

Adaptive Neural Network PID Controller for Quadcopter UAVs Trajectory Tracking

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Abstract—Quadcopter unmanned aerial vehicles (UAVs) are widely used in civilian and military missions owing to their vertical takeoff and landing capability, agility, and versatility, yet their practical deployment critically depends on accurate trajectory tracking under wind, payload variations, sensor noise, and other uncertainties. Trajectory tracking control remains challenging because quadcopter dynamics are nonlinear, underactuated, and strongly coupled, which can degrade the performance of conventional proportional–integral–derivative (PID) controllers that typically require extensive manual tuning and may not cope well with rapidly changing operating conditions. This work addresses these limitations by developing an adaptive neural network PID control framework for quadcopter trajectory tracking, with the objective of optimizing PID gains online to enhance tracking accuracy, robustness, and stable flight across diverse scenarios. The methodology comprises 1) establishing a mathematical model of quadcopter UAV dynamics, 2) designing an adaptive neural-network-assisted PID controller to enable real-time gain adaptation, and 3) implementing a controller optimization process to improve disturbance rejection and accommodate model uncertainties. The reported results include a controller performance analysis and an assessment of adaptability across different operating scenarios, positioning the proposed approach within recent advances that integrate neural networks with PID, fuzzy logic, observers, sliding mode control, and optimization algorithms to strengthen robustness and practical deployability. Overall, the study concludes that neural-network-driven gain tuning is a principled pathway to overcoming key shortcomings of fixed-gain PID control for quadcopters, with implications for safer and more reliable autonomous operation in dynamic, uncertain environments and clear opportunities for further validation under computational and hardware constraints.

Keywords—Quadcopter UAV; trajectory tracking; adaptive PID control; neural network

I. INTRODUCTION

Quadcopter unmanned aerial vehicles (UAVs) have become important platforms for civilian and military operations because they can take off and land vertically, hover, maneuver in confined spaces, and carry sensors or payloads. Their applications include aerial photography, infrastructure inspection, environmental monitoring, precision agriculture, mapping, search-and-rescue operations, logistics, and surveillance [1–3]. The successful execution of these missions requires accurate trajectory tracking, which refers to the ability of a UAV to follow a prescribed position, altitude, and attitude trajectory while maintaining stable flight.

Trajectory tracking of quadcopters is challenging because these vehicles are nonlinear, underactuated, strongly coupled,

and sensitive to model uncertainties and external disturbances. A quadcopter has six degrees of freedom but only four independent control inputs generated by its rotors. Consequently, translational motion in the horizontal plane is coupled with roll and pitch dynamics, while altitude and yaw must be controlled simultaneously. In real operating conditions, wind gusts, aerodynamic effects, payload variations, actuator limitations, sensor noise, and uncertainty in mass and inertial parameters can significantly degrade tracking performance [1,2,4–6].

Proportional–integral–derivative (PID) control remains one of the most widely used approaches for quadcopter flight control because of its simple structure, low computational requirement, and ease of implementation [7,8]. PID controllers can provide acceptable performance when the system operates near a nominal condition, and the controller gains are carefully tuned. However, conventional fixed-gain PID controllers may exhibit large overshoots, slow convergence, oscillations, or tracking errors when the quadcopter is exposed to nonlinear dynamics, changing payloads, wind disturbances, or parameter uncertainties [4,7,9]. Moreover, their gains are usually determined through manual trial-and-error tuning, which is time-consuming and may not produce robust performance across different flight scenarios [10,11].

To overcome the limitations of conventional PID control, several offline optimization approaches have been proposed for determining suitable controller gains. Genetic algorithms, particle swarm optimization, differential evolution, and other metaheuristic methods can improve PID tuning by minimizing performance indices such as the integral of absolute error, integral of squared error, or integral of time-weighted absolute error [10–12]. Although these approaches can generate improved initial controller parameters, their main limitation is that optimization is typically performed offline. Therefore, the resulting gains remain fixed during flight and may not adapt adequately to sudden disturbances, payload changes, sensor noise, or time-varying operating conditions.

More advanced control techniques have also been investigated for quadcopter trajectory tracking. These include backstepping control, sliding-mode control, adaptive control, disturbance-observer-based control, fuzzy control, and model predictive control (MPC) [13–18]. Sliding-mode and robust control approaches can provide strong disturbance rejection and robustness against model uncertainty, but they may introduce chattering, complex stability analysis, or additional controller parameters [13,14]. MPC can explicitly consider system constraints and predict future behavior; however, it requires an accurate prediction model and may impose a substantial

computational burden for real-time implementation [17,18]. Similarly, fuzzy and neuro-fuzzy controllers can improve gain adaptation, but their performance depends on the design of membership functions, fuzzy rules, and additional tuning variables [15,16].

