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RESEARCH ARTICLE

Tuning PID Controllers Based on Hybrid Arithmetic Optimization Algorithm and Artificial Gorilla Troop Optimization for Micro-Robotics Systems

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ABSTRACT Micro particles have the potentials to be used for many medical purposes in-side the human body such as drug delivery and other operations. In the present paper, a novel hybrid algorithm based on Arithmetic optimization algorithm (AOA) and Artificial Gorilla troop's optimization (GTO), (HAOAGTO) is compared with different four algorithms Arithmetic optimization algorithm (AOA), Artificial Gorilla troop's optimization (GTO), Seagull optimization algorithm (SOA), Parasitism-predation Algorithm (PPA). These approaches were used to calculate the PID controller optimal indicators with the application of different functions, including Integral Absolute Error (IAE), Integral of Time Multiplied by Square Error (ITSE), Integral Square Time multiplied square Error (ISTES), Integral Square Error (ISE), Integral of Square Time multiplied by square Error (ISTSE), and Integral of Time multiplied by Absolute Error (ITAE). Every method of controlling was presented in a MATLAB Simulink numerical model. It is observed that the PPA technique achieves the highest values of best fitness value for simulation results among other control approaches, while the HAOAGTO approach reduces the best fitness function compared to other optimization techniques used. We verified that the obtained results by application of the proposed hybrid algorithm-based AOA and GTO (HAOAGTO) is better than those obtained by Arithmetic optimization algorithm (AOA), Artificial Gorilla troop's optimization (GTO), Seagull optimization algorithm (SOA), Parasitism-predation Algorithm (PPA). it is implemented to obtain the optimal parameters of the PID for reduction the ISTES.

INDEX TERMS PID controller, arithmetic optimization algorithm, artificial gorilla troop's optimization, seagull optimization algorithm, parasitism-predation algorithm, hybrid between AOA and GTO (HAOAGTO), minimally invasive surgery.

I. INTRODUCTION

The trauma of surgical patients can be minimized by using minimal invasive surgery rather than orthodox open-heart surgery because it allows clinicians to reach all sites of the human body with much easiness and comfort.

Additionally, minimal invasive surgery also reduces the time that patients spend in hospitals, so it is also an effective option in terms of cost [1]. One of such minimal invasive surgeries performed nowadays is laparoscopy. This process uses small tools to observe images taken by the instrumental camera. Fig. 1 indicates different variations of these two surgical methods: Orthodox open-heart surgery and minimal invasive heart surgery (MIS).

When robot-used, the advantages of MIS can be revealed because it is minimally invasive. Furthermore, this method makes it easier to treat patients who could not receive operations before. To implement this robotic system, the needles are directed accurately to the required site in the human body, as diagnosis specifically requires. There is an association

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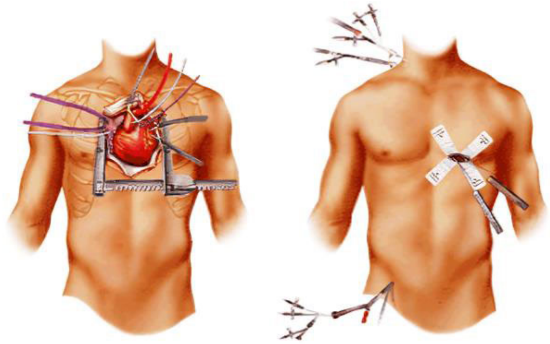

FIGURE 1. Left side: Orthodox open Heart Surgery Right side: Laparoscopy as a minimal invasive heart surgery.

between them and the human body organs through the veins, arteries and the gastrointestinal tract. The depth of penetration can be amalgamated in the human body when the robot is smaller. Therefore, medicine will go in smaller pathways with efficiency for such goal to be achieved.

Paramagnetic micro-particles were constructed efficiently for the spherical site by Keuning et al. [2]. With the system arriving to the control opposition, the settling error was 8.4μm. The diameter average of such micro-particles was 100μm, a hollow coil was employed in such experiment and water was the media used. The same experiment was simulated by Farag et al. [3], but by using a solid coil and 8μm settling error. Ghith et al. [4], [5], [6], [7], [8], [9], [10] simulated the same experiment, but with a 4μm settling error. It is ob-served that the error rate can be reduced up to 50% by using the SSA approach, as com-pared to the previous works.

The controller must be sufficiently and aptly designed for the achievement of the control goals. Due to being tunable, easily implementable and simply structured, PID is still employed despite the different control methods that have been developed [11], [12], [13], [14], [15], [16], [17]. However, it is still difficult to tune the PID control properly until it becomes efficient optimally. Many different designs have been proposed. Among these designs is the PID controller and its best-known methods: Ziegler and Nichols. However, reaching the most optimal performance of such method is not easy [18], [19]. Furthermore, it is required to use more complex mathematical calculations to perform the common method tuning. Nevertheless, different tuning methods and optimization methods based on artificial intelligence can be proposed to avoid this problem.

Using many optimization techniques in a variety of engineering fields can support meta-heuristic algorithms. These techniques do not require any gradient information and they are characterized by flexibility and ease of implementation, in comparison. The meta-heuristic techniques include single-based and population-based algorithms. As can be deduced from its name, single-base or trajectory optimization algorithms generate a single optimal solution only. However, in population-based algorithm, frequently redundant multiple solution can be generated. Five major types of optimization algorithms can be traced: Human, chemical, swarm intelligence, physics, and evolutionary-based optimization algorithm [20], [21], [22], [23], [24], [25], [26], [27].

The contribution of the present study can be highlighted in the following points:

- Applying of different modern optimization algorithms including Arithmetic optimization algorithm (AOA), Artificial Gorilla troop's optimization (GTO), Seagull optimization algorithm (SOA), Parasitism-predation Algorithm (PPA). and a novel hybrid algorithm based on AOA and GTO known as (HAOAGTO) for optimal controlling the position of the micro-robotics system.
- Assigning the optimal parameters of the proportional-integral-derivative (PID) controller for different six fitness functions including Integral Absolute Error (IAE), Integral of Time Multiplied by Square Error (ITSE), Integral Square Time multiplied by Error Squared (ISTES), Integral Square Error (ISE), Integral of Square Time multiplied by square Error (ISTSE), and Integral of Time multiplied by Absolute Error (ITAE).
- Assessing the performance of system under the optimal settings of the PID controller.
- Verifying the effectiveness of the proposed algorithms through a comprehensive comparison in terms of the considered fitness functions.

A micro-robotic system model, PID controller, fitness function types, Optimization methods are also offered in the current study in part 2. The simulation and discussion are all presented in part 3, while the study's future prospects and conclusions are presented in part 4. As an extension of this work, an experimental setup is used for data collection and some of its results are offered in [3].

II. RESEARCH METHOD

A. MATHEMATICAL MODEL

For designing particles, the paramagnetic material is used, and it is formed by iron-oxide in lactic acid. The diameter of these particles is 100μm, and their velocity depends on two factors. The magnetic forces and viscous drag are induced by micro-particle which depends upon the magnetic field of coils. Moreover, maximum velocity is achieved if acceleration reaches zero and magnetic and viscous drag forces are equal. The following equation is used to define the magnetic force.

$$F = \nabla \alpha_p V_p B^2 \tag{1}$$

In this equation, the particles volume is V_p, while magnetic flux density is B. This magnetic flux depends on both time and distance, and V_p and α_p are the constants. The equation below shows the variables used for substituting V_p for force production.

$$F = \frac{4}{3}\pi \alpha_p r_p^3 \nabla B^2 \tag{2}$$

In the above equation, the micro-particles radius is r_p, while drag force is treated by using the following equation.

$$F_d = \ -6\pi\eta r_p v \tag{3}$$

Depending on Newton's second law of motion, viscosity here is represented by η, while velocity of the micro-particle is represented by v.

$$\sum F = m_p a_p$$

$$\frac{4}{3}\pi\alpha_p r_p^3 \nabla^2 - 6\pi\eta r_p v = m_p a_p$$

$$v = \frac{\frac{4}{3}\pi\alpha_p r_p^3 \nabla B^2 - m_p a_p}{6\pi\eta r_p} \tag{4}$$

In equation (4), achieving maximum velocity by micro-particles is possible when the acceleration of the particles is equal to zero. The following equation reveals how maximum velocity is calculated:

$$v_m = \frac{2}{9}\frac{\alpha_p r_p^2}{\eta}\nabla B^2 \tag{5}$$

Spherical shape particles are regarded perfect, while F_m is used to denote the stimulated utilizing force. There is an association between the particles' speed and the drag force denoted by F_d in terms of liquid and association between particles, speed and drag in case of stable liquid. The following equation exhibits the continuous time model.

