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PI CONTROLLER OPTIMIZATION BY ARTIFICIAL GORILLA TROOPS FOR LIQUID LEVEL CONTROL

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Abstract. *In this paper a novel metaheuristic method, artificial gorilla troops optimizer, is used in order to optimize classical proportional-integral controller for liquid level system, that has wide application in many industries. In optimization process nonlinear model of the system is used. Obtained results are provided. It is shown that optimized controller represents superior solution compared to classical controller.*

Key words: *Artificial gorilla troops optimizer, liquid level control, metaheuristic optimization algorithm*

1. INTRODUCTION

Different kinds of liquid tank plants are widely used in many vary industries, including the chemical and petrochemical, food and beverage, and others. As a result, the control of liquid levels is an open problem that always needs an optimal solution.

The liquid level in tanks can be controled using a variety of techniques. Traditional feedback control systems, such proportional-integral-derivative (PID-like) controllers, are frequently employed. Compared to more complex control systems, they are less expensive and simpler, and many of these controllers are able to keep the system's output closely matching the desired value while staying within error tolerances.

When Lotfi A. Zadeh established the principles of fuzzy logic, automated control theory underwent a radical change [1]. In [2], Fuzzy Logic Controller (FLC) is applied for the liquid level control of coupled tank system. It was shown that fuzzy-PID control is significantly superior to classical control methods. Industry 4.0 encompasses application of artificial intelligence (AI) for improvement of industrial processes. In that manner, back propagation artificial neural network is used for controlling coupled water tank [3]. Combination of fuzzy logic and AI is used in [4], where Adaptive Neuro-Fuzzy Inference System (ANFIS) is designed for control of two tanks hydraulic system and in comparison with the FLC achieved few advantages. Due to their substantial nonlinearity and numerous local optima, global optimization issues are challenging to solve effectively. However, for nonlinear equations, it is necessary to confirm each equilibrium's stability [5].

A significant source of inspiration for this topic has been nature. These techniques include well-known algorithms like the particle swarm optimization (PSO), the genetic algorithm (GA), the firefly algorithm (FA), as well as some recently created algorithms like the grey wolf optimization (GWO) and the whale optimization algorithm (WOA) and some recently discovered algorithms like the artificial gorilla troops optimizer (GTO) [6]. These algorithms have many different uses and liquid level control is certainly one of them, like in [7, 8] where WOA and GWO are implemented, respectively.

In this study artificial gorilla troops optimizer (GTO) method was used to optimize the classical PI controller in the liquid level control system, as one of the newer metaheuristic optimization algorithms that is still unused for this kind of task.

2. OBJECT DESCRIPTION AND MODELING

Object that is used for the research includes two cylindrical water tanks that are the same and positioned one above another, water pump and water basin. This object is shown in Fig. 1, while the parameters that describe it are given in Table 1.

Table 1: *Parameters of the used object*

Out 1 Orifice Diameter, D_{o1}	$0.47625\cdot10^{-2}$ m
Out 2 Orifice Diameter, D_{o2}	$0.47625\cdot10^{-2}$ m
Tank 1 Inside Diameter, D_1	$4.445\cdot10^{-2}$ m
Tank 2 Inside Diameter, D_2	$4.445\cdot10^{-2}$ m
Pump Flow Constant, K_p	$5.39\cdot10^{-6}$ m^3\s\V
Gravitational constant, g	9.81 m\s^2

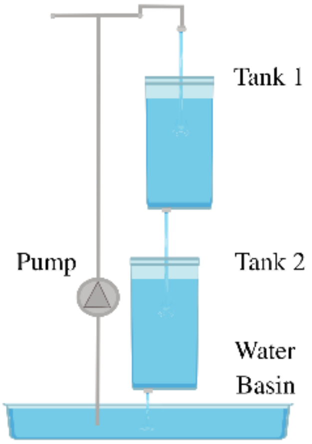

Figure 1. *Liquid level system*

Input value in the first subsystem (tank 1) is pump voltage V_p while the output is water level, H_1. Eq. (1) and Eq. (2) mathematically describe inflow and outflow of tank 1, respectively.

$$Q_{i1} = K_p V_p \tag{1}$$

$$Q_{o1} = A_{o1} V_{o1} \tag{2}$$

For tank 1 outflow velocity is marked with V_{o1} and cross-sectional opening area is marked with A_{o1}.

