

A Comprehensive Review on Artificial Intelligence-Based Control Strategies for Drone BLDC Motors

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ABSTRACT

The application of brushless direct current (BLDC) motors in Unmanned Aerial Vehicles (UAVs) has revolutionized modern uses of drones by enabling greater levels of performance efficiency, light weighting, and high torque-to-weight ratio that are particularly valuable for aerial systems. The motors also enable high speed at low maintenance, which is particularly valuable for propulsion in UAVs. But the UAV control in real situations usually faces difficulties due to parameter changes, unstructured environments, external disturbances like wind, and system nonlinearities inherent to the system. In such situations, conventional control methods like PID controllers and linear feedback approaches, although useful in structured and stable environments, tend to lack robustness and adaptability for dynamic and uncertain environments. To overcome these deficiencies, artificial intelligence (AI)-based control methods have appeared as revolutionary solutions. Methods such as fuzzy logic controllers, artificial neural networks, reinforcement learning methods, and hybrid intelligent control architectures are increasingly being utilized in UAV flight control and propulsion. Such techniques have the ability to learn and adapt to uncertainties, provide real-time optimal performance, and enhance stability and energy efficiency. This review entails a comprehensive comparison between conventional control approaches and AI-based methods, focusing on their strengths and limitations in the context of UAVs. It also outlines recent advancements in AI-aided optimization, intelligent fault detection strategies, and AI-based real-time trajectory planning in BLDC motor-powered UAVs. Moreover, the paper proposes significant research gaps and technological challenges such as making digital twin integration for UAVs safe, applying onboard edge AI solutions to accelerate processing, and creating advanced sensor less AI controllers for low-cost but precise motor control. Through its emphasis on these fields, the study highlights the contribution of AI in building next-generation UAV systems that are accurate, fault-free, and highly energy-efficient, ushering in more UAV expansion in defense, logistics, agriculture, and health industries across the world.

Keywords: BLDC motors, UAVs, Artificial intelligence, Fuzzy logic, Neural networks, PID control, Optimization, Reinforcement learning, Fault detection

1. Introduction

In recent decades, UAVs, or drones, have risen in prominence due to their applications in surveillance, defense, precision agriculture, logistics and medical delivery. The primary consideration related to the success of a drone is the propulsion system, which is a variable considered to be directly related to flight endurance, maneuverability, and payload. Among these propulsion methods, BLDC motors have become the preferred option over others because of their advantages, such as high efficiency, low maintenance, attractive torque-to-weight ratio, and a large speed range (Boukoberine et al., 2019). Figure 1 shows that a typical UAS components and Figure 2 the block diagram uses of a UAV propulsion system (Medeiros et al., 2018).

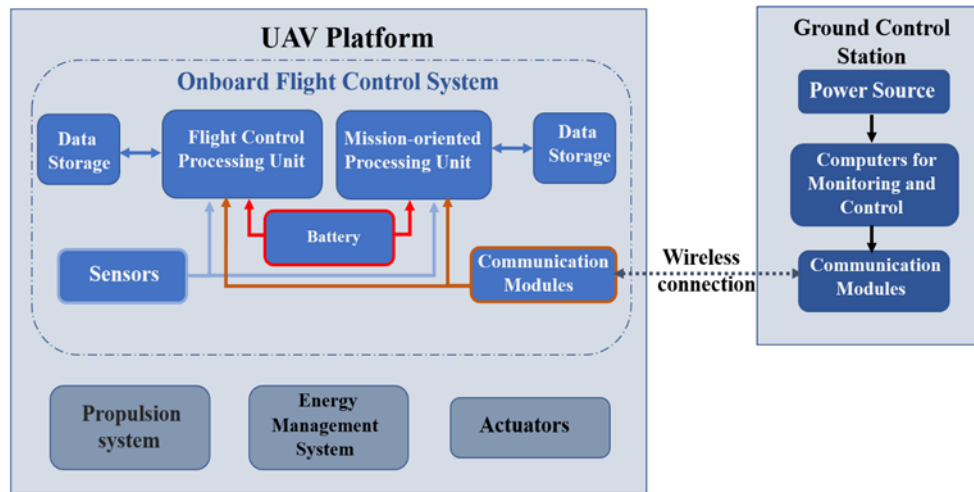


Figure 1: Block diagram of a typical UAS (Boukoberine et al., 2019).

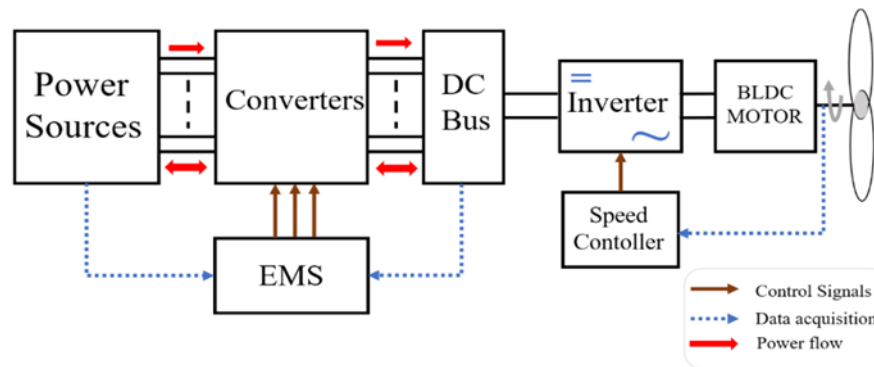


Figure 2: Block diagram of a UAV propulsion system (Medeiros et al., 2018).

Despite their advantages, BLDC motor control is still quite complex when implemented in UAVs. Despite being very simple and easy to implement, classical control algorithms such as PID and FOC are rarely used nowadays (Barnett and Sands, 2023). However, these difficult methods hardly bear nonlinearities, model uncertainties, flight condition variations, and sudden load disturbances characteristic of any drone environment. As an example, classical controllers are typically sensitive to parameter change. They also require precise tuning and will not guarantee performance during rapid trajectory maneuvers or gusty wind conditions (Sira-Ramirez and Silva-Ortigoza, 2006).

