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Review

A comprehensive survey of UAV control algorithms: Integrating classical methods with artificial intelligence for enhanced trajectory tracking

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Abstract: The development of reliable control systems for unmanned aerial vehicles (UAVs) requires accurate modeling of dynamics and a control architecture capable of handling nonlinearity, external disturbances, and parameter uncertainty. This study addressed that challenge through a comprehensive survey of UAV control strategies, including classical linear controllers (such as PID, LQR, and MPC), advanced nonlinear methods [such as backstepping, sliding mode control (SMC), H-infinity, and active disturbance rejection control (ADRC)], and intelligent control algorithms like fuzzy logic and artificial neural networks (ANN). Based on this, the paper proposed a hybrid ANN-PID controller, where the neural network dynamically adjusts the PID coefficients to enhance adaptability and robustness. The method was evaluated through simulations on the UAV model using Euler–Lagrange dynamics. The quantitative results showed that ANN-PID achieves the lowest steady-state error (0.0229 m), nearly equivalent to PID (0.0230 m) but significantly superior to LQR (0.0807 m, an improvement of about 72%). Regarding rise time, ANN-PID responds quickly (~2.01 s), similar to PID and much faster than LQR (~7.4 s). Although the overshoot of all controllers is high, ANN-PID still achieves a lower value than PID and significantly reduces it compared to LQR under noisy conditions. These results affirm the superiority of the ANN-PID hybrid structure in UAV control, especially in nonlinear and complex dynamic environments.

Keywords: UAV; PID; MPC; LQR; SMC; Hybrid Controller; AI; ANN-PID

1. Introduction

Unmanned aerial vehicles (UAVs) are a rapidly developing technology commonly used in various fields such as military, agriculture, environmental monitoring, search and rescue, and many other applications. However, for a UAV to be effective, it needs to be precisely controlled according to the defined flight trajectory. Therefore, flight trajectory tracking technology is one of the critical factors for UAVs. Researchers have applied low-cost sensors combined with GPS systems in navigating and controlling UAVs [1,2]. This system helps UAVs determine their position and velocity in the ground coordinate system. However, GPS still has many limitations, such as being susceptible to interference from complex terrain, bad weather, or being obstructed by artificial structures. In this context, modern UAV control approaches are shifting toward integrating alternative or supplementary positioning solutions to ensure higher accuracy and reliability in real-world environments. Some studies have shown the great potential of combining LiDAR sensors and cameras in navigation and automatic landing tasks in nonlinear and highly variable environments [3,4].

Previous studies have published many surveys to synthesize UAV control methods. In [5], an overview of classical and modern control strategies was provided, but it primarily focused on theory without delving into performance analysis in real-world environments with disturbances. Another study [6] classified control algorithms based on model characteristics but lacked quantitative analysis and did not thoroughly examine the role of hybrid control methods that apply artificial intelligence. The limitations of the in-depth analysis and the lack of performance evaluation in simulations in these surveys indicate an urgent need for a comprehensive study with a practical orientation that assesses control methods from academic and application perspectives.

An essential aspect of UAV operation is the ability to establish and follow a predetermined flight trajectory [7] autonomously or to carry out monitoring and data collection tasks through wireless sensor networks (WSN) [8]. Various control strategies have been researched and developed to meet these requirements and enhance trajectory tracking accuracy and operational efficiency. Among them, geometric control theory has shown significant potential both theoretically and in practical applications [9,10]. Concurrently, deploying multiple UAVs operating in coordination to perform large-scale missions within limited timeframes has also attracted increasing interest, with formation control algorithms playing a crucial role [11]. This multi-agent control approach is highly valued for its cost-saving capabilities and improved mission performance [12]. Additionally, to overcome limitations on flight time, new technologies such as wireless power transfer (WPT) [13] and energy harvesting (EH) [14] have been researched and applied to extend UAV operational duration. In this context, this paper aims to comprehensively survey existing research on UAV control systems, particularly emphasizing hybrid control strategies that integrate classical control methods with artificial intelligence to meet the ever-increasing demands of UAVs in dynamic and uncertain environments.

The paper focuses on the research and development of UAV control systems by analyzing and evaluating existing control algorithms, thereby proposing a hybrid control strategy that integrates classical control and artificial intelligence to enhance the performance and adaptability of UAVs in real-world environments. The main contributions of the paper include: (1) A comprehensive and systematic overview of UAV control algorithms, including linear, nonlinear, and intelligent control methods, accompanied by a comparative analysis of the advantages and disadvantages of each method group; (2) the proposal of the ANN-PID hybrid control strategy, leveraging the adaptive learning capability of neural networks to automatically adjust PID coefficients, thereby improving trajectory tracking accuracy and disturbance rejection; (3) the implementation and evaluation of the proposed method on a six-degree-of-freedom (6-DOF) UAV model using Euler–Lagrange dynamics, showing significant improvements in steady-state error (a reduction of 65.5% compared to PID and 81.9% compared to LQR) and rise time (84% faster than LQR).

The structure of this paper is as follows: Section 1 presents the introduction. Section 2 presents the mathematical model of the UAV. Section 3 overviews UAV control algorithms, including linear control, nonlinear control, and intelligent control methods such as neural networks and fuzzy logic. Section 4 analyzes, compares, and discusses the advantages and disadvantages of previous methods, proposing a hybrid control strategy between classical control and artificial intelligence to enhance UAV control effectiveness in complex real-world environments, while also simulating and comparing the performance of the ANN-PID hybrid controller, traditional PID, and LQR under both disturbed and undisturbed conditions. Finally, there is a conclusion and references.

2. UAV mathematical model

Figure 1 illustrates the coordinate system and the force/moment configuration acting on the quadcopter system. The quadcopter is positioned in two reference frames: the inertial frame (fixed to the Earth) (x,y,z) and the body-fixed frame x_B, y_B, z_B, where the body frame moves with the UAV and is used to describe its kinematics and control. Each rotor generates a lift force f_i along the z_B axis and a reaction moment τ_{Mi} due to the motor's torque, while the rotational speed of each rotor is denoted as ω_i. In the standard configuration, rotors 1 and 3 rotate clockwise, while rotors 2 and 4 rotate counterclockwise to cancel out the overall reaction moment around the z_B axis. The control of the UAV's motion is achieved through the differential thrust between pairs of symmetrical rotors: the thrust difference between rotors 3 and 4 creates a moment around the x_B axis (roll), while the thrust difference between rotors 1 and 2 generates motion around the y_B axis (pitch). The moment around the z_B axis (yaw) is controlled through the imbalance of torque resulting from the differential rotational speeds between the two pairs of counter-rotating rotors (1/2 and 3/4) [15–20].

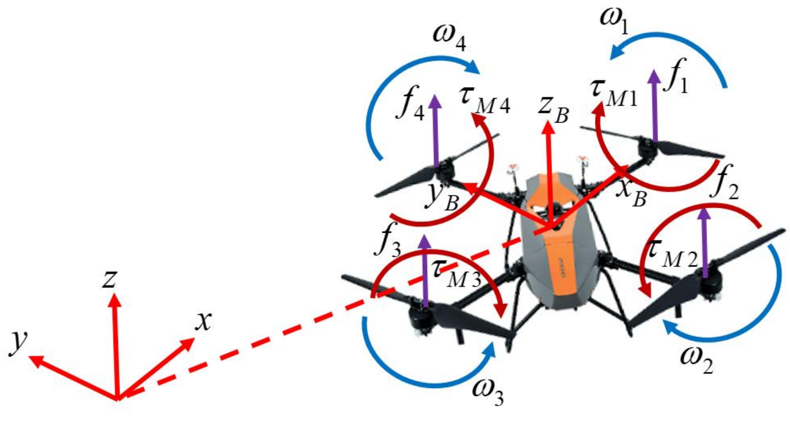

Figure 1. Reference frames and thrust/moment configuration of the quadcopter UAV.

