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Comparative performance of POA and GWO-enhanced backstepping control for robust 6DOF drone path tracking in windy conditions

Porównanie wydajności sterowania backsteppingiem POA i GWO w celu zapewnienia solidnego śledzenia ścieżki drona 6DOF w wietrznych warunkach

***Abstract**. This study proposes a comparative framework to enhance drone trajectory tracking under wind disturbances by employing two optimization-enhanced Backstepping control strategies. Specifically, we introduce two algorithms: one integrates the Grey Wolf Optimizer (GWO) with Backstepping control, and the other combines the Pelican Optimization Algorithm (POA) with Backstepping control. A standard Backstepping control model is also evaluated as a baseline. Through a systematic comparison of tracking performance across all three controllers — simple Backstepping, GWO-Backstepping, and POA-Backstepping — we demonstrate that POA-Backstepping delivers superior path stability and accuracy, particularly in response to wind disturbances. The POA-Backstepping algorithm shows enhanced adaptability, with significantly reduced tracking errors and smoother control inputs, establishing it as a highly effective solution for maintaining precision in challenging environmental conditions. This research highlights the promise of POA in optimizing drone control systems, ensuring reliable and robust performance in dynamic and unpredictable environments*

***Streszczenie.** W niniejszym badaniu proponujemy ramy porównawcze mające na celu zwiększenie precyzji śledzenia trajektorii dronów w warunkach zaburzeń wiatru poprzez zastosowanie dwóch strategii sterowania Backstepping wspomaganych optymalizacją. W szczególności przedstawiamy dwa algorytmy: pierwszy integruje Grey Wolf Optimizer (GWO) z kontrolą Backstepping, a drugi łączy Pelican Optimization Algorithm (POA) z kontrolą Backstepping. Standardowy model kontroli Backstepping również został oceniony jako punkt odniesienia. Poprzez systematyczne porównanie wydajności śledzenia dla wszystkich trzech kontrolerów – standardowego Backstepping, GWO-Backstepping i POA-Backstepping – wykazujemy, że POA-Backstepping zapewnia lepszą stabilność i dokładność trajektorii, szczególnie w odpowiedzi na zaburzenia wiatru. Algorytm POA-Backstepping wykazuje zwiększoną adaptacyjność, z istotnie zmniejszonymi błędami śledzenia i bardziej płynnymi sygnałami sterowania, co czyni go wysoce efektywnym rozwiązaniem w utrzymaniu precyzji w trudnych warunkach środowiskowych. Badanie to podkreśla potencjał POA w optymalizacji systemów sterowania dronami, zapewniając niezawodną i solidną wydajność w dynamicznych i nieprzewidywalnych warunkach.*

Keywords: trajectory tracking, backstepping control, optimization algorithms, wind disturbances
Słowa kluczowe: śledzenie trajektorii, sterowanie backstepping, algorytmy optymalizacji, zaburzenia wiatru

Introduction

In the 1990s, the PID controller [1] became foundational in UAV control systems, valued for its simplicity and reliability in maintaining basic trajectory and stabilization [2]. However, as unmanned aerial vehicles (UAVs) advanced in complexity, the limitations of PID in addressing nonlinear dynamics and time delays became clear, prompting a shift in research toward more resilient methodologies. By the early 2000s, Sliding Mode Control (SMC) [3] began gaining traction due to its robustness against system uncertainties and its stability under challenging conditions [4]. To address SMC's vulnerability to high-frequency oscillations, known as "chattering," research in the mid-2000s focused on refining this method to optimize stability under uncertain conditions [5]. With the 2010s came a heightened demand for nonlinear control strategies to manage increasingly complex UAV dynamics. Among these, Backstepping control [6] emerged, allowing engineers to decompose complex systems into manageable subsystems for improved trajectory tracking accuracy. Simultaneously, Model Predictive Control (MPC) gained popularity [7] for its predictive capabilities, supporting real-time trajectory adjustments in response to disturbances such as wind gusts [8]. As UAV applications expanded into outdoor environments—particularly for surveillance and delivery—interest in adaptive control methods intensified by the mid-2010s [8]. From the late 2010s onward, control research expanded to integrate adaptive techniques with classical methods like PID and Backstepping, enhancing both robustness and tracking precision. Advances in machine learning, notably in fuzzy logic [9] and neural networks [10], enabled UAVs to adapt dynamically to nonlinearities and environmental uncertainties. Fuzzy logic offered real-time adjustments [9], while neural networks with reinforcement learning allowed autonomous adaptation and control strategy refinement [11]. By the early 2020s, optimization algorithms such as the Grey Wolf Optimizer (GWO) became increasingly popular for enhancing controllers like PID, SMC, and Backstepping [12], leading to notable improvements in trajectory tracking and resilience to environmental disturbances.

