SIMULATION OF 1DOF AND 2DOF ADAPTIVE CONTROL OF THE WATER TANK MODEL

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KEYWORDS
Modelling, Simulation, Mathematical Model, Adaptive control, Recursive Identification, Water Tank.

ABSTRACT

The water tank is a typical nonlinear system representing several types of systems like barrels, reservoirs, tanks etc. for liquid. The simulation, similarly as in other cases, can help with the understanding of the system's static and dynamic behavior and it is starting point for the controller design. The adaptive control in this work is based on the choice of the external linear model of the nonlinear system, parameters of which are identified recursively and the controller's parameters are also recomputed recursively according to the identified system. Basic control requirements are satisfied with the use of polynomial approach together with the Pole-placement method and spectral factorization. The resulting controller has also one tuning parameter which affects mainly the speed of the control and overshoots. Two control schemes with one degree-of-freedom and two degrees-of-freedom are tested and compared in the work.

INTRODUCTION

The adaptive control belongs to relatively new control strategies (Dusek and Honc, 2009), (Honc and Dusek, 2013b) which can be used for controlling of wide range of technological processes like heat exchangers, chemical reactors, flow control, water level in the tank etc.
The big advantage of this method can be found in strong theoretical background (Åström 1989) and a number of improvements. This control strategy comes from the feature known from the nature where animals and plants "adopt" their behavior to the actual living environment. Adaptation in the control field is done mainly by the change of the structure, parameters of the controller etc.
One way how we can also influence the result of the control is the choice of the control structure (Bobal *et al.* 2005). The most common control scheme is one degree-of-freedom (1DOF) control configuration, which has controller only in the feedback part (Grimble 1994). Better results can be sometimes obtained with the use of two degrees-of-freedom (2DOF) structure (Grimble 1994), where one part of the controller lies in the feedback and the second part is in the feedforward part. This control configuration could improve control results especially at the beginning of the control.
The controlled system and also the controller act in the 1DOF and 2DOF control schemes in the form of the continuous-time transfer function. Relations for computation of the controller's parameters uses polynomial approach (Kucera 1993) together with Pole-placement method and Spectral factorization. These methods satisfy basic control requirements such as stability, reference signal tracking and disturbance attenuation. Moreover, the polynomial synthesis produces not only the structure of the controller but also relations for controller's parameters computing.
The system under the consideration is the real model of the water tank which is one part of the Process Control Teaching system PCT40 from Armfield (Armfield 2005). This four-liter model offers various types for control including continuous control of the water tank.
All experiments in this work are based on the modelling and simulation techniques which are often used nowadays because of time and mainly cost savings (Ingham *et al.* 2000). The mathematical model of the controlled water tank is described by the one nonlinear ordinary differential equation which is then solved numerically.
The paper is divided into four main parts. The adaptive approach is introduced in the first chapter. Then, the model of the controlled water tank is introduced together with the mathematical model and simulation results of the steady-state and dynamic analyses. The third part presents simulation results of control for both 1DOF and 2DOF control configurations and compares these two controllers. The last part is conclusion which summarizes main results and form recommendations for controlling of the real process.
All simulations were done in the mathematical software Matlab, version 7.0.1 which is suitable for this task and also widely used (Honc and Dusek, 2013a).

ADAPTIVE CONTROL

The adaptivity in the control strategy here is satisfied by the recursive estimation of the External Linear Model (ELM) as a linear representation of originally nonlinear system parameters of which are estimated recursively

Proceedings 29th European Conference on Modelling and Simulation ©ECMS Valeri M. Mladenov, Petia Georgieva, Grisha Spasov, Galidiya Petrova (Editors)
ISBN: 978-0-9932440-0-1 / ISBN: 978-0-9932440-1-8 (CD)

during the control and parameters of the controller are recomputed in each step according to identified parameters too (Bobal *et al.* 2005). The ELM is usually in the form of continuous-time (CT) or discrete-time (DT) transfer functions, where CT models are more accurate. On the other hand, DT models are better for online identification.

Two CT control system configurations were tested for this model – the one degree-of-freedom (1DOF) and the two degrees-of-freedom (2DOF) control configurations.

