Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7692231

A NOVEL META-HEURISTIC GREY WOLF OPTIMIZATION ALGORITHM FOR A COUPLED TANK SYSTEM

S Mohanraj[1], *T S Murugesh[2], E Sivaraman[3]

[1]Research Scholar (Part Time), Department of Electronics and Instrumentation Engineering, Faculty of Engineering & Technology, Annamalai University. Annamalai Nagar, Chidambaram, 608 002, Tamil Nadu, India.

[2]Associate Professor, Department of Electronics and Communication Engineering, Government College of Engineering Srirangam, Tiruchirappalli, 620 012, Tamil Nadu, India.

[3]Associate Professor, Department of Electronics and Communication Engineering, Government College of Engineering, Tirunelveli. 627 007. Tamil Nadu, India.

[2,3] (On Deputation from Annamalai University, Department of Electronics and Instrumentation Engineering, Faculty of Engineering & Technology, Annamalai Nagar, Chidambaram, 608 002, Tamil Nadu, India.)

Abstract

Majority of the optimization algorithms possess sluggish convergence and inadequate solution accuracy owing to the non-linear characteristics of the system. The Coupled tank system is one such classical benchmark control problem possessing nonlinear characteristics that offers difficulty as far as the control objective is concerned owing to the interaction existing between its controlled variables. Meta-heuristic optimization algorithms endeavor to obtain the best (viable) solution among all the potential solutions for an optimization problem. In this work, a novel meta-heuristic known as Grey Wolf Optimizer (GWO) algorithm for a multivariable coupled tank system is designed and presented. The GWO algorithm is a novel SI (Swarm Intelligence) optimization algorithm inspired by grey wolves which mimics their leadership hierarchy and hunting mechanism in nature. The control performance which depends on the choice of tuning parameters are optimized with the GWO algorithm to optimize the PI controller parameters to attain an optimum solution for the chosen coupled tank system. The effectiveness of the designed controller in set-point tracking and disturbance rejection with GWO algorithm is assessed and the results interpreted by means of simulation using MATLAB SIMULINK software.

Keywords: Nonlinear Process; Interaction; Multivariable; coupled tank system; Optimization; Controller design.

1. Introduction

Generally, a system consisting of inputs and outputs can be labelled under any of the mentioned four categories: SISO (single input, single output) being the simplest to design where the data (input) from one sensor controls one solitary output, SIMO (single input, multiple output) which employ data from one sensor to control many outputs, MISO (multiple input, single output) where the data from many sensors control one output, or MIMO (multiple input, multiple output). A MIMO system define processes with multiple (more than one) input and multiple output that necessitate the need for multiple control loops. Such systems tend to be complex due to their loop interactions eventually resulting in variables with unpredicted effects [1]. A process industry usually comprises of many process units that are coupled together to carry out a process operation and therefore they are naturally Multi Input and Multi Output (MIMO) systems [1]. Nevertheless, the process components are considered as SISO systems when implementing process control schemes.

The design of control algorithms for a coupled tank system, the most prevalent among coupled multivariable systems tends to be difficult and offers extra challenge in design due to its nonlinear dynamics. The process/system involves two tanks coupled together where the process fluid flows amongst them. The two tanks each contain an appropriate inlet and outlet respectively. The foremost objective in controlling such a process is to maintain a continual level of fluid in both the tanks especially if there occurs an inflow and outflow of fluid in the respective tanks. As mentioned, controlling the level in such a coupled multivariable tank system is challenging since the multivariable nature gives rise to interactions between the two connected tanks as the water in the tanks might flow in any course.

Similar to the aforesaid coupled tank system, the Continuous Stirred Tank Reactor (CSTR) is also a familiar process belonging to the nonlinear process category which is employed in several different sectors of the chemical process industries. Being also a Multi Input Multi Output (MIMO) system, the CSTR's process variables interact strongly, making it challenging to develop control strategies. Although there are multiple measured variables that make up the CSTR, it is typically seen as a Single Input Single Output (SISO) system, and when control methods or algorithms are devised, the primary objective is to keep just one process variable closer to its set point [1].

