NONLINEAR PREDICTIVE CONTROLLER: INFLUENCE OF ITERATIONS NUMBER ON REGULATION QUALITY

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Abstract

The paper deals with a nonlinear predictive controller, which is based on decomposition principle of system output predictions. Since the superposition principle doesn't hold for the used calculation approach, the controller algorithm iteratively corrects the prediction, which also improves the vector of future control actions. The number of iterations has influence on regulation quality. Assessment of its influence on regulation quality by controlling of a multivariable nonlinear system with constraints is aim of this paper.

1 INTRODUCTION

An idea to develop a predictive controller which uses utmost knowledge of a controlled system was on the beginning. The result of the effort is a Nonlinear Model Predictive Control (NMPC) controller with constraints respecting. The controller is relatively easy feasible but its operation is quite much time-consuming. The high computational performance is caused by using of a nonlinear mathematical model of a controlled system and also by iterative control actions calculation method.

The increasing number of iterations logical increases time necessary for control actions calculation. On the other hand, under certain conditions would have the increased number of iterations a positive impact on the quality of regulation. Verification of this assumption on an appropriate system is described in this paper.

2 NMPC CONTROLLER

The controller uses decomposition of system outputs prediction $\hat{\mathbf{y}}$ on predictions of free $\hat{\mathbf{y}}_{\mathbf{fr}}$ and forced $\hat{\mathbf{y}}_{\mathbf{fo}}$ responses (1) (more in [1]).

$$\hat{\mathbf{y}}\left(\mathbf{u},\mathbf{x}(k)\right)=\hat{\mathbf{y}}_{\mathbf{fr}}\left(\mathbf{u}_0,\mathbf{x}(k)\right)+\hat{\mathbf{y}}_{\mathbf{fo}}\left(\Delta\mathbf{u},\mathbf{0}\right) \tag{1}$$

where:

$\mathbf{u}$	A vector of control actions on a control horizon
$\mathbf{u}_0$	A vector of presumptive control actions on a control horizon
$\Delta\mathbf{u}$	A vector of control actions increments on a control horizon
$\mathbf{x}(k)$	A vector of current states values
$\mathbf{0}$	A zero vector

The vectors can be described by equations (2) - (4). The prediction horizon has the same length as the control horizon, thus the term 'horizon' and symbol N are used in the paper for both.

$$\mathbf{u}=\left[\mathbf{u}(k)^T \quad \mathbf{u}(k+1)^T \quad \mathbf{K} \quad \mathbf{u}(k+N-1)^T\right]^T \tag{2}$$

$$\mathbf{u}_0=\left[\mathbf{u}_0(k)^T \quad \mathbf{u}_0(k+1)^T \quad \mathbf{K} \quad \mathbf{u}_0(k+N-1)^T\right]^T \tag{3}$$

$$\Delta\mathbf{u}=\left[\Delta\mathbf{u}(k)^T \quad \Delta\mathbf{u}(k+1)^T \quad \mathbf{K} \quad \Delta\mathbf{u}(k+N-1)^T\right]^T \tag{4}$$

$$\hat{\mathbf{y}}=\left[\hat{\mathbf{y}}(k+1)^T \quad \hat{\mathbf{y}}(k+1)^T \quad \mathbf{K} \quad \hat{\mathbf{y}}(k+N)^T\right]^T \tag{5}$$

The vector $\mathbf{u}(k+j)$ is a vector of manipulated inputs at time instant *k*+*j*. Similar $\mathbf{u}_0(k+j)$ and $\Delta\mathbf{u}(k+j)$ are vectors of corresponding variables at time *k*+*j*. The vector of control actions **u** can be expressed by equation (6).

$$\mathbf{u} = \mathbf{u}_0 + \Delta\mathbf{u} \tag{6}$$

The objective function of the controller (7) consists from three parts. The first is penalization of control errors; the second is penalization of manipulated inputs time differences. The last one ensures approaching of manipulated inputs to their optimal values in steady state. Also respecting of constraints is included in the objective function.

