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**Chapter**

# Comparative Study of Interval Type-2 and Type-1 Fuzzy Genetic and Flower Pollination Algorithms in Optimization of Fuzzy Fractional Order $PI^{\lambda}D^{\mu}$ Controllers

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## Abstract

In this chapter, a comparison between fuzzy genetic optimization algorithm (FGOA) and fuzzy flower pollination optimization algorithm (FFPOA) is bestowed. In extension, the prime parameters of each algorithm adapted using interval type-2 and type-1 fuzzy logic system (FLS) are presented. The key feature of type-2 fuzzy system is alimenting the modeling uncertainty to the algorithms, and hence it is a prime motivation of using interval type-2 fuzzy systems for dynamic parameter adaption. These fuzzy algorithms (type-1 and type-2 fuzzy system versions) are compared with the design of fuzzy control systems used for controlling the dihybrid level control process subject to system component (leak) fault. Simulation results reveal that interval type-2 fuzzy-based FPO algorithm outperforms the results of the type-1 and type-2 fuzzy GO algorithm.

**Keywords:** interval type-2 fuzzy logic, fuzzy fractional order PID, fuzzy controller, genetic optimization, flower pollination

## 1. Introduction

Since many years, metaheuristic optimization algorithms have been used to solve numerical optimization problems from the defined search space without any concern of the required parameters. In this chapter, prominent bioinspired optimization algorithm like genetic optimization algorithm (GOA) and flower pollination optimization algorithm (FPOA) is presented for the problem of optimization of membership functions for a fuzzy controller.

In this chapter, two well-known metaheuristic optimization algorithms are used for a comparison in the optimization of a fuzzy system used as a controller of dihybrid level control system. The main reason for preferring GOA and FPOA algorithms is because they use the same methodology for parameter adaptation; however, these two algorithms work with similar inputs in fuzzy system but with dissimilar outputs, considering the outputs of the fuzzy system are parameters of the optimization algorithm which are dynamically adjusted for each iterations of each algorithm.

Genetic algorithms (GA) have been popular since the beginning of the 1960s; from the University of Michigan, Holland started an initial work on GA. His first contribution was based on adaption theory in natural and artificial system [1] in 1975. Genetic algorithms like neural networks are biologically inspired and represent a new computational model having its roots in evolutionary sciences. The core aspect of the GA has been well established with deep theoretical concepts and some practical domain examples in [2]. The GA is very popular in solving complex engineering problems, because of the feasibility and robustness of GA concepts. However, against the prominent advantages of a GA for determining difficult, constrained, and multi-objective functions where other approaches may have failed, the full strength of the GA in engineering application is yet to be exploited [3, 4]. The GA has inadequacy to control parameters which are dynamic in nature. The parameters of GA and a methodology for dynamic parameter adaptation are presented in Section 4.

As a novel metaheuristic algorithm, the flower pollination optimization algorithm (FPOA) is motivated by the pollination philosophy of flowers. In nature, the pollination methods for flowers associate two main types: cross-pollination and self-pollination [5]. In cross-pollination, some birds operate as global pollinators that relocate the pollen to the flowers of higher distant plants. In contradiction, in self-pollination, pollen is disseminated by the wind and only between neighboring flowers on the same plant. From the fundamental understanding of concepts of cross-pollination and self-pollination, the FPOA is created mapping between two types of pollination, core and self, with global and local pollination operators, respectively. The FPOA is gaining more and more attention in recent times due to its advantages, simple in nature, lesser parameters, and user-friendly operation.

The conventional integer proportional integral derivative (PID) controllers are tuned in [6–8] using bioinspired GOA and FPOA for various applications like DC motor, buck converter, and continuous stirred-tank reactor (CSTR) to control the plant. Several approaches had been proposed for GA, for example, in [9] an approach with GA for control vector for loss minimization of induction motor can be seen. Shopova and Vaklieva-Bancheva have introduced in detail a genetic algorithm called BASIC, designed to handle with numerous engineering optimization problems [10]. The self-organizing GA optimization method has been used for deriving PID controller parameters to escape incomplete convergence and to accomplish good optimization performance [11]. Krohling and Rey have examined a strategy to design an optimal disturbance rejection PID controller based on genetic algorithms for solving the constrained optimization problem in a servomotor system [12]. Kumar et al. have illustrated the design of GA-based controller for a bioreactor model that outperformed Ziegler-Nichols and Skogestad's tuned controller in terms of overshoot and undershoot as well as disturbance rejection and set point tracking [13].

A hybridization of the algorithms was performed in [14]; the authors publish a hybridization between the particle swarm optimization (PSO) and GO algorithms to minimize the cost and materials required for the elaboration of a metal cylinder. To increase reliability and performance of the optimization algorithm, ambiguous data, and the extension of the type-1 fuzzy sets (T1FSs) which is intuitionistic fuzzy sets (IFSs), it is used to find the optimal parameters in the algorithms. In recent scenarios, intuitionistic fuzzy logic system is an effective technique in bioinspired algorithms. A new model for decision-making is advised in [14], which is based on the IFSs; the objective of the new model is to eliminate parameter uncertainty in the data to help in the right decision-making. This techniques have been significantly enhanced timing and pressure by judgmenter. In [15], with the intention of improving the accuracy in optimization algorithms, the author proposed the

interval type-2 fuzzy set (IT2FS), which helps to find the level of membership of an object to something else in analytical terms, and this method undoubtedly improves the accuracy of membership of a data set. There are certain works by Garg et al. in which fuzzy logic has been used for the same metaheuristics [16, 17].

This is why we examine the IT2FS for parameter adaptation in bioinspired algorithms. As the major contribution of this research work, two bioinspired optimization algorithms are proposed and their fuzzy variants with dynamical parameter adjustment using type-1 fuzzy logic system and interval type-2 fuzzy logic systems as tools for modeling nonlinear complex problems, exclusively for the stability of the dihybrid level control system subject to system component (leak) faults. Despite using these algorithms as tools to optimize the fuzzy fractional order PID controller membership function, a comparison is performed with all variants of GOA and FPOA algorithms.

The rest of the chapter is organized as follows. Section 2 describes the state of the art with related works for each bioinspired optimization algorithm. Section 3 contains a more exhaustive information of the internal work of the two algorithms. Section 4 describes the methodology used to dynamically adjust the parameters of each method. Section 5 contains the versions of the algorithms with dynamic parameter adaptation using the proposed strategy with a type-1 and an interval type-2 fuzzy system. Section 6 describes briefly the problem statement in which the two bioinspired optimization algorithms were tested. Section 7 shows the results of applying the bioinspired optimization algorithms to the optimization of a fuzzy system used in control. Finally, in Section 8, the conclusion and future work of this paper are presented.

## 2. Related works

The genetic algorithm is an optimization technique based on indiscriminate search method, which can be used to optimize the complex problem and even solve the nonlinear equations. In GOA the first parameter is chromosomes (genotype or individuals); it is a set of parameters which contains the potential solution to the problem that the GA is trying to solve and derive iteratively. The second parameter is "generation"; it defines each iteration of the algorithm. The progression of the solutions is simulated over a fitness function and other genetic operators like reproduction, mutation, and crossover [18]. In the literature there are many variants and improvements of this algorithm, for example, in [19], the authors present a work, where the algorithm is combined with techniques of fuzzy logic and the algorithm parameters are tuned using fuzzy logic system, and found improved results. In addition, in [20], an empirical study of the GA is presented in that the author tuned the parameter of the GA by GA itself.

Homayouni and Tang [21, 22] propose the use of fuzzy logic-based GA for the scheduling of handling/storage equipment in an automated manner. In recent times type-1 fuzzy logic is used to optimize the crossover and mutation rate for GA; in [23, 24] the authors proposed the methods and solve the real-time problem like rail-freight crew-scheduling problem. In 2013, Maldonado et al. [25] proposed fuzzy-based system for PSO and GA optimization, and it is used for FPGA applications, and the fuzzy system is used to control the speed of DC motor.

Flower pollination optimization algorithm (FPOA) is a new high-performance heuristic optimization algorithm which is always welcome to solve real-world problems [26]. References [27–29] represent that FPOA has the promote solution and robustness than other published methods and also it has shown reasonable superiority over GA. FPOA has only one parameter $p$ (switch probability) which

causes the simple algorithm to implement and quickly reach optimum solution [30]. The other special competence of FPOA is a wide-ranging domain search with quality and the same texture solution. And hence it is used alone with DE for multi-objective optimal dispatch problem [31]. FPOA is used to solve many complex problems and also compared with various optimization algorithms [32], and its performance assure to implement for present problem.

## 3. Bioinspired optimization methods

### 3.1 Genetic algorithms for optimization

The simple genetic algorithm can be expressed in pseudo code with the following cycle.

---

**Algorithm 1.** Genetic Algorithm Optimization.

---

Generate the initial population of individuals aleatorily $P$ (0).
**While** (Number Generations <= Maximum Numbers Generations)
Do:
{
*Evaluation*;
*Selection*;
*Reproduction*;
*Generation* ++;
}
Show results
End

---

The modified GOA with parameter adaptation is modified, where the main difference with respect to original GOA is the calculation of the new crossover $K_1$ and mutation rate $K_2$.

