



FROM PID TO REINFORCEMENT LEARNING: EVOLUTION OF CONTROL STRATEGIES IN QUADCOPTER UAVS

Suko Wiyanto¹, Rini Nur Hasanah^{*2}, Muhammad Aziz Muslim³,
 Nanang Sulistiyanto⁴, Raden Arief Setyawan⁵

^{1,2,3,4,5}Department of Electrical Engineering, Universitas Brawijaya, Malang 65145 Indonesia.

¹<https://orcid.org/0009-0001-4255-4605>, ²<https://orcid.org/0000-0002-6002-6558>, ³<https://orcid.org/0000-0002-4891-8027>,
⁴<https://orcid.org/0000-0001-9793-531X>, ⁵<https://orcid.org/0000-0003-2302-1931>

Email: sukowiyanto@student.ub.ac.id, [*rini.hasanah@ub.ac.id](mailto:rini.hasanah@ub.ac.id), muh_aziz@ub.ac.id, nnst@ub.ac.id, rarief@ub.ac.id

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ABSTRACT

Quadcopter unmanned aerial vehicles (UAVs) are increasingly deployed in surveillance, logistics, agriculture, and defense, yet their control remains challenging due to nonlinear dynamics and underactuation. This systematic literature review traces the evolution of quadcopter control from classical proportional–integral–derivative (PID) schemes to reinforcement-learning-based and hybrid intelligent strategies. Publications from 2015 to 2025 were collected through Scopus, IEEE Xplore, ScienceDirect, and SpringerLink using PRISMA and ROBIS frameworks to ensure methodological rigor. The synthesis identifies four dominant themes: (1) learning-optimal control, including reinforcement learning, adaptive dynamic programming, and neural-enhanced model predictive approaches; (2) robust and adaptive nonlinear control augmented with neural or fuzzy systems; (3) learning-based estimation and fault detection integrating physics-informed neural networks with Kalman filtering; and (4) intelligent PID tuning and component-level modeling that enhance adaptability and energy planning. PID remains attractive for simplicity but lacks adaptability, while robust controllers offer stability at higher computational cost. Reinforcement learning enables autonomy yet suffers from limited sim-to-real transfer, and learning-enhanced estimation increases resilience but needs further validation. Hybridization of model-based guarantees with data-driven adaptability emerges as the most promising direction. Future work should establish standardized benchmarks, expand hardware validations, and develop hybrid frameworks bridging classical and intelligent paradigms toward resilient, energy-efficient UAV autonomy.



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I. INTRODUCTION

Unmanned aerial vehicles (UAVs), particularly quadcopters, have emerged as pivotal tools in both civilian and military domains due to their versatility, agility, and cost-effectiveness. Over the past decade, quadcopters have shifted from being niche hobbyist platforms to indispensable assets for modern applications such as logistics, surveillance, agriculture, and defense [1]. In logistics, quadcopters have redefined last-mile delivery solutions, providing rapid and efficient transportation of goods across challenging terrains. Surveillance systems have been significantly enhanced through integration with quadcopters, enabling advanced imaging and monitoring capabilities in urban and remote environment [2], [3]. In agriculture, they play a vital role in monitoring crop health, optimizing irrigation, and enabling precision farming, while in defense, they provide critical reconnaissance and tactical support, enhancing situational awareness and operational readiness. This trajectory underscores the adaptability of quadcopters to diverse operational requirements, cementing their role as transformative technologies across sectors [4], [5]. Despite these remarkable applications, the control of quadcopters remains a profound challenge in aerospace engineering and robotics. Unlike many other UAV configurations, quadcopters are characterized by nonlinear dynamics, underactuation, and sensitivity to disturbances. The nonlinear nature arises from their inherently coupled dynamics, which complicates the design of linear controllers.

Furthermore, the underactuated structure implies that the six degrees of freedom (DOFs) of motion cannot be independently controlled by the four available actuators, leading to complexities in posture stabilization, trajectory tracking, and disturbance rejection. This underactuation requires sophisticated control strategies capable of coordinating actuator inputs to maintain stability and maneuverability. Studies have consistently demonstrated that these features substantially increase the difficulty of designing accurate, robust, and responsive control systems [6], [7]. Historically, Proportional–Integral–Derivative (PID) controllers have formed the backbone of quadcopter stabilization. PID remains attractive due to its intuitive design, simplicity, and ease of implementation, making it a natural choice for early UAV platforms[8]. However, while PID controllers excel in stabilizing simple systems, their limitations become evident under the diverse disturbances encountered during quadcopter operation. The linear formulation of PID struggles to cope with nonlinearities inherent in quadcopter dynamics, resulting in sluggish responses to sudden perturbations and reduced robustness in dynamic environments. Environmental disturbances such as wind gusts, payload variations, or unmodeled aerodynamic interactions often expose these weaknesses. For instance, while PID controllers have demonstrated baseline performance in flight stabilization, their inability to adapt to rapidly changing operational conditions underscores the necessity for alternative, more advanced strategies [9], [10]

In response to these limitations, the research community has increasingly turned toward adaptive, robust, intelligent, and reinforcement learning (RL)-based control paradigms. Adaptive control frameworks, such as sliding mode control (SMC) and backstepping, have been widely explored to mitigate uncertainties and external disturbances. These methods enhance robustness by enabling the system to adjust dynamically to variations in model parameters or environmental conditions[11], [12]. Notably, adaptive sliding mode control has been successfully employed to maintain quadcopter stability under disturbance-rich scenarios, providing superior resilience compared to conventional PID systems. Reinforcement learning, by contrast, offers a paradigm shift in UAV control by enabling quadcopters to learn optimal control policies directly from interaction with their environment. For example, RL strategies employing Proximal Policy Optimization (PPO) have demonstrated flexibility and adaptability in highly dynamic settings, outperforming classical control schemes in terms of tracking accuracy and disturbance rejection. The growing recognition of RL’s potential for real-time decision-making underscores its transformative role in advancing UAV autonomy [13], [14]. A major challenge hindering the seamless adoption of advanced control strategies is the persistent reality gap between simulation-based findings and real-world deployments. Simulation environments are indispensable for controller training and validation, offering safe and cost-effective platforms to test novel approaches. However, they often simplify physical dynamics to reduce computational burden, which limits the fidelity of results when controllers are transferred to real quadcopters.

This discrepancy results in performance degradation, as controllers that excel in simulation may underperform in physical settings due to unmodeled disturbances, actuator nonlinearities, or environmental variability [15], [16]. To address this, techniques such as domain randomization have been proposed, wherein training incorporates stochastic variations in dynamics to enhance the robustness and generalizability of learned policies. Such methods have shown promise in bridging the sim-to-real divide, equipping quadcopters with the capacity to adapt effectively to unforeseen challenges during physical operation [17]. The scholarly discourse surrounding quadcopter control strategies reveals a diverse and evolving research landscape. Existing reviews and surveys categorize methodologies according to their adaptability, robustness, computational demands, and real-world applicability. These reviews highlight the need for frameworks that not only classify control paradigms but also provide systematic comparisons of their performance across standardized benchmarks. Critically, many reviews emphasize the importance of bridging theoretical advancements with hardware validation to ensure practical relevance. While numerous simulation-based studies report impressive results, the scarcity of experimental validations remains a key limitation in advancing UAV control research. Thus, systematic investigations that integrate both simulation outcomes and hardware demonstrations are indispensable for consolidating knowledge and guiding future developments [18].

