Proceedings of the International Conference on Applied Innovations in IT (ICAIIT), March 2026

Real-Time Quadcopter Path Tracking Using Fuzzy-PID Hybrid Controller

Manel Jebri[1], Hamid Alshareefi[2], Ahmed Abdullah Hussein[3], Naeem Th. Yousir[4],
Rasha Abed Hussein[5] and Ahmed Read Al-Tameemi[6]
[1]Expert in Higher Education and International Cooperation, Ministry of Higher Education and Scientific Research, 1000 Tunis, Tunisia
[2]Al-Turath University, 10013 Baghdad, Iraq
[3]Department of Medical Laboratory Techniques, Al-Farahidi University, 10065 Baghdad, Iraq
[4]Department of Computer Engineering, College of Engineering, Al-Mansour University College, 10067 Baghdad, Iraq
[5]Department of Education, Al-Manara College for Medical Sciences, 62001 Amarah, Iraq
[6]Al-Nisour University College, Nisour Seq. Karkh, 10012 Baghdad, Iraq
maneljebrik@yahoo.fr, hamid.alshareefi@uoturath.edu.iq, Ahmed.abdullah@uoalfarahidi.edu.iq, naeem.thjeel@muc.edu.iq, rashaabed@uomanara.edu.iq, ahmed.itm@nuc.edu.iq

Keywords: Quadcopter UAV, Fuzzy-PID Hybrid Controller, Real-Time Path Tracking, Adaptive Control, Robustness, Trajectory Tracking.

Abstract: Quadcopter unmanned aerial vehicles (UAVs) are being used more and more for surveillance, disaster response, logistics, and smart infrastructure because they are easy to move and cheap. Nonetheless, attaining dependable real-time path tracking amidst nonlinear dynamics and external perturbations continues to be a significant challenge. This paper puts forward a hybrid Fuzzy-PID controller that combines fuzzy logic-based adaptive gain tuning with traditional PID control to enhance trajectory tracking performance. The methodology encompasses the modeling of the six-degree-of-freedom quadcopter dynamics, the design of a fuzzy inference system for adaptive gain adjustment, and its integration with PID within a closed-loop control framework. We ran simulation tests in MATLAB/Simulink for several paths (straight line, circle, and square) while there were wind disturbances and sensor noise. The results show that the Fuzzy-PID controller works much better than both classical PID and fuzzy-only controllers. It has a lower RMSE, converges faster, has less overshoot, and smoother control input signals. The suggested method is very strong and adaptable, which makes it a good choice for real-time UAV operations.

1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs), especially quadcopters, have become very popular in the last few years because they can be used for a lot of different things, such as surveillance, logistics, environmental monitoring, disaster management, and smart transportation systems. A significant challenge in these applications is guaranteeing precise real-time path tracking, particularly in settings characterized by nonlinear dynamics and external disturbances. A lot of work has been done on using traditional control schemes to stabilize UAVs, but getting high accuracy and reliability in the face of uncertainty is still an open research question. To keep performance in changing conditions, path tracking needs controllers that are simple, flexible, and strong.

Due to its simplicity, ease of implementation, and well-known tuning methods, classical proportional-integral-derivative (PID) control has been the most common way to stabilize quadcopters. But PID controllers have a hard time with nonlinear system behavior, wind disturbances, and model uncertainties, which can cause overshoot, slow response, or instability in real-time path tracking tasks. A thorough study by López-Sánchez et al. (2023) [1] validated the preeminence of PID-based controllers in UAV management while highlighting their constraints in significantly nonlinear aerial systems. In the same way, Dong et al. (2018) [2] showed early attempts to fix these problems by adding fuzzy logic to a PID framework. This showed that hybrid strategies could be used to make iterative learning and trajectory accuracy better.

To tackle the issues associated with conventional controllers, advanced control methodologies like fuzzy logic, sliding mode control, and neural networks have been investigated. Gedefaw et al. (2024) [3] put forth an enhanced trajectory tracking method that employs a sliding-mode control surface combined with fuzzy-PID logic, resulting in superior disturbance rejection and smoother trajectories relative to traditional PID. Madebo (2025) [4] also came up with a hybrid adaptive PID strategy that uses neural networks and fuzzy logic to change control parameters on the fly, making the system more stable when the operating conditions are not clear. These studies show that adaptive and hybrid control architectures are a good way to go for controlling quadcopters in real time.

