MODELLING AND SIMULATION OF WATER TANK

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ABSTRACT

The modelling and simulation play a very important role in the industry where it can help with the description of the system and the choice of the optimal control strategy. This contribution is focused on the modelling and simulation procedure which usually precedes the design of the controller. The mathematical model is derived with the use of material balance and produces nonlinear Ordinary Differential Equation (ODE). The static analysis provides optimal working point and the dynamic analysis gives an overview about the behavior of the system. Mentioned procedure is tested on the real model of the water tank as a part of the process control teaching system PCT40 from Armfield. Results have shown that proposed mathematical model is accurate and can be used for the design of the appropriate controller.

INTRODUCTION

The modelling and simulation are important tools often used nowadays for investigating the system's behavior in the industry and also in other fields of living. Especially nowadays, when the computation power of today's personal computers is very high and the prize is relatively low the usability of the simulation grows.
The modelling stage tries to describe the system either mathematically or practically (Luyben 1989), (Maria 1997). The mathematical description for example uses material, heat etc. balances (Ingham et al. 2000) depending on the type of the system, whether it is chemical reactor (Russell and Denn 1972), heat exchanger or electric motor. On the other hand, real model is usually small representation of the originally nonlinear system and we expect that results of experiments on this model are also valid or comparable to those on the real system. The big advantage of the modelling is in its safety – experiments on some real systems could be sometime hazardous. Nevertheless, experiments on the real or abstract model are usually much cheaper that those on the original system which is sometimes big and components are expensive.
This contribution combines two modelling techniques. At first, the mathematical model of the water tank will be derived, then simulations were done on this model and results are verified by measurements on the real model of the water tank as a part of the Armfield's Process Control Teaching System PCT40. This real model represents the second modelling approach.
The mathematical model of the water tank system is mathematically described by the first order nonlinear Ordinary Differential Equation (ODE) (Luyben 1989). The simulation of this model consists of static and dynamic analyses.
The static analysis means solving of this ODE in the steady-state, i.e. the derivatives with the respect to time are equal to zero (Ingham et al. 2000). The nonlinear ODE is then reduced to the nonlinear algebraic equation which can be solved for example with the use of simple iteration methods (Saad 2003). The result of the static analysis could be optimal operating point or the range where the input variable could vary from the practical point of view.
On the other hand, the dynamic analysis observes the behavior of the system after the step change of the input quality, in this case the change of the feed volumetric flow rate inside the water tank. The dynamic analysis means mathematically the use of some numerical methods for solving of the ODE. The main groups of numerical methods are one-step methods for example Euler's method, Runge-Kutta's method, or multi-step methods Predictor-Corrector etc. (Johnston 1982). The advantage of these methods is that they are easily programmable even more they are build-in functions in the mathematical software like Matlab (Mathews and Fink 2004), Mathematica etc. (Kaw et al. 2014).
The contribution is divided into four main parts. The first part is introduction, next the modelling procedure is discussed from the theoretical point of view in the second part. The third part applies the procedure to the real model of the water tank and the last part is conclusion.
All simulations were done in Matlab, version 7.0.1.

SIMULATION PROCEDURE

As it is written above, this paper will describe the modelling and simulation procedure which usually precedes the design of the controller. This procedure could be generally divided into 6 parts which are displayed in Figure 1. Each part is important for the designing of the accurate model.

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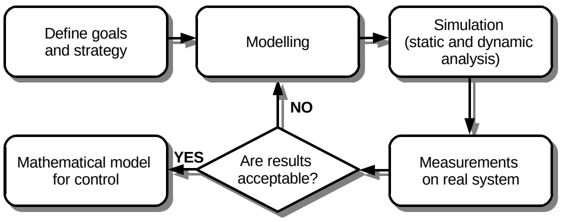

Figure 1: General modelling procedure

Goals and Strategy Definition

The first step is typically dedicated to the collection of all available information about the system. It defines the input, state and output variables and also constants and parameters of the system. Then, the output variable or variables which are important for control are chosen together with the most suitable input variables which could be used for the control.
In some cases, not every input variable can be used for control from the practical point of view. For example, the input concentration of the reactant in the chemical reactor is typical input variable but it is not very useable for control – it is hard change the input concentration quickly. The choice of the output variable is very similar – some output variables are not easily measurable.
This part of the procedure employs control engineers that have experience with the choice of the input and output variables together with process engineers which know the system from the process point of view.