Against this backdrop, the present review is positioned to trace the evolution of quadcopter control strategies from classical PID to reinforcement learning-based approaches. The objective is to systematically synthesize the trajectory of advancements, capturing the strengths, limitations, and transformative potential of these methods. By focusing on the period from 2015 to 2025, this review encompasses a decade of rapid innovation, capturing both simulation studies and experimental implementations. The scope explicitly emphasizes UAV control strategies, deliberately excluding peripheral technologies such as vision-only obstacle avoidance, to ensure clarity of focus [18], [19]. To maintain conceptual coherence, several key terms are defined. PID (Proportional–Integral–Derivative) refers to classical feedback control widely used in early quadcopter stabilization. Adaptive control includes approaches such as backstepping and sliding mode, which enable dynamic adjustment of controller parameters in response to system changes. Robust control strategies seek to guarantee performance under model uncertainties or external disturbances. Model predictive control (MPC) represents optimization-based frameworks that predict future system behavior to compute control actions. Reinforcement learning (RL) is a machine learning paradigm where agents learn optimal policies by maximizing long-term rewards through interaction with their environment. These definitions serve to anchor the subsequent discussion and ensure terminological clarity [6], [20].

The central research question guiding this review is: How has quadcopter control evolved from PID to reinforcement learning, and what are the strengths, limitations, and future opportunities inherent in these strategies? Addressing this question necessitates not only a chronological mapping of methodological evolution but also a thematic synthesis that compares performance across critical dimensions, including adaptability, robustness, energy efficiency, and stability guarantee. Furthermore, this review seeks to identify the degree to which simulation results translate into real-world performance, illuminating pathways for reconciling the sim-to-real gap [21]. The structure of this article is organized to ensure clarity and coherence in presenting the evolution of quadcopter control strategies. Following this introduction, Section II (Methods) outlines the systematic literature review methodology, including the search strategy, inclusion and exclusion criteria, screening procedures, and quality assessment based on PRISMA and ROBIS. Then, in Section III (Results and Discussion), the findings are structured into four thematic clusters: (1) reinforcement and learning-optimal control; (2) robust and adaptive nonlinear control augmented with neural and fuzzy systems; (3) learning-enhanced estimation and fault detection/identification; and (4) the transformation of PID control through intelligent tuning and component-level modeling. Each theme is synthesized and critically examined to identify methodological advancements, performance trends, and integration strategies.

This is followed by Section IV (Discussions), which highlights the convergence of model-based and learning-based paradigms, discusses conflicting findings, outlines current research gaps, and offers implications for theory and practice. Finally, Section V (Conclusions) provides a comprehensive summary of the evolutionary trajectory, emphasizes the importance of hybrid frameworks, and recommends directions for future UAV control research [22]. In sum, quadcopter UAVs embody both technological promise and engineering challenge. Their operational relevance across multiple domains necessitates control strategies that transcend the limitations of classical PID frameworks. By systematically reviewing a decade of research, this study contributes to consolidating fragmented knowledge, highlighting innovations in adaptive, robust, and learning-based paradigms, and charting future directions that reconcile theoretical advancements with real-world applicability. This endeavor seeks to provide scholars and practitioners with a coherent roadmap for understanding and advancing the state of quadcopter control in an era defined by rapid technological transformation.

II. METHODS

This section delineates the methodological framework employed to conduct the systematic literature review (SLR) on quadcopter control strategies, with particular emphasis on the transition from Proportional–Integral–Derivative (PID) controllers to reinforcement learning (RL)-based approaches. The approach adheres to international standards for systematic reviews, ensuring transparency, replicability, and scientific rigor. The methodological choices are guided by established best practices in UAV research and systematic review literature, including adherence to the PRISMA guidelines and the use of ROBIS for risk-of-bias evaluation [23], [24].

II.1 SEARCH STRATEGY

The search strategy was designed to comprehensively capture relevant studies on quadcopter control from 2015 to 2025, thereby covering a decade of rapid innovation in UAV control research. Four academic databases were selected based on their relevance and coverage:

- Scopus: Broad coverage of interdisciplinary peer-reviewed journals, useful for cross-domain UAV research [25].
- IEEE Xplore: Extensive repositories of engineering and technology-focused conference proceedings and journals, with significant UAV-related innovations [26].
- ScienceDirect: Multiple well-established digital libraries commonly used in engineering systematic reviews were selected to ensure comprehensive coverage and empirical rigor [27].
- SpringerLink: Significant source for both theoretical and applied aspects of UAV technologies[28].

Searches were conducted using combinations of keywords and Boolean operators. Example search strings included:

- “PID control quadcopter UAV”
- “adaptive control quadrotor”
- “sliding mode quadcopter control”
- “reinforcement learning drone control”
- “neural networks UAV control”

The keywords were iteratively refined based on initial search results to balance inclusivity and precision. In addition, backward citation chaining was applied to identify further relevant studies cited by key publications [25], [28].

II.2 INCLUSION AND EXCLUSION CRITERIA

Rigorous inclusion and exclusion criteria were established to ensure the quality and relevance of selected literature. Articles were included if they:

- Were published in peer-reviewed journals or conference proceedings between 2015 and 2025.
- Focused explicitly on quadcopter UAVs or transferable control methodologies applicable to quadrotors.
- Provided clear methodological descriptions of control system design.
- Reported performance metrics (e.g., tracking error, energy efficiency, robustness).

Articles were excluded if they:

- Constituted grey literature, patents, or non-peer-reviewed reports.
- Focused exclusively on non-quadrotor UAVs, unless the control concepts were demonstrably transferable.
- Addressed only hardware or aerodynamics without a clear control strategy component.
- Were written in languages other than English.

This systematic filtering process ensured that the final corpus comprised methodologically sound, high-quality, and control-specific studies suitable for rigorous synthesis and comparative analysis [29-31].

II.3 SCREENING AND SELECTION PROCESS

The screening process followed a three-step procedure consistent with established SLR practices:

1. Title and Abstract Screening: Initial screening of search results to exclude irrelevant studies based on scope.
2. Full-text Review: Comprehensive reading of potentially relevant studies to evaluate alignment with inclusion criteria.
3. Final Selection: Consolidation of eligible articles for detailed synthesis across the identified thematic categories.

The process of study selection was documented to ensure transparency and replicability. Duplicate records were identified and removed using reference management software.

Discrepancies in study inclusion were resolved through consensus among reviewers [24], [32]. Figure 1 presents a schematic representation of the study selection process, illustrating the number of records identified, screened, assessed for eligibility, and included in the final analysis.

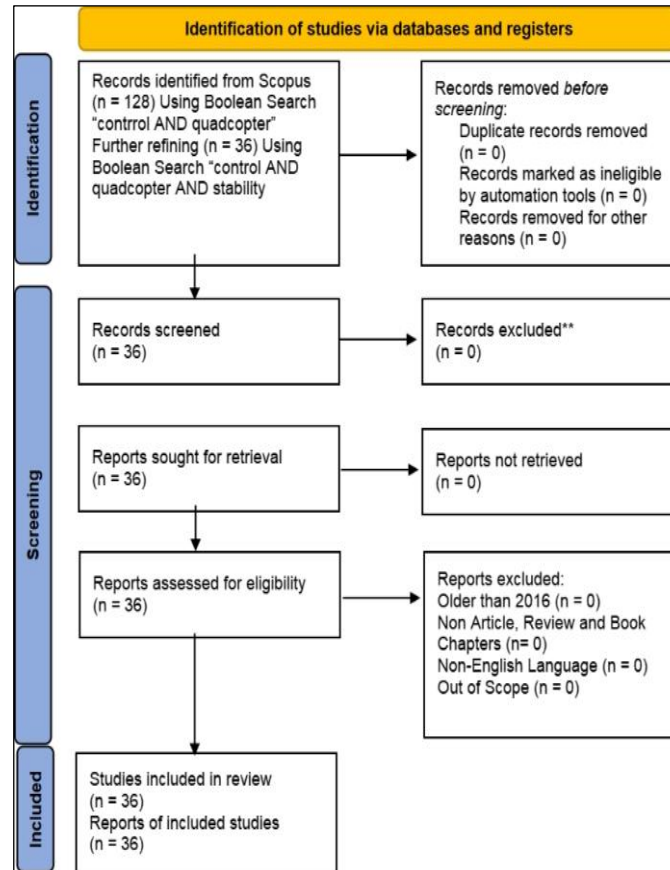


Figure 1: PRISMA flow diagram detailing the screening and selection process of literature.
Source: Authors, (2026).