Focusing on the coupled tank system, it is evident that the interaction of the controllable factors makes the control difficult. The Biggest Log Modulus Tuning (BLT) method has been employed already to build a decentralized PI controller for a networked tank system while accounting for interactions. The decentralized controllers were developed utilizing the fully coordinated design method, assuming controller parameters gained by combining Ziegler-Nichol's tuning methodology with appropriate design parameters. The stability of the system was then assessed by modifying the design parameters. The effectiveness of the constructed controller has been evaluated through simulation with the aid of the MATLAB SIMULINK software, and the results were interpreted [2].

One of the earliest population-based stochastic algorithms ever suggested was the Genetic Algorithm (GA). GA's primary operators are selection, crossover, and mutation, just like other Evolutionary Algorithms (EA). A brief overview of this algorithm and allied case studies to evaluate the effectiveness of GA is provided in [3].

Ant colony optimization (ACO) draws its inspiration from several ant species' foraging strategies. These ants leave pheromone trails on the ground to indicate a good route for the colony's other ants to take. An analogous method is used by ant colony optimization to address optimization issues. Since the early 1990s, when the first ant colony optimization algorithm was put forth, ACO has drawn the interest of a growing number of researchers, and there are now numerous successful applications. Additionally, a sizable body of theoretical findings that offer helpful suggestions for academics and practitioners in other ACO applications are becoming available [4].

In order to optimize numerical issues, Karaboga proposed the Artificial Bee Colony (ABC) algorithm in 2005. The ABC algorithm is a swarm-based meta-heuristic algorithm. It was influenced by how honey bees used intelligence in their foraging. The algorithm is especially based on the model for honey bee colony feeding behaviour put out by Tereshko and Loengarov in 2005. Foraging bees that are working and not working, as well as food sources, make up the model. The first two elements, working and unemployed foraging bees, look for abundant food sources nearby their hive, which is the third element [5].

Since its debut in 1995, Particle Swarm Optimization (PSO) has undergone numerous modifications. Researchers have created new iterations, created new applications, and published theoretical analyses of the implications of the algorithm's many parameters and characteristics as they have learnt more about the approach. It provides an overview of particle swarming from the viewpoint of the authors, covering algorithm modifications, recent and continuing research, applications, and open difficulties [6].

The leadership structure and hunting strategy of grey wolves in nature are modelled by the GWO algorithm. For the purpose of mimicking the leadership hierarchy, four different varieties of grey wolves, including alpha, beta, delta, and omega, are used. In addition, the three essential components of hunting - looking for prey, surrounding prey, and attacking prey are used. The approach is then tested against 29 well-known benchmark functions, and the outcomes are confirmed by a comparison with PSO, Gravitational Search Algorithm [7] (GSA), Differential Evolution (DE) [8], Evolutionary Programing (EP) [9, 10], and Evolution Strategy (ES) [11]. The outcomes demonstrate that, in comparison to these well-known meta-heuristics, the GWO algorithm can deliver very competitive results [12].
The meta-heuristics physics based methods involve a random set of search agents that communicate to interconnect and travel all through the search space as per the physical rules. The travel/movement is effected by employing gravitational force such as Gravitational Local Search (GLSA) [13] or Gravitational Search Algorithm (GSA) [14], ray casting such as Ray Optimization (RO) [15], electromagnetic or inertial force, weights etc.

As far as the other applications are concerned, the ideal size of system components is determined using a new hybrid meta-heuristic algorithm called the hybrid grey wolf optimiser-sine cosine algorithm (HGWOSCA), which is based on the exponential decreasing function (EDF) and has high accuracy and speed of optimization in reaching the global solution. Comparing the proposed HGWOSCA's superiority to sine cosine algorithm (SCA), GWO, and PSO approaches in developing various hybrid system configurations and under various reliability constraints [16].

Due to the nonlinearity of the problem, the majority of optimization algorithms have sluggish convergence and inaccurate solutions. To solve these problems, the modified Ant Colony Optimization (m-ACO) method is suggested in this study as a meta-heuristic approach. By employing multiple random initializations, the traditional ant colony optimization technique is enhanced, increasing the likelihood of obtaining a better start population and, thus, the possibility of achieving the near-global optimum. The effectiveness of the proposed approach is evaluated using PID controllers and traditional benchmark functions [17].

2. Coupled tank system

Numerous loops might exist within the MIMO process in which process interaction occurs, where one MV (manipulated variable) disturbs all other or more than one CV (controlled variable). The objective behind MIMO control is to retain numerous CV's at their respective SP (set point). The work focusses on controlling a MIMO system with decentralized control in which the effects of interaction are adequate. The advantages offered by decentralized control include being simple whilst offering ease of design in tuning.