### 3.2 Characteristics of bioinspired flower pollination algorithm

The flower pollination is a nature-inspired metaheuristic optimization algorithm; it is based on the concepts of "flower optimal breeding" and genetic algorithm "survival of the fittest." The primary types of the flower pollination are divided into two types: biotic and abiotic [26]. The majority flowering plants is a biotic pollination; it is around 85–90%. The transportation of the pollen is by natural resources such as birds, bees, insects, and animals. However, the remaining pollination of 15–10% takes the help of abiotic sources, for example, wind and diffusion in water. The pollination activity accomplished by self-pollination or cross-pollination is presented in **Figure 1** [26]. The term self-pollination can be defined as the fertilization of one flower from pollen of the same flower (autogamy) or the nearby flowers of the same plant (geitonogamy) [26]. It can develop when a flower consists of both male and female eggs. The basic characteristic of the self-pollination is that it takes place generally at short distance and without pollinators. It is a proof for the local pollination. In the contradictory, allogamy (cross-pollination) materialize in the case of cereal are moved to a flower from another plant. These process can be done with the help of biotic or abiotic operators as pollinators. It is observed as the global pollination. Bees and birds as biotic pollinators operate Lèvy flight behavior [27] with jump or fly distance steps which adhere to a Lèvy distribution. The FPO algorithm proposed by Yang [26] can be summed up by pseudo code for FPO Algorithm 2.
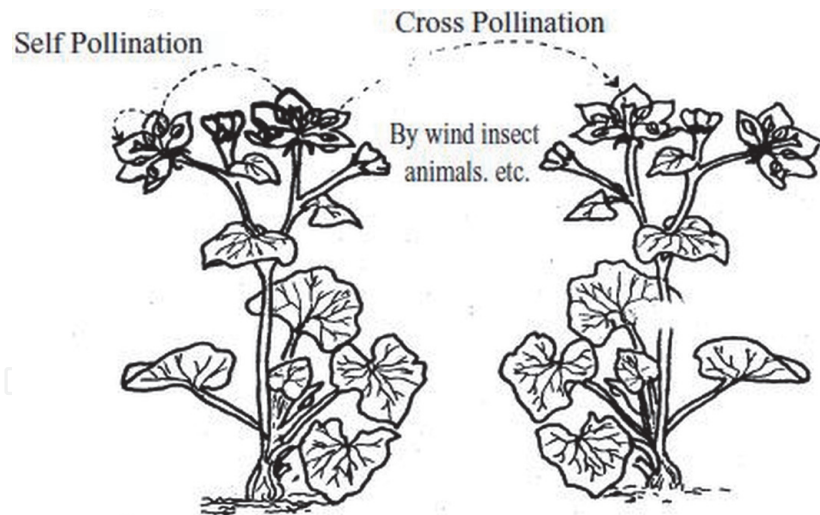
**Figure 1.**
*The behavior of FPOA in terms of fitness function and iteration count [26].*

### 3.3 Mathematical modeling of FPOA

By confirming the characteristic of the flower pollination procedure, we can define the following rules by pollinators [27]: When pollinators relocated pollen by operating Lèvy flight with procedure of global pollination, then it is treated as cross-pollination and biotic. The classes of biotic and self-pollination are foreseen from the local pollination. Now for the same attributes of flower pair, it is proportional to the probability of the breeding, and we can say it is pollinator constancy. Transformation possibility $p \in [0, 1]$ is used to control the procedure of local and global pollination. In the entire pollination process due to physical closeness and another circumstance such as wind. From the investigation of attributes of the pollination procedures, the FPOA methodology has developed; therefore, we first convert the above four rules into the mathematical equations. In the beginning, the basic steps of global pollination, pollen eggs are transferred using pollinators, for example, flying insects can fly over a long distance. This process establishes that pollination and breeding of the competent results are characterized as $f^*$. Rule 1 and flower dependability perhaps are shown as Eq. (1) [28]:

$$y_i^{t+1} = y_i^t + P(y_i^t + f^*) \tag{1}$$

where $y_i^t$ describes the pollen $i$ or vector of solution $y_i$ at generation $t$. The pattern $f^*$ presents the current optimal solution at the current no. of iterations that are constructed among all the solution. Durability of the pollination is expressed by element $P$, which is essentially a step size.

The Lèvy flight defined as the characteristics of flying insects can migrate over a large distance during transferring the pollen. That is, $0 > P$ embellished from a Lèvy distribution [28]:

$$P \sim \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{s^{1+\lambda}}, (s \gg s_0 > 0). \tag{2}$$

In Eq. (2) classic gamma function is expressed by $\Gamma(\lambda)$, and this type of distribution is applicable for large steps $0 > s$. Considered value of $\lambda$ is 1.5. Eq. (3) clarifies the local pollination, and rule 2 plus flower dependability can be mathematically modeled as [28]:

$$y_i^{t+1} = y_t^i + \in \left( y_j^t - y_k^t \right) \tag{3}$$

where pollen of different flowers of the same plant is shown by $y_j^t$ and $y_k^t$. This essentially mimics the flower constancy in a limited neighborhood. If $y_j^t$ and $y_k^t$ belong to the same category and same population, this becomes a local random walk if we express $\in$ from a uniform distribution in the range [0,1] [28].

---

**Algorithm 2.** Pseudo code for FPO Algorithm

0: Initialize objective as minimization.
   Define the population for $n$ flowers.
   Find current best solution $f^*$ in the initial population.
   Describe the switch probability $p \in [0, 1]$.
   **while** (t < MaxIteration) **do**
      **for** i=1: n **do**
         **if** rand < p **then**
            Define step size P which follow Lèvy distribution. Use Eq. (1) to perform global
            pollination.
         **else**
            Define $\in$ for uniform distribution [0,1].
            Randomly select a $j$ and $k$ among all the solution.
            Perform local pollination by Eq. (3).
         **end if**
         Calculate new solution.
         If calculate solution is better, then update it in population.
      **end for**
      Get the optimal solution $f^*$.
   **end while**

---

The modified FPOA with parameter adaptation is modified, where the main difference with respect to FPO algorithm is the calculation of switch probability $P$ and the use of a fuzzy system to calculate new switch probability $P$.

## 4. Bioinspired methods with parameter adaptation

In this work, two bioinspired optimization algorithms are used: GA and FPOA. Both the methods used in these works use the same procedure for parameter adaptation; however, small adjustment is enforced to each optimization method, because of, for parameter adaptation fuzzy logic system is used to revise the one or more parameter's value during the execution of each iteration of the algorithm. To find out the new parameter values, the fuzzy system uses as input the percentage of transpire iterations and the degree of diversity $Q(t)$ of individuals from each bioinspired method, and now from these metrics, these parameters are used as an input for the fuzzy system as defined by Eqs. (4) and (5), respectively:

$$Iteration = \frac{Current\ iteration}{Maximum\ of\ iterations} \tag{4}$$

$$Diversity(Q(t)) = \frac{1}{n_s} \sum_{i=1}^{n_s} \sqrt{\sum_{j=1}^{n_x} \left( X_{ij}(t) - \overline{X}_j(t) \right)^2}\ n_s \tag{5}$$

To implement the methodology in context, the iteration number is given in terms of percentage of what iteration we are presently in, and hence we can model the fuzzy rules for updating the parameters rely on early-mid-final iterations of

algorithm and, consequent to full knowledge of this, changing the parameters of bioinspired optimization algorithm, respectively.

The second input parameters is diversity $Q(t)$ which gives us a degree of closeness to the global best individuals with respect to individuals. From this parameter we can control the speed of the algorithm and control the local (individuals get close together) and global (individual gets removed for the rest) search.

By bringing together these two matrices such as **iteration** and **diversity**, we can easily control the performance of a bioinspired optimization algorithm by manipulating its parameters; this is of course possible; however, it requires previous knowledge of the algorithm.

## 5. Parameter adaption of bioinspired algorithm using type-1 and interval type-2 fuzzy logic system

The GO algorithm has proven to be a good technique to optimize parameters [18, 19]; that is why we perform a computerized search that grants good performance of the genetic algorithm. For this research work in the case of fuzzy controller, first we define the fitness function of the GOA, and it is a mean square error (MSE) which is shown in Eq. (6). For each mutation and for N iterations, type-1 fuzzy system design for the GOA is calculated and trying to minimize the objective function (MSE error). Accordingly, for designing the fuzzy systems, which dynamically adapt the $K_1$ and $K_2$ parameters, the iteration and diversity metrics are considered as inputs:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \tag{6}$$

where $n$ are the predictions generated from a sample of n data points on all variables, $Y_i$ is the vector of observed values of the variable being predicted, and $\hat{Y}_i$ is the predicted values of the variable.

The bifurcation of the membership functions for inputs and outputs is completed in a symmetrical appearance. The layout of input variables in terms of linguistic variables is depicted in **Figure 2** for the type-1 fuzzy logic system.

The type-1 fuzzy system is depicted in **Figure 2**, having two inputs—one is iteration, and the second one is diversity $Q(t)$—and having two outputs $K_1$ (crossover) and $K_2$ (mutation rates). In this case, each inputs were divided into three linguistic variables with triangle membership functions, and the outputs were granulated into four linguistic variables with triangle membership functions. The proposed type-1 fuzzy system consists of nine fuzzy *if-then* rules to control the performance of GOA.

Now, in **Figure 3** appreciated interval type-2 fuzzy system, it has similar *if-then* fuzzy rules and linguistic variables for inputs as well as for outputs. However the rule base is the same, meaning expert knowledge is the same but only type of membership functions is changing from the type-1 fuzzy system.

Consequently, **Table 1** presents the *if-then* fuzzy rules for both the fuzzy systems type-1 and type-2 in **Figures 2** and **3**, respectively. The rule base is designed based on past simulation results to generate the expert knowledge base from parameters of GOA and how to control the performance.