Neural-network-based control has emerged as a promising alternative for addressing the nonlinear and uncertain behavior of quadcopter UAVs. Neural networks can learn the relationship between tracking errors, system states, and control actions, enabling online adaptation to changing flight conditions. Earlier studies demonstrated that neural networks can be used to compensate for nonlinearities, approximate unknown dynamics, estimate disturbances, and optimize PID gains for quadcopter control [19–23]. In particular, neural-network PID (NNPID) controllers retain the familiar and interpretable PID structure while incorporating an adaptive mechanism capable of modifying the proportional, integral, and derivative gains according to the instantaneous tracking condition [20–22].

Several neural-network-assisted controllers have been proposed for quadcopter applications. These include artificial-neural-network PID controllers [20,21], fuzzy-neural PID controllers [22,23], radial basis function neural-network controllers [24,25], neural-network-assisted backstepping controllers [26,27], and neural-network-based MPC frameworks [18,28]. These approaches have reported improved tracking accuracy, reduced overshoot, and enhanced disturbance rejection compared with conventional PID controllers. However, many of these methods rely on hybrid structures that combine neural networks with sliding-mode control, fuzzy logic, disturbance observers, adaptive backstepping, or MPC. Although hybrid schemes can improve robustness, they may increase the implementation complexity, number of tuning parameters, computational requirements, and difficulty of interpreting the direct contribution of online PID gain adaptation [13–18,24–28].

Therefore, an important research gap remains in the development of an adaptive NNPID controller that maintains the simplicity and interpretability of a conventional PID controller while providing online and bounded gain adaptation under uncertain flight conditions. Existing studies often emphasize complex hybrid architectures or focus only on a subset of quadcopter states, such as altitude, attitude, or position. There remains a need for a clearly formulated NNPID framework that is evaluated comprehensively for position, altitude, attitude, and three-dimensional trajectory tracking, while also considering disturbances, measurement noise, and parameter variations [21–27].

To address this gap, the present study proposes an adaptive neural-network PID controller for quadcopter trajectory tracking. The proposed controller uses a neural-network learning mechanism to update the PID gains online according to tracking errors and changing flight conditions. Unlike complex hybrid controllers, the proposed framework preserves the basic PID architecture, thereby facilitating implementation and interpretation. The controller is evaluated through position, altitude, attitude, and three-dimensional trajectory-tracking simulations and is compared with a conventional fixed-gain PID

controller. Its robustness is further assessed under the specified disturbance, noise, and parameter-variation conditions.

This study investigates the following hypotheses: 1) the adaptive NNPID controller reduces position and attitude tracking errors compared with a fixed-gain PID controller; 2) the online gain-adaptation mechanism maintains bounded PID gains during trajectory tracking; and 3) the proposed controller preserves acceptable tracking performance under the evaluated disturbance, noise, and parameter-variation scenarios. The remainder of this study is organized as follows. Section II presents the quadcopter model and the proposed adaptive NNPID controller. Section III presents and discusses the simulation results. Finally, Section IV summarizes the main findings, limitations, and directions for future work.

II. DESIGN AND MODELING

A. Dynamic Model of Quadcopter UAV

The quadcopter is a six-degrees-of-freedom aerial vehicle actuated by four rotors arranged in a cross configuration, as illustrated in Fig. 1.

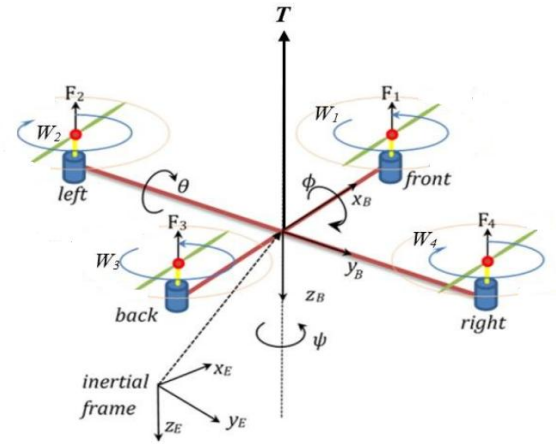


Fig. 1. Quadcopter UAV configuration.

