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Bio-Inspired Optimization of Fractional-Order Control in Drone Systems

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Abstract—Robotics has become a deeply interdisciplinary field, addressing a broad spectrum of challenges to support human activities across diverse environments on land, in the air, underwater, and even in space. This study focuses on the quadcopter, offering a detailed analysis of its modelling, control strategies, and performance optimization, particularly when navigating sharp trajectories. Stability plays a crucial role in the effectiveness of quadcopters and other robotic systems. In this context, the research explores how a fractional-order PID (FOPID) controller can enhance stability, especially in systems characterized by high sensitivity. To achieve optimal control, five fractional parameters of the FOPID controller are tuned using three distinct optimization techniques: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Bonobo Optimization (BO). The comparative evaluation reveals that the FOPID controller, when optimized particularly with the BO method, demonstrates superior control performance. It notably eliminates overshoot and improves both settling and rise times by more than 30% under consistent test conditions, outperforming conventional controllers cited in the literature.

Keywords— *Drone, FOPID, Optimization Algorithms, Bonobo, PSO, GA, Stability.*

I. INTRODUCTION

The demand for autonomous quadrotors has seen substantial growth across both military and industrial sectors, driven by the need for fast, efficient aerial solutions in applications such as emergency response, infrastructure inspection, logistics, and drone racing. Despite this momentum, developing autonomous systems capable of executing rapid and precise maneuvers remains a significant challenge. This difficulty stems from the complexity of designing real-time control algorithms that can efficiently handle nonlinear system dynamics and actuator constraints. Achieving high-speed performance and agile flight requires a deep understanding of the aerodynamic forces acting on quadrotors, including propeller thrust and drag, fuselage resistance, and turbulent airflow interactions[1], [2].

Quadrotors have become central to the unmanned aerial vehicle (UAV) domain, raising numerous research challenges particularly in improving system responsiveness through various controller design strategies. Control methods typically fall into three categories: linear controllers such as the widely-used PID in many fields of engineering [3], [4], [5]; nonlinear controllers, including FOPID and sliding mode controllers [6]; and data-driven, learning-based approaches. FOPID controllers, grounded in Fractional Calculus, extend conventional PID control by incorporating non-integer-order integrals and derivatives, thereby offering improved performance and flexibility [7], [8].

However, the increased number of tuning parameters in FOPID controllers introduces complexity in maintaining the stability of sensitive systems, necessitating the application of robust optimisation techniques for effective parameter adjustment. While traditional optimisation methods have been employed, such as those used by A. Sheta et al. [9], they often suffer from limitations in convergence speed and computational burden. To overcome these drawbacks, more advanced techniques such as the Wolf algorithm applied by M. N. Shauqee et al.[10] have been explored. Current research emphasizes the importance of achieving a balance between controller robustness and the efficiency of the optimization process, highlighting the inadequacy of relying solely on classical tuning methods[11], [12], [13].

In this context, the present study investigates the integration of FOPID controllers with modern metaheuristic optimisation algorithms to enhance the stability and dynamic performance of quadcopter systems, aiming to surpass the limitations of conventional PID-based approaches that used in many references.

This paper is organized as follows: Section I introduces the system under investigation. Section II describes the mathematical modelling of the quadcopter. Section III outlines the structure of the FOPID controllers. Section IV discusses the metaheuristic optimisation techniques and their configuration. Finally, the simulation results are presented and analyzed, followed by concluding remarks summarizing the main findings.

II. SYSTEM UNDER STUDY

A quadrotor's movement is controlled by adjusting the rotational speeds of its individual motors, which in turn alters the thrust generated by each propeller. When all four rotors increase their speed simultaneously, the quadrotor lifts off vertically. To achieve lateral movement, the system varies the speed between the left and right rotors, causing the vehicle to tilt along its longitudinal (roll) axis shifting sideways in the direction opposite the faster-spinning rotor. Similarly, forward or backward motion is achieved by modifying the speeds of the front and rear rotors, which tilts the quadrotor along its transverse (pitch) axis. Yaw motion, or rotation around the vertical axis, is governed by the relative acceleration differences between opposing rotor pairs. Consequently, the main control variables for quadrotor navigation are roll, pitch, yaw, and total thrust. As shown in Figure (1) [14], the system under investigation uses controllers to maintain quadrotor stability by generating reference speeds in response to deviations in angular orientation (roll, pitch, and yaw) and altitude. FOPID controllers each defined by five parameters introduces complexity due to the high number of variables involved. In this study, the authors addressed this challenge by successfully determining all twenty required parameters across the four controllers, thereby ensuring stable flight performance. Further technical details about quadrotor dynamics can be found in the cited references [9], [11], [15]

