APPLICATION OF CONSTRAINTS IN PREDICTIVE CONTROL OF TIME-DELAY SYSTEMS

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ABSTRACT

In industry, there are cases where the controlled process includes time-delay and it is often necessary to limit its input, output or state variables. The aim of this paper is to design and verify a predictive controller that is able to control these processes. This paper generally describes the design process of the predictive controller - from the general characteristics of predictive control to the calculation method of the control law. The next section includes a simulation verification of this design for different process parameters. All simulation verification programs are implemented in MATLAB / Simulink.

INTRODUCTION

In practice, there are processes that include various time-delays. In some cases it is necessary to eliminate this delay so as to avoid undesirable process variables levels. Several methods are used for this purpose; for example, the Smith Predictor or Predictive Control. This paper deals with the use of predictive control for processes with time-delay.
Predictive Control is typically used in discrete modifications. For its design, it is necessary to know two things. The first is a mathematical model of the controlled system; and the second is knowledge of the future values of the reference signal. The knowledge of the mathematical model of the system includes a number of time-delay steps. The prediction time horizon is suitably chosen based on the dynamics of the process and the future estimated values of the process output are calculated on this horizon. Time-delay is completely eliminated by this method (Bobál 2008).
The advantage of predictive control is the ability to control oscillating, non-minimum-phases as well as multi-dimensional systems. The ability to predict output values up to the chosen time horizon allows use of this method in processes with significant time-delay. The fundamental characteristic of predictive control is the ability to respond a few steps ahead to a change in the reference signal.
Another of the advantages of predictive control is the ability to specify the necessary constraints of the input and output (or state) variables directly into the controller design (Maciejowski 2002, Camacho and Normey-Rico 2007).
In its early days, predictive control was mainly deployed on slower processes. This was due to the large computational complexity of the problem. Today however, there are predictive control modifications which can control very fast processes in milliseconds (eg. using the Explicit Approach). This could only be achieved by the constant development of computer technology, as well as the considerable progress in the field of optimization which is crucial for predictive control.
The Generalized Predictive Control (GPC) method is used for the design of the predictive controller in this paper.

THE PRINCIPLE OF PREDICTIVE CONTROL

Predictive Control has many modifications and forms that are appropriate for different process parameters. All these methods have certain properties in common. The prediction of a process output is calculated by using a mathematical model of the process (Bobál 2008).
The main differences between the predictive control methods are in different process models used for the prediction of the output values and the cost function that needs to be minimized.
Figures 1 and 2 shows the principle of predictive control:

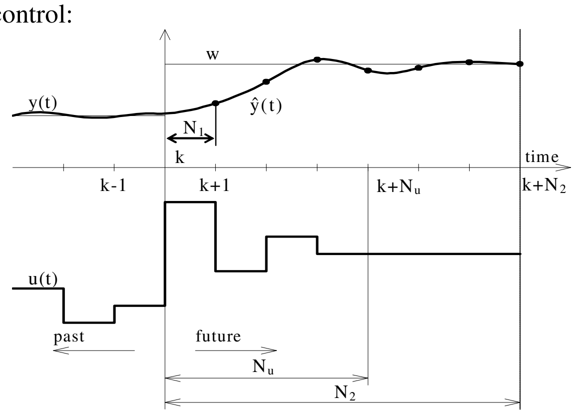

Figure 1 : Principle of predictive control

- Future output values are predicted on the chosen time interval *N*, which is called the prediction horizon, and the recalculation is performed at each new sampling period *t*. The predicted values $\hat{y}(t+k)$ for $k=1\ldots N$ are the results of previous

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measured output values, previously implemented input values and future input values of which only the first calculated value will be implemented.

- The sequence of future input values is calculated as an optimization problem for minimizing a specified cost function. This cost function usually has a quadratic form and its solution minimizes the difference between the reference and the output variable.
- Only the first input value from the whole calculated sequence is implemented. All other values until time $t+N$ are ignored, because the whole calculation algorithm is repeated in each sampling period t when the new value of output signal is taken which may be different from the predicted output value due to disturbance and noise (Rossiter 2003; Camacho and Normey-Rico 2007).

