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Hybrid metaheuristic NNHGS algorithm for PID controller tuning in UAVs

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Abstract. Controller tuning for unmanned aerial vehicles (UAVs) is a challenging task due to their nonlinear and coupled dynamics. This study validates the hybrid Neural-Network Hunger Games Search (NNHGS) algorithm, which integrates a Kohonen neural network with the Hunger Games Search (HGS) metaheuristic to dynamically adapt the search space during optimization. The proposed method is applied to optimize the PID controller parameters for UAV trajectory-tracking. Simulation results demonstrate that NNHGS converges faster and achieves lower root-mean-square error (RMSE) than the conventional HGS algorithm. Moreover, the optimized PID controller significantly reduces oscillations and improves trajectory-tracking accuracy, including under abrupt trajectory changes. The adaptive search capability provided by the Kohonen network enhances the exploration–exploitation balance, leading to more robust and efficient optimization. These findings confirm the effectiveness of NNHGS as a reliable approach for improving PID controller tuning and enhancing the performance, robustness, and tracking accuracy of UAVs in nonlinear operating conditions.
Keywords: Metaheuristics algorithms, Neural networks, Hunger Games Search Algorithm, Unmanned aerial vehicles.

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1 Introduction

Given its nonlinear nature and complexity, engineering systems are capable of showing unexpected behaviour or unwanted behavior. Nonetheless, research on nonlinear systems has made great contributions to various areas in energy, biology (Janson, 2012), medicine, robotics (Chen & Lin, 2005) and materials science (Brzozowski & Sargent, 2007). Engineering systems, beyond nonlinearity, tend to exhibit coupled dynamics, underactuation, and even chaotic behavior (Abu Arqub et al., 2023; Abu Arqub & Abo-Hammour, 2014), like the situation concerning Unmanned Aerial Vehicles (UAVs).

UAVs are extensively used in recreational, commercial, military, medical, educational, and research applications (Fan et al., 2020). Although their dynamics can be complex, their simple mechanical structure and accurate positioning have paved their success in the industrial and academic practice (Mohsan et al., 2023).

Among other challenges that UAVs face, trajectory tracking is one of the most important challenges, since it is essential to ensure that the task gets executed reliably (Mohsan et al., 2023). Design of controller involves finding a set of parameters that have a direct impact on the system performance. This is typically defined as a constrained optimization problem. The nature-inspired population-based optimization algorithms have proven to be quite effective for tuning controller parameters (Zuñiga-Peña et al., 2022; Zuñiga-Peña et al., 2024; Charkoutsis & Kara-Mohamed, 2023; Inomoto et al., 2024). These optimization methods provide the identification of controller parameters which reduce the trajectory tracking error and promote peak UAV efficiency.

For most population-based optimization algorithms, an existing knowledge of the system is essential to come up with a search space which limits the candidate solutions. Nevertheless, very nonlinear systems like UAVs have uncertain system behaviour that leads to difficulty to define proper search limits. Consequently, there is no assurance that a defined search space contains the optimal controller parameters for optimizing dynamic performance.

Recent studies confirm that neural networks can guide metaheuristic algorithms to the best areas of the problem space and accelerate convergence. Cuevas et al. (2024) added a Radial Basis Function Neural Network (RBFNN) into a metaheuristic optimizer. With each iteration, the RBFNN starts to discover the best optimal solutions, ensuring an optimization that generates better results with fewer objective function test cases to implement. Similarly, Barros-Everett et al. (2025) utilized an artificial neural network to predict population size, crossover rate, mutation rate, as well as other parameters needed for optimization. In their trained model, they get around the optimal parameters configurations and avoid the cost of manual fine-tuning, which can bring about considerable computational hassle.