$$\begin{gathered} J(\Delta\mathbf{u}) = (\hat{\mathbf{y}} - \mathbf{w})^T.\overline{\mathbf{R}}.(\hat{\mathbf{y}} - \mathbf{w}) + \mathbf{du}^T.\overline{\mathbf{Q}}.\mathbf{du} + \left(\mathbf{u} - \mathbf{u_{opt}}\right)^T.\overline{\mathbf{Q}}_2.\left(\mathbf{u} - \mathbf{u_{opt}}\right) \\ \text{subject to} \quad \mathbf{S}.\Delta\mathbf{u} \geq \mathbf{s} \end{gathered} \tag{7}$$

where:

$\mathbf{w}$	A vector of desired values on the horizon
$\mathbf{du}$	A vector of **u** time differences on the horizon
$\mathbf{u_{opt}}$	A vector of inputs optimal values at steady state
$\mathbf{S}$	A matrix of constraints (inequalities left sides)
$\mathbf{s}$	A vector of constraints (inequalities right sides)
$\overline{\mathbf{R}}$	A square diagonal weighting matrix
$\overline{\mathbf{Q}}$	A square diagonal weighting matrix
$\overline{\mathbf{Q}}_2$	A square diagonal weighting matrix

The vector $\mathbf{u_{opt}}$ contains optimal values of the process inputs to be reached at steady state. The vector of inputs time differences $\mathbf{du}$ can be rewritten to equation (8).

$$\mathbf{du} = \mathbf{E_v}.\Delta\mathbf{u} + \mathbf{E_{v2}}.\mathbf{u}_0 \tag{8}$$

The variable $\mathbf{E_v}$ is a matrix described by (9) and the matrix $\mathbf{E_{v2}}$ is described by (10), where **I** is a unit matrix and **0** is a zero matrix.

$$\mathbf{E_v} = \begin{bmatrix} \mathbf{I} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ -\mathbf{I} & \mathbf{I} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & -\mathbf{I} & \mathbf{I} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I} \end{bmatrix} \tag{9}$$

$$\mathbf{E_{v2}} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ -\mathbf{I} & \mathbf{I} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & -\mathbf{I} & \mathbf{I} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I} \end{bmatrix} \tag{10}$$

The NMPC controller calculates the prediction of the free response $\hat{\mathbf{y}}_{\mathbf{fr}}$ from a nonlinear mathematical model of the controlled system, which can be generally described by (11). The vector $\dot{\mathbf{x}}(t)$ contains derivation of states $\mathbf{x}(t)$.

$$\begin{aligned} \dot{\mathbf{x}}(t) &= f\left(\mathbf{x}(t), \mathbf{u}(t), t\right) \\ \mathbf{y}(t) &= g\left(\mathbf{x}(t), \mathbf{u}(t), t\right) \end{aligned} \tag{11}$$

The forced output prediction $\hat{\mathbf{y}}_{\mathbf{fo}}$ is calculated from a linear discreet state model (12) of the controlled system. The state model was chosen because it can be easy used for a multivariable system.

$$\begin{aligned} \bar{\mathbf{x}}(k+1) &= \mathbf{A_d}.\bar{\mathbf{x}}(k) + \mathbf{B_d}.\bar{\mathbf{u}}(k) \\ \bar{\mathbf{y}}(k) &= \mathbf{C_d}.\bar{\mathbf{x}}(k) \end{aligned} \tag{12}$$

where:

$\mathbf{A_d}$	A states matrix
$\mathbf{B_d}$	An inputs matrix
$\mathbf{C_d}$	An outputs matrix
$\bar{\mathbf{x}}$	A vector of states deviation from a linearization point
$\bar{\mathbf{u}}$	A vector of inputs deviation from a linearization point
$\bar{\mathbf{y}}$	A vector of outputs deviation from a linearization point

So the forced output prediction can be described by equation (13). The matrix **H** is described by equation (14).

$$\hat{\mathbf{y}}_{\mathbf{fo}} = \mathbf{H}.\Delta\mathbf{u} \tag{13}$$

$$\mathbf{H} = \begin{bmatrix} \mathbf{C_d}.\mathbf{B_d} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{C_d}.\mathbf{A_d}.\mathbf{B_d} & \mathbf{C_d}.\mathbf{B_d} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C_d}.\mathbf{A_d}^{N-1}.\mathbf{B_d} & \mathbf{C_d}.\mathbf{A_d}^{N-2}.\mathbf{B_d} & \cdots & \mathbf{C_d}.\mathbf{B_d} \end{bmatrix} \tag{14}$$

