Optimization Strategies for Electric Propulsion in UAVs: A Review of Technologies, Control Systems, and Environmental Impacts

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Abstract*—This paper presents a systematic literature review of recent developments in the optimization of electric propulsion systems for Unmanned Aerial Vehicles (UAVs). This review uniquely identifies underdeveloped areas such as real-world testing, integrated aerodynamic optimization, and lifecycle modeling in UAV electric propulsion systems, providing a new roadmap for future research. A total of 42 peer-reviewed articles, published between 2014 and 2024, were analyzed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method to ensure transparency and rigor in the selection process. The findings show a significant shift toward intelligent optimization techniques, especially Particle Swarm Optimization (PSO) and its hybrid variants, which are widely used for tuning Fuzzy PID controllers to enhance system performance and stability. Furthermore, innovations in lightweight composite materials and the integration of Internet of Things (IoT) technologies have demonstrated improved endurance and adaptability of UAV propulsion systems. Despite these advancements, most studies remain at the simulation stage, with limited real-world implementation. Environmental modeling, thermal-aware control, and lifecycle analysis are identified as key areas requiring further investigation. This review highlights the necessity of cross-disciplinary approaches to address the complexity of electric propulsion optimization. Recommendations for future work include the adoption of embedded Machine Learning (ML) models, experimental validation frameworks, and system-level integration with aerodynamic and mission planning subsystems.

***Keywords*—particle swarm optimization, Fuzzy Proportional-Integral-Derivative (PID) controller, composite materials, Internet of Things (IoT) integration, machine learning**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have become one of the most sought-after technologies due to their wide applications in sectors such as logistics, surveillance, agriculture, and disaster mitigation [1]. UAVs are increasingly deployed for both civil and military operations, where reliability, maneuverability, and energy efficiency are crucial. Among the various subsystems in UAVs, the electric propulsion system plays a pivotal role in determining flight endurance, energy efficiency, payload capacity, and environmental performance. However, electric propulsion faces critical challenges such as limited battery capacity, energy conversion losses, thermal management issues, and the need for adaptive control in unpredictable and dynamic conditions.

In response to global sustainability efforts and increasing concerns over environmental pollution, there has been a significant shift from internal combustion engines to electric propulsion technologies. Electric propulsion systems offer numerous advantages, including higher energy efficiency, reduced acoustic signatures, and near-zero greenhouse gas emissions [2]. These benefits align well with international calls for cleaner and more sustainable transportation technologies. However, realizing the full potential of electric propulsion systems requires addressing complex engineering challenges related to system integration, control stability, and operational resilience in varying environments.

Optimization of electric propulsion systems encompasses a wide range of approaches. These include hardware-level improvements such as the use of lightweight composite materials and high-efficiency motors, as well as software-level innovations like advanced control algorithms and intelligent optimization techniques. Recent studies emphasize the use of Machine Learning (ML) and Artificial Intelligence (AI) to improve predictive control, fault detection, and real-time decision-making in UAV systems. Similarly, Internet of Things (IoT) integration enhances situational awareness and enables adaptive control based on sensor feedback.

Control of electric propulsion systems traditionally relies on Proportional-Integral-Derivative (PID) controllers, which are simple and widely used due to their robustness and ease of implementation. However, conventional PID controllers often fall short when dealing with nonlinear, time-varying, or Multi-Input Multi-Output

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(MIMO) systems typically found in UAV operations [3]. To address these limitations, adaptive control methods such as Fuzzy PID controllers have been introduced. These methods use fuzzy logic to adjust controller gains dynamically, allowing better handling of uncertainties and disturbances [4, 5].

The effectiveness of adaptive controllers depends significantly on proper tuning of parameters. A task that is both time-consuming and prone to suboptimal solutions when done manually. To address this, researchers have applied metaheuristic optimization algorithms, especially Particle Swarm Optimization (PSO), to automate and improve the tuning process [6, 7]. The PSO-Fuzzy-PID controller achieves reduced overshoot, faster response times, and superior performance, providing a robust solution for automated greenhouse cleaning [8]. PSO simulates social behaviour of particle swarms to find the optimal control parameters efficiently. Hybrid optimization techniques that combine PSO with other algorithms such as Genetic Algorithms (GA) and Reinforcement Learning (RL) have shown promising results in solving multi-objective optimization problems [9, 10]. These hybrid strategies leverage the strengths of each algorithm to accelerate convergence, avoid local minima, and enhance solution quality.

When integrated with IoT architectures, hybrid optimization not only improves control accuracy but also supports real-time responsiveness and self-adjusting behaviours in UAV systems [11]. These capabilities are especially critical in missions requiring high autonomy, such as autonomous delivery, long-endurance surveillance, and emergency response operations.

While previous literature has addressed individual aspects such as propulsion components or flight control, there remains a lack of systematic reviews focused specifically on the optimization of electric propulsion systems in UAVs. Existing surveys often overlook the holistic integration of technological innovations, adaptive control mechanisms, and environmental impacts. This review fills the gap by focusing not only on control and optimization algorithms but also on their integration with structural, environmental, and mission-planning components, a perspective often overlooked in prior reviews.