In previous work however, the parameters of PID and PD controllers of a UAV were optimized using various population-based metaheuristic algorithms such as PSO (Particle Swarm Optimization), GWO (Grey Wolf Optimizer), HGS (Hunger Games Search), LSHADE, LSPACMA, MPA (Marine Predators Algorithm), SMA (Slime Mould Algorithm) and WOA (Whale Optimization Algorithm). HGS achieved the lowest trajectory-tracking Root Mean Square Error (RMSE) among the eight optimization methods analyzed which makes it the most effective optimizer. In addition, Zuñiga-Peña et al. (2024) simulated and experimentally evaluated performance of a Super-Twisting Sliding Mode Controller (STSMC) and PID controller. Their results showed that the STSMC delivered superior disturbance rejection, while the PID controller had diminished performance for the same operating conditions.

Recently, Zuñiga-Peña et al. (2025) incorporated the neural network in the HGS algorithm to automatically shape the search space and parameters of the STSMC controller of the UAV for payload transportation. This paper develops this work by applying the Neural Network Hunger Games Search (NNHGS) algorithm to further validate the algorithm and performance on the optimization parameters of PID controllers in an unloaded UAV trajectory-tracking system.

2 Implementation of the NNHGS Algorithm for PID Controller Parameter Tuning in a UAV

The hybridization of neural network and metaheuristic algorithmic approach is reported in Zuñiga-Peña et al. (2025). The process involves a neural network to automatically reconfigure the search space of the Hunger Games Search (HGS) algorithm.

Figure 1 shows the flowchart of the NNHGS algorithm. All parameters for the algorithm are initialized (population size, problem dimension, upper and lower values of the search space bounds and positions of all individuals at each moment in time). The solution of the optimization problem is then given by using the current position for each individual. The main difference between NNHGS and the traditional HGS takes place in the next phase, in which the search space is actively modified during the NNHGS model via Kohonen neural network. Whereas the known HGS generates potential solution for candidate problems only in the chosen search space. Then the hunger parameters are updated, and the change per individual's position is calculated for later iteration. Positions of individuals are updated based on the best solution found, and finally, the stopping criterion is checked using a comparison between the current iteration number and the maximum number of iterations.