The controller calculates the vector of control actions **u** by minimizing of the objective function (7). Because constraints are taking into account, the optimization problem has to be solved numerically, in this case by Quadratic Programming (QP). Thus it is suitable to transform the objective function (7) into QP form (15).

$$\begin{aligned} &J(\Delta\mathbf{u}) = \frac{1}{2}\Delta\mathbf{u}^T.\mathbf{M}.\Delta\mathbf{u} + \mathbf{m}.\Delta\mathbf{u} + c \\ &\text{subject to} \quad \mathbf{S}.\Delta\mathbf{u} \geq \mathbf{s} \end{aligned} \tag{15}$$

The matrix **M** and vector **m** are for the NMPC controller defined by equations (16) and (17). The variable *c* isn't important.

$$\mathbf{M} = \mathbf{H}^T.\overline{\mathbf{R}}.\mathbf{H} + \mathbf{E}_{\mathbf{v}}^T.\overline{\mathbf{Q}}.\mathbf{E}_{\mathbf{v}} + \overline{\mathbf{Q}}_2 \tag{16}$$

$$\mathbf{m} = \mathbf{H}^T.\overline{\mathbf{R}}.\left(\hat{\mathbf{y}}_{\mathbf{fr}}\left(\mathbf{u},\mathbf{x}(k)\right) - \mathbf{w}\right) + \overline{\mathbf{Q}}_2.\left(\mathbf{u}_0 - \mathbf{u}_{\mathbf{opt}}\right) + \mathbf{E}_{\mathbf{v}}^T.\overline{\mathbf{Q}}.\mathbf{E}_{\mathbf{v}2}.\mathbf{u}_0 \tag{17}$$

Key for this controller is the vector of presumptive control actions on the horizon $\mathbf{u}_0$. The vector ensures time spread iteration what enable to execute the calculation in one iteration. It is important to move the main contribution of system outputs prediction on free response because the superposition principle doesn't hold for nonlinear system generally. The free response is calculated from the nonlinear model which should give results corresponding more with reality. The vector $\mathbf{u}_0$ (say at time *k*) is generated from the previous vector of control actions **u** what can be described by equation (18).

$$\mathbf{u}_0 = \begin{bmatrix} \mathbf{u}(k+1|k-1) \\ \mathbf{u}(k+2|k-1) \\ \vdots \\ \mathbf{u}(k+N_u-1|k-1) \\ \mathbf{u}(k+N_u-1|k-1) \end{bmatrix} \tag{18}$$

The controlled system can be constrained on states $\mathbf{x}$ or inputs $\mathbf{u}$ ranges. This type of constraints is defined by equations (19) and (20) for the objective function (15).

$$\mathbf{S} = \begin{bmatrix} -\mathbf{S}_{\mathbf{u}}^{T} & \mathbf{S}_{\mathbf{u}}^{T} & -\mathbf{S}_{2\mathbf{x}}{}^{T} & \mathbf{S}_{2\mathbf{x}}{}^{T} \end{bmatrix}^{T} \tag{19}$$

$$\mathbf{s} = \begin{bmatrix} -\mathbf{u}_{\mathbf{max}} + \mathbf{u}_0 \\ \mathbf{u}_{\mathbf{min}} - \mathbf{u}_0 \\ -\mathbf{x}_{\mathbf{max}} + \mathbf{x}_{\mathbf{cfr}} \\ \mathbf{x}_{\mathbf{max}} - \mathbf{x}_{\mathbf{cfr}} \end{bmatrix} \tag{20}$$

where:

$\mathbf{u}_{\max}$	A vector of upper inputs boundaries on the horizon
$\mathbf{u}_{\min}$	A vector of lower inputs boundaries on the horizon
$\mathbf{x}_{\max}$	A vector of upper states boundaries on the horizon
$\mathbf{x}_{\min}$	A vector of lower states boundaries on the horizon
$\mathbf{x}_{\mathbf{cfr}}$	A vector of states prediction on the horizon (only states which occurs in constraints)
$\mathbf{S}_{\mathbf{u}}$	A unit matrix

