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CONTROL STRATEGIES FOR UNMANNED AERIAL VEHICLE SYSTEMS: TAXONOMY, VALIDATION MATURITY, AND PERFORMANCE EVALUATION

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Abstract- Unmanned Aerial Vehicles (UAVs) are being increasingly tasked with missions requiring stability, trajectory tracking, disturbance rejection, and real-time onboard execution under uncertain and resource-constrained conditions. In practice, controller performance is influenced by nonlinear and coupled dynamics, as well as actuator saturation, sensor noise, wind disturbances, limited computation, energy constraints, and platform-dependent flight characteristics. This paper provides a compact review of UAV control strategies focusing on three aspects that strongly affect their practical deployment: controller taxonomy, validation maturity, and performance metrics. The main families of UAV control strategies are reviewed in terms of strengths, limitations, and implementation requirements. The paper also discusses progressive levels of validation including numerical simulation, Software-in-the-Loop (SIL), Processor-in-the-Loop (PIL), Hardware-in-the-Loop (HIL) and real-flight testing. In addition, the review summarizes key performance metrics for evaluating UAV control strategies. Finally, the paper highlights the emerging trends, research gaps, and future directions in UAV control systems.

Keywords: Unmanned Aerial Vehicles, Control Strategies, Validation Levels, Performance Metrics.

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become important platforms in modern aerospace, robotics, and autonomous systems [1]. Their mobility, flexibility, and ability to operate without an onboard pilot have enabled their use in surveillance, inspection, mapping, precision agriculture, logistics, disaster response, communication support, and defense applications [2]. This expansion has been driven by advances in embedded processors, sensors, communication systems, energy-storage technologies, avionics, and flight-control hardware [3], [4].

Despite these advances, UAV control remains a challenging engineering problem. UAVs are nonlinear, coupled and often underactuated systems, and their dynamics are affected by aerodynamic forces, actuator limits, sensor noise, wind disturbances, payload variations, and limited onboard computation.

Several control strategies have been proposed to improve UAV stability, trajectory tracking, disturbance rejection, autonomy, and cooperative operation. These strategies range from classical and linear controllers to nonlinear, robust, predictive, adaptive, intelligent, hybrid, and multi-agent approaches. Nevertheless, comparing these methods remains difficult because existing studies differ in UAV models, reference trajectories, disturbance assumptions, simulation environments, tuning procedures, and performance metrics. Moreover, many works are limited to simulation and fewer studies involve SIL, PIL, HIL, or real-flight validation. This limits the practical transfer of advanced control algorithms to real UAV systems.

Unlike existing UAV control surveys that mainly classify controller families or focus on specific UAV platforms, this review adopts a deployment-oriented perspective by jointly analyzing three interconnected aspects: control taxonomy, validation maturity, and performance metrics. This combination is necessary because controller performance cannot be judged only from the control law itself. A method that performs well in simulation may still be unsuitable for practical UAV deployment if it is not validated through SIL, PIL, HIL, or real-flight testing, or if computational cost, actuator effort, energy consumption, and robustness are not reported. Therefore, this review links control strategies with validation levels and evaluation metrics to support more practical comparison, controller selection, and deployment-oriented assessment of UAV control methods. The paper's main contributions are:

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• A structured taxonomy of classical, nonlinear, robust, predictive, adaptive, intelligent, hybrid, and cooperative UAV control strategies;
• A comparative discussion of advantages, limitations, and implementation requirements of UAV control approaches;
• A validation-oriented perspective covering SIL, PIL, HIL, and real-flight evaluation;
• A synthesis of key trends, research gaps, and future directions related to UAV control strategies.

The remainder of this paper is organized as follows. Section 2 describes the review methodology. Section 3 summarizes the UAV modeling and control challenges. Section 4 presents the taxonomy and comparative analysis of the main UAV control strategies. Section 5 discusses validation methods and performance metrics. Section 6 identifies trends, research gaps, and future directions. Finally, Section 7 concludes the paper.

2. REVIEW METHODOLOGY

This paper follows a qualitative review approach. Its objective is to provide a representative synthesis of UAV control strategies, with emphasis on controller taxonomy, implementation constraints, validation maturity, and performance metrics. The review is intended to support engineering-oriented understanding of UAV controller selection, evaluation, and practical deployment.

The literature was selected from major scientific databases and publishers, including IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, Wiley Online Library, Taylor & Francis, MDPI, and IJTPE. The search focused on works related to UAV modeling, flight-control systems, classical and linear control, nonlinear and robust control, predictive control, adaptive and intelligent control, cooperative and swarm control, embedded implementation, validation methods, and performance evaluation.

The main keywords used during the literature search included combinations of the following terms: “UAV control strategies”, “quadrotor control”, “fixed-wing UAV control”, “UAV modeling”, “PID control”, “LQR control”, “sliding mode control”, “model predictive control”, “adaptive control”, “fuzzy control”, “neural network control”, “reinforcement learning UAV”, “multi-agent UAV control”, “UAV swarm control”, “software-in-the-loop”, “processor-in-the-loop”, “hardware-in-the-loop”, “real-flight validation”, “embedded control”, and “UAV performance metrics”.

The selection focused mainly on recent studies published between 2020 and 2026, while also including selected foundational works that remain relevant for UAV guidance, navigation, control, and validation. Papers were retained when they addressed at least one of the following aspects: UAV control taxonomy, modeling and control challenges, controller comparison, validation methodology, embedded implementation constraints, or performance-metric analysis. Studies were excluded when they were outside the UAV control scope, focused only on mechanical design without control relevance, addressed communication or perception without connection to control evaluation, or lacked sufficient technical relevance to the objectives of this review. To clarify the selection logic, Figure 1 summarizes the literature identification, screening, eligibility, and inclusion process used to define the representative literature set.