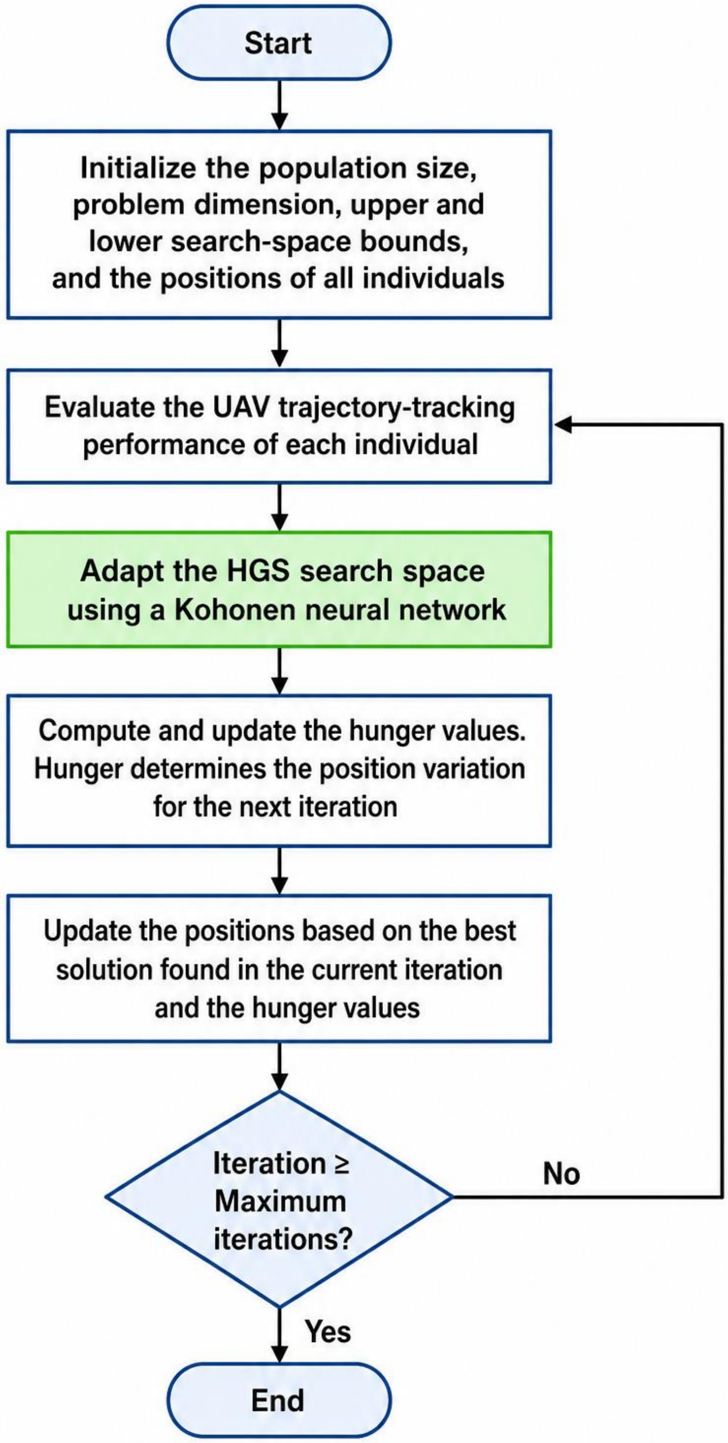

Fig. 1. Flowchart of the NNHGS Algorithm.

After the operation of the NNHGS algorithm is described, we present in Figure 2 the process for fine-tuning PID controller parameters in monitoring UAV trajectory. First, the HGS algorithm generates a set of random candidate solutions representing the PID controller gains. The controller calculates the control signals, which it applies to a UAV model for operation. The controller's performance can then be measured and compared the result of the overall reaction from the system, using the Root Mean Square Error (RMSE) which provides an objective function for the NNHGS algorithm. The optimization process is repeated until the set maximum number of iterations is reached.

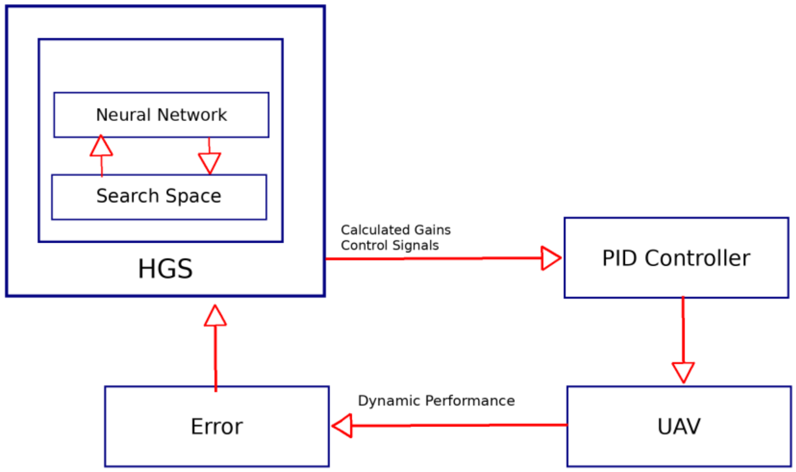

Fig. 2. PID Controller Parameter Optimization Process Using the NNHGS Algorithm.

The optimization parameters are for the PID controller gains for six controlled dynamics.

$$\boldsymbol{P} = \{k_{px}, k_{ix}, k_{dx}, k_{py}, k_{iy}, k_{dy}, k_{pz}, k_{iz}, k_{dz}, k_{p\phi}, k_{i\phi}, k_{d\phi}, k_{p\theta}, k_{i\theta}, k_{d\theta}, k_{p\psi}, k_{i\psi}, k_{d\psi}\}. \quad (1)$$

