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Control of a Liquid Level System Based on Classical and Fuzzy PID Like Controller Using the Grey Wolf Optimization Algorithm

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This paper deals with liquid level control as one of the frequent problems in industry. Several classical methods for tuning a PID like controller were applied. Furthermore, parameters for the controller were optimized using grey wolf optimizer. In addition to the classical controller, fuzzy PID like controller has also been designed and optimized using the same optimization algorithm. Experimental results obtained on the tank system are provided.

Keywords: grey wolf optimizer, fuzzy control system, liquid level control

1. INTRODUCTION

Different types of liquid tank plants have wide application in various industries such as chemical, petrochemical, food & beverage industry, etc. Consequently, the liquid level control is an open question that is always relevant and constantly requires optimal solution.

Classical Ziegler-Nichols (ZN) [1] and Cohen-Coon (CC) [2] methods are often used for tuning PID like controllers and obtained results are frequently compared with the results of newer methods. This is exactly done in [3] where the authors compared ZN, CC and Takahashi's tuning method in order to obtain optimal parameters for PI controller for liquid flow process and in [4], on coupled tank system, where performance comparison was made between ZN, CC and Ciancone tuning methods for PI and PID. Another available control technique for nonlinear systems is feedback linearization. Paper [5] proposed feedback linearization control method for level control of coupled tanks system. It concluded that achieved benefit was reducing chattering and lowering control effort with better control results. A new approach in automatic control theory appeared when Lotfi A. Zadeh laid the foundations of fuzzy logic [6]. The basis of fuzzy logic is that right value of variables can be any value from [0,1] set. Applied fuzzy logic controller (FLC) can be found in [7]. There, authors studied and implemented PID controller and FLC using Arduino for the experiment of liquid level control. The results showed that FLC can be easily formed and dominates over PID controller in removing the overshoot and steady state oscillations. The conducted research in [8] offers a comparison between ZN, CC, Chien-Hrones-Reswick (CHR) PID tuning method and tuning PID controller using fuzzy logic. Obtained overcome on four-coupled tank system showed that applied decentralized fuzzy PID controller could be used in industrial process as it provides an optimal solution. In paper [9] researchers made comparative study of fuzzy PI + fuzzy PD controller and conventional PID in feedback and cascade system configuration. In both configurations fuzzy PI + fuzzy PD controller achieved better results in liquid-level control process, especially in cascade loop configuration. Another strategy for solving this problem is finding an optimal solution in field of artificial intelligence. On coupled tanks system, neural network NARX model was used for identification and control of a non-linear process in [10]. It was proven that neural network identified model achieved sufficient accuracy. Additionally, achieved improvements in control process using neural network control scheme compared to conventional PI controller were presented. Succeeding, fuzzy logic and neural network were combined in order to improve control of non-linear process. Paper [11] demonstrated superiority of application Neuro Fuzzy Controller over the FLC for control process of coupled tank system. Further, used strategies found basis in nature process. Natural selection and genetics gave ideas for development of Genetic Algorithm (GA), that led to generation of high-quality solutions to optimization problems. The article [12] researched optimal PID controller for coupled tank liquid level control. ZN method has been applied for tuning PID and optimized with bat algorithm in various time domain. In [13] authors proposed Takagi-Sugeno fuzzy model optimized with the whale optimization algorithm for control of a liquid level system. Paper [14] presented comparison of ZN, CC, minimum effort criteria (ISE, IAE, IATE) and GA tuning method of PID controller for three tank liquid level process. Research [12-14] concluded that GA provided superior solution and gave better results of output signal characteristic such as decreased pick overshoot, rise and settling time.

In this study liquid level control system was conducted using classical and fuzzy PI controller optimized with grey wolf optimization (GWO) algorithm.

2. SYSTEM DESCRIPTION

Physical values and parameters, that describe system used in the study are given in Table 1.

Table 1: System parameters

Pump Flow Constant, K_p	$5.39 \cdot 10^{-6}$ m^3/s/V
Out 1 Orifice Diameter, D_{o1}	$0.47625 \cdot 10^{-2}$ m
Out 2 Orifice Diameter, D_{o2}	$0.47625 \cdot 10^{-2}$ m
Tank 1 Inside Diameter, D_1	$4.445 \cdot 10^{-2}$ m
Tank 2 Inside Diameter, D_2	$4.445 \cdot 10^{-2}$ m
Gravitational constant, g	9.81 m/s^2

System consists of two identical cylindrical tanks placed one above another, water pump and reservoir. Water from reservoir is pumped vertically through pumping system into water tank in higher position. The water level of the second tank needs to be controlled. Fig. 1 represents diagram of the used system.