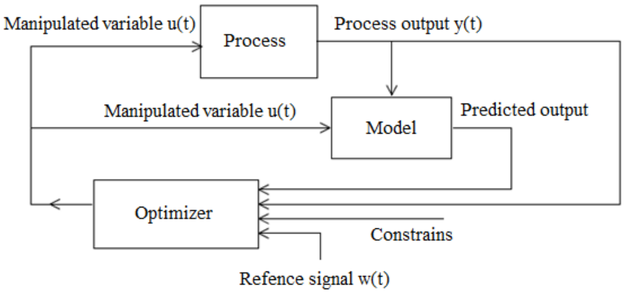

Figure 2 : Block diagram of Predictive Control

GENERALIZED PREDICTIVE CONTROL

The cost functionthat GPC minimizes is:

$$J = \sum_{j=N_1}^{N_2} \delta(j)\left[\hat{y}(k+j) - w(k+j)\right]^2 + \\ +\sum_{j=1}^{N_u} \lambda(j)\left[\Delta u(k+j-1)\right]^2 \qquad (1)$$

Where $\hat{y}(k+j)$ is the predicted system output, N_1 is a minimum time horizon, N_2 is a maximum time horizon, N_u is a control horizon, δ(j) and λ(j) are weighting coefficients and $w(k+j)$ is the sequence of the future values of the reference signal. Values $\Delta u(k+j-1)$ are the future control increments that need to be calculated.
The time horizons for prediction are chosen with regard to the time-delay. The minimum time horizon: $N_1 = d+1$, the maximum time horizon: $N_2 = N+d$ and the control horizon: $N_u = N = N_2 - d$. Only the control horizon $N_u = N$ is chosen, because the value of the time-delay d is known in the design of the predictive control. This horizon should be chosen with regard to the dynamics of the controlled process in order to handle step response (Rossiter 2003; Moudgalya 2007; Bobál 2008).
The mathematical model used in the GPC predictive control method is the CARIMA model:

$$A\left(z^{-1}\right)y(k) = z^{-d}B\left(z^{-1}\right)u(k-1) + \frac{C\left(z^{-1}\right)}{D\left(z^{-1}\right)\Delta}e(k) \qquad (2)$$

where $\Delta = \left(1-z^{-1}\right)$, d is the time-delay and $e(k)$ is the white noise. The polynoms $C\left(z^{-1}\right)$ and $D\left(z^{-1}\right)$ describe the character of the noise. This character is difficult to determine, thus the polynoms $C\left(z^{-1}\right)$ and $D\left(z^{-1}\right)$ are chosen to be equal to one. In this case, this model is represented in the following way (Camacho and Normey-Rico 2007):

$$\tilde{A}\left(z^{-1}\right)y(k) = z^{-d}B\left(z^{-1}\right)\Delta u(k-1) + e(k) \qquad (3)$$

where polynom $\tilde{A}(z^{-1})$ is:

$$\tilde{A}\left(z^{-1}\right) = A\left(z^{-1}\right)\left(1-z^{-1}\right) = 1 - \tilde{a}_1 z^{-1} \ldots - \tilde{a}_{na+1} z^{-na-1} = \\ = 1 - \left(1-a_1\right)z^{-1} - \left(a_1 - a_2\right)z^{-2} - \ldots - a_{na} z^{-na-1} \qquad (4)$$

The white noise $e(k)$ and its future values are considered as equal to zero for the prediction of the future output values. Prediction of the output values is following (Camacho and Normey-Rico 2007):

$$\hat{y}(k+j) = \sum_{i=1}^{na+1} \tilde{a}_i y(k+j-i) + \sum_{i=2}^{nb+1} b_{i-1} \Delta u(k-d-i+j) \qquad (5)$$

It is appropriate to divide the prediction of the output values into two steps, due to the time-delay. Prediction of the output values for time from $k+1$ to $k+d$ are calculated in the first step followed by the prediction for time from $k+d+1$ to $k+N$ in the second step. The system output values up to the time-delay are affected by previously implemented input signal; for this reason, it is possible to calculate them immediately (Camacho and Normey-Rico 2007).