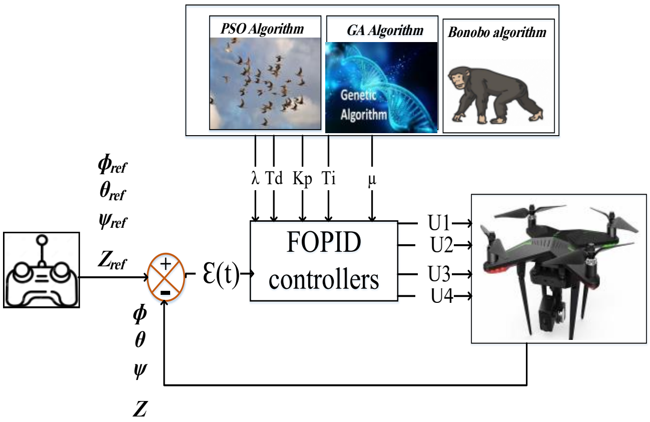

Fig.1. Drone model.

III. QUADROTOR MATHEMATICAL MODEL

Equations (1) to (6) represent the nonlinear dynamic model that governs the motion of the quadcopter, accounting for external disturbances and system uncertainties[16]:

$$\ddot{\phi} = \frac{I_{yy}-I_{zz}}{I_{xx}}\dot{\theta}\dot{\psi} + \dot{\theta}\frac{I_m}{I_{xx}}\Omega_m + \frac{U_2}{I_{xx}} + \delta_\phi(t) \tag{1}$$

$$\ddot{\theta} = \frac{I_{zz}-I_{xx}}{I_{yy}}\dot{\phi}\dot{\psi} - \dot{\phi}\frac{I_m}{I_{yy}}\Omega_m + \frac{U_3}{I_{yy}} + \delta_\theta(\mathrm{t}) \tag{2}$$

$$\ddot{\psi} = \frac{I_{xx}-I_{yy}}{I_{zz}}\dot{\phi}\dot{\theta} + \frac{U_4}{I_{zz}} + \delta_\psi(t) \tag{3}$$

$$\ddot{z} = g - \frac{(\cos(\phi)\cos(\theta))U_1}{m} + \delta_z(t) \tag{4}$$

$$\ddot{x} = U_1(\cos(\phi)\sin(\theta)cos\psi + \sin(\phi)\sin(\psi))/m \tag{5}$$

$$\ddot{y} = U_1(\cos(\phi)\sin(\theta)\sin(\psi) - \sin(\phi)\cos(\psi))/m \tag{6}$$

where the control inputs U_i are given in (7) as [16]:

$$\begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ U_4 \\ \Omega_m \end{bmatrix} = \begin{bmatrix} b(\omega_1^2+\omega_2^2+\omega_3^2+\omega_4^2) \\ bL(\omega_4^2-\omega_2^2) \\ bL(\omega_1^2-\omega_3^2) \\ d(-\omega_1^2+\omega_2^2-\omega_3^2+\omega_4^2) \\ -\omega_1+\omega_2-\omega_3+\omega_4 \end{bmatrix} \tag{7}$$

Some key parameters of the system include the rotational speed of each motor, represented as ω_i (where i ranges from 1 to 4), and the gravitational acceleration, denoted by g (9.81 m/s²). External disturbances affecting the quadrotor's motion are represented by (roll), θ (pitch), ψ (yaw), and z (altitude). Additional physical characteristics include the total mass m, the thrust and drag coefficients b and d, the arm length L, and the motor's moment of inertia I_m. The inertial moments about the principal axes are given by I_{xx}, $I_{\gamma\gamma}$, and Izz for the x, y, and z directions, respectively.

