Modeling and Control of a Liquid Level System Based on the Takagi-Sugeno Fuzzy Model Using the Whale Optimization Algorithm

Radiša Jovanović, Vladimir Zarić, Mitra Vesović and Lara Laban

Abstract—**The liquid level control remains an important task for research and is used by process control engineers. Linear models for the tank system were obtained based on empirical techniques. From these identified linear models Takagi-Sugeno model was obtained and later a fuzzy controller was designed based on the parallel distributed compensation method (PDC). A comparison was made between local linear PI controllers and the parallel distributed compensation controller. The evaluation criteria which was considered in this paper is the step response. In addition to all of the above stated, the whale optimization algorithm is implemented to fine tune parameters and to obtain optimized Takagi-Sugeno plant model. Moreover, the PDC from optimized model is compared to the first parallel distributed controller, which was based on identified models.**

Index Terms—**Takagi-Sugeno; liquid level control; parallel distributed compensation; whale optimization algorithm.**

I. Introduction

The liquid level control has a wide range of applications in the process industries such as petro-chemical, waste water treatment and purification, biochemical, spray coating, beverages and pharmaceutical industries.

In [1] authors have conveyed and stressed the issue of performance analysis of three control schemes, PI (based on pole placement, Ziegler Nichols and Ciancone correlation tuning methods), PI-plus-feedforward and model predictive control. Moreover, paper [2] addresses the nonlinear control design problem for a liquid level system. A model-based backstepping controller and an adaptive backstepping controller are developed for the liquid level system. Following, the article [3] dabbles with the fuzzy-PID controller applied to the nonlinear dynamic model of the liquid level of the coupled tank system, all the while taking into account the effects of noise. The fuzzy model proposed by Takagi and Sugeno [4] is described by fuzzy IF-THEN rules which depict local linear input-output relations of a nonlinear system. Fuzzy logic has many varieties that can be implemented for control purposes. For instance, one of them is parallel distributed compensation (PDC). The PDC offers a chance to use a technique to design a fuzzy controller from a given TS fuzzy model. In paper [5], a fuzzy controller is constructed based on a PDC method and it is implemented in an experimental tank level control system. The paper [6] suggests a procedure used to make two-variable fuzzy logic controllers (FLCs) set for the levels in a laboratory coupled-tank system. The plant input and output experimental data are then used for derivation via genetic algorithms optimization of a Takagi-Sugeno-Kang (TSK) plant model needed for FLC improvements. The TSK model is validated on a different set of experimental data and used in designing of two variable linear proportional-plus-integral PI controller and PDC with local linear PI controllers. In [7] a novel modification to the original PDC method is submitted, so that, besides the stability issue, the closed-loop performance of the system can be considered at the design stage. The strong point is that, for example, a faster response can be obtained, for a given bound on the control input. The following paper [8] gave a unified approach to a nonlinear model following control that contains the regulation and servo control problems as distinctive cases. A parallel distributed compensation (PDC) for fuzzy reference models was proposed. As a result of the following paper [9] a captivating method that improves the quality of robust control by interpolating a robust and optimal controller is presented. That paper introduces a new method called advanced robust parallel distributed compensation (ARPDC) for automatic control of nonlinear systems.

The fuzzy design can be considered as an optimization problem, where the structure, antecedent, and consequent parameters are required to be identified. Metaheuristic methods as global optimization algorithms can deal with non-convex, nonlinear, and multimodal problems subject to linear or nonlinear constraints with continuous or discrete decision variables. The synergy of fuzzy models and nature-inspired optimization algorithms belongs to the actual trends in soft computing, where all individual contributing technologies are seamlessly structured together. Attractive points of view on this combination are treated in the literature [10]. Recently, several metaheuristic methods have been proposed. Some of them include the genetic algorithm (GA) [11], particle swarm optimization (PSO) [12]-[15], gray wolf optimization (GWO) [16], whale optimization algorithm (WOA) [17] and ant colony optimization algorithm (ACO) [18]. Notwithstanding, the paper [19] explores the potentiality of a bat algorithm for tuning the PID controllers. A modified WOA (MWOA) is used to tune the AFPID (adaptive fuzzy logic PID) parameters and showed improved performance when compared with conventional PID [14].