$$\ddot{m}x + \ C_d * \dot{}x = \ F_m \tag{6}$$

There is a continuous design of the drag via drag Stokes of Reynolds as low, noted by C_d, while $\ddot{x}$ represents the acceleration. $\dot{x}$ represents the velocity, while the particle's mass is represented by m. The micro-particle's transfer role is exemplified by the equation below:

$$\frac{X(s)}{F_m(s)} = \frac{1}{ms^2 + C_d * s} \tag{7}$$

B. PID CONTROLLER

Ideal-PID is one of the main controller types used in the industrial field. It can be used for the improvement of steady-state and transient errors. Nevertheless, when disturbances occur, the high performance of the ideal-PID is lost. Feedback control loops customarily use the same algorithms (or its variations) [11]. The gains are considered proportional gain K_p, integral gain K_i, and derivative gain K_d. The error commonly reached by the measured variable subtraction (the output that the user inserts from a set point) can be acted upon by each gain. Equation (8) presents the PID controller transfer function. In Fig. 2, the PID controller standard form is illustrated, while the PID controller basic structure is presented in Fig. 3.

$$C_{PID}(s) = \frac{Y(s)}{E(s)} = K_p + \frac{K_i}{s} + \ K_d s \tag{8}$$

Tuning PID controller has five key components: the fitness function, optimization techniques, PID, process, and the sensor.

C. FITNESS FUNCTIONS TYPES

To design any controller type, different optimum control parameters are required. It is imperative to calculate distinct parameters for the reduction of the objective function. Multiple functional objectives are required by the time-dependency error. The equations below [28], [29], [30] represent the different fitness function types:

Integral Absolute Error (IAE):

$$IAE = \int_0^\infty |e(t)|\, dt \tag{9}$$

Integral Square Error (ISE):

$$ISE = \int_0^\infty e^2(t)dt \tag{10}$$

Integral of Time multiplied Absolute Error (ITAE):

$$ITAE = \int_0^\infty t\, |e(t)|\, dt \tag{11}$$

Integral of Time multiplied square Error (ITSE):

$$ITSE = \int_0^\infty te^2(t)dt \tag{12}$$

Integral Square Time multiplied square Error (ISTES):

$$ISTES = \int_0^\infty [t^2 e(t)]^2 dt \tag{13}$$

Integral of Square Time multiplied by square Error (ISTSE):

$$ISTSE = \int_0^\infty t^2 e^2(t)dt \tag{14}$$

The optimization problem can be formulated by the rules below, while minimizing the objective function and subjecting it to the following:

$$K_{pmin} < K_p < K_{pmax}$$
$$K_{imin} < K_i < K_{imax}$$
$$K_{dmin} < K_d < K_{dmax}$$

D. OPTIMIZATION METHODS

Techniques of optimization have supported different meta-heuristic algorithms which have become popular within the engineering applications and fields. This is due to the need for flexibility for such trivial ideas which are easy in iimplementation and where gradient information is not required. Such techniques are required to pass the local optima and to be updated for tackling the wide problems that cover different disciplines and fields. These meta-heuristic and nature-inspired algorithms are capable of solving multiple problems of optimization which are used to represent the biological and physical phenomena.

Meta-heuristic techniques are mainly divided into two main algorithm categories: single-based and population-based algorithm. Single-based algorithm is capable of generating a single optimal solution on every run. It is also called

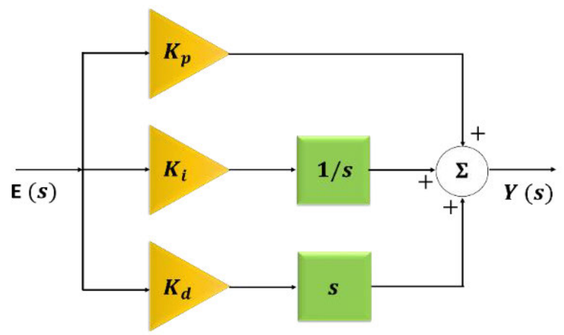

FIGURE 2. Block diagram of the chief ideal PID Controller.

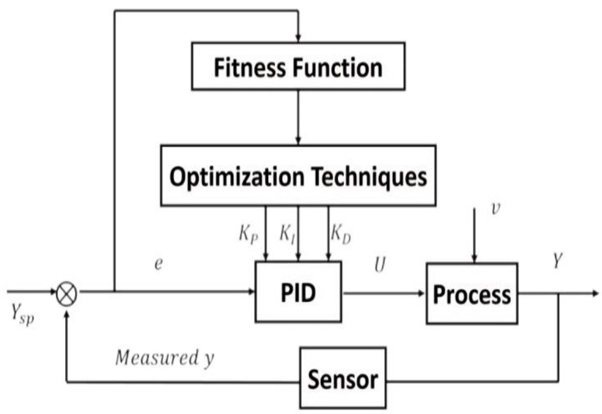

FIGURE 3. Block diagram of tuning PID Controller.

trajectory algorithm, and it is enhanced when a neighboring methodology is used. The population-based algorithm generates multiple solutions on every run and is further classified into five types: Swarm intelligence, human, physical-, chemical, and evolutionary-based algorithms.

In this evolutionary-based algorithm, the techniques use three main operations: Mutation, recombination, and selection. These techniques are inspired by nature's evolutionary phenomenon. For a swarm intelligent algorithm, the information is gathered on the basis of a collective behavior adopted by nature. Physical-based algorithm gathers information according to different theories obtained from the multiverse concept. Chemical-based algorithm uses chemical compounds and chemical rules for optimization, while humans and their actions are associated with human-based algorithm. Population-based algorithms have a standard feature in common as per their nature, and the search processes in such algorithms are categorized into two phases: Exploitation and exploration [31], [32], [33], [34], [35], [36], [37], [38]. This meta-heuristic classification is presented in Fig.4.

Nature inspired optimization algorithms (NIOA) common flow are divided into four main steps [39]. The first step is set the initial parameter values and these values describe the possible solutions to a specific optimization technique. To generate the initial parameters random approaches are proposed based on ensuring that it reaches the solution space as much as it can, and at the end of the first step we should determine the upper, lower bounds of the variables, number of population size, and the maximum number of iterations. The second step relies on calculating the fitness function based on the initial population. Then, check if the current iteration reached the maximum number of iterations.

The third step applies the optimization algorithms on the reached solutions, and then it continues checking the termination condition (Stopping Criteria). The last step returns the optimal and best solution of the variable. Fig. 5 shows the common procedure of the NIOA in terms of steps.

1) ARITHMETIC OPTIMIZATION ALGORITHM (AOA)

One of the novel meta-heuristic optimization techniques is the arithmetic optimization algorithm (AOA) [40]. It is inspired from main behavior of the arithmetic operators in the processors of the PC or mathematics. Four main operations are used in calculations such as division (D), multiplication (M), addition (A), and subtraction (S). The exploration and the exploitation phases rely on the math accelerated optimizer (MOA) function. The MOA function is defined using the following equation:

$$MOA(iter) = Min + iter x \ (\frac{Max - Min}{Max_{iter}}) \tag{15}$$

The current and the maximum iterations are defined using *iter* and Max_{iter} respectively, while *Min* and *Max* are known as the minimum and maximum values of the accelerated functions respectively [41].

Exploration phase: The position updated using the math operator in the original AOA in the direction of the optimum area is shown in Fig. 6. The exploration phase is divided into two main strategies which are the multiplication (M) and the division (D). The aim of the former strategies is to find the optimal solution. The positions are updated in the exploration phases using the following equation:

$$x_{i,j}\,(iter+1) = \begin{cases} best\left(x_j\right) \div \ (MOP+\epsilon)\, x \left(\left(ub_j - lb_j\right) x\ \mu +\ lb_j\right), \\ \qquad r2 > 0.5 \ (a) \\ best\left(x_j\right) x\, (MOP+\epsilon)\, x \left(\left(ub_j - lb_j\right) x\ \mu +\ lb_j\right), \\ \qquad otherwise \ (b) \end{cases} \tag{16}$$

The *j*th position of the *i*th solution at the current position is defined using $x_{i,j}\ (iter+1)$, while the best solution reached so far is represented by $best\ (x_j)$ at the *j*th position. *u* and *MOP* are defined as the control parameter and the probability math optimizer respectively. *MOP* is defined using the following equation:

$$MOP(iter) = 1 - \left(\frac{iter^{1/\propto}}{Max\_iter^{1/\propto}}\right) \tag{17}$$

$\propto$ is known as the sensitive parameter.