IV. FRACTIONAL ORDER PID CONTROL

FOPID or $PI^\lambda D^\mu$ Controller is a nonlinear controller it can be derive its model algorithm from (8)[17]:

$$u(t) = K_p\left(e(t) + \frac{1}{T_i}\mathcal{D}^{-\lambda}e(t) + T_D\mathcal{D}^{\mu}e(t)\right) \tag{8}$$

The fractional operator $\mathcal{D}$ can be defined as Riemann-Liouville, wherein λ and μ are non-integer orders of the integral and derivative terms, accordingly, where $(\lambda, \mu) \in \mathrm{R}^+$.it can explain this parameter in (9) [16] [18], [19]:

$$\mathcal{D}^{-n}f(t) = \frac{1}{\Gamma(n)}\int_0^t f(y)(t-y)^{n-1}dy \tag{9}$$

Γ is the gamma function, *n* is a real number that is not an integer, and *y* is an integration virtual variable. Control rule in (8) combines the present, cumulative, and anticipated error, the three natural techniques of accounting for error just as the classical version. Left-side Riemann-Liouville fractional integral ${I_0}_T^\lambda(t)$ of the error $e(\tau)$ where τ is the independent variable has been taken into consideration for integral action in (10),(11)[17]:

$${I_0}_T^\lambda(t) = \int_0^t e(\tau)dg_t(\tau) \tag{10}$$

$$g_t(\tau) = \frac{1}{\Gamma(\lambda+1)}\left(t^\lambda - (t-\tau)^\lambda\right) \tag{11}$$

$g_t(\tau)$ is the kernel function or weighting function utilized in the fractional integral.

The transfer function in the domain of Laplace is given in (12) [18], [19]:

$$C(s) = \frac{U(s)}{E(s)} = K_P\left(1 + \frac{1}{T_i}s^{\lambda} + T_D s^{\mu}\right) \tag{12}$$

V. METAHEURISTIC ALGORITHMS

A. Particle Swarm Optimization

In the domain of Swarm Intelligence (SI) algorithms, PSO is widely recognized as a highly effective metaheuristic technique for solving complex engineering optimization problems. Introduced by James Kennedy and Russell Eberhart in 1995, PSO draws inspiration from the collective behaviour of natural swarms such as flocks of birds or schools of fish which exhibit remarkable coordination and communication while pursuing shared objectives like locating food. Unlike hierarchical systems with centralized control, PSO operates on the principle that each individual in the swarm contributes valuable insights and experiences toward achieving the overall goal. Much like birds adjusting their flight paths based on the movements of nearby flock members, particles in PSO dynamically update their positions by considering both their own past performance and the performance of others. This distributed, collaborative mechanism leverages the diverse perspectives of all particles, significantly enhancing the swarm's ability to find optimal solutions. The method is particularly suitable for systems involving multi-grain controllers, as illustrated in the flowchart presented in Figure (2) [20], [21].

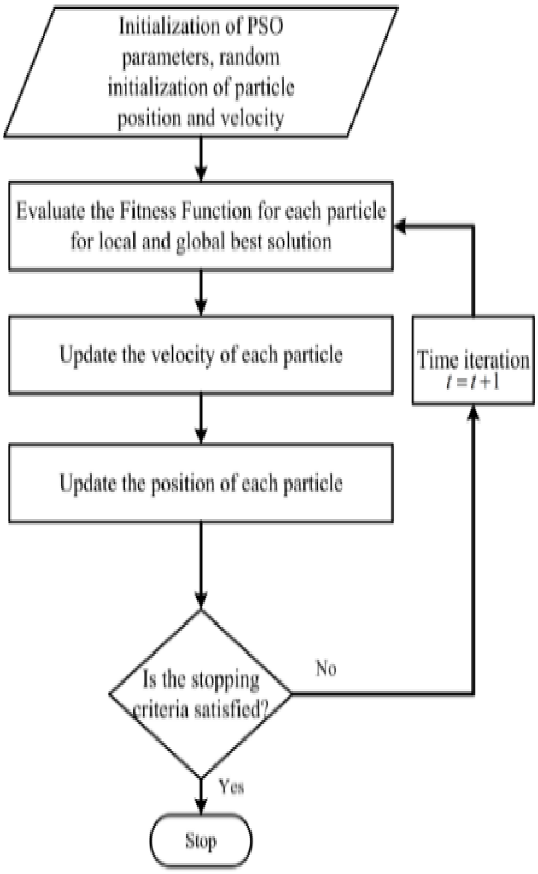

Fig.2. Flowchart of the PSO.