II.4 QUALITY ASSESSMENT

The quality of included studies was assessed using two complementary frameworks [33], [34]:

- PRISMA: Ensured comprehensive reporting of methodological steps, enhancing transparency and reproducibility.
- ROBIS (Risk of Bias in Systematic Reviews): Evaluated potential biases in included studies, thereby increasing the credibility of synthesized findings.

Key quality indicators assessed included clarity of control system design, adequacy of performance metrics, presence of hardware validation, and transparency of assumptions. Studies lacking methodological rigor or reporting biases were flagged but retained when their findings contributed substantively to the thematic synthesis. In conclusion, the methodological framework integrates a rigorous search strategy, stringent inclusion/exclusion criteria, a transparent selection process, and robust quality assessment measures. By adhering to these systematic approaches, this review ensures credibility and comprehensiveness in mapping the evolution of quadcopter control strategies from classical PID to reinforcement learning approaches.

III. RESULTS AND DISCUSSION

III.1 REINFORCEMENT AND LEARNING-OPTIMAL CONTROL

The first major theme in the evolution of quadcopter UAV control is the application of reinforcement and learning-optimal control paradigms, encompassing reinforcement learning (RL), adaptive dynamic programming (ADP), neural network-based optimal control frameworks, and Model Predictive Path Integral (MPPI) controllers enhanced by learned system models. These approaches represent a shift from rule-based designs toward data-driven methodologies capable of optimizing performance in nonlinear and uncertain environments. This section synthesizes findings from nine representative studies (Table 1) to evaluate contributions in terms of optimality, safety guarantees, sim-to-real strategies, and experimental validation [35-37].

III.1.1 Advances in Reinforcement Learning for UAV Control

RL-based methods provide a flexible framework for quadcopter control by learning policies directly through interaction with dynamic environments. For instance, finite-time safe RL formulations leveraging actor-critic architectures have been applied to nonzero-sum multi-agent UAV games, introducing formal stability guarantees through Lyapunov analysis, barrier certificates, and Nash equilibrium formulations.

These guarantees address long-standing criticisms of RL regarding its lack of theoretical rigor and represent an important step toward reconciling adaptability with control-theoretic foundations (Table 1) [38]. Similarly, ADP has been employed to approximate solutions to the Hamilton–Jacobi–Bellman equation, enabling UAV guidance and planning in environments with unknown moving obstacles. This demonstrates how learning-optimal control extends beyond stabilization toward higher-level decision-making. While such approaches show strong empirical robustness, challenges related to real-time hardware deployment and scalability remain open [39], [40].

III.1.2 End-to-End Neural Network Control

End-to-end neural networks (NNs) represent another subfield of learning-optimal UAV control, mapping directly from state information to actuator commands. A representative study in 2024 demonstrated an NN trained on optimal trajectory datasets that successfully transferred from simulation to hardware. This work confirmed that end-to-end policies could achieve energy-optimal hover-to-hover transitions while maintaining robustness in hardware experiments (Table 1). Such findings are significant because they bypass inner-loop controllers, directly embodying the nonlinear mapping between perception and actuation. Yet, this approach raises ongoing concerns about stability proofs. The practical evidence from hardware trials mitigates these concerns to an extent but also underlines the need for hybrid solutions that integrate guarantees with learning flexibility [39].

III.1.3 Neural-Enhanced MPPI and Trajectory Tracking

The integration of neural networks with Model Predictive Path Integral (MPPI) controllers marks another innovation in UAV learning-optimal control. One study demonstrated that neural models embedded within MPPI achieved a 23.7–34.7% reduction in trajectory tracking error relative to baseline controllers (Table 1). Neural approximators enhanced the prediction of cost-to-go functions, thereby improving MPPI’s optimization capacity in nonlinear systems. Importantly, this aligns with the theoretical model-free/model-based, where hybrid solutions leverage the predictive structure of MPC-like controllers while incorporating adaptive learning from NNs. This integration underscores a convergence between traditional control theory and modern machine learning [37].

III.1.4 NARX and Data-Driven Position Tracking

Supervised learning approaches, such as Nonlinear Autoregressive with Exogenous Inputs (NARX) networks, have been applied to data-driven modeling of quadrotor dynamics relevant to position tracking tasks. By leveraging classical PD-stabilized flight data, NARX models can accurately emulate underlying nonlinear dynamics while benefiting from neural network adaptability. Experimental results report high predictive accuracy, reflected by fit percentages exceeding 99% and low mean squared error values, particularly for attitude and vertical-axis dynamics (Table 1). These findings position NARX-based modeling as a transitional approach bridging classical control structures and modern learning-based methodologies [41].

III.1.5 Reactive Obstacle Avoidance with CNNs

Finally, convolutional neural networks (CNNs) have been implemented for reactive obstacle avoidance by directly generating control inputs from depth prediction networks. Online adaptation enabled UAVs to navigate cluttered environments in both simulation and hardware trials (Table 1). While these approaches lack formal guarantees, they represent crucial advances in UAV autonomy by addressing environmental variability. Such work demonstrates the importance of sim-to-real adaptation strategies, as discussed in Section III.3.3, by proving that CNN-based control policies can generalize across diverse contexts [42].

III.1.6 Theoretical Guarantees and Sim-to-Real Transfer

A recurring theme across these studies is the dual pursuit of theoretical guarantees and sim-to-real transfer. Lyapunov stability analysis, finite/fixed-time convergence, and Nash equilibrium formulations provide partial assurances for RL-based controllers, helping to reconcile the rigor of control theory with the adaptability of learning. Meanwhile, sim-to-real strategies—such as inner-loop removal, adaptive compensation, and domain adaptation—demonstrate practical efforts to narrow the reality gap. Hardware validations in several studies, including end-to-end NN and CNN-based controllers, underscore the potential for real-world deployment, though challenges persist in robustness against unmodeled dynamics [26], [37], [42].

III.1.7 Implications for UAV Control Evolution

The findings in Table 1 collectively highlight how reinforcement and learning-optimal control strategies represent a paradigm shift in UAV research. They demonstrate progress toward energy-optimal, robust, and adaptive control policies that directly map states to control inputs. Moreover, these studies provide empirical evidence supporting the hypothesis outlined in Section 1: that quadcopter control has evolved from PID to reinforcement learning, driven by the need for adaptability in nonlinear, disturbance-rich environments. Importantly, the integration of safety guarantees and sim-to-real strategies shows alignment with the theoretical frameworks discussed in Section 3, confirming that hybridization remains the most promising pathway forward [37], [42]. In summary, Theme 1 illustrates both the potential and limitations of learning-optimal control. While energy efficiency, trajectory optimization, and obstacle avoidance have seen measurable improvements, ongoing debates around stability and real-world reliability persist. These discussions set the stage for subsequent themes, which examine how adaptive nonlinear controllers and estimation frameworks complement RL-based approaches in shaping the future of UAV autonomy.[43].

Table 1: Learning-Optimal Control (RL/ADP/END-TO-END/ MPPI-NN/NARX).