This study pioneers the application of the Pelican Optimization Algorithm (POA) in quadcopter control, integrating it with the Backstepping approach alongside the Grey Wolf Optimizer (GWO) [13] to enhance efficiency and robustness under dynamic conditions, particularly in response to wind disturbances [14]. As the first work globally to employ POA for UAV control, this research provides new insights into adaptive control strategies for quadcopters, demonstrating the algorithm's potential for optimizing performance in complex, real-world scenarios.

Quadrotor dynamics

The quadrotor dynamics model in this study is structured to comprehensively capture the vehicle's six degrees of freedom (6-DOF) in both linear and rotational motions. Specifically, this 6-DOF model accounts for the quadrotor's linear displacements along the x, y, and z axes and its rotational behaviour through roll, pitch, and yaw angles [15][19]. Designed with an X-configuration, the quadrotor's four rotors operate in a counter-balancing arrangement: two rotors (M1 and M3) rotate clockwise, while the remaining two (M2 and M4) rotate counter way. This setup allows for precise control over critical manoeuvres, including vertical take-off, landing, and directional adjustments [15][16][20]. The model integrates a dual-coordinate system framework to ground its dynamics accurately in space. At the core, a local coordinate system cantered at the quadrotor's center of gravity is used for relative movement, while a global Earth-Fixed (EF) frame -aligned with the X, Y, and Z axes- provides a stable reference for absolute orientation [15][16].

The vehicle's posture is represented in this global frame using Euler angles (φ for roll, θ for pitch, and ψ for yaw), along with a rotation matrix $Rxyz$, which jointly describe its 3D orientation in space [16][17][21].

$$Rxyz = \begin{bmatrix} Cs\,\psi\, Cs\,\theta & Cs\,\psi\, Sn\,\phi\, Sn\,\theta - Cs\,\phi\, Sn\,\psi & Sn\,\phi\, Sn\,\psi + Cs\,\phi\, Cs\,\psi\, Sn\,\theta \\ Cs\,\theta\, Sn\,\psi & Sn\,\phi\, Sn\,\psi\, Sn\,\theta + Cs\,\phi\, Cs\,\psi & Cs\,\phi\, Sn\,\psi\, Sn\,\theta - Cs\,\psi\, Sn\,\phi \\ -Sn\,\theta & Cs\,\theta\, Sn\,\phi & Cs\,\phi\, Cs\,\theta \end{bmatrix} \quad (1)$$

Where: Cs = Cos, and Sin = Sn.

While previous studies [17] primarily focus on acceleration in the 6-DOF quadrotor model, they often overlook velocity. In response, this research develops a nonlinear model that integrates both acceleration and velocity vectors for a more precise representation as shown in equation 2. Using the Euler-Newton framework, we derive nonlinear equations (2, 3, 4 and 5) that describe the 3D motion of the 6-DOF system.

$$(2)\quad \begin{cases} \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix} = [Rotxyz] \begin{bmatrix} u \\ v \\ w \end{bmatrix} \\ \begin{bmatrix} \dot{u} \\ \dot{v} \\ \dot{w} \end{bmatrix} = \begin{bmatrix} 0 & r & -q \\ -r & 0 & p \\ q & -p & 0 \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix} + g \begin{bmatrix} -\sin\theta \\ \sin\phi\cos\theta \\ \cos\phi\cos\theta \end{bmatrix} + \frac{1}{m} \begin{bmatrix} f_{wx} \\ f_{wy} \\ f_{wz} - f_t \end{bmatrix} \\ \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \dfrac{\sin\phi}{\cos\theta} & \dfrac{\cos\phi}{\cos\theta} \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \\ \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} \dfrac{I_y - I_z}{I_x} \\ \dfrac{I_z - I_x}{I_y} \\ \dfrac{I_x - I_y}{I_z} \end{bmatrix} \begin{bmatrix} rq \\ pr \\ pq \end{bmatrix} + \begin{bmatrix} \dfrac{1}{I_x} u_2 \\ \dfrac{1}{I_y} u_3 \\ \dfrac{1}{I_z} u_4 \end{bmatrix} \end{cases}$$

