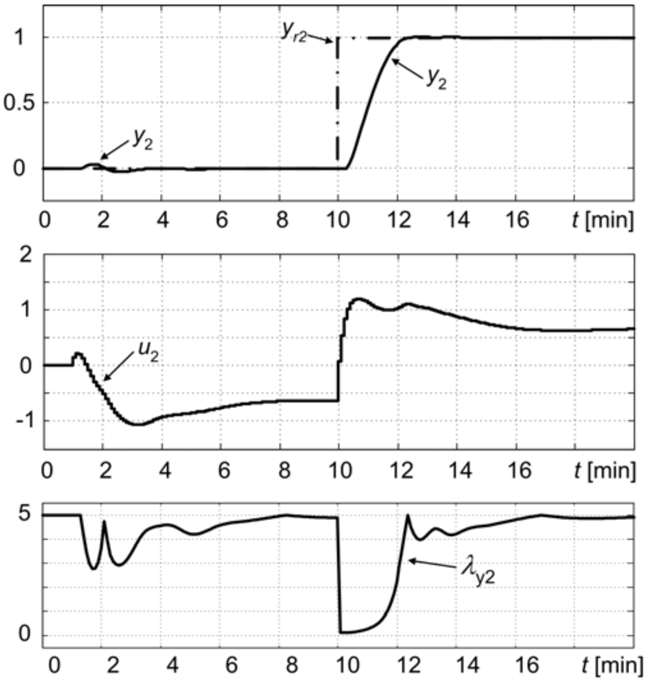
with $\lambda_{y1,\max}$=2, $\lambda_{y2,\max}$=5, $\lambda_{y1,\mathrm{damp}}$=20 and $\lambda_{y2,\mathrm{damp}}$=25 in this case.

Fig. 8 shows that the weighting factors of those controlled variables whose reference signal was changed were temporarily significantly reduced and the other weighting factor is remained big, this behaviour is in opposite to Fig. 6.

The control is slightly slower than with the changing of the weighting factors at the reference signal changes (Fig. 6) but the control is still fast and the decoupling is better than before. The automatic adaptation of the control error weighting factors shows about 3.2% maximal control error (related to the changes of y_{r2}) in the controlled variable y_1, and about 3.1% (related to the changes of y_{r1}) in the controlled variable y_2.



a) GPC of output y_1



b) GPC of output y_2

Fig. 8. TITO GPC with control error-dependent adaptation of λ_y

6.2 Control error-linear dependent adaptation of PFC parameters

The settling times can be set proportional to the related control error; therefore the settling time of the controlled variable whose reference signal was changed will be higher than the settling time of the controlled variable whose reference signal was kept constant. Consequently the controlled variable whose reference signal was not changed will be controlled faster, that acts as a forced decoupling.

The following linear dependence of the desired settling times on the control error were applied in the simulation:

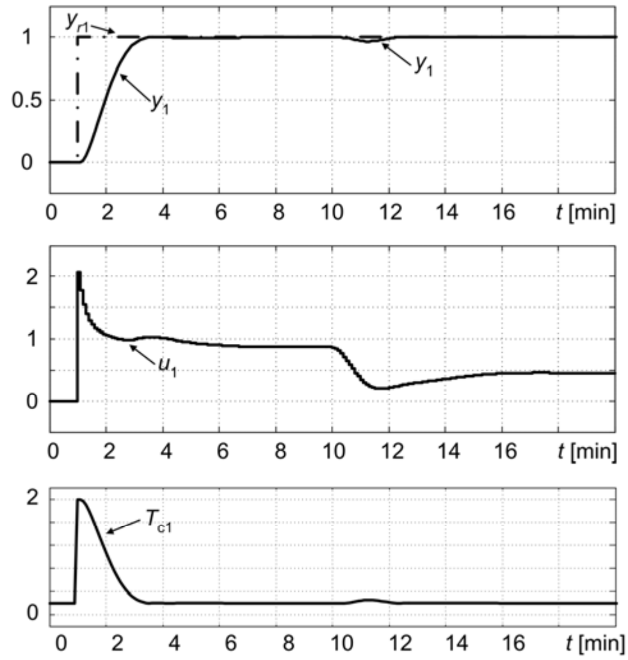
$$T_{ci} = T_{ci,\min} + (T_{ci,\max} - T_{ci,\min})\left|e_i(k)\right|$$

with $T_{c1,\max}$=2 min; $T_{c2,\max}$=1.5 min; $T_{c1,\min}$=0.2 min and $T_{c2,\min}$=0.15 min.