Modelling

While all variables and relations between them are collected we can move on to the description of the system in some way – we collect a model of the observed plant.
There are two main types of models – *physical* (*real*) *models* and *abstract models*. The real model is represented by the copy of the system, usually small or similar to the original one. On the other hand, the mathematical model is usually used as an abstract model of the system.
The real system could be often nonlinear, unstable – generally very complex or partly misunderstood. The mathematical description of all quantities and relations between them lead to very complex and mostly insoluble mathematical model. Thus mathematical models do not strictly describe all the properties and relations inside the system, but pick up the most important ones and introduce constants and simplifications which reduce the complexity of the system.
Common simplifications could be found assumptions that volumes, heat capacities etc. are constant during the measurements. In some cases they are not constant but its changes are negligible. On the other hand, too many simplifications could lead to very simple mathematical model behavior of which is different from the real system. To find compromise between the simpler but proper mathematical model are the most important part of modelling.
One tool which is employed here are balances inside the system. There are several types of balances – a material, a heat etc. The material balance in the steady-state, e.g. in state where state variables are steady and do not change, can be generally described in the word form in Figure 2:

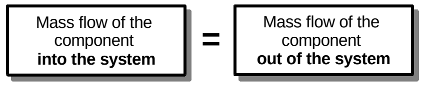

Figure 2: The word form of the mass balance in the steady-state

Unfortunately, most of the variables vary in time and steady-state balance is not suitable. We can introduce the dynamic material balance which contains changes with respect to time in the form of the accumulation – see the word equation in Figure 3:

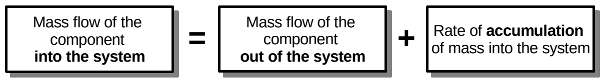

Figure 3: The word form of the mass balance in the dynamics

The collection of all balances inside the system results in one or more linear or nonlinear mathematical model usually in the form of algebraic or differential equations.

Simulation

Ones we have the mathematical model of the system we can observe the behavior of the system in the steady-state and the dynamics. It means that the mathematical model is solved with the use of iterations methods or numerical methods for solving of differential equations.
The *steady-state analysis* for stable systems involves computing values of state variables in time $t \rightarrow \infty$, when changes of these variables are equal to the zero. That means that all equations which consist of derivations with the respect to zero have these derivations equal to the zero, i.e.

$$\frac{d(\bullet)}{dt} = 0 \tag{1}$$

There are many methods for solving of this problem. If the system is linear, the set of differential equations can be rewritten to the set of linear equations which can be solved by general, well known, methods like matrix-inversion, Gauss elimination etc. or with the use of some types of iterative methods. However, the most of processes are nonlinear which leads us to the set of nonlinear equations. Despite the fact that there is a possibility of the analytical solution, iterative methods are used more often.

For example, the *simple iterative method* (Saad 2003) is often used for solving of nonlinear equations. This method leads to the exact solution for an appropriate choice of initial iteration and for the fulfilled convergence condition. Its advantage is that it does not need special modifications and side calculations according to other iterative methods like Newton's method etc. Although this method converges slower than Newton's method, this disadvantage is unimportant nowadays, when the speed of computers is very high. This method will be used for solving of a steady-state.

The second, *dynamic*, *analysis* uses results from the steady-state as an initial conditions and solve mathematical model, usually in the form of one or more differential equation. Systems where state variable are dependent only to the one variable, for example time, are called lumped-parameters systems. Mathematical model of these systems is described by ordinary differential equations (ODE). The second types are systems, where state variable depends on more than one variable – e.g. time and space variable and the mathematical model consists of partial differential equations (PDE).

There are a lot of numerical methods for solving of differential equations, such as an Euler method, Runge-Kutta's methods, a predictor-corrector method etc. The advantage of these methods is that they have good theoretical background, modifications and even more they are mostly build-in functions in mathematical software such as Matlab (Mathews and Fink 2004) or Mathematica (Kaw et al. 2014).