Control Methods of System

This research employs a state-space framework to rigorously model the quadrotor's dynamic response, where differential equations serve to interconnect system inputs, outputs, and state variables. Defined within an inertial frame, this approach encapsulates the quadrotor's state vector, supporting the detailed dynamic formulation presented in Equation (3). Key inertial coefficients -denoted as a_1, a_2, and a_3- wish the inertia is mentioned by I_x, I_y and I_z, describe fundamental mass properties along the primary axes, while J_r quantifies the rotor's inertia around the z-axis. Orientation transfer functions further refine control over stability and spatial orientation, enabling adaptive response across varying operational conditions [18].

$$(3)\quad \begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = a_1 x_4 x_6 + b_1 u_2 \\ \dot{x}_3 = x_4 \\ \dot{x}_4 = a_4 x_2 x_6 + b_2 u_3 \\ \dot{x}_5 = x_6 \\ \dot{x}_6 = a_3 x_2 x_4 + b_3 u_4 \\ \dot{x}_7 = x_8 \\ \dot{x}_8 = \dfrac{\cos(x_1)\cos(x_2)}{m} U_{1-g} \\ \dot{x}_9 = x_{10} \\ \dot{x}_{10} = \dfrac{U_y}{m} U_1 \\ \dot{x}_{11} = x_{12} \\ \dot{x}_{12} = \dfrac{U_x}{m} U_1 \end{cases}$$

Where: $\begin{cases} a_1 = {}^{I_y - I_z}/_{I_z},\ a_2 = {}^{I_z - I_x}/_{I_y},\ a_3 = {}^{I_x - I_y}/_{I_z} \\ b_1 = \frac{d}{I_x},\ b_2 = \frac{d}{I_y},\ b_3 = \frac{d}{I_z} \end{cases}$

And: $\begin{cases} U_x = \cos(x_1)\cos(x_3)\cos(x_5) + \sin(x_1)\sin(x_5) \\ U_x = \cos(x_1)\sin(x_3)\sin(x_5) - \sin(x_1)\cos(x_5) \end{cases}$

A. Backstepping Controller

Backstepping control is a recursive design method that structures the control of a complex system by breaking it down into smaller, manageable subsystems. For the quadcopter, each subsystem is assigned a specific control law, starting with primary elements such as roll, pitch, and yaw angles, followed by positional controls in the X, Y, and Z axes. Using Lyapunov functions, stability is assessed and ensured at each stage, allowing for a comprehensive control law that governs the entire system. This layered approach enables precise handling of the quadcopter's dynamics, making it well-suited for systems with nonlinearities and external disturbances. Following this framework, equation (2) and based on the work of Bouziane G, et al [18], we find:

$$(4)\quad \begin{cases} \text{Angle } \varphi: U_2 = \frac{1}{b1}[\varepsilon_1 - k_1 x_2 - a_1 x_4 x_6 + k_2 \varepsilon_2] \\ \text{Angle } \theta: U_3 = \frac{1}{b2}[\varepsilon_3 - k_3 x_4 - a_3 x_2 x_6 + k_4 \varepsilon_4] \\ \text{Angle } \psi: U_4 = \frac{1}{b3}[\varepsilon_5 - k_5 x_6 - a_5 x_2 x_4 + k_6 \varepsilon_6] \\ \text{Position Z}: U_1 = \frac{m}{\cos(x_1)\cos(x_2)}[-\varepsilon_7 + g - k_7 x_8 - k_8 \varepsilon_8] \\ \text{Position Y}: U_y = \frac{m}{U_1}[-\varepsilon_9 - k_9 x_{10} - k_{10} \varepsilon_{10}] \\ \text{Position X}: U_x = \frac{m}{U_1}[-\varepsilon_{11} - k_{11} x_{12} - k_{12} \varepsilon_{12}] \end{cases}$$

B. Grey Wolf Optimization

The Grey Wolf Optimization (GWO) Algorithm represents a meta-heuristic optimization method introduced by Mirjalili et al. in 2014 [23]. Inspired by the hierarchical social structure and cooperative hunting techniques of grey wolves, GWO mimics their behavior through stages such as tracking, encircling, and attacking prey. Wolves are organized into ranks -Alpha, Beta, Delta, and Omega- that mirror their real-life roles within the pack. This hierarchy is integral to the algorithm's functionality, where the Alpha represents the best current solution, with Beta and Delta supporting the guidance process [23][24]. The algorithm operates through distinct phases:

- Searching for Prey: Wolves spread out based on the positions of Alpha, Beta, and Delta, which diversifies the search across the solution space [25].
- Encircling the Prey: Using specific equations, each wolf's position is adjusted in relation to the target, simulating an encircling behavior.
- Attacking the Prey: Wolves converge on the prey, symbolizing the optimization of the final solution [23].