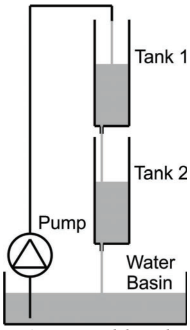

Figure 1: Liquid level system

3. SYSTEM MODELLING

3.1. Nonlinear model

System of the study is consisted of two subsystems, tank 1 and tank 2. The input value in tank 1 is pump voltage V_p, and the output is water level in tank 1, H_1. The flow into tank 1 can be expressed as

$$Q_{i1} = K_p V_p . \quad (1)$$

The outflow from tank 1 is a product of outflow velocity, V_{o1} and the cross-sectional opening area of the first tank, A_{o1},

$$Q_{o1} = A_{o1} V_{o1} . \quad (2)$$

Finally, mass balance equation for the first subsystem is

$$A_1 \frac{dH_1}{dt} = Q_{i1} - Q_{o1} = K_p V_p - A_{o1}\sqrt{2gH_1} , \quad (3)$$

where A_1 is cross-sectional area of the first tank. Outflow from the tank 2 is a product of outflow velocity V_{o2} and the cross-sectional opening area of the second tank A_{o2},

$$Q_{o2} = A_{o2} V_{o2} . \quad (4)$$

The second subsystem mass balance equation is determined as

$$A_2 \frac{dH_2}{dt} = Q_{i2} - Q_{o2} = A_{01}\sqrt{2gH_1} - A_{o2}\sqrt{2gH_2} . \quad (5)$$

By choosing state variables $X_1 = H_1$, $X_2 = H_2$, output variable $Y = H_2$ and control variable $U = V_p$ nonlinear state space model is obtained as,

$$\dot{X}_1 = \frac{K_p}{A_1} U - \frac{A_{o1}}{A_1}\sqrt{2gX_1} , \quad (6)$$

$$\dot{X}_2 = \frac{A_{o1}}{A_2}\sqrt{2gX_1} - \frac{A_{o2}}{A_2}\sqrt{2gX_2} , \quad (7)$$

$$Y = X_2 . \quad (8)$$

3.2. Linearized model

For a steady state condition it is considered that water level in tank 2 has constant nominal value, and herefore, water level in tank 1 and pump voltage have constant values as well.

$$H_1 = H_{1N},\ H_2 = H_{2N},\ V_p = V_{pN} . \quad (9)$$

The following step is approximating nonlinear functions (10), (11) using Tailor's series representation at nominal values (9).

$$f_1 = \frac{dH_1}{dt} = \frac{K_p V_p}{A_1} - \frac{A_{o1}\sqrt{2gH_1}}{A_1} , \quad (10)$$

$$f_2 = \frac{dH_2}{dt} = \frac{A_{o1}\sqrt{2gH_1}}{A_2} - \frac{A_{o2}\sqrt{2gH_2}}{A_2} . \quad (11)$$

The result is polynomials of the following form

$$\dot{h}_1 = a_1 h_1 + b_1 v_p ,\ \dot{h}_2 = a_2 h_2 + b_2 h_1 . \quad (12)$$

In equations (12) variables h_1, h_2, v_p represent deviations from a nominal values,

$$h_1 = H_1 - H_{1N},\ h_2 = H_2 - H_{2N},\ v_p = V_p - V_{pN}, \quad (13)$$

and coefficients a_1, a_2, b_1, b_2 are determined as in the following expressions,

$$a_1 = -\frac{A_{o1}\cdot g}{A_1\sqrt{2gH_{1N}}}, b_1 = \frac{K_p}{A_1} , \quad (14)$$

$$a_2 = -\frac{A_{o2}\cdot g}{A_2\sqrt{2gH_{2N}}}, b_2 = \frac{A_{o1}\cdot g}{A_2\sqrt{2gH_{1N}}} . \quad (15)$$

Thus, taking into account the defined state variables and (13), from (12) follows linear state space model:

$$\dot{x}_1 = a_1 x_1 + b_1 u , \quad (16)$$

$$\dot{x}_2 = a_2 x_2 + b_2 x_1 , \quad (17)$$

$$y = x_2 . \quad (18)$$

Based on the previous equations, the transfer functions of each subsystem can be easily obtained, which will be discussed in more detail in the next section.

3.3. Identified model

The identification method was used based on the plant's step response. In this study, system transfer function was obtained based on measured input output data using MATLAB 'System Identification Toolbox'. In the Table 2 all nominal values and transfer functions of linearized and identified model, for tank 1 and tank 2 can be found.