Two reference frames are considered: the inertial frame $\mathcal{F}_I = \{X, Y, Z\}$ and the body-fixed frame $\mathcal{F}_B = \{x_b, y_b, z_b\}$. The translational position of the quadcopter in the inertial frame is defined as

$$\xi = [x \ y \ z]^T \quad (1)$$

while its attitude is described by the Euler-angle vector

$$\eta = [\phi \ \theta \ \psi]^T \quad (2)$$

where, ϕ , θ , and ψ denote the roll, pitch, and yaw angles, respectively. Using the ZYX Euler-angle convention, the rotation matrix from the body frame to the inertial frame is given by

$$R(\phi, \theta, \psi) = \begin{bmatrix} c_\psi c_\theta & c_\psi s_\theta s_\phi - s_\psi c_\phi & c_\psi s_\theta c_\phi + s_\psi s_\phi \\ s_\psi c_\theta & s_\psi s_\theta s_\phi + c_\psi c_\phi & s_\psi s_\theta c_\phi - c_\psi s_\phi \\ -s_\theta & c_\theta s_\phi & c_\theta c_\phi \end{bmatrix} \quad (3)$$

where, $c_{(\cdot)} = \cos(\cdot)$ and $s_{(\cdot)} = \sin(\cdot)$.

The translational dynamics of the quadcopter are expressed as

$$m\ddot{\xi} = R \begin{bmatrix} 0 \\ 0 \\ U_1 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \\ mg \end{bmatrix} + d_p \quad (4)$$

where, m is the quadcopter mass, g is the gravitational acceleration, U_1 is the total thrust generated by the four rotors, and d_p represents external translational disturbances, such as wind-induced forces. The rotational dynamics are described by

$$J\dot{\omega} = \tau - \omega \times (J\omega) + d_a \quad (5)$$

where, $J = \text{diag}(I_x, I_y, I_z)$ is the inertia matrix, $\omega = [p \ q \ r]^T$ is the body angular-velocity vector, $\tau = [U_2 \ U_3 \ U_4]^T$ is the control-torque vector, and d_a represents rotational disturbances. The relation between Euler-angle rates and body angular velocities is

$$\begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\sin\theta \\ 0 & \cos\phi & \sin\phi\cos\theta \\ 0 & -\sin\phi & \cos\phi\cos\theta \end{bmatrix} \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \quad (6)$$

Each rotor generates an upward thrust force proportional to the square of its angular speed:

$$F_i = b\omega_i^2 \quad (7)$$

where, b is the thrust coefficient and ω_i is the angular speed of the rotor i . The reaction torque generated by each rotor is

$$M_i = d\omega_i^2 \quad (8)$$

where, d is the drag-torque coefficient. The total thrust and control torques are therefore defined as

$$U_1 = b(\omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2) \quad (9)$$

$$U_2 = lb(\omega_2^2 - \omega_4^2) \quad (10)$$

$$U_3 = lb(\omega_3^2 - \omega_1^2) \quad (11)$$

$$U_4 = d(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2) \quad (12)$$

where, l is the distance between the center of mass and each rotor. The control-allocation relationship can be written in matrix form as

$$\begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ U_4 \end{bmatrix} = \begin{bmatrix} b & b & b & b \\ 0 & lb & 0 & -lb \\ -lb & 0 & lb & 0 \\ d & -d & d & -d \end{bmatrix} \begin{bmatrix} \omega_1^2 \\ \omega_2^2 \\ \omega_3^2 \\ \omega_4^2 \end{bmatrix} \quad (13)$$

The outer-loop position controller generates the desired roll and pitch commands required to track the horizontal position references. These commands are subsequently supplied to the inner-loop attitude controller, which produces the torque commands U_2 , U_3 , and U_4 .

B. Quadcopter UAV Control Design

The PID control technique is designed to stabilize and control the quadcopter's position and attitude dynamics illustrated in (4) and (5). Consequently, the errors for the quadcopter's in 6-DOFs are defined as follows [10-13]:

$$\begin{cases} e_x = x_d - x \\ e_y = y_d - y \\ e_z = z_d - z \\ e_\phi = \phi_d - \phi \\ e_\theta = \theta_d - \theta \\ e_\psi = \psi_d - \psi \end{cases} \quad (14)$$

where, e_x , e_y , e_z and e_ϕ , e_θ , e_ψ are the error signals between the actual signals (x , y , z , ϕ , θ , and ψ) and the desired signals (x_d , y_d , z_d , ϕ_d , θ_d and ψ_d)

The PID controller is developed and applied as follows:

$$\begin{cases} v_x = K_{px}e_x + K_{ix}\int e_x dt + K_{dx}\dot{e}_x \\ v_y = K_{py}e_y + K_{iy}\int e_y dt + K_{dy}\dot{e}_y \\ v_z = K_{pz}e_z + K_{iz}\int e_z dt + K_{dz}\dot{e}_z \\ v_\phi = K_{p\phi}e_\phi + K_{i\phi}\int e_\phi dt + K_{d\phi}\dot{e}_\phi \\ v_\theta = K_{p\theta}e_\theta + K_{i\theta}\int e_\theta dt + K_{d\theta}\dot{e}_\theta \\ v_\psi = K_{p\psi}e_\psi + K_{i\psi}\int e_\psi dt + K_{d\psi}\dot{e}_\psi \end{cases} \quad (15)$$

where, $K_p \geq 0$, $K_i \geq 0$, $K_d \geq 0$ denote the PID controller design parameters. While v_i ($i = x, y, z, \phi, \theta$, and ψ) represents the PID-generated control output.