A coupled tank system which is a common TITO (Two Input Two Output) process is considered in which the decentralized control designed by employing Biggest Log modulus Tuning (BLT) method is optimized to attain an optimum solution.

The main problem prevalent in majority of the process industries is in controlling the flow between the tanks and liquid level control in the tanks. Since the coupled tank system is most common in petro chemical as well as paper industries for treatment of chemicals or mixing process, a brief description of the same is provided along with the difficulties in controlling the level. The diagrammatic representation illustration of a typical coupled tank system is provided in Fig. 1 in which two identical cylindrical tanks with the same cross sectional area are coupled with an inter-connecting pipe. The levels of tank1 (h_1) and tank2 (h_2) are the measured variables whereas the known input variables are the inflow to tank1 (F_{in1}) and tank2 (F_{in2}). A variable speed pump with due voltage variations regulates the inputs to the tank. The discharge from the tank is supposed to be proportional to the square root of the difference amongst the altitudes of the liquid level in the coupled tanks. Additionally, the liquid density is assumed to be constant all the way through. The schematic arrangement consists of the pump speed adjustments (two inputs) that can be suitably manipulated to control the two tank levels (outputs). It can be seen that the structure possesses interacting multivariable dynamics since each of the adjustment in pumps affects both the outputs.

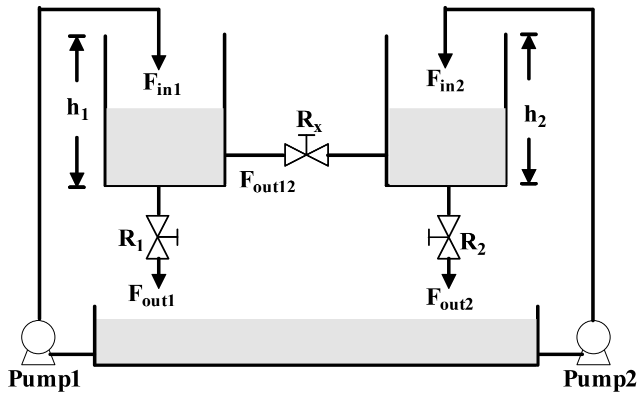

Fig. 1. Coupled tank system schematic

The mass balance equation is made use of in obtaining the mathematical model of the system while Bernoulli's law is employed to measure the tanks inflow and outflow. In Fig.1, h_1 and h_2 constitute the water level in tanks 1 and 2 correspondingly.

$$\frac{dh_1}{dt} = \frac{k_{pp1} u_1}{A_T} - a_1 \frac{\beta_1}{A_T}\sqrt{2gh_1} - a_{12}\frac{\beta_x}{A_T}\sqrt{2g(h_1 - h_2)} \tag{1}$$

$$\frac{dh_2}{dt} = \frac{k_{pp2} u_2}{A_T} - a_2 \frac{\beta_2}{A_T}\sqrt{2gh_2} + a_{12}\frac{\beta_x}{A_T}\sqrt{2g(h_1 - h_2)} \tag{2}$$

The notations, u_1 and u_2 in (1) and (2) constitute the pump speeds (manipulated inputs), a_1, a_2 are the cross sectional area of the outlet pipes; a_{12} is the cross sectional area of the connecting pipe; A_T is the area of both the tanks 1 and 2; g is the acceleration due to gravity; β_1, β_2 are the ratio of valve openings for tank1 and tank2 respectively and β_{12} is the ratio of valve opening between the tanks 1 and 2.

The Parameters and nominal operating point of coupled tank process are referred entirely from [2] after ascertaining that the system is completely controllable as well as observable with the aid of state diagram of the same. From the open loop step response of the process, the transfer function model [18] is obtained as below.

$$G_p(s) = \begin{bmatrix} \frac{16.99\, e^{-12.89s}}{(214.03s+1)} & \frac{6.69\, e^{-72.57s}}{(204.93s+1)} \\ \frac{9.23\, e^{-35.01s}}{(256.44s+1)} & \frac{11.38\, e^{-25.04s}}{(169.15s+1)} \end{bmatrix}$$