Control System Synthesis

The first control structure with one degree-of-freedom has controller only in the feedback part – see Figure 1.

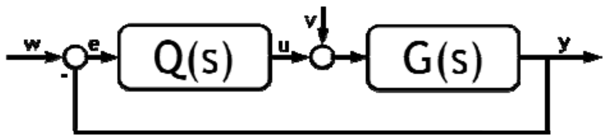

Figure 1: 1DOF control configuration

The block $G(s)$ represents the transfer function of the controlled system, in our case ELM chosen for example from the dynamic analysis. The second block $Q(s)$ is feedback controller again in the form of the transfer function. Signal w is reference signal, e.g. wanted value of the output variable y and e denotes control error, $e = w - y$. The computed output signal u from the controller is action value and v is random error.

The polynomial approach together with the Pole-placement method and spectral factorization are employed in the controller design.

The transfer function of the controlled system is then with the use of polynomial approach

$$G(s) = \frac{b(s)}{a(s)} \tag{1}$$

where $\deg b(s) \le \deg a(s)$ due to properness condition and the transfer function of the controller is

$$Q(s) = \frac{q(s)}{p(s)} \tag{2}$$

and $\deg q(s) \le \deg p(s)$ again due to properness. The asymptotic tracking of the reference signal is satisfied if the polynomial $p(s)$ include the least common divisor of the Laplace transform of the reference signal w and the random error v. If we consider these signals from the ring of step functions, the least common divisor is s and polynomial $p(s)$ in the denominator of (2) is $p(s) = s \cdot \tilde{p}(s)$.

Polynomials $a(s)$ and $b(s)$ are known in each step from the recursive identification and the task of the controller is to compute parameters of polynomials $p(s)$ and $q(s)$. These parameters are computed from the so called Diophantic equation (Kucera 1993)

$$a(s) \cdot s \cdot \tilde{p}(s) + b(s) \cdot q(s) = d(s) \tag{3}$$

by the Method of uncertain coefficients which compares coefficients of individual s-powers.

Degrees of the polynomials $\tilde{p}(s)$ and $q(s)$ are

$$\begin{aligned} \deg \tilde{p}(s) &= \deg a(s) - 1 \\ \deg q(s) &= \deg a(s) \end{aligned} . \tag{4}$$

The polynomial $d(s)$ on the right side of equation (3) is stable optional polynomial and the degree of this polynomial is

$$\deg d(s) = \deg a(s) + \deg \tilde{p}(s) + 1 \tag{5}$$

The simplest way how to choose this polynomial is to use the Pole-placement method which defines this polynomial with several poles, number of which depends on the degree of this polynomial, i.e.

$$d(s) = (s + \alpha)^{\deg d} \tag{6}$$

with α as a tuning constant with condition $\alpha > 0$. Disadvantage of this method is that there is no general rule how to choose α. Our experiments (Vojtesek and Dostal 2012) have shown that it is good to connect the choice of the polynomial $d(s)$ with the parameters of the controlled system, for example with the use of spectral factorization of the polynomial $a(s)$ in the numerator of $G(s)$ in (1) known from the recursive identification

$$n^*(s) \cdot n(s) = a^*(s) \cdot a(s) \tag{7}$$

The polynomial $d(s)$ in (6) is then divided into two parts – the first, $n(s)$, is computed from the spectral factorization (7) and the second from the Pole-placement method in (6), i.e.

$$d(s) = n(s) \cdot (s + \alpha)^{\deg d - \deg n} \tag{8}$$

The second control configuration with two degrees-of-freedom (2DOF) has the controller divided into feedback part $Q(s)$ and feedforward part $R(s)$ – see Figure 2.

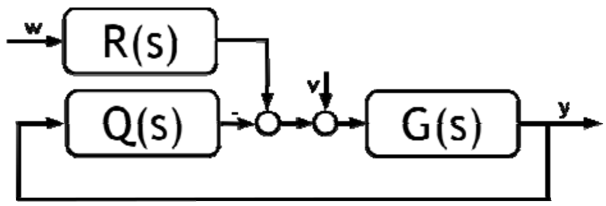

Figure 2: 2DOF control configuration

The main benefit of this control configuration can be found in the better reference signal tracking which is satisfied by the feedforward part of the controller $R(s)$.