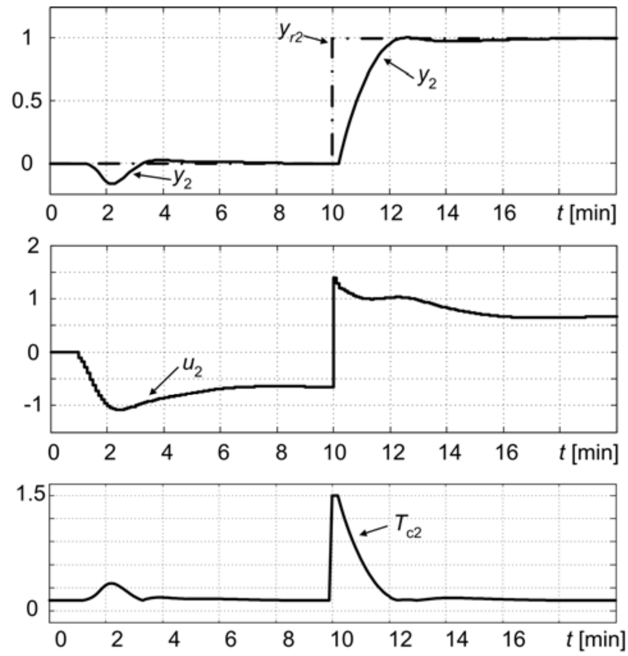
Fig. 9 shows that the desired settling times of those controlled variable whose reference signal was changed were temporarily significantly increased and the other settling time is remained small, this is in opposite to Fig. 7.

The maximal control error is about 3.2% (related to the changes of y_{r2}) in the controlled variable y_1, and about 16.3% (related to the changes of y_{r1}) in the controlled variable y_2.

This shows that the automatic adaptation of PFC parameters is not as good as the automatic adaptation of GPC parameters but the decoupling effect became much better in comparison with the manual adaptation in Fig. 7. And as mentioned already the realization of this control error-dependent adaptation is easier than detecting changes in the reference signals.



a) PFC of output y_1



b) PFC of output y_2

Fig. 9 TITO PFC with control error-linear dependent adaptation of T_c

6.3 Control error-exponential dependent adaptation of PFC parameters

The settling times can be set as an exponential function in the other control error; therefore the settling time of the controlled variable whose reference signal was kept constant will be smaller than the settling time of the controlled variable whose reference signal was changed, (Zabet, Haber, 2010).

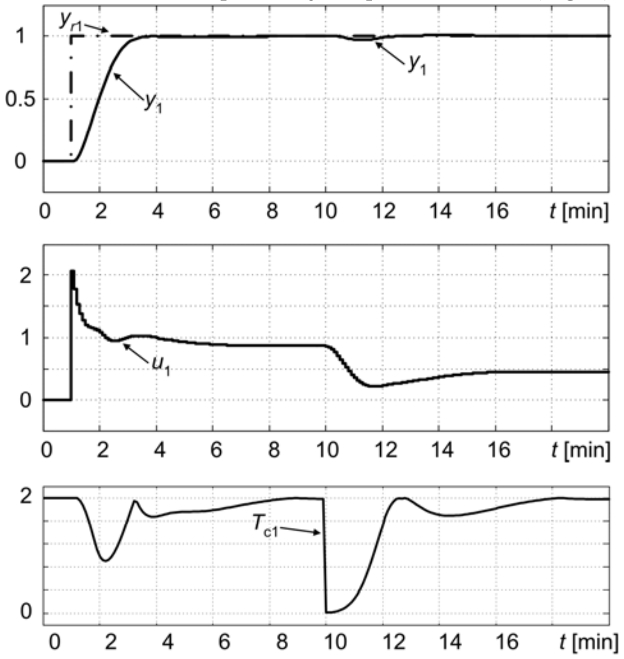
The following exponential dependence was designed:

$$T_{ci} = T_{ci,\max} \cdot \exp\left(-T_{cj,damp} \cdot \left|e_j(k)\right|\right) \quad \forall i, j = 1,2 \quad ; \quad i \neq j$$