In this research, GWO is used to optimize the backstepping control of a quadcopter, aiming to improve its tracking precision and resilience against environmental disturbances [26][27][28]. The following is the pseudo code for GWO algorithm [23]:

Initialize the grey wolf population $\vec{X_i}\ (i = 1, 2, \dots, n)$
Initialize α, A and C
Calculate the fitness of each search agent
X_α *= the first best search agent*
X_β *= the second best search agent*
X_δ *= the third best search agent*
while *(t < Max number of iterations)*
for *each search agent*
Update the position of current search agent
end for
Update α, A and C
Calculate the fitness of each search agent

```
Update X_α, X_β and X_δ
t = t + 1
end while
return X_α
```

C. Pelican Optimization Algorithm

The Pelican Optimization Algorithm (POA) is a nature-inspired meta-heuristic optimization technique, modeled on the cooperative hunting behavior of pelicans. In nature, pelicans often hunt in groups, using synchronized movements and strategy to locate, encircle, and catch fish. POA translates this cooperative strategy into an optimization framework by simulating stages of exploration and convergence. The algorithm's "pelicans" represent agents in the solution space, dynamically adjusting their positions based on both individual and collective experiences to locate optimal solutions. The algorithm operates in two main stages:

- Encircle: In this stage, pelicans in the algorithm spread out across the search space and adjust their positions to "encircle" potential optimal solutions.
- Catch Fish: Once the solution space is sufficiently narrowed, the pelicans converge to capture the optimal solution, analogous to the act of catching fish.

This balance between exploration and exploitation enables POA to handle complex, multi-dimensional problems effectively, making it applicable in fields requiring high precision and adaptability, such as robotics, control systems, and engineering optimization.

```
Initialize the pelican population Xi (i = 1, 2, ..., n)
Initialize parameters for exploration and convergence
Calculate the fitness of each pelican
Identify the top − performing pelicans as leaders
while (t < Max number of iterations)
  # Step 1: Exploration and Encircling
  for each pelican (agent)
    if (exploration phase)
    Move the pelican to explore the search space broadly
    else if (encircling phase)
    Adjust the pelican's position to converge towards the
    leader positions, simulating group coordination
    endif
  endfor
  # Step 2: Updating Leaders
  Calculate the fitness of each pelican
  Reevaluate and update the leader positions based on
     the best solutions found in this iteration
  Gradually shift parameters to transition from
     exploration to convergence
  t = t + 1
end while
return the best solution found
```

Simulation, Results and discussion

This research investigates the effectiveness of enhanced backstepping controllers for precise trajectory tracking in drones, comparing a conventional backstepping controller with controllers optimized using the Grey Wolf Optimizer (GWO) and the Pelican Optimization Algorithm (POA).

The drone dynamics were modeled and simulated in MATLAB 2021a, with initial tests conducted on two distinct trajectory paths. To establish a baseline, the performance of a standard backstepping controller was first evaluated, and then compared to both GWO- and POA-enhanced controllers. Table 1 outlines the parameters of the proposed quadcopter model, the design specifications for the Backstepping controller aimed at ensuring precise trajectory tracking, and the configuration adjustments optimized by the GWO to minimize disturbance impact to the fullest extent.

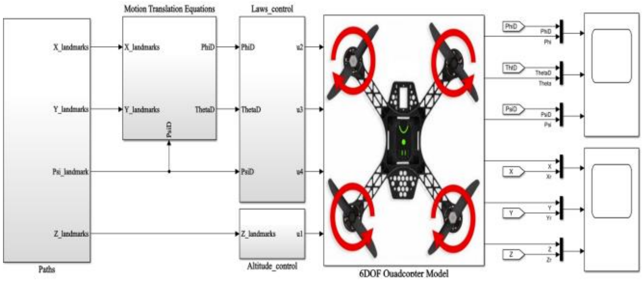

Fig. 1. Simulation bloc for 6DOF Quadcopter using backstepping controller [18].