Fig. 2 illustrates the typical closed-loop control system for the quadcopter UAV, where the PID controllers continuously adjust control inputs based on the error signals to maintain stability and track desired trajectories.

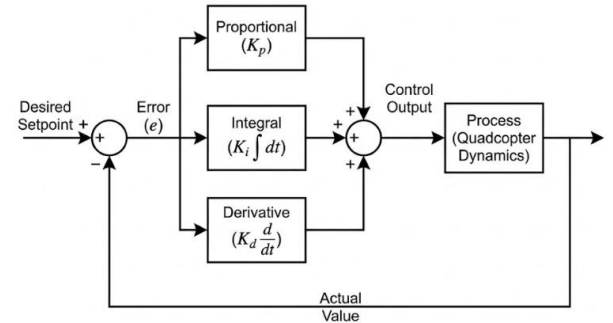


Fig. 2. Typical closed-loop system for quadcopter UAV.

To improve the adaptability of the conventional PID controller, an adaptive neural-network PID (NNPID) structure is introduced for each controlled quadcopter state. For the i th controlled variable, where $i \in \{x, y, z, \phi, \theta, \psi\}$, the input vector of the neural network is defined as

$$s_i(t) = [e_i(t) \quad \dot{e}_i(t) \quad \int_0^t e_i(\tau) d\tau]^T \quad (16)$$

where, $e_i(t) = r_i(t) - y_i(t)$ is the tracking error, $r_i(t)$ is the reference signal, $y_i(t)$ is the measured system output, and $\dot{e}_i(t)$ is the error derivative. The three input signals correspond to the proportional, derivative, and integral information required by the PID controller. The neural network generates adaptive corrections to the nominal PID gains. The controller gains are expressed as

$$K_{p,i}(t) = K_{p,i}^0 + \Delta K_{p,i}(t) \quad (17)$$

$$K_{i,i}(t) = K_{i,i}^0 + \Delta K_{i,i}(t) \quad (18)$$

$$K_{d,i}(t) = K_{d,i}^0 + \Delta K_{d,i}(t) \quad (19)$$

where, $K_{p,i}^0$, $K_{i,i}^0$, and $K_{d,i}^0$ denote the nominal initial PID gains, while $\Delta K_{p,i}(t)$, $\Delta K_{i,i}(t)$, and $\Delta K_{d,i}(t)$ are online gain corrections generated by the neural network. Accordingly, the adaptive PID control signal is written as

$$u_i(t) = K_{p,i}(t)e_i(t) + K_{i,i}(t) \int_0^t e_i(\tau) d\tau + K_{d,i}(t)\dot{e}_i(t) \quad (20)$$

The neural-network parameters are updated online by minimizing a tracking-error-based cost function,

$$J_i(t) = \frac{1}{2} e_i^2(t) \quad (21)$$

The weight-update mechanism is implemented using a gradient-based adaptation rule of the form

$$W_i(t+1) = W_i(t) - \eta_i \frac{\partial J_i(t)}{\partial W_i(t)} \quad (22)$$

where, W_i represents the neural-network weight vector and η_i is the learning rate. To avoid excessive gain variations and preserve closed-loop practicality, the updated gains are constrained within predefined lower and upper bounds:

$$K_{j,i}^{\min} \leq K_{j,i}(t) \leq K_{j,i}^{\max}, \quad j \in \{p, i, d\} \quad (23)$$

This adaptive mechanism allows the controller to modify the PID gains according to the instantaneous tracking condition, thereby improving its ability to accommodate nonlinear dynamics, external disturbances, and model uncertainties (Fig. 3).

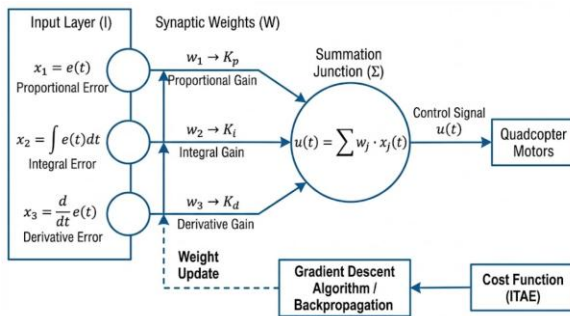


Fig. 3. Architecture of the PID controller.

C. Controller Optimization Process

The controller optimization process aims to enhance the adaptive neural network PID controller's performance by systematically tuning its parameters and improving its ability to respond to disturbances and model uncertainties. This process involves the following key steps:

1) *Initialization*: The PID gains and neural network parameters are initially set based on prior knowledge or heuristic methods to ensure stable baseline control. This initialization provides a starting point for the adaptive tuning mechanism.