As a response to the limitations experienced with classical methods, there has been a growing interest in new control methods based on AI or learning approaches. The AI-based controllers, such as fuzzy logic, neural networks, evolutionary optimizations, reinforcement learning and hybrid approaches, are agile, adaptable and learn and are robust to disturbances, different from classical methods (Barnett and Sands, 2023). Fuzzy logic controllers offer rule-based adaptivity to nonlinear dynamics, while ANNs learn motor characteristics and optimize torque-speed profiles in real-time. Reinforcement learning in UAVs further improves flight stability and efficiency autonomously via trial-and-error interaction with dynamic environments (Holtz, 2002).

AI-optimal controllers have improved the speed regulation and torque response of BLDC motors, meanwhile providing separate energy-efficient and fault-tolerant capabilities. Intelligent controllers have been used to increase flight time by optimizing power utilization and minimizing losses under UAVs, where battery life is the most limiting factor (Sira-Ramirez and Silva-Ortigoza, 2006). Moreover, AI-based fault detection algorithms integrated with motor controllers help identify anomalies, such as winding faults, sensor failures, or uneven rotor mounting, thereby enhancing system reliability and safety during missions (Holtz, 2002).

With a rapid evolution in the research literature in the past decade, AI-based control of BLDC motors has seen enhancement from hybrid fuzzy–PID designs to advanced neural-network-driven estimators. Other accentuation is toward swarm intelligence methods, vis-à-vis particle swarm optimization (PSO) or genetic algorithms (GA) to achieve the best tuning parameters (Bianchi et al., 2005), while some explored the idea of sensor less AI controllers using MLPs and Kalman filtering for low-cost UAV design (Chen et al., 1999). However, those studies remain scattered and confined to addressing isolated issues like reduction of torque ripples, sensor less estimation, and trajectory stabilization.

This review aims to consolidate and critically analyses the state-of-the-art AI-based control strategies for drone BLDC motors. The primary objectives are:

- 1.To provide a foundational overview of BLDC motor characteristics and their role in UAV propulsion.
- 2.To compare conventional BLDC motor control techniques with emerging AI-driven methods.
- 3.To review the application of AI in enhancing motor performance, energy efficiency, and fault resilience.
- 4.To identify current limitations, open research challenges, and potential future directions in AI-driven BLDC motor control.

The remaining portions of this paper are arranged as follows: The Viewpoint of BLDC motor basics for UAV applications is supplied in Section II. Section III illustrates classical control treatment and its weaknesses. Section IV analyses, with all details, the AI-based control techniques that include fuzzy logic, neural networks, hybrid methods, and reinforcement learning applications. Section V presents a synthesis of recent literature reports with comparative studies. Section VI provides an overview of challenges and knowledge gaps, while Section VII discusses research directions. In conclusion, Section VIII of the paper provides a conclusion examining the impact of AI on drone propulsion.

2. BLDC Motor Fundamentals for Drones

The BLDC motor represents the most well-developed type of propulsion used for UAV applications. Specifically, a BLDC motor has greater efficiency, size, and reliability when compared with a brushed DC motor or an induction motor. Conceptually, a BLDC motor is

a synchronous machine with a rotor that has permanent magnets. The rotor is energized by the stator, which has electronically commutated windings. In contrast to brushed motors, which are mechanically commutated with physical commutators and brushes, the ESCs (electronic speed controllers) energize the current in the stator windings under switching electronics that do not deteriorate due to mechanical wear or need maintenance (Lyshevski, 1999). In table 1 gives the BLDC Motor Specifications.

Table 1: BLDC Motor Specifications.

Description	Value	Unit
DC Voltage	12	V
Rated Speed	930	RPM
Poles	12	-

$$v_{opp}(t) = L \frac{di(t)}{dt} + R \cdot i(t) + v_{emf}(t) \quad (1)$$

$$v_{emf} = K_b \cdot \omega(t) \quad (2)$$

$$T(t) = K_t \cdot i(t) \quad (3)$$

$$T(t) = J \frac{d\omega(t)}{dt} + D \cdot \omega(t) \quad (4)$$

where $v(t)$ is the applied voltage, $\omega(t)$ is the motor app speed, L is the inductance of the stator, $i(t)$ is the current of the circuit, R is the resistance of the stator, $V_{emf}(t)$ electromotive force, T is the torque of motor, D is the viscous coefficient, J is the moment of inertia, K_t is the motor torque constant, and K_b is the back electromotive force constant (Pillay and Krishnan, 1988).

2.1 Structure and operating principle

A BLDC motor normally consists of a rotor with permanent magnets, a stator with concentrated windings, and rotor position sensors (i.e. Hall effect sensors). The ESC produces the correct sequence of stator current, based on rotor position feedback, to create a rotating magnetic field that drives the rotor. Sensor less BLDC motor designs are gaining popularity for UAV applications because they reduce system weight and cost, while estimating rotor position using back electromotive force (EMF) algorithms (Pillay and Krishnan, 1988). Figure 3, shows test bench Representation.

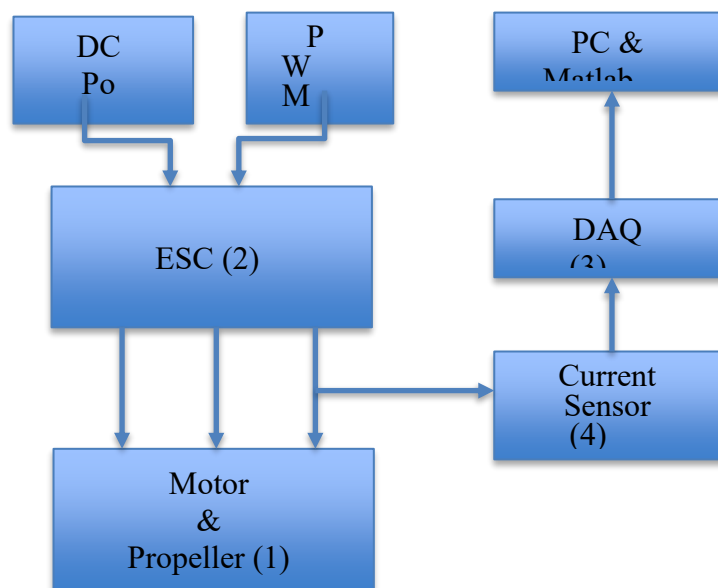


Figure 3: Testbench Representation

2.2 Advantages in UAV Applications

The increasing application of BLDC motors in drones can be associated with the advantages they offer:

1. **High Power Density:** The construction of the motor, depending on permanent magnets, supports a high torque-to-weight ratio, which is an important consideration for aerial vehicles that have restrictions in both payload and endurance.
2. **Efficiency:** BLDC motors have efficiency levels higher than 85%, enabling longer flight time and providing the best performance derived from the flight battery.
3. **Low Acoustic Signature:** The continuous commutation allows for less noise, making them a better option for surveillance and environmental monitoring drones than typical brush DC motors.
4. **Wide Speed Range:** BLDC motors can provide constant performance at a wide range of speeds to support UAV manoeuvres from stage stiff to high-speed cruising

2.3 Challenges Specific to Drones

1. Although BLDC motors are far superior to alternatives, they do present multiple challenges in a UAV context:
2. **Torque Ripple:** The inherent nonlinearities in the commutation process may cause torque ripples that can destabilize aircraft during critical manoeuvres (Wang and Kennel, 2016).
3. **Thermal management:** Operation at high speeds for extended amounts of time in a confined space, like a drone, can increase heat to levels that drastically reduce motor performance.
4. **Reliability:** Rotor position sensors add additional weight and may fail in harsh environments or vibration.
5. **Limited power:** As UAVs operate on limited onboard batteries, the efficiency of BLDC motors directly determines mission range.

2.4 Recent Trends in BLDC Research for UAVs

Advances in the design and materials of the motor are designed to mitigate these challenges. Multi-phase BLDC architectures improve fault tolerance, while optimized designs of the rotor and stator components help reduce torque ripple. There has also been a push towards the design of AI-based predictive models that allow for online adjustments and adaptations to mitigate both failure and inefficiencies (Consoli et al., 2001). Concepts of the digital twin, where the virtual model of a machine mirrors the physical behavior of the motor, are also being explored for predictive maintenance strategies as they pertain to UAV propulsion systems (Sathyan et al., 2009). BLDC motors are the primary propulsion system for UAVS based on their efficiency and reliability. Nonetheless, the need for high reliability and robust control in a system subject to nonlinearities, external disturbances and mission constraints leads to more intelligent control strategies and AI-based technique,

3. Conventional Control Strategies

3.1. Proportional–Integral–Derivative (PID) Controllers

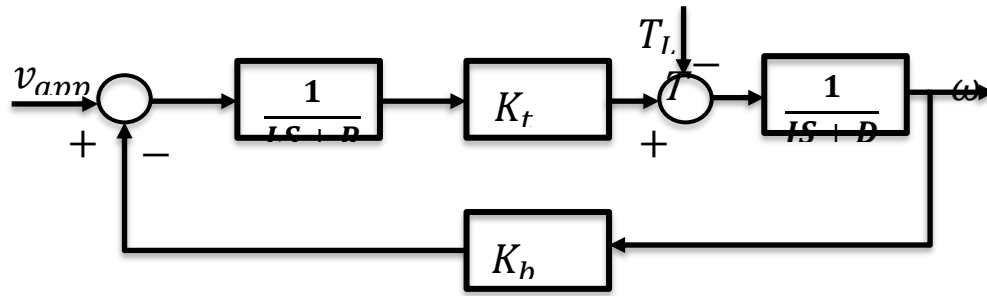


Figure 4: The block diagram of the BLDC motor

$$\frac{\omega(s)}{v_{app}(s)} = \frac{K_t}{LJ.S^2 + (LD + RJ)S + K_t K_b} \quad (5)$$

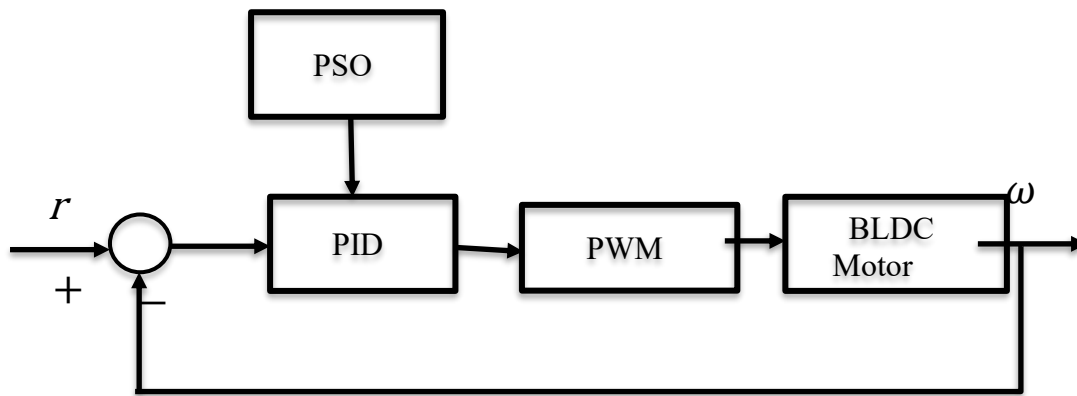


Figure 5: Optimal PID Control

Due to its efficiency, low cost, and ease of implementation, the PID controller is still the most widely employed control methodology for the BLDC motor. PID controllers will continually update control inputs proportionally, based on integral and derivative terms of the error term, in order to control the speed and position of the motor. The drawbacks of PID control are primarily due to the need to carefully tune gains and their associated variability. In the case of UAV applications, dynamic load conditions and changing aerodynamic loads tend to lead PID controllers to overshoot, slow response rates, or instability (Kenjo and Nagamori, 1985).