Prediction of Output Values from *k*+1 to *k*+*d*

The prediction of the output values in this time horizon is affected by the prior implementation of the input signal and the measured output values. These estimations can be calculated immediately due to this reason. Estimations of the output values for the time from $k+1$ to $k+d$ are important for further predictions of the output. Each output prediction can be calculated recursively (Camacho and Normey-Rico 2007). Equations for the output prediction can be written in a matrix form:

$$\begin{bmatrix} \hat{y}(k+1) \\ \hat{y}(k+2) \\ \vdots \\ \hat{y}(k+d) \end{bmatrix} = \boldsymbol{G} \begin{bmatrix} \Delta u(k-d) \\ \Delta u(k-d+1) \\ \vdots \\ \Delta u(k-1) \end{bmatrix} + \boldsymbol{H} \begin{bmatrix} \Delta u(k-d-1) \\ \Delta u(k-d-2) \\ \vdots \\ \Delta u(k-d-nb) \end{bmatrix} + \\ + \boldsymbol{S} \begin{bmatrix} \hat{y}(k) \\ \hat{y}(k-1) \\ \vdots \\ \hat{y}(k-na) \end{bmatrix} \tag{6}$$

Matrices $\boldsymbol{G}$, $\boldsymbol{H}$ and $\boldsymbol{S}$ are constant and their dimensions are: $\boldsymbol{G} = [d \times d]$, $\boldsymbol{H} = [d \times nb]$ and $\boldsymbol{S} = [d \times na+1]$.
This equation can be written as:

$$\hat{\boldsymbol{y}}_d = \boldsymbol{G}\boldsymbol{u}_d + \boldsymbol{H}\boldsymbol{u}_1 + \boldsymbol{S}\boldsymbol{y}_1 \tag{7}$$

Prediction of Output Values from *k*+*d*+1 to *k*+*d*+*N*

The prediction of the output values in this time horizon is used to minimize the cost function. Each output prediction can be calculated recursively. Equations for the output prediction can be written in a matrix form:

$$\begin{bmatrix} \hat{y}(k+d+1) \\ \hat{y}(k+d+2) \\ \vdots \\ \hat{y}(k+d+N) \end{bmatrix} = \boldsymbol{G} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N-1) \end{bmatrix} + \boldsymbol{H} \begin{bmatrix} \Delta u(k-1) \\ \Delta u(k-2) \\ \vdots \\ \Delta u(k-nb) \end{bmatrix} + \\ + \boldsymbol{S} \begin{bmatrix} \hat{y}(k+d) \\ \hat{y}(k+d-1) \\ \vdots \\ \hat{y}(k+d-na) \end{bmatrix} \tag{8}$$

Matrices $\boldsymbol{G}$, $\boldsymbol{H}$ and $\boldsymbol{S}$ are constant and their dimensions are: $\boldsymbol{G} = [N \times N], \boldsymbol{H} = [N \times nb]$ and $\boldsymbol{S} = [N \times na+1]$ (Rossiter 2003; Camacho and Normey-Rico 2007).
This equation can be written as:

$$\hat{\boldsymbol{y}} = \boldsymbol{G}\boldsymbol{u} + \boldsymbol{H}\boldsymbol{u}_2 + \boldsymbol{S}\boldsymbol{y}_2 \tag{9}$$

The vector of future control increments $\boldsymbol{u}$ will be calculated and its first element $\Delta u(k)$ will be implemented.

CONSTRAINTS

Process control in industrial practice often requires certain process variables constraints. This may be the constraint of the absolute value of the control input signal that limits actuators and sensors itself. These constraints are the most common types since certain devices can only work in a certain range of the output values. For example, a valve cannot be opened to more than 100%. Control increment limitation is another type of constraint. That means that certain actuators can only handle limited step changes of their input signal; otherwise, it can lead to their overloading and possible destruction. The constraints can also be implemented on output variables which can only be within a certain range of values (Maciejowski 2002; Bobál 2008).
The saturation of the result of an analytic solution without constraints is one of possible options how achieve these constraints. This is the simplest solution; however, it does not guarantee optimal results. This solution can lead to the so-called "wind-up effect". This limitation option only allows us to control the input signal constraints, but not the output values (Bobál 2008).
The predictive control cost function allows us to solve constraints in the optimization calculation. This option allows us to use system input and output signal constraints. It is possible to constrict inner states when a state model is used (Maciejowski 2002; Bobál 2008).
The most common constraints are:

- Constraint of control increments: $\Delta u_{\min} \le \Delta u(k) \le \Delta u_{\max}$
- Constraint of the absolute control input signal: $u_{\min} \le u(k) \le u_{\max}$
- Constraint of the output value: $y_{\min} \le y(k) \le y_{\max}$

The vector of the future control increments is calculated by the minimization of cost function. Therefore, all of the constraints have to be expressed as control increment constraints. All of these constraints can be written in one equation:

$$\boldsymbol{A}\boldsymbol{u} \le \boldsymbol{b} \tag{10}$$

where $\boldsymbol{u}$ is the vector of the future control increments, $\boldsymbol{A}$ is a matrix and $\boldsymbol{b}$ is the vector of constraints.
The control increment constraints can be expressed as:

$$\begin{gathered} \Delta u(k) \le \Delta u_{\max} \\ \boldsymbol{I}\boldsymbol{u} \le \boldsymbol{\Delta u}_{\max} \end{gathered} \tag{11}$$

$$\begin{gathered} \Delta u(k) \ge \Delta u_{\min} \\ -\Delta u(k) \le -\Delta u_{\min} \\ -\boldsymbol{I}\boldsymbol{u} \le -\boldsymbol{\Delta u}_{\min} \end{gathered} \tag{12}$$

The control input signal constraints can be expressed as:

$$\begin{gathered} u(k) \le u_{\max} \\ u(k-1) + \Delta u(k) \le u_{\max} \\ \Delta u(k) \le u_{\max} - u(k-1) \\ \boldsymbol{T}\boldsymbol{u} \le \boldsymbol{u}_{\max} - \boldsymbol{u}_{k-1} \end{gathered} \tag{13}$$

$$\begin{gathered} u(k) \ge u_{\min} \\ -u(k-1) - \Delta u(k) \le -u_{\min} \\ -\Delta u(k) \le -u_{\min} + u(k-1) \\ -\boldsymbol{T}\boldsymbol{u} \le -\boldsymbol{u}_{\min} + \boldsymbol{u}_{k-1} \end{gathered} \tag{14}$$

The system output constraints can be expressed as:

$$y(k) \le y_{\max}$$
$$\boldsymbol{Gu} + \boldsymbol{y}_0 \le \boldsymbol{y}_{\max}$$
$$\boldsymbol{Gu} \le \boldsymbol{y}_{\max} - \boldsymbol{y}_0 \quad (15)$$

$$y(k) \ge y_{\min}$$
$$-\boldsymbol{Gu} - \boldsymbol{y}_0 \le -\boldsymbol{y}_{\min}$$
$$-\boldsymbol{Gu} \le -\boldsymbol{y}_{\min} + \boldsymbol{y}_0 \quad (16)$$

All of these constraints can be expressed in one equation:

$$\boldsymbol{Au} \le \boldsymbol{b}$$
$$\begin{bmatrix} \boldsymbol{I} \\ -\boldsymbol{I} \\ \boldsymbol{T} \\ -\boldsymbol{T} \\ \boldsymbol{G} \\ -\boldsymbol{G} \end{bmatrix} \boldsymbol{u} \le \begin{bmatrix} \boldsymbol{\Delta u}_{\max} \\ -\boldsymbol{\Delta u}_{\min} \\ \boldsymbol{u}_{\max} - \boldsymbol{u}_{k\text{-}1} \\ -\boldsymbol{u}_{\min} + \boldsymbol{u}_{k\text{-}1} \\ \boldsymbol{y}_{\max} - \boldsymbol{y}_0 \\ -\boldsymbol{y}_{\min} + \boldsymbol{y}_0 \end{bmatrix} \quad (17)$$