Measurements on the Real System and Verification

Important part is the verification of the abstract mathematical model by reference measurements on the real system or its model. These experiments show accuracy of the mathematical model. The best way is to do the measurements for the same values and conditions on the real system and the mathematical model and then compare results if they are acceptable or we must recollect the mathematical model in the different way or take into the account some of assumptions made in the previous step.

This step is not feasible in every case but the mathematical model without this verification is not 100% trustworthy.

Mathematical Model for Control

If the mathematical model describes the system in proper way we can continue with the choice of input and output variables and the optimal control strategy. The simulation of the dynamic behavior could help us for example in the choice of the External Linear Model (ELM) in the adaptive control (Bobal et al. 2005), (Vojtesek and Dostal 2012).

REAL MODEL – WATER TANK

The procedure described in the previous chapter was tested on the real model of the water tank which is one part of the Multifunctional process control teaching system PCT40 from Armfield – see Figure 4. This equipment includes also other models of processes such as Continuous Stirred Tank Reactor (CSTR) or heat exchanger.

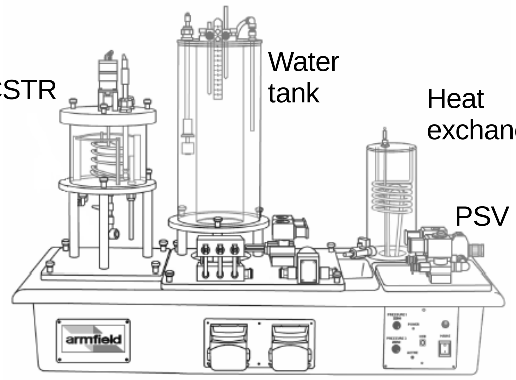

Figure 4: Multifunctional process control teaching system PCT40

Goals and Strategy Definition

This system combines both modelling techniques – it is small representation of the water tank with the volume of 4-liter original of which is usually much bigger with huge volume. The mathematical model of this system could be also easily derived. The schematic representation of the water tank can be found in Figure 5.

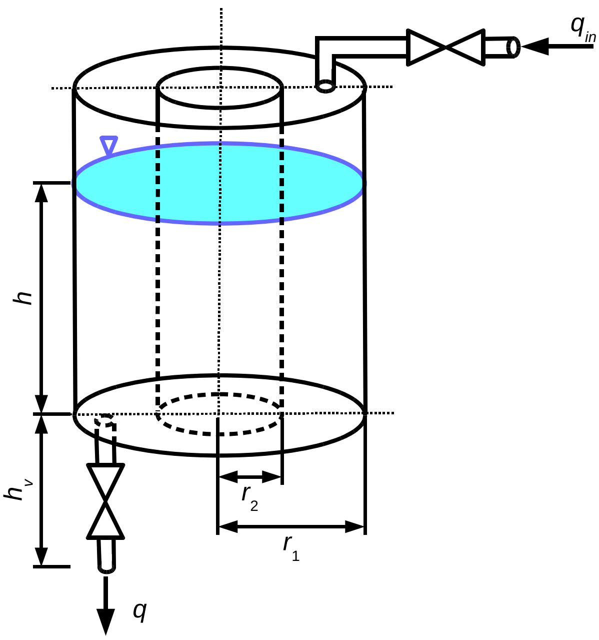

Figure 5: Schematic representation of the water tank

The model consists of plastic transparent cylinder with inner radius $r_1 = 0.087\ m$. There is another plastic transparent cylinder inside due to quicker dynamic response of the system lower usage of feeding water. The outer radius of this smaller cylinder is $r_2 = 0.057\ m$ and the maximal water level in the tank is $h_{max} = 0.3\ m$.

In the Figure 5, q denotes the volumetric flow rate, h is used for the water level and r are radiuses of inner and outer cylinders. The input variable is the volumetric flow rate of the feeding water q_{in} and state variables are water level h in the tank and output volumetric flow rate of the water which comes from the tank, q.

The goal of the modelling is to create the mathematical model which describes dependence of the water level, h, on the input volumetric flow rate, q_{in}.

Modelling of the Water Tank

The modelling uses material balance described in the general word form as in Figure 3. In this concrete case it could be rewritten to the word equation displayed in Figure 6.