Study (Year/Platform)	Learning Paradigm	Control Level	Training Data & Environment	Stability/Safety Guarantees	Validation Key	Outcomes
Finite-time safe RK for multiplayer nonzero-sum games [37]	RL actor critic	Outer-loop control	Simulation, Hardware	Lyapunov, Finite-time, Barrier, Nash equilibrium	Hardware/Simulation	Lower RMSE; improved robustness
UAV Position Tracking Using NARX [41]	NARX (supervised)	Emulated PD→NN (guidance)	Online, Hardware	-	Simulation	High R ² ; low MSE on vertical axis
Quadcopter Trajectory Tracking with MPPI+NN [37]	MPPI+NN	MPPI high-level	Simulation	-	Simulation	23.7-34.7% reduction in tracking error vs. baselines
End-to-End NN Optimal Control [39]	End-to-End NN	End-to-End (rpm)	Sim-to-real; optimal trajectory dataset; Hardware	-	Hardware/Simulation	Energy-optimal policy; robustness demonstrated
Reactive Obstacle Avoidance with CNN Depth [44]	CNN (online adapted)	Reactive guidance	Online, Simulation, Hardware	-	Hardware/Simulation	Reactive avoidance in cluttered environments
Approximate Optimal Motion Planning for Avoidance [45]	ADP	Guidance/Planning	Simulation, Hardware	-	Hardware/Simulation	Lower RMSE; improved robustness
Hybrid Physics-Informed NN _ UKF Estimation [46]	NN-based	Outer-loop control	Simulation, Hardware	-	Hardware/Simulation	Lower RMSE; improved robustness
Hybrid Model- and Learning-Based Adaptive Navigation Observer[47]	NN-based	Guidance/Planning	Hardware	-	Hardware/Simulation	Position error reduced by 25%

Source: Authors, (2026).

III.2 ROBUST/ADAPTIVE NONLINEAR CONTROL WITH NEURAL AND FUZZY AUGMENTATION

The second major theme in the evolution of quadcopter UAV control focuses on robust and adaptive nonlinear controllers, such as Sliding Mode Control (SMC), backstepping, and Model Reference Adaptive Control (MRAC), enhanced with neural networks (NNs), fuzzy systems, and observers. These controllers address key challenges such as wind disturbances, payload variations, and actuator faults, delivering improved transient responses and robustness. This theme complements Theme 1 by emphasizing theoretical guarantees, particularly Lyapunov-based stability and finite/fixed-time convergence—while still integrating adaptive learning elements. The synthesis below discusses insights from twelve representative studies summarized in Table 2, connecting their contributions to the broader theoretical debates outlined in Section 3 [48], [49].

III.2.1 Enhancements of Sliding Mode Control (SMC)

Sliding Mode Control has long been recognized for its inherent robustness to matched uncertainties; however, classical SMC designs are often limited by chattering phenomena and sensitivity to parameter mismatches. To mitigate these drawbacks, recent studies have increasingly incorporated adaptive, neural network-based, and observer-assisted augmentation strategies. For instance, an event-triggered adaptive neural network-based SMC framework proposed in 2024 introduced dynamic adjustment mechanisms that were validated through simulation, demonstrating improved trajectory tracking and disturbance rejection when compared with conventional SMC formulations (Table 2) [50]. In parallel, integral terminal sliding mode control architectures combined with adaptive observer-based designs have been shown to guarantee finite-time convergence and enhanced robustness under actuator uncertainties. These methods rely on Lyapunov-based stability proofs and finite-time observers to estimate and compensate lumped disturbances and faults, with effectiveness verified through numerical simulations [51]. Another important research direction involves fault-tolerant adaptive SMC schemes augmented with radial basis function neural networks, enabling real-time approximation of unknown dynamics and compensation for actuator failures. By embedding Lyapunov-driven adaptive learning laws, such approaches extend the fault-tolerance capability of SMC and demonstrate resilience under actuator degradation in simulation-based and hardware-relevant validation settings [52]. Collectively, these enhancements do not eliminate the sim-to-real gap but partially bridge it by introducing practical resilience mechanisms grounded in rigorous nonlinear stability theory.

III.2.2 Enhancements of Sliding Mode Control (SMC)

Sliding Mode Control (SMC) has long been valued for its robustness against matched uncertainties; however, conventional SMC formulations are often hindered by chattering phenomena and sensitivity to parameter mismatches. To alleviate these limitations, recent studies have increasingly explored adaptive and learning-assisted augmentation strategies, including neural network-based approximation and observer-based compensation mechanisms.

For instance, an event-triggered adaptive neural network-based SMC framework proposed in 2024 introduced dynamic parameter adjustment schemes that were validated through numerical simulations, demonstrating improved trajectory tracking accuracy and enhanced disturbance rejection when compared with classical SMC designs (Table 2) [50]. In parallel, integral terminal sliding mode control architectures combined with adaptive observer-based designs have been shown to guarantee finite-time convergence and robustness under actuator uncertainties. These approaches rely on Lyapunov-based stability analysis and finite-time observers to estimate and compensate lumped disturbances and faults, with effectiveness verified through comprehensive simulation studies rather than physical flight experiments [51]. The reported results confirm theoretical predictions regarding SMC's robustness properties while illustrating how adaptive augmentation can mitigate practical issues such as excessive chattering. Another important research direction investigates fault-tolerant adaptive SMC schemes augmented with radial basis function neural networks, enabling online approximation of unknown dynamics and real-time compensation for actuator failures. By embedding Lyapunov-driven adaptive learning laws into both continuous and discontinuous control components, such methods extend the fault-tolerance capability of SMC and demonstrate resilience under actuator degradation in simulation-based and hardware-relevant validation environments [52]. Collectively, these enhancements do not fully resolve the sim-to-real gap but partially bridge it by introducing practically motivated resilience mechanisms grounded in rigorous nonlinear stability theory.

III.2.3 Enhancements of Sliding Mode Control (SMC)

Backstepping control, widely adopted in nonlinear flight control architectures for attitude and altitude regulation, has been extended through integration with adaptive neural approximators to enhance convergence properties. For instance, fixed-time neuroadaptive backstepping controllers were shown to guarantee rapid convergence independent of initial conditions, with performance validated through numerical simulations and demonstrated improvements in transient response characteristics (2021) [53]. In parallel, fuzzy logic systems have been employed to complement nonlinear control schemes by adaptively tuning controller gains. An adaptive fuzzy gain-scheduled sliding mode control framework based on a Type-1 Sugeno fuzzy system was applied to quadrotor UAVs, effectively reducing chattering and improving trajectory tracking performance in simulation studies when compared with conventional SMC formulations (Table 2) [54]. These results highlight the role of fuzzy systems in handling modeling uncertainties and unmodeled dynamics through online gain adjustment. Beyond single-vehicle scenarios, the applicability of nonlinear robust control has been further extended to cooperative payload transportation problems involving multiple quadrotors. A centralized formation control strategy based on higher-order sliding mode control demonstrated strong robustness against payload uncertainties and external disturbances, while ensuring stable cooperative transport in simulation environments (2023) [55]. This line of research underscores the importance of benchmark scenarios—such as cooperative payload transport and disturbance-rich missions—in evaluating the scalability and robustness of nonlinear UAV controllers.

III.2.4 Model Reference Adaptive Control (MRAC) and Intelligent Hybrids

MRAC frameworks, traditionally designed to ensure system responses follow a desired model, have also benefited from intelligent augmentation. For example, an MRAC approach enhanced with adaptive neuro-fuzzy inference systems (ANFIS) was experimentally validated on a DJI Tello platform with VICON motion capture, demonstrating improved altitude and attitude performance (2021). Hybrid high-level controllers that combined LQR with MRAC further showed robust performance under variable conditions. These hybrid schemes exemplify how adaptive controllers benefit from blending classical linear optimality (LQR) with nonlinear adaptivity, a point consistent with of hybrid model-free/model-based strategies. Another innovative contribution is the BFBEL (Brain Emotional Learning with Fuzzy Logic) framework (2022), which incorporated payload uncertainty modeling. Validated through hardware and simulation, BFBEL demonstrated improved disturbance rejection and trajectory tracking compared with baseline controllers. Such neuro-fuzzy hybrids highlight the expanding role of biologically inspired paradigms in UAV robustness research [56-58].