Where $\boldsymbol{I}$ is an identity matrix, $\boldsymbol{T}$ is a lower triangular matrix and $\boldsymbol{G}$ is a square matrix of dimension $[N \times N]$. On the right side of the equation are column vectors of length N. The vector $\boldsymbol{y_0}$ is the system free response.

$$\boldsymbol{y}_0 = \boldsymbol{Hu}_2 + \boldsymbol{Sy}_2 \quad (18)$$

COST FUNCTION AND CONTROL INPUT SIGNAL CALCULATION

The individual summation elements of the cost function in Equation (1) can be written in matrix form. By substituting these matrices into the cost function, its matrix form will be (Rossiter 2003; Camacho and Normey-Rico 2007; Bobál 2008):

$$J = \left(\boldsymbol{Gu} + \boldsymbol{Hu}_2 + \boldsymbol{Sy}_2 - \boldsymbol{w}\right)^T \boldsymbol{Q}_\delta \left(\boldsymbol{Gu} + \boldsymbol{Hu}_2 + \boldsymbol{Sy}_2 - \boldsymbol{w}\right) + \\ + \boldsymbol{u}^T \boldsymbol{Q}_\lambda \boldsymbol{u} \quad (19)$$

where $\boldsymbol{Q}_\delta$ and $\boldsymbol{Q}_\lambda$ are diagonal weighting matrices of a dimension $[N \times N]$, and their elements are the weighting coefficients δ(*j*) and λ(*j*).
The minimization of the cost function and the calculation of the control input signal cannot be done by an analytic calculation, if constraints exist. In this case, quadratic programming methods are used for the minimization of the quadratic cost function which need to be modified to (Bobál 2008):

$$J = \frac{1}{2}\boldsymbol{u}^T \boldsymbol{H}_c \boldsymbol{u} + \boldsymbol{g}^T \boldsymbol{u} \quad (20)$$

where

$$\boldsymbol{H}_c = 2\left(\boldsymbol{Q}_\lambda + \boldsymbol{G}^T \boldsymbol{Q}_\delta \boldsymbol{G}\right) \quad (21)$$

$$\boldsymbol{g}^T = 2\left(\boldsymbol{Hu}_2 + \boldsymbol{Sy}_2 - \boldsymbol{w}\right)^T \boldsymbol{Q}_\delta \boldsymbol{G} \quad (22)$$

The MATLAB/SIMULINK function "*quadprog(H$_c$, g, A, b)*" can be used for the calculation of the optimal solution of the cost function with constraining conditions.

IDENTIFICATION

It is necessary to identify the mathematical model of the controlled system as accurately as possible for correct and precise function of the predictive control. Two groups of identification methods can be used for this identification. The first are one-time (offline) methods and the second are ongoing (online) methods. The online identification methods can be used for self-tuning GPC. Designed predictive controller was simulation verified for transfer function of the laboratory heat exchanger model. Following methods was used for the identification of this model.

Offline Identification Methods

Two offline identification methods were used to the identification of the laboratory model. The first is the least squeares method (LSM) and the second is fminsearch function implemented in MATLAB.
The least squeares method is based on minimizing the sum of squared subtraction of measured and model output value. Estimates of the model parameters are calculated according to equation:

$$\hat{\boldsymbol{\theta}} = (\boldsymbol{F}^T \boldsymbol{F})^{-1} \boldsymbol{F}^T \boldsymbol{y} \quad (23)$$

where $\hat{\boldsymbol{\theta}}$ is a vector of estimated model parameters of dimension (2*n*), $\boldsymbol{F}$ is a matrix of dimension (*N*-*n*-*d*, 2*n*), $\boldsymbol{y}$ is a data vector of dimension (*N*-*n*-*d*). *N* is a number of measured data, *n* is an order of the system transfer function, *d* is number of steps of the time-delay (Camacho and Normey-Rico 2007; Bobál et al. 2012).
MATLAB function fminsearch finds the minimum of entered function without the restricting conditions. The entered function can be singlevariable or multivariable. Fminsearch function uses the simplex search method for finding the minimum of a function. This is a direct search method that does not use numerical or analytic gradients.