Table 1. Parameters of Quadcopter and Controller

Type	Parameters	Units
X moment of inertia	I_{xx}	2.2 x 10^{-2} kg.m²
Y moment of inertia	I_{yy}	2.2 x 10^{-2} kg.m²
Z moment of inertia	I_{zz}	4.39 x 10^{-2} kg.m²
Distance to center	*l*	2.25 x 10^{-6} m
Acceleration Gravity	*g*	9.81 m/s²
Quad Mass	*m*	0.18 kg
Drag factor	*d*	1
Comment Algorithms	*Dimension*	3
Grey Wolf Optimization Parameters	*Max Wolves*	50
	Iteration's	100
Pelican Optimization Algorithm Parameters	*Max Pelicans*	50
	Iteration's	100
	Upper Bounds	50
	Lower Bounds	1

In the first trajectory test, a conical path in the XY and Z axes, the standard backstepping controller exhibited significant tracking errors, particularly along the Z-axis during the transient phase, as well as in the X and Y axes within the first few seconds. The GWO-enhanced controller improved tracking precision but still displayed minor errors across the Z, X, and Y axes. In contrast, the POA-optimized controller demonstrated superior accuracy, closely aligning with the reference trajectory across all dimensions. The results shown in figure 2 and 3.

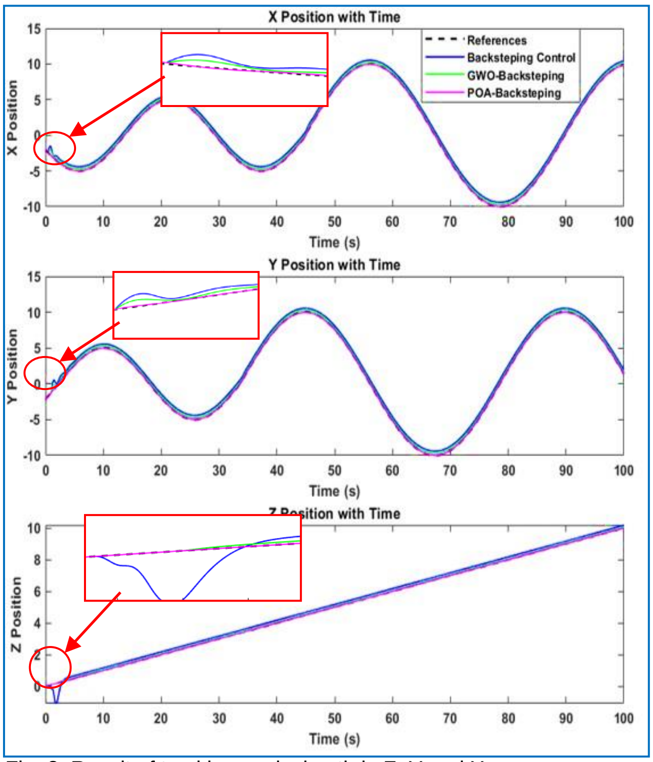

Fig. 2. Result of tracking conical path in Z, Y and X axes

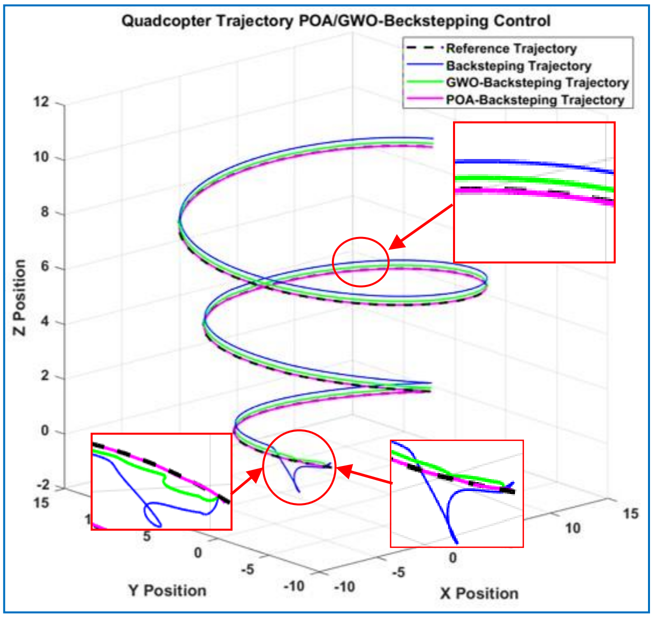

Fig. 3. 3D Quadcopter Tracking Trajectory: Conical Path

For the second test, which followed a helical path, similar trends were observed. As mentioned in following figures (Fig 4 and Fig 5) this time, the GWO-enhanced controller displayed slightly weaker performance, with minor inconsistencies in tracking accuracy. In contrast, the POA-optimized controller consistently outperformed both the standard and GWO-enhanced controllers, demonstrating superior adherence to the desired trajectory and greater stability throughout the path.