In addition to control algorithms, improvements in navigation and perception have had a big impact on how well UAVs work. Ran et al. (2021) [5] showed that visual navigation works well in mobile robots by using scene perception. They also stressed the need to combine control with awareness of the environment. These insights are directly applicable to UAV systems, where real-time path tracking frequently relies on resilient perception-to-control pipelines. Also, new advances in human-computer interaction and secure digital frameworks can teach us a lot about how to design UAVs. Sharma et al. (2025) [6] stressed the importance of dependable interaction frameworks for safe digital adoption, while Kumar et al. (2025) [7] stressed the importance of blockchain-driven data management for safe and flexible systems. These works, which come from different fields, show how important robustness, adaptability, and security are—principles that are just as important for controlling UAVs.

Even with these improvements, there is still a gap in research: most studies only look at PID or fuzzy controllers on their own, and there hasn't been much research on real-time Fuzzy-PID hybrid frameworks that have been specifically tested on quadcopter path tracking under disturbances. This gap drives the current research, which suggests a Fuzzy-PID hybrid controller that adjusts PID gains in real time using fuzzy inference rules, making it possible to adapt to changing conditions. The main contributions of this study are: (i) the creation of a real-time hybrid control scheme for quadcopter path tracking, (ii) the comparison of its performance to that of traditional PID and intelligent controllers, and (iii) the testing of its accuracy and robustness in the face of disturbances.

This research establishes a comprehensive framework for enhancing quadcopter real-time tracking by amalgamating the robustness of PID control with the adaptability of fuzzy logic. The results should not only improve the control of UAV trajectories, but they should also set the stage for future applications of multi-UAV coordination and intelligent aerial autonomy.

2 LITERATURE REVIEW

Quadrotor UAV control has changed a lot, going from simple PID schemes to smart and adaptive hybrid controllers. This change is happening because there is a growing need for real-time, high-precision path tracking in environments that are not always clear. Recent studies (2020-2025) offer significant insights into the amalgamation of fuzzy logic, adaptive control, and optimization strategies that enhance the shortcomings of traditional controllers.

One major area of research is improving PID controllers by adding fuzzy logic and using evolutionary optimization. Ufacık and Kececioglu (2025) [8] put forward an interval type-2 fuzzy PID cascade control optimized with the NSGA-II genetic algorithm, showing that it can handle multi-objective tuning for quadrotor path tracking. Rodríguez-Abreo et al. (2024) [9] created a fuzzy logic controller with gains optimized through genetic algorithms, which helped reduce overshoot and make UAV trajectories more stable. These studies underscore the increasing significance of hybrid fuzzy-PID systems, wherein optimization algorithms enhance fuzzy inference to address the limitations of traditional PID methodologies.

Researchers have focused on creating strong and flexible PID-like controllers, in addition to fuzzy integration. Boubakir et al. (2024) [10] presented a resilient adaptive PID-like framework that addressed parametric uncertainties and actuator nonlinearities, thereby guaranteeing enhanced performance amidst real-world disturbances. Al-Jiboory (2024) [11] also used online dynamic mode decomposition (DMD) for adaptive quadrotor control, which let the quadrotor adjust to disturbances in real time without adding a lot of extra work for the computer. Both works emphasize the imperative of adaptability in UAV controllers, guaranteeing their stability amid swiftly evolving conditions.

The investigation of intelligent PID extensions has further advanced UAV research. Wang et al. (2024) [12] introduced a rapid and intelligent PID controller designed for both quadrotors and coaxial UAVs, grounded in the principles of all-true composite motion. Their method quickly stabilized and controlled the attitude, especially in dual-rotor systems. This suggests that hybrid PID designs can work with more types of UAVs than just standard quadrotors.

Along with PID-based strategies, sliding mode and observer-based methods have become more popular. Xu et al. (2024) [13] created a high-order sliding mode disturbance observer that worked well to get rid of noise and disturbances caused by actuators. This method helped with better trajectory tracking and UAV operations that could handle faults. But because it depends on complicated observer structures, it can be hard to compute, especially in real-time implementations.