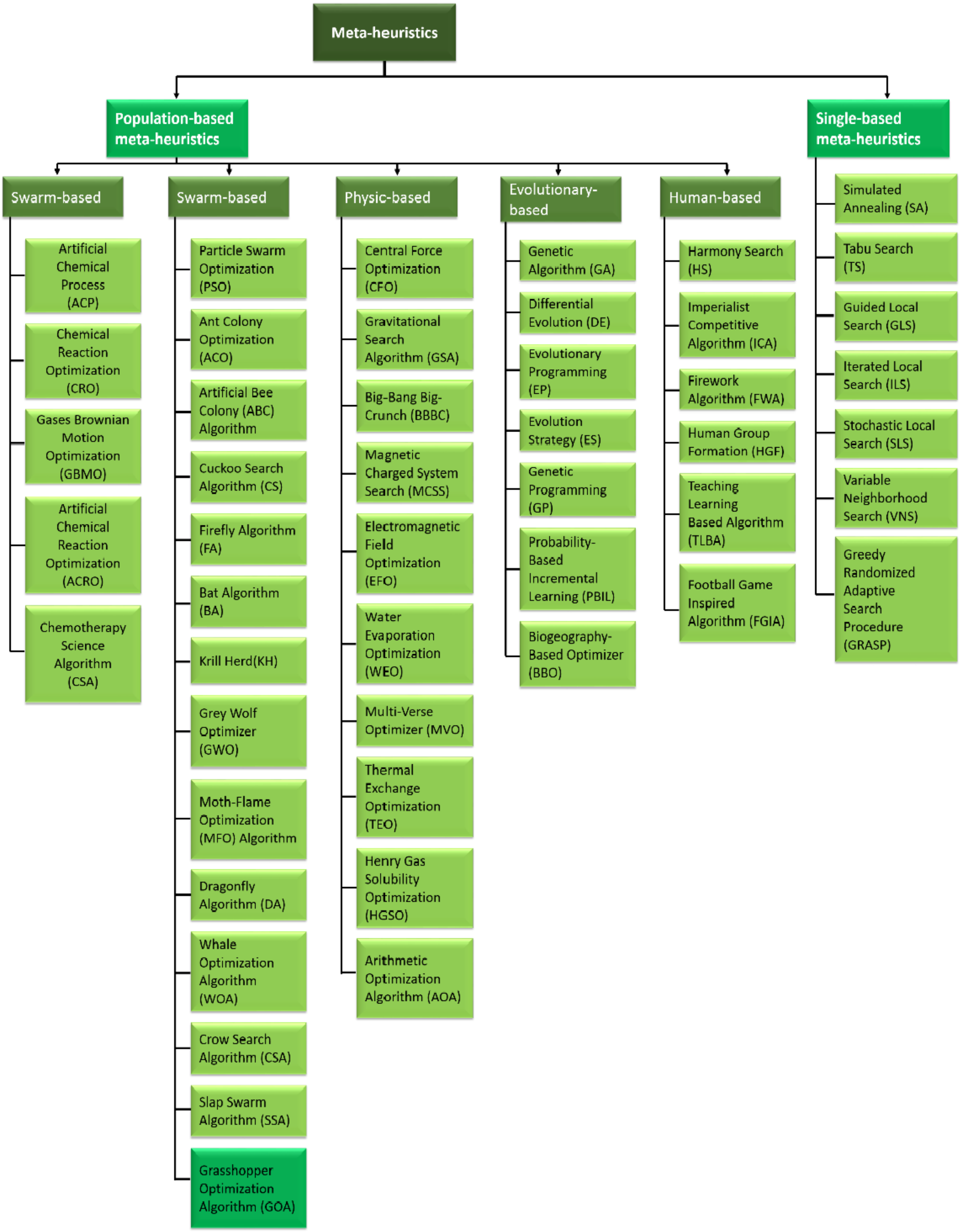

FIGURE 4. Meta-heuristic optimization categorization methods [34].

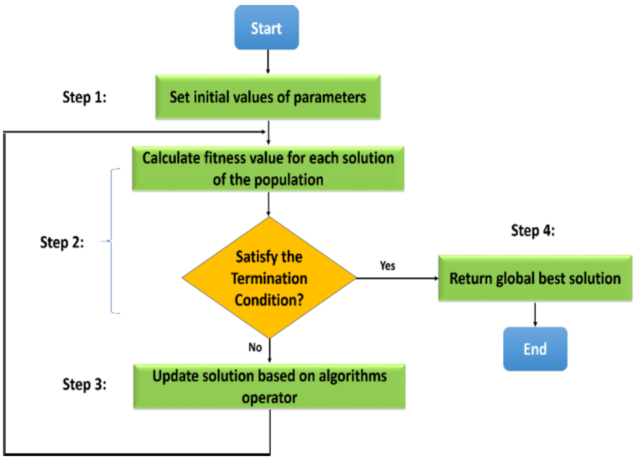

FIGURE 5. Logical flowchart of NOIA.

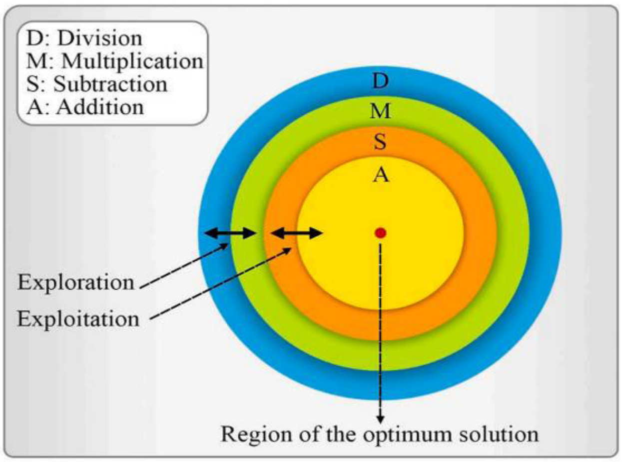

FIGURE 6. The Updated position of the operators relying on the AOA algorithm in the direction of the optimum area.

Exploitation phase: This phase in the AOA relies on two main operators which are the subtraction (S) and the addition (A). The aim of this phase is to obtain high-dense and optimal solutions:

$$x_{i,j}\,(iter+1) = \begin{cases} best\,(x_j) - \ (MOP+\epsilon)\,x\ \left(\left(ub_j - lb_j\right)x\ \mu +\ lb_j\right), & r3 > 0.5 \\ best\,(x_j) + (MOP+\epsilon)\,x\ \left(\left(ub_j - lb_j\right)x\ \mu +\ lb_j\right), & otherwise \end{cases} \tag{18}$$

Finally, the methodology of the AOA is represented in a flowchart form as shown in Fig.7.

2) GORILLA TrOOPS OPTIMIZATION (GTO)

One of the main meta-heuristic optimization techniques is the artificial gorilla troops optimization (GTO) [42]. The algorithm is inspired from the natural intelligence of the gorillas. Five main operators represent the behaviors of the natural

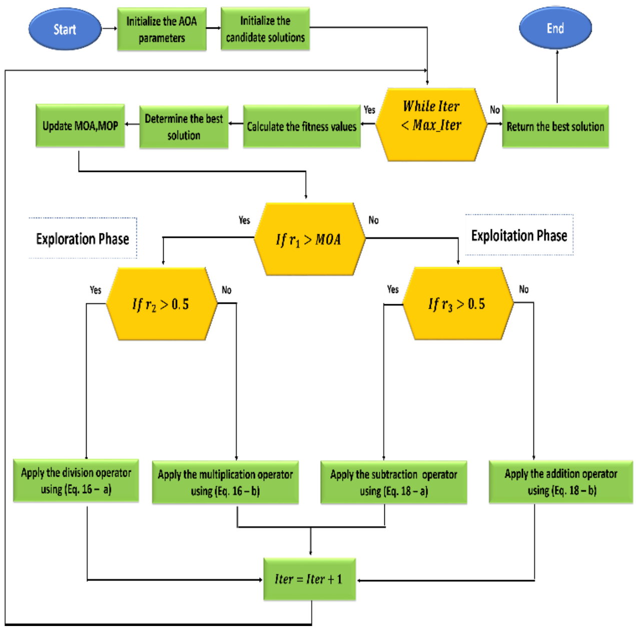

FIGURE 7. AOA Flowchart Methodology.

gorilla. Two of the operators describe the exploitation phase, while the three operators represent the exploration phase. The three operators that describe the phase of exploration or sometimes called strategies are known by migration to unknown places, migration to known places, and the movement to another gorilla. On the other hand, the exploitation phase as mentioned before uses two operators. The two operator are known by follow the silverback and the competition for adult female. The main details of the five operators for the exploration and the exploitation phases are defined in Fig. 8. A competition begins between the females of adult so that they can follow the silverback [43].