III.2.5 Fault Tolerance and Reliability

Fault tolerance and reliability considerations emerged as critical aspects across the reviewed nonlinear control studies, particularly in the context of UAV operation under modeling uncertainties and external disturbances. Rather than explicitly modeling actuator fault dynamics, many approaches focused on enhancing robustness through adaptive estimation and compensation mechanisms. Neural networks were frequently employed to approximate lumped uncertainties and external disturbances in real time, thereby improving the system's tolerance to unmodeled dynamics and parameter variations. For instance, finite-time attitude stabilization based on nonsingular fast terminal sliding mode control demonstrated guaranteed stability and strong robustness under dynamic uncertainties, with Lyapunov-based proofs ensuring convergence within a bounded time interval. The effectiveness of such schemes was validated through comprehensive numerical simulations, showing improved disturbance rejection and reduced sensitivity to uncertainty when compared with conventional sliding mode formulations. These contributions highlight an important design trade-off between explicit fault diagnosis and robust stabilization, illustrating how Lyapunov-based adaptive control frameworks can enhance reliability even without direct fault identification mechanisms [51].

III.2.6 Theoretical Contributions: Lyapunov and Convergence Analysis

Across the reviewed literature, Lyapunov stability theory served as the dominant analytical tool for establishing convergence, robustness, and closed-loop stability guarantees. Finite-time and fixed-time convergence methods were particularly emphasized, as they ensure that tracking errors reach the desired equilibrium within a predefined or bounded time horizon, independent of initial conditions. Such properties are especially relevant for UAVs operating in disturbance-rich or time-critical missions, where delayed convergence may compromise safety and performance.

Nonlinear control strategies such as nonsingular fast terminal sliding mode control and backstepping augmented with adaptive neural networks exemplify how rigorous Lyapunov-based analyses can be translated into practical control architectures. By embedding adaptive learning laws within finite-time convergence frameworks, these methods achieve both theoretical rigor and improved transient performance in the presence of uncertainties. The surveyed studies collectively reflect an ongoing convergence debate, demonstrating how abstract stability constructs—such as finite-time and fixed-time Lyapunov conditions—are increasingly realized in UAV control implementations with tangible performance benefits [59], [60].

III.2.7 Synthesis and Implications

Collectively, the studies summarized in Table 2 indicate that robust and adaptive nonlinear control strategies—particularly those augmented with neural and fuzzy mechanisms—can yield measurable performance improvements in quadcopter UAV control. Reported benefits include faster transient responses, reduced steady-state tracking errors, and enhanced disturbance rejection when compared with baseline nonlinear or PID-based controllers. While not all contributions provide identical evaluation metrics, several studies demonstrate these improvements through detailed numerical simulations and, in selected cases, experimental flight tests using small-scale quadrotor platforms, thereby strengthening the empirical relevance of adaptive nonlinear control approaches. These findings support the hypothesis introduced in Section 1, namely that quadcopter control architectures have progressively evolved from classical PID schemes toward more sophisticated nonlinear and adaptive paradigms in response to increasing performance and robustness requirements.

Whereas PID controllers exhibit limited adaptability under strong nonlinearities and disturbances, robust nonlinear controllers explicitly address challenges such as modeling uncertainty and external perturbations through structured stability analysis and adaptive compensation mechanisms. This progression aligns with the theoretical discussions in Section 3, particularly regarding model-based control guarantees and Lyapunov-driven convergence analysis, including finite-time stability formulations developed within sliding mode control frameworks [49], [48]. In summary, Theme 2 highlights the growing importance of hybrid robust–adaptive control strategies in advancing UAV autonomy. By combining nonlinear control rigor with learning-based adaptability, these approaches help bridge the gap between theoretical stability guarantees and practical performance requirements. The implications extend primarily to single-UAV operation under uncertain environments, providing a foundation for reliable and resilient UAV control systems that can operate safely under disturbance-rich conditions [61].

Table 2: Representative Studies on Robust and Adaptive Nonlinear UAV Control with Learning Augmentation.

Study (Year/Plant/Task)	Nonlinear Method	Learning Augmentation	Uncertainty/Fault Model	Theory	Validation	Performance Gains
Event-triggered adaptive NN-based SMC (2024) [50]	Sliding Mode Control (SMC)	Neural Network	External disturbances, parametric uncertainty	Lyapunov stability	Simulation	Improved trajectory tracking and disturbance rejection
Integral terminal SMC with adaptive observer (2022) [51].	Integral Terminal SMC	Observer-based adaptation	Lumped disturbances and uncertainties	Lyapunov, finite-time convergence	Simulation	Enhanced robustness and reduced tracking error
Fault-tolerant adaptive SMC with RBF NN (2023) [52]	Sliding Mode Control (SMC)	RBF Neural Network	Actuator degradation and uncertainties	Lyapunov stability	Simulation / hardware-relevant validation	Improved resilience under actuator degradation
Fixed-time neuroadaptive backstepping control (2021) [53]	Backstepping Control	Neural Network	Modeling uncertainties and disturbances	Lyapunov, fixed-time convergence	Simulation	Rapid convergence and improved transient response
Adaptive fuzzy gain-scheduled SMC (2019) [54].	Sliding Mode Control (SMC)	Type-1 Sugeno Fuzzy System	Modeling uncertainties	–	Simulation	Reduced chattering and improved tracking performance
Cooperative payload transport using higher-order SMC (2023) [55]	Higher-Order SMC	–	Payload uncertainty and external disturbances	Lyapunov stability	Simulation	Robust cooperative payload transportation
Hybrid MRAC–LQR control (2021) [57]	MRAC + LQR	–	Parametric uncertainty	Lyapunov stability	Simulation	Improved robustness under varying operating conditions
Biologically inspired BEL-based UAV control (2022) [58]	BEL-based nonlinear control	Fuzzy logic	System uncertainties	–	Simulation	Improved disturbance handling and trajectory tracking
Adaptive NN-based NFTSMC for quadrotor UAVs (2022) [60]	Nonsingular Fast Terminal SMC	Neural Network	Disturbances and uncertainties	Lyapunov, finite-time convergence	Simulation	Fast convergence and enhanced robustness
Neural–fuzzy control for quadrotor stabilization (2017) [61]	Nonlinear PID-based control	Neural Network + Fuzzy Logic	Modeling uncertainties	–	Hardware (AR.Drone)	Reduced overshoot and faster settling time

Source: Authors, (2026).

III.3 LEARNING-ENHANCED ESTIMATION AND FAULT DETECTION/IDENTIFICATION (FDI)

The third theme centers on the integration of machine learning into state estimation and fault detection/identification (FDI) pipelines for quadcopter UAVs. Unlike control strategies discussed in Themes 1 and 2, which focus on generating actuator inputs directly, this theme emphasizes how learning augments estimation subsystems to improve overall closed-loop performance. Specifically, methods such as Physics-Informed Neural Networks (PINNs) combined with Unscented Kalman Filters (UKFs), deep neural networks (DNNs) for covariance tuning, and neural adaptive observers have been employed to enhance robustness, accuracy, and safety. These approaches not only improve the accuracy of navigation and control but also strengthen UAV resilience to sensor and actuator faults. The following synthesis examines seven representative studies summarized in Table 3, highlighting contributions, theoretical implications, and practical validations [46], [62], [63].