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In this study, the structure and consequent parameters are known (number of rules, shapes of input membership functions and linear models in the consequent part of the rules), and antecedent parameters are determined using WOA.

II. SISTEM MODEL

The plant consisting of a pump integrated with a water basin and the tank as shown on Fig. 1. A practical industrial applications of such plant can be found in the processing system of petro-chemical, paper making, and/or water treatment plants, to name a few.

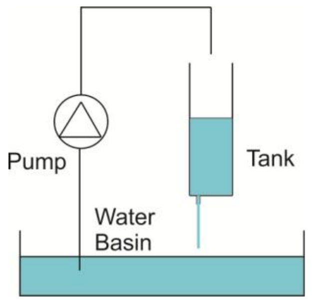

Fig. 1. The liquid level system.

A. *Mathematical modeling*

The input into the process is the voltage to the pump V_p and its output is the water level in tank, $H(t)$. In acquiring the tank equation of motion the mass balance principle can be applied to the water level in tank, i.e.

$$A_t \dot{H} = Q_i - Q_o = KV_p - A_o V_o = KV_p - A_o \sqrt{2gH}, \quad (1)$$

where A_t is the area of tank, A_o is an area of the outlet orifice, while Q_i and Q_o are the inflow rate and outflow rate, respectively. The volumetric inflow rate to tank is supposed to be directly proportional to the applied pump voltage, such that Applying Bernoulli's equation for small orifices, the outflow velocity from tank, V_o, can be expressed by a succeeding relationship

$$V_o = \sqrt{2gH}, \quad Q_o = A_o V_o, \quad (2)$$

The nonlinear differential equation that describes the change in level in tank is:

$$\dot{H} = \frac{K}{A_t} V_p - \frac{A_o}{A_t} \sqrt{2gH}. \quad (3)$$

B. *Takagi Sugeno fuzzy model and identification*

The main idea of the TS fuzzy modeling method is to partition the nonlinear system dynamics into several locally linearized subsystems, so that the overall nonlinear behavior of the system could be captured by fuzzy blending of such subsystems. Thus, a fuzzy model and identification of a liquid level system will be implemented in accordance with the TS model containing three rules. The fuzzy rule associated with the i th linear subsystem, can then be defined as i th rule:

IF $x(t)$ is M_i THEN

$$\dot{x}(t) = a_i x(t) + b_i u(t), \quad i = 1, 2, 3, \quad (4)$$

$$y(t) = c_i x(t), \quad i = 1, 2, 3. \quad (5)$$

Here M_i is the fuzzy set, $x(t)\in\mathbb{R}$, is the state variable, $u(t)\in\mathbb{R}$ is the input, $y(t)\in\mathbb{R}$ is the output variable, $a_i\in\mathbb{R}$, $b_i\in\mathbb{R}$, $c_i\in\mathbb{R}$. In our case, the selected state space variable is equal to the output variable $x(t)=y(t)=H(t)$.

The overall output, using the fuzzy blend of the linear subsystems, will then be as follows:

$$\dot{x}(t) = \frac{\sum_{i=1}^{3} w_i(x)\{a_i x(t) + b_i u(t)\}}{\sum_{i=1}^{3} w_i(x)}, \quad (6)$$

$$\dot{x}(t) = \sum_{i=1}^{3} h_i(x)\{a_i x(t) + b_i u(t)\}, \quad (7)$$

$$y(t) = \frac{\sum_{i=1}^{3} w_i(x) c_i x(t)}{\sum_{i=1}^{3} w_i(x)} = \sum_{i=1}^{3} h_i(x) c_i x(t), \quad (8)$$

where $w_i(x)=M_i(x)$. The linear models in the consequent rules (4) can be obtained by utilizing an analytical linearization of a non-linear equation. Besides that, another approach is to apply the methods of identification in accordance with the measured input output data. In this paper, the identification methods were used based on the step response, since they turned out to be a more adequate approximation of the real system; which was in succession confirmed with the experimental results. In this study it was proven that the identified mathematical models are more reasonable than the analytical ones, and therefore those will be used below. Linear models can be represented by following transfer function,

$$G(s) = \frac{H(s)}{V_p(s)} = \frac{K_1}{\tau_1 s + 1}, \quad (9)$$

where K_1 and τ_1 are tank's gain and time constant, respectively. Nominal levels in the tank H_{Ni}, nominal voltages V_{pNi} and corresponding identified transfer functions are given in Table 1.