At the time of fuzzy system designing, symmetric triangle membership functions for inputs and outputs for type-2 FLS were taken. Type-1 FLS and interval type-2 FLS have the same number of fuzzy *if-then* rules and use Mamdani style.
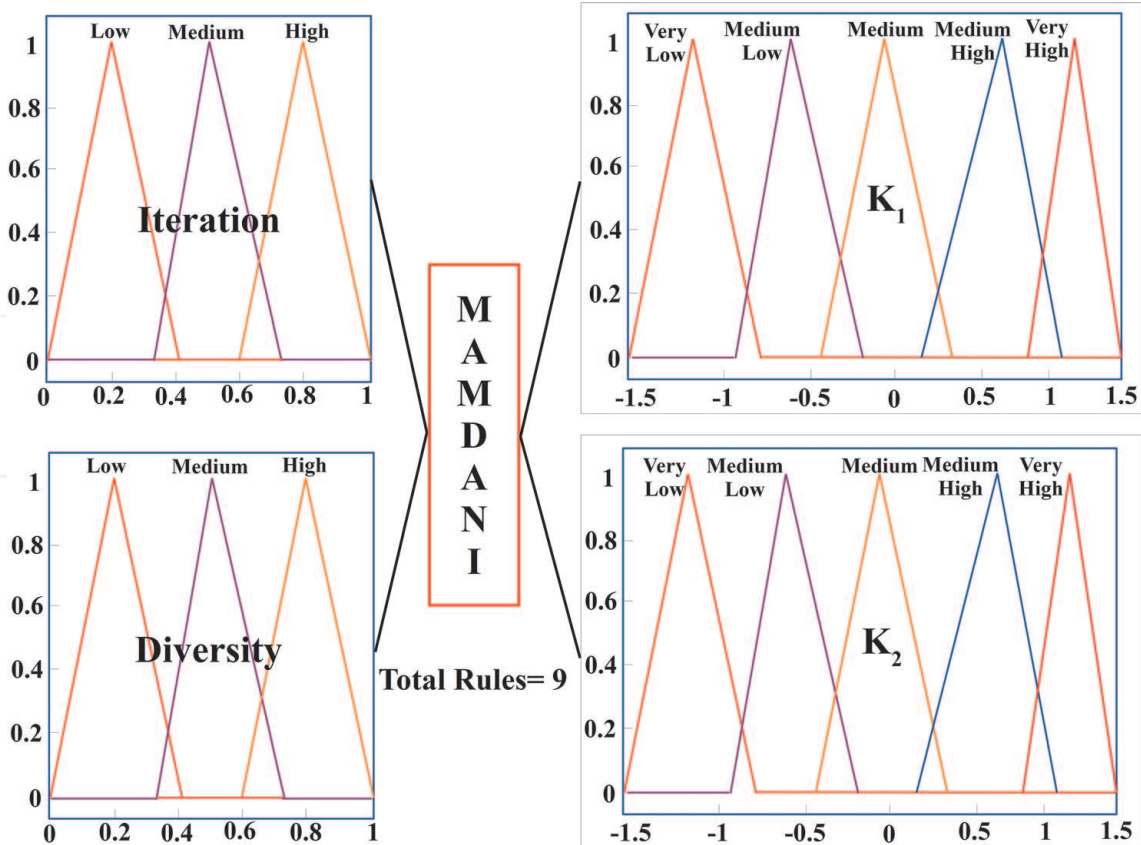
**Figure 2.**
*Type-1 fuzzy system for dynamic parameter adaptation in genetic algorithm optimization (GAO).*
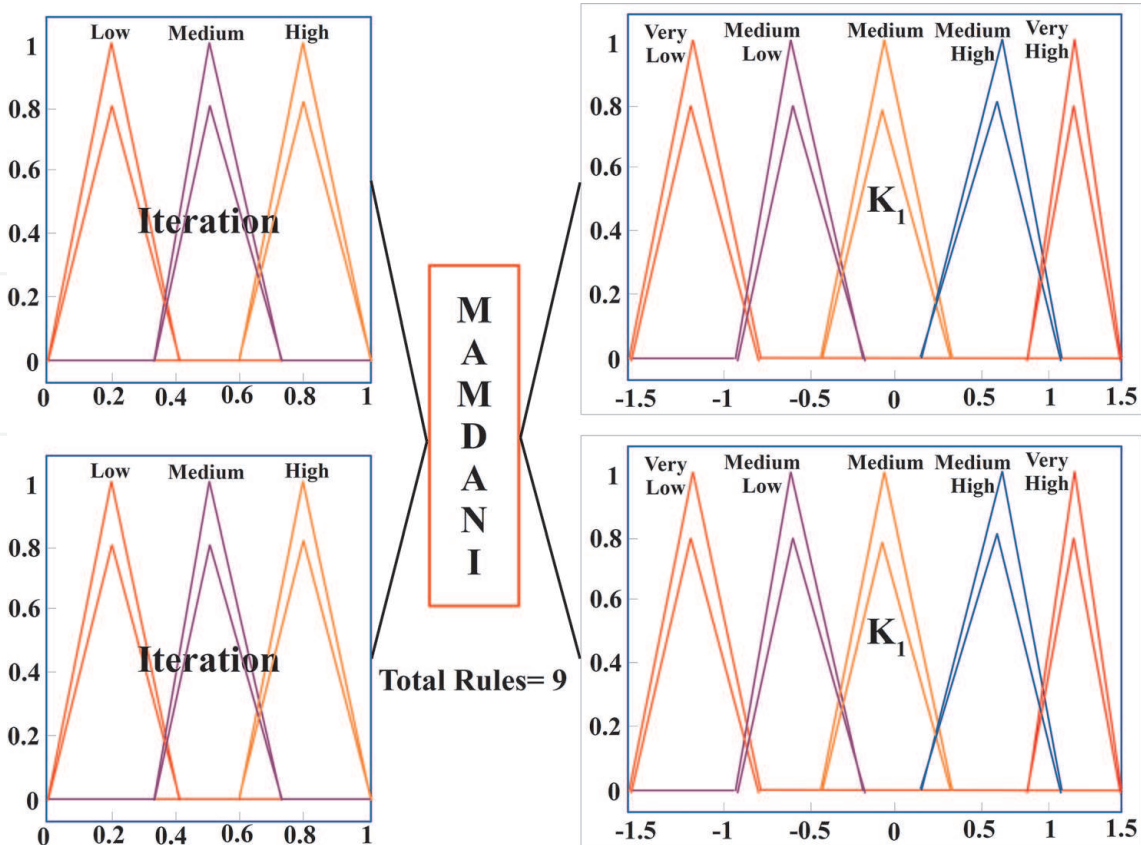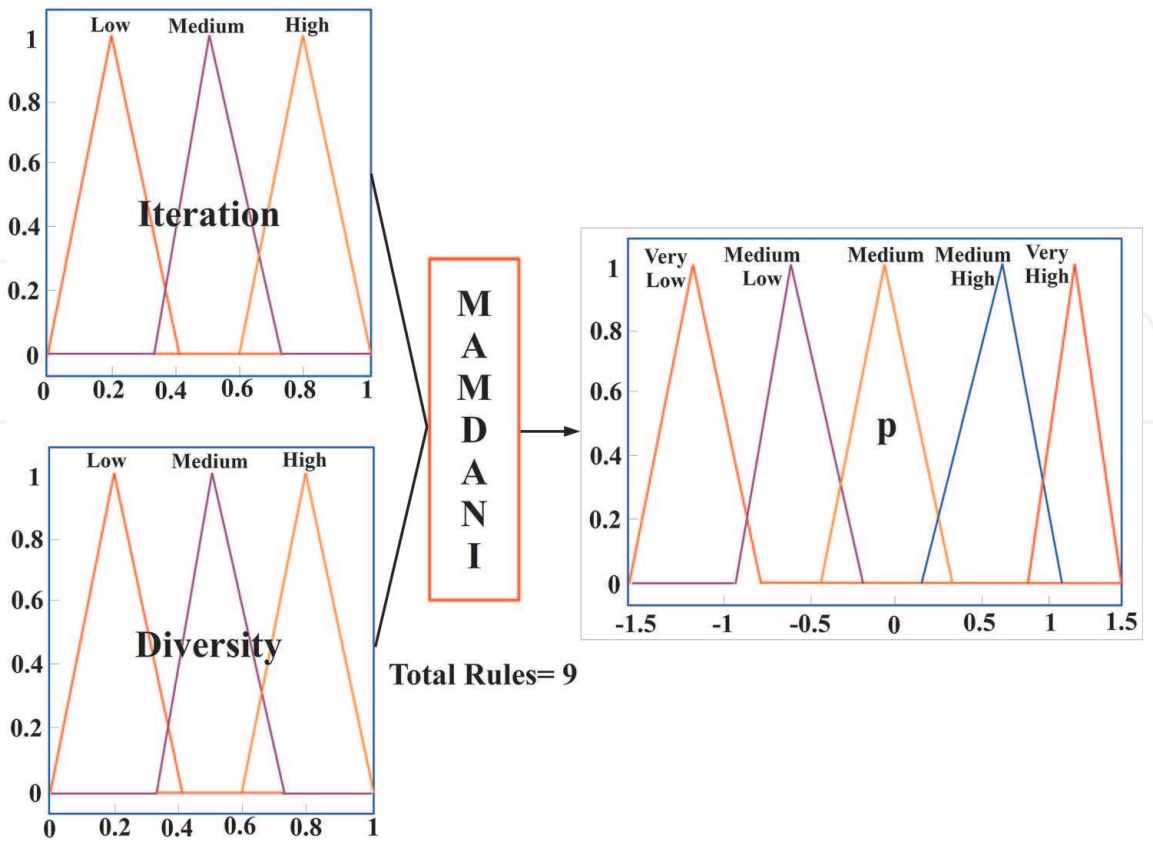


**Figure 3.**
*Interval type-2 fuzzy system for dynamic parameter adaptation in GAO.*

From the illustrated strategy for parameter adaptation of bioinspired optimization algorithm in Section 4, only one parameter can play the vital role in performance of the FPOA, and it is the best parameter, which is the switch probability $P$ from Eq. (2). So controlling this parameters can control the entire FPO algorithm behavior. For the parameter adaptation in FPOA, the same like GOA type-1 and interval type-2 FLC is designed.

| No. | Inputs | | Outputs | |
|-----|--------|--|---------|--|
| | Iteration | Diversity | $K_1$ | $K_2$ |
| 1. | Low | Low | Very high | Very low |
| 2. | Low | Medium | Medium high | Medium |
| 3. | Low | High | Medium high | Medium low |
| 4. | Medium | Low | Medium high | Medium low |
| 5. | Medium | Medium | Medium | Medium |
| 6. | Medium | High | Medium low | Medium high |
| 7. | High | Low | Medium | Very high |
| 8. | High | Medium | Medium low | Medium high |
| 9. | High | High | Very low | Very high |

**Table 1.**
*Fuzzy rules for dynamic $K_1$ and $K_2$.*



**Figure 4.**
*Type-1 fuzzy system for dynamic parameter adaptation in flower pollination optimization algorithm (FPOA).*

**Figures 4** and **5** present the type-1 fuzzy system and the interval type-2 fuzzy system used to dynamic parameter adaptation of the parameters of flower pollination optimization algorithm (FPOA), using as inputs metric iteration and diversity.