Input value in subsystem 2 (tank 2) is outflow from tank 1, and output is water level in that tank, H_2. Outflow from the tank 2 is represented in Eq. (3) in which A_{o2} is cross-sectional opening area of the second tank and V_{o2} is outflow velocity.

$$Q_{o2} = A_{o2} V_{o2} \tag{3}$$

Mass balance equations for the first and the second subsystem are respectively:

$$A_1 \frac{dH_1}{dt} = Q_{i1} - Q_{o1} = K_p V_p - A_{o1}\sqrt{2gH_1}\,, \tag{4}$$

$$A_2 \frac{dH_2}{dt} = Q_{i2} - Q_{o2} = A_{o1}\sqrt{2gH_1} - A_{o2}\sqrt{2gH_2}\,. \tag{5}$$

Finally, nonlinear state-space model can be presented using following Eq. (6)-(8):

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

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

$$Y = X_2. \tag{8}$$

In state-space model state variables are $X_1 = H_1$, $X_2 = H_2$, control variable is $U = V_p$ and output variable is $Y = H_2$.

3. OPTIMIZATION OF PI CONTROLLER USING THE GTO

Output value from PI controller is control signal and it can be represented via Eq. (9).

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau \tag{9}$$

In Eq. (9) error signal, *e(t)* is the difference between desired and obttained liquid level in the second tank.

The algorithm used for optimization of PI controller is described below [6].

In the GTO method, each gorilla is a candidate solution, and the silverback gorilla is the best candidate solution at each phase of the optimization process.

For the exploration phase, GTO comprises of the following mechanisms: migration to an uncharted location, migrating to a known location, and moving to other gorillas. If *rand* is less than *p*, the first mechanism is chosen. However, if *rand* is larger than or equal to 0.5, the strategy of migration toward other gorillas is chosen. Finally, migration to a known location is decided when *rand* is less than 0.5. Eq. (10) was used to replicate the processes in the exploration phase, where *GX(t + 1)* is the gorilla candidate position vector in the next *t* iteration and *X(t)* is the current vector of the gorilla position. Additionally, each iteration updates the random numbers in the range of 0 to 1 that make up r_1, r_2, r_3, and *rand*.

$$GX(t+1) = \begin{cases} (UB - LB)\times r_1 + LB, & rand < p, \\ (r_2 - C)\times X_r(t) + L\times H, & rand \geq 0.5, \\ X(i) - L\times(L\times X(t) - GX_r(t)) + r_3\times(X(t) - GX_r(t)), & rand < 0.5, \end{cases} \tag{10}$$

Prior to performing an optimization operation within the same range *p* must be provided. The upper and lower bounds are denoted, respectively, by *UB* and *LB*. *Xr* is a gorilla in the group that was randomly chosen from the total population, and *GXr* is one of the vectors of potential gorilla positions that was also randomly chosen, but it includes the positions that were updated in each phase. The final calculations for C and L are:

$$C = F \times (1 - It / MaxIt), \quad (11)$$

$$F = \cos(2 \times r_4) + 1, \quad L = C \times l. \quad (12)$$

It is the current iteration value in this case, and *MaxIt* is the most iterations possible. Additionally picked at random, l is an integer between -1 and 1. Additionally, in Eq. (10), H is expressed as

$$H = Z \times X(t), \quad (13)$$

whereas Z is determined by Z = [-C,C]. At the completion of the exploration phase, a group formation operation is performed, and all GX solutions' costs are calculated. The *GX(t)* solution is used in place of the *X(t)* solution if the cost is *GX(t)* < *X(t)*. The best solution developed during this stage is therefore known as a silverback.

During the exploitation stage of the GTO algorithm, one of the two behaviors can be chosen by using the C value. The silverback mechanism is utilized if $C \geq W$ is chosen, but the adult females' competition is employed if $C < W$. Prior to the optimization procedure, W must be provided. Eq. (14), in which *X(t)* is the gorilla position vector and *Xsilverback* is the silverback gorilla position vector, best describes the first type of behavior, the silverback. Each probable candidate's vector location in iteration t is represented by *GXi (t)*. The number N represents the total number of gorillas, and Eq. (15) is used to model the second type of behavior, competition. Here, the impact force is represented by

$$Q = 2 \times r_5 - 1, \quad (16)$$

where r_5 and *rand* are random values between 0 and 1.

$$GX(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t), \quad M = \left(\left| \frac{1}{N} \sum_{i=1}^{N} GX_i(t) \right|^g \right)^{\frac{1}{g}}, \quad g = 2^L. \quad (14)$$

$$GX(i) = X_{silverback} - \left(X_{silverback} \times Q - X(t) \times Q \right) \times A, \quad E = \begin{cases} N_1, & rand \geq 0.5, \\ N_2, & rand < 0.5. \end{cases} \quad (15)$$

The value E is used to simulate the influence of violence on solution dimensions, and the coefficient vector $A = \beta \times E$ is used to determine the level of violence in conflicts. The parameter β is provided prior to the optimization process. At the end of the exploitation phase, the costs of all GX solutions are assessed. If the costs of *GX (t)* < *X (t)*, the *GX(t)* solution is used as the *X(t)* solution, and the best solution produced among the population is viewed as a silverback. The suggested PI controller has two parameters, K_P and K_I, which can be changed to generate the best dynamical response. The adjustment of these gains has been the exclusive subject of this research. Moreover, the GTO optimization strategy was applied to create the best PI controller. In addition, each of the aforementioned parameters is programmed into a single agent, which in our scenario is given a vector with two parameters. The objective function uses the integral of absolute errors (IAE):

$$IAE = \int t |\varepsilon(t)| \, dt \quad (17)$$

In the proposed GTO algorithm, the maximum number of iterations and the number of search agents are set at 100 and 50, respectfully. Additionally, each agent represents a single potential best controller. All of the parameter values used in the GTO application were provided by the original study [6].