TABLE I
NOMINAL VALUES AND LINEAR MODELS

i	H_{Ni} [m]	V_{pNi} [V]	$G_i(s)$
1	0.077	4.4	$\frac{0.002313}{s+0.04758}$
2	0.1665	6	$\frac{0.002627}{s+0.04235}$
3	0.2415	7.1	$\frac{0.002642}{s+0.03469}$

Voltage deviation represent control deviations so we can write $u(t)=v_p(t)$. Constants for the state space plant model a_i and b_i are given in Table II.

TABLE II

CONSTANTS FOR THE STATE SPACE SYSTEM MODEL

i	1	2	3
a_i	-0.04758	-0.04235	-0.03469
b_i	0.002313	0.002627	0.002642

In this article a nonlinear model is obtained by combining three linear models around 0.08 m, 0.16 m and 0.24 m. The membership functions have a triangular shape and are depicted in Fig. 2. Moreover, the predefined parameters are arbitrary function parameters, and it is assumed that they are symmetric.

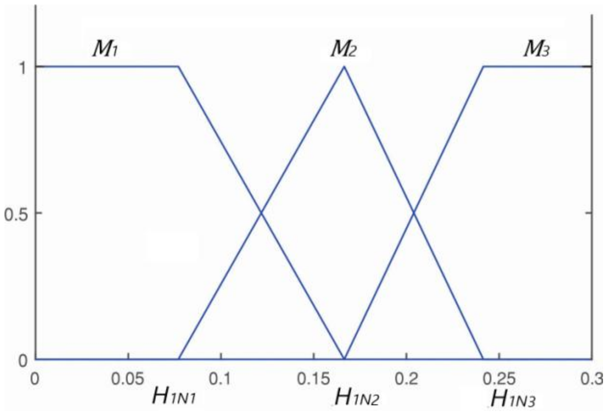

Fig. 2. Membership functions.

III. THE WHALE OPTIMIZER

Whale Optimization Algorithm has proven to be outstanding at resolving a variety of modes, multimodal and problems that are not linear. The foremost supremacies of this algorithm, and all metaheuristic algorithms in general, are that it has random distribution, which avoids getting stuck in the local minimum. WOA was first suggested by Seyedali Mirijalili and Andrew Lewis in [17]. The paper was inspired by a dozen whales, working together in a sophisticated way to harvest the krill. A curtain of bubbles and the hunting horn hold a secret to an indigenous ways of fishing - the bubble net feeding. The leader whale (bubble blower) dives a couple of meters deep into the ocean. It's his job to find the fish. The rest follow information. Each takes exactly the same position in every lunch. Once the leader has located the fish, he blows a net of bubbles in a spiral shape, which completely encircles the prey. Another whale calls to synchronize the group. Panicked by the hearing sound of the blinding bubbles barrier the fish herds will be captured, allowing whales to swim up toward them. The hunt contains three phases. The first one is encircling the prey by defining the best search agent and updating the position of others. The mathematical model of this phase is proposed using the distance vector **D** and vector **X** which is used to update the position:

$$\mathbf{D} = \left|\mathbf{C}\mathbf{X}^{'}(t) - \mathbf{X}(t)\right|, \tag{10}$$

$$\mathbf{X}(t+1) = \mathbf{X}^{'}(t) - \mathbf{AD}, \tag{11}$$

$$\boldsymbol{A} = 2\boldsymbol{ar} - \boldsymbol{a}, \tag{12}$$

where t indicates the current iteration, **A** and **C** indicate coefficient vectors; adjusting those values improves positions around the best agent ***a***; where ***a*** is a random value between [0,2] which linearly decreases during the course of iterations. **X′** is the position vector of the best solution obtained so far and **X** is the position vector. The second phase – exploration is given either with shrinking encircling mechanism (defining the new position of the searching agent using **A**), or with spiral updating position (first calculation distance between whale and prey using helix – based movement. The new position of the agent is located between the current best agent and the original position. The function for this approach is:

$$\mathbf{X}(t+1) = \begin{cases} \mathbf{X}'(t) - \mathbf{AD} & \text{if} \quad p < 0.5 \\ \mathbf{D}' - e^{bl}\cos(2\pi l) + \mathbf{X}'(t) & \text{if} \quad p \geq 0.5 \end{cases}, \tag{13}$$

where p is a random number in [0,1], b is a constant for defining the shape of the logarithmic spiral, l is a random number in [-1,1] and ***D′*** indicates the distance of the i-th whale from the prey [17]. The third one, exploration phase, is based on a random search, that provides a good balance between the last two phases. This is called adoptive variation that depends of the value search vector **A.**

IV. TAKAGI-SUGENO MODEL OPTIMIZATION

In the Fig. 2 we observe the beforehand mentioned TS model which was obtained based on the symmetric shape of the membership functions. The configuration of the functions is triangular, the centers of the membership functions are located in the selected nominal points in which the linear models are identified. However, in order to achieve a better approximation of the non-linear characteristics and overall behavior of the object, a more adequate approximation of the non-linear model is presented by adjusting the parameters of the membership function. We can view the parameters as the width of the membership function. So in conclusion, in this case we only optimized the parameters that were located in the rule premise. Moreover, the mentioned TS parameters are all coded into one whale, per say one agent, that is presented with a vector which contains the premise parameters, in our case it has four parameters. In the proposed WOA algorithm the population is set to 20, while the total number of iterations is set to 30. Furthermore, in this optimization method, one agent represents one potential optimal fuzzy model. The mean square error (MSE) is taken as an objective function and it can be calculated as

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(y(i) - y_m(i)\right)^2, \tag{14}$$

where n is the number of data points, y(i) is the measured output of the plant, $y_m(i)$ is the output of the model.

Each agent that is utilized represents a potential optimal fuzzy model. A dataset for the learning process of the WOA algorithm, in other words the optimization of the TS model is obtained from the plant operation in precisely 1600 seconds. All of the parameter values that were used in the implementation of the WOA were taken from the original paper [17]. In the aim of identification we bring the input voltage which has a shape as depicted in Fig. 3.

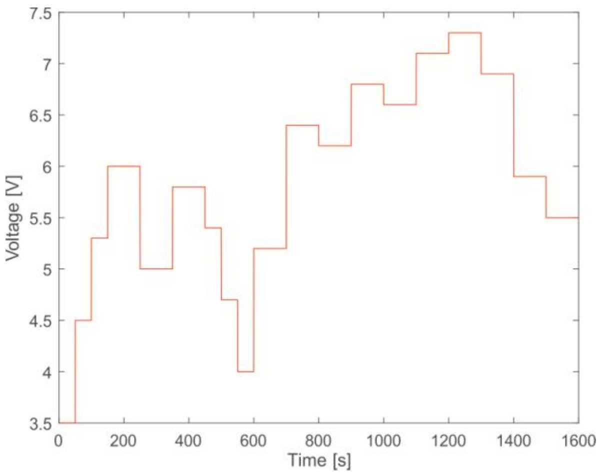

Fig. 3. Voltages used for model optimization.

There it should be observed that the values are between the nominal voltages, this is done in order to cover the range of interest. Optimized membership functions are shown on Fig. 4.

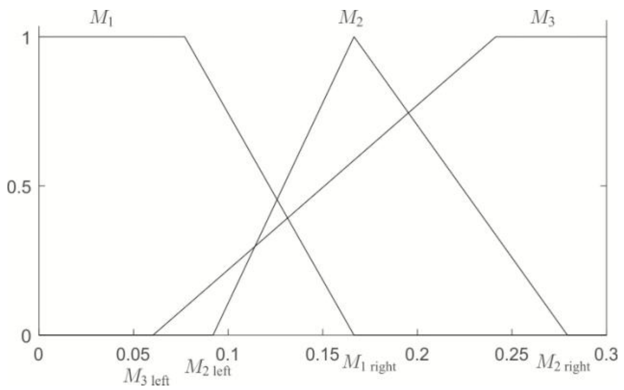

Fig. 4. Optimized membership functions.

where M_{2left}=0.092, M_{1right}=0.1665, M_{3left}=0.0603, M_{2right}=0.2793. Comparison of the TS model based on initial membership functions and the TS model based on optimized membership functions is showed on Fig. 5.