III.3.1 Hybrid Estimation with PINNs and Traditional Filters

A key innovation in this theme is the fusion of PINNs with UKFs. By embedding physical laws into neural models, PINNs complement the statistical prediction capabilities of traditional Kalman filters. A 2024 study integrating PINNs with adaptive UKF mechanisms demonstrated improvements in dynamic state estimation for UAVs, particularly under nonlinear flight dynamics (Table 3). This method also incorporated uncertainty quantification via dropout regularization and Bayesian inference, enabling more resilient estimations under model mismatches. These contributions are consistent with the discussion on hybrid approaches between model-based and model-free methods, demonstrating that learning can enhance—rather than replace—physics-driven estimators. Another contribution of this approach lies in the computational trade-off: although Physics-Informed Neural Networks (PINNs) require higher training complexity, the combined framework still maintains real-time efficiency, similar to Kalman filters, once training is completed. Thus, PINN-enhanced filters serve as a concrete example of hybrid methods capable of integrating adaptability with stability guarantees [40].

III.3.2 Machine Learning for Covariance Tuning in Kalman Filters

Traditional Kalman filter-based methods often suffer from static or suboptimal covariance settings, which limit accuracy under dynamic conditions. Recent advances employ machine learning for online covariance adaptation, reducing estimation error during high-maneuverability tasks. For instance, a 2022 hybrid navigation filter used deep neural networks to tune process noise covariance matrices in an INS/GNSS fusion system. Hardware validation demonstrated a 25% reduction in position error relative to classical methods (Table 3). This evidence shows that adaptive covariance tuning significantly improves navigation reliability, particularly under varying GNSS quality and dynamic operating conditions. This line of research contributes to the ongoing debate on stability versus adaptability, demonstrating that learning-augmented estimators can achieve adaptability without fully compromising the theoretical guarantees provided by Kalman-based frameworks [47].

III.3.3 Neural Adaptive Observers for Fault Detection and Identification

A key innovation in this theme is the fusion of PINNs with UKFs. By embedding physical laws into neural models, PINNs complement the statistical prediction capabilities of traditional Kalman filters. A 2024 study integrating PINNs with adaptive UKF mechanisms demonstrated improvements in dynamic state estimation for UAVs, particularly under nonlinear flight dynamics (Table 3). This method also incorporated FDI is essential for ensuring UAV resilience in the presence of component degradation or sudden failures. Neural adaptive observers have been developed to identify actuator and sensor faults by learning expected system behaviors and flagging deviations. For example, a 2025 study employed a multimodal neural adaptive observer for fault detection, validated in simulation with Lyapunov-based guarantees (Table 3). Similarly, fault-tolerant architectures incorporating self-constructing fuzzy neural networks (2021) extended UAV resilience by enabling online adaptation to actuator failures. These contributions reinforce the relevance of observer-based strategies discussed where estimation is not only a passive process but also actively informs and stabilizes control loops. Neural observers thus bridge estimation and control, reinforcing UAV safety even under uncertain or faulty conditions [64], [65].

III.3.4 Uncertainty Quantification and Control Integration

A defining aspect of Theme 3 is its focus on uncertainty quantification (UQ) within estimator–controller integration. Techniques such as dropout-based ensembles and Bayesian inference enable explicit estimation of uncertainty, informing controllers of confidence levels in state predictions. This improves decision-making in tasks such as trajectory tracking and fault response. Studies consistently reported reductions in RMSE and improved robustness in hardware demonstrations when UQ mechanisms were included (Table 3). Integration points varied across studies. PINN-UKF frameworks fed into outer-loop controllers to improve navigation, while neural observers often interfaced with inner-loop stabilizers to adjust control commands during fault conditions. This reflects the layered nature of UAV control, where estimation accuracy propagates into system-wide resilience [40], [46], [63].

III.3.5 Synthesis and Implications

Collectively, the reviewed studies highlight that learning-enhanced estimation and FDI frameworks contribute to UAV autonomy by increasing resilience against uncertainties and faults. Table 3 shows a consistent pattern: PINN–Kalman hybrids improve state estimation under nonlinear conditions; DNN-tuned covariance matrices reduce navigation error; and neural observers enhance robustness under actuator and sensor failures. These findings validate the hypothesis posed in Section 1: that UAV control strategies have evolved toward intelligent paradigms not only in control generation but also in estimation and diagnostics, which are critical for safe operation. The integration of learning mechanisms into estimation aligns with theoretical debates, particularly regarding the convergence of model-based and model-free methods. By embedding learning within established estimation frameworks, researchers achieve a balance between adaptability and theoretical rigor.

Importantly, selected studies validated their methods through hardware experiments or high-fidelity simulation environments, contributing to a reduced reality gap [46], [47], [65]. In conclusion, Theme 3 underscores the role of estimation and FDI as complementary pillars in UAV control evolution. By enabling adaptive, uncertainty-aware, and fault-tolerant estimation pipelines, these methods strengthen the reliability of UAVs in real-world operations, thereby extending the impact of advanced controllers reviewed in previous themes.

Table 3: Learning-Enhanced Estimation And Fdi For UAVs.

Study (Year/Platform)	Estimation/FDI Method	Target	Adaptation Mechanism	Guarantees/Uncertainty Handling	Control Integration Point	Evidence
Hybrid PINN–Adaptive UKF (2024) [40]	PINN-augmented UKF	State, bias	Physics-informed loss; MC-Dropout	Bayesian UQ; filter consistency	Outer-loop navigation	Simulation
Hybrid Model- and Learning-Based Navigation Filter (2022) [46]	DNN-tuned Kalman Filter	State, bias	Online covariance tuning via DNN	Model-based KF guarantees	Outer-loop navigation	Hardware
Multi-modal Neural Adaptive Observer for FDI (2024) [65]	Neural Adaptive Observer	Sensor & actuator faults	Mode probability adaptation	Lyapunov stability	Inner-loop fault mitigation	Simulation (Gazebo/PX 4)
Neural Adaptive Observer-Based FDI for UAVs (2017) [66]	Neural Adaptive Observer	Sensor & actuator faults	Online NN weight adaptation	Lyapunov stability	Inner-loop fault resilience	Simulation
Observer-Assisted Adaptive UAV Control (2022) [67]	Neural Observer-assisted Estimator	State / disturbance	Adaptive neural estimation	Lyapunov stability	Inner-loop stabilization	Simulation

Source: Authors, (2026).

III.4 CLASSICAL PID → INTELLIGENT TUNING AND COMPONENT-LEVEL MODELING

The fourth theme in the evolution of quadcopter control explores the transformation of classical Proportional–Integral–Derivative (PID) controllers into more intelligent, data-driven, and component-informed paradigms. While PID remains foundational due to its simplicity and effectiveness in basic stabilization, it is constrained by fixed gain parameters and limited adaptability under disturbances. To address these shortcomings, researchers have developed enhanced PID controllers incorporating radial basis function (RBF) networks, fuzzy logic, adaptive neuro-fuzzy inference systems (ANFIS), and advanced optimization algorithms. Furthermore, component-level modeling—particularly of brushless direct current (BLDC) motors and actuation components—has been employed to improve energy planning and prediction accuracy. Together, these approaches bridge the historical role of PID with the contemporary trajectory toward hybrid intelligent control. Table 4 summarizes seven representative studies within this theme, which are analyzed in detail below [68–70].