This article is organized as follows. Section II presents the systematic review methodology based on Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). Section III synthesizes findings into three thematic areas: (1) Specific Technological Aspects, (2) Control Systems and Optimization, and (3) Environmental and Operational Impacts. Section IV discusses key challenges, unresolved research gaps, and future directions. Finally, Section V concludes with insights and recommendations for advancing the development of high-performance and sustainable UAV electric propulsion systems.

II. Methodology of Systematic Literature Review

This study uses a Systematic Literature Review (SLR) methodology based on PRISMA. The aim is to ensure transparency and reproducibility. The literature search was conducted using Scopus with keywords including “optimization”, “electric propulsion”, and “UAV”. Inclusion criteria were: (1) focus on electric propulsion systems, (2) includes optimization methods or experimental/simulation results, (3) indexed in Scopus, and (4) published between 2014 and 2024.

The search was conducted in January 2024 using the Boolean query: (UAV OR “Unmanned Aerial Vehicle”) AND (“electric propulsion” OR “BLDC” OR “optimization”). Sources included Scopus and Garuda. A total of 42 articles were selected after the PRISMA screening process. The review follows the PRISMA methodology to ensure transparency and reproducibility, in line with systematic guidelines proposed [12] and prior bibliometric analyses [13]. The structured approach adopted here is consistent with best practices in conducting literature-based reviews [14, 15].

Fig. 1 presents the annual trend of publications from 2014 to 2024, showing growing interest in electric propulsion optimization for UAVs. Meanwhile, Fig. 2 summarizes the number of articles retained at each stage of the PRISMA framework: identification, screening, eligibility, and inclusion.

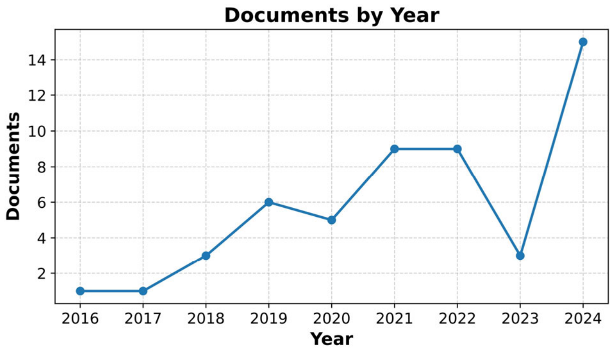

Fig. 1. Trends in UAV electric propulsion optimization publications (2014–2024).

The figure illustrates the trend in the number of publications related to electric UAV propulsion optimization from 2014 to 2024. In the early years, the number of studies remained relatively low and stable. A steady increase began around 2018, indicating growing research interest in this field. The most significant surge occurred in 2024, reflecting the heightened focus on developing efficient and sustainable UAV technologies. Overall, the trend suggests that electric propulsion optimization has become an increasingly important topic within the UAV research community.

Fig. 2 shows the PRISMA flowchart of the article selection process. The review began with a total of 179 articles identified from Scopus (151 articles) and Garuda (28 articles). After removing duplicates, 124 unique articles remained and were screened based on title and abstract. Of these, 57 full-text articles were assessed for eligibility, resulting in 42 articles that met all inclusion criteria and were included in the final analysis. This systematic process ensures transparency and rigor in selecting relevant studies for review. The final dataset now excludes secondary reviews and meta-analyses. Only original studies with quantitative or simulation results were analyzed.

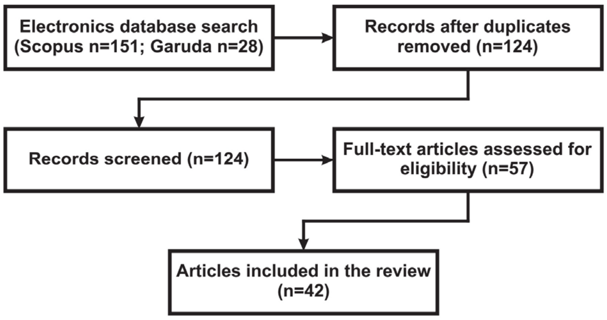

Fig. 2. PRISMA article selection summary.

To provide further clarity, Table I categorizes the selected articles based on their primary focus. This classification highlights the balanced distribution across three domains: specific technologies, control and optimization systems, and environmental/operational impact.

TABLE I. CLASSIFICATION OF REVIEWED ARTICLES BY FOCUS AREA

Focus Area	Number of Articles
Technological Innovation	14
Control and Optimization	16
Environmental & Operational	12
Total	42

In addition to the focus area classification presented in Table I, a further analysis was conducted to group the optimization methods applied in the 42 reviewed articles. Fig. 3 illustrates the distribution of articles by optimization method category. The results show that PSO-based methods, both standalone and hybrid (e.g., PSO-GA, PSO-Fuzzy), dominate the literature. Meanwhile, other approaches such as Fuzzy PID, GA, and RL are also present but in smaller proportions. This distribution reflects the research community's growing inclination to leverage the robustness of PSO in combination with other techniques to address the complexity of modern UAV propulsion systems.