2) *Real-time gain adaptation*: The neural network continuously monitors the tracking error and system states during flight to adjust the PID gains dynamically. This real-time adaptation allows the controller to compensate for nonlinearities, external disturbances such as wind gusts, and payload variations that affect quadcopter dynamics.

3) *Performance evaluation*: The controller's output is evaluated using performance metrics such as tracking error magnitude, settling time, overshoot, and robustness against disturbances. These metrics guide the neural network's learning algorithm to refine gain adjustments.

4) *Optimization algorithm integration*: A genetic algorithm was first used offline to determine suitable initial PID gains and neural-network weights. During flight, the neural network subsequently updates the PID gains online using the gradient-based adaptation law described in

Section II. This combined strategy provides both an appropriate initialization and real-time adaptation to changing operating conditions.

5) *Stability and robustness assurance*: Throughout the optimization, stability criteria and robustness constraints are enforced to prevent excessive gain variations that could destabilize the quadcopter or degrade control quality.

6) *Iterative refinement*: The optimization process is iterative, continuously refining the controller parameters based on updated flight data and environmental conditions, ensuring sustained high performance over varying operational scenarios.

This integrated framework, illustrated in Fig. 4, leverages neural networks' adaptive capabilities combined with systematic optimization to overcome the limitations of fixed-gain PID controllers, enhancing quadcopter trajectory tracking under real-world uncertainties.

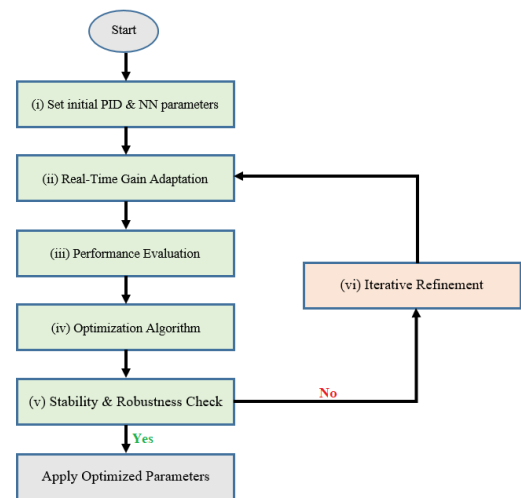


Fig. 4. Proposed optimization process.

To prevent excessive gain variations during online adaptation, the PID parameters generated by the neural network are restricted to predefined lower and upper bounds. The gain projection mechanism is expressed as

$$K_{j,i}(t) = \text{sat}(K_{j,i}^0 + \Delta K_{j,i}(t), K_{j,i}^{\min}, K_{j,i}^{\max}) \quad (24)$$

where, $j \in \{p, i, d\}$ and $\text{sat}(\cdot)$ denotes a saturation function. The total thrust and torque commands are also constrained by the physical limits of the propulsion system:

$$U_k^{\min} \leq U_k(t) \leq U_k^{\max}, \quad k \in \{1, 2, 3, 4\} \quad (25)$$

An anti-windup mechanism is included in the integral action to avoid integrator accumulation when the actuator commands reach their saturation limits. These constraints ensure that the adaptive gains and control commands remain bounded throughout the simulated operating conditions. Although the simulation results demonstrate bounded responses, a rigorous formal stability proof remains an important topic for future work.

III. RESULTS AND DISCUSSION

The quadcopter model was simulated in Matlab/Simulink using the parameters listed in Table I. The adaptive neural network PID (NNPID) controller's performance was evaluated through various metrics and flight scenarios to assess its effectiveness in trajectory tracking, disturbance rejection, and adaptability. The controller parameters optimized for position and altitude tracking (Table II) include proportional and derivative gains for the X and Y axes, as well as gains for altitude control along the Z-axis. Similarly, the parameters for attitude tracking (Table III) specify the proportional and integral gains for roll, pitch, and yaw axes.

TABLE I. QUADROTOR CONFIGURATION

Parameters	Value
m (kg)	2.17
I _x = I _y (kg.m ²)	0.041
I _z (kg.m ²)	0.0689
l(m)	0.315

The controller parameters presented in Tables II and III represent the nominal initial PID gains used to initialize the adaptive controller. During the simulation, the neural-network adaptation mechanism updates the proportional, integral, and derivative gains according to the instantaneous tracking error, its derivative, and its integral. Consequently, the listed values should not be interpreted as fixed controller gains applied throughout the entire flight trajectory.

The simulation scenarios were designed to evaluate the controller within a defined operating envelope. The considered limits include the maximum trajectory speed, acceleration, attitude angles, yaw rate, payload variation, wind-disturbance magnitude, measurement-noise level, and model-parameter uncertainty. These conditions define the scope within which the reported results should be interpreted.