Table 2: Nominal values and transfer functions

	Tank 1	Tank 2
Nominal water level	$H_{1N} = 0.1273$ m	$H_{2N} = 0.13$ m
Linearized model	$G_1(s) = \frac{0.0034734}{s + 0.07126}$	$G_2(s) = \frac{0.071258}{s + 0.07051}$
Identified model	$G_1(s) = \frac{0.002577}{s + 0.04471}$	$G_2(s) = \frac{0.06278}{s + 0.05793}$
$V_{pN} = 5.32$ V		

Figure 2 represents comparison of measured open loop system output signal, with nonlinear, linearized and identified model of the system when deviation from a nominal pump voltage equals $v_p = 0.3$ V. In order for the results to be observed better, the filtered measured response (labeled as "Experiment") is shown in Fig. 2. The same moving average filter with a span of 100 data points has been used for every measured signal in this paper.

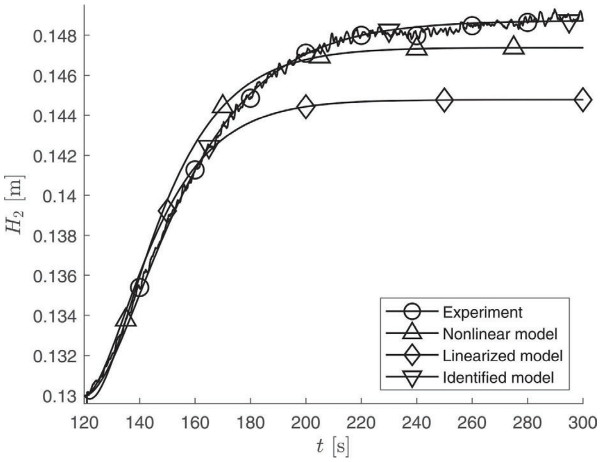

Figure 2: Comparison of measured open loop system output with nonlinear, linearized and identified model

4. CLASSICAL PI CONTROLLER

Block diagram of control system with PID like controller is shown on Fig. 3.

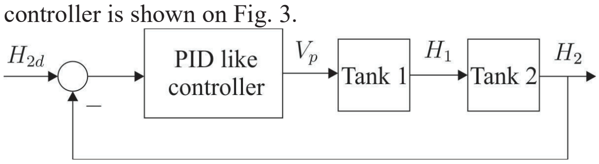

Figure 3: Block diagram of liquid level control system

Controller input is error signal

$$e(t) = H_{2d}(t) - H_2(t) \quad (19)$$

and output is control signal expressed with

$$u(t) = K_P\left(e(t) + \frac{1}{T_I}\int_0^t e(\tau)\mathrm{d}\tau\right) = K_P e(t) + K_I e_I(t) . \quad (20)$$

PI controller transfer function equals

$$G_{PI}(s) = K_P\left(1 + \frac{1}{T_I s}\right). \quad (21)$$

Proportional gain and integral time constant are determined by K_P and T_I, respectively. Parameters of PID like controllers could be tuned by many different methods. In this research, well known Ziegler-Nichols and Cohen-Coon tuning methods will be applied for comparison with the methods described bellow.

4.1. Ziegler-Nichols tuning method

Observed system is the second order and stable that implies utilization of ZN open-loop tuning technique [15]. Primarily, step response of the open-loop is obtained.

Table 3: Ziegler-Nichols formula

	K_p	T_I	T_D
P	T / KL	-	-
PI	$0.9T / KL$	$3.3L$	-
PID	$1.2T / KL$	$2L$	$0.5L$

Further, the response is used for finding parameters necessary for tuning, as dead time L, time constant T and process gain K, as it is shown on Fig. 4. Table 3 gives insight in ZN formula for determination P, PI and PID parameters.

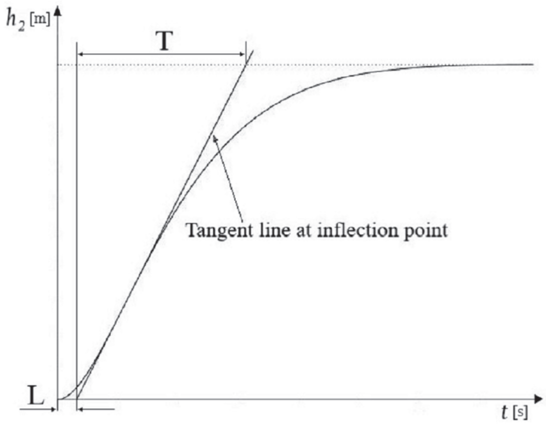

Figure 4: Tangent method

4.2. Cohen-Coon tuning method

For CC tuning method typical process reaction curve was used in the same way as in Fig. 5.