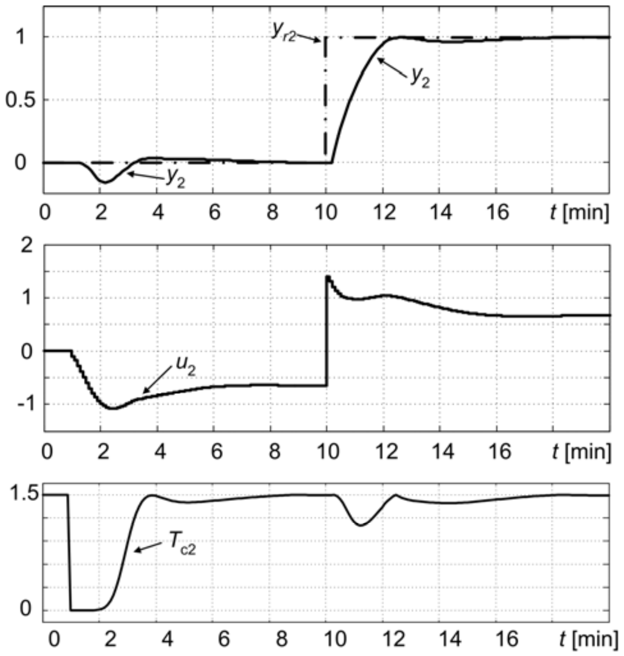
$T_{c1,\max}$=2min; $T_{c2,\max}$=1.5min; $T_{c1,\mathrm{damp}}$=10 and $T_{c2,\mathrm{damp}}$=5.

Fig. 10 shows that the desired settling times of those controlled variables whose reference signal was kept constant were temporarily significantly reduced in the moment of the other reference signal change as in Fig. 7.

The maximal control error of y_1 is about 3.1% (related to the changes of y_{r2}), and about 16% (related to the changes of y_{r1}) in the controlled variable y_2. This shows that this automatic adaptation method is worse than with GPC controller but the decoupling effect became better in comparison with the linear dependency adaptation method (Fig. 9).



a) PFC of output y_1



b) PFC of output y_2

Fig. 10 TITO PFC with control error-exponential dependent adaptation of T_c

CONCLUSION

TITO predictive control was illustrated with two different predictive control algorithms: GPC and PFC. The controller parameters in both methods were first fixed in the simulation of the TITO control.

New simple methods were presented for reducing the decoupling effect of the TITO GPC/PFC control with proper adaptation of the controller parameters. The two methods (1) reference signal change-dependent controller parameters as an event dependent adaptation method, and (2) control error-dependent controller parameters as a signal-dependent adaptation method were designed and simulated. Both methods have shown improved decoupling effects.

With GPC algorithm the controlled variables were perfectly decoupled by both adaptation methods. The second method (control error-dependent adaptation) was prior to the first method (reference signal change-dependent adaptation).

The decoupling became better with both adaptation methods using the PFC algorithm; this fact is clarified more for a slower controlled variables. With the first method the control error was a bit smaller than without any adaptation. In the second method the linear dependency (control error-linear dependent adaptation) was better than the first method, but a bit worse than with exponential dependency (control error-exponential dependent adaptation).

The adaptation of GPC controller parameters has more affect on the decoupling feature than the adaptation of PFC controller parameters for the studied set of parameters.

Among the two controller parameter adaptation method the second one (control error dependent-adaptation) is easier to realize in practice. The presented idea can also be extended for processes with more than two controlled variables.

8. ACKNOWLEDMENTS

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