$$x = \text{fminsearch('name\_fcn'}, x_0) \quad (24)$$

Online Identification Methods

Online identification methods are used to continuously refine the estimates of the model parameters from the initial estimates. The algorithm of calculation is repeated in each sampling period. Due to this approach these methods are capable to react on some changes in the controlled system behavior.
The recursive least squares method (RLSM) was used for the online identification of the laboratory model. This method was used on the second order ARX model (Bobál et al. 2012).

$$y(k) = \boldsymbol{\theta}^T(k)\boldsymbol{\Phi}(k) + n_c(k) \quad (25)$$

where $\boldsymbol{\theta}$ is the vector of model parameters:

$$\boldsymbol{\theta}^T(k) = \begin{bmatrix} a_1 & a_2 & b_1 & b_2 \end{bmatrix} \quad (26)$$

$\boldsymbol{\Phi}$ is the regresion vector:

$$\boldsymbol{\Phi}^T(k) = \left[-y(k-1) \quad -y(k-2) \quad u(k-d-1) \quad u(k-d-2) \right] \tag{27}$$

Identification of Laboratory Model

Identification was done at laboratory heat exchanger model.

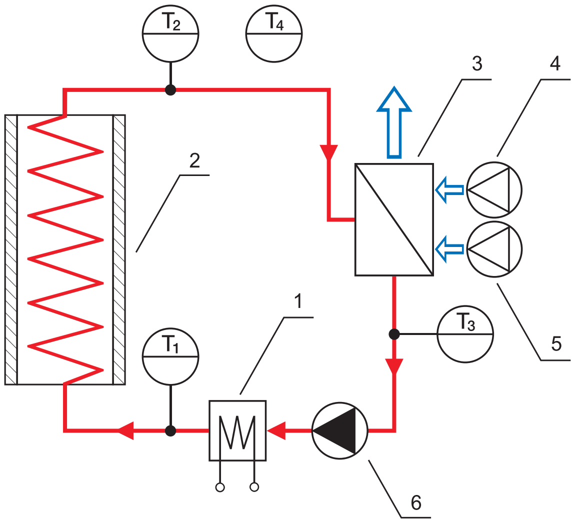

Figure 3 : Scheme of laboratory model

A scheme of the laboratory heat equipment is depicted in Figure 3. The heat transferring fluid (e. g. water) is transported using a continuously controllable DC pump (6) into a flow heater (1) with max. power of 750 W. The temperature of a fluid at the heater output T_1 is measured by a platinum thermometer. Warmed liquid then goes through a 15 meters long insulated coiled pipeline (2) which causes the significant delay (20 – 200 s) in the system. The air-water heat exchanger (3) with two cooling fans (4, 5) represents a heat-consuming appliance. The speed of the first fan can be continuously adjusted, whereas the second one is of on/off type. Input and output temperatures of the cooler are measured again by platinum thermometers as T_2, respective T_3. The platinum thermometer T_4 is dedicated for measurement of the outdoor-air temperature. The laboratory heat equipment is connected to a standard PC via a technological multifunction I/O card MF 624. This card is designed for the need of connecting PC compatible computers to real world signals. The card is designed for standard data acquisition, control applications and optimized for use with Real Time Toolbox for SIMULINK. The MATLAB/SIMULINK environment was used for all monitoring and control functions.

Two types of input signal were used for identification of the laboratory model as is shown in Figures 4 and 5. Input signals were generated by MATLAB function idinput.

$$u = \text{idinput}(N, type, band, levels) \tag{28}$$

This function generates N values of input signal u. Parameter *type* defines type of generated signal: 'rgs' for random Gaussian signal, 'rbs' for random binary signal, 'prbs' for pseudorandom binary signal and 'sine' for signal composed with sum of sinusoids.

Sum of squared subtraction of measured and model output value criterion was used for analysis of identificated models.

$$S_y = \frac{1}{N}\sum_{k=1}^{N}\left[y(k) - \hat{y}(k) \right]^2 \tag{29}$$

where N is number of measured data, $y(k)$ is measured output value, $\hat{y}(k)$ is estimated output value.