The fuzzy system illustrated in **Figure 4** is type-1, has iteration and diversity as inputs, and has the parameter $P$ as output. For this case, the inputs were divided into three different linguistic triangle membership functions and the outputs into five triangle membership functions. The proposed Mamdani fuzzy system contains the nine *if -then* fuzzy rules that control the behavior of FPOA.

The fuzzy system in **Figure 5** is an interval type-2 and has the same number of membership per input and output, but now as type-2 triangular membership functions, the fuzzy rule base is the same as in the type-1 because the knowledge is not changing, only the type of membership functions.
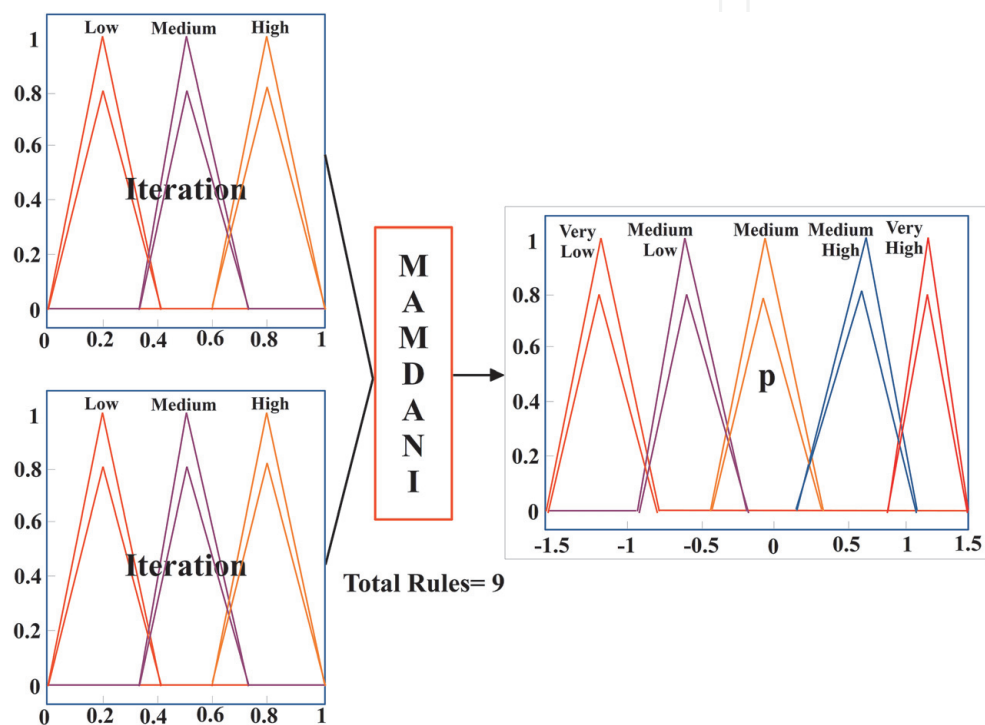


**Figure 5.**
*Interval type-2 fuzzy system for dynamic parameter adaptation in FPOA.*

| No. | Inputs | | Outputs |
|---|---|---|---|
| | Iteration | Diversity | *P* |
| 1. | Low | Low | Very high |
| 2. | Low | Medium | Medium high |
| 3. | Low | High | Medium high |
| 4. | Medium | Low | Medium high |
| 5. | Medium | Medium | Medium |
| 6. | Medium | High | Medium low |
| 7. | High | Low | Medium |
| 8. | High | Medium | Medium low |
| 9. | High | High | Very low |

**Table 2.**
*Fuzzy rules for dynamic parameter adaption in FPOA.*

**Table 2** contains the fuzzy rules used for the fuzzy systems in **Figures 4** and **5**; these rules were designed based on several experiments to create knowledge of the parameters of FPOA and how to control its behavior.

## 6. Formulation of the problem

To test the proposed methods with dynamic parameter adaptation, a complex problem was selected which is commonly used in various industries like petro-chemical, pharmaceutical, food processing, chemical, etc. In this case, the optimization of a fuzzy system design used for controlling a dihybrid level control system subject to system component (leak) fault, the task of the fuzzy controller is to provide a way to control the two inlet flow rates of the dihybrid tank 1 and tank 3 in order to minimize the steady-state error. The type-1 fuzzy logic is used to design the fractional order PID controller. The prototype model of the dihybrid system is illustrated in **Figure 6** and has three tanks; out of these two side-by-side tanks are identical. The system has two identical pumps which provide the inlet flow rate to the tank 1 and tank 3. The intermediate tank is unique in terms of dynamics of the tank, which added nonlinear response to the outer tanks. The dynamics of dihybrid system subject to leak faults represented by the following set of equations from [33]

$$S\frac{dh_1(\mathbf{t})}{dt} = f_1(t) - sign[h_1(t) - h_2(t)] f_{12}(t) - f_{l1}(t) \tag{7}$$

$$S'\frac{dh_2}{dt} = sign[h_1(t) - h_2(t)]f_{12}(t) - sign[h_2(t) - h_3(t)]f_{23}(t) \tag{8}$$

$$S\frac{dh_3(\mathbf{t})}{dt} = f_2(t) + sign[h_2(t) - h_3(t)]f_{23}(t) - f_{l3}(t) \tag{9}$$

where $S' = \frac{\pi}{3}\left[3r_{b2}^2 + 6r_{b2}\left(\frac{R-r_{b2}}{H_2}\right)h_2 + 3\left(\frac{R-r_{b2}}{H_2}\right)^2 h_2{}^2\right]$
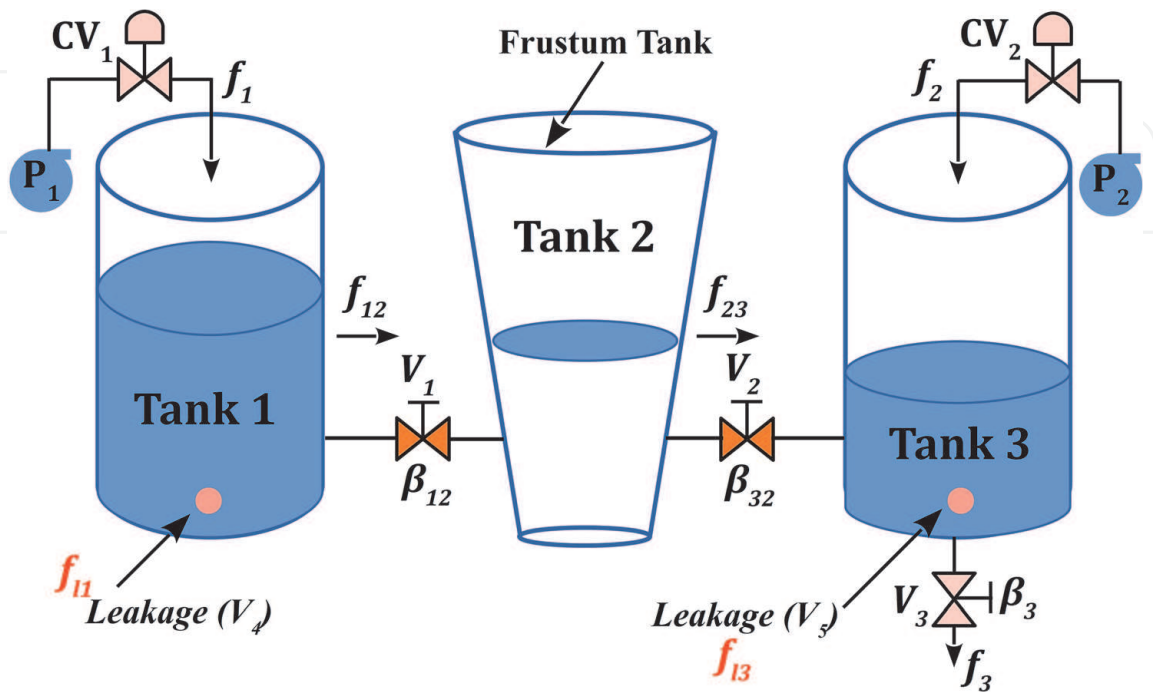


**Figure 6.**
*Prototype model of the dihybrid system [33, 34].*

The $S'$ equation given above is the area of conical frustum tank at any height of tank given by equation [33, 35, 36].

The proposed control strategy is depicted in **Figure** 7.

The fuzzy system is shown in **Figure** 8 and is used for the complex plant to control the level of tank 1 and tank 3 of the dihybrid level control system. This is the fuzzy system that the bioinspired optimization algorithms will optimize; in this case, only the parameters of the membership functions are optimized. The fuzzy controller of **Figure** 8 has two inputs, the error $e(s)$ and derivative of error $de(s)/dt$,
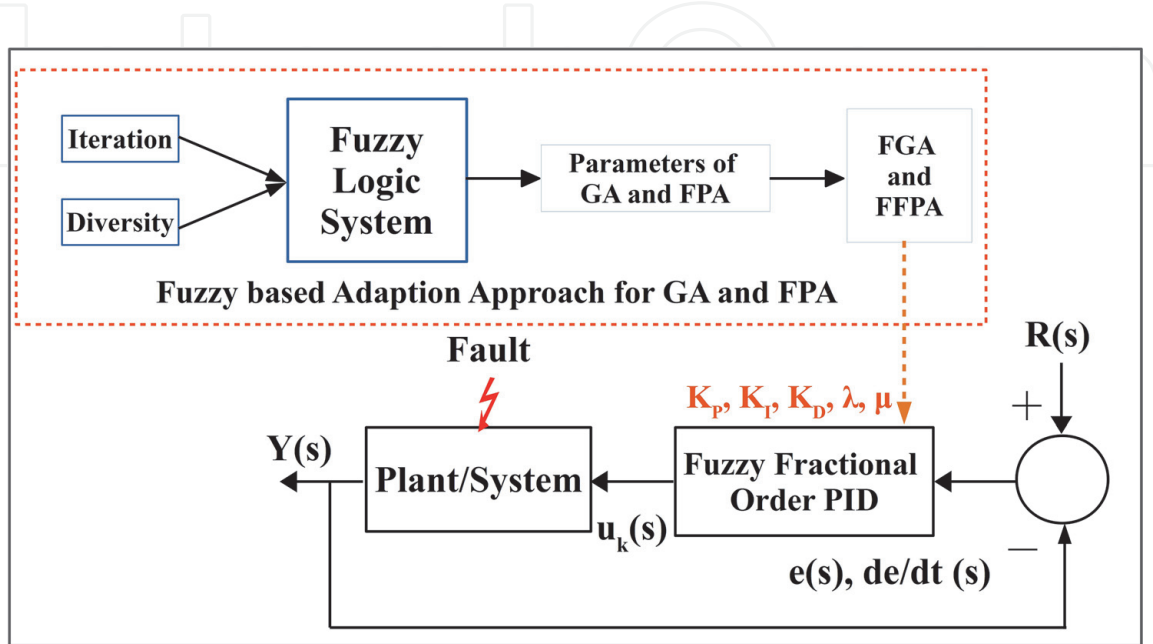