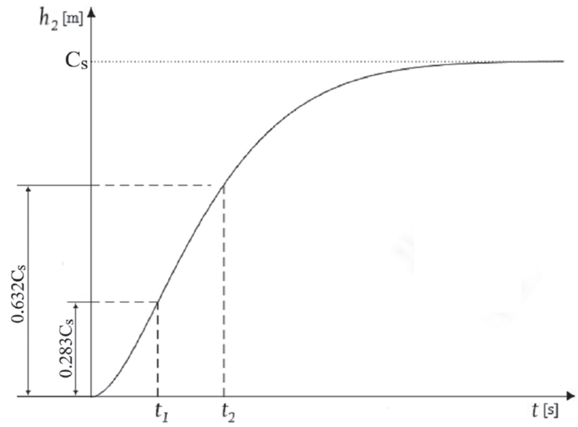

Figure 5: Process reaction curve

CC tuning formula [14] is given in Table 4.

Table 4: Cohen-Coon formula

	K_P	T_I	T_D
P	$\frac{\theta}{K\tau}\left(1+\frac{\tau}{3\theta}\right)$	-	-
PI	$\frac{\theta}{K\tau}\left(0.9+\frac{\tau}{12\theta}\right)$	$\frac{\tau\left(30+\frac{3\tau}{\theta}\right)}{9+\frac{20\tau}{\theta}}$	-
PID	$\frac{\theta}{K\tau}\left(\frac{4}{3}+\frac{\tau}{4\theta}\right)$	$\frac{\tau\left(32+\frac{6\tau}{\theta}\right)}{13+\frac{8\tau}{\theta}}$	$\frac{4\tau}{11+\frac{2\tau}{\theta}}$

Values from Table 4 are

$$\theta = \frac{3}{2}(t_2 - t_1), \quad (22)$$

$$\tau = t_2 - \theta . \quad (23)$$

Finally, the calculated values for identified model from Table 2 are given in Table 5.

Table 5: Parameters for PI controller

	Ziegler-Nichols			Cohen-Coon		
	K_P	T_I	T_D	K_P	T_I	T_D
PI	140.4	18.19	-	48.989	20.226	-

5. FUZZY PI LOGIC CONTROLLER

Fuzzy logic controllers are designed in order to avoid using complicated mathematical models that are crucial in conventional control. Fuzzy logic is inspired by human intelligence and knowledge where defining value of variable is not numerically strict and precise. Input sets in fuzzy controller are linguistic variables. Values that can be used in fuzzy rules for fuzzy PI controller as inputs are error (19) and integral of error, that from (20) can be defined as

$$e_I(t) = \int_0^t e(\tau)\mathrm{d}\tau . \qquad (24)$$

Membership functions for error, derivative of error and control are defined on the normalized domain [-1, 1]. Input and output membership functions and depicted in Fig. 6 and Fig. 7, respectively.

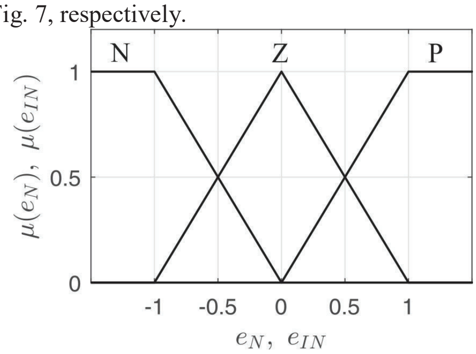

Figure 6: Input membership functions

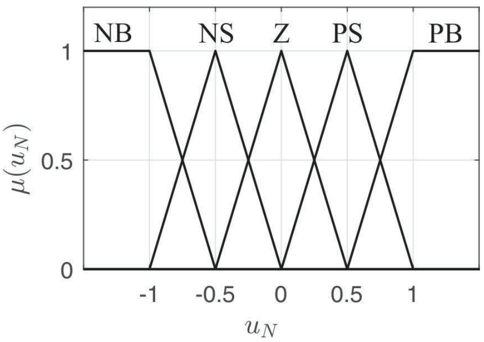

Figure 7: Output membership functions

Rules for PI controller are given in Table 6. Linguistic values from Table 6 have usual meaning NB – negative big, PB – positive big, NS – negative small, PS – positive small, Z – zero.

Table 6: Rules for PI controller

$e_N \backslash e_{IN}$	N	Z	P
N	NB	NS	Z
Z	NS	Z	PS
P	Z	PS	PB

Centre of area (COA) is used as defuzzification method. Fig. 8 shows the fuzzy PI controller that will be used later in this paper. It is important to realize that the scaling factors K_{Pf}, K_{If} and K_f are not the only parameters that can be tuned to improve the performance of the fuzzy control system. Sometimes, what is needed is a more careful consideration of how to specify better membership functions or additional rules.