B. Genitec Algorithm

GA is a powerful class of evolutionary computation techniques. Research in this domain has seen notable advancements, particularly in the development of innovative crossover and mutation operators. The crossover operator generates new offspring by recombining genetic information from existing individuals within the population, whereas the mutation operator introduces random alterations to maintain diversity and prevent premature convergence to local optima. Figure (3) illustrates the fundamental working principle of the GA.

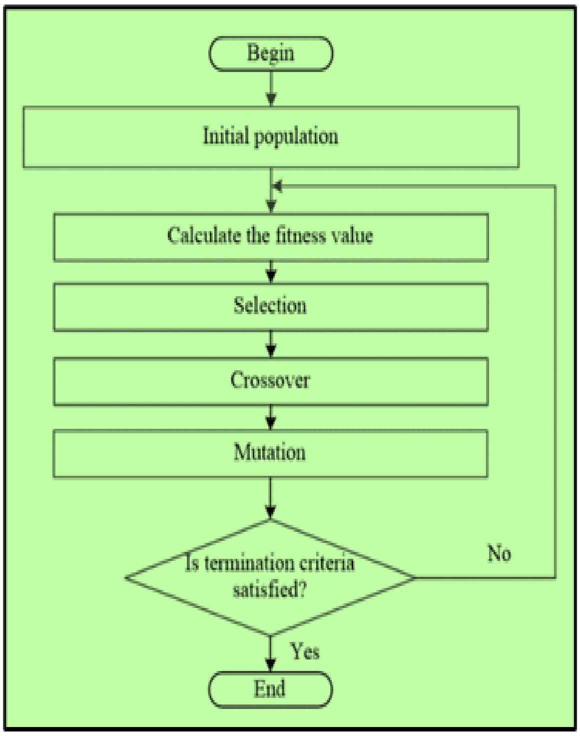

Fig.3.Flowchart of GA optimizer

C. Bonobo algorithm

BO is a relatively recent optimization method introduced in 2019. It adopts an intelligent search strategy based on the fission-fusion social structure, where individuals dynamically alternate between forming large groups (fusion) and splitting into smaller subgroups (fission) depending on the situation. This flexible grouping mechanism enhances the algorithm's ability to balance exploration and exploitation during the search process. In this study, BO is evaluated for its effectiveness in tuning controller parameters and is compared against other established optimization techniques. The core working principle of the BO algorithm is illustrated in the flowchart shown in Figure (4) [14].

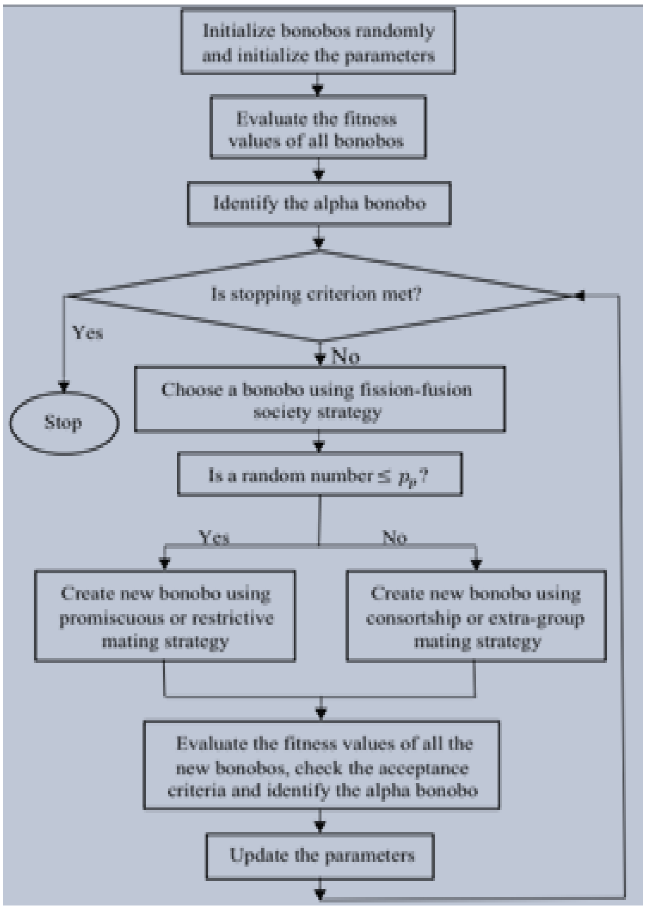

Fig.4. Flowchart of the Bonobo Optimizer

D. *Configuration of Optimization Methods*

Fitness functions play a crucial role in defining objectives and guiding actions to achieve them, thus impacting the overall performance of a system. In the context of system stability, fitness functions help determine the necessary actions to optimize and select the best controller gains. The accuracy of fitness functions greatly affects the system's ability to efficiently identify the optimal solution within specified parameters and time frames. In this study, we will utilize the Integral of Time-weighted Absolute Error (ITAE) as the performance criterion to minimize controller error, as outlined in (13)[11], [20]. The ITAE criterion is particularly effective in improving system stability and response by emphasizing errors over time, ensuring that long-term deviations are minimized.