4. RESULTS AND DISSCUSION

The results obtained by optimization are compared with the results obtained by using a PI controller whose gains are determined by the trial and error method. Using the trial and error method obtained coefficients for PI controller are K_p = 95, and K_i = *5*. On the other hand, using GTO optimization algorithm, obtained coefficients for PI controller are K_p = 100.0660, and K_i = 3.4522.

Fig. 2 shows the system response if desired value is set to 0.18m. Control signal in this case is shown in Fig. 3.

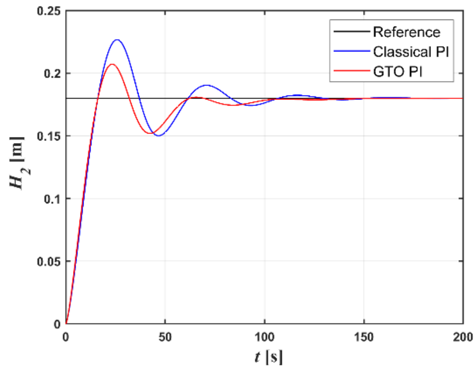

Figure 2. *System response for desired value H_2*

Even when a function that changes values over time is given as a desired value to the object, the control algorithm will succeed in making the system follow the set values, Fig. 3, and control signal Fig. 4.

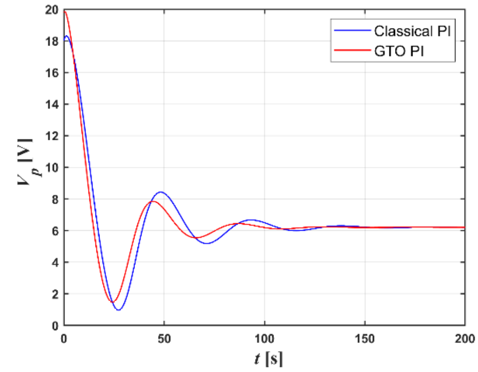

Figure 3. *Control signal for desired value H_2*

The response of the object controlled by the optimized controller gives a smaller overshoot and a shorter settling time (Fig. 2). Also the optimized control gives better results in terms of the objective function than the classical controller: $IAE_{optimized}$ = 0.2597 and $IAE_{classical}$ = 0.3613, respectively.

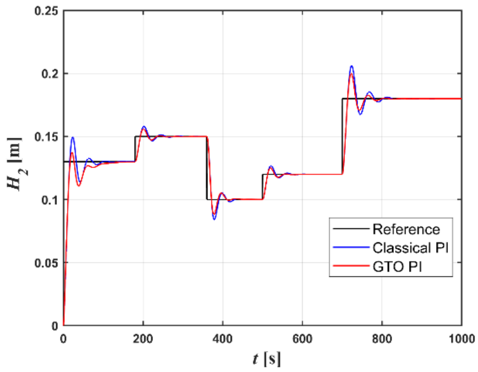

Figure 4. *System response if desired value, H_2, changes over time*

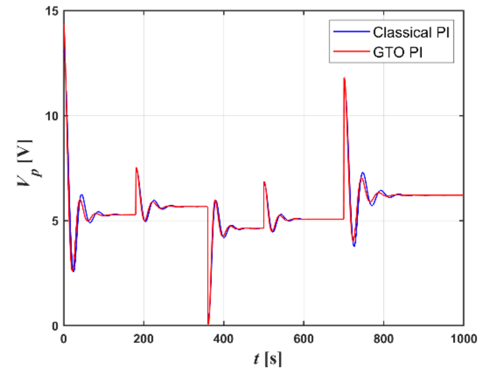

Figure 5. *Control signal if desired value, H_2, changes over time*

5. CONCLUSION

In this paper, the liquid level system in the coupled tanks is controlled using the proportional-integral PI algorithm, whose gains were found using the novel metaheuristic GTO algorithm. The accurate nonlinear model of the system is introduced. Following that, the theory of the GTO approach is provided. Finally, in the Matlab environment, it was demonstrated that the proposed algorithm was capable to control the object and obtain the specific positions. Desired and actual position are similar in all of the situations studied. The proposed control strategy may be used to operate more complicated and larger systems.

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