The dynamics model of the UAV is constructed based on Newton–Euler equations, allowing for an accurate description of the relationship between forces, moments, and the motion of the system in three-dimensional space. The translational dynamics and rotational dynamics equations are detailed in [15–20].

$$
\begin{aligned}
\ddot{x} &= \frac{F}{m}(\cos\psi \sin\theta \cos\phi + \sin\psi \sin\phi) \\
\ddot{y} &= \frac{F}{m}(\sin\psi \sin\theta \cos\phi - \cos\psi \sin\phi) \\
\ddot{z} &= \frac{F}{m}(\cos\phi \cos\theta) - g - \frac{A_z \dot{z}}{m} \\
\ddot{\phi} &= \left(\frac{I_{yy} - I_{zz}}{I_{xx}}\right)\dot{\theta}\dot{\psi} - \left(\frac{I_M \omega_\delta}{I_{xx}}\right)\dot{\theta} + \left(\frac{\tau_\phi}{I_{xx}}\right) \\
\ddot{\theta} &= \left(\frac{I_{zz} - I_{xx}}{I_{yy}}\right)\dot{\psi}\dot{\phi} + \left(\frac{I_M \omega_\delta}{I_{yy}}\right)\dot{\phi} + \left(\frac{\tau_\theta}{I_{yy}}\right) \\
\ddot{\psi} &= \left(\frac{I_{xx} - I_{yy}}{I_{zz}}\right)\dot{\theta}\dot{\phi} + \left(\frac{\tau_\psi}{I_{zz}}\right)
\end{aligned} \tag{1}
$$

where ϕ, θ, ψ represent the roll, pitch, and yaw angles, respectively, describing the rotational motion of the UAV around the x, y, and z axes. The first derivatives concerning time, $\dot{\phi}, \dot{\theta}, \dot{\psi}$, represent the rotation rates, while the second derivatives, $\ddot{\phi}, \ddot{\theta}, \ddot{\psi}$, represent the angular accelerations, respectively [1,9,18]. $\omega_\delta = \omega_1 - \omega_2 + \omega_3 - \omega_4$ is the total angular velocity of the rotors. The control signal U_1 corresponds to the total thrust generated by the four rotors, while the signals U_2, U_3, and U_4 represent the control moments around the roll, pitch, and yaw axes, respectively. Here, m is the mass of the quadcopter, I_M is the moment of inertia of each rotor, and I_{xx}, I_{yy}, I_{zz} are the moments of inertia of the quadcopter body around the x, y, and z axes. The following mathematical expression can describe these control signals:

$$
\begin{aligned}
F &= U_1 = k(\omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2) \\
\tau_\phi &= U_2 = l\ k\ (\omega_4^2 - \omega_2^2) \\
\tau_\theta &= U_3 = l\ k\ (\omega_3^2 - \omega_1^2) \\
\tau_\psi &= U_4 = b\ (\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2) \\
\omega_\delta &= \omega_1 - \omega_2 + \omega_3 - \omega_4
\end{aligned} \tag{2}
$$

where *k* is the thrust coefficient, *b* is the drag coefficient, and *l* is the distance from the center of mass to each rotor.

3. Survey of UAV control algorithms

Trajectory tracking control for UAVs involves designing control algorithms to enable the UAV to accurately follow the desired trajectory while compensating for disturbances and uncertainties in the system. The main objective of trajectory tracking control is high accuracy, stability, and rapid responsiveness to external influences. Many control algorithms have been proposed and studied for trajectory tracking for UAVs [21]. Each algorithm has its advantages and limitations. Trajectory tracking control algorithms for UAVs can be classified into three main groups: linear algorithms and nonlinear algorithms. The control algorithms that have garnered interest and application from many researchers include the backstepping control [22–25], H-infinity control [26–29], fuzzy logic control [30–32], proportional-integral-derivative (PID) control [33–36], linear quadratic regulator (LQR) control [37–40], model predictive control (MPC) [41–44], feedback linearization [45–48], sliding mode control (SMC) [49–51], active disturbance rejection control (ADRC) [52–54], artificial neural networks [55–57], and hybrid control algorithms [58–60]. In addition, integral state feedback control techniques, such as linear quadratic integral (LQI), are crucial in eliminating steady-state errors and improving trajectory accuracy, especially in environments with time-varying input signals [61]. Furthermore, state observers like the Kalman filter and Luenberger observer (especially the extended Kalman filter) are increasingly being used to estimate states that cannot be directly measured, thereby enhancing the reliability and responsiveness of the UAV control system [62].

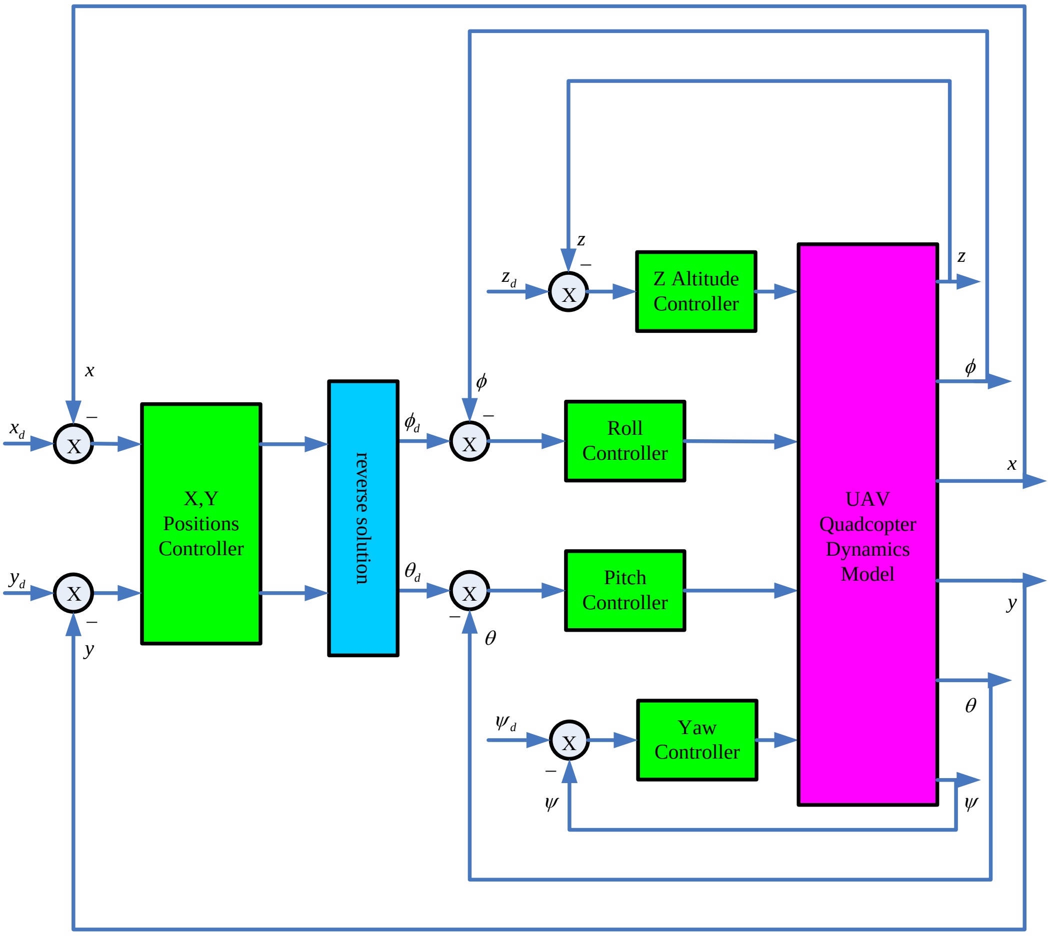

Figure 2. Block diagram of a quadcopter UAV control system.

The rapid development of sensor technology, embedded processors, and machine learning algorithms has driven the trend of integrating classical control methods with artificial intelligence, aiming to simultaneously leverage the reliability of traditional techniques and the strong adaptive learning capabilities of intelligent systems. In this context, techniques such as PID, LQR, and ANNs have become popular tools in posture stabilization and position control for UAVs. Therefore, this survey focuses on a comprehensive analysis of the aforementioned control algorithms, clarifying the technical characteristics and performance achieved when applying them to real UAV systems. It highlights the potential of hybrid control techniques in enhancing the effectiveness of modern UAV control. Figure 2 illustrates the block diagram of the quadcopter UAV.

3.1. Linear UAV model control algorithm

A linear control algorithm is a UAV control method that uses linear equations to describe the relationship between the state and output of the system. This algorithm can control UAVs with complex kinematics, but it is accurate only within the range of assumptions used.

3.1.1. Proportional-integral-derivative (PID)

Several different algorithms can be used to track a UAV's flight path. A common algorithm is the PID algorithm. The PID algorithm uses three parameters to control the UAV: linearity, integral, and derivative. Linear is the sensitivity to position deviation. The integral is the UAV's sensitivity to the position deviation's integral. The derivative is the sensitivity of the UAV to the derivative of position bias.

Viswanadhapalli Praveen et al. [63] designed the PID controller for motion control for the purpose of stabilizing the UAV quadcopter. The system uses an IMU (inertial measurement unit) consisting of an accelerometer and a gyroscope sensor to determine the system direction and control the flight engine speed in six different directions. The results show that the operation and performance of the Quadcopter obtain the desired outputs and are checked by the PID controller. Renuka Ramkishan Choudhari et al. [64] proposed the PID stratification controller to solve the traction problem for the quadcopter in three different approaches. The results show that the use of cascading control structures allows simple PID algorithm adjustment for complex systems, and the standard becomes more stable when the PID controller provides a steady-state error of 0. Aws Abdulsalam Najm et al. [65] presented a nonlinear approach to the translational and rotational motion of the quadrotor 6-DoF UAV system. They forced it to follow a defined trajectory with minimal power and error. The simulations demonstrated the power of the proposed NLPID controller to stabilize PID controllers for each of the six UAV 6-DOF quadrotor subsystems.