The initial search space for each optimization variable is defined as:

$$S = [0, 10] . \quad (2)$$

The objective function minimized by the NNHGS algorithm is the Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(\chi_d^i - \chi^i)^2} , \quad (3)$$

where N is the number of system dynamics, which in this study is six, as shown in the UAV dynamic model, showed in (4). The quadrotor analyzed in this study utilizes a conventional X-configuration, with four rotors symmetrically positioned at equal distances from the vehicle's center of mass. The nonlinear dynamic model described in Eq. (4) employs the classical Newton–Euler rigid-body formulation, which is extensively documented in the literature. This model, based on the approach introduced by Bouabdallah and subsequent studies, incorporates parameters such as vehicle mass m, gravity g, principal moments of inertia I_x, I_y, I_z and Aerodynamic friction coefficients $k_1, k_2, \dots, k_6$ (Zuñiga-Peña et al., 2022).

The following assumptions are considered in deriving the mathematical model:

- the quadrotor is modeled as a rigid body;
- the vehicle has a symmetric X configuration;
- the center of mass coincides with the geometric center;
- the propellers are identical;
- aerodynamic interference between propellers, ground effect and wall effect, structural flexibility, actuator dynamics, wind disturbances, and parameter variations are neglected.

The physical parameters used in the simulation are listed in Table 1. In the RMSE equation, χ represents the actual system response, whereas χ_d represents the desired response.

$$
\begin{aligned}
\ddot{x} &= \left(\frac{1}{m}\right)(\cos(\psi)\sin(\theta)\cos(\phi) + \sin(\phi)\sin(\psi))u_1 - \left(\frac{k_1}{m}\right)\dot{x} \\
\ddot{y} &= \left(\frac{1}{m}\right)(\sin(\psi)\sin(\theta)\cos(\phi) - \sin(\phi)\cos(\psi))u_1 - \left(\frac{k_2}{m}\right)\dot{y} \\
\ddot{z} &= \left(\frac{1}{m}\right)(\cos(\phi)\cos(\theta))u_1 - g - \left(\frac{k_3}{m}\right)\dot{z} \\
\ddot{\phi} &= \left(\frac{I_y - I_z}{I_x}\right)\dot{\theta}\dot{\psi} - \left(\frac{k_4}{I_x}\right)\dot{\phi}^2 + \frac{u_2}{I_x} \\
\ddot{\theta} &= \left(\frac{I_z - I_x}{I_y}\right)\dot{\phi}\dot{\psi} - \left(\frac{k_5}{I_y}\right)\dot{\theta}^2 + \frac{u_3}{I_y} \\
\ddot{\psi} &= \left(\frac{I_x - I_y}{I_z}\right)\dot{\phi}\dot{\theta} - \left(\frac{k_6}{I_z}\right)\dot{\psi}^2 + \frac{u_4}{I_z}
\end{aligned}
\tag{4}
$$

Table 1. Physical Parameters of the UAV Used in the Simulation.

Parameter	Value
Mass	$0.4\ kg$
Moments of inertia	$I_x = I_y = 0.005, I_z = 0.010$
Translational drag coefficients	$k_{1,2,3} = 5.56\ x\ 10^{-4}$
Aerodynamic friction coefficients	$k_{4,5,6} = 0.3729$
Gravitational acceleration	$9.81\ m/s^2$

The proposed controller follows a cascaded PID architecture composed of an outer-loop position controller and an inner-loop attitude controller. The outer loop generates the control input $\boldsymbol{u_1}$ and the desired attitude references ($\boldsymbol{\emptyset_d}, \boldsymbol{\theta_d}$), whereas the inner loop computes the control inputs $\boldsymbol{u_2}, \boldsymbol{u_3}$, and $\boldsymbol{u_4}$, which are applied to the nonlinear quadrotor model. The complete implementation of this architecture is described in detail in our previous work (Zuñiga-Peña et al., 2022).