Transfer functions of the controller are generally

$$Q(s) = \frac{q(s)}{p(s)} = \frac{q(s)}{s \cdot \tilde{p}(s)}; \; R(s) = \frac{r(s)}{p(s)} = \frac{r(s)}{s \cdot \tilde{p}(s)} \tag{9}$$

for $\deg q(s) \leq \deg p(s)$ and $\deg r(s) \leq \deg p(s)$ and polynomials $\tilde{p}(s)$, $q(s)$ and $r(s)$ are computed from Diophantine equations

$$\begin{aligned} a(s)\cdot s\cdot \tilde{p}(s)+b(s)\cdot q(s)&=d(s) \\ t(s)\cdot s+b(s)\cdot r(s)&=d(s) \end{aligned} \tag{10}$$

with the same stable polynomial $d(s)$ on the right side which is again constructed by the Pole-placement method and the spectral factorization described above. Polynomial $t(s)$ in the second Diophantine equation is an auxiliary stable polynomial. Coefficients of this polynomial are not used for computing of coefficients of the polynomial $r(s)$.

Recursive Identification

Important part of the adaptive approach here is the on-line recursive identification of the ELM. The simple Recursive Least-Squares (RLS) method (Fikar and Mikles 1999) is used in this work for this task. The big advantage of this method is that it can be easily expanded by the additional "forgetting" techniques and also programmable in standard program languages. The RLS method used for estimation of the vector of parameters $\hat{\boldsymbol{\theta}}_\delta^T$ could be described by the set of equations:

$$\begin{aligned} \varepsilon(k)&=y(k)-\boldsymbol{\varphi}^T(k)\cdot\hat{\boldsymbol{\theta}}(k-1) \\ \gamma(k)&=\left[1+\boldsymbol{\varphi}^T(k)\cdot\mathbf{P}(k-1)\cdot\boldsymbol{\varphi}(k)\right]^{-1} \\ \boldsymbol{L}(k)&=\gamma(k)\cdot\mathbf{P}(k-1)\cdot\boldsymbol{\varphi}(k) \\ \mathbf{P}(k)&=\frac{1}{\lambda_1(k-1)}\left[\mathbf{P}(k-1)-\frac{\mathbf{P}(k-1)\cdot\boldsymbol{\varphi}(k)\cdot\boldsymbol{\varphi}^T(k)\cdot\mathbf{P}(k-1)}{\frac{\lambda_1(k-1)}{\lambda_2(k-1)}+\boldsymbol{\varphi}^T(k)\cdot\mathbf{P}(k-1)\cdot\boldsymbol{\varphi}(k)}\right] \\ \hat{\boldsymbol{\theta}}(k)&=\hat{\boldsymbol{\theta}}(k-1)+\boldsymbol{L}(k)\varepsilon(k) \end{aligned} \tag{11}$$

Where $\boldsymbol{\phi}$ is regression vector, ε denotes a prediction error, $\mathbf{P}$ is a covariance matrix and λ_1 and λ_2 are forgetting factors. For example constant exponential forgetting (Fikar and Mikles 1999) uses $\lambda_2 = 1$ and

$$\lambda_1(k)=1-K\cdot\gamma(k)\cdot\varepsilon^2(k) \tag{12}$$

where K is a very small value (e.g. $K = 0.001$).

MODEL OF THE WATER TANK

The model under the consideration is real model of the water tank as a small representation of usually big tank or reservoir for the water or other liquids. Real models offers to make experiments with lower time demands and mainly costs for experiments than on the real system and we expect that results obtained on the real model are similar to those which can be obtained on the real system.

The real model here is part of the Process Control Teaching system PCT40 from Armfield which has various models that can work separately or even better they can be connected and used together. The main parts are a heat exchanger, a water tank and a continuous stirred-tank reactor (CSTR) but it could be expanded by the electronic console for connection of the commercial PID controller, PLC etc. or by a pneumatic valve accessory. The scheme of PCT40 is shown in Figure 3 (Armfield 2005).