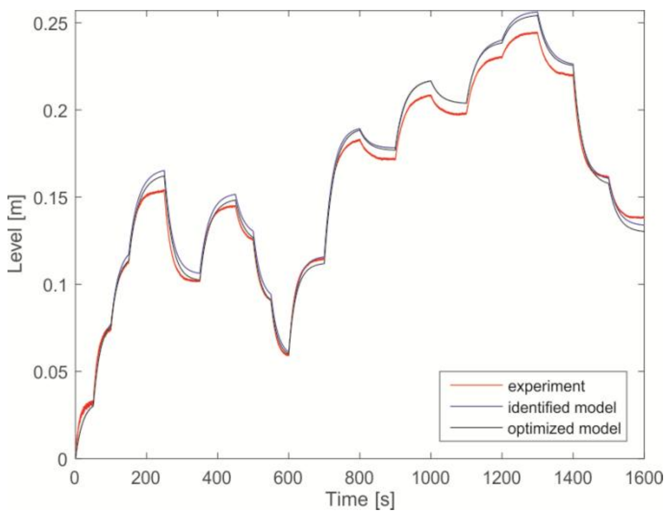

Fig. 5. Comparison of identified and optimized TS model.

V. CONTROL SYSTEMS DESIGN

The main control objective is to maintain the liquid level in tank at a desired level by adjusting the pump flow rate. The requirement is that the control systems for all three operating points should satisfy the following specifications: the steady state error should be zero; the ppercentage overshot in tank has to be less than 5%, the PO ≤ 5%; the settling time for the tank should be less than 30 seconds, Ts ≤ 30 sec.

The history of the purported (PDC) was set in motion with a model-based design procedure proposed by Kang and Sugeno, [20]. The PDC proposes a procedure to design a fuzzy controller from a given TS fuzzy model. Furthermore, each control rule is designed from the corresponding rule of a TS fuzzy model during the construction of a PDC design. As a consequence, the designed fuzzy controller shares the same fuzzy sets as the fuzzy model in the premise parts. For our concrete model in this paper we have defined for each of the linearized models - a linear PI controller was designed into the bargain. The rules of the fuzzy controller via PDC are as follows:

Control rule i: IF $x(t)$ is about H_{Ni}, THEN the controller is C_i.

The overall fuzzy controller is represented by

$$C(t) = \frac{\sum_{i=1}^{3} w_i(x) C_i}{\sum_{i=1}^{3} w_i(x)} = \sum_{i=1}^{3} h_i(x) C_i, \quad (15)$$

where C_i = K_{Pi} + K_{Ii}/s, i=1,2,3. Parameters for all three controllers C_i, were obtained based on the linear theory and according to the control objective. Meanwhile, proportional and integral gains for all of the above stated controllers are given in Table 3.

TABLE III
PARAMETERS OF CONTROLLERS

i	1	2	3
K_{Pi}	94.72	85.389	87.803
K_{Ii}	16.139	14.21	14.129

VI. EXPERIMENTAL RESULTS

In order to display the effectiveness of the utilized methods we performed a couple of experiments and verified the efficiency of the optimization and identification, subsequently. Thus, the Fig. 6 depicts the difference between the plant that is controlled by a local linear PI controller and the plant that is controlled by the PDC. The synthesis of a controller was done for a linear model obtained by identification on around 0.08 m. In addition, Fig. 6 shows that the response is better and that all conditions are fulfilled if we use the PDC, because it is a direct combination of three controllers.

With all that being said, the PDC achieves a better performance than the local PI cause when we are operating in the range of 0.08 m to 0.12 m, both controllers that are designed to operate around 0.08 m and 0.16 m are active, see Fig. 2.