$$F_{ITAE} = \int_0^t t|e(t)|dt \tag{13}$$

Where t is the time and e is the error.

VI. SIMULATION AND RESULTS

This research investigates the efficiency of three optimization techniques PSO , GA, and Bonobo Optimization BO in addressing the complex task of tuning FOPID controllers. The quadcopter system under study is illustrated in Fig.1, with controller parameters adjusted according to the procedure detailed in the preceding section. The optimization objective focuses on the system's dynamic response across key flight variables: altitude, roll, pitch, and yaw.To maintain consistency and fairness in comparison, the population sizes for all algorithms were kept equivalent, recognizing that the number of agents directly influences simulation outcomes. Standard settings for the optimization processes include a population size of 50 and a maximum of 50 iterations. Each algorithm was executed multiple times to ensure result reliability and mitigate the influence of random variation.The simulation scenario was defined using target reference values: an altitude of 2 meters (Z), a roll angle of 0.4 rad (ϕ), a pitch angle of 0.4 rad (θ), and a yaw angle of 0.2 rad (ψ). While only part of the altitude control scheme is explicitly illustrated, the roll, pitch, and yaw controls follow an analogous implementation. The physical and dynamic parameters of the quadcopter employed in the study are provided in Table 1, whereas Table 2 outlines the tuning boundaries and permissible ranges for the FOPID controller gains, determined through both literature review and additional empirical testing.

TABLE.1 Quadcopter Parameters

Parameters	**Values**
m (kg)	0.3
b (Nm^2)	2.4 $\times 10^{-6}$
d (Nms^2)	9.93 $\times 10^{-10}$
L (m)	0.24
$I_m (kg.m^2)$	6.6 $\times 10^{-7}$
I_{xx}, I_{yy}, I_{zz} $(kg.m^2)$	I_{xx}, I_{yy}=7.6 $\times 10^{-3}$, I_{zz}=1.4$\times 10^{-2}$

TABLE. 2 Optimization Constants & Boundary Settings

Algorithm	Parameter	Value
GA	Number of genes	50
	Mutation ratio	0.1
	Crossover ratio	0.8
	Lower bound	0
	Upper bound	100
	Number of iterations	50
PSO	Number of particles	50
	Inertia weight (w)	1
	Cognitive parameter (a)	1.5
	Lower bound	0
	Upper bound	100
	Number of iterations	50
BO	Number of Bonobos	50
	Sharing coefficient for alpha bonobo	1.9
	Sharing coefficient for selected bonobo	1.9
	Rate of change in phase probability	0.003
	Max. value of temporary sub-group size factor	0.2
	Lower bound	0
	Upper bound	100
	Number of iterations	50

This study presents an integrated approach to controlling a quadcopter system by combining FOPID controllers with four distinct optimization techniques. The performance of these combinations was evaluated using standard control metrics, including Integral of Time-weighted Absolute Error

(ITAE), overshoot, rise time, and settling time. The results, as depicted in the figures, indicate that the FOPID controllers regardless of the optimization method used successfully eliminated overshoot.

Among the tested algorithms, BO consistently delivered the most favorable outcomes, as illustrated in the figures and summarized in the tables. The corresponding controller gains derived from each optimization method are listed in Table 3. Figures (5) and (6) highlight the altitude and pitch control responses of the quadcopter using FOPID controllers optimized via GA, PSO, and BO, respectively. In these scenarios, BO demonstrated superior performance compared to PSO.A comparative summary of altitude control responses is provided in Table 4. Figures (7) and (8) show the roll and yaw angle responses under the influence of enhanced FOPID controllers optimized with GA, PSO, and BO. Further performance data for pitch, roll, and yaw control are detailed in Tables 5, 6, and 8. Figures (9) displays the convergence behavior of the GA, PSO and BO methods. Overall, the study concludes that BO outperforms the other techniques, with GA and PSO showing weaker results under certain conditions. Notably, the FOPID controller delivered robust system-wide performance, especially in controlling roll and pitch dynamics. This observed performance variation may be attributed to the complexity of tuning FOPID's fractional-order parameters, which often demands a higher number of iterations and population members, thus increasing computational time. Despite these demands, the FOPID controller consistently achieved satisfactory control performance, as evidenced by the results in Table 8.