On one hand, the former three strategies of the exploration phase are defined using the following equations:

$$GX(t+1) = \begin{cases} (UB - LB) \times r_1 + LB, \\ (r_2 - C) \times X_r(t) + L \times H \\ X(i) - L \times (L \times (X(t) - GX_r(t))\ 0 \\ \qquad\qquad +r_3 \times (X(t) - GX_r(t))) \end{cases} \tag{19}$$

$$C = F \times \left(1 - \frac{it}{MaxIt}\right) \tag{20}$$

$$F = \cos\,(2 \times r_4) + 1 \tag{21}$$

$$L = C \times l \tag{22}$$

$$H = Z \times X(t) \tag{23}$$

$$Z = [-C, C] \tag{24}$$

where *UB* and the *LB* are defined as the upper and lower limits. The chosen position is defined in iteration (it) using $GX(it+1)$, while current position is donated by $X(it)$. The maximum number of iterations are known by Max_it. The probability of the migration is defined with a parameter p and

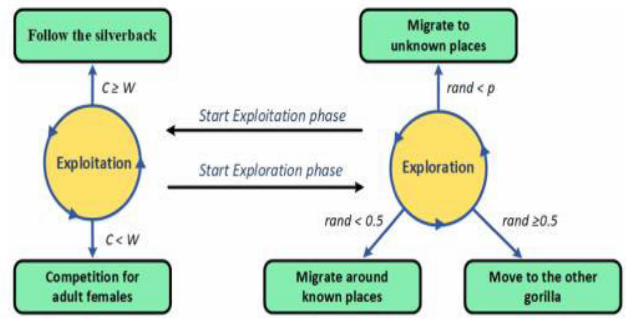

FIGURE 8. The Five phases of the Gorilla Troops Optimizer.

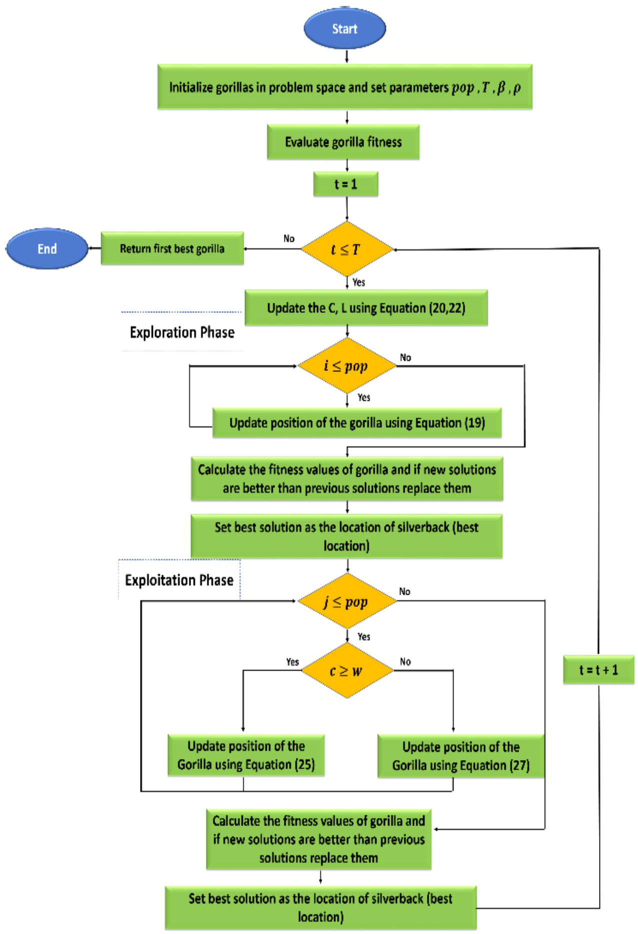

FIGURE 9. GTO Flowchart Methodology.

the range of this probability is defined in range from [0, 1]. Finally, the exploration phase ends by allowing the solution $GX(it)$ to replace the $X(it)$ and this solution is known to be the silverback and it this occurs when $X(it)$ is higher than the $GX(it)$.

The competition and the follow strategies are defined using the equations from (21) to (27):

$$X(t+1) = L \times M \times (\mathrm{X(t)} - \mathrm{X_{silverback}}) + \mathrm{X(t)} \tag{25}$$

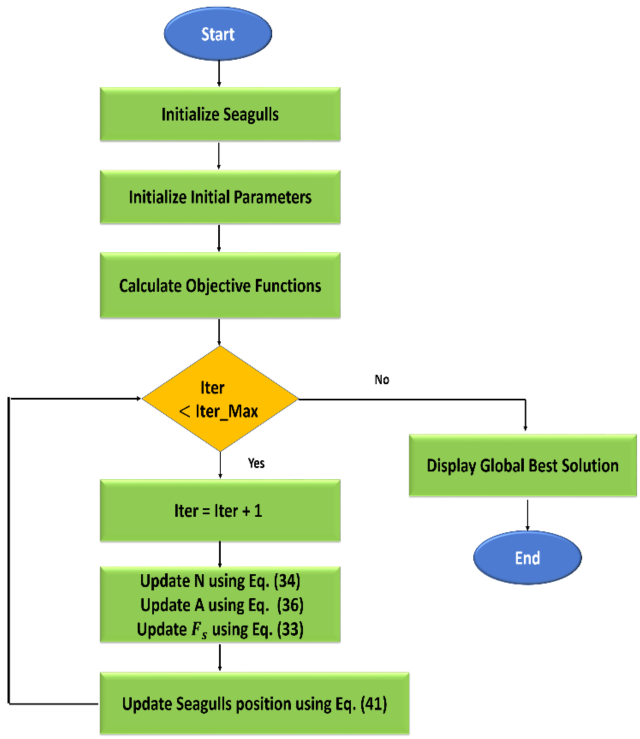

FIGURE 10. SOA Flowchart Methodology.

$$\mathrm{M} = \left(\left| \frac{1}{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{GX_i(t)} \right|^{\mathrm{g}} \right)^{\frac{1}{\mathrm{g}}} \tag{26}$$

$$\mathrm{g} = 2^{\mathrm{L}} \tag{27}$$

$$\mathrm{GX\ (i)} = \mathrm{X_{silverback}} - (\mathrm{X_{silverback}} \times Q - X\ (\mathrm{t}) \times Q)\ \mathrm{xA} \tag{28}$$

$$\mathrm{Q} = 2 \times \mathrm{r_5} - 1 \tag{29}$$

$$\mathrm{A} = \beta \times \mathrm{E} \tag{30}$$

$$\mathrm{E} = \begin{cases} \mathrm{N_1}, & \mathrm{rand} \geq 0.5, \\ \mathrm{N_2}, & \mathrm{rand} < 0.5 \end{cases} \tag{31}$$

The main flowchart of the GTO algorithm is defined in step and shown clearly in fig.9.

3) SEAGULL OPTIMIZATION ALGORITHM (SOA)

Laridae, the scientific name for seagulls, are clever birds that often inhabit the shorelines of seas and oceans around the world [44], [45]. The length and mass of seagulls can be used to distinguish between different species. Seagulls typically fall under the category of omnivores and are likely to eat fish, By using a second parameter "N" to determine the position of the new search agent ($\overrightarrow{F_s}$) with the given information, collision avoidance between searching agents in SOA can be accomplished.

$$\overrightarrow{F_s} = N_x \overrightarrow{D_s}(t) \tag{32}$$

$\overrightarrow{D_s}$ represents the seagull's current location, while "t" denotes the current iteration. Modelling the

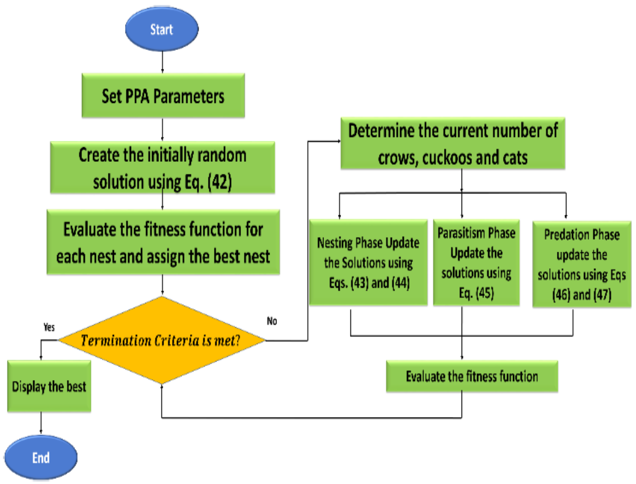

FIGURE 11. PPA Flowchart Methodology.