**Figure 7.**
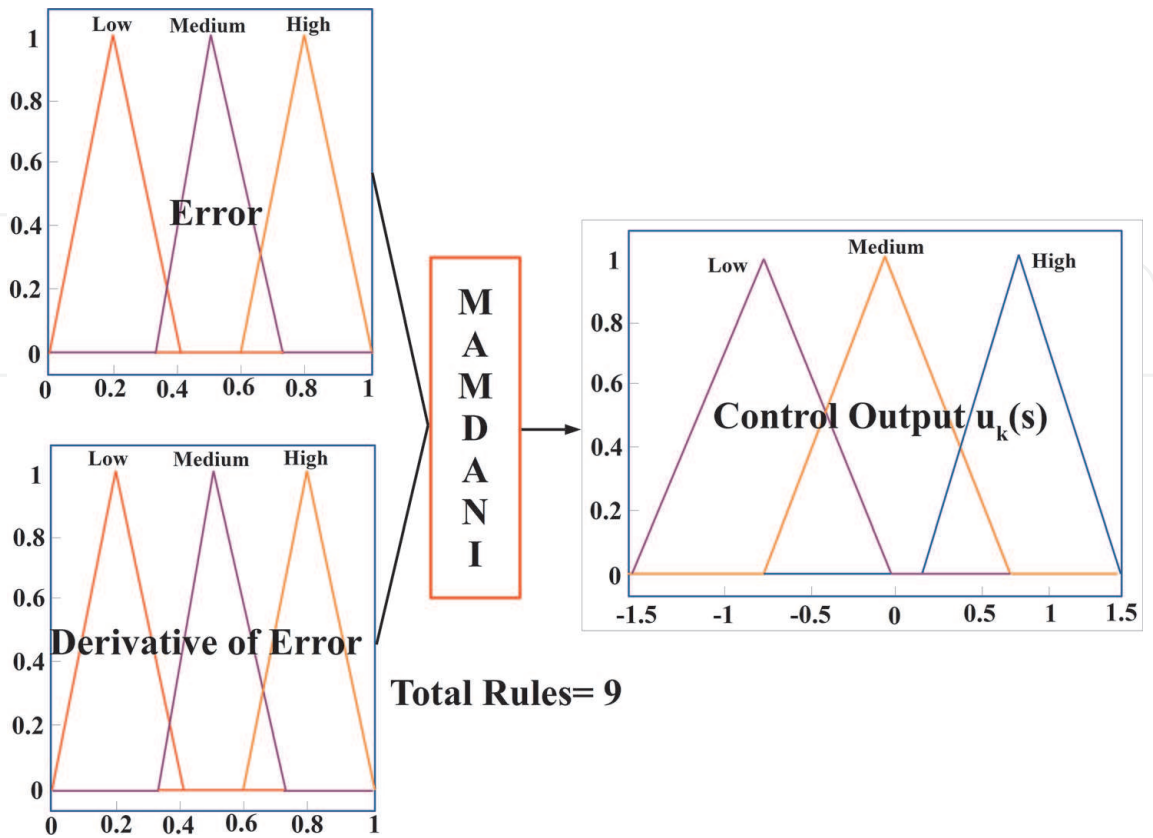*Proposed control scheme.*



**Figure 8.**
*Membership functions for input and output of type-1 FLC.*

and one output, control signal $u_k(s)$, for each control valve of the dihybrid level control system. The inputs are granulated into three triangle membership functions, and the outputs are granulated into three triangular membership functions. Also this fuzzy controller uses the fuzzy rule set from **Table 3**. The desired reference trajectory for level is illustrated in result figures, where it starts from 0 to 80 cm and system component (leak) fault is added into tank 1 and tank 3, in order to create a complex control problem [33, 35]. The main difference between the type-1 and interval type-2 fuzzy systems is the ability of the latter to handle uncertainty; thus, to simulate this problem and to provide better tools to perform the comparison, a modification of the original plant is added, where leak fault is added to the desired reference trajectory.

| No. | Inputs | | Outputs |
| --- | --- | --- | --- |
| | $e(s)$ | $\dot{e}(s)$ | $u_k(s)$ |
| 1. | Low | Low | Low |
| 2. | Low | Medium | Medium |
| 3. | Low | High | Medium |
| 4. | Medium | Low | Medium |
| 5. | Medium | Medium | Medium |
| 6. | Medium | High | High |
| 7. | High | Low | Medium |
| 8. | High | Medium | High |
| 9. | High | High | High |

**Table 3.**
*Fuzzy rules for fuzzy controller.*
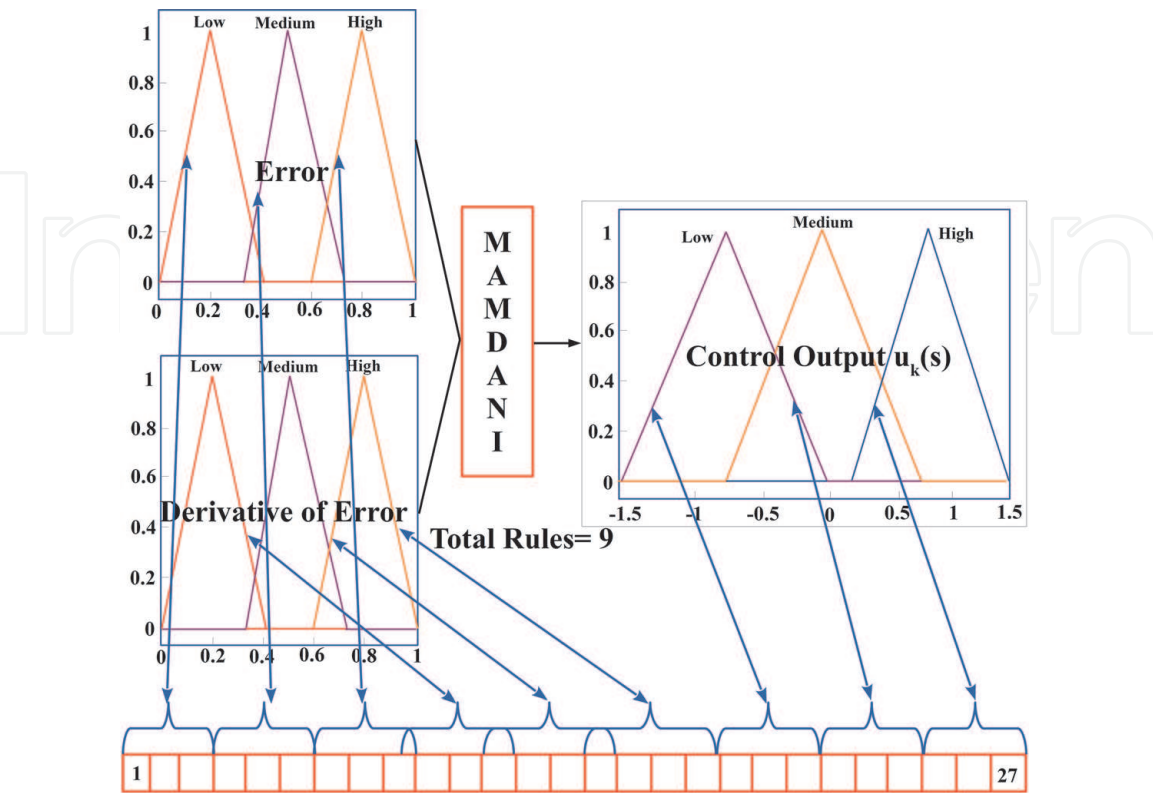


**Figure 9.**
*Optimization problem (points of the membership functions).*

The optimization problem can be stated as follows: to optimize all the points of the membership functions of the fuzzy system used for control from **Figure 8**, this is illustrated in **Figure 9** where for each membership function, the bioinspired methods will try to find the best values for each point. In this case, the fuzzy controller has two inputs with three triangle membership functions and one input each and one output with three triangular membership functions; for each triangle membership function, the bioinspired methods need to find four values and three values for each triangular membership function, with a total of 27 points (values) for these particular fuzzy system for control as optimization problem. In this case the fuzzy rule set from **Table 3** was not modified, and only the membership functions were optimized.

The objective function is to minimize the trajectory error created by the optimized fuzzy FOPID controller using Eq. (6); this means that each bioinspired method will try to find the best values for each point of each membership function, and with this the optimized fuzzy FOPID controller creates a trajectory with the lowest possible error.

## 7. Simulation results

The proposed bioinspired optimization algorithm with parameter adaptation is now tested on problem of dihybrid level control system subject to system component (leak) faults. This system taken for the testing is novel in terms of its dynamics; the system is a highly nonlinear and interacting process. Also the system has two system component (leak) faults; one is $f_{sys1}$ leak in tank 1, and the second is $f_{sys2}$ leak in tank 3. So we proposed the novel system like dihybrid level process and tested proposed fuzzy bioinspired optimization algorithms such as GOA and FPOA. The result section presents the comparisons of different variants of GOA and FPOA based on fuzzy logic system.