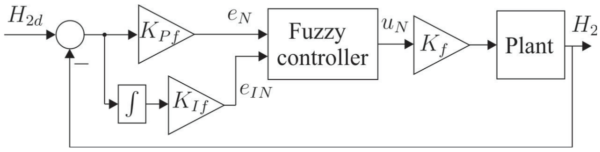

Figure 8: Fuzzy PI controller for liquid level system

The problem with this could be that there are too many parameters to tune (e.g., membership function shapes, positioning, type and number of rules) and often there is no clear connection between design objectives (e.g., smaller overshoot) and method that should be used to tune parameters.

Increasing scaling factors K_{Pf} will often make the system respond faster. Increasing K_{If} leads to reducing error but increases overshoot. In addition to these two parameters, the fuzzy PI controller has one more parameter K_f that provides the possibility of finer settings.

6. THE GREY WOLF OPTIMIZER

The GWO algorithm represents type of metaheuristic optimization technique whose characteristic such as simplicity, applicability to different types of a problem and derivation-free mechanisms allow application on constrained and unconstrained problems of nonlinear systems. GWO algorithm was first proposed in [17]. Inspiration for developing this optimization algorithm was found in hierarchical organization of a pack of grey wolves and their hunting way. Pack of grey wolves can be divided into four hierarchical levels, α, β, δ, ω where α represents the most dominant wolves that lead the pack. Next, β level is consisted of subordinate wolves that help alpha in making decisions and replace alpha in case of dead or oldness. The ω level wolves have to submit to the will of all others more dominant pack members, and wolves from δ level submit to wolves from first two levels and dominates over omega wolves. Capturing pray takes place through several phases. In the first phase wolves that participate in hunt encircle prey. Grey wolf can change its position depending on position of the prey in any random location. Mathematical description of this phase is given by the following equations

$$\mathbf{D} = \left|\mathbf{C}\cdot\mathbf{X}_\mathbf{p}(t) - \mathbf{X}(t)\right| , \qquad (25)$$

$$\mathbf{X}(t+1) = \mathbf{X}_\mathbf{p}(t) - \mathbf{A}\cdot\mathbf{D} . \qquad (26)$$

Vector $\mathbf{X_p}$ indicates the position vector of the prey, $\mathbf{X}$ is the position vector of a wolf and t indicates the current iteration. Equations for calculating coefficient vectors $\mathbf{A}$ and $\mathbf{C}$ are

$$\mathbf{A} = 2\boldsymbol{a}\cdot\boldsymbol{r}_1 - \boldsymbol{a} , \qquad (27)$$

$$\mathbf{C} = 2\cdot\boldsymbol{r}_2 . \qquad (28)$$

In equations (27) and (28) components of vector $\boldsymbol{a}$ are linearly decreasing from 2 to 0 during the iterations and vectors $\boldsymbol{r}_1$ and $\boldsymbol{r}_2$ are random vectors from [0,1]. Following phase is hunting. Assuming that alpha, beta and delta participate in hunting and that alpha leads the hunt it is possible to suppose that they know potential location of the pray, especially alpha. Three best solutions of potential location of the pray are saved and rest of the search agents are obligated to change their positions according to position of agent that is the nearest to the pray. This phase can be described mathematically by following equations,

$$\mathbf{D}_\alpha = \left|\mathbf{C}_1 \cdot \mathbf{X}_\alpha - \mathbf{X}\right|, \quad (29)$$

$$\mathbf{D}_\beta = \left|\mathbf{C}_2 \cdot \mathbf{X}_\beta - \mathbf{X}\right|, \quad (30)$$

$$\mathbf{D}_\delta = \left|\mathbf{C}_3 \cdot \mathbf{X}_\delta - \mathbf{X}\right|, \quad (31)$$

$$\mathbf{X}_1 = \mathbf{X}_\alpha - \mathbf{A}_1\left(\mathbf{D}_\alpha\right), \quad (32)$$

$$\mathbf{X}_2 = \mathbf{X}_\beta - \mathbf{A}_2\left(\mathbf{D}_\beta\right), \quad (33)$$

$$\mathbf{X}_3 = \mathbf{X}_\delta - \mathbf{A}_3\left(\mathbf{D}_\delta\right), \quad (34)$$

$$\mathbf{X}(t+1) = \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3}. \quad (35)$$

When the prey stops moving grey wolves begin attacking and then starts exploitation phase. Decreasing the value of **a** from 2 to 0 is mathematical approach related to lowering the distance between grey wolves and pray. It is possible to conclude that vector **A** can be any value in [-2**a**, 2**a**] and when **A** takes value in [-1,1] search agent can change its position into any position between position of the prey and its momentary position. In other words, when |**A**| < 1 wolves start to attack. The last phase is exploration phase which implies searching for prey. When |**A**| > 1 grey wolves are forced to search for the prey and then wolves split up in order to complete the task which mathematically means that **A** consists of random values. Also, vector **C** of random values is used to provide weights for prey in order to point up exploration process during all iterations.