3 Results and Discussion

So as to validate the performance of the proposed NNHGS algorithm, the PID controller optimization process parameters are compared with conventional HGS. We optimized controller gains defined in Equation (1) with both algorithms and the resulting parameters are listed in Table 2. Although the derivative gains obtained by the proposed optimization algorithm may appear relatively small, they represent the parameter set that minimizes the selected objective function for the operating conditions considered in this study. Since PID tuning constitutes a multi-objective optimization problem, various combinations of controller gains may yield comparable closed-loop performance. Moreover, the optimal gains typically depend on the flight regime and operating conditions. Therefore, alternative operating regions may require different PID parameters, as is commonly addressed through gain scheduling and adaptive tuning strategies (Lopez-Sanchez & Moreno-Valenzuela, 2023).

The initial search space for all PID parameters was defined as [0, 10], representing a sufficiently broad positive interval to initialize the optimization without requiring prior knowledge of the optimal controller gains. This interval serves only as the initial search domain. Unlike conventional metaheuristics, as HGS, the proposed NNHGS algorithm dynamically adapts and expands the search space whenever more promising solutions are identified outside the initial bounds. Such is the case with this experiment, climbing to as high as 23.5157. Consequently, the final optimized gains are not restricted by the initial interval, making the proposed approach less sensitive to the initial definition of the search domain.

Figure 3 summarizes convergence behavior of HGS and NNHGS over 50 iterations, for a population of 100 individuals, and a single optimization run. The NNHGS algorithm converges faster, and achieves a lower objective function value compared to a conventional HGS algorithm. In comparison to NNHGS algorithm which resulted in a minimum RMSE of 0.0886, HGS obtained a minimum RMSE of 0.1452.

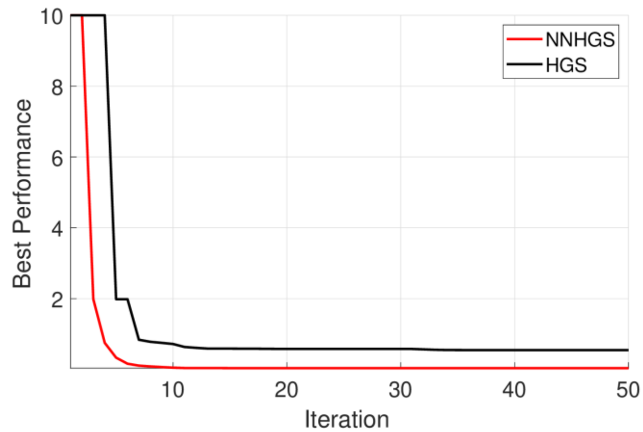

Fig. 3. Convergence Performance of the HGS and NNHGS Algorithms Over 50 Iterations.

The responses for the six UAV dynamics under Equation (4) are shown in Figures 4–9. Figures 4 and 5 depict the translational movement of the UAV as it maneuvers based on a reference direction trajectory with drastic turns in orientation, making the tracking task much more difficult. While both optimized PID controllers can effectively control the trajectory of the UAV, the PID controller tuned with the NNHGS algorithm has lower oscillatory frequency and smaller tracking error compared to that optimized with the HGS algorithm.

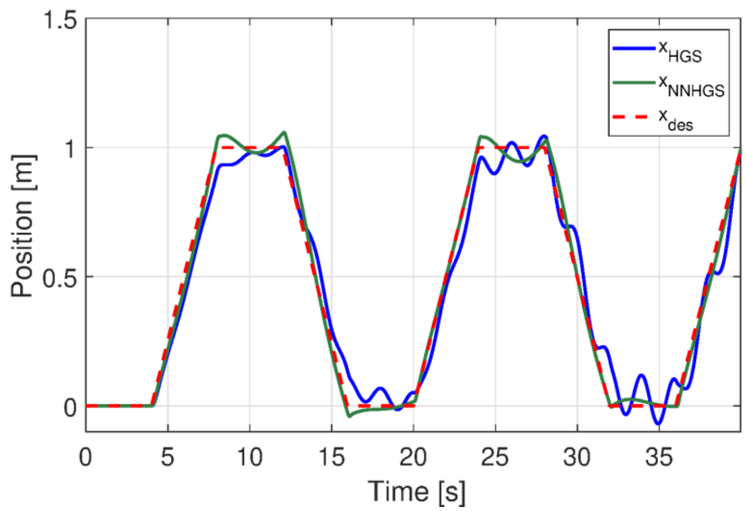

Fig. 4. UAV Trajectory Tracking Along the X-Axis.