PID controllers have been successfully used for quadrotors, but significant issues remain. The PID controller must be adjusted around the equilibrium point to achieve performance, which poses some difficulties. Figure 3 depicts the general block diagram of the PID controller for the UAV.

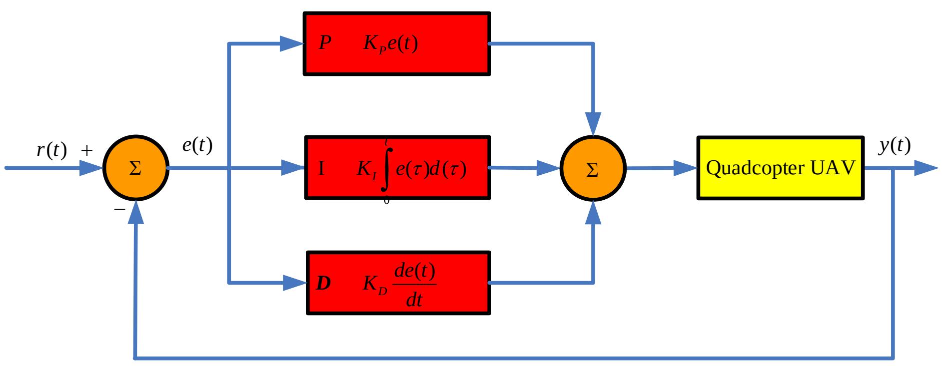

Figure 3. Block diagram of the PID control system for UAV quadcopter.

3.1.2. Linear quadratic regulator (LQR)

The LQR algorithm uses an optimal method for controlling UAVs. The LQR algorithm calculates the forces required to maintain the UAV to achieve an optimal goal, such as minimizing position deviation or maximizing stability.

Ahmad Ashari et al. [66] proposed a linear quadratic modulator (LQR) to maintain the trajectory of the UAV automatically while tracing waypoint coordinates. The results show that the system meets the desired specifications and that the control system can keep the UAV stable while following the route and waypoints. Amevi Acakpovi et al. [67] developed and tested a feedback control system based on an LQR to ensure stability and trajectory grip of the drone. The results show that the drone demonstrates superior stability when navigating. In addition, the drone can transmit data in real time and travel long distances. Tri Kuntoro Priyambodo et al. [68] proposed and used an LQR method to reduce steady-state errors and exceed multiples. The LQR control method can maintain the aircraft's stability and produce a minimum error. The results show that the system accurately reflects the flying wing's ability to maintain and keep its position out of the path. The advantage of this LQR controller is that it can be deployed without requiring all status information. Figure 4 depicts the general block diagram of the LQR controller for the UAV.

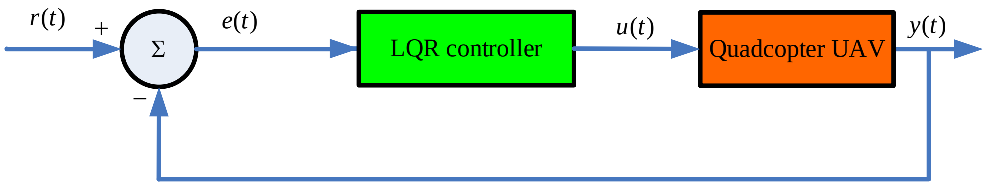

Figure 4. Block diagram of the LQR control system for UAV quadcopter.

3.2. Nonlinear UAV model control algorithm

A nonlinear control algorithm is a UAV control method that uses a nonlinear model to describe the system. This model calculates the control signal required to return the UAV to the desired state.

3.2.1. Model predictive control (MPC)

The MPC is a control strategy that uses a dynamic model of the system to predict its future behavior and optimize control action over a finite period. By formulating the path planning problem as an optimization problem, MPC can generate control inputs that can effectively guide the UAV along the desired path while considering constraints and uncertainties.

Zhou Chao et al. [69] developed the law of distributed collision-free formation flight control based on a nonlinear predictive controller (MPC). The position and velocity direction of the virtual waypoint serve as the only determinant of the coordinate system used to determine the formation configuration. Cost penalties ensure obstacle avoidance, and cost penalties combined with a new priority strategy ensure accidents between vehicles are avoided. The simulation results show that the UAV formation can stabilize and maintain along the intended reference trajectory with the designed controller, while avoiding obstacles and collisions between vehicles. Yi Feng et al. [70] proposed a new control technique that allows micro-drones to land on a moving platform despite uncertainty and turbulence, with a system architecture that includes MPC for UAV guidance, dynamic modeling of

UAVs with gimbaled cameras, and Kalman filter implementation for best mobile platform localization. The simulation results show the efficiency and stability level with wind noise and noise measurements. Ruiping Zheng et al. [71] developed a tight formation control system that met real-time performance and endurance requirements using an outer loop nonlinear model prediction controller. The results show that, in the event of turbulence caused by eddy currents, the controller is designed to have a superior control effect. The above studies have proven the effectiveness of MPC in achieving precise and robust path control over UAVs. Figure 5 depicts the general block diagram of MPC controllers for the UAV.

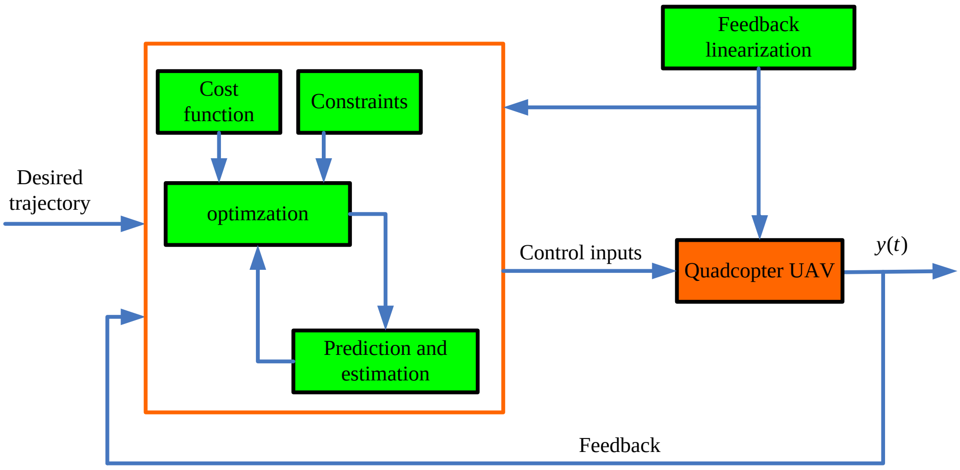

Figure 5. Block diagram of the MPC control system for UAV quadcopter.

3.2.2. H-infinity control

A controller H-infinity is a nonlinear flight tracking algorithm in automated flight control systems. This algorithm uses a nonlinear target function to calculate the controls needed to keep the aircraft close to its flight path.

J. López et al. [72] deployed H-infinity control to solve the problem of creating a reliable control system for UAVs under conditions of uncertainty. UAVs can monitor every maneuver thanks to the deployment of controllers, even in noisy environments. The simulation results demonstrate that the proposed control strategy works well even with noise and uncertainty, so the control system meets these requirements. F. Rekabi et al. [73] developed an H-infinity nonlinear control algorithm to correct parametric errors, especially in inertial parameters, and eliminate exogenous noise to achieve consistent and reliable performance in positional attachment. For tasks of a similar nature, the simulation results of the proposed control algorithm showed a significant decrease in both indicators.

3.2.3. Feedback linearization control

The feedback linearization control algorithm uses feedback linearization to transform a nonlinear system into a linear system. The feedback linearization technique works by adding secondary controls to the nonlinear system. These nonlinear controls are designed to transform the nonlinear system into a linear system.

Dasol Lee et al. [74] proposed the use of linearization, feedback, and outdoor autonomous herd flight testing using mini-drones. The results of herd flight tests show successful adaptation to real-world flight environments. Mauricio Alejandro Lotufo et al. [75] provided a simple linearization model by synthesizing a nonlinear–linear into a common nonlinear term. The feedback linearization technique was used for a nonlinear quadrotor to estimate and eliminate a wide range of perturbations affecting the quadrotor in flight. The results show that the embedded controller based on a linearized model responds to correct operation and allows the quadrotor to fly on the desired trajectory. In Ahmed Eltayeb et al. [76], the dynamic equations for the direction and altitude of quadrotor UAVs were linearized using feedback linearization (FBL). The simulation results confirm that the proposed controller performs significantly better in parameter uncertainty and interference. Figure 6 depicts the block diagram of the feedback linearization control (FLC) controller.