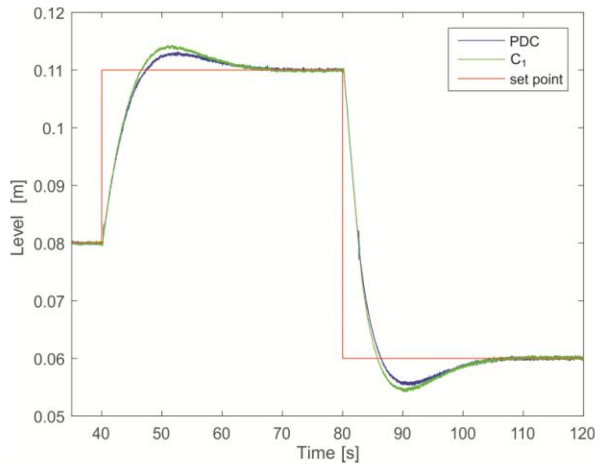

Fig. 6. Comparison of PDC and PI controller system around 0.08 m.

The same analysis applies to the operation of the plant around 0.16 m, which is shown in the Fig. 7. In this case with the PDC, all three local linear controllers that are designed to operate around 0.08 m, 0.16 m and 0.24 m are active, as can be seen from the Fig. 2.

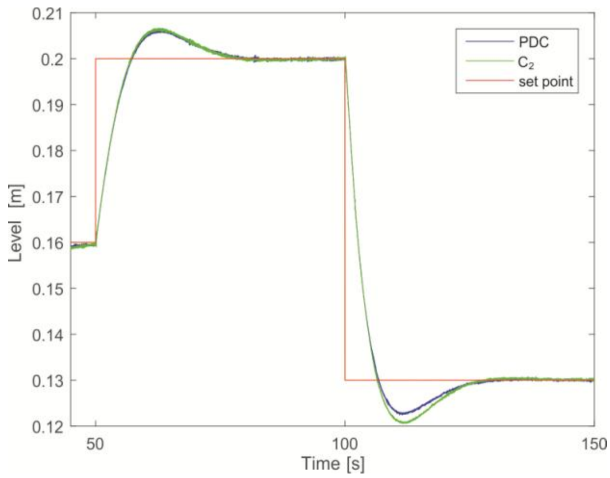

Fig. 7. Comparison of PDC and PI controller system around 0.16 m.

Finally, the PDC controller was compared with the specifically designed controller for the nominal point 0.12 m. As to say, that the most grandiose and onerous challenge for the PDC is precisely this, since the values of 0.12m are pinpointed between the local PI controllers designed for 0.8 m and 0.16 m.

An even more disadvantageous case for a PDC is when we compare it with a controller that is designed to work around 0.12 m, seeing that it is exactly between 0.08 m and 0.16 m. The requirements for this local linear PI controller are the same. In the same way we obtained parameters K_{P_i}=67.384 and K_{I_i}=12.081. A juxtapose of the operation of this local PI controller with the PDC is shown in Fig. 8.

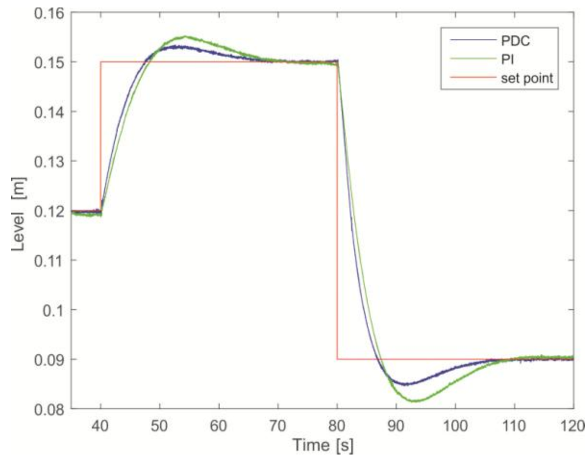

Fig. 8. Comparison of PDC and PI controller system around 0.12 m.

A smaller overshoot, while the rise time and settling time stayed the same, was obtained when the plant was controlled using a PDC that contains information about the optimized model, than when the plant was controlled by a PDC with initial membership functions. In order for our results to be observed better, the filtered responses are shown in Fig. 9. The same moving average filter with a span of 30 data points has been used for both of the signals.