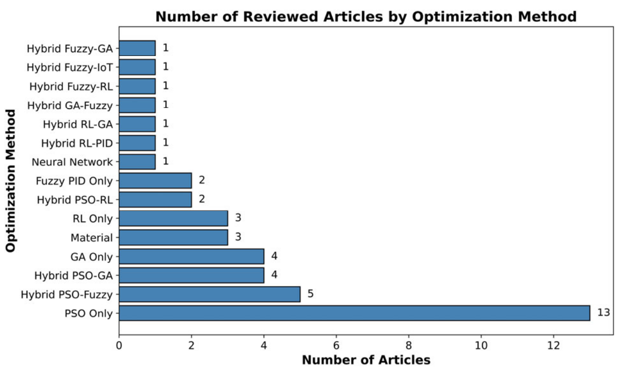

Fig. 3. Number of reviewed articles by optimization method.

The results depicted in Fig. 3 reinforce the significant reliance on PSO and its hybrid variants in recent UAV propulsion research. This tendency suggests that while individual optimization techniques offer value, their combination often provides more robust performance, especially in handling nonlinear and multi-objective challenges. The prevalence of these methods reflects a broader trend in the field: the pursuit of adaptive, intelligent, and efficient control strategies to meet the evolving demands of UAV operations in complex and uncertain environments. These insights form the foundation for the thematic synthesis presented in the next section.

Although this review focuses on electric UAV propulsion, insights from classical propulsion modeling such as turbofan simulation [3] remain foundational in understanding thrust dynamics. Machine learning-based strategies for UAV energy management have been broadly surveyed in recent literature [16], reinforcing the relevance of data-driven optimization. The comparative assessment of Fuzzy PID and classical PID control structures continues to inform hybrid controller design [17]. Energy-optimized UAV deployment scenarios, particularly in emergency logistics, highlight the growing demand for endurance-aware systems [18].

III. RESULTS AND DISCUSSIONS

This section integrates the synthesis of the reviewed literature with critical discussions around the findings. The analysis is structured into three primary thematic categories: (1) Specific Technological Aspects, (2) Control Systems and Optimization, and (3) Environmental and Operational Impact. Each theme explores the current state of the art, identifies gaps, and proposes directions for future research.

A. *Specific Technological Aspects*

Technological innovations in UAV electric propulsion systems have focused heavily on integrating machine learning techniques, advanced materials, and IoT-based control infrastructures. Applications include UAV-based crop spraying in precision agriculture, autonomous surveying in forestry, and IoT-enabled aerial monitoring systems for real-time decision-making [19]. RL and Deep Neural Networks (DNN) are utilized for real-time UAV trajectory planning and energy optimization in dynamic environments [20, 21]. Material innovation is represented by the use of nanomaterials, such as graphene and carbon fibre composites, which improve strength-to-weight ratios and enhance aerodynamic performance [22–24]. Furthermore, the integration of IoT enables UAVs to perform real-time data acquisition and responsive decision-making, thus enhancing endurance and reliability [25, 26].

Machine learning algorithms significantly improve system adaptability and efficiency but introduce challenges in computational complexity and data dependency. UAVs, particularly lightweight aerial platforms, often have constrained processing power and limited onboard memory, which complicates the implementation of deep learning or RL models in real-time applications. Lightweight ML models, including shallow networks or edge-optimized algorithms, should be a priority for future research.

Material advancements such as graphene-infused propellers and carbon-reinforced airframes offer promising performance benefits but remain costly and inconsistent in production quality. Standardization of composite materials and scalable manufacturing processes are essential to transition these technologies from laboratory research to field-ready solutions. Additionally, many studies explore these technologies in isolation; integrated simulations combining material, aerodynamic, and control parameters are necessary to evaluate their combined effectiveness.

The IoT-enabled propulsion frameworks enable real-time monitoring of battery health, motor temperature, and atmospheric data. However, reliability under network loss, bandwidth limitations, and energy cost of communication are practical concerns that require low-power communication protocols and fault-tolerant systems. These technological advancements, ranging from material innovation to IoT integration, form the foundation for the optimization strategies discussed in the next section. Improvements in structural components and data-driven architectures directly influence the design of more adaptive and intelligent control systems for UAV propulsion.

B. Control Systems and Optimization

To better understand recent advancements in UAV control strategies, several studies have explored optimization techniques and innovative control approaches that go beyond conventional methods. Some research highlights the application of intelligent optimization algorithms and alternative control architectures designed to improve UAV stability, dynamic response, and energy efficiency. Cárdenas [27] leveraged a multi-objective PSO to optimize PID parameters in the ø-axis control of a Parrot Mambo FPV quadrotor simulation. The optimized controller achieved superior performance in metrics such as settling time, overshoot, steady-state error, and energy effort, surpassing traditionally tuned PID. In another innovative approach, Sanguino and Lozano [28] designed a Coandă effect-based UAV and compared Fuzzy Logic Control (FLC) optimized via Genetic Algorithms against a classical PID. Results demonstrated that FLC reduced settling time by 35%, indicating its efficacy in stabilizing UAVs with unconventional aerodynamics.