collision avoidance variable "N" as

$$N = E_c - (t * \left(\frac{E_c}{Max.Iter}\right)) \tag{33}$$

In order to control the change in a variable that can be reduced linearly from E_c to 0, the collision avoidance parameter's value of "2" was selected for this study. After completing the avoidance phenomenon in the collision mechanism, the search agents make an effort to travel closer to the location of the ideal person by

$$\overrightarrow{M_s} = A_x \left(\overrightarrow{P_{bs}}(t) - \overrightarrow{D_s}(t)\right) \tag{34}$$

To obtain the tendency of equilibrium between the phases of exploitation and exploration, the parameter "A" is randomized and can be calculated as

$$A = 2 * N^2 * rand\ () \tag{35}$$

Later, the following changes will be made to each search agent's position:

$$\overrightarrow{R_s} = \left|\overrightarrow{F_s} + \overrightarrow{M_s}\right| \tag{36}$$

Seagulls frequently alter their speed and attacking angle while migrating based on experience. The migration behaviour of seagulls in three dimensions can be represented as

$$S' = r * \cos(j) \tag{37}$$

$$T' = r * \sin(j) \tag{38}$$

$$U' = r * j \tag{39}$$

The seagulls' spiral movement's radius is denoted by "r," and the random number chosen from among (0–2). The positions of the remaining searching agents will be updated as soon as the best solution has been saved.

$$\overrightarrow{D_s}(k) = (\overrightarrow{M_s} * S' * T' * U') + \overrightarrow{P_{bs}}(k) \tag{40}$$

The flowchart in Fig. 10 depicts the process involved in SOA optimization in pictures. insects, earthworms, amphibians, and reptiles. Seagulls have unique glands at the base of their necks, and their bodies are coated with white feathers. The authors Dhiman and Kumar proposed the SOA based on seagull movement patterns and attacking prey (2019). This algorithm's coding was done in accordance with the tactics used by a flock of seagulls as they moved from one location to another during their migratory phase and as they attacked their prey.

TABLE 1. The proposed system parameters.

Name	Values	Units
Radius (r)	50	μm
Density of Water (ρ)	998.2	kgm^{-3}
Dynamic Viscosity (ζ)	1	mPa s
Mass (m)	7.33*10^(-10)	Kg
Drag Coefficient (cd)	0.94*10^(-6)	N S m^{-1}

TABLE 2. Optimization techniques input parameters.

Optimization Techniques	Parameters	Values
All	Dimension min values for Kp, Ki, Kd max values for Kp, Ki, Kd Iter. max Number of population	3 [0 0 0] [100 1 1] 25 30
AOA	MOP_Max MOP_Min Alpha Mu	1 0.2 5 0.499
GTO	Beta (β) W p	3 0.8 0.03
PPA	C	1
SOA	Control Parameter (A) fc	[2,0] 2
HGTOAOA	Beta (β) = 3, W = 0.8, p = 0.03, MOP_MAX = 1, MOP_MIN = 0.2, Alpha = 5, Mu = 0.499	

4) PARASITISM-PREDATION ALGORITHM (PPA)

One of the famous population optimization algorithms is the parasitism predication algorithm. This algorithm follows the nature of the crow-cuckoo cat optimization in its steps. The swarm is represented in the form of the crow, while the cuckoos are parasitizing their eggs in the nest with the aim of saving the children crow from any types of predators. The predator which is known to be the cat starts to attack the nest of the crow and the cuckoo aims to face this predator and protect its nest [46], [47] Therefore, this optimization algorithm works based on three main phases which are

- Nesting stage for the diversification of the crow nest places.
- Parasitism stage for exchange some crow's eggs by cuckoo's eggs.
- Predation phase based on resisting and the defending themselves against these cats.

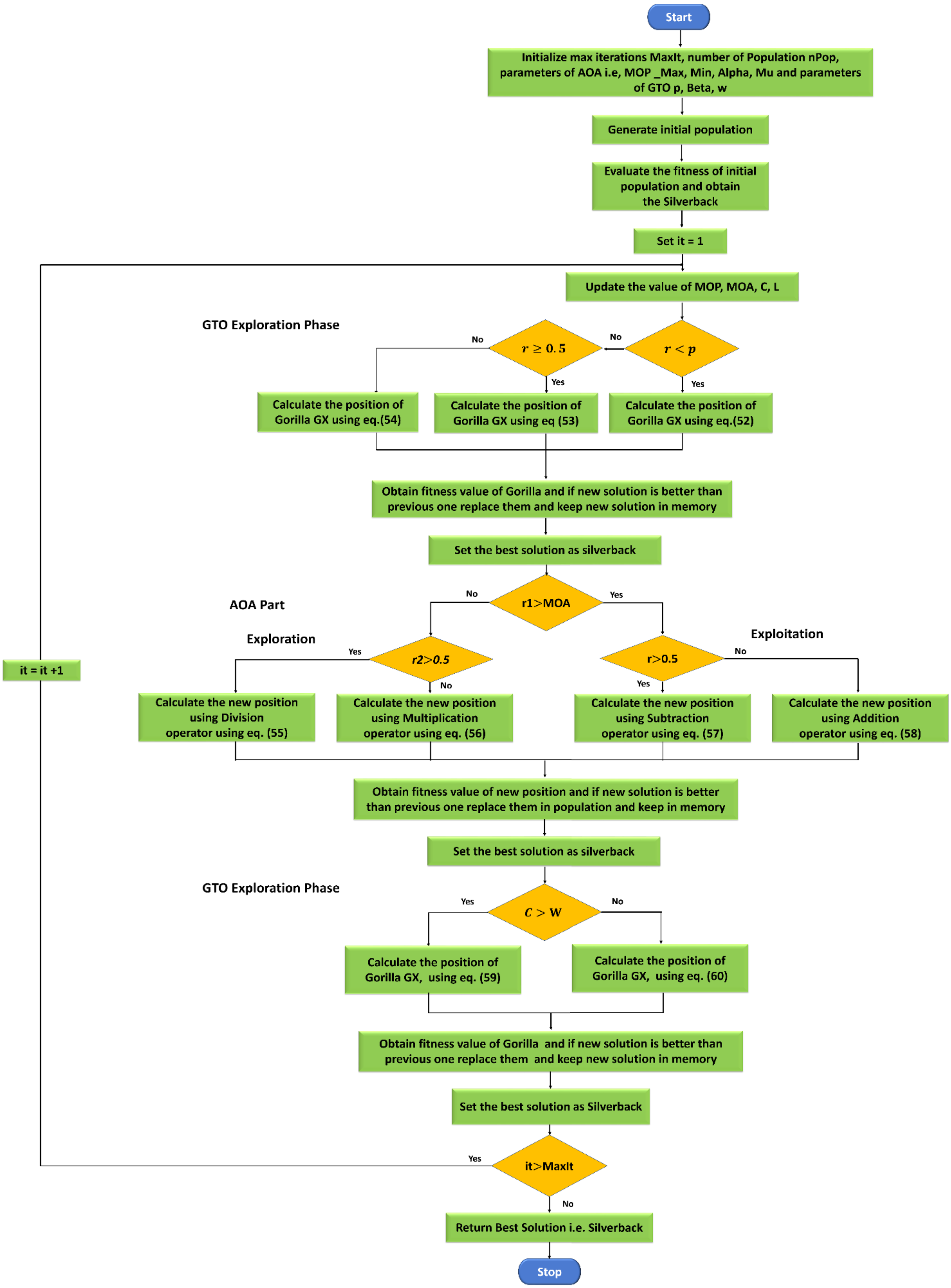

FIGURE 12. HGTOAOA Flowchart Methodology.

TABLE 3. The output result of various opimization techniques in terms of time response with different fitness functions.