In the proposed GWO algorithm the total number of iterations is set to 30 while the population is set to 20. The number of iterations and the population size are determined based on a series of experiments with different values. In this optimization method one agent represents one potential optimal controller. Additional optimization requirement is that the value of control signal should be in the allowable range of 0-12V. The integral of squared errors (ISE) is taken as an objective function and it can be calculated as

$$J = \int_0^t \left(H_{2d}(t) - H_2(t)\right)^2 \mathrm{d}t. \quad (36)$$

6.1. Optimization of classical PI controller

In order to achive better performance of the plant a more adequate control signal, relative to classical PI controllers, is achieved by adjusting the parameters of the controller gains. The mentioned parameters are all coded into one wolf, per say one agent that is presented with a vector which has two parameters (K_P and T_I) in case of optimized classical PI controller. As a result of optimization, the following values were obtained.

Table 7: Parameters for optimized classical PI controller

PI GWO	
K_P	T_I
298.45	294.59

6.2. Optimization of fuzzy PI controller

When it comes to optimization of fuzzy PI controller, there are three parameters which are all coded into one wolf. Optimized parameters K_{Pf}, K_{If} and K_f from Fig. 8 are given in Table 8.

Table 8: Parameters for optimized fuzzy PI

Fuzzy PI GWO		
K_{Pf}	K_{If}	K_f
200	0.17832	10.481

7. SIMULATION RESULTS

In this section, the simulations show the behavior of the plant controlled by different controllers that were designed in the previous sections. Simulation results for change in level H_2 controlled by four different PI controllers are given in Fig. 9. Change in control signals for all implemented controllers is shown in Fig. 10.

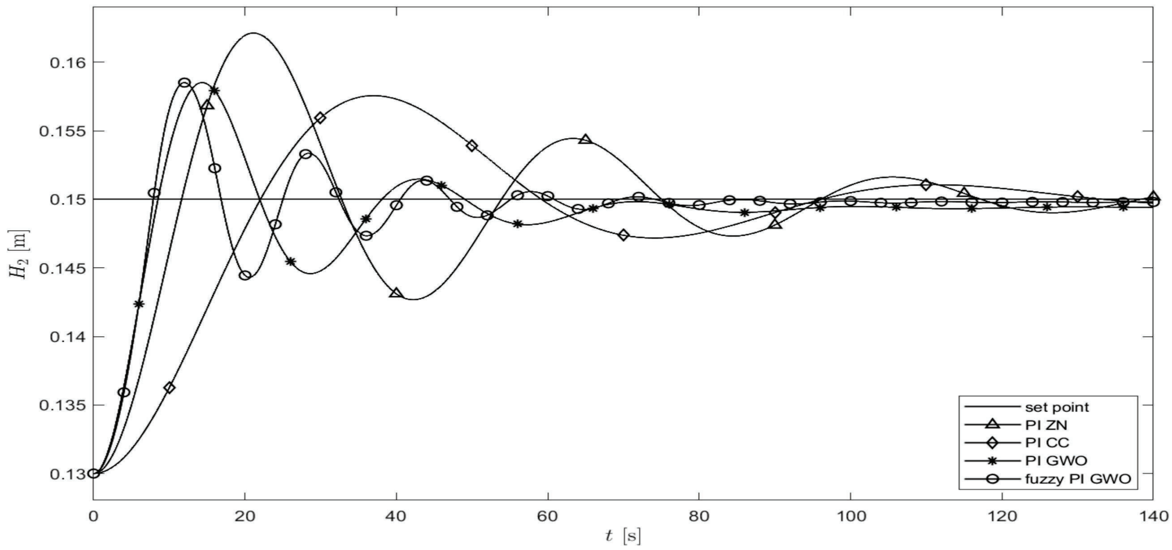

Figure 9: Simulation results of level H_2 controlled by different PI controllers

According to the values from Table 9, it can be expected that optimized fuzzy PI controller achieve the best result on the experiment as its ISE was the lowest. Numerical ISE values from Table 9, were calculated based on the operation of the system for 200 seconds, while in order to achieve better visibility, only the first 140 seconds are shown in the figures. The same goes for Table 10 and experimental results. Comparative display of overshoot, rise time and settling time is given in the same Table 9.