The matrix $\mathbf{S}_{2\mathbf{x}}$ is defined by equation (21).

$$\mathbf{S}_{2\mathbf{x}} = \begin{bmatrix} \mathbf{C_c}.\mathbf{B_d} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{C_c}.\mathbf{A_d}.\mathbf{B_d} & \mathbf{C_c}.\mathbf{B_d} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C_c}.\mathbf{A_d}^{N-1}.\mathbf{B_d} & \mathbf{C_c}.\mathbf{A_d}^{N-2}.\mathbf{B_d} & \cdots & \mathbf{C_c}.\mathbf{B_d} \end{bmatrix} \tag{21}$$

The controller uses time spread iteration, nevertheless more than one iteration can be executed what should have positive influence on regulation quality. The vector of presumptive control actions $\mathbf{u}_0$ is for the next iteration calculated by equation (22) in such case.

$$\mathbf{u}_0^{(i+1)} = \mathbf{u}_0^{(i)} + \Delta\mathbf{u}^{(i)} \tag{22}$$

The vector of control actions on the horizon $\mathbf{u}$ (the controller output) corresponds to the vector $\mathbf{u}_0^{(i+1)}$ from equation (22) for the last iteration. More complex description of the NMPC controller is in [2], where is also described the controller realization.

3 Controlled system

The experiment should be realized on a system, by which is possible to predict the directions of all states changes on the prediction horizon in every moment of any control process.

An experimental model of Hydraulic-Pneumatic System (HPS) was chosen for the experiment. This model was realized within the Czech Science Foundation project 102/03/0625. The model is multivariable with internal connections. A complete technical description of the experimental model was published in [3] and schematic representation of this model is shown as figure 1.

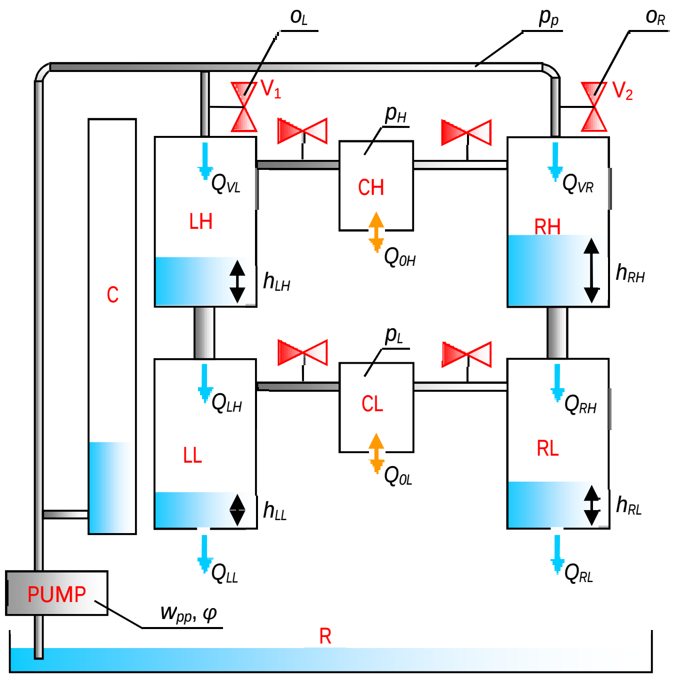

Figure 1: Schema of the experimental model

The experimental model is comprised of four hydraulic tanks and two pneumatic volumes (air tanks). The hydraulic tanks on the high part, LH and RH, are connected by a shared pneumatic volume CH. The hydraulic tanks are interconnected to one another. The hydraulic tanks of the low part, LL and RL, are connected in the same way (pneumatic volume CL).

The system has four feasible inputs in sum - openings of inflow valves V_1 and V_2 - o_L, o_R, incoming power of the pump j and desired overpressure of the liquid in an inflow pipe[1] w_{p_p}. Only three inputs can be manipulated in the same moment. It is possible to choose between pump incoming power and desired value of the liquid overpressure.

The air chamber C influences the dynamic features of pressure regulation in the inflow pipe. Each hydraulic tank has an outlet hole in the tank bottom. Liquid is drained from the high tanks to the low tanks. A high tank output is a low tank input. The air tanks (pneumatic volumes) are provided with orifices. The orifices have very small diameters and they are used for pressure settlement by dynamic actions in the system.