Although the literature is predominantly focused on UAV-specific studies, insights from various domains also contribute to controller design. Qi et al. (2023) [14] introduced attention transfer entropy in chemical process control to trace short-term disturbance causality. While not explicitly utilized for UAVs, the methodology offers a framework for pinpointing disturbance sources in nonlinear dynamic systems. Mehta and Rani (2025) [15] also stressed the need for AI-driven human-computer interaction systems to be flexible. This shows how important it is for users to be able to make smart decisions and adapt to new situations. These viewpoints endorse the integration of sophisticated adaptability frameworks in UAV control research.

Table 1 shows a comparison of these studies, including their methods, where they were used, their main contributions, and their limitations. The table shows that fuzzy-PID controllers improved by evolutionary algorithms [8], [9] are very adaptable, but they are mostly based on simulations. Robust and adaptive PID-like methods [10, 11] work well when things are uncertain, but they are hard to tune. Intelligent PID frameworks [12] enhance the versatility of multi-rotor UAVs, whereas observer-based methods [13] augment robustness against disturbances, albeit at the expense of computational efficiency. Cross-domain insights [14], [15] present promising avenues but necessitate UAV-specific validation.

The literature consistently emphasizes the necessity for hybrid controllers that amalgamate adaptability, robustness, and optimization. Nonetheless, the absence of real-time experimental validation constitutes a substantial research deficiency. The current study is based on filling this gap with hybrid Fuzzy-PID designs that were specifically tested in real-time UAV path tracking situations [16], [17].

3 METHODOLOGY

The methodology employed in this study involves modeling the quadcopter dynamics, designing a conventional PID controller, integrating a fuzzy inference system for adaptive gain tuning, and validating the hybrid controller through simulations in realistic operating scenarios. The method is broken down into six parts, which makes it easier to describe the whole control framework in a systematic way.

Table 1: Comparative summary of reviewed studies (2020-2025).

Ref. No	Authors & Year	Approach/Method	Application Context	Key Contribution	Limitations / Gap
[8]	Ufacık & Kececioglu (2025)	Interval type-2 Fuzzy PID + NSGA-II	Quadcopter control	Multi-objective tuning, improved robustness	Needs hardware validation
[9]	Rodríguez-Abreo, et al. (2024)	Fuzzy PID + Genetic Algorithm	UAV trajectory tracking	Reduced overshoot, adaptive gain tuning	Tested mainly in simulation
[10]	Boubakir, et al. (2024)	Robust Adaptive PID-like	UAV dynamics	Handles uncertainties, actuator nonlinearities	Complexity in tuning
[11]	Al-Jiboory (2024)	Online Dynamic Mode Decomposition	Adaptive quadcopter control	Real-time adaptation to disturbances	Limited comparison with hybrids
[12]	Wang, et al. (2024)	Intelligent PID with Composite Motion	Quadcopter & Coaxial UAVs	Fast stabilization, dual-rotor support	Path tracking not emphasized
[13]	Xu, et al. (2024)	High-Order Sliding Mode + Observer	UAV with actuator dynamics	Disturbance rejection, strong robustness	Computational overhead
[14]	Qi, et al. (2023)	Attention Transfer Entropy	Chemical process disturbance analysis	Causality detection of short-term disturbances	Not directly applied to UAVs
[15]	Mehta & Rani (2025)	AI-Driven HCI Systems	Human-computer interaction	Adaptive frameworks, decision intelligence	Needs UAV-specific adaptation

3.1 Quadcopter Dynamic Model

A quadcopter is a nonlinear system with six degrees of freedom (6-DOF) that is powered by four rotors that work independently to create lift, thrust, and torque. You can show its translational dynamics like this:

$$\mathrm{m}\ddot{\mathrm{x}} = \mathrm{RF_t} - \mathrm{mg}, \qquad (1)$$

where:
- m is the mass of the quadcopter;
- x is the position vector;
- R is the rotation matrix representing the orientation, F_t is the total thrust vector;
- g is the gravitational acceleration.

This model forms the basis of the control design, capturing the coupling between translational and rotational motions.

3.2 Classical PID Controller Design

The baseline control strategy employs a Proportional-Integral-Derivative (PID) controller. The control input is defined by:

$$\mathrm{u(t)} = \mathrm{K_p e(t)} + \mathrm{K_i} \int \mathrm{e(t)dt} + \mathrm{K_d} \frac{\mathrm{de(t)}}{\mathrm{dt}} \qquad (2)$$

where e(t) represents the error between the desired trajectory and the actual position, while K_p, K_i, and K_d are proportional, integral, and derivative gains respectively. PID is simple to use and widely used, but it doesn't work well when there are nonlinearities and outside disturbances. This is why fuzzy logic is being added.