Table 9: Simulation step response characteristics

	PI ZN	PI CC	PI GWO	fuzzy PI GWO
ISE	0.00462	0.00513	0.00235	0.00215
Overs.[%]	60.6	37.8	42.5	42.5
Rise t.[s]	11.6	22.0	8.5	7.9
Set. t.[s]	115.1	112.0	64.0	52.6

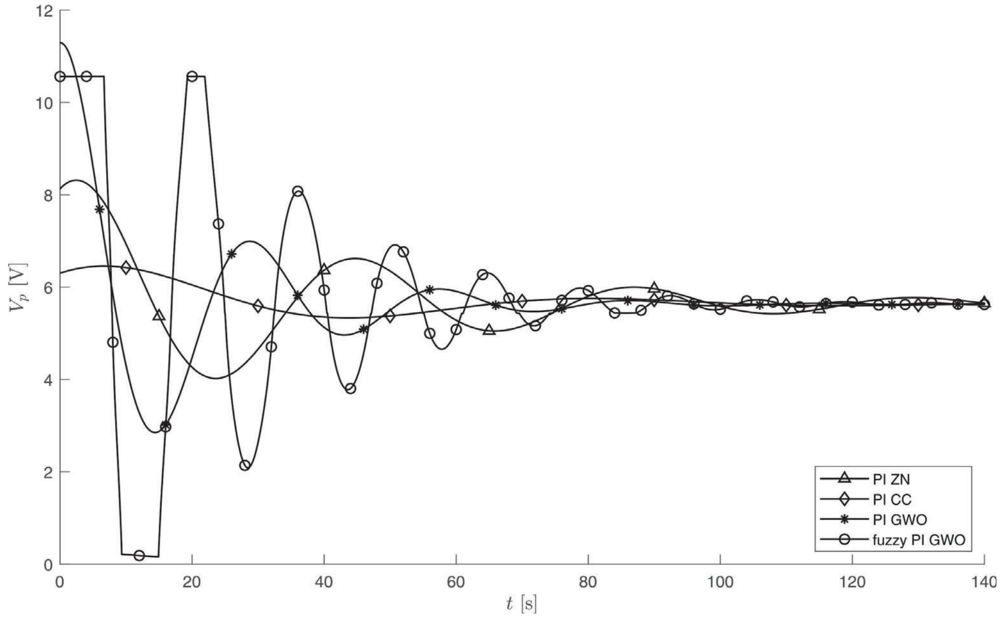

Figure 10: Control signals for PI controllers obtained by simulation

8. EXPERIMENTAL RESULTS

This section presents the results of the experiments performed for the PI controller parameters determined in the previous sections. Change in level H_2 controlled by all four PI controllers is shown in Fig. 11.

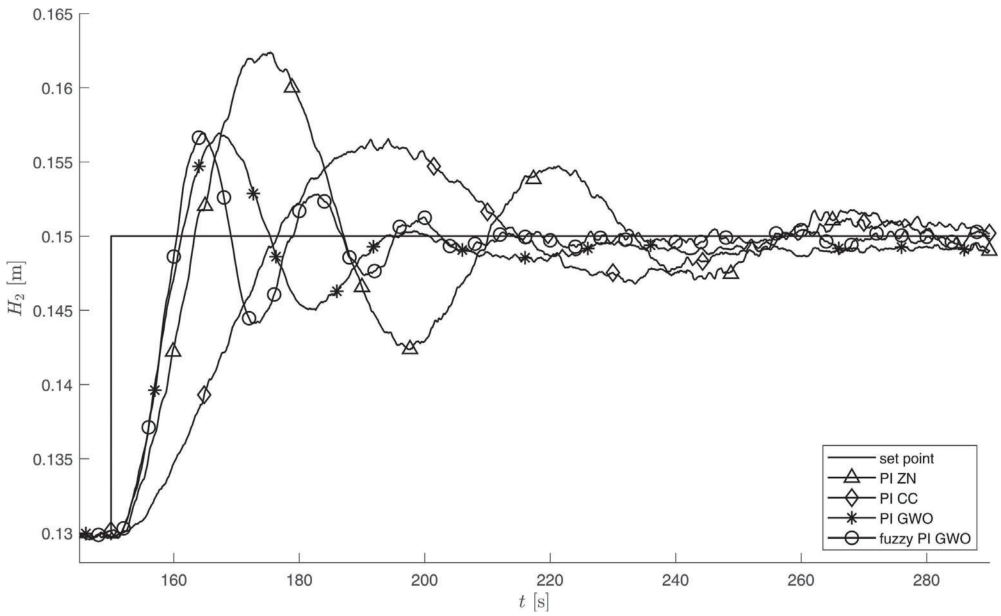

Figure 11: Experimental results of level H_2 controlled by different PI controllers

To explicitly see the improvement caused by the optimization, the numerical values of an ISE calculated using (36), are given. Mentioned values for four different controllers (PI ZN, PI CC, PI GWO, fuzzy PI GWO) are given in Table 10. Step response characteristics are in the similar relationship to that previously given for simulation responses and are also shown in Table 10.