It is possible to measure seven system states and atmospheric pressure p_A. Measured states are levels of liquid in all hydraulic tanks (four levels - $h_{LH}, h_{RH}, h_{LL}, h_{RL}$), pressures on high and low levels p_H, p_L and overpressure of the liquid in the inflow pipe p_p.

Mathematical models of HPS are necessary for the experiment (specifically a linear and a nonlinear model). Valves, hydraulic and pneumatic tanks have to be incorporated to them, as follows from chapter 4.

[1] The liquid overpressure is controlled by PSD controller in this mode.

3.1 Nonlinear mathematic model of HPS

The nonlinear mathematical model used in this work is based on the first principle because such models correspond mostly to real processes and they respect mass and energy balances.

Detailed description of Hydraulic - Pneumatic part of the mathematical model development was published in [4]. Two mathematical models were developed in this work. The more complicated variant respects temperature changes inside the system. The second variation doesn't respect them. It was determined by custom simulations that the simplified mathematical model without respect to temperature changes, suffices for the laboratory model description (for the chosen operating conditions). The static characteristic of valves has been published in [5]. Original equations had to be modified from identification reasons. The complete modified nonlinear mathematical model of HPS and its parameters values were published in [2]. The model can be general described by equation (11), where the time dependent variables are described by equations (23) to (25).

$$\mathbf{x}(t)=\left[h_{LH}(t)\ \ h_{RH}(t)\ \ h_{LL}(t)\ \ h_{RL}(t)\ \ p_H(t)\ \ p_L(t)\right]^T \tag{23}$$

$$\mathbf{y}(t)=\left[h_{LL}(t)\ \ h_{RL}(t)\right]^T \tag{24}$$

$$\mathbf{u}(t)=\left[o_L(t)\ \ o_R(t)\ \ w_{p_p}(t)\right]^T \tag{25}$$

3.2 Linear mathematical model

A linear mathematical model of the plant is also necessary for the NMPC controller composition. The linear model was obtained by linearization of the simplified nonlinear mathematical model in this case what is described in [2].

Linearization of this model was realized for a steady state according to equation (26), where $\frac{d\tilde{\mathbf{x}}}{dt} \approx \mathbf{f}\left(\mathbf{x_{lin}},\mathbf{u_{lin}}\right)$ and $\tilde{\mathbf{x}}$ is approximation of states. The index **lin** determines value of the variable in the point of linearization.

$$\begin{aligned} \frac{d\left(\tilde{\mathbf{x}}-\mathbf{x_{lin}}\right)}{dt} &= \left.\frac{\partial \mathbf{f}}{\partial \mathbf{x}}\right|_{\substack{\mathbf{x}=\mathbf{x_{lin}}\\ \mathbf{u}=\mathbf{u_{lin}}}} .\left(\tilde{\mathbf{x}}-\mathbf{x_{lin}}\right)+\left.\frac{\partial \mathbf{f}}{\partial \mathbf{x}}\right|_{\substack{\mathbf{x}=\mathbf{x_{lin}}\\ \mathbf{u}=\mathbf{u}_0}} .\left(\mathbf{u}-\mathbf{u_{lin}}\right) \\ \tilde{\mathbf{y}} &\approx \mathbf{y_{lin}}+\left.\frac{\partial \mathbf{g}}{\partial \mathbf{x}}\right|_{\substack{\mathbf{x}=\mathbf{x_{lin}}\\ \mathbf{u}=\mathbf{u_{lin}}}} \left(\tilde{\mathbf{x}}-\mathbf{x_{lin}}\right)+\left.\frac{\partial \mathbf{g}}{\partial \mathbf{x}}\right|_{\substack{\mathbf{x}=\mathbf{x_{lin}}\\ \mathbf{u}=\mathbf{u_{lin}}}} \left(\mathbf{u}-\mathbf{u_{lin}}\right) \end{aligned} \tag{26}$$

This equation was used for the mathematical model linearization, but not every equation of the nonlinear mathematical model could be linearized in manner. The gas mass flows on both levels had to be approximated by another linear formula. The final linear model expressed in state space form (12) and its parameters values are available in [2].