The control scheme of the overall design is presented in **Figure 7**. The bioinspired optimization algorithms were applied to the optimization of the fuzzy system (fractional order PID controller) (**Figures 8** and **9**) for control of the dihybrid level control system, using the same parameters, such as population, iterations, and number of experiments described in **Tables 4** and **5** for the GOA and FPOA.

These parameters were selected based on several experiments with all the methods applied to the optimization of some benchmark mathematical function, such as Rosenbrock, just to search for the best parameters, while also trying to use almost the same parameters for all the bioinspired methods.

The metric used to evaluate the performance of all methods is the mean square error described in Eq. (6), calculated from the desired reference trajectory and the

| Parameter | Original GOA | Proposed fuzzy GOA |
|---|---|---|
| Population | 100 | 100 |
| Iterations | 40 | 40 |
| Crossover ($K_1$) | Single point crossover | Dynamic |
| Mutation rates ($K_2$) | Uniform | Dynamic |
| Encoding | Binary | Binary |
| Selection | Uniform | Uniform |

**Table 4.**
*Parameters for the GOA method original/proposed.*

trajectory created by the optimized fuzzy controller. In addition, each method is applied 40 times to each problem and presents the average, best, worst, and standard deviation of those experiments. The fractional order PID controller parameters are chosen as $K_P$ = 5.9801, $K_I$ = 2.0781, $K_D$ = 2.09681, $\lambda$ = 0.5491, and $\mu$ = 0.2349.

For comparison purposes, there are two variations of GOA, which are described below. All of these variations use the parameters described in **Table 4**.

**GOA + T1FS** is the GOA method with parameter adaptation using the type-1 fuzzy system illustrated in **Figure 2**.

**GOA + IT2FS** is the GOA method with parameter adaptation using the interval type-2 fuzzy system illustrated in **Figure 3**.

**Table 6** contains the results of applying the variations of FPOA to the optimization of the membership functions from the fuzzy FOPID controller illustrated in **Figure 9**, using the plant without fault shown in **Figure 7**. In this case, results in bold are the best from all methods on each category.

From the results in **Table 6**, the proposed FPOA + IT2FS method obtains the best results on average, best, worst, and standard deviation, when compared with the FPOA + T1FS.

For comparison, there are two variants of the genetic optimization algorithm, GOA + T1FS, which is the GOA algorithm with type-1 fuzzy system for dynamical parameter adaptation, and GOA + IT2FS, which is the GOA algorithm with interval type-2 fuzzy system for dynamical parameter adaptation.

**Table 7** contains the results of applying the variations of the GOA to the optimization of the membership functions from the fuzzy controller illustrated in

| Parameter | Original FPOA | Proposed fuzzy FPOA |
|---|---|---|
| Population size | 100 | 100 |
| Iterations | 40 | 40 |
| Probability $P$ | 0.8 | Dynamic |
| Dimension | 3 | 3 |

**Table 5.**
*Parameters for the FPOA method original/proposed.*

| MSE | FPOA +T1FS | FPOA +IT2FS |
|---|---|---|
| Average | $4.013 \times 10^{-2}$ | $4.63 \times 10^{-3}$ |
| Best | $6.284 \times 10^{-2}$ | $2.291 \times 10^{-3}$ |
| Worst | 5.7816 | $4.701 \times 10^{-2}$ |
| Standard deviation | $4.9218 \times 10^{-2}$ | $8.1219 \times 10^{-3}$ |

**Table 6.**
*Comparison of results of the plant without system fault for the FFPOA.*

| MSE | GOA + T1FS | GOA + IT2FS |
|---|---|---|
| Average | 10.79 | **9.091** |
| Best | $1.7 \times 10^{-3}$ | $2.09 \times 10^{-3}$ |
| Worst | 68.91 | **64.12** |
| Standard deviation | **14.93** | 15.61 |

**Table 7.**
*Comparison of results of the plant without system fault for the FGOA.*

**Figure 9**, using the plant without system component (leak) fault. **Table 8** contains the results of applying the variations of the GOA algorithm to the optimization of the membership functions from the fuzzy controller illustrated in **Figure 9**, using the plant with noise shown in **Figure 6**. Results highlighted in bold are the best from all methods on each category.

Results in **Table 6** show that the FPOA, which uses an interval type-2 fuzzy system for parameter adaptation, can obtain on average better results than FPOA as well as the lowest MSE in both the cases without system component (leak) fault. This is the best of all controllers; its worst results are lower on MSE than on the FPOA methods and finally also obtain the lowest standard deviation.

**Table 9** contains a comparison of results with the best methods using the plant with system component (leak) fault. In this case, from the FPO algorithm, it is FPOA + T1FS, and from FPO Algorithm, it is FPOA + IT2FS.

The next result figures illustrate the best trajectories from each method, for visual comparison purpose; note that, in each figure, all trajectories from the optimized fuzzy system used for control are very similar to desired trajectory.

**Table 10** contains the results with the Rosenbrock function for proposed bioinspired optimization method with parameter adaptation using an interval type-2 and type-1 fuzzy system.

**Figure 10** contains the comparison of the best trajectory from IT2FS variations of GOA and FPOA for tank 1 and tank 3 of dihybrid level control system, in this case using original IT2FS GOA with a MSE $2.191 \times 10^{-3}$.

**Figure 11** contains the comparison of the trajectory from T1FS variations of GOA and FPOA for tank 1 and tank 3 of dihybrid level control system, in this case using original T1FS GOA with a MSE 3.8212.

The results shows that an interval type-2 fuzzy system used for parameter adaptation can help FPOA to obtain better quality results than GOA, even when GOA methods use the same methodology for dynamic parameter adaptation and also use a type-1 or interval type-2 fuzzy system for the same task.

The second simulations are carried out with the system component (leak) faults introduced into tank 1 and tank 3 of dihybrid level control system. The proposed

| MSE | GOA + T1FS | GOA + IT2FS |
|---|---|---|
| Average | **15.61** | 15.78 |
| Best | 2.89 | **2.36** |
| Worst | **78.15** | 77.91 |
| Standard deviation | 17.83 | 17.81 |

**Table 8.**
*Comparison of results of the plant with system fault for the FGOA.*

| MSE | FPOA + T1FS | FPOA + IT2FS |
|---|---|---|
| Average | 4.8253 | **3.3771** |
| Best | 3.8212 | **2.5614** |
| Worst | 5.8916 | **4.0941** |
| Standard deviation | $5.0628 \times 10^{-2}$ | $4.1494 \times 10^{-2}$ |

**Table 9.**
*Comparison of results of the plant with system fault for the FFPOA.*

| Rosenbrock function | | | | | | |
|---|---|---|---|---|---|---|
| Population size | Dimensions | Iterations | FPOA + IT2FS | FPOA + T1FS | GOA + IT2FS | GOA + T1FS |
| 20 | 10 | 500 | 10.3481 | 15.3791 | 13.5471 | 17.2019 |
| | 20 | 1000 | 24.5901 | 29.7513 | 26.9416 | 32.4569 |
| | 30 | 1500 | 42.5822 | 49.4692 | 46.87651 | 58.5821 |
| 40 | 10 | 500 | 5.6792 | 8.9389 | 6.9021 | 9.8093 |
| | 20 | 1000 | 11.4911 | 15.0921 | 12.9916 | 17.8137 |
| | 30 | 1500 | 19.0921 | 23.5821 | 21.9091 | 25.9810 |

**Table 10.**
*Comparison against all variations of FGOA and FFPOA.*
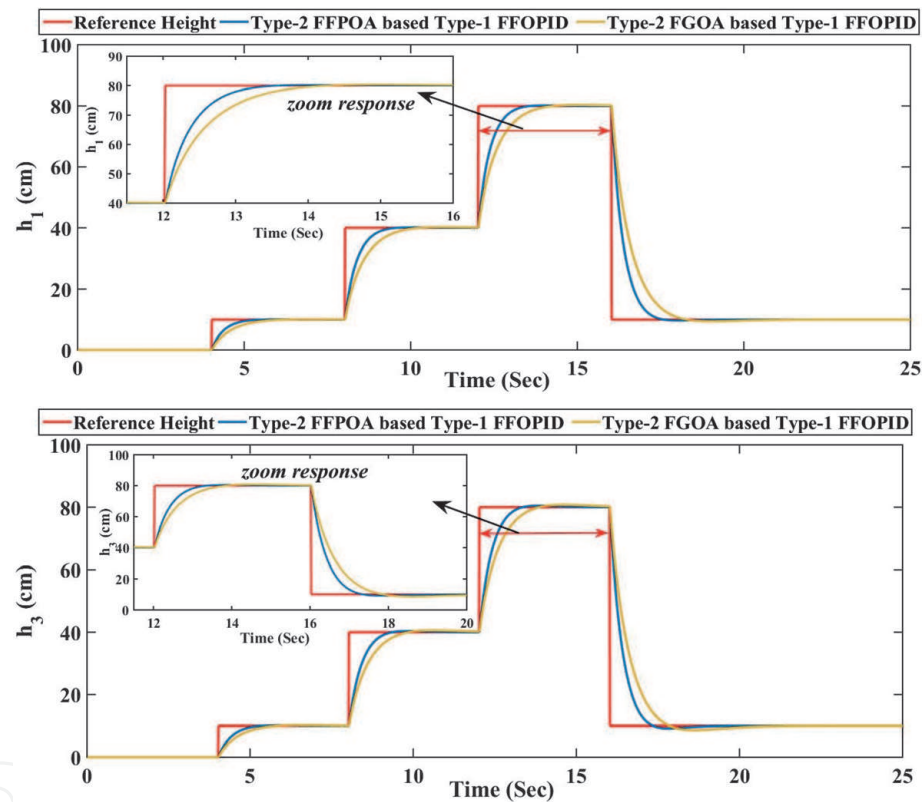


**Figure 10.**
*Best simulation of GO and FPO algorithm with IT2FS variations for the dihybrid level control system without system component (leak) fault.*

fuzzy-based parameter adaption techniques are applied, and results are produced with very good accuracy. There are two simultaneous leak faults $f_{sys}1$ and $f_{sys2}$ introduced into system at time t = 10 sec and t = 14 sec, respectively.