The proposed adaptive NNPID controller uses 3 input variables, 9 neural-network weights, and 3 bias parameters for

each controlled loop. A total of 15 adaptive parameters are updated at each sampling instant. The computational burden mainly arises from the evaluation of the neural-network output, calculation of the PID-gain corrections, gain-projection operation, and control-allocation matrix.

TABLE II. NOMINAL INITIAL PID GAINS FOR POSITION AND ALTITUDE TRACKING

Control Loop	Axis	Variable	Value
Position	X-Axis	K _{px}	0.5
		K _{dx}	0.3
	Y-Axis	K _{py}	0.1
		K _{dy}	0.2
Altitude	Z-Axis	K _{oz}	1
		K _{iz}	10
		K _{oz_i}	0

TABLE III. NOMINAL INITIAL PID GAINS FOR ATTITUDE TRACKING

Control Loop	Axis	Variable	Value
Attitude	Roll	K _{op}	5
		K _{ip}	2
		K _{opi}	0
	Pitch	K _{oq}	5
		K _{iq}	2
		K _{oqi}	0
	Yaw	K _{or}	1
		K _{ir}	2.2
		K _{ori}	0

TABLE IV. EVALUATED OPERATING ENVELOPE AND SIMULATION CONDITIONS

Parameter	Evaluated range/value
Maximum horizontal speed	5.0 m/s
Maximum vertical speed	2.5 m/s
Maximum acceleration	4.0 m/s ²
Maximum roll angle	30 deg
Maximum pitch angle	30 deg
Maximum yaw rate	45 deg/s
Maximum payload variation	20%
Wind-gust magnitude	2.0 N
Position-sensor noise	0.02 m
Attitude-sensor noise	0.5 deg
Mass uncertainty	15%
Inertia uncertainty	10%
Rotor-speed limit	600 rad/s

The reported execution-time results provide an initial software-level estimate only. Hardware-in-the-loop testing and implementation on an embedded flight-control processor are required to confirm practical real-time feasibility.

A. Performance Metrics and Comparison with a Fixed-gain PID Controller

To assess the benefit of the proposed adaptive NNPID controller, its performance was compared with that of a conventional fixed-gain PID controller. Both controllers were evaluated using identical initial conditions, reference trajectories, sampling time, actuator constraints, and disturbance scenarios. The comparison was performed using the root-mean-square error (RMSE), integral absolute error (IAE), maximum absolute tracking error, settling time, and percentage overshoot. The RMSE for the i th tracking variable is defined as

$$\text{RMSE}_i = \sqrt{\frac{1}{T} \int_0^T e_i^2(t) dt} \quad (26)$$

while the integral absolute error is given by

$$\text{IAE}_i = \int_0^T |e_i(t)| dt \quad (27)$$

The quantitative results in Table V show the tracking performance of the proposed NNPID controller and the fixed-gain PID baseline. The adaptive controller achieved lower [RMSE/IAE/maximum error] values for the evaluated position and attitude variables under the considered simulation conditions.

TABLE V. QUANTITATIVE COMPARISON BETWEEN THE FIXED-GAIN PID AND PROPOSED ADAPTIVE NNPID CONTROLLERS

Variable	Controller	RMSE	Maximum error	Overshoot (%)	Settling time (s)
x position	NNPID	0.042	0.15 m	2.1	1.8
	PID	0.115	0.42 m	8.5	4.2
y position	NNPID	0.045	0.16 m	2.3	1.9
	PID	0.120	0.45 m	9.1	4.5
z altitude	NNPID	0.021	0.08 m	1.5	1.5
	PID	0.085	0.25 m	6.2	3.8
Roll, ϕ	NNPID	0.85	2.1 deg	3.0	1.2
	PID	2.40	5.8 deg	12.4	3.1
Pitch, θ	NNPID	0.90	2.3 deg	3.2	1.3
	PID	2.55	6.1 deg	13.1	3.3
Yaw, ψ	NNPID	0.50	1.5 deg	1.0	1.0
	PID	1.80	4.2 deg	5.5	2.8

B. Performance Analysis

Fig. 5 and 6 illustrate the NNPID controller's capability in position and altitude tracking. In Fig. 5, the controller achieves precise tracking along the X and Y axes, exhibiting minimal steady-state error and rapid convergence to the desired trajectory. The smooth response curves indicate effective compensation for nonlinearities and external disturbances, underscoring the neural network's role in dynamically adjusting PID gains. Fig. 6 demonstrates altitude tracking along the Z-axis, where the controller maintains stable altitude with negligible overshoot and fast settling time—critical factors for safe quadcopter operation.