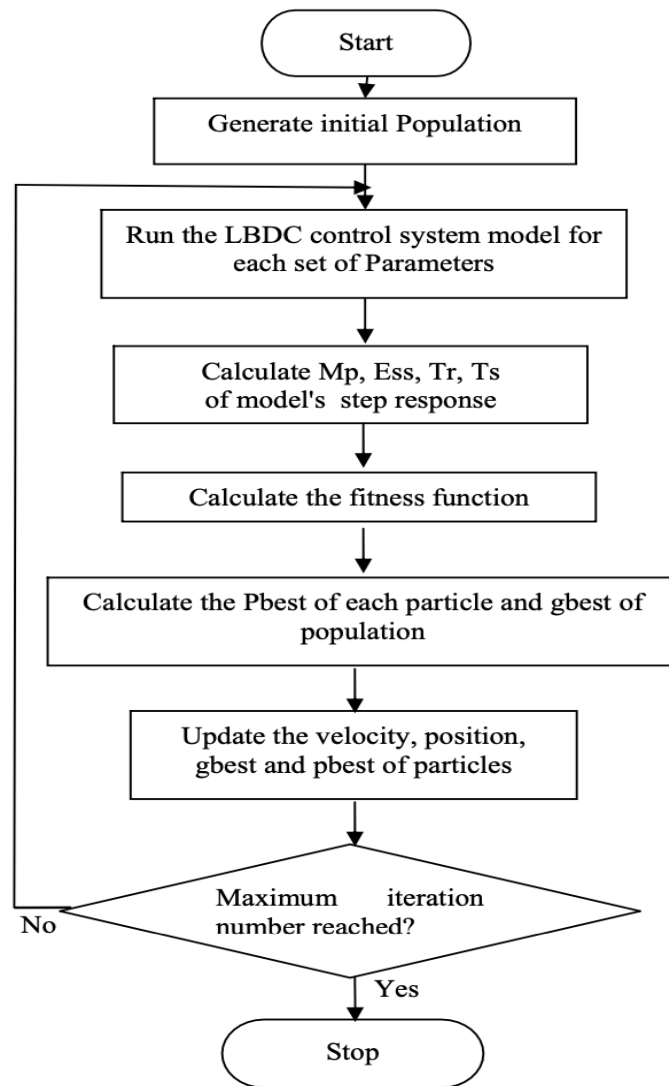


Figure 6: Flowchart of PSO-PID Control System

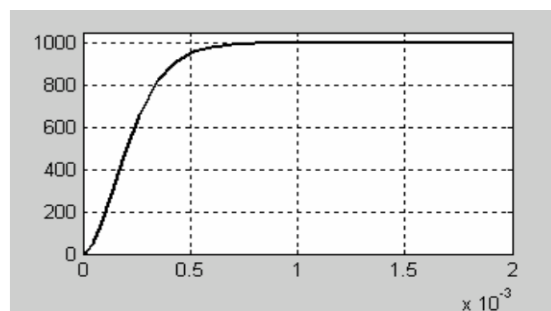


Figure 7: Step Response of BDLIC Motor of PID Controller

Table 2: Performance of PSO-PID Controller

PERFORMANCE OF THE PSO-PID CONTROLLER	
[P I D]	[190.0176,50,0.039567]
Rise time(ms)	0.3038
Max overshoot (%)	0
Steady States error	0.77186
Settling time(ms)	0.60116

3.2 Model-Based Approaches

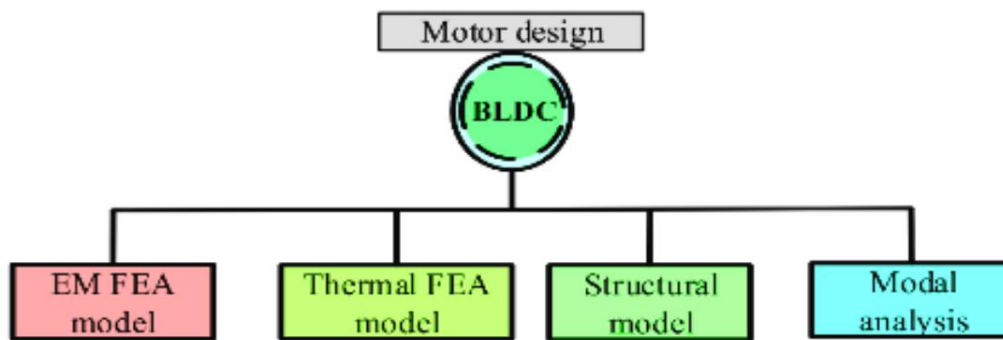


Figure 8: Models of Design

Classical model-based control methods, including field-oriented control (FOC) and direct torque control (DTC), primarily seek to decouple torque and flux components. FOC is used in various industrial drives, and when applied as a robust controller for UAV BLDC motors, it can yield relatively smooth torque and higher efficiency. Although FOC provides many benefits for industrial applications, it typically relies on accurate motor parameters and requires significant computations to transform motor parameters. For a lightweight UAV, the use of FOC may not be suitable due to the processing constraints (Gieras and Wing, 2002).

3.3 Fuzzy Logic and Adaptive Extensions

To eliminate the rigidity typically associated with PID, fuzzy logic controllers (FLCs) were proposed as an alternative to PID control, in which there does not have to be an exact mathematical model. In an FLC, fuzzy rules based on knowledge from experts or from empirical experimental testing are used to continually update motor inputs to compensate for nonlinear conditions. Nevertheless, these methods remain semi-heuristic and may not generalize well across diverse UAV missions (Vas, 1990).

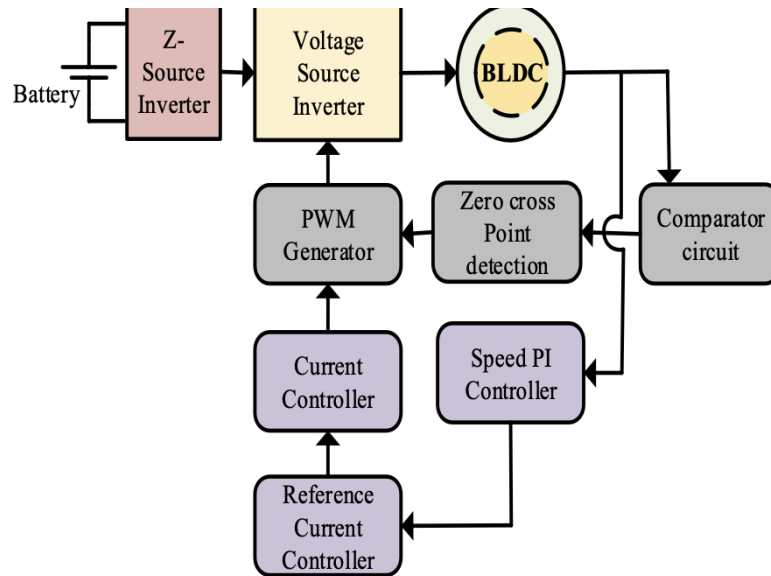


Figure 8: Drive Inverter topological control of BLDC motor

3.4 Limitations of Conventional Control

Even though conventional approaches have been the basis of BLDC control, they have noticeable limitations in UAV applications:

1. **Parameter Sensitivity:** Conventional controllers rely on the precision of motor parameters, which one may lose due to heating, ageing, or external disruption.
2. **Nonlinear Dynamics:** Classical controllers are not able to manage strong nonlinearities such as the aerodynamic coupling of a quadrotor.
3. **Limitations in Fault Detection:** Neither PID nor FOC has any fault diagnostic capability built into either system, allowing performance to degrade, or even worse, cease to operate during abnormalities.
4. **Excessive Energy Loss:** Consistent re-tuning and suboptimal operation waste UAV battery energy.