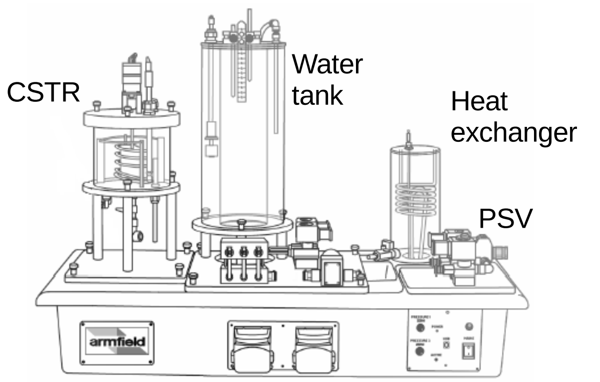

Figure 3: Multifunctional process control teaching system PCT40

The water tank model itself is plastic transparent cylinder with inner radius $r_1 = 0.087$ m. The model has due to quicker dynamics and reduction of the water consumption also another transparent cylinder inside with outer diameter $r_2 = 0.057$ m. The maximal water level in the tank is $h_{max} = 0.3$ m which means that the maximal volume of the tank is $V_{max} = 4.1$ l.

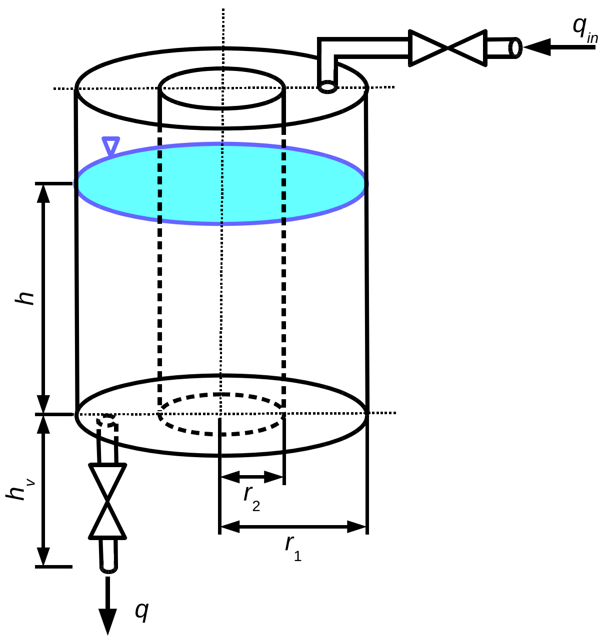

Figure 4: Scheme of the water tank model

The model offers three various types of control – the maximal level on/off control, the difference water level

control between the lower and the upper bound and direct continuous water level control to the set value. The third control option is used here – the input into the system is water with input volumetric flow rate q_{in}, and comes out through the output valve with volumetric flow rate q. The water level, h, is measured by the pressure level sensor. Figure 4 shows schematic representation of the water tank model.
The input volumetric flow rate q_{in} could be set and controlled by the Proportional Solenoid Valve (PSV) in the range $q_{in} = <0;\ 2.5\cdot10^{-5}>\ m^3.s^{-1}$ which is also for better imagination $q_{in} = <0;\ 1.5>\ l.min^{-1}$.

Mathematical Model of the Water Tank

The mathematical model comes from the material balance inside the tank. The input variable is volumetric flow rate, q_{in}, and the state variable is the water level, h. The differential equation describing the mathematical model of the water tank is then

$$\frac{dh}{dt} = \frac{q_{in} - k\cdot\sqrt{h}}{F} \tag{13}$$

where k is a valve constant and F is the area of the base, in this case
$F = \pi\cdot r_1^2 - \pi\cdot r_2^2 = 1.36\cdot10^{-2}\,m^2$
This model was derived and discussed in (Vojtesek *et al.* 2014) and it was shown, that there was a small problem with the computation of the valve constant k. This constant was computed from the steady-state, where $dh/dt = 0$ in (13) which means that

$$q^s = k\cdot\sqrt{h^s} \Rightarrow k = \frac{q^s}{\sqrt{h^s}} \tag{14}$$

where we know q_{in} and steady-state water level h^s. It was proofed, that also the height of the output valve $h_v = 0.076\ m$ must be included into the computation, e.g.