Techniques	(Ideal-PID)	Control parameter KP	KI	KD	Time response tr	ts	Best Fitness Value
AOA	IAE	100	0.6664	0	6.9367	12.0922	3033.86
	ISE	100	1	0	6.9674	12.0471	1636466.12
	ISTES	100	0.26866	0	6.8897	12.0746	186687807.46
	ISTSE	100	0.60416	0	6.9311	12.0948	6967332.91
	ITAE	100	0.28996	0	6.8930	12.0777	8961.89
	ITSE	100	1	0	6.9674	12.0471	2288060.00
GTO	IAE	100	0.6670	0	6.9368	12.0921	3160.07
	ISE	100	1	0	6.9674	12.0471	1636466.12
	ISTES	100	0.2672	0	6.8896	12.0744	186686866.87
	ISTSE	100	0.6048	0	6.9312	12.0948	6967332.13
	ITAE	100	0.2926	0	6.8933	12.0781	8961.32
	ITSE	100	1	0	6.9674	12.0471	2288236.16
SOA	IAE	100	0.66766	0	6.9369	12.0921	3033.8468
	ISE	100	1	0	6.9674	12.0471	1636466.1176
	ISTES	100	0	0	6.8426	12.0120	226413991.68
	ISTSE	100	0.602118	0	6.9309	12.0948	6967346.1867
	ITAE	100	0.2924643	0	6.8933	12.0781	8961.3613
	ITSE	100	1	0	6.9674	12.0471	2288069.9989
PPA	IAE	99.9894	0.668842	0.606813	6.9612	12.1141	3038.3442
	ISE	99.9737	0.983121	0.44999	6.9769	12.0764	1637834.3631
	ISTES	99.9834	0.296026	0.610816	6.9013	12.0978	188462143.1363
	ISTSE	99.9869	0.694713	0.009803	6.9313	12.0968	6970778.1641
	ITAE	99.9886	0.26112	0.630324	6.9071	12.1026	8998.6936
	ITSE	99.9316	0.998962	0.607693	6.9736	12.0738	2298100.4874
HGTOAOA	**IAE**	**100**	**0.6664**	**0**	**6.9367**	**12.0922**	**3033.83647**
	ISE	**100**	**1**	**0**	**6.9674**	**12.0471**	**1636466.117663**
	ISTES	**100**	**0.26720**	**0**	**6.8896**	**12.0744**	**186686866.870096**
	ISTSE	**100**	**0.6048**	**0**	**6.9312**	**12.0948**	**6967306.491788**
	ITAE	**100**	**0.29266**	**0**	**6.8933**	**12.0781**	**8961.324021**
	ITSE	**100**	**1**	**0**	**6.9674**	**12.0471**	**2288069.998916**

PPA algorithm starts with an initialization phase based on selecting some produced solutions X in a random way. Each solution has a dimension size of N x D. The number of search candidates and problem dimensions are represented by N and D respectively.

$$X_i^{new} = X_i^{min} + r_1 \left(X_i^{max} - X_i^{min}\right) \tag{41}$$

X_i^{max} and X_i^{min} are the vectors that represent the maximum and minimum bound reached from the search landscape, and r_1 is a random value in a range from [0, 1]. After the initialization stage, the PPA starts its three main phases which are the nesting, parasitism, and predation.

• Nesting Phase

This phase is sometimes called the exploration or the diversification phases. It is identified by two main states.

First State: The recent location of the ith crow is obtained by selecting a random position for the crow based on the following equation:

$$X_i^{t+1} = X_i^t + lv\, x \left(X_{r1} - X_i^t\right) \quad \forall \in n_{crow} \tag{42}$$

X_i^t and X_{r1} are known as the locations of the ith crow and the random chose crow respectively, and n_{crow} is considered to be the total number of crows.

Second state: It relies on the modification of the dimension that allows the ability to move outside the boundaries of the landscape and this is designed using the following equation:

$$X_{i,\text{out}}^{\text{Update}} = X_{i,\text{out}}^{min} + r_1 x \left(X_{i,\text{out}}^{max} - X_{i,\text{out}}^{min}\right) \text{rand}[0, 1] \quad \forall \text{ out} \tag{43}$$

where $X_{i,\text{out}}^{\text{Update}}$ and r_1 are the update solution and a random number that is found in the range from 0 to 1

• Parasitism Phase

The optimal functions in this phase aim to swap the eggs obtained from the host with the cuckoos. The high degree of parasitism is achieved through the creation of new nests. The equation that is responsible for creating a new nest for the cuckoo is described using the following equation:

$$X_{i,\text{new}}^{\text{Cuckoo}} = X_{i,\text{old}}^{\text{Cuckoo}} + r_2\, x\, \left(X_{r2} - X_{r3}\right)\, x\, \alpha \tag{44}$$

$X_{i,\text{old}}^{\text{Cuckoo}}$ is the solution reached using the roulette wheel tool, while $X_{i,\text{new}}^{\text{Cuckoo}}$ is the final version solution after replacing

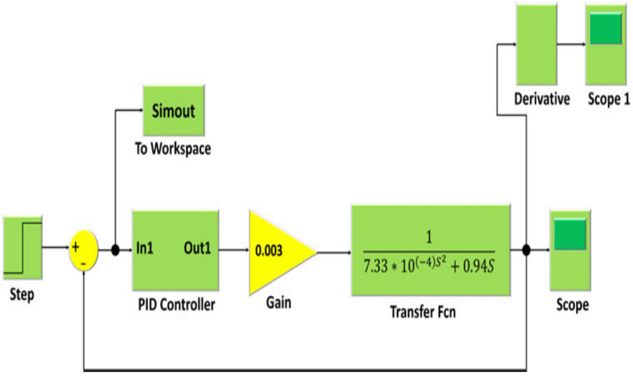

FIGURE 13. Simulink diagram of the micro-robotic system with different advanced control techniques.

the eggs of the crow with a new ones obtained from the cuckoo. X_{r2} *and* X_{r3} are random selected solution, α is the calculated binary matrix value.

- **Predation Phase**

In this phase the cuckoo start to provide an unpleasant secretion that makes the cats move away from the nest. And once the tracking process start a higher predation percentage of cats shows a spread cat production and a great reduction in the growth of cuckoos and crows. The formula that represents this phase is manifested in the following equation:

$$X_{kd} = X_{kd} + v_{kd} \tag{45}$$

where X_{kd} and v_{kd} are known as the position and the velocity of the cat at a specific dimension. The velocity can be defined using the following equation:

$$v_{k,d} = v_{k,d} + r_3 \ x \ e \ x \left(x_{best,d} - x_{k,d}\right), d = 1, 2, \cdots, ., M \tag{46}$$

$x_{best,d}$ and r_3 are the best final solution and a random number respectively, and finally e is a constant coefficient. The flowchart of PPA is represented in figure. 4.32

5) HYBIRD GTO AND AOA (HGTOAOA)

GTO Algorithm consists of Exploration and Exploitation stages, which involves five different operators for every individual (3 for Exploration: (either migration to an unknown location or movement towards other gorillas or migration to a known location) and 2 for Exploitation: (either following the silverback or Competition for adult females)).

While in AOA Algorithm every individual goes through either Exploration (either Division or Multiplication operator) or Exploitation (either Subtraction or Addition operator) phase and not both.

In this Hybrid AOA-GTO Algorithm, The AOA Phase (Exploration/Exploitation) is put in between Exploration and Exploitation phases of GTO Algorithm. The flowchart of HGTOAOA is manifested in Fig. 12. The pesudocode of the HGTOAOA algorithm is manifested in algorithm.1.

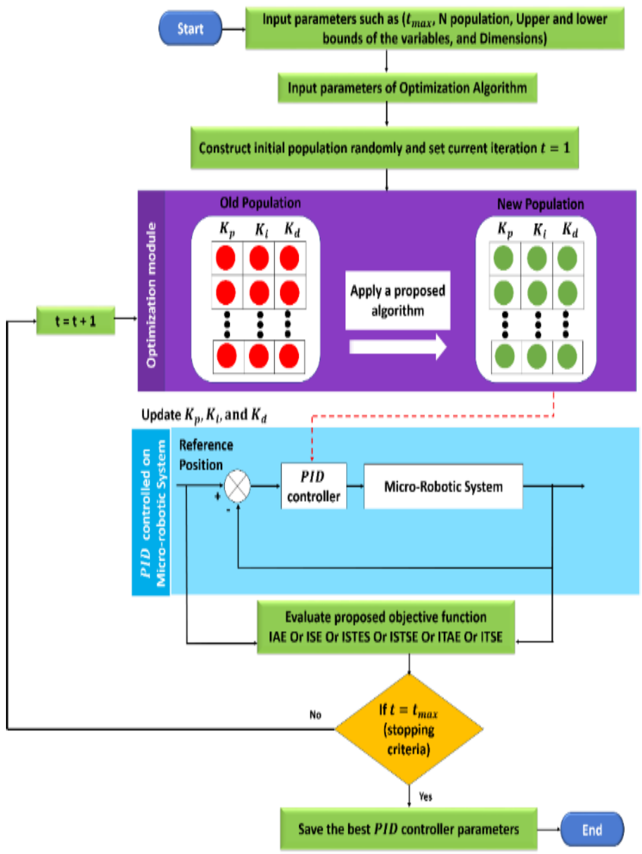

FIGURE 14. General design of tuning PID Controller for Micro-robotic Systems using modern optimization techniques.