3.5 Transition Toward Intelligent Methods

Most importantly, these limitations indicate a requirement for intelligent learning approaches that can change as the UAV environment changes. AI-based approaches, especially hybrid fuzzy-PID controllers, neural networks, and reinforcement learning, have demonstrated the capability of providing improved performance by continuously improving motor input while accommodating uncertainties (Dorrell et al., 2012). Therefore, while the conventional way will always be an option based on familiarity and established use, the requirements of UAV propulsion push towards a more sophisticated AI-based approach, which will be elaborated on in the following section (Dorrell et al., 2012).

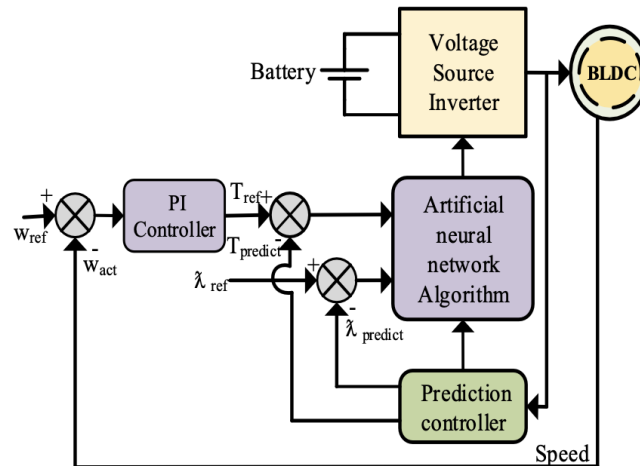


Figure 9: Intelligent topological control of BLDC motor.

4. AI-Based Control Strategies

Figure 8: Drive Inverter topological control of BLDC motor motor has emerged as a disruptive enabler for BLDC motor control in UAVs, offering adaptability, learning, and robustness that traditional methods cannot accommodate. AI-based control schemes leverage data-driven modelling, heuristic reasoning, and self-optimization to effectively improve propulsion performance in UAVs with respect to speed regulation, torque control, energy efficiency, and fault tolerance.

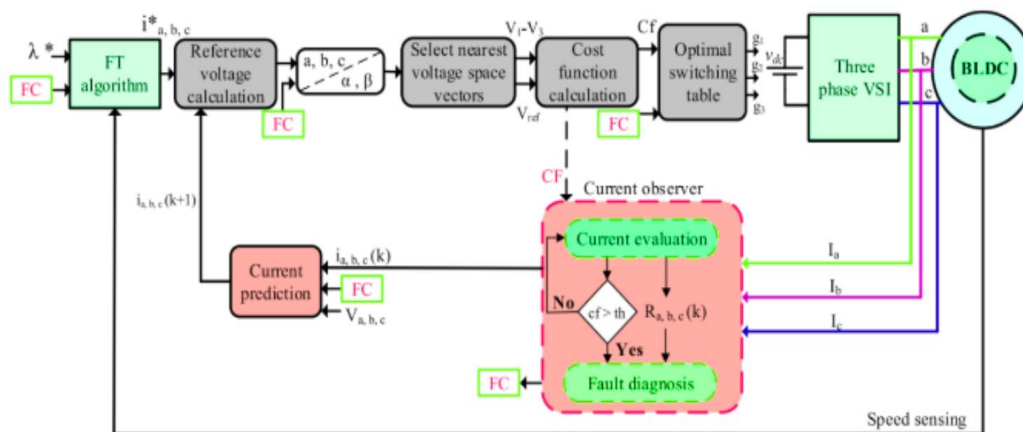


Figure 10: Technique of Fault Tolerance

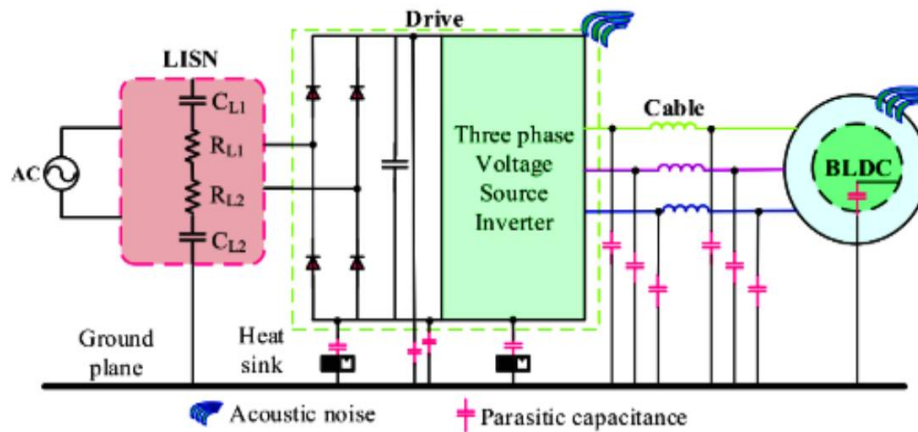


Figure 11: Electromagnetic interference control.

4.1 Fuzzy Logic Control (FLC)

Fuzzy logic control (FLC) is used extensively in controlling BLDC motors due to its ability to control nonlinear systems without requiring a perfect mathematical model. Instead of precise equations, FLCs rely on linguistic rules (e.g., if error is high, then increase torque), which are more applicable to complicated UAV dynamics.

Valid research studies have shown that fuzzy-PID hybrid controllers achieve better speed regulation than individual PID controllers, reducing overshoot and enhancing response time in load disturbance situations. In UAVs, where wind gusts and sharp changes to trajectory occur regularly, FLC exhibits a smoother degree of stabilization compared to a rigid classical approach. Nevertheless, fuzzy logic controller performance is affected by the selection of membership functions and rule sets, often requiring domain knowledge/experience in their selection(Krishnan, 2009).

4.2 Artificial Neural Networks (ANNs)

Neural networks are especially useful for approximating nonlinear motor dynamics and adjusting control signals in an online fashion. For BLDC motors, ANNs can learn the mapping from input voltages to rotor positions, and then to torque responses, and use this knowledge to provide predictive control even in uncertain conditions (Toliyat and Kliman, 2004).