2(a). Pairing of variables in coupled tank process

The most common Relative Gain Array (RGA) matrix is employed to pair the variables in the chosen coupled tank process where the leading diagonal pairing is subjectively defined as controlling the (variable) level (h_1) of tank1 with pump1 (u_1) and level of tank2 (h_2) with pump2 (u_2). On the other hand, the off diagonal pairing is for controlling the variable tank1 level with voltage of pump2 and level of tank2 with pump1. The RGA matrix for the coupled tank process considered is obtained as below.

$$\lambda = \begin{bmatrix} 1.4692 & -0.4692 \\ -0.4692 & 1.4692 \end{bmatrix}$$

Since the off diagonal elements both occur negative, diagonal pairing is desired i.e. pairing of h1 with u1 and h2 with u2.

3. Metaheuristic algorithms

Metaheuristic algorithms attempt to find the best (feasible) solution out of all possible solutions in an optimization problem. To this end, they evaluate potential solutions and perform a series of operations on them in order to find different, better solutions. Meta-heuristic optimization algorithms such as the familiar Genetic Algorithm (GA), Ant Colony Optimization (ACO) Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) find application in many fields of study. The reason lies in their easiness, being flexible, offering derivation free mechanism (the optimization procedure commences with arbitrary solution, without the need for computing the search spaces derivative to find the optimum) and avoidance of local optima where the algorithm executes quite a lot of runs in tandem to avoid getting stuck on the same local optima each time. The Swarm Intelligence (SI) techniques emanate generally from natural colonies (ACO), flock (Starling PSO), herds (Horse Optimization Algorithm - HOA), and schools (Fish School Search (FSS)) etc.

3(a). Grey Wolf Optimization (GWO) algorithm

The scientific name given for wolves is Canis Lupus. “Lupus” in Latin means “wolf,” whereas “canis” in Latin refers to “dog”. These apex predator wolves belonging to the Canidae family are located at the crest of food chain along other flesh-eating species. These predators usually wander as a pack with the size of that pack ranging from 5 to 12 on an average. Their firm dominant social pyramid is represented by 4 categories alpha (α), beta (β), gamma (δ) and omega (ω) as represented in Figure 2. In the pyramid represented of Fig. 2 the dominance level is seen to decrease from top (α) to bottom (ω).

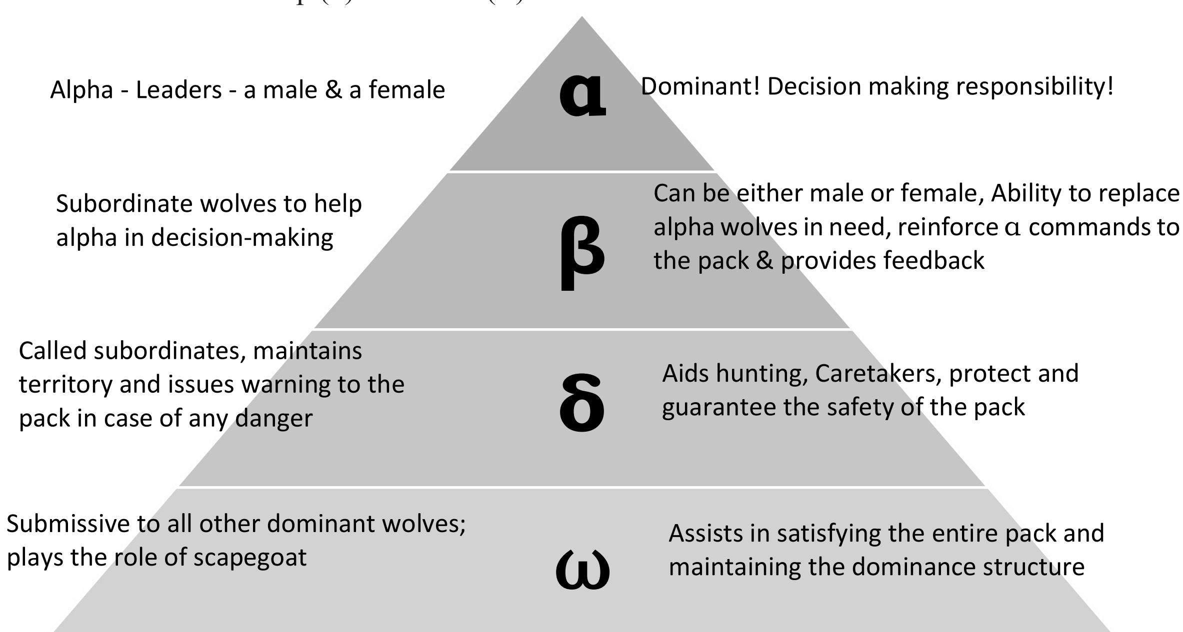

Fig. 2. Grey Wolf Hierarchy (dominance increases from bottom to top)

3(b). Implementation of GWO algorithm

The implementation of the GWO algorithm [12] is briefly explained in this section.