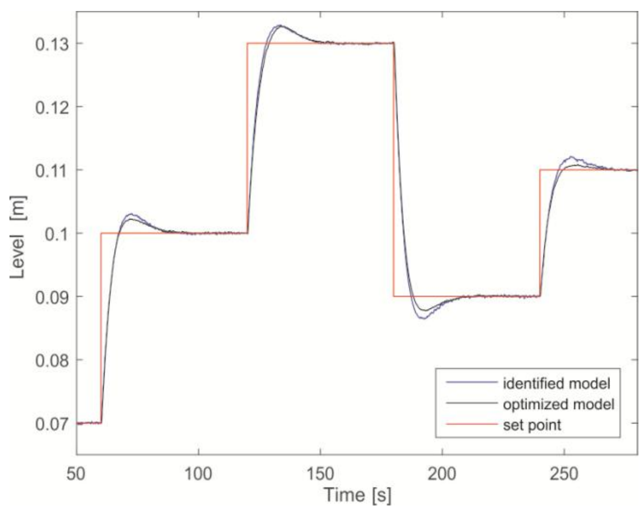

Fig. 9. Comparison of PDCs with an identified and optimized plant model (experiment with moving average filter).

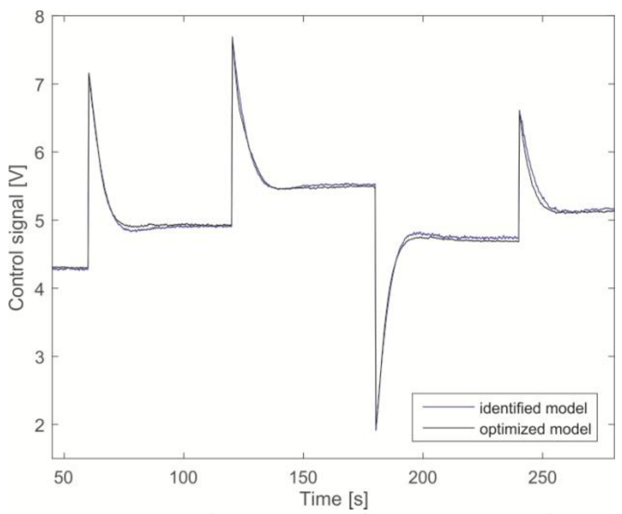

Fig. 10. Comparison of control signals of PDCs with an identified and optimized plant model.

Comparison of control signals of PDCs with an identified and optimized plant model is shown on the Fig. 10 above.

Comparison of system response percentage overshoots for the identified and optimized TS model is showed in Table 4.

TABLE IV
PERCENTAGE OVERSHOOT FOR DIFFERENT STEP RESPONSES

Step [m]	0.09-0.13	0.13-0.09	0.1-0.13	0.07-0.1
Id. [%]	10	8.75	9.3	10
Op. [%]	4	5.5	8.7	7.3

Comparison of system response settling times, in seconds, for the identified and optimized TS model is showed in Table 5.

TABLE V
SETTLING TIME FOR DIFFERENT STEP RESPONSES

Step [m]	0.09-0.13	0.13-0.09	0.1-0.13	0.07-0.1
Id. [s]	24	25.3	22.7	26
Op. [s]	23.6	25	21	21

VII. CONCLUSION

Initially, in this paper, the mathematical model of the liquid level system was obtained. After it has been experimentally confirmed that identified models describe system better than analytical ones, TS model was obtained based on three identified local linear models. Regardless of the superiority in “catching” the nonlinear behavior, TS model was optimized using WOA metaheuristic and verificated by comparing with the original. Consequently, based on the given requirements three local linear PI controllers were designed. Then, by using the PDC method, two fuzzy controllers were designed based on identified and optimized TS model. The designed controllers, which were based on the PDC, were implemented in an experimental setup in order to prove their performance. Given the very satisfying results, the developed TS model is tremendously simple and consists only of three fuzzy rules. Future research will focus on exploiting these possibilities in terms of using more fuzzy rules.

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