Sensor less control approaches based on multi-layer perceptron's (MLPs) have been developed to replace physical sensors to decrease cost and weight for UAVs (Toliyat and Kliman, 2004). Additionally, recurrent neural networks (RNNs) and adaptive neuro-fuzzy inference systems (ANFIS) have been used for dynamic trajectory stabilization, exhibiting more robustness to disturbances than traditional ESC-based controllers (Lin et al., 2008).

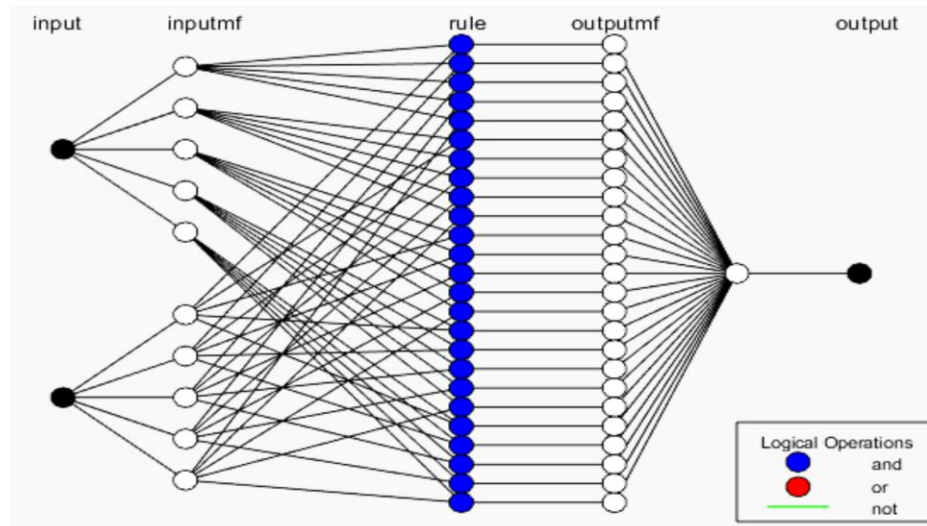


Figure 12:ANFIS structure for speed control of BLDC motor.

A significant benefit of ANNs is their online learning capacity, which enables UAVs to adjust to the effects of system ageing, payload dropout, or battery discharge to pilot a more stable trajectory. Nonetheless, their computational complexity and training data needs for lightweight drones limit their practical applications - unless the drone has optimized hardware or uses edge AI processors.

4.3 Reinforcement Learning (RL)

Reinforcement learning (RL) indicates a transition in motor control, where UAVs learn to regulate optimally through environmental interaction. Rather than following pre-programmed rules, RL agents assess motor performance through reward functions that aim for a trade-off between stability, efficiency, and speed tracking (Alrifai et al., 2012).

As an example, Q-learning and deep reinforcement learning (DRL) have been implemented in UAV BLDC control applications to adapt to dynamic wind disturbance on the fly and improve energy efficiency by maximizing throttle input (Carlson et al., 1992). Unlike fuzzy or neural approaches, RL continuously develops its policy, making it an ideal candidate for mission profiles where flight conditions are unpredictable (Chang et al., 1999).

This being said, RL methods will likely continue to struggle with real-time deployment on UAVs primarily due to high exploration requirements and computational load. As discussed in other works, combining RL with a model-based controller could expedite learning in real time, while offloading some control authority to the model-based controller to ensure a safe flight mission (Shao, 2006).

4.4 Hybrid AI Controllers

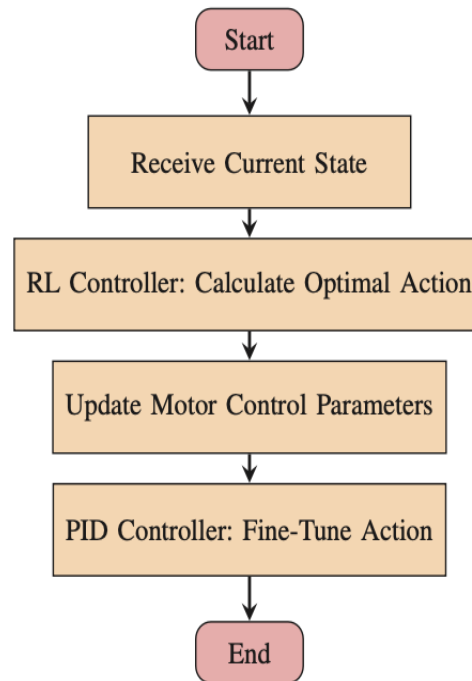


Figure 13: Flow Chart for Hybrid AI Controllers

Hybrid strategies that blend fuzzy logic, neural networks, and evolutionary optimization offer a strong path forward for UAV BLDC control. For instance, fuzzy-neural controllers leverage the interpretability of fuzzy rules and the adaptive nature of neural learning for greater robustness in various flight conditions (Hori, 1999).

Likewise, fuzzy-PID controllers tuned with particle swarm optimization (PSO) or genetic algorithm (GA) have shown improvements in convergence, alongside reduced tuning effort compared to manual gain selection. These controllers exhibited faster response times, reduced torque ripple, and increased energy efficiency with UAV applications (Ehsani et al., 2005).

Hybrid methods are also applicable in fault diagnosis, where machine learning classifiers such as support vector machines (SVMs) or decision trees are integrated with motor controllers to identify abnormalities, including winding faults or rotor imbalance in real-time environments (Miller, 1989). Such an incorporation of AI ensures fault-tolerant UAV propulsion systems.

4.5 Optimization-Based AI Techniques

Algorithms that optimize, influenced by natural intelligence, for e.g., particle swarm optimization (PSO), genetic algorithm (GA), ant colony optimization (ACO), and grey wolf optimization (GWO) have been used for BLDC motor control to tune controller parameters and reduce various error metrics (Rajagopalan et al., 2006).