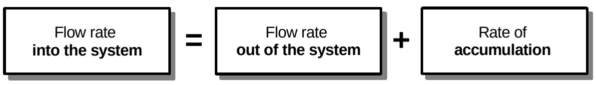

Figure 6: Material balance inside the water tank

Which is mathematically:

$$q_{in} = q + \frac{dV}{dt} \tag{2}$$

where V is a volume of the water inside the tank and t is used for the time.

The volume of the tank is generally

$$V = F \cdot h \tag{3}$$

for F as a area of the base due to cylindrical shape of the tank. It means, that balance (2) could be rewritten to the form

$$q_{in} = q + F \cdot \frac{dh}{dt} \tag{4}$$

where F is in this case

$$F = \pi \cdot r_1^2 - \pi \cdot r_2^2 = 1.36 \cdot 10^{-2} m^2 \tag{5}$$

It is also known, that volumetric flow rate through the water valve is nonlinear function of the water level, i.e.

$$q = k \cdot \sqrt{h} \tag{6}$$

where k is a valve constant which is specific for each valve and depend on the geometry and type of the valve.

If we put equation (6) inside (4) the resulting mathematical model is:

$$\frac{dh}{dt} = \frac{q_{in} - k \cdot \sqrt{h}}{F} \tag{7}$$

There should be introduced one simplification – the height of the discharging valve, h_v in Figure 5, is neglected.

The unknown constant k could be computed for example from the steady state (variables with superscript $(\cdot)^s$), where $q_{in}^s = q^s$ and equation (6) is

$$q^s = k \cdot \sqrt{h^s} \Rightarrow k = \frac{q^s}{\sqrt{h^s}} \tag{8}$$

The water tank is fed via Proportioning Solenoid Valve (PSV) which could be operated in the range 0 – 100%. This range is practically $0 - 2.5 \cdot 10^{-5}\ m^3.s^{-1}$.

We have made measurements on the real model for the 60% of valve operation which represents input flow rate $q_{in} = 1.5 \cdot 10^{-5}\ m^3.s^{-1}$. The result of the measurement is shown in Figure 7.

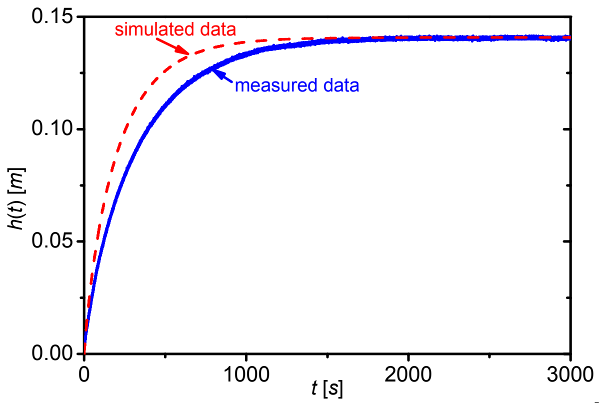

Figure 7: Measured and simulated data for $k = 4.01 \cdot 10^{-5}$ and $q_{in} = 1.5 \cdot 10^{-5}\ m^3.s^{-1}$

The final (steady-state) value of the water level h is for this flow rate $h^s = 0.141\ m$. It means, that the valve constant k is

$$k = \frac{q_{in}}{\sqrt{h^s}} = \frac{1.5 \cdot 10^{-5}}{\sqrt{0.141}} = 4.0107 \cdot 10^{-5} \tag{9}$$

The mathematical model (7) is now complete and we can move on to simulation analyses.

Simulation and Verification of the Model

The simulation is very often connected to the verification part because it is good to know if the derived mathematical model is accurate enough.

The result of the first simulation analysis for the same input volumetric flow rate $q_{in} = 1.5 \cdot 10^{-5}\ m^3.s^{-1}$ is shown in Figure 7 – the dashed line. It is clear, that although simulated and measured outputs reaches the same final value, the dynamics is much different – the mathematical model has quicker output response.

There were done five more reference measurements for different volumetric flow rate and the results for the final value and values of the valve constant, k, are shown in Table 1.