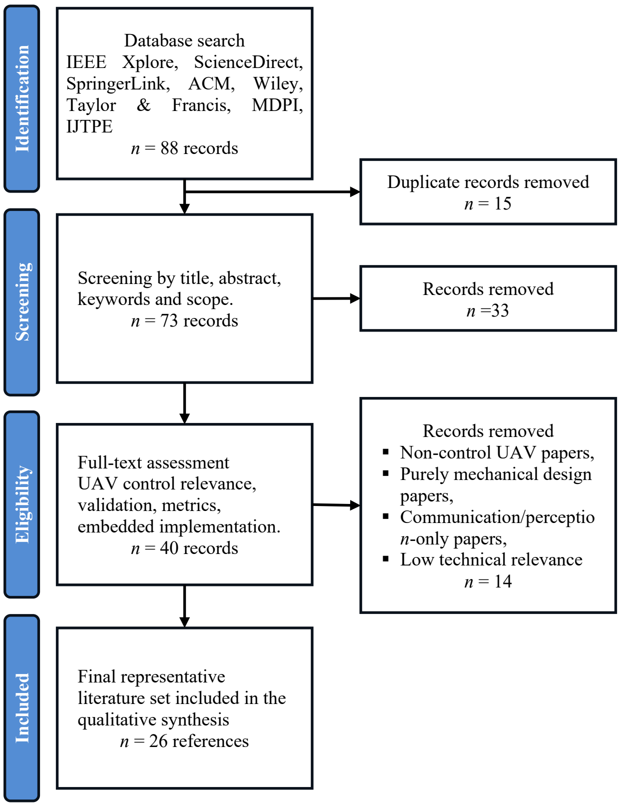

Figure 1. Literature selection workflow used to build the qualitative UAV control review

This methodology does not aim to provide exhaustive bibliometric statistics. Instead, it synthesizes representative and technically relevant literature in order to identify major trends, practical limitations, and future directions in UAV control systems.

The final set of 26 references was then classified according to UAV platform type, control family, validation level, and reported performance metrics. This classification supports the taxonomy, comparative tables, validation-maturity analysis, and performance-metric synthesis presented in the following sections.

3. CHALLENGES IN UAV MODELING AND CONTROL

The design of UAV control systems, illustrated in Figure 2, depends strongly on the vehicle configuration, dynamic model, sensing architecture, actuator limits, and mission requirements. UAVs operate in a three-dimensional environment where translational and rotational motions are coupled, and their behavior is influenced by aerodynamic forces, gravity, inertial effects, actuator dynamics, environmental disturbances, sensor noise, and onboard computational limits.

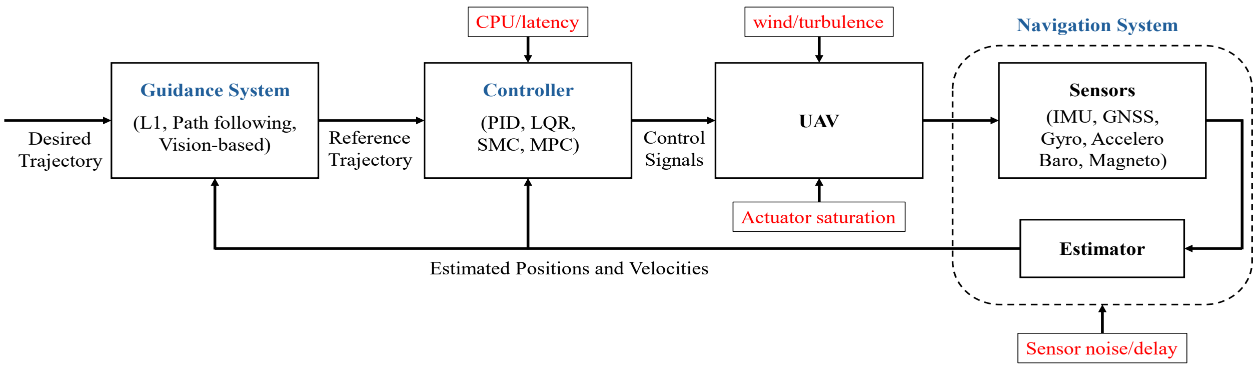

Figure 2. Generic UAV closed-loop control architecture under environmental, sensing, actuation, and embedded real-time constraints

UAV modeling provides the basis for controller design, simulation, stability analysis, and validation. Newton-Euler formulations, nonlinear state-space models, transfer-function models, and quaternion-based representations are commonly used modeling approaches [5]. Newton-Euler models are widely used because they directly describe translational and rotational dynamics. Nevertheless, in some advanced controllers, quaternion-based models are preferred because they avoid the attitude singularities associated with Euler-angle representations. Quadrotors and multirotor UAVs are typically modeled as six-degree-of-freedom rigid bodies with fewer independent control inputs than controlled states, making them underactuated, nonlinear, and strongly coupled systems [6]. Fixed-wing UAVs present different challenges as their dynamics are highly dependent on airspeed, angle of attack, aerodynamic coefficients, control-surface deflections, and flight-envelope constraints. The modeling complexity is further increased by hybrid and VTOL UAVs whose dynamics vary between hover, transition and forward-flight modes.