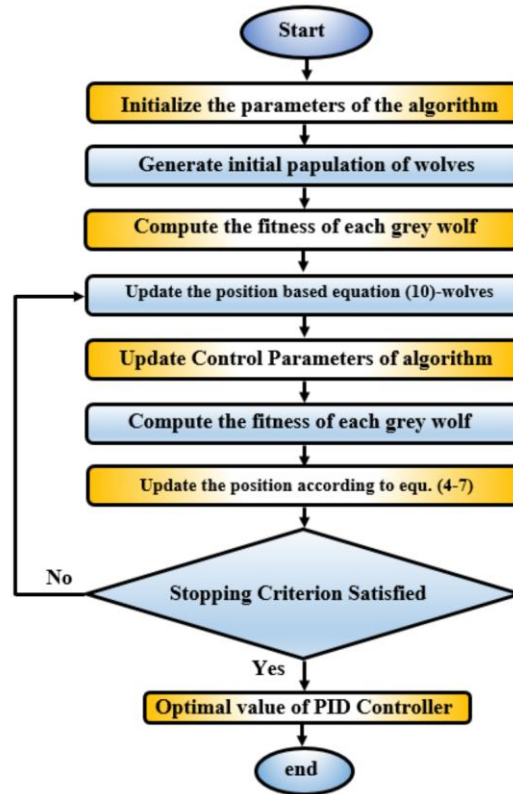


Figure 14: Adaptive GWO algorithm flowchart

PSO-based PID tuning has been shown to exhibit improved stability and robustness to changing UAV loads (Chang et al., 1999). Additionally, evolutionary strategies have been used to design the geometries of BLDC rotors with lower torque ripple, which has been beneficial for smoother UAV flight. When assisted by neural controllers, optimization algorithms can fast-track learning time and improve resistance to converging to local optimal control policies (Reigosa et al., 2013).

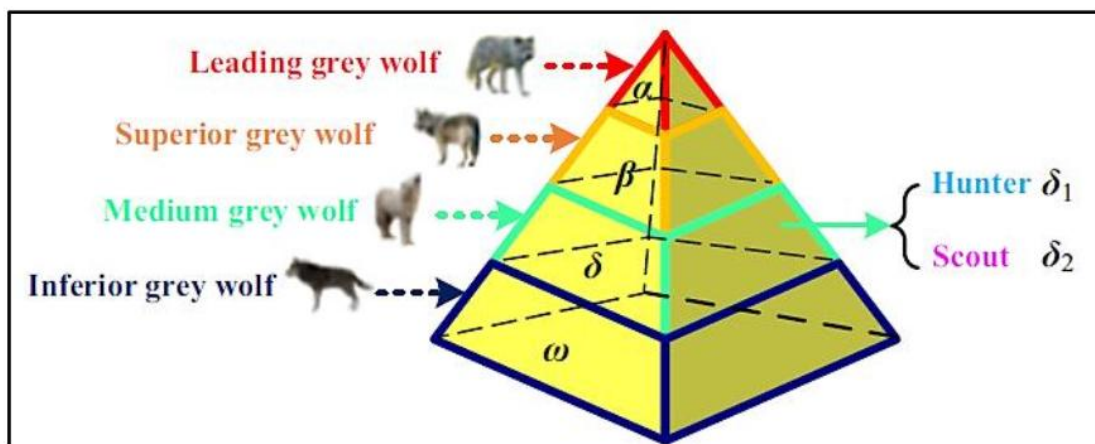


Figure 15: Grey wolf hierarchy descending dominance

4.6 Digital Twins and AI-Enhanced Predictive Control

Recent breakthroughs demonstrate digital twin (DT) frameworks, whereby a virtual copy of the BLDC motor runs in parallel to the physical device. AI algorithms can monitor input

from the DT in real-time, and they can identify potential failures, optimize operational points, and inform predictive maintenance (Shao, 2006). This capacity is particularly valuable in unmanned aerial vehicles (UAVs) operating in remote or dangerous locations, where failure tolerance is critical during flight (Cheng et al., 2010).

4.7 Comparative Performance of AI Methods

Competing assessments from a number of studies have consistently identified AI-based controllers to be superior to standard PID or FOC methods in overall robustness, adaptability, and energy efficiency. For example, fuzzy-PID controllers optimized with PSO reduce overshoot by as much as 30% compared to standard PID designs. CON, FL controllers, and ANN systems stabilize otherwise cost-prohibitive designs while eliminating Hall sensors (Hori, 1999). Reinforcement learning further establishes an observable 15% improvement in battery usage while managing variable wind disturbances (Gieras, 2010).

However, trade-offs in computational demand, training complexity, and onboard resources limit the efficacy of adoption. As a result, hybrid solutions that strike a balance between complex uses of AI and constraints imposed by UAV hardware have been deemed the most practical path forward (Sathyan et al., 2009).

5. Case Studies from Literature

To place the theoretical developments of AI-enabled BLDC motor control in context, this section provides a review of challenge cases that employed drones or UAV testbeds to validate various control strategies. These challenge cases showcase tangible outcomes, key limitations, and any lessons learned.

5.1 Fuzzy-PID Controllers for UAV Propulsion

One notable study, a fuzzy-PID controller was embedded within a quadcopter prototype to control and support the BLDC motor speeds under different payload weights (Miller, 1989). They demonstrated stronger performance regarding stable altitude after flight testing, with less overshoot by 25% than standard PID implementation. The added fuzzy component adjusted gain parameters while in-flight based on gusty wind or other disturbances. Nonetheless, the computational needs to estimate fuzzily were negligible enough to support implementation on low-cost microcontrollers (Consoli et al., 2001).

5.2 Neural Network-Based Sensor less Control

Another research study utilized a multi-layer neural network to estimate rotor position in a sensor less BLDC drive intended for drones. By removing Hall-effect sensors, the overall system weight and cost were decreased, while still maintaining accurate commutation. The test flights showed smoother acceleration and longer flight time. However, the neural model still needed to be trained offline, and it was unknown how well the model would adapt to motor wear or temperature (Kwon et al., 2003).