4 Experiment

This paper is focused on influence of iterations number on regulation quality. The influence is assessed by a simulation experiment where the NMPC controller is applied on HPS (see chapter 3). The control objective is to follow known future desired values trajectories of low liquid levels $w_{h_{LL}}$, $w_{h_{RL}}$. The controller has to take into account constraints on states and inputs. Manipulated inputs of the controlled system in this experiment are inflow valves openings o_L, o_R and desired value of the liquid overpressure in the inflow pipe w_{p_p}. Such inputs choice provides much simpler mathematical model then the other one, more in [2].

4.1 Experiment conditions

Constraints of the controlled system are given by the construction and physics laws. Openings of valves are lower and upper bounded. The overpressure in the inflow pipe can't be negative and also is upper bounded by a maximal pumping power. Naturally, the liquid levels can't be smaller than zero but they are also limited on the maximum. Only constraints of the gas pressures on the high and low levels are not considered.

The reference trajectories were designed to simulate all basic types of situation that can arise during a control process. It was also necessary to avoid some unfavorable control condition (unfavorable control condition allows better approving of the iterations number influence on regulation quality). That's why the reference trajectories are built from step changes by which the desired values change between upper and lower boundaries of the controlled outputs. The time between step changes was set on 600 seconds what suffices for the outputs steady states reaching. The basic types of situations are:

- Growth of both low liquid levels is required.
- Descending of both low liquid levels is required.
- Growth of one low liquid level and descending of second are required.
- Change of one low liquid level is required (second doesn't change).

The length of each simulation experiment is 4200 seconds. The sample time of the controller is 5 seconds and the length of horizon is 100 seconds. The choosing of sample time and horizon length is a compromise between regulation requirements and hardware limitations and it is explained in [2].

Settings of weighting matrices have been found with the aid of simulation for following requirements:

- Following of reference trajectories as close as possible without big overshoots.
- Minimize the pump output (i.e. minimize desired value of the liquid overpressure in the inflow pipe).

Their setting during the experiment is equal with the matrices setting in [2]. The number of iterations interval is one to fifteen for the experiment. The controller and also the whole experiment was realized in MATLAB. The optimization is realized by QP active set method. Functions and scripts are published in [2] and are also attached on the CD. The simulations start from steady states (for left side: h_{LL} upper boundary, for right site: h_{RL} lower boundary).

4.2 Experiment outputs

Fifteen simulation experiments have been realized in all (for different numbers of iterations). An example of regulation is shown on figures 2 and 3. The figure 2 shows behavior of the controlled system states during the experiment (red marked). The green marks desired values of system outputs and blue dash line symbolized states constraints. The figure 3 captures manipulated system inputs behaviors of the same experiment. The red color corresponds to system inputs, blue dash line is again used for the constraints symbolizing.

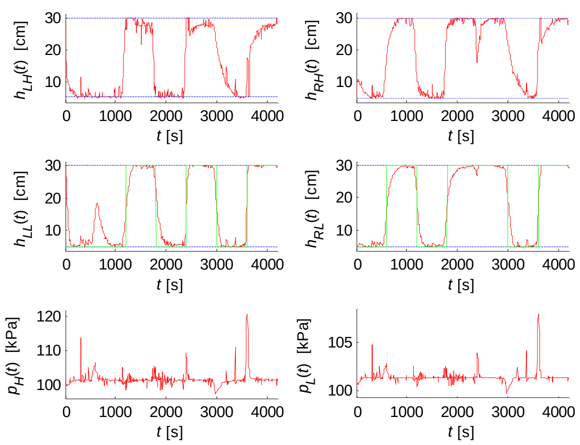

Figure 2: States behavior, number of iterations 2

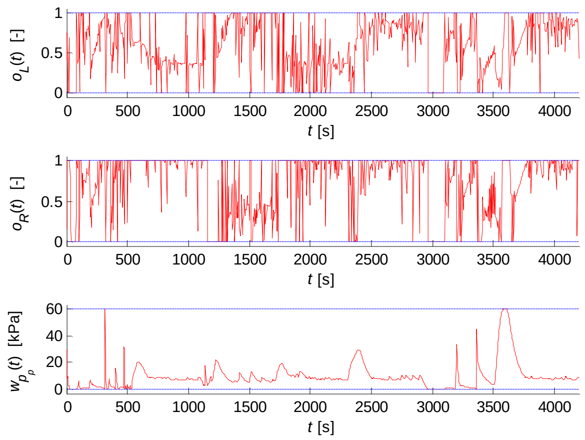

Figure 3: Inputs behavior, number of iterations 2

The regulation quality assessment is realized via two criterions. The first keeps under review control errors. This criterion is described by equation (27). The criterion can be described as sum of absolute values of all system outputs control errors during an experiment.