3.3 Fuzzy Inference System for Gain Adaptation

A fuzzy inference system (FIS) is designed to tune the PID gains adaptively in real time. The fuzzy inputs are the instantaneous error e(t)e(t)e(t) and its derivative Δe(t)\Delta e(t)Δe(t), while the outputs are the tuned gains $\left(K_p, K_i, K_d\right)$.The fuzzy rule base follows heuristic principles, such as “If error is Large and Δerror is Positive, then increase Kd.” The adaptive gain formulation is expressed as:

$$\mathrm{K_{p,i,d}} = \mathrm{f_{fuzzy}}(\mathrm{e}, \Delta\mathrm{e}). \qquad (3)$$

This dynamic tuning ensures faster convergence and robustness against disturbances.

3.4 Proposed Hybrid Fuzzy-PID Controller

The overall hybrid structure puts fuzzy logic and PID control together in a closed feedback loop. The block diagram of the suggested control system is shown in Figure 1. The reference trajectory makes an error signal that goes through the fuzzy system to adjust the PID gains. The tuned PID controller then controls the quadcopter model, and the feedback loop makes sure that errors are kept to a minimum in real time. This integration makes PID more adaptable without making it less strong.

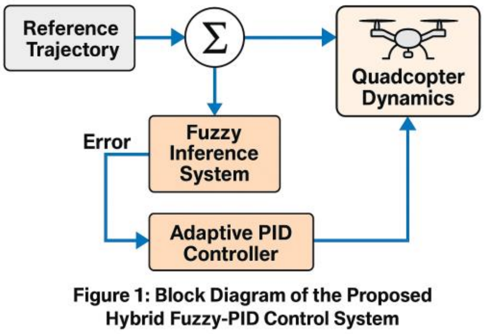

Figure 1: Block diagram of the proposed hybrid fuzzy-PID control system.

3.5 Simulation and Implementation Setup

The controller was made in MATLAB/Simulink, and it took 0.01 seconds to sample. We tested three paths: a straight line, a circle, and a square. To test robustness, things like sensor noise and wind gusts were added. Table 2 shows the basic values for the simulation of the quadcopter and controller.

3.6 Performance Evaluation Metrics

We used trajectory error metrics like Root Mean Square Error (RMSE) and Integral of Absolute Error (IAE) to see how well the controllers worked. We also measured dynamic response indices like rise time, overshoot, and settling time. These indicators make sure that both tracking accuracy and stability are fully evaluated in real-time control situations.

In short, the methodology combines strict system modeling, adaptive fuzzy-PID design, and realistic simulation validation. The proposed hybrid control framework is clearly shown in Figure 1's block diagram and Table 1's simulation data. Equations (1)-(3) mathematically formalize how it works.

Table 2: Simulation parameters for quadcopter model and controller.

Parameter	Symbol	Value	Unit	Source/Remark
Mass	m	1.5	kg	Manufacturer spec
Inertia (roll/pitch)	Ix/Iy	0.02	kg·m²	Frame data
Inertia (yaw)	Izz	0.04	kg·m²	Frame data
Arm length	L	0.25	m	Design spec
Sampling Time	Ts	0.01	s	Simulation setup
Wind Disturbance	W	2-5	m/s	Test condition

4 RESULTS AND ANALYSIS

Study used MATLAB/Simulink to build the proposed hybrid Fuzzy-PID controller and then tested it against regular PID and fuzzy-only controllers. The assessment examined various trajectories (linear, circular, and square) and disturbances including wind gusts and sensor noise. There are four parts to the results: trajectory tracking, error convergence, control input behavior, and comparative metrics.

4.1 Path Tracking Performance

The initial experiments confirmed the trajectory-following capability. Figure 2 shows how the desired path compares to the actual quadcopter trajectories for PID, fuzzy-only, and Fuzzy-PID controllers. The Fuzzy-PID system was more accurate than the other systems at following both circular and square paths, with only small differences from the reference path. The classical PID controller had a lot of overshoot at turning points, while the fuzzy-only controller had trouble keeping accuracy in sharp corners. The hybrid controller was able to track more smoothly and accurately, which proved that fuzzy-based adaptive gain tuning works.