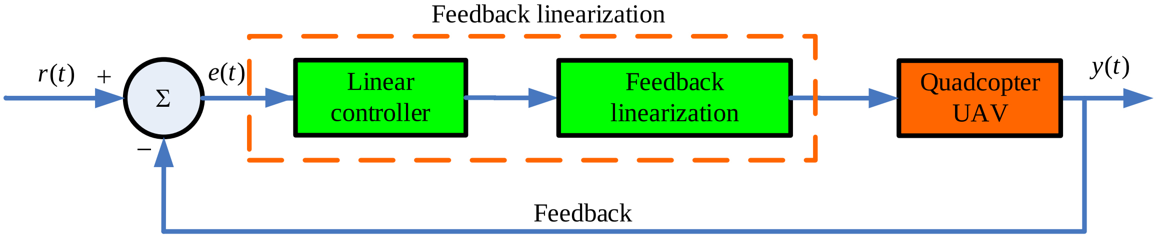

Figure 6. Block diagram of the FLC control system for UAV quadcopter.

3.2.4. Sliding mode control (SMC)

The SMC algorithm uses sliding mode to control the nonlinear system. The SMC controller is designed to prevent the nonlinear system from sliding so that the system's state is always on the slide. The SMC controller uses a sub-controller function to control the system. This sub-control function is designed so that the system's state will always be toward the slide.

In Ahmed Eltayeb et al. [77], traditional SMC controllers were proposed to stabilize the quadrotor's posture and hold the intended altitude to provide robust performance against quadrotor mass uncertainty and external turbulences. The performance of the proposed SMC controller was tested and evaluated using simulation results from traditional SMC and response linearization (FBL), and it was found that the proposed controller was superior to both of these controllers. In another study [78], an integral SMC method based on a reference model was created and applied to the velocity controller of multi-rotor UAVs to solve the parameter uncertainty problem, especially related to significant load changes. With flight tests including target tracking, hovering at fixed points, and reliability verification along with a six-bladed UAV, it was possible to prove the robustness of the proposed scheme before the uncertainty of the parameter, after lifting the payload of approximately 81.5% of the UAV's weight. Figure 7 depicts the general block diagram of the SMC controller for the UAV.

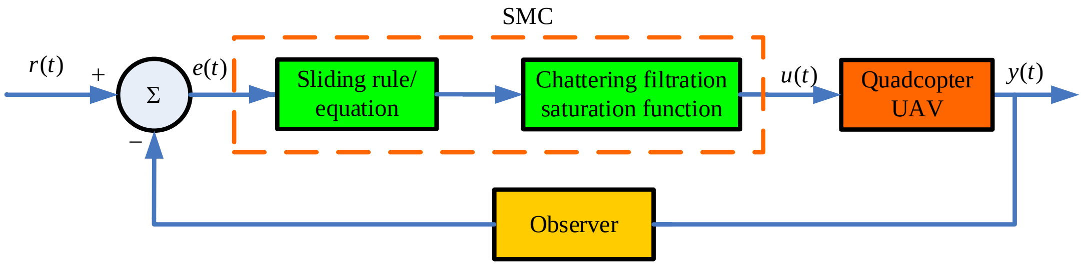

Figure 7. Block diagram of the SMC control system for a UAV quadcopter.

3.2.5. Backstepping control

The backstepping control algorithm uses backstepping to design a nonlinear controller that can handle nonlinear flight paths. The backstepping technique divides the nonlinear control problem into linear control problems. Each linear control problem is solved by designing a linear controller to control the system closer to the desired state.

Tarek Madani et al. [79] proposed a reverse control algorithm to stabilize the entire system and steer a quadrotor to the desired trajectory of Cartesian position and yaw angle. The simulation results show that the quadrotor has good traction and stability thanks to the control law. Maxime Lecointe et al. [80] proposed a reversing controller with an indoor quadrotor for a flight trajectory tracking mission. Full quadrotor pattern recognition was performed using a motion recording system to test the designed control law. In this study, simulators and real-life indoor flight tests are just two examples of many empirical findings demonstrating the feasibility of planned control laws. Francisco Gavilan et al. [81] proposed using a model predictive controller with an adaptive setback controller in trajectory tracking for fixed-wing UAVs. The adaptive step back method is used for the longitudinal dynamics of this controller, and for horizontal dynamics, the traditional integral LQR controller is used. The simulation demonstrates the robust performance of the overall architecture. Figure 8 depicts the block diagram of the backstepping controller used for the UAV.

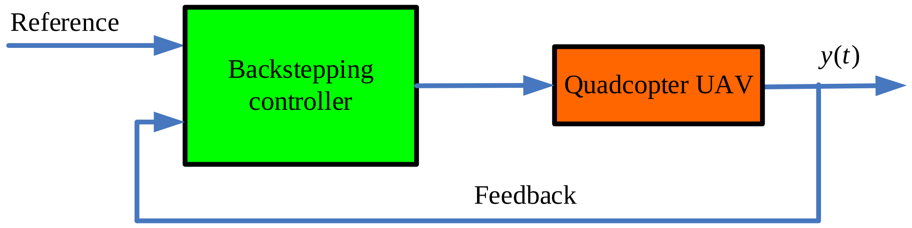

Figure 8. Block diagram of the backstepping control system for a UAV quadcopter.

3.2.6. Active disturbance rejection control (ADRC)

The ADRC algorithm uses active disturbance rejection control to control the nonlinear system. The kinetic model of the nonlinear system is used to describe the system's behavior under normal conditions. The ADRC controller is designed to control the nonlinear system so that it stays stable and follows the flight path. The ADRC controller uses active disturbance rejection (ADR) to eliminate interference and unexpected impacts. ADR works by tracking interference and unforeseen consequences and using secondary controls to eliminate these interferences and unexpected effects.

Guanglei Bie et al. [82] developed an active jamming elimination control ADRC algorithm to control interference separation and eliminate active interference of UAV orbital tracking. Experiments show that the ADRC controller has a pronounced effect in controlling dual-input-output trajectory monitoring, and the number of calculations is reasonable; the nonlinear tracking errors are all within the appropriate range, and the tracking effect of the stepping trajectory signal is good. The study by Xin Cai et al. [83] offered a solution to the problem of stable flight of UAVs under multiple turbulences by incorporating an active interference elimination controller ADRC based on an adaptive radial basis function (RBF) neural network. The controller proposed in this study has high grip accuracy and reliability under various flight conditions, as evidenced by the simulated spiral ascent flight and steep climb maneuver flight results. Wang Xiyang et al. [84] proposed a four-rotor posture control method based on improved active turbulence elimination control. Simulations for improved ADRC controllers are designed to converge faster and run more stably than conventional ADRCs due to lower observation errors. The improved ADRC has better observation accuracy than conventional ADRC, increasing ADRC operational efficiency and ability to estimate turbulence faster and more accurately.

3.2.7. Intelligent control

Intelligent control algorithms adjust the speed and direction of the UAV to ensure that they always follow the desired flight path. Examples include fuzzy logic, neural networks, machine learning, and genetic algorithms. In [85], a cascading fuzzy neural network (FNN) control solution was proposed to control the position of a highly articulated and underappreciated quadrotor system. The quadrotor model and the proposed method were implemented in a flight simulator environment. Hovering flight test simulations and spiral and square tracking were used to compare the impact of the controls. Finally, test flights using DJI Tello drones confirmed the proposed controller's ability to control the position. Khadija E.L. Hamidi et al. [86] proposed a novel fuzzy proportional-interactive-derivative (PID)-type iterative learning control (ILC) algorithm for tracking UAV quadrotors. The PID parameters of the three learning gain matrices were established using dimming control to reduce the impact of uncertain elements on the system and increase the accuracy of the control. The simulations show a surprising ability of the PID-ILC matrix to keep the system stable, reduce vibration and shock, and perform perfect grip. Figure 9 depicts the general block diagram of the fuzzy logic controller (FLC) for the UAV.