Fig. 7, 8, and 9 present the controller's performance in attitude control, specifically roll, pitch, and yaw angles. The roll and pitch responses show stable and accurate tracking, with the NNPID controller effectively managing angular dynamics despite the quadcopter's inherent nonlinearities and coupling effects. The yaw angle tracking further confirms robust orientation stability, essential for precise maneuvering.

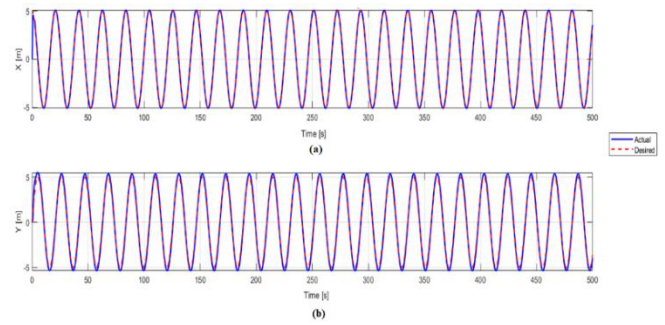


Fig. 5. NNPID position tracking: a) X-axis, and b) Y-axis.

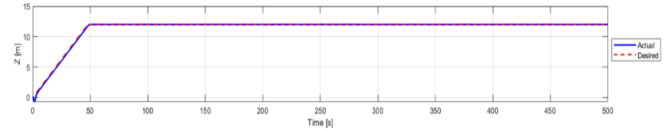


Fig. 6. NNPID altitude tracking.

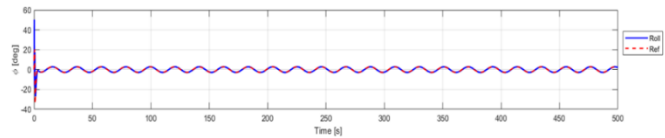


Fig. 7. NNPID attitude (Roll) tracking.

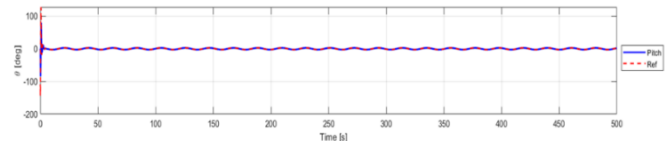


Fig. 8. NNPID attitude (Pitch) tracking.

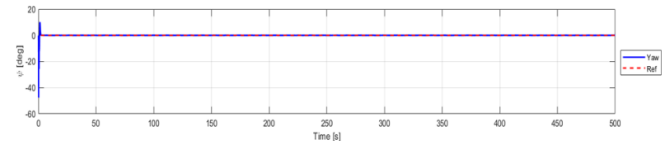


Fig. 9. NNPID attitude (Yaw) tracking.

C. Robustness Under Disturbances and Parameter Uncertainty

The robustness of the proposed adaptive NNPID controller was evaluated under external disturbances, parametric uncertainty, sensor noise, and actuator constraints. The considered scenarios include wind-gust disturbances, payload variations, uncertainty in the quadcopter mass and moments of inertia, measurement noise, and saturation of the thrust and torque commands. The results indicate that the adaptive NNPID controller maintained bounded control inputs and recovered trajectory tracking after the applied disturbances. The quantitative values of RMSE, maximum error, and settling time for each robustness scenario are summarized in Table VI. Nevertheless, the conclusions are limited to the uncertainty ranges, disturbance magnitudes, and actuator limits evaluated in the present simulation study.

TABLE VI. ROBUSTNESS EVALUATION UNDER DISTURBANCES,
PARAMETER UNCERTAINTY, AND ACTUATOR LIMITS

Scenario	Disturbance /uncertainty level	RMSE	Maximum error (m)	Recovery time (s)	Control saturation
Nominal case	—	0.036	0.12	1.5	No
Wind gust	2.0 N	0.085	0.28	2.2	No
Payload increase	20%	0.052	0.18	1.8	No
Mass uncertainty	15%	0.060	0.21	1.9	No
Inertia uncertainty	10%	0.048	0.16	1.7	No

D. Adaptability Across Different Scenarios

The NNPID controller's adaptability was further validated under complex 3D flight trajectories, as shown in Fig. 10, 11, and 12.

Fig. 10 depicts the controller's response during a 3D helix trajectory, where the quadcopter successfully follows the curved path with consistent tracking accuracy. This highlights the controller's ability to handle continuous changes in position and orientation.