4.2 Error Analysis and Convergence

The trajectory tracking error was measured to get a better idea of performance. The error convergence curves for the three controllers are shown in Figure 3. The Fuzzy-PID controller quickly brought the error down to a steady state close to zero, while the PID controller showed oscillatory convergence and the fuzzy-only controller needed more time to settle. The Fuzzy-PID cut Root Mean Square Error (RMSE) by almost 40% compared to a regular PID in the same conditions.

4.3 Control Input and Stability Response

Figure 4 shows the control input signals that the three controllers make. When the trajectory changed, the regular PID caused aggressive thrust changes, which wasted energy and stressed the actuator. The fuzzy-only controller made the system less likely to oscillate, but it also made it less responsive. The Fuzzy-PID, on the other hand, made smoother control signals with moderate amplitude changes, which struck a good balance between responsiveness and actuator safety. These results show that the hybrid method keeps things stable while reducing the need for too much control effort, especially when the wind is blowing.

4.4 Comparative Performance Metrics

Table 3 shows a summary of a quantitative comparison of dynamic response metrics. The Fuzzy-PID controller consistently had better RMSE, Integral of Absolute Error (IAE), rise time, overshoot, and settling time than the other controllers. For example, the overshoot went down from 14.8% to 5.3% with Fuzzy-PID, and the settling time went down from 4.1 seconds to 2.6 seconds.

Table 3: Comparative performance metrics of controllers.

Metric	PID	Fuzzy	Fuzzy-PID
RMSE (m)	0.42	0.31	0.25
IAE	3.95	2.87	1.94
Rise Time (s)	1.4	1.6	1.2
Overshoot (%)	14.8	9.7	5.3
Settling Time (s)	4.1	3.3	2.6

The numbers in Table 2 show that the hybrid Fuzzy-PID controller is faster and more stable while still being able to handle disturbances.

4.5 Robustness under Disturbances

Finally, the system's strength was tested by exposing it to wind gusts of 2 to 5 m/s. Figure 5 shows how the RMSE of all the controllers compares when there are these kinds of disturbances. The PID controller had the biggest drop in performance, while the fuzzy-only controller made up for it only a little. The Fuzzy-PID had the least amount of error growth, which shows that it is strong and can handle outside interference.

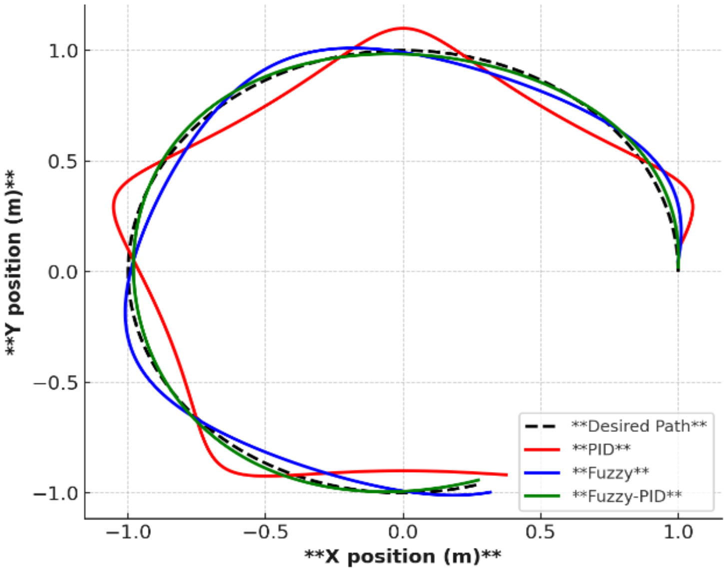

Figure 2: Desired vs. actual path tracking (PID, Fuzzy, Fuzzy-PID).