The main control challenges include nonlinearity, underactuation, dynamic coupling, wind disturbances, model uncertainty, actuator saturation, sensor noise, and delay. In quadrotors, translational motion is indirectly achieved by changing attitude, necessitating a coordinated inner-loop/outer-loop control architecture. In fixed-wing UAVs, path following and stability depend on maintaining sufficient airspeed and respecting aerodynamic limits [7]. Wind gusts, turbulence, payload changes, battery-voltage variations, and unmodeled aerodynamic effects can all degrade the tracking accuracy and stability. These problems motivate the use of robust, adaptive, predictive, and intelligent controllers in addition to classical fixed-gain methods.

Actuator and sensor limitations are also a major factor in UAV control. Multirotor motors and propellers have thrust limits, rate limits, and efficiency variations, while fixed-wing control surfaces are constrained by deflection and rate limits. Ignoring these constraints may lead the controller to request infeasible commands, resulting in saturation, degraded performance, or instability. Simultaneously, UAV feedback depends on sensors such as IMU, GPS/GNSS, barometers, magnetometers, cameras, LiDAR, optical flow sensors and airspeed sensors. These measurements may be affected by noise, bias, drift, latency, and environmental degradation. Therefore, state estimation and sensor fusion are crucial for reliable control, particularly in GPS-denied or disturbed environments.

Another important constraint is real-time implementation. UAV controllers must operate within strict sampling periods in embedded processors with limited memory, computational capacity, and energy availability. In general, PID and LQR controllers are computationally efficient, while nonlinear MPC, neural-network-based control and reinforcement-learning policies may require more computation depending on model complexity, prediction horizon, network size and inference time. Therefore, controller performance should be assessed not only by tracking accuracy but also by execution time, latency, CPU load, memory footprint, actuator activity, and energy consumption. Table 1 summarizes the main modeling and control challenges.

Table 1. Main UAV modeling and control challenges

Challenge	Effect on UAV control	Control implication
Nonlinear dynamics	Linear models valid only near nominal conditions	Nonlinear, robust, or adaptive control
Under actuation	Not all degrees of freedom are directly controlled	Hierarchical inner/outer-loop control
Dynamic coupling	Position and attitude dynamics interact	Coordinated control architecture
Wind and disturbances	Tracking error and instability may increase	Disturbance-rejection capability
Model uncertainty	Nominal performance may degrade	Robust/adaptive/learnin g-based control
Actuator saturation	Commands may exceed physical limits	Constraint-aware control and allocation
Sensor noise and delay	Feedback quality decreases	State estimation and sensor fusion
Computational limits	Advanced methods may be difficult onboard	Real-time feasibility must be evaluated
Energy constraints	Control effort affects endurance	Energy-aware metrics should be reported
Validation gap	Simulation may not reflect real implementation	SIL, PIL, HIL, and flight tests are needed

4. TAXONOMY AND COMPARATIVE ANALYSIS OF UAV CONTROL STRATEGIES

UAV control strategies can be broadly classified into classical and linear control, nonlinear and robust control, predictive and optimization-based control, adaptive and intelligent control, and cooperative multi-agent control. Each family presents different advantages and limitations in terms of modeling requirements, robustness, computational cost, real-time feasibility, and suitability for different UAV platforms. Figure 3 presents the taxonomy of UAV control strategies.