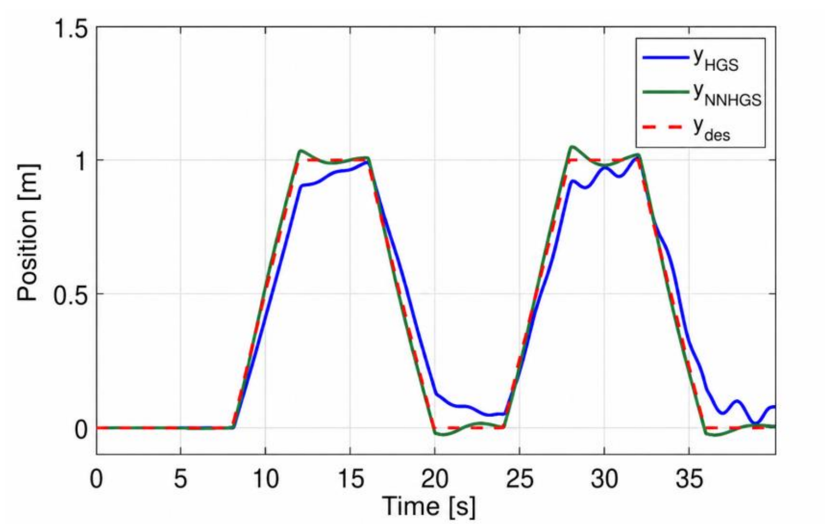

Fig. 5. UAV Trajectory Tracking Along the X-Axis.

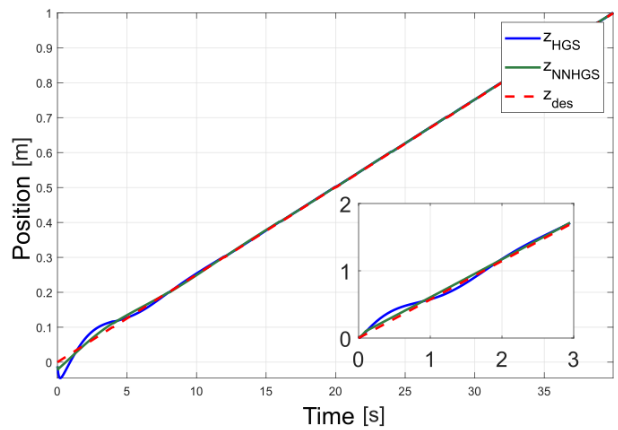

Fig. 6. UAV Trajectory Tracking Along the X-Axis.

As the altitude behavior is depicted in Figure 6, we can see that the trajectory derived from the NNHGS-based controller has lower amplitude oscillations than those produced by the controller optimized by the HGS algorithm. The attitude dynamics of the UAV are shown in Figures 7–9. The roll and pitch angles, in whose direction, are presented in Figures 7 and 8, being transient peaks generated by the rapid transformation of the translational dynamics. For the two variables (ϕ and θ), an overshoot due to the direction changes in the directions is seen in both (ϕ and θ).

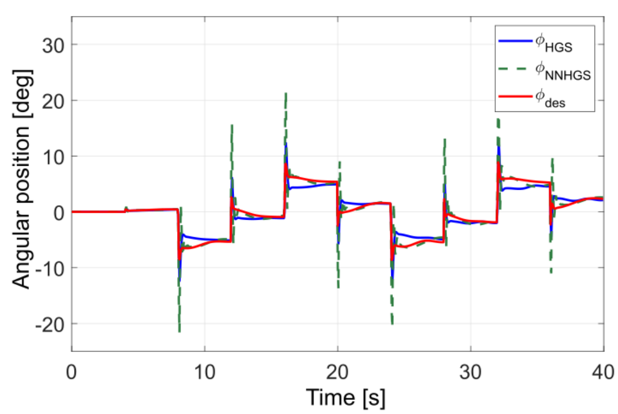

Fig. 7. UAV Attitude Response in the Roll Angle (ϕ).