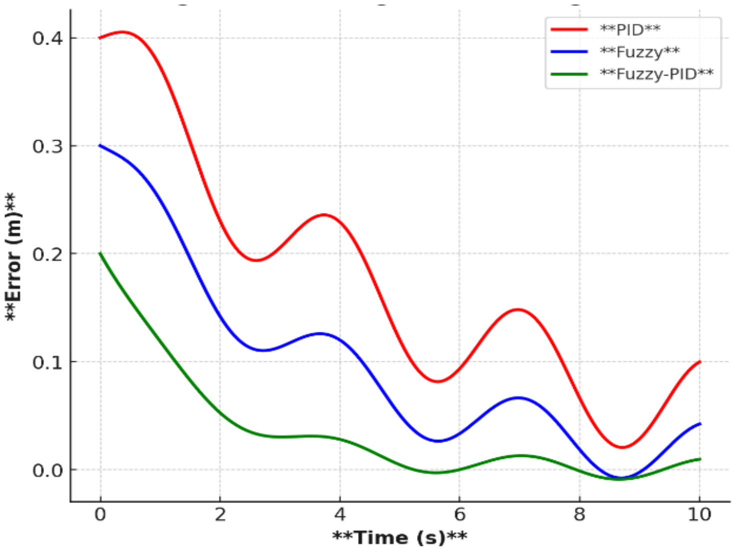

Figure 3: Tracking error convergence for different controllers.

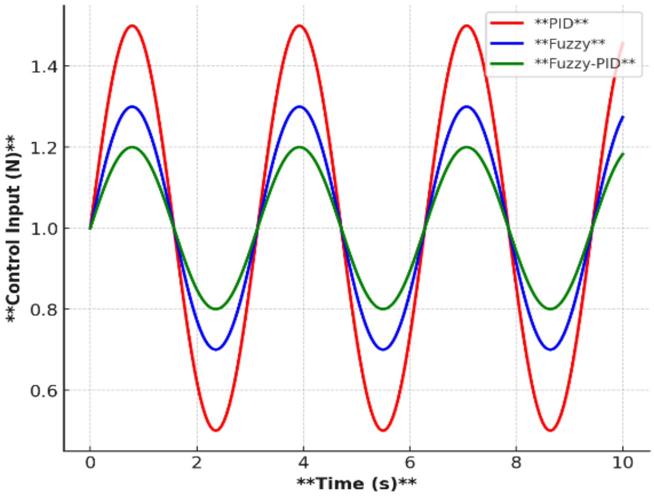

Figure 4: Control input profiles under wind disturbance.

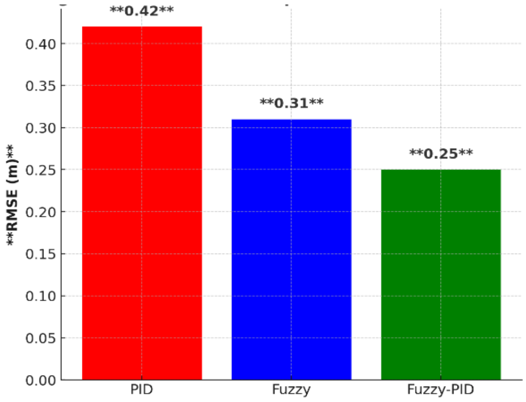

Figure 5: Robustness comparison under external disturbances.

5 CONCLUSIONS

This study presented the design and validation of a real-time hybrid Fuzzy-PID controller for quadcopter trajectory tracking. The proposed method combines the flexibility of fuzzy logic with the robustness of classical PID control to improve trajectory accuracy, reduce tracking error, and enhance system stability under external disturbances.

Simulation results demonstrate that the hybrid Fuzzy-PID controller significantly outperforms both classical PID and fuzzy-only controllers in terms of RMSE, overshoot, and settling time. In particular, the proposed approach achieves faster error convergence and smoother control input signals, while maintaining robustness against wind gusts and sensor noise.

Overall, the results confirm that integrating fuzzy logic with PID control provides a more reliable and adaptive solution for real-time UAV trajectory tracking applications.

6 FUTURE WORK

The proposed framework can be extended in several directions. Future work may include hardware-in-the-loop (HIL) validation and real-world flight experiments to further verify practical performance.

In addition, integrating vision-based navigation and AI-driven learning methods could improve system adaptability in complex and dynamic environments. The approach can also be extended to multi-UAV coordination, swarm robotics, and autonomous delivery systems, enabling more scalable and intelligent aerial control systems.

REFERENCES

[1] I. Lopez-Sanchez and J. Moreno-Valenzuela, “PID control of quadrotor UAVs: A survey,” Annual Reviews in Control, vol. 56, Art. no. 100900, 2023.