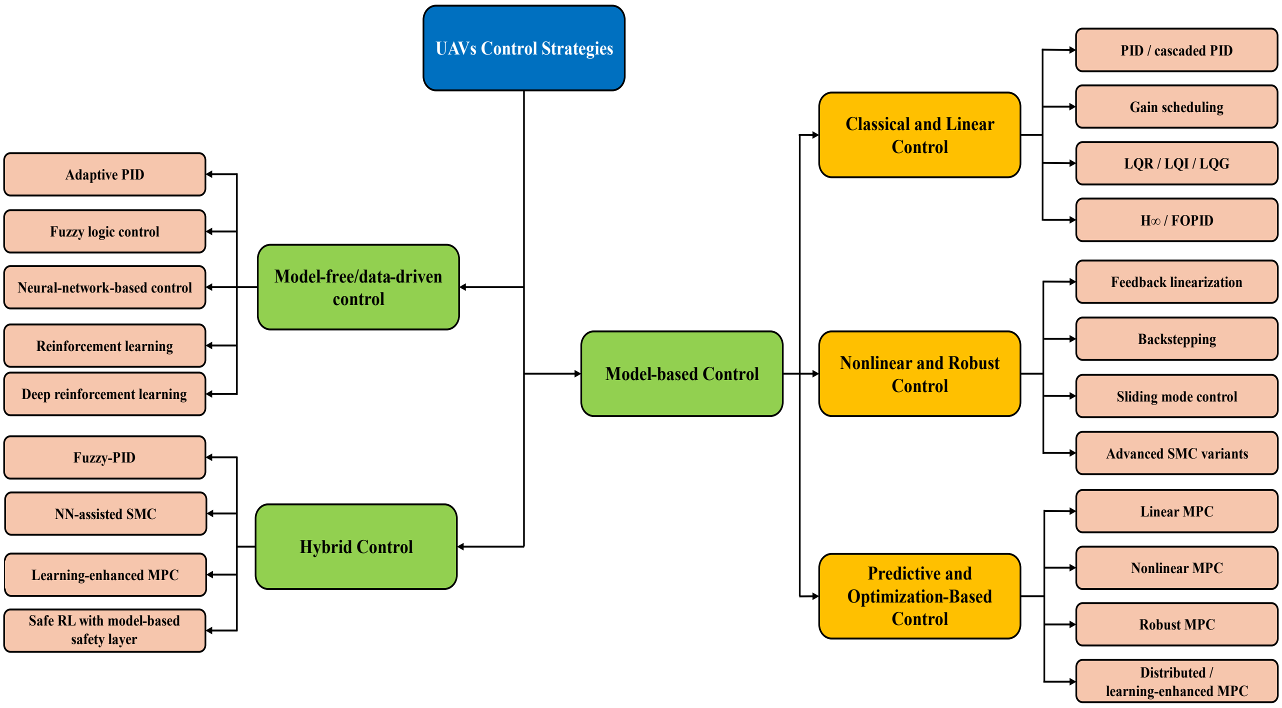

Figure 3. Taxonomy of UAV control strategies

4.1. Model-Based Control

4.1.1. Classical and Linear Control

Classical and linear controllers remain widely used in UAV systems because of their simplicity, interpretability, and low computational cost [8]. PID and cascaded PID controllers are commonly applied to attitude stabilization, altitude regulation, and position control, especially in quadrotor autopilots. Cascaded PID structures separate outer-loop position or altitude control from inner-loop attitude control, making them practical for underactuated UAVs. In practice, fixed-gain PID controllers are sensitive to tuning and may lose performance due to wind disturbances, payload variations, actuator saturation, or nonlinear flight conditions.

Gain-scheduled PID and fuzzy gain-scheduled PID improve adaptability by adjusting controller gains according to flight conditions or error dynamics. LQR and LQI controllers provide a more systematic design approach by minimizing a quadratic cost function of tracking error and control effort. H∞ control improves robustness to disturbances and uncertainties, while Fractional-Order PID (FOPID) provides more tuning flexibility than the conventional PID. However, most linear approaches require linearization of the model around nominal operating points and may not be sufficient for aggressive or highly nonlinear maneuvers.

4.1.2. Nonlinear and Robust Control

Nonlinear and robust controllers are developed to overcome the limitations of linear methods under nonlinear dynamics, uncertainty, and disturbances [9]. Feedback linearization aims to cancel nonlinear terms and convert the system into an equivalent linear form, but its effectiveness depends strongly on model accuracy [10]. Backstepping control is applicable to cascaded UAV dynamics and uses recursive Lyapunov-based design, but it can be mathematically complex and model dependent [11].

SMC is one of the most widely studied robust methods for UAVs due to its strong disturbance-rejection capability and robustness to matched uncertainties [12]. It has been used for attitude stabilization, altitude control and trajectory tracking. Despite these advantages, classical SMC suffers from chattering, which can increase actuator stress, excite unmodeled dynamics, and reduce energy efficiency. Advanced SMC variants, including terminal SMC, super-twisting SMC, adaptive SMC, neural-network-based SMC, event-triggered SMC, and backstepping-SMC, have been proposed to improve convergence, reduce chattering, and enhance robustness. These methods are powerful but generally require more careful tuning and validation than classical controllers.

4.1.3. Predictive and Optimization-Based Control

MPC has become an important approach in UAV control because it can explicitly handle constraints, multi-variable dynamics, actuator limits, and mission objectives [13]. At each sampling instant, MPC predicts the future behavior of the UAV over a finite horizon and solves an optimization problem that minimizes tracking error, control effort, constraint violation, or energy-related criteria. This makes it attractive for trajectory tracking, obstacle avoidance, autonomous landing, fault-tolerant control, moving-platform landing, and cooperative missions.

Linear MPC is computationally efficient but is mainly valid near the linearization point. Nonlinear MPC better represents UAV dynamics during aggressive maneuvers or landing phases, but is more computationally demanding. Robust MPC accounts for uncertainty and disturbances, whereas distributed MPC supports cooperative missions of UAVs. Learning-enhanced MPC exploits data-driven models, adaptation, prediction, and constraint handling. However, MPC implementation is still challenging for small UAVs due to the real-time optimization requirement, limited onboard computation and sensitivity to model accuracy [14].

4.2. Model-Free and Data-Driven Control

Adaptive and intelligent controllers are designed to improve UAV performance under changing dynamics, uncertainty, and complex operating environments. Adaptive PID and model-reference adaptive schemes adapt the control parameters online to account for payload variations, aerodynamic uncertainty, and actuator changes. Fuzzy Logic Control (FLC) provides rule-based adaptation without requiring a precise model. Fuzzy gain-scheduled PID combines the simplicity of PID with the ability to adjust the gains in real time [15].

Neural-network-based control can approximate nonlinear dynamics, estimate disturbances, or support adaptive compensation [16]. RL and DRL enable UAVs to learn control policies by interacting with the environment and have been studied for tracking, navigation, wind disturbance rejection and autonomous decision-making [17], [18]. However, learning-based controllers face major challenges such as training cost, explainability, safety guarantees, generalization, sim-to-real transfer, and embedded deployment.

Cooperative and multi-agent UAV control generalizes the problem from single-vehicle stabilization to formation keeping, collision avoidance, distributed sensing, task allocation, and communication-aware coordination [19], [20]. Common methods are leader-follower, virtual structure, consensus-based, behavior-based, and artificial-potential-field approaches [21]. Recent studies investigate cooperative DRL and MARL for scalable swarm coordination [22]. These approaches are promising for complex missions, but they pose additional challenges in terms of communication delays, packet loss, scalability, safety, and decentralized decision-making.

4.3. Hybrid Learning-Assisted Control

Hybrid learning-assisted control is a promising direction in UAV control, combining the reliability of model-based methods with the adaptability of data-driven and learning-based techniques. Hybrid architectures aim to maintain stability, robustness, and physical interpretability, while improving adaptation to uncertain dynamics, external disturbances, actuator nonlinearities, and changing mission conditions.