**Figure 12** shows the best results of GO and FPO algorithm from IT2FS variations, and result clearly shows that FPOA + IT2FS outperforms all the variants of GOA and FPOA + T1FS even though system component (leak) faults are present in the dihybrid level control system.

In the same manner, **Figure 13** shows the results of GO and FPO algorithm from T1FS variations, and result clearly shows that FPOA + IT2FS outperforms the GOA + IT2FS even though system component (leak) faults are present in the dihybrid level control system.
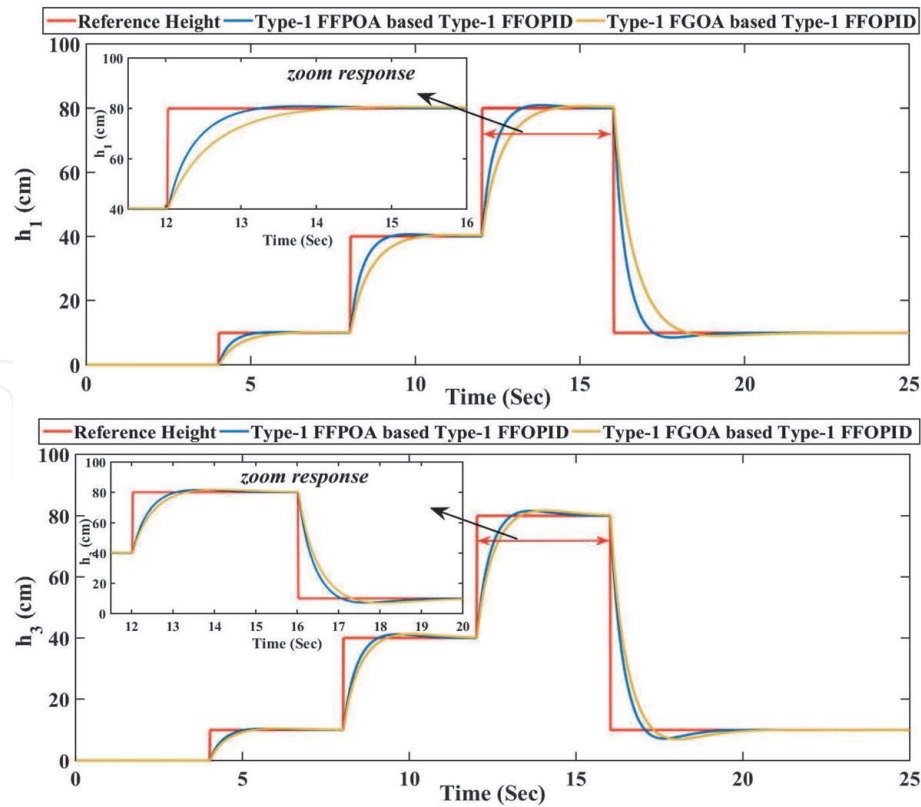
**Figure 11.**
*Best simulation of GO and FPO algorithm with T1FS variations for the dihybrid level control system without system component (leak) fault.*
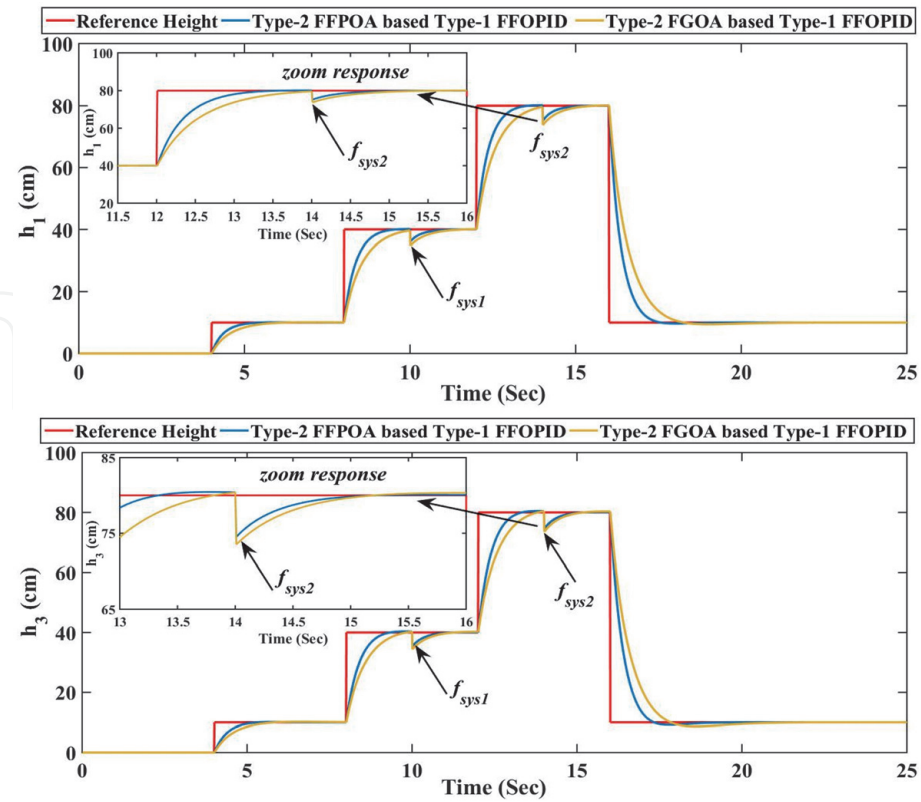


**Figure 12.**
*Best simulation of GO and FPO algorithm with IT2FS variations for the dihybrid level control system with system component (leak) fault.*
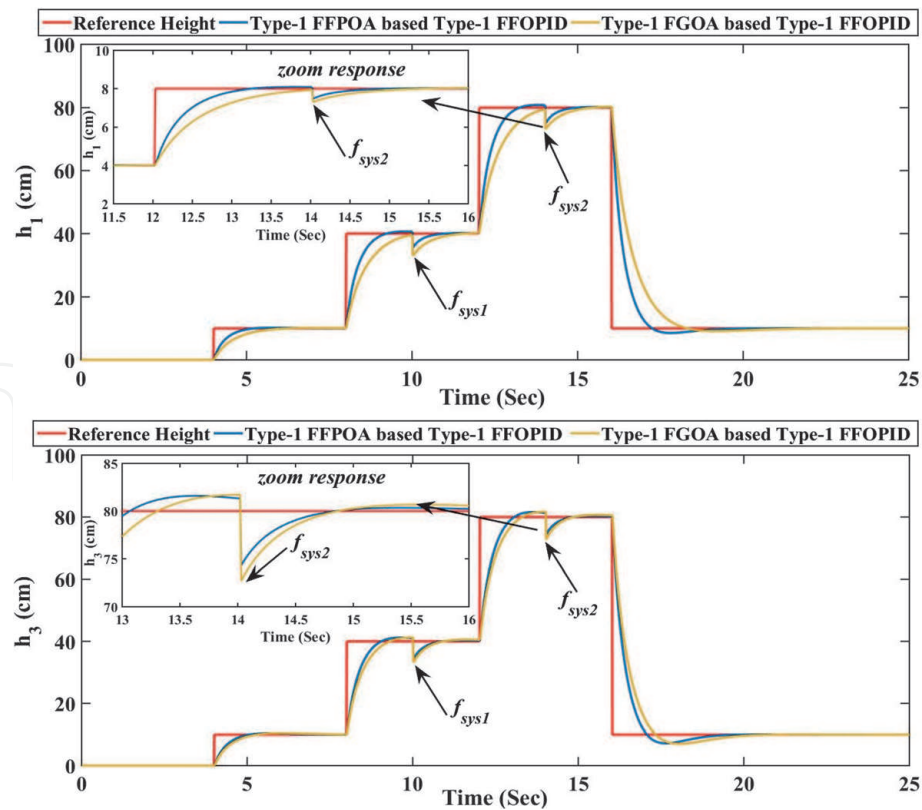
**Figure 13.**
*Best simulation of GO and FPO algorithm with T1FS variations for the dihybrid level control system with system component (leak) fault.*

From observing the simulation results, FPOA + IT2FS gives better results than GOA + IT2FS, GOA + T1FS, and FPOA + T1FS with a MSE of 2.5614.

Aside from the results with the dihybrid level control system, a comparison against a fuzzy GOA and FPOA is also presented. The following results (contained in **Table 10**) were obtained using the same parameters. In addition, results highlighted in bold are the best results. **Table 10** contains the results with the Rosenbrock function for FPOA + IT2FS, FPOA + T1FS, GOA + IT2FS, and GOA + T1FS. From the results in **Table 10**, it is clear that our IT2FS + GOA obtains on average better results than the other methods.

# 8. Conclusions

Flower pollination and genetic algorithms are an exceptional good bioinspired optimization algorithms; it is adequate to handle complex engineering problems and achieve impressive results. In this particular case, we optimize the membership functions from a fuzzy FPID controller. From the results, in the observation of two variations of FPOA, the FPOA + IT2FS version, which uses an interval type-2 fuzzy logic system for dynamic parameter adaptation, it can give exceptional results than FPOA + T1FS version.

The flower pollination optimization algorithm is used to optimize membership functions of a fuzzy logic controller applied to track the trajectory of dihybrid level control process subject to system component (leak) fault, with the motive of diminishing an error. Subsequently from examining and interpreting the obtained results, we can summarize that GOA is competent in optimizing the problems. In this case, two versions of GOA, GOA + IT2FS and GOA + T1FS, can achieve decent

results; however, the algorithm presents unsatisfactory results when the fault occurred into the system, but it will maintain the system stability, i.e., some simulations are good, and some are bad.

The motivation for the advancement of this research work was to authenticate the improvement with our proposed methodology for parameter adaptation through fuzzy logic system, applied to different bioinspired methods. The main contribution of this work is a comparative study based on two bioinspired algorithms for the design and implementation of fuzzy fractional order PID controllers. In addition, a comparative study proposed methods with parameter adaptation using type-1 and interval type-2 fuzzy logic systems as tools for modeling complex problems in control engineering.