$$h_r = \sum_{j=1}^{n_y} \sum_{i=1}^{\frac{t_{sim}}{T_s}} \left| w_j(i) - y_j(i) \right| \tag{27}$$

where:

h_r	Control errors criterion
n_y	Number of controlled system outputs
t_{sim}	Experiment duration
T_s	The controller sample time
w_i	A system output desired value
y_i	A system output

The dependence of this criterion on iterations number is shown on figure 4.

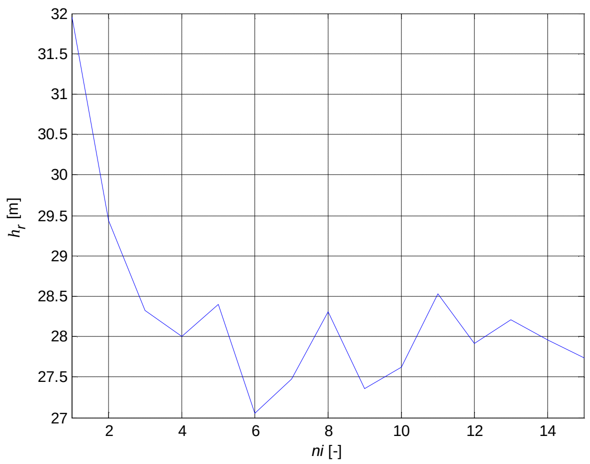

Figure 4: Dependence of control errors criterion on iterations number

The second criterion qualifies the regulation quality in term of constraints respecting. The criterion is described by equation (28). The criterion can be described as a sum of absolute values of states constraints overshoots.

$$h_c = \sum_{j=1}^{n_{xc}} \sum_{i=1}^{\frac{t_{sim}}{T_s}} \left| x_{c,j}(i) - x_{c_{\lim},j}(i) \right|$$
$$x_c \notin \left\langle x_{c_{\min}}, x_{c_{\max}} \right\rangle ; x_{c_{\lim}} \in \left[x_{c_{\min}}, x_{c_{\max}} \right] \quad (28)$$

where:

h_c	States constraints overshoots criterion
n_{xc}	Number of states with some boundary
x_c	A state with some boundary
$x_{c_{\lim}}$	A state boundary (upper or lower)
$x_{c_{\max}}$	An upper state boundary
$x_{c_{\min}}$	A lower state boundary

The dependence of the second criterion on iterations number is shown on figure 5.

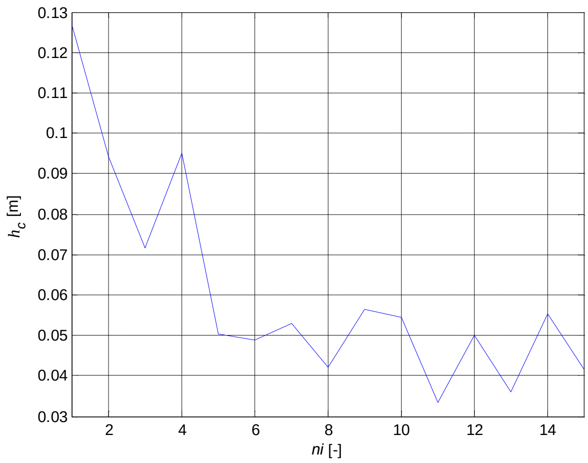

Figure 5: Dependence of states constraints overshoots criterion on iterations number

5 Conclusion

The simulation experiments have shown that the increasing number of iterations has really positive influence on regulation quality in this case. It is also necessary to say that it isn't necessary to execute a great number of iteration in every sample time. For the chosen system are optimal three iterations what is positive from the time consuming point of view.

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