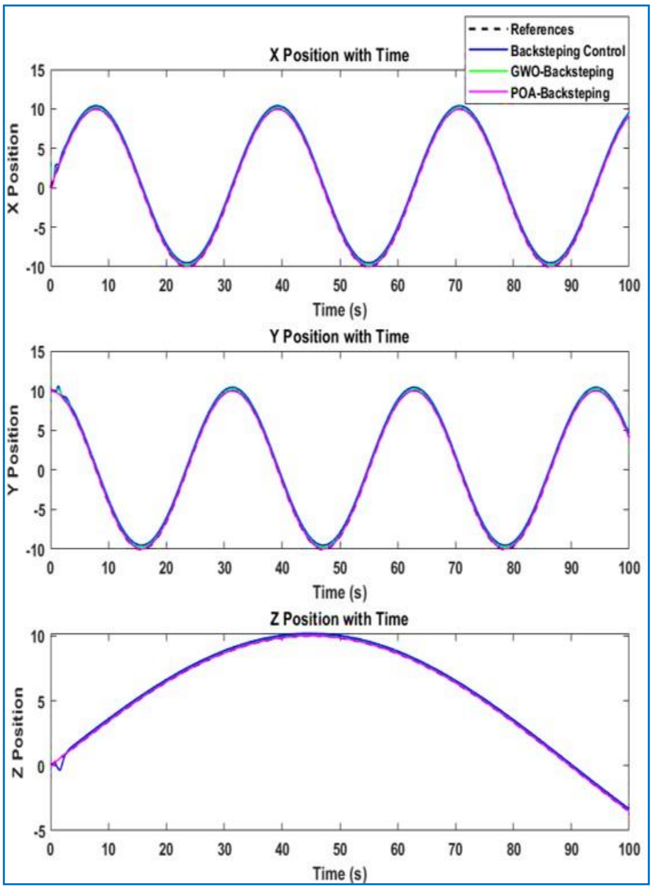

Fig. 4. Result of tracking helical path in Z, Y and X axes

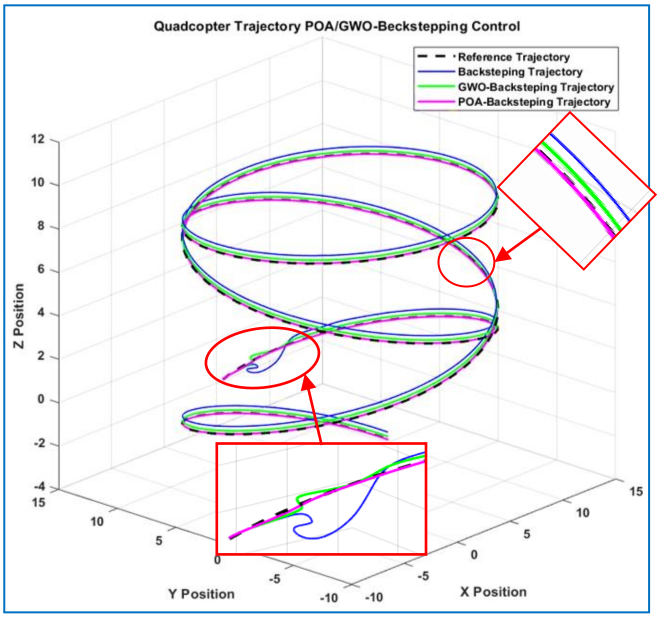

Fig. 5. 3D Quadcopter Tracking Trajectory: Helical Path

In a subsequent phase of the evaluation, wind disturbances were introduced as step of 5 at the 30-second mark to assess robustness under environmental challenges. Across both trajectory paths, the standard backstepping controller experienced substantial deviation upon the introduction of wind, while the GWO-enhanced controller displayed better resilience but still deviated slightly. The POA-optimized controller, however, maintained close alignment with the reference paths despite the wind disturbance, showcasing exceptional robustness in trajectory tracking. These results underscore the benefits of incorporating POA into the backstepping control framework, demonstrating its superior effectiveness compared to both the standard and GWO-optimized controllers for managing dynamic environmental disturbances and ensuring precise trajectory tracking.