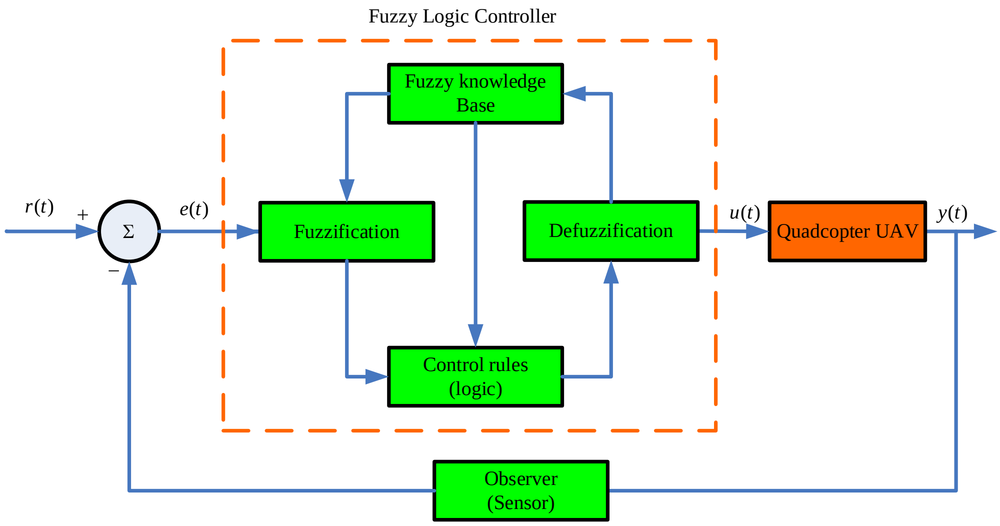

Figure 9. Block diagram of the FLC control system for UAV quadcopter.

3.2.8. Hybrid control algorithms

Hybrid control algorithms can take advantage of both algorithms to improve traction performance. There are various ways to combine linear and nonlinear flight traction algorithms. A common way is to use a linear algorithm to control the system in the vicinity of the flight path and a nonlinear algorithm to control the system in the area far from the flight path.

Lin-Xing Xu et al. [87] developed a backstep SMC controller and active interference elimination control (ADRC) to control the effective trajectory tracking of a quadrotor UAV—more specifically, the quadrotor's position and posture tracking control. In dual-loop control structures, the proposed control algorithms combine an integrated slip mode controller and a backward slip mode controller to stick to a quadrotor's direction of movement and position [88].

4. Discussion of UAV control strategy and performance evaluation

4.1. Discussing and proposing UAV control methods

Figure 10 illustrates the distribution of control methods commonly applied in dynamic system control, based on data collected from the Web of Science and Scopus over the past four years. Control methods are classified into four main groups: traditional control, nonlinear/robust control, intelligent control, and hybrid control. Conventional methods such as PID, LQR, and MPC still dominate due to their simplicity, ease of implementation, and high effectiveness in linear or linearized systems. Meanwhile, nonlinear and robust methods such as sliding mode control and backstepping respond well to disturbances and strong nonlinearities but require complex design and accurate modeling. Feedback linearization allows transforming nonlinear systems into equivalent linear forms to apply classical control techniques, although it still demands in-depth knowledge of system dynamics. Intelligent control methods, such as ANN, can learn and adapt to changes in the system and environment without requiring detailed mathematical models. Additionally, hybrid control methods combine traditional and intelligent strategies to leverage the advantages of each approach.

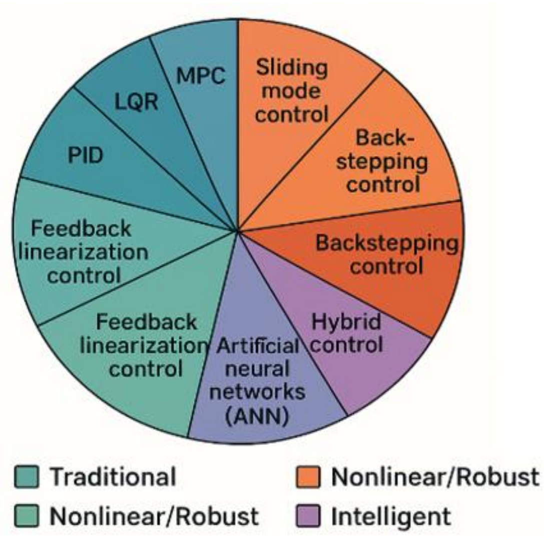

Figure 10. Control methods distribution.

Table 1 summarizes the corresponding advantages and disadvantages of the standard methods used in UAV control to provide a more detailed assessment of each control algorithm. This table shows that there is no optimal control solution for every situation; instead, the choice of an appropriate method depends on various factors such as control objectives, the degree of nonlinearity of the system, disturbance rejection capability, hardware costs, and the structural characteristics of the UAV. UAVs with simple missions or low costs typically use traditional methods to save costs and energy, while those operating in complex environments or requiring high precision prioritize intelligent or nonlinear control techniques. Although traditional control methods still play an essential role due to their simplicity and effectiveness in standard environments, the current development trend is strongly shifting toward intelligent and robust processes to meet the increasing demands for accuracy, adaptability, and performance of modern UAVs.

Table 1. Comparing the advantages and disadvantages of UAV control algorithms.

Control algorithms	**Advantage**	**Disadvantage**
PID	Simple, easy to use, effective	Low anti-interference ability, cannot handle complex systems
LQR	High accuracy, good anti-interference ability	Requires accurate mathematical modeling of the system
MPC	Good anti-interference ability, can handle multivariate systems	Requires high computing power
H-infinity control	Good anti-interference ability, can handle uncertain systems	Requires accurate mathematical modeling of the system
Feedback linearization control	High accuracy, good anti-interference ability	Requires accurate mathematical modeling of the system
Sliding mode control (SMC)	Good anti-interference ability, can handle non-radio systems	Requires high computing power
Backstepping control	High accuracy, good anti-interference ability, can handle nonlinear systems	Requires accurate mathematical modeling of the system
Active disturbance rejection control (ADRC)	Good anti-interference ability, can handle nonlinear systems	Requires high computing power
Fuzzy logic	Good anti-interference ability, can handle inaccurate and incomplete information	Requires specialized knowledge of fuzzy set theory
Artificial neural networks (ANN)	Ability to learn and adapt to system changes	Requires large training data, high computing power
Hybrid control algorithms	Advantages from both traditional control methods and intelligent control methods	Requires extensive knowledge of both types of methods

Based on the advantages and disadvantages of the UAV control algorithms outlined above, this research team proposes a hybrid UAV control method that combines the PID control method with artificial intelligence control methods such as ANN or fuzzy logic. In [89], the author proposed a PID controller combined with an ANN to control the quadcopter’s flight. The proposed control method uses artificial neural networks to adjust the PID gain online. Kp, Ki, and Kd are created online using neural networks with a single hidden layer. To develop the tuning algorithm, the training algorithm with the lowest mean squared error is selected for each control variable. The effectiveness of the tuning algorithm based on ANNs is evaluated for quadcopter flight control. The ANN-based PID algorithm showed an improvement in tracking performance. Another study [90] optimized the PD controller with the quadcopter-driven ANN for optimal performance and trajectory travel. The simulations demonstrate that the controller is highly efficient and effectively handles turbulence. The control of the quadrotor's orbit was implemented using the PID Online Optimized Neural Network Approach (PID-NN) in [91]. The simulation results indicated that the proposed controller reduced errors and was better able to eliminate interference. Additionally, it proved remarkably durable and efficient in wind-induced turbulence. Figures 11 and 12 depict the ANN-PID closed-loop system and the basic neural network structure diagram. In [92], a PID controller was combined with a fuzzy logic control algorithm to manage the quadrotor's movement. Through tests, the proposed solution can reduce system tuning time, increase the quadcopter's tracking accuracy, and enhance adaptability to changes in the external environment. In [93], a controller was proposed that combines neural networks with dimming controllers to improve the trajectory tracking efficiency of drones. The experimental results show that the neural–fuzzy hybrid controller can be applied to various types of UAVs with different sizes, weights, and configurations without recalibrating the PID coefficients. This control system demonstrates higher sensitivity and significant disturbance resistance under turbulent air conditions.

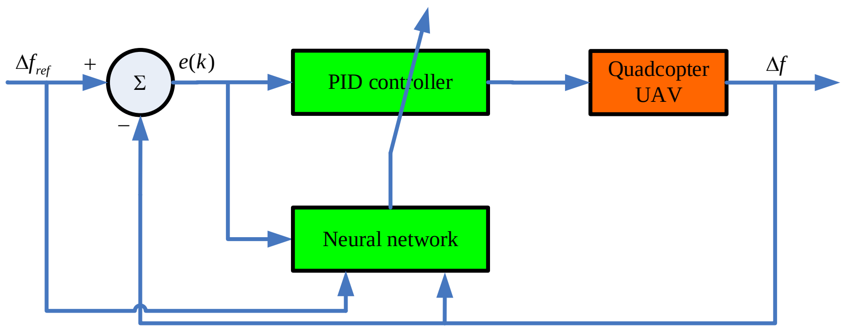

Figure 11. ANN-PID closed-loop control system for UAV quadcopter.