Fig. 3. GWO algorithm implementation

The implementation steps that are part of the Fig. 3 are briefed below.

1. Consider the fittest solution as alpha (α) followed by next best solutions as beta (β) and delta (δ) respectively. Assume the rest of the candidate solutions as omega (ω). The optimization (hunting process) is guided by α, β, and δ wolves with the ω wolves following the three.
2. Model the encircling behavior by updating the position of wolves with the following equations.

$$\vec{D} = |\vec{C}.\vec{X}_p(t) - \vec{X}(t)| \quad (3)$$

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A} \cdot \vec{D} \quad (4)$$

In the above equations (3) and (4), t specifies the current iteration, $\vec{A}$ and $\vec{C}$ are the coefficient vectors. $\vec{X}$ and $\vec{X}_P$ indicate the position vectors of a grey wolf and the prey to be hunted respectively. The vectors $\vec{A}$ and $\vec{C}$ are computed as below.

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \quad (5)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (6)$$

The constituents of $\vec{a}$ in (3) are linearly reduced from 2 to 0 during the iteration progress. $r_{1,}$ in (5) and r_2 in (6) are the random vectors in [0, 1].

3. Save the first three best solutions obtained and indulge the other search agents (including the submissive omegas) to update their positions as per the position of the best search agents by employing the equations (7), (8) and (9).

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \quad (7)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \quad (8)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \quad (9)$$

4. Search agents update their position based on the location of the alpha, beta, and delta. Finish the hunt by attacking the prey when it stops moving.
5. Termination is done upon obtaining a satisfactory end criterion. The GWO algorithm needs just the adjustment of two main parameters a and C.
   The generalized flow chart of the employed GWO algorithm is depicted in Figure 4.

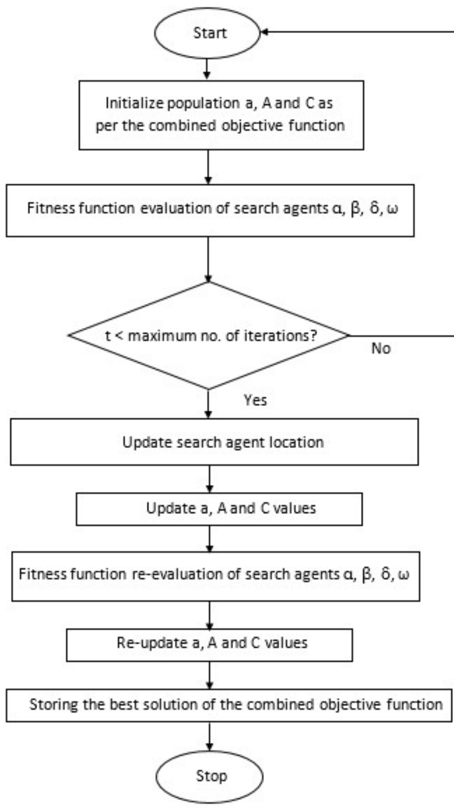

Fig. 4 Flow chart of the Grey Wolf Optimization Algorithm

4. Simulation studies

Simulations are conducted using MATLAB Simulink software to validate the performance of the optimized controller using GWO algorithm. The design of decentralized PI controller settings for the coupled tank process employing BLT method for loop1 is already obtained vide [2] and the optimization algorithm [12] is implemented on it.

The GWO optimized closed loop response of the coupled tank system for set point change effected in tank1 from its nominal operating value (level) of 18.32 cm to 25 cm is depicted in Fig. 5. Similarly, the closed loop response of tank2 for set point change effected to 17 cm from its nominal operating value of 12.23 cm is shown in Fig. 6.