Several hybrid strategies have been proposed in the UAV control literature. Fuzzy-PID and gain-scheduled PID controllers keep the basic PID structure, but the controller gains are adjusted by fuzzy logic or scheduling mechanisms according to operating conditions or error dynamics [23]. In neural-network-assisted robust control, neural networks are used to approximate unknown nonlinearities, estimate disturbances, or compensate for modeling errors, while the main stabilization action is provided by backstepping, SMC, or adaptive control. Learning-enhanced MPC also combines prediction and constraint handling with data-driven models, learned disturbance compensation or online adaptation, and is attractive for constrained trajectory tracking and autonomous landing.

Reinforcement-learning-based controllers can also be combined with model-based safety mechanisms. For example, RL or DRL can be used to make high-level decisions, adapt policies, or generate trajectories, while a lower-level PID, SMC, MPC, or safety-filter layer ensures stability, actuator feasibility, and constraint satisfaction. These combinations are especially interesting for UAVs operating in uncertain environments where learning can lead to increased flexibility, but model-based safeguards are still required for safe deployment.

Nevertheless, hybrid learning-based controllers pose additional challenges. The performance of such systems depends not only on tracking accuracy but also on training quality, data representativeness, inference latency, memory footprint, computational load, and robustness under unseen operating conditions. Moreover, the interaction between the learning module and the model-based controller should be carefully considered, as it may result in instability, large control effort, or unsafe behavior. Therefore, hybrid UAV controllers should be validated progressively by simulation, SIL, PIL, HIL, and real-flight tests before practical deployment.

Hybrid learning-assisted control offers a promising trade-off between robustness, adaptability, and real-time feasibility. It is expected to play a significant role in future UAV control architectures, especially when combined with safety-aware learning, uncertainty estimation, energy-aware control, and embedded validation frameworks.

4.4. Comparative Synthesis

No single UAV control strategy is optimal for all platforms and missions. PID and LQR controllers are attractive for embedded implementation because of their simplicity and low computational cost, but their robustness may be limited under strong uncertainty. SMC and backstepping can improve robustness and nonlinear control performance, although they may introduce chattering, tuning difficulties, or design complexity. MPC is effective for constrained and mission-oriented control, but its implementation can be computationally demanding. Adaptive and intelligent controllers enhance flexibility and autonomy, but they require rigorous validation before real-world deployment. Cooperative and MARL-based approaches extend UAV control toward swarm autonomy, yet they remain challenging in terms of safety, communication, scalability, and real-time execution.

Therefore, future UAV control architectures are likely to be hybrid and hierarchical, combining the reliability of model-based control, the robustness of nonlinear methods, the constraint-handling capabilities of MPC, and the adaptability of learning-based approaches. Table 2 summarizes the main UAV control strategy families in terms of representative methods, advantages, limitations, and typical applications.

Table 2. Comparative summary of UAV control strategy families

High-level category	Control family	Representative methods	Advantages	Limitations	Applications
Model-based control	Classical/linear	PID, cascaded PID, LQR, LQI, H∞, FOPID	Simple; interpretable; low cost; embedded-friendly	Tuning sensitivity; limited robustness; nominal-model dependence	Attitude control; altitude control; baseline autopilots
	Nonlinear	Feedback linearization, backstepping	Handles nonlinear dynamics; supports stability analysis	Model dependence; mathematical complexity	Trajectory tracking; nonlinear attitude control
	Robust	SMC, TSMC, ST-SMC, adaptive SMC	Strong disturbance rejection; uncertainty tolerance	Chattering; actuator stress; tuning difficulty	Wind rejection; robust tracking
	Predictive	Linear MPC, nonlinear MPC, robust MPC, distributed MPC	Constraint handling; multivariable optimization	High computation; model sensitivity	Autonomous landing; constrained tracking; obstacle avoidance
Model-free/Data-driven control	Adaptive/intelligent	Adaptive control, FLC, NN, RL, DRL	Adaptation; autonomy; nonlinear approximation	Training cost; safety; explainability; sim-to-real gap	Adaptive tracking; navigation; wind rejection
Hybrid control	Gain-scheduled/fuzzy	Gain scheduling, fuzzy-PID	More adaptive than fixed-gain PID	Rule/schedule design; limited generalization	Variable operating conditions; altitude/position control
	Learning-assisted	NN-SMC, learning-enhanced MPC, safe RL	Robustness; adaptability; constraint handling	Design complexity; validation burden	Uncertain environments; safety-critical UAV control

5. VALIDATION METHODS AND PERFORMANCE METRICS

The evaluation of UAV control strategies should go beyond demonstrating stability in numerical simulation. A controller intended for practical deployment must satisfy several requirements simultaneously, including tracking accuracy, disturbance rejection, actuator feasibility, real-time execution, energy efficiency, and safe operation under uncertainty. However, the reviewed literature shows that UAV control studies often use different models, trajectories, disturbance profiles, sampling rates, tuning methods, and performance indicators, making direct comparison difficult [24], [25].

5.1. Validation Maturity Levels for UAV Control Strategies

Validation maturity can be organized into five progressive levels. Numerical simulation is the most common validation method because it is fast, repeatable, and safe. It is useful for early controller design, but it may overestimate performance if actuator dynamics, sensor noise, communication delay, aerodynamic uncertainty, or battery effects are simplified. SIL validation tests the controller software within a simulated environment and helps detect implementation and interface issues. PIL validation executes the controller on the target processor, allowing evaluation of execution time, memory usage, numerical precision, and real-time feasibility.