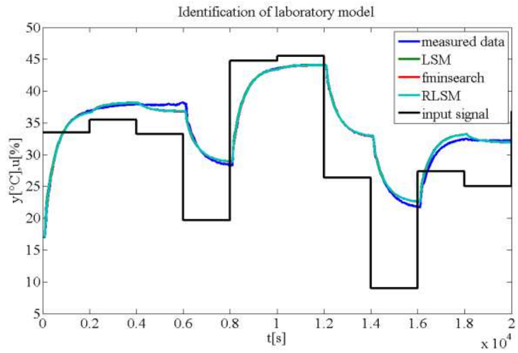

Figure 4 : Identification for 'sine' type input signal

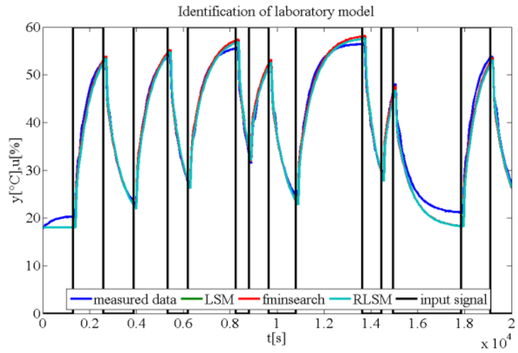

Figure 5 : Identification for 'rbs' input signal

Following table shows results of identification of laboratory model.

Table 1 : Analysis of identification

	S_y_LSM [°C^2]	S_y_fminsearch [°C^2]	S_y_RLSM [°C^2]
sine	296.17	294.09	295.13
rbs	297.36	307.03	297.36

SIMULATION RESULTS OF PREDICTIVE CONTROL

Transfer function that provide the greatest accordance with measured data was chosen from identified models.

$$G(z^{-1}) = \frac{0.0995z^{-1} - 0.0477z^{-2}}{1 - 1.0215z^{-1} + 0.1088z^{-2}} z^{-2}$$

Figures 6 to 11 shows simulation results for different weighting coefficients and constraints.