Recent studies have demonstrated the effectiveness of Fractional-Order PID (FOPID) controllers in UAV applications. Delgado Reyes showed that fractional-order PID improves quadrotor hover stability under nonlinear dynamics [29]. Rosmadi implemented a FOPID-based controller for Tello EDU quadrotor drones to enhance safe landings during propeller failure scenarios [30]. More complex control frameworks, such as Distributed Multicircular Circulation Control (DMCC), also benefited from FOPID's smoother control and coordination capabilities [31]. Fractional-Order Internal Model Control (FOIMC) has been proposed to enhance robustness by integrating fractional-order filtering into an IMC framework. Ranjan and Mehta [32] demonstrated improved tracking and gain or phase margin-based robustness in cascade systems. Wen demonstrated that FOIMC outperforms conventional PID and IMC approaches in redundant actuation control, improving force tracking accuracy and disturbance rejection during simulation [33]. Recent advancements include neural network–based MPC, as demonstrated by Jiang *et al.* [34], which achieved a 40% reduction in trajectory tracking error under simulation and controlled indoor flight conditions in quadrotor UAVs. Furthermore, a comprehensive review by Panjavarnam *et al.* [35] highlights various MPC strategies for autonomous UAV landings, spanning topics such as sensor fusion, fault tolerance, and real-time computation challenges. Recent advancements in Sliding Mode Control (SMC) include event-triggered fractional-order SMC, as presented by Pouzesh and Mobayen [36], which stabilizes quadrotor UAVs under disturbances while reducing computational load. Another promising approach is Fixed-Time SMC (FTSMC), proposed by Olguín-Roque *et al.* [37], achieving robust tracking with guaranteed convergence time even under external perturbations.

Control strategies in electric UAV propulsion systems have advanced from classical PID controllers to intelligent control methods like Fuzzy PID, adaptive control, and optimization-enhanced frameworks. Fuzzy PID controllers exhibit superior handling of nonlinear dynamics, environmental disturbances, and uncertainty in payload conditions [38–40]. PSO is one of the most widely used optimization algorithms to tune control parameters, demonstrating high performance in stability, overshoot reduction, and fast convergence [6–8]. Hybrid methods such as PSO-GA and RL-PSO are employed to balance global exploration with local refinement [9, 10]. Comparative studies reveal the advantages and trade-offs between optimization algorithms, showing that GA may outperform PSO in global search but requires longer computation time [41–43]. Recent developments in FOPID control, such as PI^{λ}-D^{μ} configurations, offer improved performance in trajectory tracking under parameter uncertainty and external disturbances. These control methods can complement fuzzy-based and PSO-tuned approaches.

The preference for PSO-based methods stems from their efficiency in parameter tuning and adaptability to non-linear, multi-input systems common in UAV applications. However, pure PSO can suffer from premature convergence and local optima trapping, especially under multi-objective conditions or rapidly changing environments. While PSO offers fast convergence, studies rarely benchmark against real-time constraints. GA may improve accuracy but with higher complexity. These trade-offs are seldom discussed explicitly in the literature. Hybridization with GA or RL addresses these shortcomings, though at the cost of increased complexity and processing demands.

Simulation-based results dominate the literature, with only a few studies implementing the algorithms on real hardware or during flight tests. Future research should incorporate Hardware-In-the-Loop (HIL) simulations, embedded processor integration, and field trials to validate real-world performance. Furthermore, while many studies focus on controller performance metrics (e.g., rise time, settling time), fewer address energy consumption and thermal behaviour under load, which are critical metrics in mission-critical UAV deployments.

In terms of architecture, centralized optimization techniques may not scale well for swarm UAVs or distributed systems. Research into decentralized and cooperative optimization, especially those using distributed PSO or federated RL, is recommended for fleet-level propulsion control. The intelligent control strategies described here are closely tied to both the technological enablers outlined in Section A and the environmental demands discussed in Section C. Robust and adaptive controllers not only ensure flight stability but also play a critical role in achieving energy efficiency and emission reduction.

C. Environmental and Operational Impact

A significant number of articles address the role of propulsion optimization in achieving sustainability and operational efficiency. Energy consumption models optimized via trajectory control, battery selection, and propeller-motor matching [44]. Drones can reduce the energy consumption by 94% and 31% and GHG emissions by 84% and 29% per package delivered, as reported in [45]. Battery behavior under varying BLDC motor loads has been experimentally analyzed, revealing insights critical for improving energy distribution and endurance planning [46]. Designs considering payload configuration and altitude have demonstrated endurance improvements up to 20% [18, 47]. Environmental factors such as ambient temperature, wind gusts, and humidity are modelled and controlled using adaptive control methods including SMC and fuzzy logic [48, 49].