HIL validation connects physical hardware to a real-time simulation, making it useful for assessing embedded constraints, communication delays, actuator limits, and energy-aware behavior. Real-flight testing is the highest validation level because it exposes the controller to real aerodynamics, sensor imperfections, actuator nonlinearities, and environmental disturbances, but it is more costly, risky, and less repeatable [26].

Figure 4 illustrates the progressive validation hierarchy used for UAV controller evaluation. The process starts with model-based simulation or Model-in-the-Loop testing, where both the controller and the plant are virtual, and gradually increases implementation fidelity through SIL, PIL, HIL, and real-flight testing.

Table 3 summarizes the recommended validation levels for UAV controller evaluation.

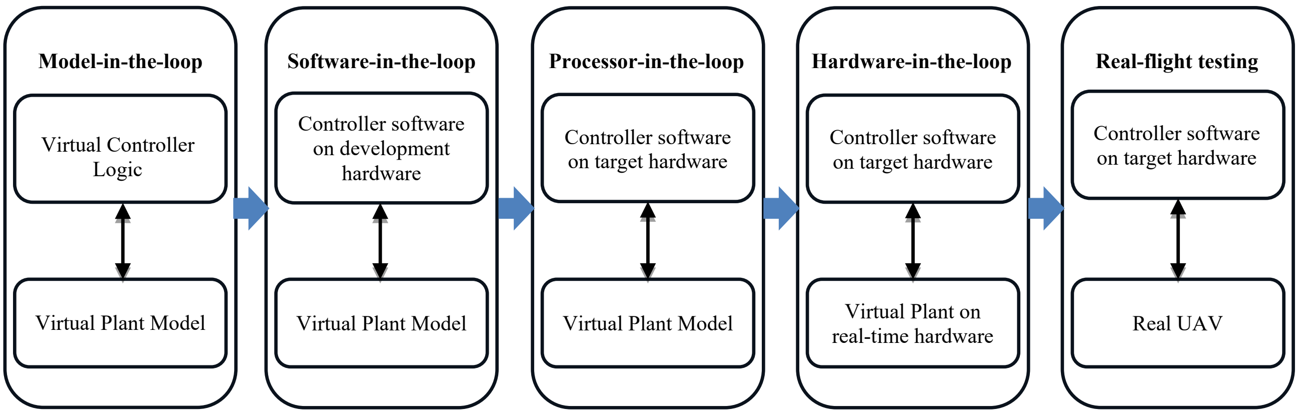

Figure 4. Progressive validation hierarchy for UAV controller evaluation, from model-based simulation to real-flight testing

Table 3. Validation levels for UAV control evaluation

Validation level	Main elements	Purpose
Numerical simulation/MIL	MATLAB/Simulink, Python, Gazebo, X-Plane, model-based simulation	Early design, fast testing, repeatability
SIL validation	Real control software with simulated UAV dynamics	Software verification and interface testing
PIL validation	Controller executed on target processor	Execution time, memory usage, numerical feasibility
HIL validation	Real hardware connected to real-time simulation	Embedded behavior, timing, actuator and energy constraints
Real-flight testing	Physical UAV experiments	Final practical validation under real conditions

5.2. Performance Metrics for UAV Control Strategies Evaluation

Performance evaluation should be multidimensional. Tracking accuracy is commonly assessed using RMSE, MAE, maximum error, cross-track error, attitude error, or altitude error. Transient performance is characterized through settling time, rise time, peak time, overshoot, and steady-state error. Robustness metrics include disturbance-induced error, recovery time, wind sensitivity, payload-variation response, sensor-noise sensitivity, and uncertainty tolerance. Control-effort metrics, such as RMS input, actuator saturation, command-rate variation, and chattering index, are essential because aggressive controllers may improve tracking while increasing actuator stress or energy consumption. This is particularly important for SMC-based controllers, because chattering can reduce actuator smoothness.

Computational feasibility is also critical for practical UAV deployment. Controllers must operate within strict sampling periods on embedded processors with limited memory, processing capacity, and power. Therefore, execution time, CPU load, memory usage, latency, jitter, and real-time deadline violations should be reported, especially for nonlinear MPC, neural-network control, and reinforcement-learning-based methods. Energy efficiency should also be included through metrics such as total power consumption, battery usage, control energy, actuator activity, and mission endurance. HIL-based comparisons show that controller selection can affect not only settling time and overshoot, but also power consumption and energy-aware performance.

For learning-based UAV controllers, additional metrics are required. These include reward convergence, training time, sample efficiency, policy generalization, success rate, safety-violation rate, inference time, and sim-to-real performance. For cooperative and multi-agent UAV systems, suitable metrics include formation error, inter-agent distance, collision rate, communication load, task-completion rate, scalability, and coordination efficiency. These metrics are necessary because swarm-control performance cannot be evaluated only through single-UAV tracking accuracy.

Figure 5 maps the main UAV control strategy families against the performance metrics reported in the retained studies. It highlights commonly used evaluation criteria and practical indicators that remain less frequently reported.