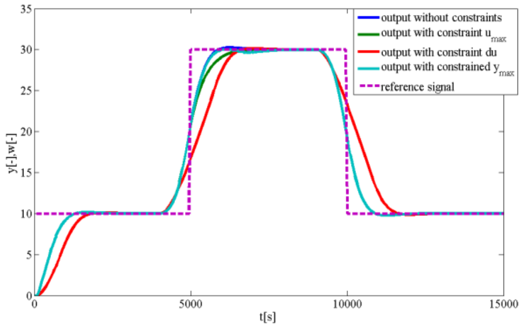

Figure 6 : System output signals with λ=2, δ=0.5

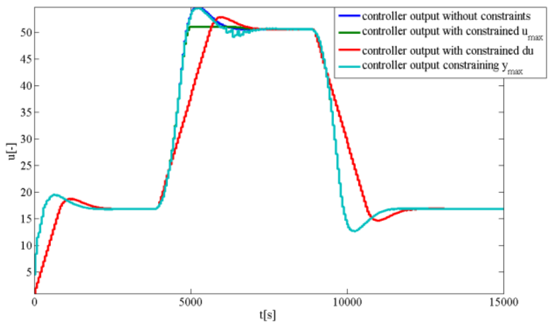

Figure 7 : System input signals with λ=2, δ=0.5

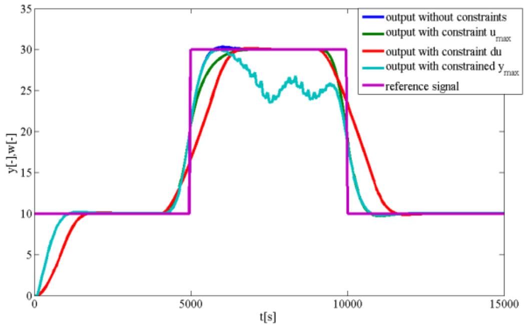

Figure 8 : System output signals with λ=2, δ=1

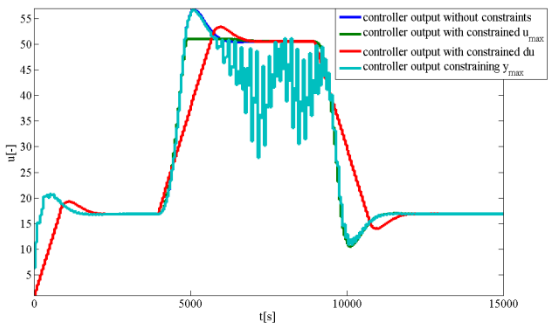

Figure 9 : System input signals with λ=2, δ=1

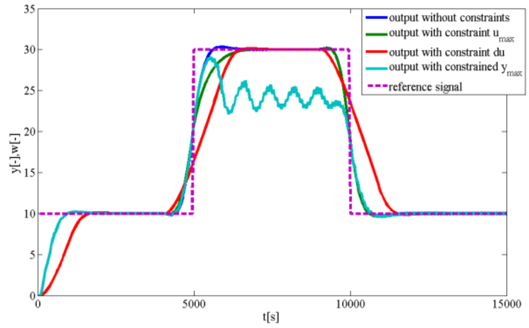

Figure 10 : System output signals with λ=1, δ=1

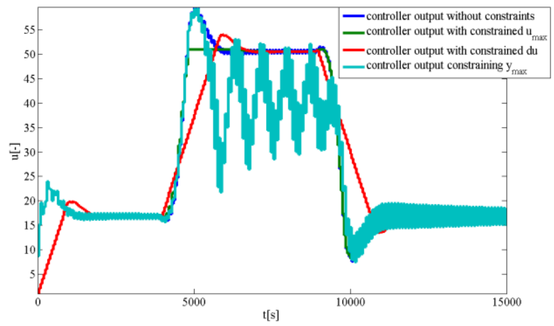

Figure 11 : System inputs signal with λ=1, δ=1

A quadratic criterion of a difference between the output and the reference signal and a quadratic criterion of the control increments is chosen for an analysis of control quality.

$$S_u = \frac{1}{N}\sum_{k=1}^{N}\Delta u^2(k) \tag{30}$$

$$S_e = \frac{1}{N}\sum_{k=1}^{N}\left[w(k) - y(k)\right]^2 \tag{31}$$

Tables of simulation results analysis:

Table 2 : Results for simulation with λ=2, δ=0,5

	Without constraints	With constraints		
		Δu_{max} = 1, Δu_{min} = -1	u_{max} = 51	y_{max} = 30
Su [%^{2}]	0.6893	0.2883	0.6627	0.7061
Se [°C^2]	7.3190	15.9372	7.6457	7.3442

Table 3 : Results for simulation with λ=2, δ=1

	Without constraints	With constraints		
		Δu_{max} = 1, Δu_{min} = -1	u_{max} = 51	y_{max} = 30
Su [%^{2}]	1.0096	0.3029	0.9338	17.0091
Se [°C^2]	6.2507	16.0116	6.8054	11.0470

Table 4 :Results for simulation with λ=1, δ=1

	Without constraints	With constraints		
		Δu_{max} = 1, Δu_{min} = -1	u_{max} = 51	y_{max} = 30
Su [$\%^2$]	2.1734	0.3168	1.8542	39.1709
Se [°C^2]	5.3405	16.3072	6.1423	15.4587

CONCLUSION

Simulations represent an ideal state when the parameters of a controlled system precisely match with the model of the controlled system used for the system output prediction and no noise or disturbance was applied on the controlled system. Simulations were performed for transfer function of real system, laboratory model of a heat exchanger. This transfer function was identified by three identification methods and the one with the best value of the quadratic criterion S_y was chosen. The values of the quadratic criterions S_e and S_u shows the influence of the constraints and weighting coefficients. The criterion S_e represents fitting quality of reference signal by the system output and criterion S_u represents value of the control increments. The system input signal without constraints provides the best fit between output and reference signal. Each of constraints may impair the fitting of reference signal. The constraint of the control increments provides the least value of S_u criterion. Weighting coefficients may have influence on system stability. Figures 6 to 11 show that they have the greatest influence in case with constraining the system output value. The predictive control is able to eliminate the time-delay and time-delay presence have no impact on application of consraints in control process.

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