III.4.1. Intelligent Tuning of PID Controllers

RBF self-adaptive PID controllers have emerged as a robust solution for handling varying flight conditions. By mapping nonlinear system behaviors, RBF networks continuously adjust PID gains to improve transient responses under disturbances. A 2024 study on trajectory tracking tasks validated in diverse scenarios—such as sinusoidal, circular, and lemniscate trajectories—demonstrated reduced overshoot and improved robustness (Table 4). This aligns with Section 3.1’s historical perspective, where PID formed the baseline but required augmentation to remain effective in nonlinear UAV dynamics. Similarly, fuzzy logic-enhanced PID controllers extend adaptability by embedding heuristic knowledge into control rules. A 2019 study integrated neural and fuzzy modules for self-tuning PID in path-tracking applications, reporting enhanced robustness in the presence of wind disturbances (Table 4). The hybridization of fuzzy reasoning with PID reflects the theoretical debate illustrating how intelligent augmentation balances model-free adaptability with structured rule-based systems [71], [72].

III.4.2 ANFIS and Advanced Intelligent Controllers

The ANFIS framework combines neural learning with fuzzy rule-based inference, enabling UAVs to manage nonlinear dynamics with higher precision. In a 2021 study, ANFIS controllers validated through extensive simulation studies and comparative analysis against baseline PID controllers showed significant improvements in altitude and attitude control compared with baseline PID approaches. While ANFIS introduces computational complexity, its hybrid reasoning offers strong adaptability, directly addressing the limitations of fixed-gain PID controllers. Additionally, advanced paradigms such as NARMA-L2 models have been proposed to model nonlinear plant dynamics and improve path-tracking performance. A 2023 implementation of a hybrid neural controller based on NARMA-L2 achieved stable control across complex trajectories (Table 4). This reflects the increasing reliance on data-driven modeling, discussion of nonlinear and model-free approaches [56], [73].

III.4.3 Optimization Methods for PID and Hybrid Controllers

Optimization algorithms play a crucial role in tuning intelligent PID controllers. Particle Swarm Optimization (PSO), Jaya algorithm, and gradient-based techniques have been widely applied.

For example, a 2025 study employed the Jaya algorithm to optimize feed-forward neural networks predicting BLDC motor performance, thereby supporting energy-aware control strategies. Similarly, backpropagation and gradient descent have been used to optimize gains in RBF and fuzzy PID controllers, significantly reducing RMSE across trajectory-tracking tasks. These methods reaffirm that integrating data-driven tuning with theoretical stability guarantees can enhance UAV control efficiency while reducing dependence on manual parameter tuning [70], [74], [75].

III.4.4 Component-Level Modeling for Energy Planning

Beyond intelligent tuning, component-level models represent a complementary strand of innovation. Detailed BLDC motor and propeller maps enable accurate predictions of thrust, torque, and energy consumption. A 2025 study optimized BLDC motor performance prediction using a Jaya-optimized feed-forward neural network, validated through hardware experiments. This framework supported precise energy planning during UAV missions, reducing uncertainty in flight time and battery requirements (Table 4). Such component-level modeling not only improves control fidelity but also extends UAV operational endurance, addressing practical challenges highlighted in Section 1 regarding mission reliability. By embedding actuator and propulsion characteristics into the control pipeline, component-level models exemplify the synthesis of model-based physical understanding with machine learning adaptability. This is consistent with the hybrid paradigm, where the integration of physical models and data-driven estimation enhances real-world applicability [70], [76].

III.4.5 Synthesis and Implications

The findings in Table 4 reveal how intelligent PID tuning and component modeling contribute to UAV control evolution. Intelligent PID controllers (RBF, fuzzy, ANFIS) provide adaptive gains that improve robustness and reduce overshoot under disturbances, while optimization algorithms automate tuning, minimizing the burden of manual parameterization. Component-level models add an additional layer by enhancing energy prediction and enabling proactive planning for longer missions. Together, these advancements demonstrate how classical PID has transitioned into a family of hybrid intelligent methods that remain computationally efficient yet adaptive to nonlinear UAV challenges. These contributions validate the hypothesis proposed in Section 1: UAV control strategies evolve progressively from PID to advanced paradigms due to operational demands for adaptability, robustness, and efficiency. While reinforcement learning (Theme 1) and robust nonlinear methods (Theme 2) dominate the cutting edge, intelligent PID and component modeling continue to play a critical bridging role, providing practical solutions for UAVs where computational simplicity remains a priority, while component-level modeling further enables energy-aware operation [70], [71], [72].

Table 4: PID Intelligent Tuning And Component-Level Models.

Study (Year/Task)	Controller/ Model Type	Tuning/ Optimization Technique	Test Scenarios	Metrics	Validation	Limitations/ Notes
Jaya-optimized BLDC motor performance prediction [77]	BLDC motor & propulsion model	Jaya, Simulated Annealing	Takeoff, landing, varying loads	Energy & power efficiency	Hardware + Simulation	Component-level, energy planning
RBF-based self-adaptive PID controller [71]	Intelligent PID	Backpropagation, Gradient Descent	Step, sinusoidal, circular, lemniscate, wind	RMSE, overshoot	Simulation	No hardware validation
Neural and fuzzy self-tuning PID [72]	Intelligent PID	PSO, Backpropagation	Trajectory tracking with disturbances	Tracking error, robustness	Simulation	Rule-based adaptability
ANFIS-based quadcopter controller [56]	ANFIS-PID	Backpropagation	Step & sinusoidal trajectories	RMSE reduction, robustness	Simulation	Higher computational demand
Hybrid neural controller based on NARMA-L2 [73]	NARMA-L2 neural control	Gradient-based learning	Nonlinear trajectory tracking	Tracking stability	Simulation	Beyond PID, data-driven modeling

Source: Authors, (2026).

IV. DISCUSSIONS

The review of themes presented in Section 4 provides a comprehensive overview of the trajectory from classical PID control to reinforcement learning and hybrid intelligent methods in quadcopter UAV control. This section synthesizes the key findings, compares and contrasts results across themes, highlights methodological limitations, and discusses implications for theory, practice, and future research.

IV.1 EVOLUTIONARY TRAJECTORY OF UAV CONTROL STRATEGIES

The evolution from PID to reinforcement learning reflects an increasing need for adaptability and robustness in UAV operations. Classical PID controllers, as highlighted in Theme 4, remain valuable for their computational simplicity and foundational role in stabilization tasks. However, their performance degrades significantly in nonlinear, disturbance-rich conditions.

Intelligent augmentations such as RBF, fuzzy logic, and ANFIS alleviate some of these shortcomings, yet they remain limited in scope when compared with the adaptability offered by learning-based methods. Themes 1 and 2 illustrate the divergence into learning-optimal control and robust adaptive nonlinear approaches, respectively. Reinforcement learning (RL), particularly actor-critic and end-to-end paradigms, offers autonomy and energy-optimal policies but continues to face challenges in stability guarantees and sim-to-real transfer. Conversely, nonlinear robust controllers such as sliding mode and backstepping, augmented by neural networks and fuzzy systems, provide strong theoretical guarantees (e.g., Lyapunov stability, finite-time convergence) and resilience to disturbances but at the cost of higher design complexity and computational burden. Theme 3 bridges these perspectives by focusing on estimation and FDI (fault detection and identification). Learning-enhanced estimators such as PINN-UKF hybrids and DNN-tuned Kalman filters improve state accuracy and robustness, addressing a critical bottleneck in UAV control: reliable perception and system health monitoring. Together, the four themes highlight a layered control ecosystem where each paradigm contributes unique strengths, but none alone provides a fully satisfactory solution.