Despite promising results in energy optimization, few studies offer a comprehensive lifecycle analysis of UAV electric propulsion systems. Focus is often on mission-specific metrics (e.g., flight time or consumption per trip) without integrating full system emissions from production, operation, and disposal. This is a key area for future sustainability-focused studies.

Furthermore, many studies simulate ideal weather or neglect turbulence, battery thermal degradation, or vibration effects. Realistic environmental modelling, such as wind fields, altitude-pressure-temperature profiles, and sudden load variations, must be incorporated into test scenarios. These variables are vital not only for controller robustness but also for optimizing mission profiles (e.g., high-altitude delivery, search-and-rescue operations).

Battery performance under different environmental conditions is another underexplored area. Most studies assume constant battery behaviour, while in practice, temperature fluctuations can significantly impact internal resistance, charge/discharge efficiency, and safety. Future work should include thermal-aware battery models and dynamic load-sharing between propulsion components. Environmental optimization efforts are deeply interconnected with both material selection and control design. As highlighted in Sections A and B, choices in materials and control strategies can significantly influence battery performance, flight duration, and environmental resilience. A holistic view that integrates these domains is essential for sustainable UAV development.

The three themes discussed above collectively address the research gaps outlined in the Introduction. Technological innovations (Section A) provide enablers for adaptive control systems (Section B), which in turn directly impact energy efficiency and sustainability goals (Section C). By synthesizing these domains, this review builds a conceptual framework for electric UAV propulsion optimization that integrates control strategies, material innovation, and environmental adaptation. This framework helps guide future research toward more robust, scalable, and environmentally aligned UAV systems.

While many studies focus on mission-specific metrics such as flight duration or energy consumed per trip, only a few adopt a full Lifecycle Assessment (LCA) perspective. LCA approaches consider emissions and energy costs from the production of UAV components, operation, and end-of-life disposal. Sustainability metrics like cradle-to-grave energy use, carbon intensity per kilometer, and material recyclability are still underreported in the literature. Moreover, recent studies emphasize the significance of real-world battery degradation, where factors like thermal cycling, state-of-charge variability, and ambient temperature fluctuations impact long-term energy capacity, safety, and mission reliability. These findings suggest a pressing need for thermal-aware control and battery health monitoring systems integrated into UAV platforms.

IV. Synthesis and Implications

To provide a more structured understanding of the optimization landscape in UAV electric propulsion systems, Table II presents a summary of UAV control techniques. Table III presents a classification of reviewed studies based on their main contributions, themes, and application topics. Each entry reflects how the research contributes to technological innovation, control system advancement, or environmental and operational improvements in UAV performance. To complement the classification, Table IV summarizes the performance outcomes of various optimization algorithms used in UAV propulsion studies. It includes the targeted aspect of optimization, the improvements achieved, relevant performance metrics, and references to the original studies.

To synthesize the findings from the literature, Tables II and III classify and compare the contributions based on their thematic focus (technology, control, environmental impact) and optimization outcomes. Each study was categorized according to its primary objective, algorithm type, and performance metric. This classification directly reflects the research gaps identified earlier, particularly in terms of real-world validation, integrated control-material-environment frameworks, and sustainability metrics.

TABLE II. SUMMARY OF UAV CONTROL TECHNIQUES

Controller Type	Principle and Strengths	Limitations	Key References
PID	Classical feedback controller that adjusts proportional, integral, and derivative gains to minimize error; widely used for its simplicity and robustness	Limited capability to handle system nonlinearities, model uncertainties, and external disturbances	[27, 28]
FOPID (Fractional-Order PID)	Extends PID with fractional calculus to fine-tune proportional, integral, and derivative actions, improving stability and transient response under disturbances	Tuning complexity; requires advanced optimization methods for parameter selection	[29, 30, 50, 51]
FOIMC (Fractional-Order Internal Model Control)	Combines internal model control with fractional-order filtering to enhance robustness and tracking accuracy, especially under model uncertainties	Limited UAV-specific implementations; fractional filter tuning complexity	[32, 33]
MPC (Model Predictive Control)	Predictive optimization based on system model; handles constraints effectively and can anticipate future states for smooth trajectory tracking	High computational demand; requires accurate model for optimal performance	[35, 52]
SMC (Sliding Mode Control)	Variable-structure control robust to model uncertainties and disturbances; suitable for aggressive maneuvers and fault-tolerant UAV control	Chattering phenomenon may cause wear and instability in actuators if not mitigated	[36, 37]