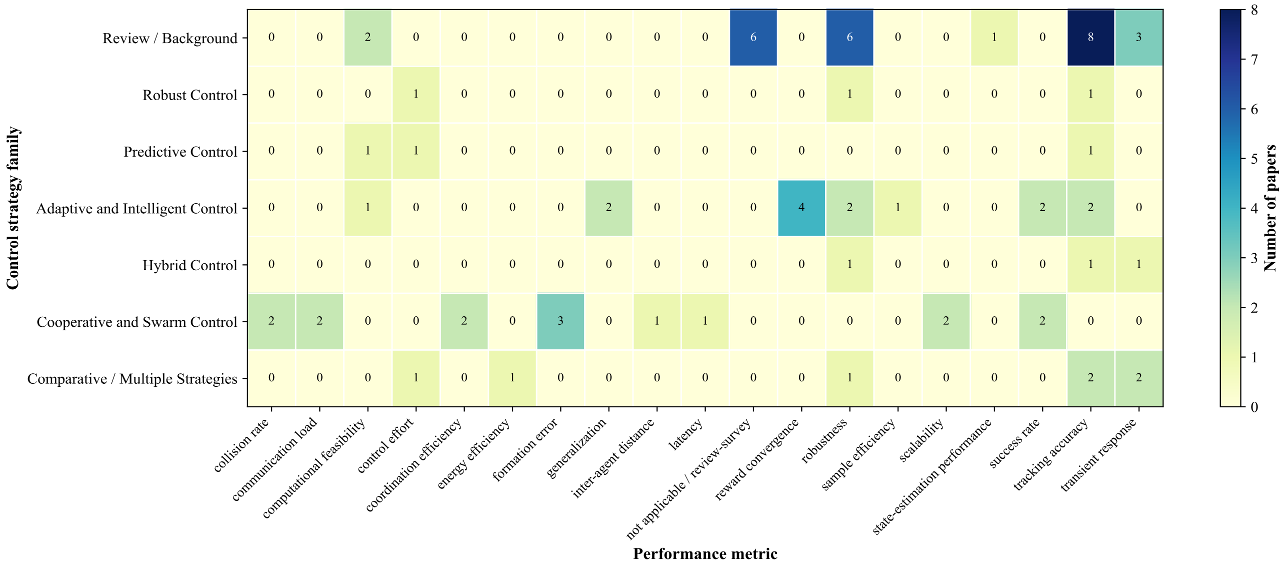

Figure 5. Mapping between UAV control strategy families and reported performance metrics in the retained literature

Figure 5 shows that tracking accuracy and robustness are the most common metrics across the reviewed control families. Adaptive/intelligent and cooperative/swarm approaches add specific metrics such as reward convergence, formation error, communication load, and scalability. However, computational feasibility, energy efficiency, and actuator-related metrics appear less consistently reported, confirming the need for more deployment-oriented UAV control evaluation.

Table 4 summarizes the recommended performance metrics for UAV controller evaluation. A rigorous UAV control study should combine several of these metrics and should progress, whenever possible, from simulation to SIL, PIL, HIL, and real-flight validation.

Table 4. Performance metrics for UAV control evaluation

Metrics	Main elements	Purpose
Tracking metrics	RMSE, MAE, maximum error, cross-track error, attitude/altitude error	Measures reference-following accuracy
Transient metrics	Settling time, rise time, steady-state error, overshoot	Evaluates response quality
Robustness metrics	Wind rejection, recovery time, uncertainty tolerance, payload variation	Assesses performance under disturbances
Control-effort metrics	RMS input, actuator saturation, command rate, chattering index	Evaluates actuator feasibility and smoothness
Computational metrics	Execution time, CPU load, memory usage, latency, jitter	Determines real-time embedded feasibility
Energy metrics	Power consumption, battery usage, control energy, endurance	Evaluates mission efficiency
Learning / cooperative metrics	Reward convergence, success rate, formation error, collision rate, communication load	Evaluates intelligent and multi-UAV control

6. RESEARCH GAPS AND FUTURE DIRECTIONS

While much progress has been made in UAV control, several gaps still limit the transition from algorithm design to robust real-world deployment. Current research trends point toward intelligent autonomy, hybrid model-based/data-driven architectures, real-time adaptability, energy-aware operation, cyber-resilience and scalable multi-UAV coordination. However, these trends are constrained by limited benchmarking, simulation-dominated validation, lack of computational and energy reporting, safety concerns, and sim-to-real transfer issues.

A first major gap concerns the absence of standardized benchmarks. Fair comparison remains difficult, since existing studies use different UAV models, trajectories, disturbance profiles, sampling rates, controller tuning procedures, and performance metrics. Future work should define common benchmark missions for attitude stabilization, altitude regulation, trajectory tracking, autonomous landing, wind rejection, actuator saturation and energy-aware control. Such benchmarks would make controller comparison more transparent and reproducible.

Another important direction is the growing use of AI and Machine Learning (ML)-assisted control. NN, RL, DRL and MARL are increasingly being investigated for trajectory optimization, obstacle avoidance, adaptive tracking, autonomous decision making and swarm coordination.

However, learning-based controllers still have major limitations in terms of training cost, explainability, formal stability guarantees, certification readiness and sim-to-real transfer. Future studies should explore safe learning-based control, uncertainty-aware policies, domain randomization, control barrier functions, Lyapunov-guided learning, and HIL-based validation.

Hybrid model-based/data-driven control is also a promising direction. Classical controllers remain attractive for low-level stabilization, robust controllers are useful for disturbance rejection, MPC is suitable for constraint handling, and learning-based modules can improve adaptation and high-level decision-making. Combining these paradigms may provide a better trade-off between robustness, autonomy, and real-time feasibility. However, hybrid architectures can increase design complexity, computational burden, and validation difficulty. Therefore, future studies should evaluate hybrid controllers using both tracking performance and deployment-oriented indicators.

Validation maturity remains a key research gap. Building on the evaluation framework discussed in Section 5, future studies should move beyond simulation-only assessment and adopt progressive validation pipelines for computationally demanding or safety-critical controllers.

Energy-aware and resilient control should also receive greater attention. Future work should integrate energy, actuator-effort, and resilience indicators into controller evaluation, especially as UAV autonomy and connectivity increase.