$$k = \frac{q^s}{\sqrt{h^s + h_v}} \tag{15}$$

There were done several reference measurements due to accuracy of the model and the mean value of k used in this work is

$$k = 3.2282\cdot10^{-5}\,m^{5/2}.s^{-1} \tag{16}$$

Steady-state Analysis

The simulated steady-state characteristic together with verified steady-state values measured on the real model are shown in Figure 5.
Computed steady-state values show expected nonlinearity of the system and the main result of the steady-state analysis is the limitation of the input volumetric flow rate, q_{in}, which is $q_{in} = <8.86\cdot10^{-6};\ 1.98\cdot10^{-5}>\ m^3.s^{-1}$.

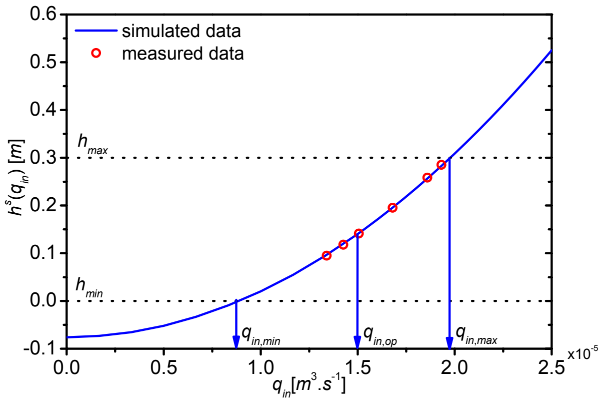

Figure 5: Steady-state characteristic

Dynamic Analysis

The dynamic analysis observes the behavior of the system after the step change of the input volumetric flow rate, Δq_{in}. The operating volumetric flow rate was set in the middle of the working interval in Figure 5, $q_{in,op} = 1.5\cdot10^{-5}\ m^3.s^{-1}$. Input and output variables are then

$$u(t) = \frac{q_{in}(t) - q_{in,op}}{q_{in,op}}\cdot 100\,[\%];\ y(t) = h(t)\,[m] \tag{17}$$

Several changes $u(t)$ were performed and results are in Figure 6.

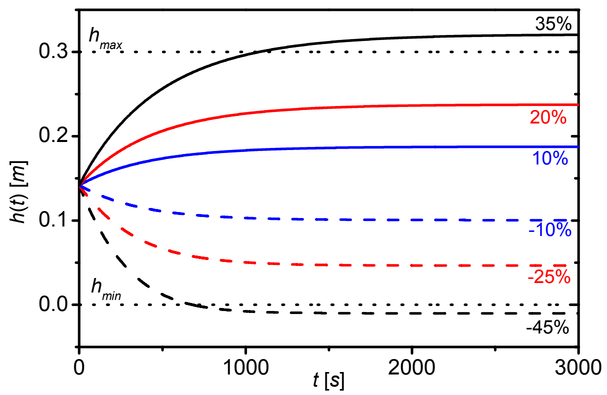

Figure 6: Dynamic characteristic

The dynamic analyses in Figure 6 show that the input variable is limited in the range approximately $u(t) = <-40\%;\ +30\%>$ for this operating point $q_{in,op}$. Lower or higher values result in very small or too high volumetric flow rates which are useless from the practical point of view.

SIMULATION OF ADAPTIVE CONTROL

As it is written in the theoretical part, the adaptive approach is based on the recursive identification of the ELM. The choice of the ELM could be based on results from the dynamic analysis displayed in Figure 6.
Proposed control strategies were tested by the simulation on the mathematical model of the water tank

described by equations (13)-(15). The output responses are then described by the first or the second order transfer functions. Although we have tested the first order transfer function in (Vojtesek *et al.* 2014), the second order transfer function was used here because it is more accurate and can cover bigger range of systems and different states of systems. The CT ELM (1) is then

$$G(s)=\frac{b(s)}{a(s)}=\frac{b_1 s+b_0}{s^2+a_1 s+a_0} \tag{18}$$

The on-line identification of CT ELM (18) could cause a problem. It is solvable for example with the use of differential filters as it is shown for example in (Vojtesek and Dostal 2005). The second way is to apply so called δ-models (Middleton and Goodwin 2004) which belong to the class of discrete-time models, but input and output variables are related to the sampling period which makes them more similar to those parameters in CT model (18) (Stericker and Sinha 1993). On-line identification of the discrete model is much easier from the mathematical point of view – we can read input and output variables only in the time intervals defined by the sampling period.