Table 1: Results of reference measurements on the real model

Flow rate q_{in} $[m^3.s^{-1}]$	Steady-state water level h^s $[m]$	Valve constant k [-]	New valve constant k_n [-]
$1.34 \cdot 10^{-5}$	0.095	$4.346 \cdot 10^{-5}$	$3.239 \cdot 10^{-5}$
$1.43 \cdot 10^{-5}$	0.118	$4.153 \cdot 10^{-5}$	$3.239 \cdot 10^{-5}$
$1.50 \cdot 10^{-5}$	0.141	$4.011 \cdot 10^{-5}$	$3.233 \cdot 10^{-5}$
$1.68 \cdot 10^{-5}$	0.195	$3.804 \cdot 10^{-5}$	$3.227 \cdot 10^{-5}$
$1.86 \cdot 10^{-5}$	0.258	$3.658 \cdot 10^{-5}$	$3.216 \cdot 10^{-5}$
$1.93 \cdot 10^{-5}$	0.285	$3.618 \cdot 10^{-5}$	$3.215 \cdot 10^{-5}$

It can be seen that resulted values of the valve constant, k, in Table 1 vary in relatively big range $3.618 \cdot 10^{-5}$ - $4.346 \cdot 10^{-5}$ which produces very inaccurate results – similar as in Figure 7. The reason for these inaccurate and very different values can be found in the simplification introduced in the modelling part, where the height of the discharging valve was neglected. This height h_v = 0.076 m has, of course, impact to the dynamics of the system and also to the valve constant. Table 1 also shows in the last column recomputed values of valve constant, k_n, for the measurements, where the height of the valve is taken into the account. These values are very close to each other and output responses of the mathematical model with this new constant k_n are much closer to the measured ones – see Figure 8 which presents results for $1.5 \cdot 10^{-5}$ $m^3.s^{-1}$ (i.e. 60% of maximal q_{in}) and $1.93 \cdot 10^{-5}$ $m^3.s^{-1}$ (i.e. 78%).

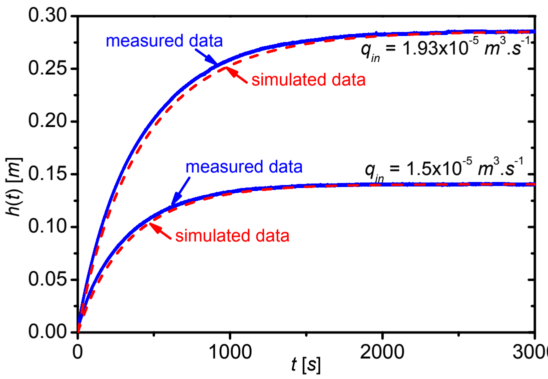

Figure 8: Measured and simulated data for $k_n = 3.23 \cdot 10^{-5}$ and $q_{in} = 1.5 \cdot 10^{-5}$ $m^3.s^{-1}$

As a result, the mean value of the new valve constant, k_n, is taken into account for the next computations, i.e.

$$k_n = 3.2282 \cdot 10^{-5} \tag{10}$$

The height of the valve h_v is then reflected in the new valve constant, but the water level in the next analyses is measured from the bottom of the water tank because all measuring devices have an zero water level at the floor of the tank – a proportional pressure sensor for accurate measuring and the reference visual scale at the cover of the plastic tank.

The Steady-state Analysis.

The steady-state analysis means that we solve the mathematical model with the condition $d(\cdot)/dt$ = 0, i.e. ODE (7) is transferred to the nonlinear algebraic equation:

$$h^s(q_{in}) = \left(\frac{q_{in}}{k}\right)^2 \tag{11}$$

where the optional variable is the input volumetric flow rate, q_{in}. There were done simulation analysis for the range q_{in} = <0; $2.5 \cdot 10^{-5}$> $m^3.s^{-1}$ and results are shown in the Figure 9.