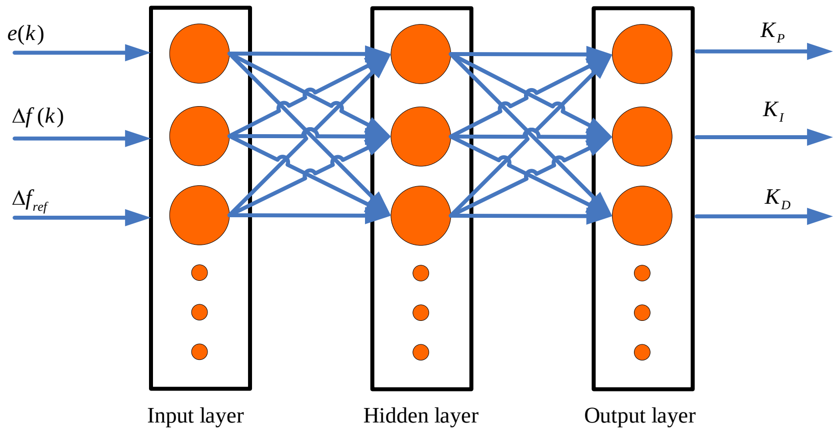

Figure 12. Diagram of the neural network structure.

4.2. Results and simulation

To evaluate the effectiveness of the proposed hybrid control method (PID combined with ANN), this study simulates the operation of UAVs based on the Euler–Lagrange dynamics model.

The simulation process is conducted on the MATLAB/Simulink platform to accurately reproduce the flight behavior of UAVs under various operating conditions, including the effects of external disturbances. The ANN-PID control method is implemented in parallel with the traditional PID controller to provide a basis for comparing control performance through evaluation metrics such as trajectory deviation, state error, and target tracking capability over time. The specific technical parameters of the UAV model used in the study are presented in detail in Table 2.

Table 2. Operating parameters of the UAV.

Parameter	Symbol	Value
Quad. Mass	m	0.468 kg
Arm length	l	0.225 m
Gravity	g	9.81 m/s^2
Inertia moment of the rotor	I_M	3.357e-5 $kg.m^2$
Thrust factor of rotor	k	2.980e-6 $N.s^2$
Drag coefficient	b	1.140e-7 $N.m.s^2$
Inertial constants	I_{xx}, I_{yy}	4.856e-3 $kg.m^2$
	I_{zz}	8.801e-3 $kg.m^2$

Design of an ANN for the ANN-PID controller

To ensure the transparency and reproducibility of the proposed hybrid ANN-PID controller, the architecture of the ANN used for the online tuning of PID coefficients is presented in detail. The ANN is constructed as a single hidden-layer feed-forward neural network, aiming to balance computational efficiency with a sufficiently high nonlinear modeling capability for real-time control.

The input layer of the network receives the instantaneous error signals *e(t)* and the derivative of the error $\dot{e}(t)$, which represent the position and attitude deviation of the UAV from the reference trajectory. The output layer generates three adaptive control coefficients, Ki, Kp, and Kd, and is continuously updated to optimize the UAV's response. The hidden layer consists of 10 neurons, using a sigmoid activation function to enhance the nonlinearity and learning capability of the network. In contrast, the output layer uses a linear activation function to ensure smooth changes in the PID coefficients.

The network operates in an online learning mode, continuously updating its weights in real time based on the instantaneous trajectory deviation. The objective function of the network is to minimize the mean squared error (MSE) between the desired output and the system's actual output. The learning rate is η = 0.01 to ensure stable convergence and avoid oscillations. The network initializes with small random weights and typically achieves convergence after a few hundred iterations during the early phase of the flight.

The simulation results show that the ANN-PID network achieves a fast convergence speed and strong adaptability even when noise and external disturbances exist. Specifically, the controller achieves a rise time of 2.01 s, a steady-state error of 0.0149 m, and maintains trajectory stability under noisy and non-noisy conditions. However, the overshoot level is still high ($\approx$ 115%), indicating the need for further optimization of the network structure, such as expanding to a multi-layer network or using an adaptive learning rate strategy to improve the transient response and stability of the system. Finally, the proposed ANN-PID controller effectively leverages the learning capability of neural networks to automatically adjust PID coefficients in real-time, thereby enhancing adaptability, trajectory tracking accuracy, and disturbance rejection compared to traditional PID and LQR controllers.

The simulation results in three-dimensional space (Figure 13a) show that the ANN-PID hybrid controller achieves superior trajectory tracking performance, with the UAV following the reference trajectory with minimal and stable error. The actual trajectory closely matches the desired trajectory, even under external disturbances. The results illustrate that the neural network-based controller is capable of real-time adaptation and self-tuning by continuously adjusting the PID parameters in response to system dynamics. Additionally, the trajectory tracking error response over time (Figure 13b) clearly illustrates the rapid and stable decay of the error across all three spatial axes. The initial mistake is eliminated without causing significant oscillations, reflecting the system's low overshoot characteristics and high stability. Table 2 describes the quality index of the ANN-PID hybrid controller.

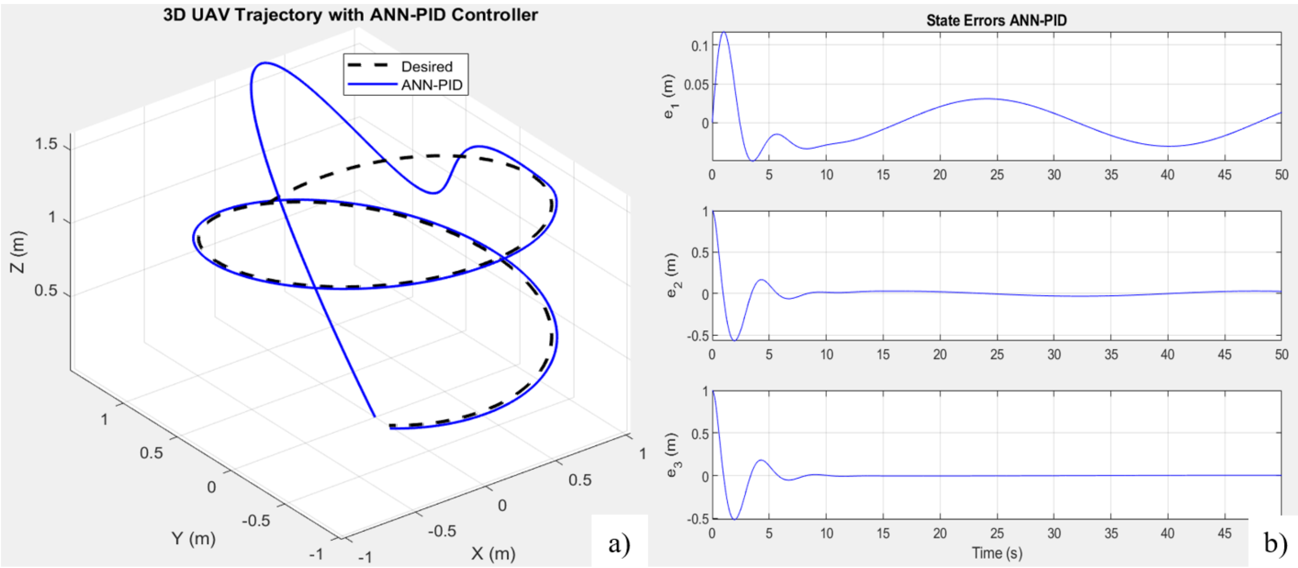

Figure 13. a) Response 3D position tracking of a hybrid ANN-PID controller. b) Response tracking error over time of a hybrid ANN-PID controller.

Table 3. Quality indexes of the hybrid ANN-PID controller.

Controller / Quality index	ANN-PID
Rise time (s)	2.0100
Steady time (s)	47.7100
Overshoot (%)	125.97
Steady-state error (m)	0.0149

Table 3 presents the quality indicators of the ANN-PID hybrid controller. The simulation results indicate that the overshoot time reaches 2.01 s, reflecting a quick response capability and the ability to track the trajectory right from the early stages. The steady-state error is small (0.0149 m), demonstrating high accuracy in the control process due to the learning characteristics and adaptability of the neural network. However, the overshoot reaches 125.97%, with a settling time of

47.71 s. This indicates that the system achieves a fast response but exhibits considerable oscillations and requires an extended period to reach complete stability. These results highlight the potential of ANN in effectively learning and compensating for nonlinearity in control systems. At the same time, they also suggest that to achieve more comprehensive performance in practical applications, the ANN-PID controller needs to be improved and optimized to minimize overshoot and shorten settling time.