III. SIMULATION AND RESULTS

In this section, thorough details are offered regarding the investigation of the micro-robotic system performance by employing various advanced control methods. The performance of the multiple control techniques is executed and assessed by using different tests. Different approaches are evaluated at a specific position for standardization. For example, for command reference, $1000\,\mu$m is used. In fig. 13, the Simulink diagram that exhibits different micro- robotic system techniques is presented. Table 1 offers the proposed system parameters, while Table 2 provides a summary of the parameters of various techniques for the maintenance and control of the micro-robotic system position at $1000\,\mu$m. robotic system techniques is presented. Table 1 offers the proposed system parameters, while Table 2 provides a summary of the parameters of various techniques for the maintenance and control of the micro-robotic system position at $1000\,\mu$m. These parameters required for implementation are adjusted by 30 times running of all algorithms.

Fig. 14 represent the general schema or structure for tuning the PID controller using advanced optimization techniques. It starts by initializing the parameters of the controls especially the lower and upper bounds. Then, set the input parameters of the optimization techniques. Afterwards, the optimization techniques are applied and the best solution or parameter of the PID is obtained.

Algorithm 1 Hybrid GTO-AOA (HGTOAOA).

Stage1 (Initialization):

Stepl: Initialize max iterations MaxIt, number of Population nPop, parameters of AOA i.e, MOP_Max, MOP_Min, Alpha, Mu and parameters of GTO p, Beta, w

Step2: Initialize the random population K

Step3: Calculate the fitness values of the initial population

Step4: Obtain the best solution Ksilverback from initial population

Set Iter = 1

Step5:

- Update the value of C using Equation:

$$C = F * (1 - It/MaxIt) \tag{47}$$

where, F = cos(2* rand)+1

- Update the value of L using Equation:

$$L = C * (2 * rand - 1) \tag{48}$$

- Update the value of MOP using Equation:

$$MOP = 1 - \left(\frac{It^{\frac{1}{\propto}}}{MaxIt^{\frac{1}{\propto}}}\right) \tag{49}$$

- Update the value of MOA using Equation:

$$MOA = MOP\_Min + It * \left(\frac{MOP\_Max - MOP\_Min}{MaxIt}\right) \tag{50}$$

Stage2 (GTO Phase):

Step6 (Exploration Phase):

- Generate a randon number r
- If r< p
  Select the mechanism of migration to an unknown location
  Calculate the location Gorilla using Equation

$$GX_i = (Kmax - Kmin) *rand + Kmin \tag{51}$$

- Else If r>= 0.5
  Select the mechanism of movement towards other gorillas
  Calculate the location Gorilla using Equation

$$GX_i = (rand - C) * K_r + L * H \tag{52}$$

where, $H = Z.*K_i$ and, $Z = unifrnd(-C, C, 1, N)$

- Else, Select the mechanism of migration to a known location
  Calculate the location Gorilla using Equation

$$GX_i = K_i - L * (L * (K_i - GX_r) + rand * (K_i - GX_r)) \tag{53}$$

where, GXi is gorilla candidate position vector, GXr is gorilla candidate position vector randomly selected and Kr is one member of the gorillas in the group randomly selected from entire population.

- End If
- Calculate the fitness values of Gorilla
- if New Solutions (GX) are better than previous solutions (K), replace them
  Update Ksilverback as the location of silverback (best location)

Step7 (AOA Phase):

- Generate a random number r1
- If r1 > MOA then, Exploration phase
  Generate random number r2

Algorithm 1 *(Continued.)* Hybrid GTO-AOA (HGTOAOA).

- If r2 > 0.5
  Apply Division Math operator (÷)
  Calculate the positions of solutions (gorillas) using Eq:

$$K\_new_{i,j} = \frac{K_{Silverback\,j}}{(MOP + eps)} * \left(\left(Kmax_j - Kmin_j\right) *Mu + Kmin_j\right) \tag{54}$$

- Else, Apply Multiply Math operator (*)
  Calculate positions of solutions (gorillas) using Eq:

$$K_{new_{i,j}} = K_{Silverback\ j} * MOP * \left(\left(Kmax_j - Kmin_j\right) * Mu + Kmin_j\right) \tag{55}$$

- Else, Exploitation phase
  - If r > 0.5
    Apply Subtraction Math operator (-)
    Calculate positions of solutions (gorillas) using Eq:

$$K_{new_{i,j}} = K_{Silverback\ j} - MOP * \left(\left(Kmax_j - Kmin_j\right) * Mu + Kmin_j\right) \tag{56}$$

  Apply Addition Math operator (+)
  Calculate the positions of solutions (gorillas) using Eq:

$$K_{new_{i,j}} = K_{Silverback\ j} + MOP * \left(\left(Kmax_j - Kmin_j\right) * Mu + Kmin_j\right) \tag{57}$$

  where, i is the population member and j is the dimension.
  Calculate the fitness values of Gorilla
  - If New Solutions (K_new) are better than previous solutions (K), replace them in population and also in memory(GX)
  - Update Xsilverback as the location of silverback (best location)

Stage3 (GTO Phase):

Step 8 (Exploitation Phase)

- If |C| ≥ w then
  Select the mechanism of following the silverback
  Calculate the location Gorilla using Equation

$$GX_i = L * delta * (\ K_i - K_{Silverback}\ ) + K_i \tag{58}$$

Where, $\left(\left|\frac{1}{N}\sum_{i=1}^{N} GX_i\right|^{g}\right)^{1/g}$ and g = 2L
- Else, Select the mechanism of Competition for adult females
  Calculate the location Gorilla using Equation

$$GX_i = K_{Silverback} - (K_{Silverback} * (2 * \ rand\ - 1) - K_i * (2 * \ rand\ - 1)) * (\beta * \ h) \tag{59}$$

If rand ≥0.5 , value of h will be equal to random values in the normal, distribution and the problem's dimensions, but if rand < 0.5 , h will be equal to a random value in the normal distribution
Where, i is the population member and j is the dimension.
- End If
- Calculate the fitness values of Gorilla
- if New Solutions (GX) are better than previous solutions (K), replace them
- Update Xsilverback as the location of silverback (best location)
  Iter = Iter + 1
  - While (Iter < MaxIt)
- Return best solution i.e, Xsilverback, and Silverback_Score

This scenario provides five main advanced optimization techniques based on AOA, GTO, PPA, SOA and HGTOAOA. Table 3 shows the output results in terms of time response relying on various fitness functions (simulation). Figure 15