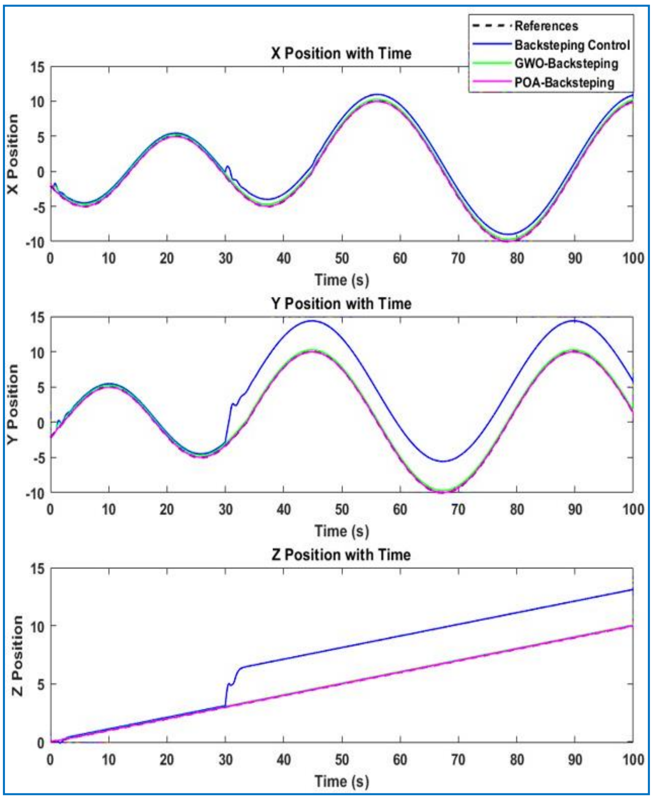

Fig. 6. Quadcopter's conical path in windy environment

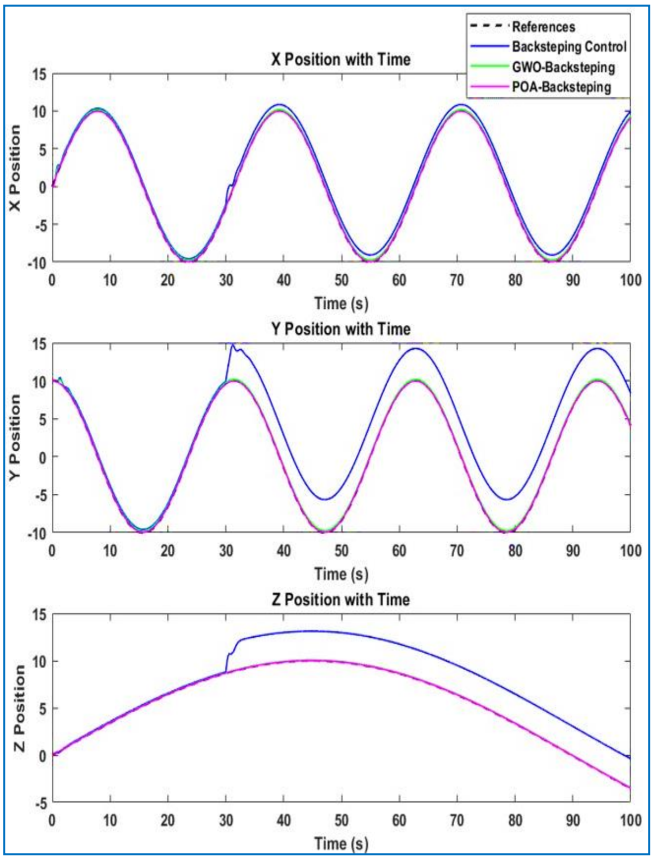

Fig. 7. Quadcopter's Helical path in windy environment

Figures 6, 7, 8, and 9 clearly demonstrate the POA-optimized controller's superior performance over both the standard and GWO-enhanced controllers. In each trajectory test, the POA achieves notably higher tracking accuracy, minimized error margins, and improved resilience under disturbance conditions. The outcomes presented in these figures affirm the POA's effectiveness in significantly enhancing trajectory stability and robustness, setting it apart as the most reliable control method in dynamic and challenging environments