TABLE III. CLASSIFICATION OF CONTRIBUTION ANALYSIS AND OPTIMIZATION FOCUS AREA

Main Contribution	Theme	Optimization Focus Area	Reference
GA for material and weight optimization	Technological	GA Material Optimizer UAV	[6]
Graphene-based propellers improve lift efficiency	Technological	Graphene Propeller Optimization	[24]
IoT and fuzzy for adaptive UAV response	Technological	Fuzzy IoT UAV Adaptation	[11]
IoT enables adaptive propulsion control	Technological	IoT-Integrated UAV with PSO	[26]
IoT-based routing for energy savings	Technological	UAV IoT Energy Routing	[26]
Material choice reduces weight and increases endurance	Technological	Material Optimization for UAV	[23]
Neural optimization improves overall UAV system	Technological	Neural UAV Optimization	[21]
Optimizing materials for endurance	Technological	Material-Driven Endurance Optimization	[23]
RL improves real-time trajectory tracking	Technological	RL-Based UAV Trajectory Optimization	[20]
Altitude control via PSO	Control	PS Optimization in UAV Altitude	[6]
Comparison of metaheuristics for UAV control	Control	GA vs PSO for UAV Path	[41]
Fuzzy PID enhances nonlinear system stability	Control	Fuzzy PID for UAV Stability	[39]
Fuzzy PID improves quadcopter attitude control	Control	Fuzzy PID for Quadcopter	[38]
Fuzzy-RL improves coordination in UAV flight	Control	Fuzzy-RL UAV Coordination	[25]
GA for optimal flight paths	Control	Trajectory Optimization with GA	[41]
GA-based tuning for trajectory precision	Control	GA-PID for Trajectory	[41]
Greenhouse UAV control with PSO	Control	PSO for UAV Cleaner	[8]
Hybrid PSO for dynamic system modeling	Control	Hybrid PSO Pattern Search	[49]
Hybrid PSO-GA enables robust multi-objective tuning	Control	Hybrid PSO-GA for UAV	[9]
Hybrid RL-GA for adaptive mission control	Control	Hybrid RL-GA UAV Controller	[10]
Hybrid fuzzy-GA for responsive control	Control	GA-Fuzzy Control UAV	[42]
Hybrid fuzzy-GA improves system resilience	Control	Fuzzy-GA Optimized UAV	[42]
Hybrid fuzzy-PID for efficient control	Control	PID-Fuzzy with PS	[7]
Improves convergence in control systems	Control	PSO-GA for Multi-Objective Optimization	[9]
Navigation system optimized using PSO	Control	PSO Navigation System	[41]
Neural-based PSO-GA controller	Control	PSO-GA Neural UAV	[6]
Optimizing trajectory using multi-objective PSO	Control	Multi-Objective UAV PSO	[6]
PID tuning with IoT feedback	Control	IoT-PID Tuning UAV	[11]
PID-FLC hybrid for large motor stability	Control	Hybrid PID-FLC-PSO	[46]
PSO control for battery energy regulation	Control	Battery-Aware UAV Control via PSO	[6]
PSO improves BLDC motor efficiency	Control	PSO for BLDC UAV	[6]
PSO tunes PID for better performance	Control	PSO-Tuned PID UAV Control	[7]
PSO-Fuzzy for inverter control applied to UAV	Control	Fuzzy-PSO on PV Inverter (UAV-related)	[53]
PSO-based control for UAV motor system	Control	PSO-PID on DC Motor (UAV-like)	[6]
RL applied to UAV flight dynamics	Control	RL Optimized UAV Flight	[10]
RL-PSO improves dynamic performance in energy systems	Control	RL-PSO UAV Energy Optimization	[10]
Reduces overshoot in greenhouse UAV application	Control	Fuzzy-PSO UAV Greenhouse	[8]
Stability improvement in wind environments	Control	PSO-Controlled UAV in Wind	[49]
Adaptive neuro-fuzzy inference control for gas supply system in UAV	Control	Neuro-Fuzzy Gas Supply Control in UAV	[4]
Fuzzy adaptive neuron-based trajectory control for multirotor UAV	Control	Fuzzy Adaptive Neuron UAV Trajectory Control	[5]
Adaptive PID using RL for high altitude	Environmental	RL-PID for High Alt UAV	[54]
Eco-routing with PSO for UAV	Environmental	Green UAV with PSO	[6]
PSO-based adaptive UAV propulsion	Environmental	UAV Optimization with Adaptive PSO	[46]
RL for dynamic environment response	Environmental	Reinforcement Learning-based Adaptive UAV	[10]
Multi-objective optimization of fuel-cell UAV propulsion systems	Environmental	Performance Evaluation of PEM Fuel Cell Propulsion System	[2]