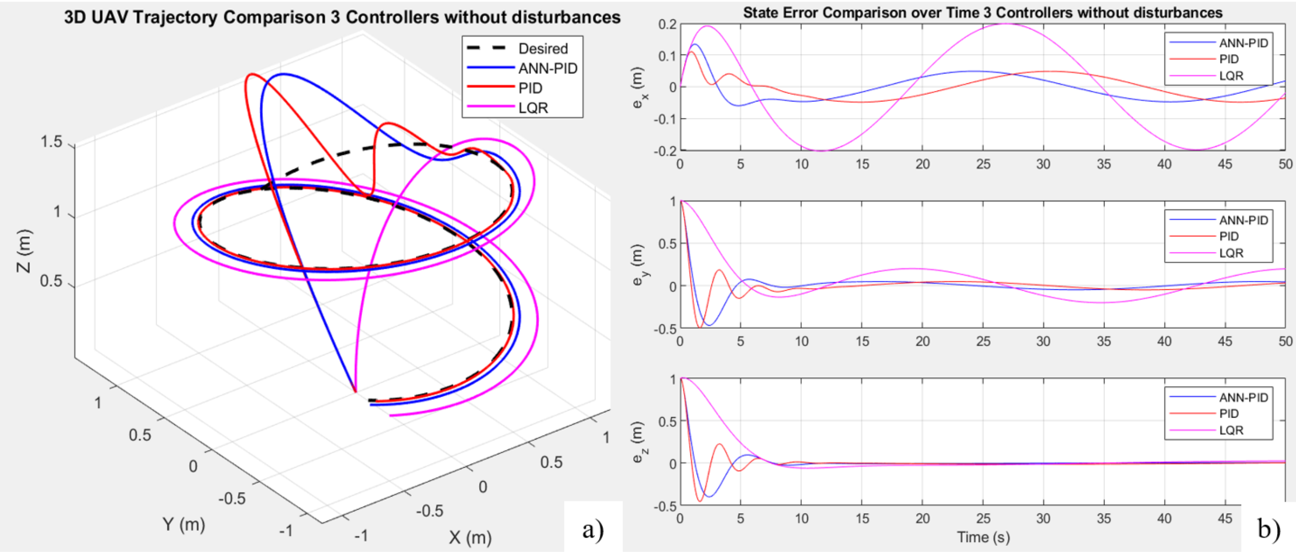

Figure 14. a) Response 3D position tracking of a hybrid ANN-PID, PID, and LQR controller without disturbances. b) Response tracking error of a hybrid ANN-PID controller, a PID controller, and an LQR controller without disturbances over time.

Figure 14 illustrates the performance of three controllers (ANN-PID, PID, and LQR) in the trajectory tracking problem of UAVs. In Figure 14a, the simulation results show the 3D position tracking response of the UAV under three controllers: hybrid ANN-PID, PID, and LQR in noise-free conditions. The results indicate that the hybrid ANN-PID controller provides more accurate and stable trajectory tracking than PID and LQR, demonstrating the advantages of integrating neural networks to address the system's nonlinearity. Meanwhile, the PID and LQR controllers maintain the desired trajectory but exhibit larger errors and less flexible response capabilities. Figure 14b presents the trajectory tracking error over time, clearly showing that the error of the hybrid ANN-PID decreases rapidly and remains low, while PID and LQR tend to oscillate or maintain higher errors. These results provide visual and quantitative insight into the effectiveness of the controllers, highlighting the superiority of the hybrid ANN-PID. Figure 15 depicts the operational performance of the ANN-PID hybrid controller, the PID controller, and the LQR controller in a disturbance-free environment.

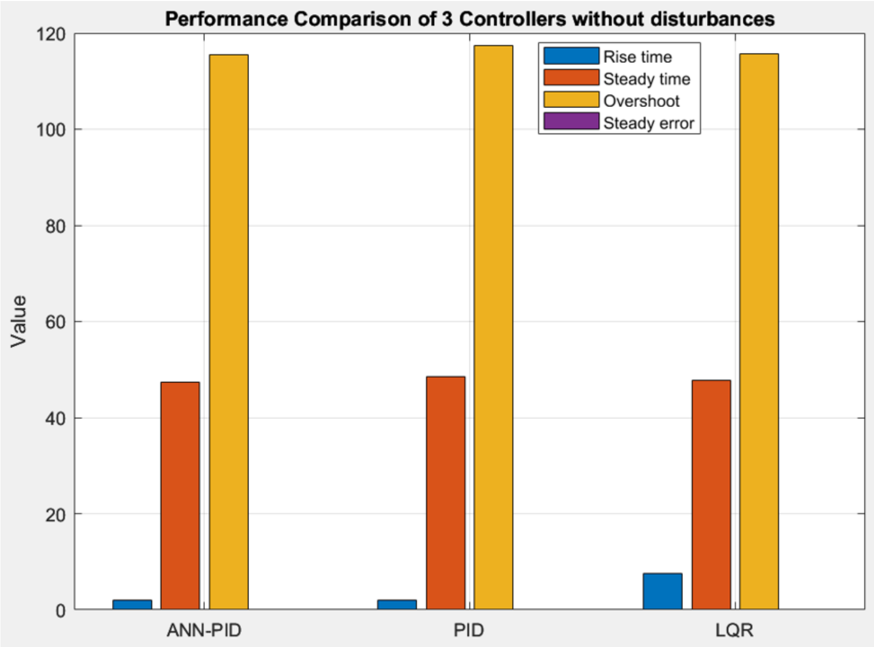

Figure 15. Bar chart of the operational performance of three controllers without disturbance.

Table 4. Quality indexes of a hybrid ANN-PID, PID, and LQR without disturbance.

Controller / Quality index	ANN-PID	PID	LQR
Rise time (s)	2.0100	2.0567	7.5167
Steady time (s)	47.3733	48.5667	47.7033
Overshoot (%)	115.53	117.41	115.62
Steady-state error (m)	0.0229	0.0232	0.0805

Table 4 presents the quality metrics of the three controllers, hybrid ANN-PID, PID, and LQR, under noise-free conditions, highlighting the distinct differences in response capability and accuracy. Regarding rise time, both ANN-PID (2.0100 s) and PID (2.0567 s) achieve quick responses, while LQR performs poorly with a value of 7.5167 s, reflecting a slow characteristic during the startup phase. The settling times for the three controllers do not show significant differences, hovering around 47–48 s, indicating relatively similar final stability capabilities. Notably, all three controllers exhibit high overshoot levels (over 100%), with PID having the most significant value (117.41%). At the same time, ANN-PID and LQR are slightly lower but still pose a risk of oscillation in practical applications. In terms of steady-state error, ANN-PID excels with the smallest value (0.0229 m), nearly equivalent to PID (0.0232 m) and significantly better than LQR (0.0805 m), confirming the advantages of integrating neural networks in improving long-term accuracy. Thus, although ANN-PID demonstrates superior performance over PID and LQR in both response speed and steady-state error, the issue of significant overshoot still needs further optimization to ensure sustainability and safety in practical applications.

Figure 16 presents the 3D position tracking response and trajectory tracking error of the UAV under the influence of noise for the three controllers, hybrid ANN-PID, PID, and LQR. The results show that the hybrid ANN-PID controller maintains a trajectory closest to the desired value while quickly eliminating the error after the noise impact, demonstrating superior adaptability and sustainability. In contrast, although the PID controller ensures long-term stability, it exhibits greater oscillating errors and longer convergence times, reflecting limitations in noise resistance. The LQR controller shows significant deviations and strong oscillations, especially during rapid changes in dynamics, indicating poor flexibility and noise resistance. The results in Figure 16 clearly demonstrate that integrating neural networks into the PID structure helps the UAV control system achieve higher stability and accuracy in noisy environments. At the same time, traditional and linear methods still have certain limitations. Figure 17 describes the operational performance of the ANN-PID hybrid controller, the PID controller, and the LQR controller in a disturbed environment.