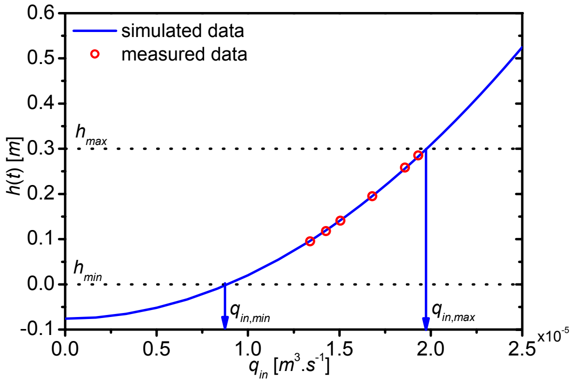

Figure 9: The steady-state analysis of the mathematical model

This analysis shows nonlinear behavior of the system and also we can choose the volumetric flow rate in the range q_{in} = <$8.86 \cdot 10^{-6}$; $1.98 \cdot 10^{-5}$> $m^3.s^{-1}$ because lower value of q_{in} means that we did not get enough water in the tank and vice versa – the flow rate bigger than q_{in} = $1.98 \cdot 10^{-5}$ $m^3.s^{-1}$ results in bigger water level than its maximal value h_{max}. Red dots in the Figure 9 display results of measured steady-state value of the water level from Table 1.

The Dynamic Analysis.

The dynamic analysis solves the ODE with the use of some numerical methods. In this case, the Runge-Kutta's standard method was used because it is easily programmable and even more it is build-in function in used mathematical software Matlab. The working point was characterized by the input volumetric flow rate $q_{in}^s = 1.5 \cdot 10^{-5} m^3 \cdot s^{-1}$ which is somewhere in the middle of the operating interval defined after the static analysis in the Figure 9.

The input variable, $u(t)$, is the change of the initial q_{in}^s and the output variable is the water level in the tank. The input and the output variables are then generally:

$$u(t) = \frac{q_{in}(t) - q_{in}^s}{q_{in}^s} \cdot 100\,[\%];\; y(t) = h(t)\,[m] \tag{12}$$

The simulation time was 3000 s, six step changes of the input variable $u(t)$ were done and results are shown in Figure 10.

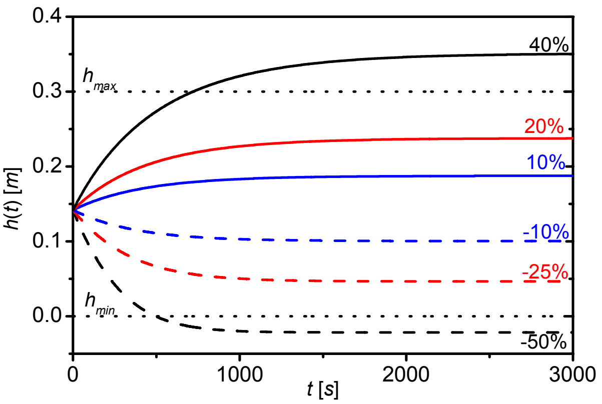

Figure 10: The dynamic analysis for various step changes of the input volumetric flow rate q_{in}

Output responses show that this output has asymmetric responses – the final value is different in sign and also in order for positive and negative step changes. Even more, for it is inappropriate to choose the input step change of the volumetric flow rate lower than approximately -41% and bigger than +31% because the resulted water level is lower or higher than physical properties of the water tank.

Mathematical Model for Control

The last step in the procedure defined in the theoretical part is description of the system from the control point of view. This description depends on the chosen control strategy. For example, one strategy of an adaptive control uses the External Linear Model (ELM) of the originally nonlinear system for construction of the adaptive controller parameters of which are recomputed in each sampling period according to the recursively identified parameters of the ELM (Vojtesek and Dostal 2012).
In this case, all output responses in Figure 10 could be expressed by the first or the second order transfer functions (TF), for example in the continuous-time

$$G_1(s) = \frac{b(s)}{a(s)} = \frac{b_0}{s + a_0}$$
$$G_2(s) = \frac{b(s)}{a(s)} = \frac{b_1 s + b_0}{s^2 + a_1 s + a_0} \tag{13}$$

or in the discrete time

$$G_1(s) = \frac{B(z^{-1})}{A(z^{-1})} = \frac{b_1 z^{-1}}{1 + a_1 z^{-1}}$$
$$G_2(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})} = \frac{b_1 z^{-1} + b_0 z^{-2}}{1 + a_1 z^{-1} + a_0 z^{-2}} \tag{14}$$

We can do now simple least-squares method for the off-line identification of the simulated data from the dynamic analysis to investigate parameters of polynomials A (z^{-1}) and $B(z^{-1})$ from the (14). The qualitative criterion S_e in this case is sum of squared differences between the simulated output y_{sim} and the identified output y_{id}:

$$S_e = \sum_{i=1}^{N} \left(y_{sim}(i) - y_{id}(i) \right)^2 \quad \left[m^2 \right] \tag{15}$$

where N is a number of steps, i.e. $N = T_f/T_v$ when T_f is final time and T_v is sampling period. Results of this off-line identification for both the first and the second order transfer functions for example for step changes $u(t)$ = -40 and +50 % are shown in Figure 11 and Figure 12.