TABLE IV. PERFORMANCE OF ALGORITHM OPTIMIZATION

Algorithm	Optimization Target	Improvement Achieved	Performance Metric	Reference
PSO	PID tuning for BLDC motor	Faster convergence, better control	Rise time ↓ 30%, SSE ↓	[6]
Fuzzy PID	Attitude control in quadrotor	Enhanced nonlinear response	Overshoot ↓, stability ↑	[38, 39]
Hybrid PSO-GA	Multi-objective tuning	Improved exploration and convergence	Settling time ↓, energy use ↓	[9]
Reinforcement Learning (RL)	UAV trajectory planning	Real-time adaptive planning	RMSE ↓, fewer collisions	[20]
PSO-Fuzzy	Control for greenhouse UAV	Reduced overshoot and response time	Overshoot ↓ 35.5%, response time = 3s	[8]
Hybrid RL-PSO	Adaptive UAV control	Adaptive tuning with learning	Trajectory error ↓, RMSE ↓	[10]
GA Only	Trajectory optimization	Accurate trajectory path	Path error ↓, control stability ↑	[41]
Fuzzy-GA	Robust flight control	Improved control robustness	Adaptive gain tuning, steady response	[42]
Hybrid PID-FLC	Stability for large motor	Stable voltage under load	Stable output, ripple ↓	[46]
IoT + PSO	Energy-efficient routing	Battery-aware adaptive routing	Energy savings ↑, response time ↓	[26]
Fuel Cell Optimization (MOO)	Fuel cell UAV propulsion	Improved endurance and energy profile	Energy consumption ↓, endurance ↑	[2]
Adaptive Neuro-Fuzzy	Gas supply control system	Adaptive flow rate and responsiveness	Dynamic flow error ↓	[4]
Fuzzy Adaptive Neuron	Trajectory tracking for multirotor	Accurate tracking and parameter tuning	Trajectory error ↓	[5]
PSO-Fuzzy PID (BLDC)	Control tuning for BLDC system	Low overshoot and fast response	Rise time ↓, overshoot ↓	[7]
Deep Learning Optimization	Design optimization via DNN	Reduced design time and higher prediction accuracy	Design accuracy ↑	[21]
IoT + Energy Routing	Energy-efficient IoT routing	Reduced power consumption during missions	Energy savings ↑	[25]
Material Optimization	Composite material for UAV frame	Improved strength-to-weight ratio	Weight ↓, strength ↑	[23]
Nano-Additives in Propulsion	Nano-enhanced UAV propeller performance	Higher vibration and buckling resistance	Impact resistance ↑	[24]
Environmental Battery Modeling	Battery response under environment	Improved battery stability and lifespan	Thermal drift ↓	[48]
Thermal-Aware UAV Control	Gust wind adaptive flight	Improved control under wind gusts	Tracking error ↓ in gusty winds	[49]
Altitude-Based Propeller Tuning	Payload-endurance optimization	Increased efficiency at high altitude	Flight time ↑, energy loss ↓	[49]

Note: ↓ indicates a decrease or improvement (e.g., reduced error, time, or energy consumption); ↑ indicates an increase or enhancement (e.g., improved stability, accuracy, or endurance).

The technological contributions primarily center on material selection, IoT integration, and the use of neural or evolutionary algorithms for system optimization. Notably, references [23, 24, 26] highlight the strategic role of materials and IoT frameworks in enhancing endurance, weight reduction, and real-time adaptability of propulsion systems.

Control-related studies dominate the reviewed literature, reflecting the importance of stable, responsive, and intelligent control mechanisms in UAV applications. Contributions in this category span from classical PID enhancements, such as PSO-tuned PID [6, 7] to hybrid fuzzy and learning-based controllers [10, 38, 42]. This diversity underscores the need for control strategies that can handle nonlinearities and dynamically adapt to mission requirements

The environmental theme, although less represented, reveals critical insights into how optimization methods contribute to sustainability and resilience. Studies like [2, 47, 48] emphasize battery-aware routing, fuel cell endurance optimization, and environmental adaptation strategies key to advancing UAV deployments under real world constraints.

Among the most cited methods, PSO consistently demonstrates its strength in controller tuning, as shown by rise time and steady-state error reductions [6, 7]. Feature selection and dynamic modeling in UAV control have also benefited from PSO-based approaches, enabling more efficient and accurate system identification [54]. Hybrid variants such as PSO-GA and RL-PSO further improve exploration capabilities and adaptiveness, especially in multi-objective scenarios [9, 10]. Comparative analysis indicates that GA outperforms PSO in global search accuracy, while PSO converges faster. Hybrid methods balance both but increase complexity.

Fuzzy based algorithms, including Fuzzy PID, Fuzzy-GA, and adaptive neuro-fuzzy inference systems [4, 5, 38], are effective in handling nonlinear control problems, offering smooth responses and robustness across varying load conditions. The implementation of Fuzzy-PID controllers on BLDC motors, especially in quadrotor systems, has demonstrated improved trajectory tracking and robustness under dynamic conditions [53]. Recent studies have also explored deep learning-based adaptive controllers for satellite-aided UAV operations, which may be integrated into future hybrid control systems for enhanced autonomy and adaptability [17].

Innovations in energy efficiency are also evident. IoT-based optimization [25, 26] and deep learning techniques [18] provide significant improvements in mission adaptability and energy savings. Furthermore, material innovations [23, 24] and thermal-aware models [48, 49] address structural integrity and environmental stability emerging as crucial factors for long term UAV operation.