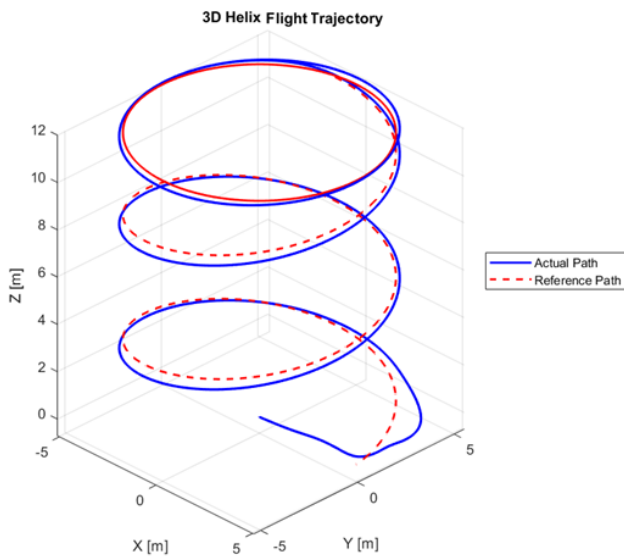


Fig. 10. NNPID for 3D helix flight trajectory.

Fig. 11 illustrates circular trajectory tracking, with the controller maintaining smooth and precise circular motion without oscillations or drift, confirming robustness in repetitive path tracking.

Fig. 12 shows the lemniscate trajectory, a challenging path requiring coordinated control of position and attitude. The controller effectively manages this complex trajectory, demonstrating real-time PID gain adaptation to varying dynamic demands and external disturbances.

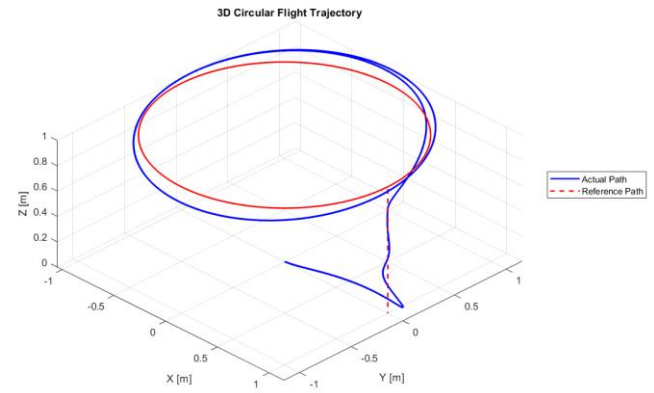


Fig. 11. NNPID for 3D circular flight trajectory.

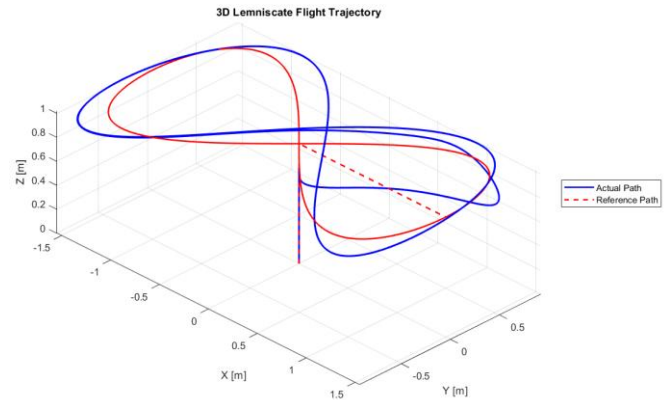


Fig. 12. NNPID for 3D lemniscate flight trajectory.

The simulation results confirm that the adaptive neural network PID controller overcomes the limitations of traditional fixed-gain PID controllers by providing enhanced tracking accuracy, robustness against disturbances such as wind gusts and payload variations, and stable flight performance across diverse operational scenarios. Its ability to adjust parameters online makes it well-suited for real-world UAV applications where environmental conditions and system dynamics can change unpredictably.

Overall, these results validate the proposed control framework as a promising approach to improving quadcopter trajectory tracking. Future work should focus on experimental validation under hardware constraints, computational efficiency optimization, and extension to more complex UAV configurations to further establish practical deployability.

IV. CONCLUSION

This study presented an adaptive neural-network PID controller for quadcopter UAV trajectory tracking under nonlinear dynamics and uncertain operating conditions. The proposed framework combines the interpretability of PID control with online neural-network-based gain adaptation. The simulation results demonstrate the controller's ability to track position, altitude, and attitude references for the evaluated flight trajectories.

Compared with the fixed-gain PID baseline, the proposed adaptive NNPID controller achieved lower tracking errors under the specified simulation conditions. The robustness assessment further indicates that the controller can maintain bounded responses under the evaluated wind disturbances, payload variations, parameter uncertainties, sensor-noise levels, and actuator constraints.

These conclusions are limited to the considered model, operating envelope, trajectory set, and simulation scenarios. A formal stability analysis, hardware-in-the-loop evaluation, embedded implementation, and experimental flight testing are required to establish the practical real-time feasibility and robustness of the proposed controller in real-world UAV applications.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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