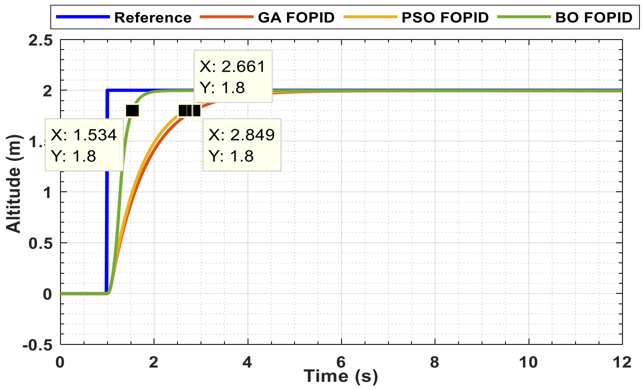

Fig.5. Quadcopter's altitude using optimized FOPID.

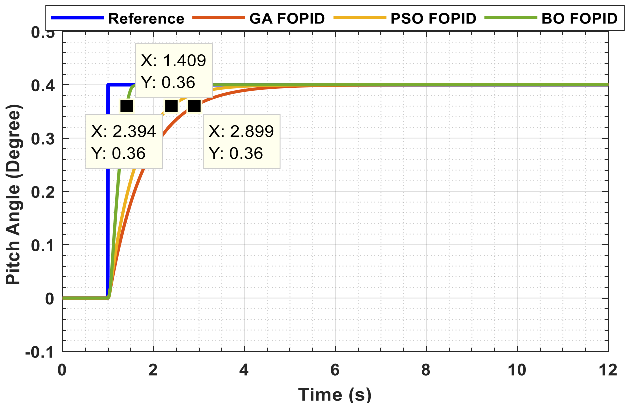

Fig.6. Quadcopter 's Pitch angle using optimised FOPID.

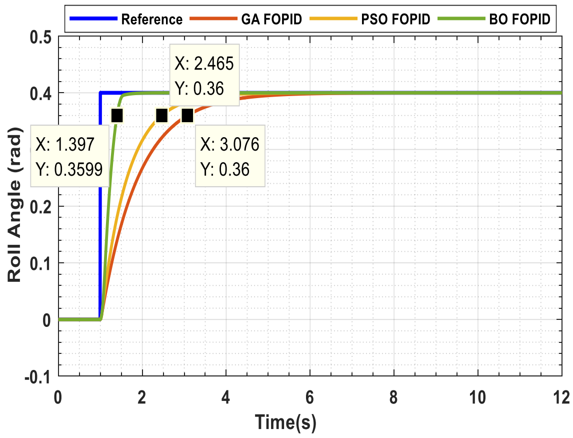

Fig.7 Quadcopter 's Roll angle using optimised FOPID.

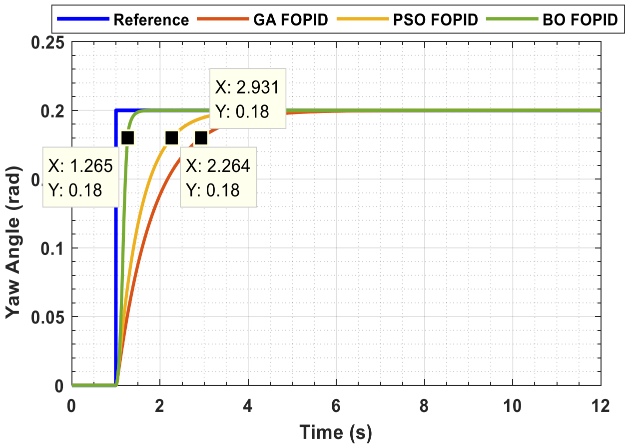

Fig.8. Quadcopter 's Yaw angle using optimised FOPID.