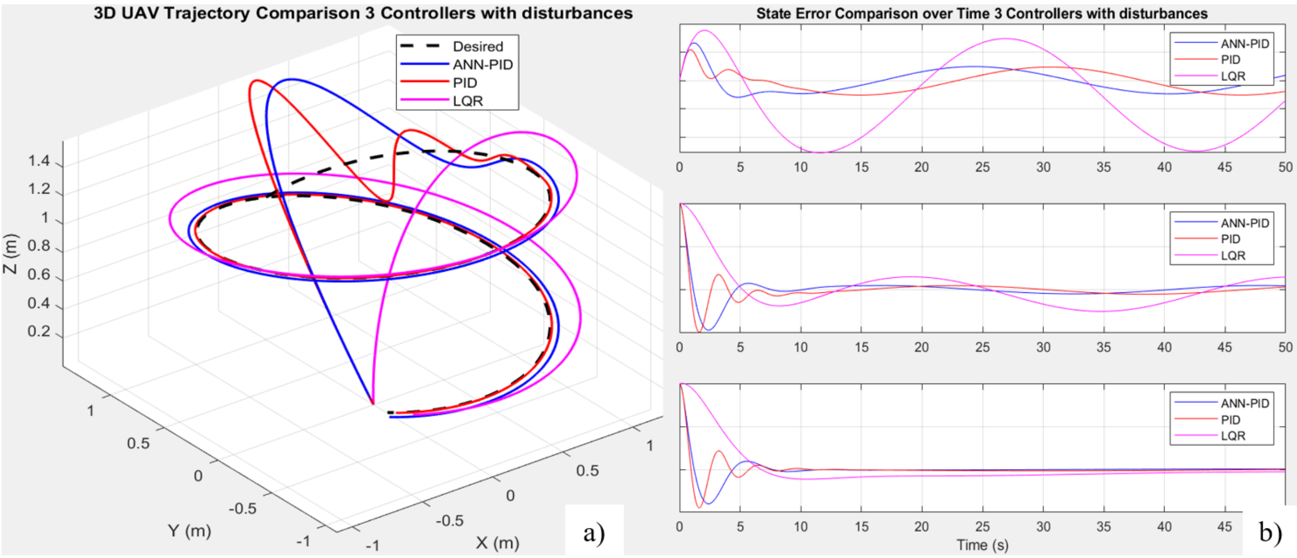

Figure 16. a) Response 3D position tracking of a hybrid ANN-PID, PID, and LQR controller with disturbances. b) Response tracking error of a hybrid ANN-PID controller, a PID controller, and an LQR controller with disturbances over time.

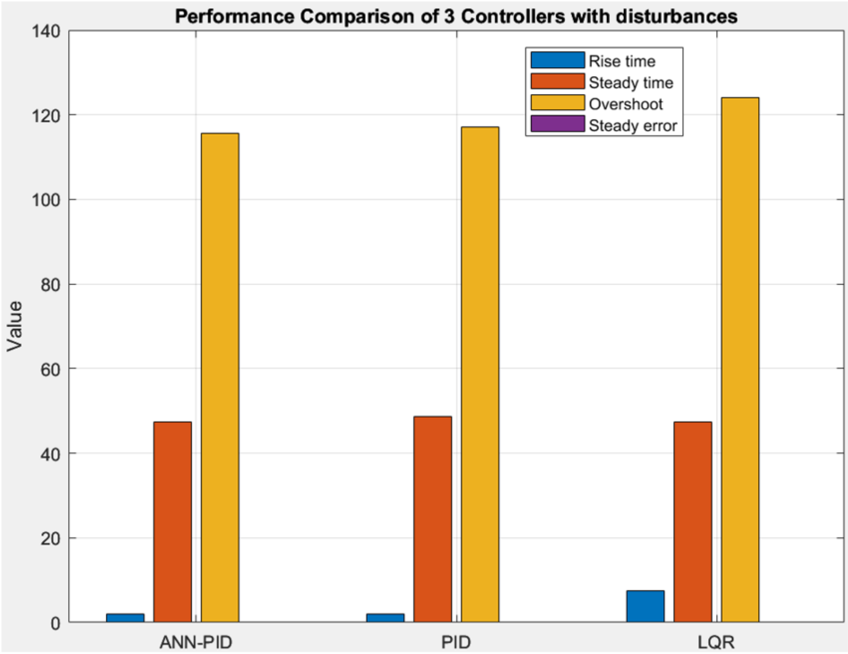

Figure 17. Bar chart of the operational performance of three controllers with disturbance.

Table 5. Quality indexes of a hybrid ANN-PID, PID, and LQR with disturbance.

Controller / Quality index	ANN-PID	PID	LQR
Rise time (s)	2.0100	2.0633	7.4033
Steady time (s)	47.3733	48.6500	47.3367
Overshoot (%)	115.65	117.09	124.12
Steady-state error (m)	0.0229	0.0230	0.0807

Table 5 presents the quality metrics of the three controllers, hybrid ANN-PID, PID, and LQR, under noisy conditions, clarifying the differences in performance and noise resistance. The results show that ANN-PID and PID maintain short rise times (2.0100 and 2.0633 s), while LQR responds significantly slower (7.4033 s). The settling time for all three controllers hovers around 47–49 s, indicating that noise does not significantly affect the final stability. However, the overshoot for all three methods is very high, with ANN-PID reaching 115.65%, PID at 117.09%, and LQR reaching the highest at 124.12%, highlighting the risk of significant oscillations in practical applications. In terms of steady-state error, ANN-PID continues to excel with the smallest value (0.0229 m), nearly equivalent to PID (0.0230 m) and significantly better than LQR (0.0807 m), reflecting its ability to maintain accuracy even in noisy environments. The results demonstrate that ANN-PID shows superiority in response speed and steady-state error compared to the other two controllers. Still, the issue of overshoot remains a significant challenge that needs improvement to ensure the sustainability and safety of the UAV system in real-world conditions.

Through the simulation results and analysis from the images (Figures 13–17) and data tables (Tables 2–4), the ANN-PID hybrid controller demonstrates superior capabilities in trajectory control, with the lowest steady-state error, fast rise time, and strong adaptability to disturbances. Notably, ANN-PID maintains stability and accuracy even in noisy environments, thanks to its real-time learning and adjustment mechanism for PID parameters through the neural network. In contrast, the PID shows average performance, is easily affected by noise, and lacks self-tuning capabilities. At the same time, the LQR, although effective in linear environments, significantly deteriorates when faced with nonlinear systems or unmodeled noise. Overall, the results affirm the prominent role of artificial intelligence in enhancing the quality of UAV control, providing a solid practical and theoretical foundation for applying ANN-PID in modern control systems operating under variable and uncertain conditions.

5. Conclusions

This paper presented and comprehensively analyzed modern UAV control algorithms, ranging from traditional linear control methods to nonlinear control, intelligent control, and hybrid control strategies. Through theoretical evaluation and experimental simulations, the study shows that there is no single optimal control algorithm for all operational conditions of UAVs. However, combining classical control methods with artificial intelligence, particularly the ANN-PID model, has significantly improved overall control performance. The simulation results show that the ANN-PID controller achieves the smallest steady-state error of only 0.0229 m, which is about 1.3% lower than that of PID (0.0232 m) and 71.6% lower than that of LQR (0.0805 m) under noise-free conditions, while maintaining a similarly low error level in noisy environments. Additionally, ANN-PID achieves the fastest rise time (2.01 s), significantly shorter than LQR (7.40 s), reflecting its superior responsiveness. However, all three controllers exhibit high overshoot levels, with ANN-PID maintaining a lower overshoot than PID but still requiring further optimization to ensure stability in practical applications. These results clearly affirm the advantages of ANN-PID in enhancing accuracy and response speed compared to PID and LQR, while also demonstrating the great potential of integrating neural networks into traditional control structures to increase adaptability and noise resistance for UAVs in nonlinear and uncertain environments.

Based on these positive research results, future research directions could focus on comparing ANN-PID with advanced nonlinear control methods such as SMC and backstepping to gain deeper insights into compatibility and effectiveness under extreme operating conditions. Additionally, combining ANN with robust controllers like SMC or MPC to form hybrid architectures such as ANN-SMC or ANN-MPC is a promising approach to enhance the system’s sustainability and rapid response capabilities. Furthermore, integrating reinforcement learning algorithms into the current control architecture will improve decision-making capabilities in highly uncertain environments, thereby expanding the application range of UAVs in complex and dynamic real-world missions.

In future studies, a more detailed presentation of the structure of the ANNPID neural network is needed, including the number of network layers, the number of neurons in each layer, the type of activation functions, and training parameters such as learning rate and number of epochs. Clearly describing these factors will enhance the transparency and reproducibility of the research. Additionally, to more comprehensively evaluate the performance of the proposed method, comparisons in simulations should be expanded from linear methods (PID, LQR) to advanced nonlinear processes such as backstepping, sliding mode control (SMC), or active disturbance rejection control (ADRC). This approach will enable a more comprehensive analysis of the controller’s adaptability and robustness when operating in nonlinear environments and under strong external disturbances. Finally, implementing and validating the ANN-PID method on real hardware is an important research direction to enhance its technical application value. Combining simulation with experimental testing will confirm the method's feasibility and effectiveness and help assess the practical challenges related to sensors, embedded computing, and energy limitations in UAV applications.

Author contributions

Vo Van An and Trinh Luong Mien: writing – review & editing, writing – original draft, visualization, methodology, investigation, formal analysis, conceptualization; Trinh Luong Mien and Nguyen Van Binh: methodology, writing – review & editing, investigation, formal analysis.

Use of Generative-AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare there is no conflict of interest in this paper.

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