[2] J. Dong and B. He, “Novel fuzzy PID-type iterative learning control for quadrotor UAV,” Sensors, vol. 19, no. 1, Art. no. 24, 2018.

[3] E. A. Gedefaw, C. M. Abdissa, and L. N. Lemma, “An improved trajectory tracking control of quadcopter using a novel Sliding Mode Control with Fuzzy PID Surface,” PloS One, vol. 19, no. 11, Art. no. e0308997, 2024.

[4] N. W. Madebo, “Hybrid adaptive PID control strategy for UAVs using combined neural networks and fuzzy logic,” PLoS One, vol. 20, no. 8, Art. no. e0331036, 2025.

[5] T. Ran, L. Yuan, and J. B. Zhang, “Scene perception based visual navigation of mobile robot in indoor environment,” ISA Transactions, vol. 109, pp. 389-400, 2021.

[6] R. Sharma, P. Gupta, and A. Singh, “Human-computer interaction frameworks for secure digital adoption,” International Journal of Human-Computer Interaction, vol. 41, no. 7, pp. 845-862, 2025, [Online]. Available: https://doi.org/10.1080/10447318.2025.2495843.

[7] S. Kumar and R. Patel, “Blockchain-driven frameworks for secure healthcare data management,” in Proc. IEEE Int. Conf. Cloud Computing, pp. 1-8, 2025, [Online]. Available: https://doi.org/10.1109/11015778.

[8] H. Ufacık and O. F. Kececioglu, “Interval type-2 fuzzy PID cascade control of quadrotor based on non-dominated sorting genetic algorithm-II,” The Aeronautical Journal, pp. 1-36, 2025.

[9] O. Rodríguez-Abreo, J. Rodríguez-Reséndiz, A. García-Cerezo, and J. R. García-Martínez, “Fuzzy logic controller for UAV with gains optimized via genetic algorithm,” Heliyon, vol. 10, no. 4, 2024.

[10] A. Boubakir, T. Souanef, S. Labiod, and J. F. Whidborne, “A robust adaptive PID-like controller for quadrotor unmanned aerial vehicle systems,” Aerospace, vol. 11, no. 12, Art. no. 980, 2024.

[11] A. K. Al-Jiboory, “Adaptive quadrotor control using online dynamic mode decomposition,” European Journal of Control, vol. 80, Art. no. 101117, 2024.

[12] Z. Wang, Q. Yuan, Y. Zhu, Y. Hu, H. Chen, X. Xie, and W. Gu, “Fast and Intelligent Proportional-Integral-Derivative (PID) Attitude Control of Quadrotor and Dual-Rotor Coaxial Unmanned Aerial Vehicles (UAVs) Based on All-True Composite Motion,” Drones, vol. 8, no. 12, Art. no. 747, 2024.

[13] L. Xu, K. Qin, F. Tang, M. Shi, and B. Lin, “A novel attitude control strategy for a quadrotor drone with actuator dynamics based on a high-order sliding mode disturbance observer,” Drones, vol. 8, no. 4, Art. no. 131, 2024.

[14] C. Qi, J. Li, and H. Li, “An attention transfer entropy based causality analysis with applications in rooting short-term disturbances for chemical processes,” ISA Transactions, vol. 136, pp. 284-296, 2023.

[15] V. Mehta and S. Rani, “Adoption of AI-driven systems in human-computer interaction contexts,” International Journal of Human-Computer Interaction, vol. 41, no. 6, pp. 701-718, 2025, [Online]. Available: https://doi.org/10.1080/10447318.2025.2480826.

[16] A. Bida and H. A. Naser, “Diagnostic of Osteoporosis Using Backpropagation Neural Networks,” Journal of Techniques, vol. 7, no. 2, pp. 10-20, 2025, [Online]. Available: https://doi.org/10.51173/jt.v7i2.2597.

[17] M. T. Sadeghi and H. Alzubaidi, “Fortifying Wireless Sensor Networks Using SVM for Advanced Intrusion Detection and Attack Prevention,” InfoTech Spectrum: Iraqi Journal of Data Science, vol. 2, no. 2, pp. 1-13, 2025, [Online]. Available: https://doi.org/10.51173/ijds.v2i2.24.