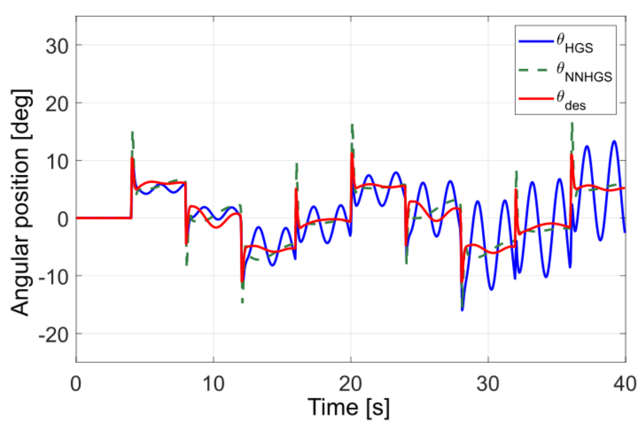

Fig. 8. UAV Attitude Response in the Pich Angle (θ).

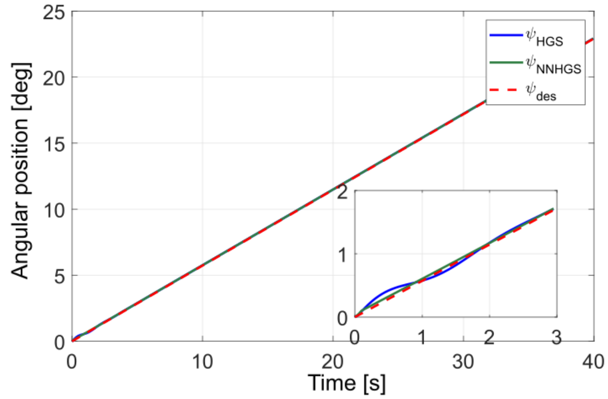

Fig. 9. UAV Attitude Response in the Pich Angle (Ψ).

While the NNHGS based controller generates a little bit more of an overshoot than HGS controller overshoot, the tracking error for the rest of the trajectory is kept small by the non-linear NNHGS using the controller. Figure 9 presents the yaw-angle response with the similar yaw-angle response in both regions where, as per state variables before, the NNHGS optimized controller is found to provide smaller tracking errors than the HGS-based controller.

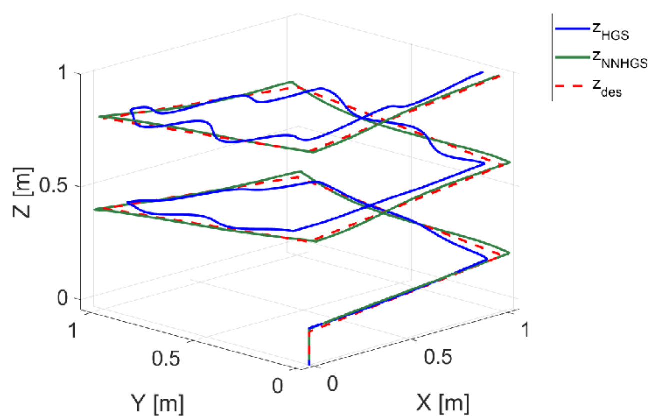

Fig. 10. Three-Dimensional Trajectory Tracking Performance of the UAV.

We can see the translational trajectories in terms of three-dimensional space (see Figure 10). The performance of the PID controller tuned using the proposed NNHGS algorithm outperforms that of the HGS-optimized and yields lower trajectory-tracking error overall.