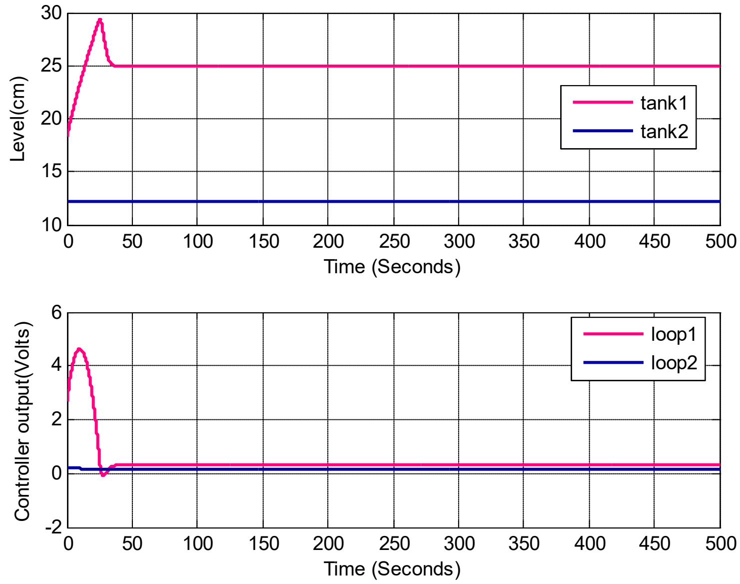

Fig. 5. Closed loop response of coupled tank process for set point change in tank1

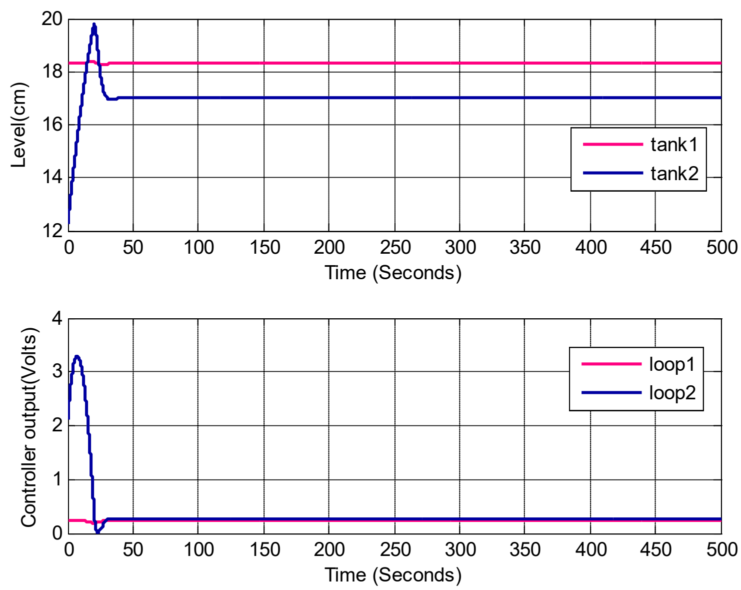

Fig. 6. Closed loop response of coupled tank process for set point change in tank2

5. Results & Discussion

From the two responses (Fig. 5 and Fig. 6) depicted above, it can be inferred that, any set point change effected in tank1 has an impact in the level of tank2 owing to the interaction effects that acts as a disturbance for the level in tank2. Likewise, the set point change effected in tank2 owing to the interaction effect acts as a disturbance to the level in tank1.

The performance indices which are the function of error signal, ISE (integral of square error) and IAE (integral of absolute error) of the optimized GWO algorithm for the coupled tank process obtained is presented in Table 1.

Table 1. Performance Measure of GWO algorithm

Set point change in tank1				Set point change in tank2			
Loop1		Loop2		Loop1		Loop2	
ISE	IAE	ISE	IAE	ISE	IAE	ISE	IAE
243.92	88.89	0.004144	0.38	0.02969	0.881	91.9	45.49

6. Conclusions

The interaction effect observed in multiple input, multiple output (MIMO) system has a significant role in designing controllers for multivariable systems. When the controller for a coupled tank system is designed, neglecting the interaction effects between the variables, it leads to vitiating the overall performance of the system while also affecting the closed loop stability of such a system. This work, addresses the challenge by employing GWO algorithm by appropriately considering the interactions in the coupled tank system and the performance of the designed system is evaluated by means of ISE and IAE indices.

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