For future work, we want to broaden the proposed technique for parameter adaptation to other bioinspired methods (i.e., differential evolutionary algorithm) as well as use other potential engineering applications, such as the optimization of neural networks, fuzzy systems applied to other problems, or even a hybridization of two or more bioinspired algorithms.

## Acknowledgements

## Funding

## Conflict of interest

The authors declare no conflict of interest.

## Notes/Thanks/Other declarations

Compliance with ethical standards.

## Nomenclature

| | |
|---|---|
| IT2FS | interval type-2 fuzzy system |
| T1FS | type-1 fuzzy system |
| DEA | differential evolutionary algorithm |
| FOPID | fractional order proportional integral derivative |
| FFOPID | fuzzy fractional order proportional integral derivative |
| GOA | genetic optimization algorithm |
| FPOA | flower pollination optimization algorithm |

| FGOA | fuzzy genetic optimization algorithm |
| FFPOA | fuzzy flower pollination optimization algorithm |
| FPGA | field programmable gate array |
| PSO | particle swarm optimization |
| CSTR | continuous stirred-tank reactor |

## Abbreviations

| $f_{sys1}$ | system component (leak) fault 1 |
| $f_{sys2}$ | system component (leak) fault 2 |
| $K_P$ | proportional gain |
| $K_I$ | integral gain |
| $K_D$ | derivative gain |
| $\lambda$ | fractional order integral parameter |
| $\mu$ | fractional order derivative parameter |
| $K_1$ | crossover |
| $K_2$ | mutation rate |
| $P$ | pollination switch probability |

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## References

[1] Fogel DB. An introduction to simulated evolutionary optimization. IEEE Transactions on Neural Networks. 1994;**5**(1):3-14. [Accessed: 14 November 2018]

[2] Man KF, Tang KS, Kwong S. Genetic Algorithms: Concepts and Designs. Heidelberg: Springer; 1999. [Accessed: 18 January 2018]

[3] Back T, Fogel DB, Michalewicz Z, editors. Handbook of Evolutionary Computation. Oxford: Oxford University Press; 1997. [Accessed: 01 November 2017]

[4] Castillo O, Valdez F, Melin P. Hierarchical genetic algorithms for topology optimization in fuzzy control systems. International Journal of General Systems. 2007;**36**(5):575-591. [Accessed: 02 July 2018]

[5] Wiangtong T, Sirapatcharangkul J. PID design optimization using flower pollination algorithm for a buck converter. In: 17th International Symposium on Communications and Information Technologies (ISCIT); Cairns, QLD; 2017. pp. 1-4. DOI: 10.1109/ISCIT.2017.8261202 [Accessed: 12 June 2018]

[6] Dwi L, Muhammad RD, Widodo IR. Optimization of PID controller design for DC motor based on flower pollination algorithm. In: 2015 International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM 2015); Aryaduta Hotel, Medan; 2015. DOI: 10.13140/RG.2.1.3028.6963. [Accessed: 12 June 2018]

[7] Jayachitra A, Vinodha R. Genetic algorithm based PID controller tuning approach for continuous stirred tank reactor. Advances in Artificial Intelligence. 2014;**2014**:791230. DOI:

10.1155/2014/791230. [Accessed: 12 June 2018]

[8] Kim D, Hirota K. Vector control for loss minimization of induction motor using GAPSO. Applied Soft Computing. 2008;**8**:1692-1702. [Accessed: 12 June 2018]

[9] Shopova EG, Vaklieva-Bancheva NG. BASIC: A genetic algorithm for engineering problems solution. Computers and Chemical Engineering. 2006;**30**(8):1293-1309. [Accessed: 28 June 2018]

[10] Zhang J, Zhuang J, Du H, Wang S. Self-organizing genetic algorithm based tuning of PID controllers. Information Sciences. 2009;**179**(7):1007-1018. [Accessed: 28 June 2018]

[11] Krohling RA, Rey JP. Design of optimal disturbance rejection PID controllers using genetic algorithms. IEEE Transactions on Evolutionary Computation. 2001;**5**(1):78-82. [Accessed: 28 June 2018]

[12] Kumar SMG, Jain R, Anantharaman N, Dharmalingam V, Begum KMMS. Genetic algorithm based PID controller tuning for a model bioreactor. Indian Chemical Engineering. 2008;**50**(3):214-226. [Accessed: 28 June 2018]

[13] Garg H. A hybrid PSO-GA algorithm for constrained optimization problems. Applied Mathematics and Computation. 2016;**274**:292-305. [Accessed: 28 June 2018]

[14] Garg H. Performance analysis of an industrial system using soft computing based hybridized technique. Journal of the Brazilian Society of Mechanical Sciences and Engineering. 2017;**39**:1441-1451. [Accessed: 28 July 2019]

[15] Singh S, Garg H. Distance measures between type-2 intuitionistic fuzzy sets and their application to multicriteria decision-making process. Applied Intelligence. 2017;**46**:788-799. [Accessed: 28 July 2019]

[16] Garg H. Reliability, availability and maintainability analysis of industrial systems using PSO and fuzzy methodology. Mapan. 2014;**29**:115-129. [Accessed: 28 July 2018]

[17] Garg H. An approach for solving constrained reliability-redundancy allocation problems using cuckoo search algorithm. Beni-Suef University Journal of Basic and Applied Sciences. 2015;**4**: 14-25. [Accessed: 28 July 2018]

[18] Man KF, Tang KS, Kwong S. Genetic algorithms: Concepts and applications. IEEE Transactions on Industrial Electronics. 1996;**43**(5):519-534. [Accessed: 02 August 2018]

[19] Fevrier V, Patricia M, Oscar C. Fuzzy Logic for Parameter Tuning in Evolutionary Computation and Bio-inspired Methods. LNAI 6438. Berlin/Heidelberg: Springer-Verlag; 2010. pp. 465-474. [Accessed: 22 August 2018]

[20] Bernd F, Michael H. Optimization of Genetic Algorithms by Genetic Algorithms. Artificial Neural Nets and Genetic Algorithms. Vienna: Springer; 1993. [Accessed: 28 August 2018]

[21] Homayouni S, Tang S. A fuzzy genetic algorithm for scheduling of handling/storage equipment in automated container terminals. International Journal of Engineering and Technology. 2015;**7**(6):497-501. [Accessed: 28 August 2018]

[22] Lau HCW, Nakandala D, Zhao L. Development of a hybrid fuzzy genetic algorithm model for solving transportation scheduling problem. Journal of Information Systems and Technology Management. 2015;**12**(3):505-524. [Accessed: 28 August 2018]

[23] Plerou A, Vlamou E, Papadopoulos V. Fuzzy genetic algorithms: Fuzzy logic controllers and genetics algorithms. Global Journal For Research Analysis. 2016;**5**:497-500. [Accessed: 28 August 2018]

[24] Khmeleva E, Hopgood AA, Tipi L. Fuzzy-logic controlled genetic algorithm for the rail-freight crew-scheduling problem. Künstliche Intelligenz. 2018;**32**(1):61-75. [Accessed: 02 September 2019]

[25] Maldonado Y, Castillo O, Melin P. Particle swarm optimization of interval type-2 fuzzy systems for FPGA applications. Applied Soft Computing. 2013;**13**(1):496-508. [Accessed: 02 September 2018]

[26] Yang X-S. Flower Pollination Algorithm for Global Optimization. Berlin Heidelberg: Springer; 2012. [Accessed: 02 September 2018]

[27] Huang S-J, Gu P-H, Su W-F, Liu X-Z, Tai T-Y. Application of flower pollination algorithm for placement of distribution transformers in a low-voltage grid. In: IEEE International Conference on Industrial Technology (ICIT); 2015. pp. 1280-1285 [Accessed: 02 September 2018]

[28] Oda ES, Abdelsalam AA, Abdel-Wahab MN, El-Saadawi MM. Distributed generations planning using flower pollination algorithm for enhancing distribution system voltage stability. Ain Shams Engineering Journal. 2017;**8**(4):593-603. [Accessed: 02 September 2018]

[29] Draa A. On the performances of the flower pollination algorithm qualitative and quantitative analyses. Applied Soft Computing. 2015;**34**:349-371. [Accessed: 02 September 2018]

[30] Abdelaziz EA, Abd Elazim S. Optimal sizing and locations of capacitors in radial distribution systems via flower pollination optimization algorithm and power loss index. Engineering Science and Technology. 2016;**19**(1):610-618. [Accessed: 02 September 2018]

[31] Dubey HM, Pandit M, Panigrahi BK. A hybrid flower pollination algorithm with time-varying fuzzy selection mechanism for wind integrated multi-objective dynamic economic dispatch. Renewable Energy. 2015;**83**:188-202. [Accessed: 02 September 2018]

[32] Dubey HM, Pandit M, Panigrahi BK. A biologically inspired modified flower pollination algorithm for solving economic dispatch problems in modern power systems. Cognitive Computation. 2015;**7**(5):594-608. [Accessed: 02 September 2018]

[33] Patel HR, Shah VA. Stable fuzzy controllers via LMI approach for nonlinear systems described by type-2 T-S fuzzy model. In: 15th European Workshop on Advanced Control and Diagnosis; Bologna, Italy; November 21–22, 2019

[34] Patel HR, Shah VA. Actuator and system component fault tolerant control using interval type-2 Takagi-Sugeno fuzzy controller for hybrid nonlinear process. International Journal of Hybrid Intelligent Systems. 2019;**15**(3):143-153

[35] Lakshmanaprabu SK, Wahid Nasir A, Sabura Banu U. Design of Centralized Fractional order PI controller for two interacting conical frustum tank level process. Journal of Applied Fluid Mechanics. 2017;**10**:23-32

[36] Patel HR, Shah VA. Stable fault tolerant controller design for Takagi-Sugeno fuzzy model based control systems via linear matrix inequalities: Three conical tank case study. Energies. 2019;**12**(11):2221