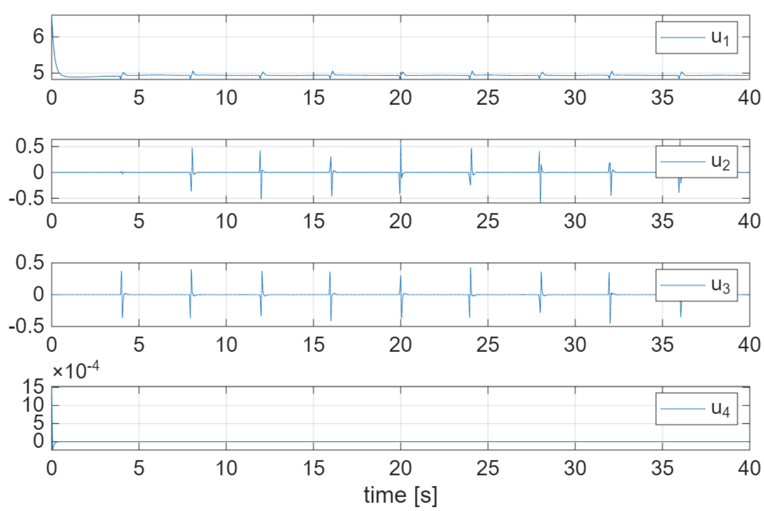

Fig. 11. Control-input signals generated by the optimized PID controller using NNHGS during the trajectory-tracking task.

Finally, Figure 11 shows the control inputs generated by the optimized NNHGS-PID controller. The collective thrust (u_1) rapidly converges to its steady-state value required to balance the vehicle weight, while the torque control inputs (u_2, u_3 , and u_4) remain close to zero except during reference changes, where short transient corrections are produced to achieve the desired attitude and trajectory tracking. Although the optimization objective only minimizes the tracking error, the resulting control signals remain bounded and do not exhibit excessive control effort under the simulated operating conditions.

Table 2. PID Controller Parameters Obtained Using the HGS and NNHGS Algorithms.

Dynamics	Parameter	PID + HGS	PID + NNHGS
x	kp	3.5459	11.2957
	ki	6.6104	10.0094
	kd	0.0430	10.0095
y	kp	2.2957	10.0095
	ki	6.6552	10.0095
	kd	0.1117	22.5573
z	kp	6.3008	10.0095
	ki	8.3816	23.5157
	kd	7.0435	10.0094
ϕ (Roll)	kp	7.8814	10.0095
	ki	4.2124	17.8811
	kd	5.2233	17.1263
θ (Pitch)	kp	9.1119	0.3830
	ki	0.2998	0.3830
	kd	0.2439	0.0100
ψ (Yaw)	kp	6.1416	10.0095
	ki	1.2908	10.0095
	kd	3.7881	10.0094

4 Conclusions

Finally, we see that the proposed NNHGS algorithm yields better performance in optimizing PID controller parameters for the UAV than the conventional HGS algorithm. Not only does NNHGS achieve faster convergence towards smaller error values, it also dynamically adapts the search space to provide a more exploratory strategy during the optimization process. For the translational dynamics, the NNHGS-optimized PID controller leads to smaller oscillations and trajectory-tracking error than the HGS-optimized controller when tracking trajectories with abrupt direction changes. In a few angles of attitude, slightly larger initial overshoots occur; however, as tracking errors are minimized in subsequent segments, the NNHGS-based controller exhibits better overall accuracy and robustness than the conventional HGS algorithm. In future work, the NNHGS algorithm is to be used to optimize more robust control methods for UAV in a design reducing oscillations and overshoots as seen from control by a conventional PID controller.

Future research will focus on validating the algorithm under external disturbances, parameter uncertainties, and real-time experimental conditions using a physical UAV platform. Additionally, the proposed NNHGS approach will be benchmarked against conventional PID tuning techniques, neural network-based optimization approaches, and other well-established metaheuristic algorithms under equivalent operating conditions and performance criteria. Further investigations will also evaluate the scalability of NNHGS for multi-objective optimization problems, considering simultaneously trajectory-tracking accuracy, control effort, energy consumption, and robustness. These studies are expected to further demonstrate the applicability of the proposed optimization framework to autonomous aerial systems operating in complex and dynamic environments.

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