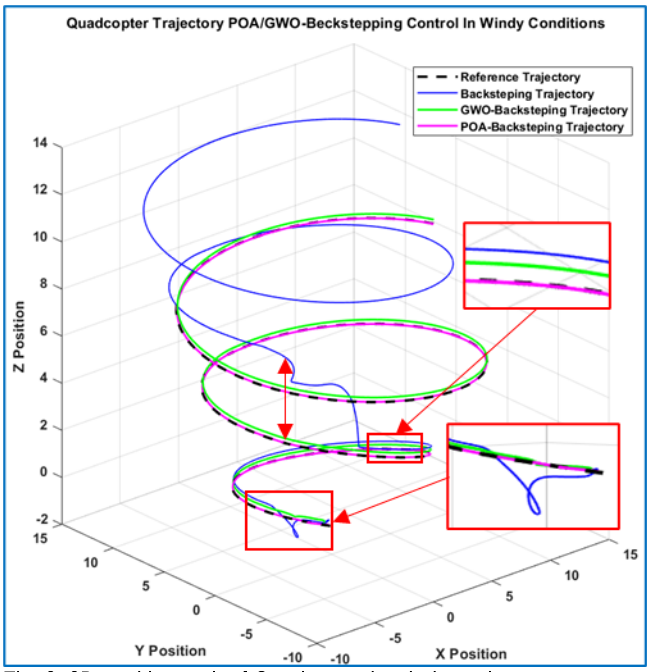

Fig. 8. 3D tracking path of Quadcopter in windy environment: Conical path

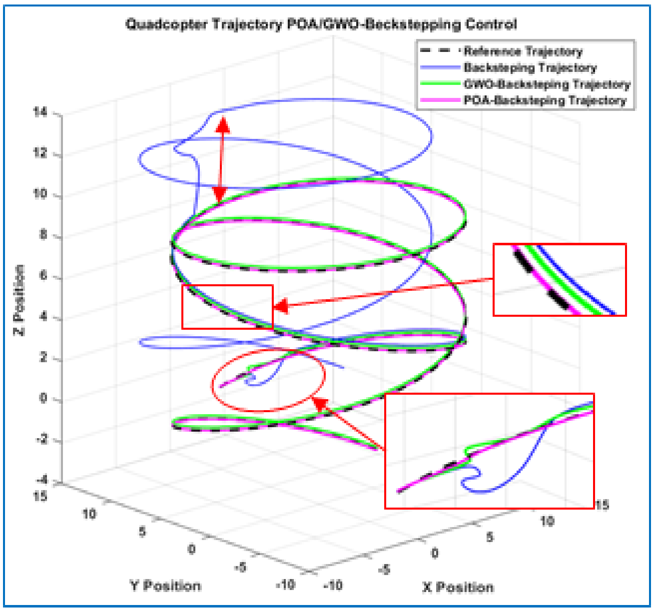

Fig. 9. 3D tracking path of Quadcopter in windy environment: Helical path

Conclusion

In this study, we developed an advanced control framework for quadcopter trajectory tracking by evaluating the effectiveness of both Grey Wolf Optimizer (GWO)- and Pelican Optimization Algorithm (POA)-enhanced backstepping controllers. Starting with baseline tests using a standard backstepping controller, we observed its limitations in tracking accuracy and robustness, particularly under external disturbances. The GWO-enhanced controller demonstrated improved stability and precision but showed minor tracking errors under complex trajectory conditions and disturbance scenarios. Our comparative analysis highlighted the POA-optimized controller as the superior solution, consistently outperforming both the standard and GWO-enhanced controllers across all trajectory tests. The POA demonstrated robust resilience against wind disturbances, minimized error in tracking both conical and helical paths, and exhibited exceptional stability, as evidenced in Figures 6 through 9. These findings validate the POA's effectiveness in enhancing the backstepping control framework, establishing it as the most reliable option in complex and dynamic environments.

Future work will explore advanced control strategies, including MPC-backstepping, Neural-MPC, and Neural-backstepping frameworks, with the aim of further optimizing trajectory tracking. Integrating neural networks and model predictive control (MPC) promises even greater adaptability and precision, potentially yielding new results that push the boundaries of UAV control. This research not only confirms the POA's current advantages but also lays the groundwork for these next-generation methodologies, contributing a significant advancement to UAV control systems.

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