Table 10: Experimental step response characteristics

	PI ZN	PI CC	PI GWO	fuzzy PI GWO
ISE	0.00527	0.00547	0.00269	0.00247
Overs.[%]	62	33	34.7	34.7
Rise t. [s]	13.3	26.6	11.2	10.5
Set. t. [s]	129	129	75.1	50.4

Taking into account minimum integral of squared errors as the criterion for comparison, the results show that the lowest value is obtained when using an optimized fuzzy PI controller (fuzzy PI GWO) and the highest when using a Ziegler Nichols PI controller (PI ZN). According to this criterion the optimized classical PI controller (PI GWO) performed worse than the optimized fuzzy PI controller (fuzzy PI GWO).

A comparison of control signals obtained by using different PI controllers is given in Fig. 12.

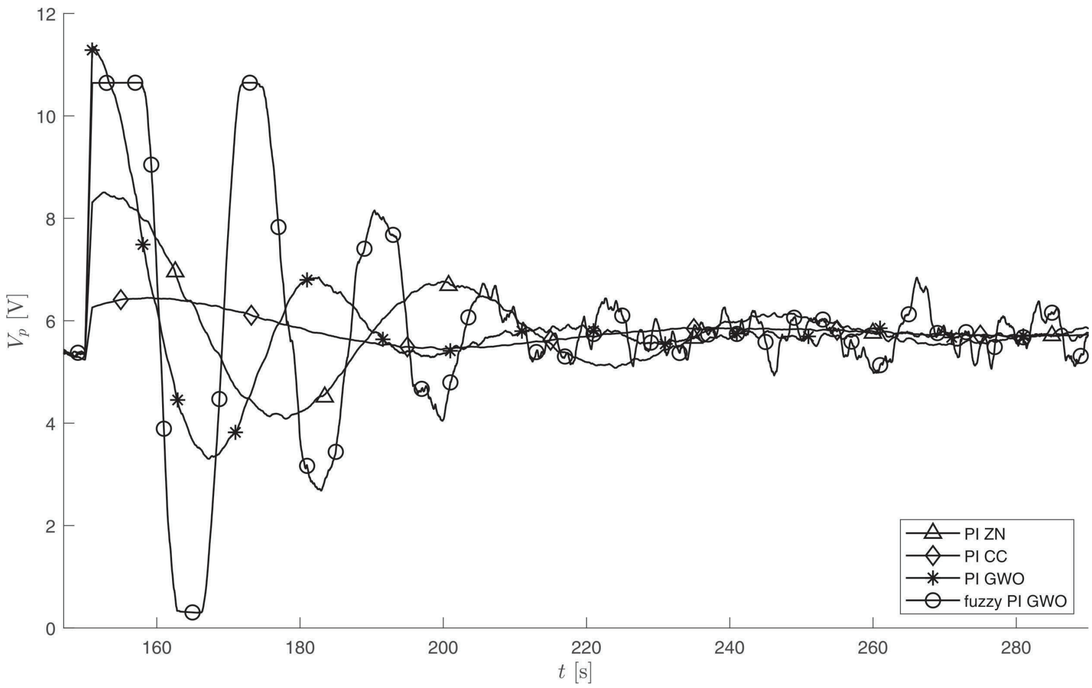

Figure 12: Control signals for PI controllers obtained by experiment

9. CONCLUSION

This research concerned optimization of classical and fuzzy controllers using GWO algorithm and its impact on the liquid level control of coupled tanks as one of the current problems in industry.

Firstly, analytical nonlinear, linearized and identified model were compared to obtained experimental results for noncontrolled system. It was shown that identified model was suitable for describing real system.

This paper covers process control using PI controllers. GWO algorithm was used for optimization of classical and fuzzy PI controller. In order to verify effectiveness of their performance a comparison was made with two different classical tuning methods.

All of the designed controllers were tested in simulation and experimentally and all obtained results were analyzed and compared to each other using minimum integral of squared errors criteria. Experiment confirmed expectations from simulations, but ISE had higher values in the experiment. Nevertheless, the difference between values was not drastic.

The best result in general was obtained by applying optimized fuzzy PI controller, according to the mentioned criteria. Also, its result achieved better step response characteristics that is an argument more for the application of this type of controller in liquid level process control.

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