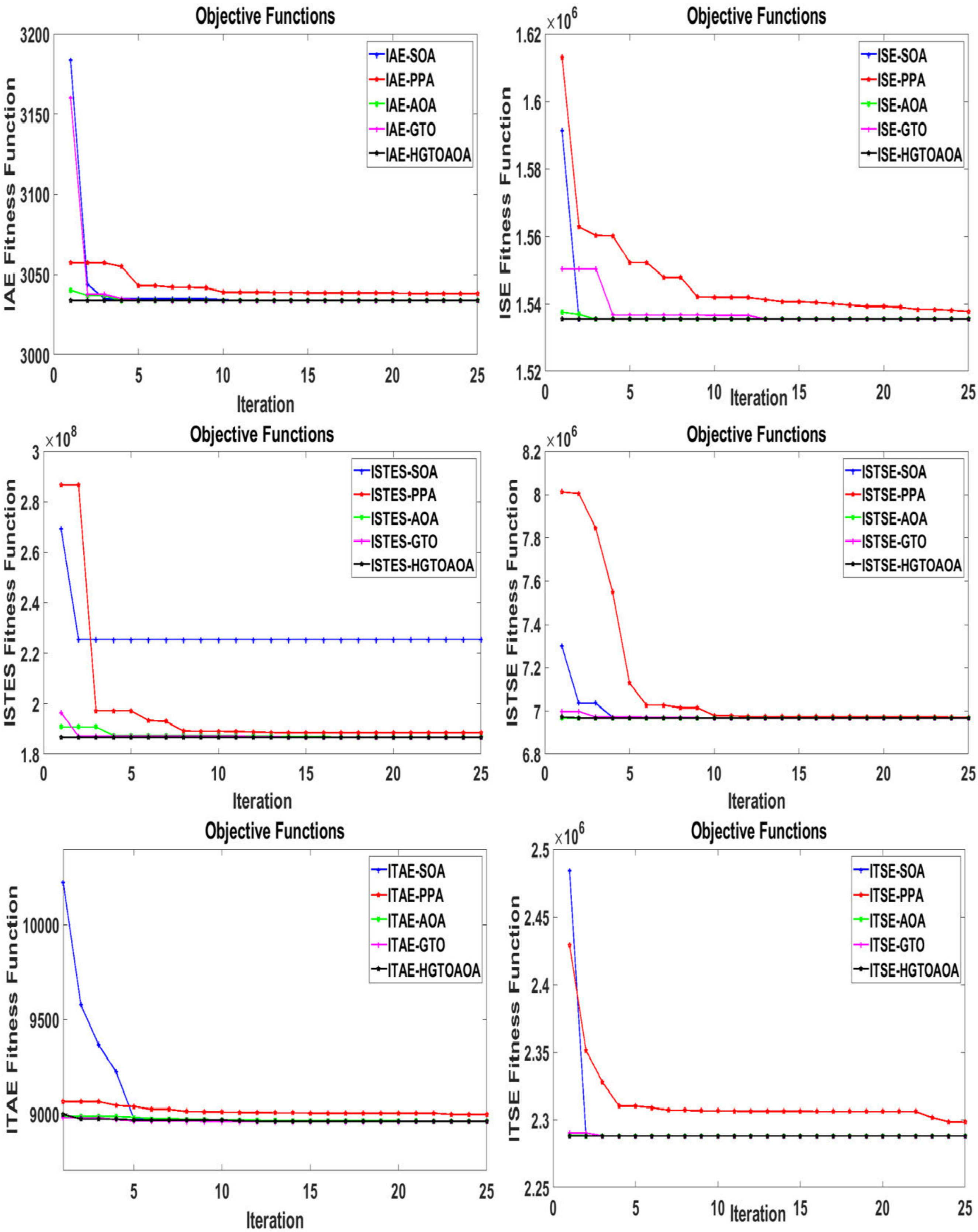

FIGURE 15. Convergence Curves of various types of fitness functions for different number of iterations, AOA, GTO, SOA, PPA, and HGTOAOA.

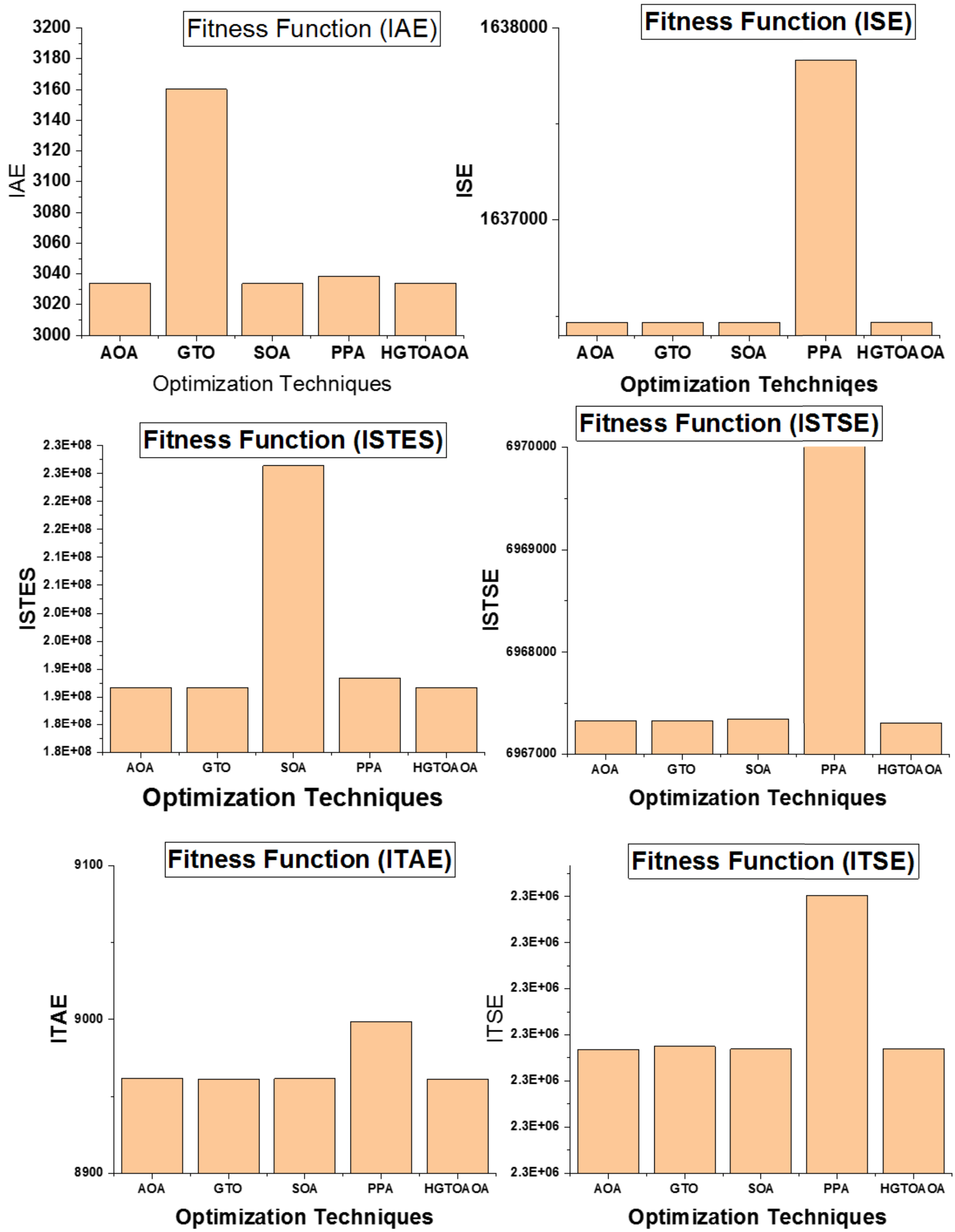

FIGURE 16. Bar chart representing best fitness values for different fitness function using AOA, GTO, SOA, PPA, and HGTOAOA.

shows the results of six fitness functions in terms of the AOA, GTO, PPA, SOA and HGTOAOA based on convergence curves. It was realized that HGTOAOA showed highest performance over AOA, GTO, and PPA. The best fitness function is ISTES. Figure 16 manifests the bar chart for best six fitness function values using AOA, GTO, SOA, PPA, and HGTOAOA.

IV. DISCUSSION

In this section, the five optimization techniques are thoroughly compared depending upon different fitness functions. The parameters consist of rising, settling time, and best fitness value relying on the six-fitness function. Table 3 exhibits the results of the measurements AOA, GTO, SOA, PPA, and HAOAGTO which have been recorded earlier. HAOAGTO exhibits the highest amount of rising, settling time and best fitness value. It was observed that the PPA technique achieves the highest values of the rise time, settling time and best fitness value for simulation results among other control approaches. It can be concluded that the HAOAGTO techniques is a promising approach for predicting real-time for the micro-robotics system. Finally, the limitations and drawbacks of the proposed method are complexity, computational time and the selection of input parameters such as control beta, weight(w), probability, maximum math optimizer probability ($MOP_{max.}$), minimum math optimizer probability ($MOP_{min.}$), Alpha, and Mu of a novel hybrid algorithm should be properly chosen to given the best performance. To avoid this issue, the proposed HGTOAOA algorithm are adjusted by 30 times running of this algorithm and consumes more time for select the optimum parameters.

V. APPLICATION

The proposed algorithm may be used in different applications with minor modifications as follows:

- The temperature control system of an industry.
- The maximum power point tracking charge controller or MPPT charge controller.
- Power converters.
- Various research, development, and testing organizations such as chemical, pharmaceutical, and manufacturing industries.
- pH, flow, and speed control devices

VI. CONCLUSION

The paper consists of five different techniques of optimization of PID controller tuning. Based on a set of different fitness functions to discover the best performance, the ISTES achieves the highest performance. Techniques were compared on the basis of different algorithms including AOA, GTO, SOA, PPA, and HAOAGTO. It is observed that among all four, HAOAGTO outperforms all other techniques when their rising time, setting time, and best fitness value are compared, and thus HAOAGTO is recommended for the tuning of PID parameters based on the best fitness function (ISTES). It is observed that HAOAGTO enhances the parameter efficiency of systems. For future aspects, hybrid algorithm based on two or more algorithms such as Honey Badger Algorithm (HBA), Spotted Hyena Optimization (SHO), etc. It may also be a good idea to use the FOPID, PIDA or Fuzzy PID controllers as more stable options.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

AUTHOR CONTRIBUTIONS

Ehab Saif Ghith: methodology, software, validation, writing–original draft preparation, and formal analysis. Farid Abdel Aziz Tolba: supervision, conceptualization, and reviewing and editing. All authors have read and approved the final manuscript.

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