The δ–model introduces a new complex variable γ_δ

$$\gamma_\delta=\frac{z-1}{T_v} \tag{19}$$

and the differential equation derived from concrete ELM in (18) will be

$$\begin{aligned} y_\delta(k)&=b_0^\delta u_\delta(k-1)+b_1^\delta u_\delta(k-2)-\dots \\ &\dots-a_0^\delta y_\delta(k-1)-a_1^\delta y_\delta(k-2) \end{aligned} \tag{20}$$

where b_0^δ, b_1^δ, a_0^δ, a_1^δ are δ-parameters similar to those in (18) and delta values of input and output variables in Equation (20) can be computed as

$$\begin{aligned} &y_\delta(k)=\frac{y(k)-2y(k-1)+y(k-2)}{T_v^2} \\ &y_\delta(k-1)=\frac{y(k-1)-y(k-2)}{T_v} \quad u_\delta(k-1)=\frac{u(k-1)-u(k-2)}{T_v} \\ &y_\delta(k-2)=y(k-2) \quad u_\delta(k-2)=u(k-2) \end{aligned} \tag{21}$$

Where T_v is sampling period and the regression vector $\boldsymbol{\varphi}_\delta$ and the vector of parameters $\boldsymbol{\theta}_\delta$ are then

$$\begin{aligned} &\boldsymbol{\varphi}_\delta(k-1)=\left[-y_\delta(k-1),-y_\delta(k-2),u_\delta(k-1),u_\delta(k-2)\right]^T \\ &\boldsymbol{\theta}_\delta(k)=\left[a_1^\delta,a_0^\delta,b_1^\delta,b_0^\delta\right]^T \end{aligned} \tag{22}$$

The differential equation (20) has then vector form

$$y_\delta(k)=\boldsymbol{\theta}_\delta^T(k)\cdot\boldsymbol{\varphi}_\delta(k-1)+e(k) \tag{23}$$

where $e(k)$ is a general random immeasurable component and the task of the identification is to estimate the vector of parameters $\boldsymbol{\theta}_\delta$ from known data vector $\boldsymbol{\varphi}_\delta$.

The input variable $u(t)$ is the input volumetric flow rate q_{in} of the water which could be adjustable by the Proportional Solenoid Valve (PSV) in Armfield's PCT40 model. On the other hand, the output variable $y(t)$ is the water level inside the tank measured by the pressure sensor, e.g.

$$u(t)=q_{in}\left[m^3.s^{-1}\right]; \quad y(t)=h\left[m\right] \tag{24}$$

1DOF Control Results

The first control simulation study is done for the 1DOF control configuration described above. As the ELM is of the second order, the degrees of polynomials of the controller's transfer functions are

$$\begin{aligned} &\deg\tilde{p}(s)=\deg a(s)-1=1 \\ &\deg q(s)=\deg a(s)=2 \end{aligned} \tag{25}$$

The transfer function of the feedback controller (2) is then

$$Q(s)=\frac{q(s)}{s\cdot\tilde{p}(s)}=\frac{q_2 s^2+q_1 s+q_0}{s\cdot(s+p_0)} \tag{26}$$

and parameters of polynomials $\tilde{p}(s)$ and $q(s)$ are computed from the Diophantine equation (3) where the polynomial $d(s)$ is of fourth degree and (8) is

$$d(s)=n(s)\cdot(s+\alpha)^2 \tag{27}$$

Parameters of all simulations were the same due to comparability – the simulation time was 2 700 *s* (45 *min*), the sampling period was 1 *s* and several different step changes of the reference signal were done. There were done three simulation studies for the tuning parameter α = 0.02, 0.04 and 0.4 and the results are shown in Figure 7 and Figure 8.