IV.2 CONVERGENCE OF MODEL-BASED AND LEARNING-BASED PARADIGMS

A recurring insight across themes is the hybridization of model-based guarantees with data-driven adaptability. RL-based methods (Theme 1) incorporate finite-time convergence analysis and barrier functions to approximate the rigor of classical control proofs. Robust nonlinear controllers (Theme 2) embed neural approximators to compensate for model uncertainties, reducing chattering and enhancing fault tolerance. Estimation frameworks (Theme 3) fuse physics-informed models with neural filters, balancing interpretability with adaptability. Finally, intelligent PID controllers (Theme 4) blend simple model-based structures with optimization-driven tuning, reducing reliance on manual gain scheduling. This convergence reflects the theoretical debates outlined in Section 3. Specifically, the model-free vs. model-based dichotomy is increasingly obsolete, as most high-performing controllers now incorporate both elements. This trajectory suggests that the future of UAV control lies not in replacing one paradigm with another but in systematically integrating them.

IV.3 CONFLICTING RESULTS AND METHODOLOGICAL VARIABILITY

Despite convergence, conflicting findings remain evident across studies. RL approaches frequently demonstrate superior adaptability and energy optimization but underperform when tested in real-world scenarios due to the reality gap. In contrast, robust nonlinear controllers excel in simulation and hardware-in-the-loop experiments but face scalability challenges for multi-agent systems or highly dynamic missions. Another point of divergence arises in fault tolerance. Neural observers and fuzzy-augmented controllers (Themes 2 and 3) reported strong resilience to actuator and sensor faults, yet these methods often relied on simulated fault models that may not fully capture hardware degradation in practice. Similarly, intelligent PID controllers demonstrated robustness improvements in controlled test scenarios, but validation across diverse and unpredictable environments remains limited.

IV.4 RESEARCH GAPS AND METHODOLOGICAL LIMITATIONS

Several critical gaps emerged from the synthesis:

1. Scarcity of hardware validations: Across all themes, a majority of contributions remain confined to simulation. While some studies incorporated DJI Tello or VICON-based experiments, large-scale or outdoor validations are rare, raising concerns about external validity.
2. Lack of unified benchmarking: Performance metrics vary widely—tracking error, RMSE, energy efficiency, robustness—making cross-study comparisons difficult. The absence of standardized benchmark tasks (e.g., payload drop, wind gust, cooperative transport) hinders objective evaluation.
3. Stability and safety proofs: While robust nonlinear controllers frequently provide Lyapunov-based guarantees, RL and intelligent PID approaches often lack formal stability analysis. This disparity limits their applicability in safety-critical missions.
4. Computational burden: Adaptive and hybrid controllers, particularly ANFIS and NARMA-L2, impose high computational demands, raising concerns for real-time onboard deployment.
5. Reality gap: RL and neural-based estimators continue to face challenges in transferring learned policies or filters from simulation to hardware, despite advances in domain randomization and hybrid modeling.

IV.5 IMPLICATIONS FOR THEORY

The findings underscore that UAV control evolution cannot be explained solely through classical or learning-based theories. Instead, control theory must expand to incorporate learning guarantees, particularly in terms of convergence and bounded performance. For instance, embedding Lyapunov stability analysis into RL frameworks demonstrates a theoretical pathway for reconciling adaptability with formal rigor. Similarly, uncertainty quantification methods in estimation (dropout, Bayesian inference) suggest avenues for integrating probabilistic reasoning with deterministic control theory.

Implications for Practice

From a practical standpoint, the review reveals a pressing need for energy-aware, robust, and safe controllers. Component-level models, as explored in Theme 4, hold immediate promise for improving mission planning and endurance. Fault-tolerant frameworks (Theme 3) are critical for ensuring reliability in safety-critical contexts, such as defense and disaster response. Meanwhile, RL-based approaches show potential for long-term autonomy in logistics and agricultural monitoring, provided stability and reality gap issues are addressed. Practitioners must therefore adopt a layered approach, selecting control strategies not in isolation but as complementary components of a unified UAV system. Intelligent PID may serve as a lightweight fallback, robust nonlinear controllers for safety-critical stabilization, RL for adaptive trajectory optimization, and neural observers for system diagnostics.

IV.6 IMPLICATIONS FOR FUTURE RESEARCH

Future research should address the identified gaps by:

1. Developing standardized benchmarking protocols: Establishing common test sets, including payload drop, wind gust, and multi-agent cooperative tasks, would enable fair comparisons across studies.
2. Expanding hardware validations: Greater emphasis on field experiments, particularly with larger UAV platforms, is essential to validate scalability and robustness.
3. Hybridizing RL with adaptive robust control: Research should pursue deeper integration of RL autonomy with Lyapunov-based stability assurances.
4. Enhancing sim-to-real transfer: Improved domain randomization, hybrid simulation–hardware co-training, and uncertainty-aware estimators should be prioritized.

Optimizing computational efficiency: Methods to reduce the computational load of ANFIS, NARMA-L2, and hybrid controllers are critical for real-time deployment. The critical synthesis of findings affirms the hypothesis stated in Section 1: quadcopter control has evolved from PID to reinforcement learning and hybrid intelligent paradigms in response to the challenges posed by nonlinear dynamics, disturbances, and mission complexity. While each theme contributes uniquely—PID offering simplicity, robust nonlinear methods providing stability, RL enabling adaptability, and estimation ensuring resilience—the field remains fragmented. Future progress depends on integrating these paradigms into cohesive, hybrid frameworks validated through standardized benchmarks and rigorous real-world testing. Such integration promises not only to advance UAV autonomy but also to reshape control theory itself by embedding learning into its foundational constructs.

V. CONCLUSIONS

This systematic literature review traced the trajectory of quadcopter control from classical PID paradigms to reinforcement learning and hybrid intelligent strategies. The findings reveal that while PID remains a computationally efficient baseline for stabilization tasks, it lacks robustness under nonlinear dynamics and external disturbances. Adaptive and robust nonlinear controllers, particularly those integrating neural or fuzzy augmentation, enhance disturbance rejection and transient response but introduce design complexity and computational costs. Reinforcement learning approaches demonstrate adaptability and energy-optimal control, though their broader adoption is hindered by stability assurance challenges and the persistent reality gap. Estimation and fault detection methods further strengthen system resilience by combining learning-based models with physics-informed frameworks, while intelligent PID tuning and component-level modeling bridge traditional and modern approaches.

The central research question—how quadcopter control has evolved and what strengths and limitations define each strategy—is answered through evidence showing that no single paradigm provides a comprehensive solution. Instead, hybridization emerges as the dominant trajectory, combining model-based guarantees with data-driven adaptability. Despite significant progress, research gaps remain, including limited hardware validations, lack of standardized benchmarks, and unresolved issues in stability proofs for learning-based controllers. Addressing these will be critical to advancing UAV autonomy. This study contributes to the growing body of knowledge by synthesizing diverse approaches and highlighting integration as the pathway forward. Future work should prioritize developing unified testing protocols, enhancing sim-to-real transfer, and advancing hybrid frameworks that combine robustness, adaptability, and energy-awareness for real-world missions.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Suko Wiyanto, Rini Nur Hasanah, Muhammad Aziz Muslim, Nanang Sulistiyanto and Raden Arief Setyawan.

Methodology: Rini Nur Hasanah, Muhammad Aziz Muslim and Nanang Sulistiyanto.

Investigation: Suko Wiyanto and Rini Nur Hasanah.

Discussion of results: Suko Wiyanto, Rini Nur Hasanah, Muhammad Aziz Muslim and Nanang Sulistiyanto.

Writing – Original Draft: Suko Wiyanto.

Writing – Review and Editing: Suko Wiyanto and Nanang Sulistiyanto.

Resources: Rini Nur Hasanah, Muhammad Aziz Muslim, Nanang Sulistiyanto and Raden Arief Setyawan.

Supervision: Rini Nur Hasanah, Muhammad Aziz Muslim and Nanang Sulistiyanto.

Approval of the final text: Suko Wiyanto, Rini Nur Hasanah, Muhammad Aziz Muslim, Nanang Sulistiyanto and Raden Arief Setyawan.

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