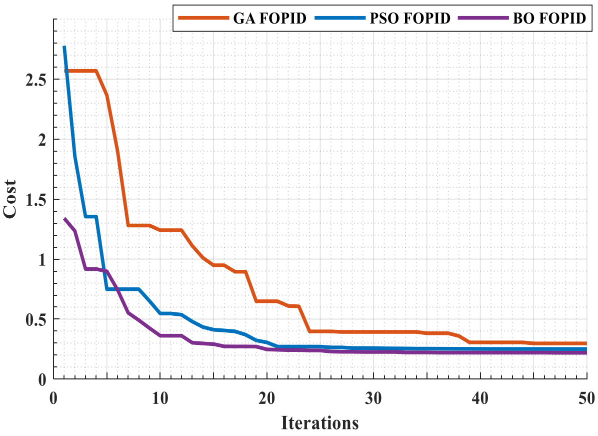

Fig.9 Convergence curves of optimization methods.

TABLE.3 FOPID Controllers Gains

	Altitude					**Roll**					**Pitch**					**Yaw**				
	K_p	K_i	λ	K_d	μ	K_p	K_i	λ	K_d	μ	K_p	K_i	λ	K_d	μ	K_p	K_i	λ	K_d	μ
GA	67.3	64.4	0.8	40.7	0.7	61.4	90.7	0.9	9.4	1.3	93.2	51.4	0.5	100	0.5	27.1	82.3	0.7	100	0.5
PSO	73.4	49.5	1.3	9.1	1.3	97.5	34.2	1.1	78.7	0.7	63.7	64.2	0.8	29.3	1.1	67.8	33.6	1.2	34.9	0.8
BO	99.1	0.0	1.0	16.2	1.3	99.6	0.0	0.7	100	0.5	70.6	9.5	0.5	75.8	1.2	98.9	0.0	1.1	76.6	0.5

TABLE.4 Performance criteria of Altitude

	Altitude			
	ITAE	Overshoot (%)	Rising Time(s)	Settling Time(s)
GA	38.4116	0.00	1.8400	2.1590
PSO	34.0935	0.00	1.660	1.8310
BO	10.4565	0.00	0.53	0.802

TABLE.5 Performance criteria of Pitch angle

	Pitch			
	ITAE	Overshoot (%)	Rising Time(s)	Settling Time(s)
GA	7.1373	0.00	1.89	2.214
PSO	4.2760	0.00	1.39	1.6
BO	1.9372	0.00	0.4	0.504

TABLE.6. Performances criteria of Roll angle.

	Roll			
	ITAE	Overshoot (%)	Rising Time(s)	Settling Time(s)
GA	9.5151	0.00	2.07	2.1780
PSO	6.9500	0.00	1.46	2.476
BO	3.6202	0.00	0.39	0.501

TABLE.7 Performance criteria of Yaw angle

	Yaw			
	ITAE	Overshoot (%)	Rising Time(s)	Settling Time(s)
GA	4.1876	0.00	1.93	2.269
PSO	2.7086	0.00	1.26	1.634
BO	0.7902	0.00	0.26	0.396

TABLE.8 Best cost and Time results of each process.

	Time	Best Cost
GA	12964	0.2969
PSO	13104	0.2749
BO	15438	0.2192

VII. CONCLUSION

This study presents an in-depth exploration of quadcopter systems within the realm of control engineering, with a particular emphasis on the challenges associated with control strategies and parameter tuning. Through a comprehensive review of theoretical foundations and prior research, the work highlights critical issues inherent in the design and operation of such systems. The investigation confirms the intricate dynamics involved in quadcopter flight and demonstrates how thrust distribution across four rotors, combined with sophisticated control mechanisms, enables both stability and maneuverability.The study provides a detailed explanation of fractional-order FOPID controllers and evaluates the effectiveness of metaheuristic optimization techniques. Simulation results affirm the superior performance of FOPID controllers in achieving precise and stable control. Among the optimization methods assessed, BO proved notably efficient, outperforming alternatives like PSO and GA, especially in terms of convergence speed and computational efficiency.The findings underscore the pivotal role of robust control strategies in enhancing quadcopter functionality and reliability. Looking ahead, further advancements are expected through the continued evolution of control methodologies and the refinement of both single- and multi-objective optimization techniques. Ultimately, this research contributes valuable insights and practical approaches to the field, paving the way for more efficient, reliable, and high-performance quadcopter applications. Ongoing innovation in this area holds significant promise for the future of aerial robotic systems.

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