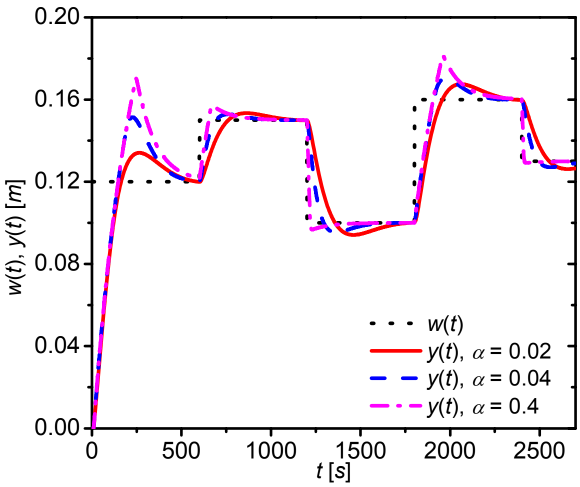

Figure 7: The course of the reference signal, $w(t)$, and the output variable, $y(t)$, for different α, 1DOF configuration

Obtained simulation results clearly show, that increasing value of the parameter α results in quicker output response but also bigger overshoots. It is the most visible at the very beginning of the control after the first step change. Next step changes produce not so big overshoots. The course of the input variable $u(t)$ in Figure 8 shows, that the smallest value of α has the best course of the input variable.

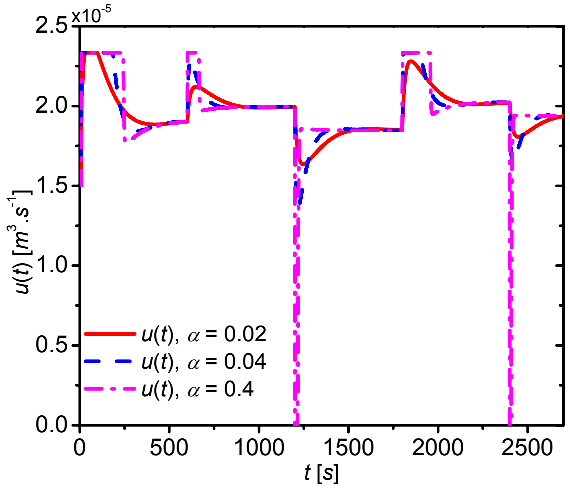

Figure 8: The course of the input variable, $u(t)$, for different α, 1DOF configuration

2DOF Control Results

The goal of the second simulation experiment is to apply 2DOF control configuration to this type of system. The same simulation parameters, step changes and even tuning parameters $\alpha = 0.02$, 0.04 and 0.4 were used. The simulation results are displayed in Figure 9 and Figure 10.

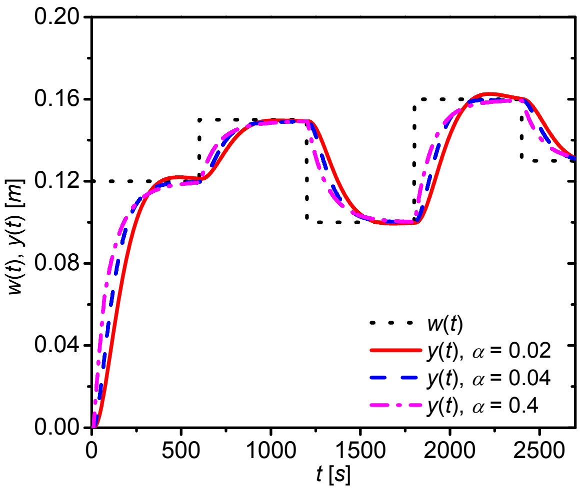

Figure 9: The course of the reference signal $w(t)$ and the output variable, $y(t)$, for different α, 2DOF configuration

The effect of the choice of the parameter α is the same as in previous control strategy – increasing value of this parameter results in the quicker output response in Figure 9. Courses of the input volumetric flow rate in Figure 10 are in this case very similar and comparable.