Finally, the reviewed literature remains mainly centered on quadrotors and multirotors, while control of fixed-wing, hybrid, and VTOL UAVs is less represented. Further work is needed on fixed-wing path following, coordinated turns, airspeed regulation, landing, flight-envelope protection, and VTOL transition control. More research is also needed on scalable coordination and communication-aware control, collision avoidance, decentralized decision-making, and multi-agent safety in cooperative and swarm UAV systems.

Table 5 summarizes the main trends, gaps, and future directions identified from the reviewed UAV control literature. The emphasis is placed on practical deployment challenges, including validation maturity, embedded feasibility, energy-aware evaluation, safety, and scalable coordination.

Table 5. Emerging trends, research gaps, and future directions in UAV control systems

Trend	Current relevance	Main gap	Future direction
AI/ML-assisted control	Supports autonomy, trajectory optimization, obstacle avoidance, and adaptive decisions	Training cost; explainability; safety; sim-to-real transfer	Safe lightweight learning; stability constraints; HIL/flight validation
Hybrid model-based/data-driven control	Combines robustness, adaptability, and constraint handling	Higher design and validation complexity	Integrate SMC, MPC, adaptive control, and AI with real-time safeguards
Swarm and multi-UAV control	Enables formation flight, distributed sensing, and task allocation	Scalability; communication delay; collision avoidance	Communication-aware and decentralized control for heterogeneous UAV teams
Real-time adaptive control	Needed under wind, turbulence, payload changes, uncertain dynamics	Limited embedded validation	Online adaptation with CPU, memory, latency, and energy reporting
Energy-aware control	Affects endurance, mission duration, and operational radius	Energy metrics often omitted	Include power, battery use, actuator effort, and endurance in evaluation
Secure and resilient control	UAV autonomy increases exposure to spoofing, jamming, and data corruption	Cybersecurity rarely integrated with flight control	Real-time detection, tolerance, and mitigation of cyber-physical faults
Validation-oriented design	Bridges theory and deployable UAV controllers	Many studies remain simulation-based	Use SIL, PIL, HIL, real-flight tests, and deployment-oriented metrics

7. CONCLUSION

This paper presented a qualitative review of major UAV control strategies, including classical and linear control, nonlinear and robust control, predictive and optimization-based control, adaptive and intelligent control, hybrid control, and cooperative multi-agent control. The analysis shows that UAV control remains challenging because of nonlinear dynamics, underactuation, coupling effects, actuator constraints, sensor noise, wind disturbances, energy limitations, and onboard computational constraints.

Classical controllers such as PID, cascaded PID, LQR, LQI, H∞, and FOPID remain attractive because of their simplicity, interpretability, and suitability for embedded real-time implementation. However, their performance may degrade under strong nonlinearities, uncertainty, disturbances, and aggressive maneuvers. Nonlinear and robust controllers, including feedback linearization, backstepping, and SMC, improve robustness and disturbance rejection, but may introduce design complexity, chattering, actuator stress, and tuning difficulties. MPC provides explicit constraint handling and mission-oriented optimization, making it suitable for autonomous landing, constrained tracking, and obstacle avoidance, although real-time implementation remains challenging on small UAV platforms.

Adaptive and intelligent controllers, including FLC, NN, RL, DRL, and MARL, are promising for uncertain and complex environments. Nevertheless, their practical deployment is still limited by training cost, interpretability, safety guarantees, sim-to-real transfer, certification, and embedded implementation. Cooperative and multi-agent control can improve UAV autonomy and mission capability, but it introduces challenges related to communication, scalability, collision avoidance, and decentralized decision-making.

A central conclusion of this review is that no single control strategy is optimal for all UAV platforms and missions. Controller selection should consider the UAV type, mission requirements, operating environment, robustness needs, actuator limits, onboard hardware, energy consumption, and validation maturity. Future research should move toward hybrid and hierarchical architectures that combine the reliability of model-based control, the robustness of nonlinear methods, the constraint-handling capability of MPC, and the adaptability of learning-based approaches. Standardized benchmarks, SIL/PIL/HIL validation, real-flight testing, computational profiling, energy-aware metrics, and safety-oriented intelligent control will be essential for transforming UAV control algorithms into reliable and deployable systems.

In practical terms, the next step for UAV control research is not simply to develop increasingly sophisticated controllers, but to demonstrate that these methods remain reliable under the conditions encountered in real operation. This requires a stronger connection between controller design, embedded implementation, energy use, safety, and progressive validation.

NOMENCLATURES

1. Acronyms

AI	Artificial Intelligence
CPU	Central Processing Unit
DRL	Deep Reinforcement Learning
FLC	Fuzzy Logic Control
FOPID	Fractional-Order Proportional-Integral-Derivative
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HIL	Hardware-in-the-Loop
IMU	Inertial Measurement Unit
LiDAR	Light Detection and Ranging
LQI	Linear Quadratic Integral
LQR	Linear Quadratic Regulator
MAE	Mean Absolute Error
MARL	Multi-Agent Reinforcement Learning
ML	Machine Learning
MPC	Model Predictive Control
NN	Neural Network
PID	Proportional-Integral-Derivative
PIL	Processor-in-the-Loop
RL	Reinforcement Learning
RMSE	Root Mean Square Error
SIL	Software-in-the-Loop
SMC	Sliding Mode Control
ST-SMC	Super-Twisting Sliding Mode Control
TSMC	Terminal Sliding Mode Control
UAV	Unmanned Aerial Vehicle
VTOL	Vertical Take-Off and Landing

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