In addition to control and material innovations, structural factors such as airframe configuration and fuselage shape significantly impact propulsion efficiency, as discussed in [55, 56]. Furthermore, the mechanical balance and control of BLDC motors under varying loads remains a critical consideration for flight stability [57].

From the reviewed literature, it is evident that the optimization of electric UAV propulsion systems is a multidisciplinary effort involving control theory, materials engineering, artificial intelligence, and environmental modelling. Hybrid PSO-based methods stand out due to their wide applicability and consistent performance, but they must evolve to meet computational constraints and real-world unpredictability.

The findings also underscore the importance of transitioning from simulation to physical implementation. There is a need for more experimental studies, benchmarking frameworks, and open access datasets that allow reproducibility and cross comparison of optimization techniques.

The integration of propulsion optimization with other UAV subsystems, such as navigation, communication, and structural design, remains a key frontier. Optimization efforts must be holistic, system-aware, and aligned with sustainability and operational efficiency goals. This integrated perspective will ensure that future UAV platforms are not only high-performing but also resilient and environmentally responsible.

From the classification, it is evident that control-related optimization dominates the field, especially using PSO-based approaches. However, relatively few studies integrate control with environmental modeling or validate findings experimentally. The data also reveals a lack of attention to lifecycle impact and system-level integration. These insights suggest that future research should prioritize hybrid optimization for real-world UAV systems, cross-domain frameworks, and robust environmental adaptability. The structured synthesis presented here is intended to guide researchers in identifying underexplored but impactful directions.

Emerging challenges in UAV control stem from the increasing complexity of operational environments and mission requirements. Modern UAVs must maintain robust performance under highly dynamic conditions, including unpredictable wind gusts, sudden payload changes, and GPS-denied navigation scenarios. Controllers are also expected to operate within stringent computational constraints, as real-time optimization and sensor fusion must be performed on lightweight embedded processors with limited resources. The integration of AI and machine learning–based adaptive control introduces additional challenges related to training data quality, online adaptability, and explainability of decisions in safety-critical missions. Furthermore, achieving a balance between high-precision control and energy efficiency remains a critical issue, particularly for battery-powered UAVs where every control action directly impacts endurance. Addressing these challenges requires innovative control strategies that combine robustness, adaptability, and computational efficiency, paving the way for future advancements in UAV technology.

V. Conclusions and Recommendations

This study systematically reviewed 42 articles on the optimization of electric propulsion systems for UAVs, focusing on technological advancements, control system optimization, and environmental and operational impacts. The analysis revealed that optimization strategies, particularly those integrating PSO and hybrid approaches, play a central role in improving system stability, energy efficiency, and adaptability in dynamic conditions.

From the technological perspective, machine learning algorithms and material innovations contribute significantly to UAV propulsion performance, although practical implementation still faces limitations in scalability and real-time deployment. In terms of control systems, the transition from conventional PID to Fuzzy-PID and hybrid-optimized controllers marks a crucial evolution in addressing nonlinear and time varying dynamics. On the environmental side, propulsion optimization has been shown to substantially reduce energy consumption and emissions, supporting the development of more sustainable UAV operations.

The review also highlights several research gaps:

(1) A lack of experimental validation and real-world deployment, with most studies confined to simulation.
(2) Limited integration between propulsion optimization and other UAV subsystems such as aerodynamics, communication, and structural design.
(3) Underdeveloped models for environmental variability and thermal behaviour, especially regarding battery dynamics under extreme conditions.

Despite offering a comprehensive overview, this review is subject to several limitations that may affect the generalizability of its conclusions. First, the majority of the included studies rely heavily on simulation-based results, with limited experimental validation or real-world deployment. This restricts the extent to which performance outcomes can be extrapolated to practical UAV operations. Second, integration between propulsion, structural, and environmental aspects is still underdeveloped across studies, limiting system-level insights. Third, variations in data reporting, evaluation metrics, and publication bias may also skew the perceived effectiveness of certain optimization methods. These limitations highlight the need for caution in interpreting aggregated findings and reinforce the importance of experimental research moving forward.

Recommendations for Future Research:

(1) Develop lightweight, energy-efficient ML models suited for embedded UAV platforms.

(2) Explore decentralized optimization algorithms for swarm UAVs and real-time fleet coordination.
(3) Advance experimental frameworks, including HIL simulation and in-flight trials.
(4) Conduct life-cycle assessments of propulsion systems, incorporating sustainability metrics beyond energy consumption.
(5) Pursue holistic design frameworks that integrate propulsion control with aerodynamic and mission-specific considerations.

In conclusion, while significant progress has been made in optimizing electric UAV propulsion systems, future research must bridge the gap between simulation and application, ensuring solutions are scalable, robust, and environmentally aligned. The continued convergence of AI, materials science, and systems engineering will be vital to the development of the next generation of intelligent, efficient, and sustainable UAV platforms.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

EEP collected and reviewed articles, analyzed data, and wrote the paper; RA is responsible for the paper writing method; MK improved the quality of the paper and reviewed the process; all authors have approved the final version of the manuscript.

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