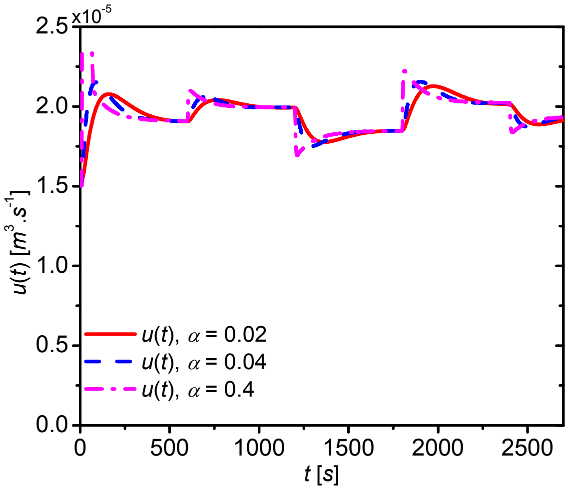

Figure 10: The course of the input variable, $u(t)$, for different α, 2DOF configuration

The significant improvement of 2DOF control strategy can be found in the suppression of the overshoots which is also compared in Figure 11 and Figure 12.

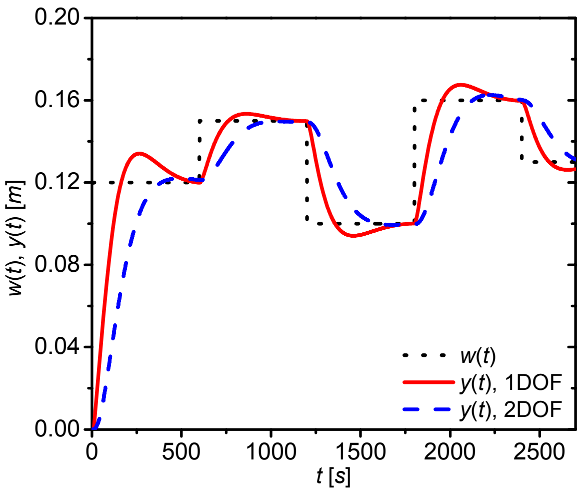

Figure 11: Comparison of the output response of 1DOF and 2DOF control configurations for $\alpha = 0.02$

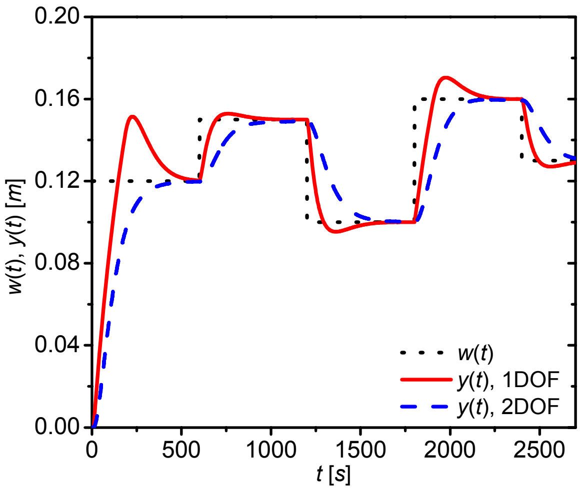

Figure 12: Comparison of the output response of 1DOF and 2DOF control configurations for $\alpha = 0.04$

On the other hand, the same choice of the parameter α produces slower course of the output variable in 2DOF control configuration than in the 1DOF configuration. The choice of the optimal control configuration then depends on what is important for us – a quicker output response or a bit slower response but without the overshoots.

CONCLUSIONS

The paper shows simulation results of the adaptive control with two control configurations applied on the mathematical model of the water tank as a typical nonlinear system. The adaptivity is fullfiled by the recursive identification of the external linear model as a linear representation of the originally nonlinear system. The controller is constructed with the use of the polynomial approach and Pole-placement method that satisfy basic control requirements such as stability, reference signal tracking and disturbance attenuation. The control response could be tuned by the choice of the position of the root in the Pole-placement method and it was shown, that increasing value of this parameter results in the quicker response but overshoots of the output. The main difference between 1DOF and 2DOF control configurations can be found in the suppression of these overshoots of the output variable in the use of the 2DOF configuration which has controller in the feedback and also in the feedforward part of the control scheme. The advantage of 2DOF is also in the reduction of the control input demands which is important from the practical point of view. On the other hand, 2DOF output response has slower output response compared with the 1DOF configuration with the same settings. The future work will be focused on the verification of obtained results by measurements on the real model of the water tank.

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