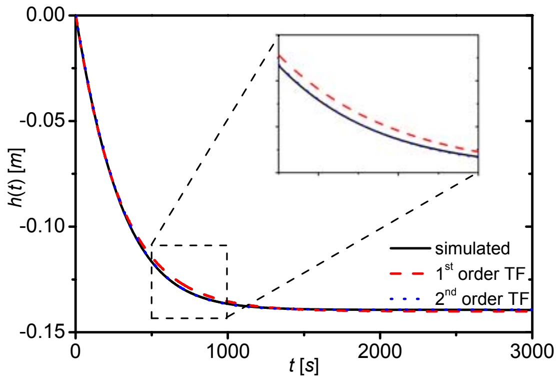

Figure 11: Results of off-line identification for step change $u(t)$ = -40%

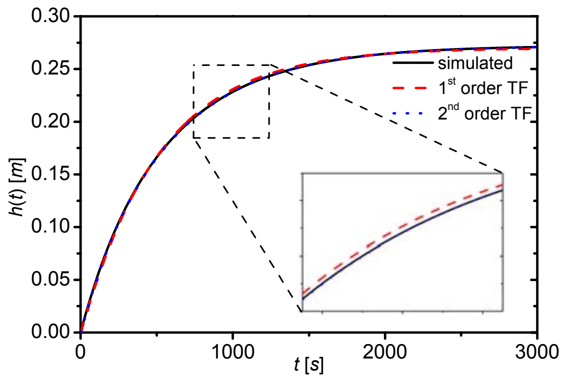

Figure 12: Results of off-line identification for step change $u(t)$ = +50%

It is clear that both TF in (14) describes simulated data relatively well, visually worse course is for the 1st order TF for negative step change $u(t)$ = -40% - see detailed cuts in Figure 11 and Figure 12.
Table 2 shows values of S_e for both 1st and 2nd order TF for all step changes. We can say, that the 2nd order TF describes the controlled output in more accurate way.

Table 2: Computed quality criterion S_e for 1st order and 2nd order transferfer function (TF)

$u(t)$ [%]	1st order TF S_e [m^2]	2nd order TF S_e [m^2]
-40	$3393.30 \cdot 10^{-6}$	$16.28 \cdot 10^{-6}$
-20	$237.46 \cdot 10^{-6}$	$36.35 \cdot 10^{-6}$
-10	$21.71 \cdot 10^{-6}$	$9.27 \cdot 10^{-6}$
+10	$21.71 \cdot 10^{-6}$	$9.95 \cdot 10^{-6}$
+25	$500.54 \cdot 10^{-6}$	$66.01 \cdot 10^{-6}$
+50	$6555.60 \cdot 10^{-6}$	$308.80 \cdot 10^{-6}$

CONCLUSIONS

The goal of this contribution was to show the procedure of modelling and simulation before the design of the controller. The system properties together with the most important quantities and relations between them are sketch out, then the mathematical model was derived with the use of balances inside the system and finally the steady-state and dynamic analyses were done to obtain the behavior of the system.

Important part of the modelling is the verification of the simulated data on the real system or its model. This comparison shows an accuracy of the mathematical model. The procedure was tested on the real model of the water tank as a part of laboratory equipment. The first simulation studies have shown that introduced simplification leads to inaccurate results. The height of the discharging valve, which was previously neglected, has affected the value of the valve constant and consequently the course of the output in the significant way and it must be taken into the account. The steady-state analysis produces the range of the input volumetric flow rate in which the measurements have practical meaning. The second, dynamic, analysis has shown that the output could be described rather by the second order transfer function then the first order one because of the accuracy of the description. The next work will be focused on the choice of the optimal control strategy, simulation experiments and again verifications on the real model.

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