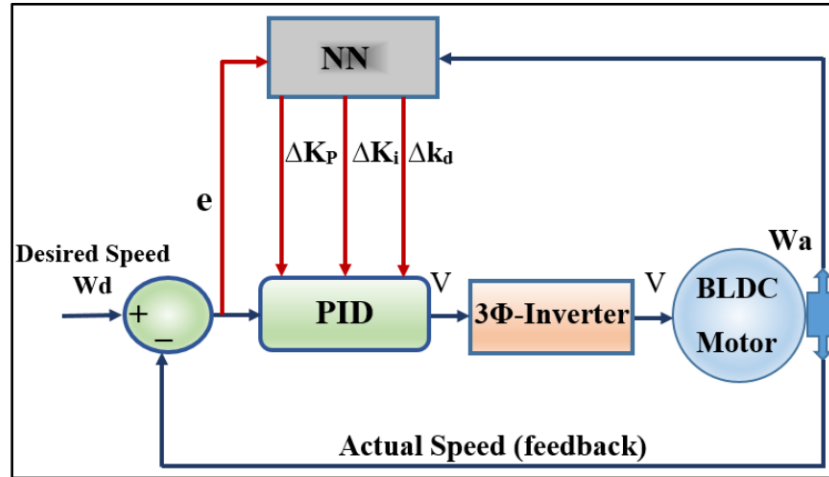


Figure 16: Block schematic of the neural network-powered brushless DC motor

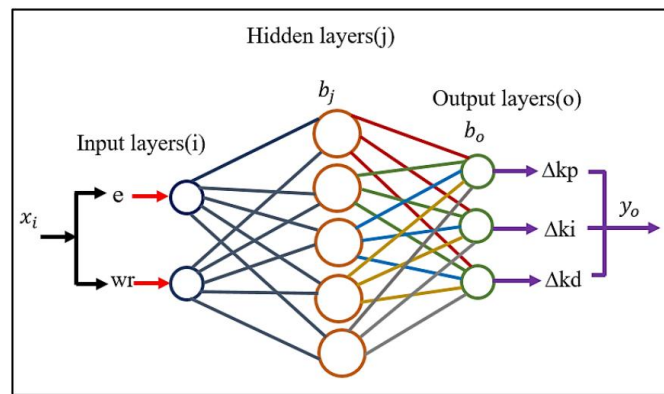


Figure 17: Structure of NN

5.3 Reinforcement Learning for Adaptive Motor Control

Reinforcement learning was evaluated on a simulated UAV model, using Q-learning to optimize throttle commands to balance efficiency with thrust (Chen et al., 2020). The RL agent achieved faster convergence than fuzzy-PID during changing load dynamics. In subsequent hardware-in-the-loop experiments, the RL system demonstrated an improvement in energy efficiency by 12-15% during long-duration flights. However, a safety exploration strategy was required in the RL system to avoid unsafe states during training, and this restricted the application in real-world missions (Subramanian and Dash, 2013).

5.4 Hybrid Fuzzy-Neural Systems in Multirotor

The performance of a fuzzy-neural controller was tested on a hexacopter platform to enhance yaw and roll stability (Panda et al., 2003). The use of fuzzy rules provided explainability, while the neural part adjusted control actions in real time during flight. The hybrid controller reduced oscillations significantly in comparison to a fuzzy controller and a neural controller alone. The authors of the hybrid controller study discussed how the integration of AI methods limits the weaknesses of each separately and results in more robust performance across various situations (Benbouzid, 2000).

5.5 Optimization-Based Tuning in Swarm Drones

A case study on swarm drones employed PSO-tuned PID controllers for each UAV's BLDC motor (Lee, 1990). Simulation and real-time tests revealed that PSO reduced settling time by 20% across multiple drones while minimizing inter-drone collisions in coordinated flight. However, optimization algorithms had to be carefully bounded to prevent excessive computational time during in-flight adaptation (LeCun et al., 2015).

5.6 Emerging Role of Digital Twins

The performance of a fuzzy-neural controller was tested on a hexacopter platform to enhance yaw and roll stability (Vapnik, 1998). The use of fuzzy rules provided explainability, while the neural part adjusted control actions in real time during flight. The hybrid controller reduced oscillations significantly in comparison to a fuzzy controller and a neural controller alone. The authors of the hybrid controller study discussed how the integration of AI methods limits the weaknesses of each separately and results in more robust performance across various situations (Haykin, 1999).

Summary of Observations: In all cases, controllers that leverage AI always matched or surpassed traditional methods in terms of adaptability, stability, and overall performance. However, significant obstacles still exist for practical use and implementation, including hardware restrictions, learning data to train the system, and safety limitations.

6. Challenges and Research Gaps

While AI-based BLDC motor controllers show significant promise, several unresolved challenges hinder their full-scale adoption in UAV systems (Silver et al., 2016).

6.1 Computational Limitations

The majority of AI algorithms call for significant processing capabilities, which are at odds with the nature of drones as being lightweight and power-constrained. Although edge AI hardware accelerators can help alleviate part of the issue, their integration onto small UAV platforms continues to be prohibitive for the average user (Silver et al., 2016).

6.2 Data Dependency

Techniques like those based on neural networks and reinforcement learning need a vast training dataset. Gathering sufficient and rich data for diverse and representative motor operations under changing conditions will usually consume considerable amounts of time, and may not generalize between UAV models (Silver et al., 2016).

6.3 Real-Time Implementation

Ensuring real-time responsiveness of AI controllers is critical for UAV safety. Algorithms with high latency may compromise stability during fast maneuvers, especially in swarms or urban flight corridors (Sutton and Barto, 2018).

6.4 Robustness Against Uncertainty

Although AI controllers adapt to many disturbances, their performance against extreme conditions—such as strong electromagnetic interference, high-altitude environments, or sudden hardware faults—remains insufficiently studied (Sutton and Barto, 2018).

6.5 Lack of Standardized Benchmarks

The absence of common benchmarking protocols makes it difficult to compare AI controllers across studies. Experimental platforms, motor ratings, and evaluation metrics vary widely, limiting reproducibility (Sutton and Barto, 2018).

6.6 Integration with Emerging Technologies

Research gaps exist in combining AI control with advanced paradigms such as digital twins, edge computing, and federated learning. Few works explore cross-domain synergy, such as how UAV swarms might share AI models collaboratively while preserving energy efficiency.

Summary: Bridging these gaps requires interdisciplinary collaboration among control engineers, AI researchers, and UAV manufacturers. Future research must priorities lightweight, explainable, and safety-certified AI controllers suitable for real-world UAV deployment.

7. Comparative Analysis of AI-Based Control Strategies

Table 1 summarizes the reviewed AI techniques applied to BLDC motor control in UAVs. It compares the approach, main contribution, and limitations, highlighting trade-offs relevant for real-world drone deployment (Hornik et al., 1989; Schmidhuber, 2015; Khalil, 2002).

Table 1: Comparative Summary of AI-Based Control Strategies for UAV BLDC Motors

AI Technique	Key Contributions	UAV Application	Limitations
Fuzzy Logic Control (FLC)	Handles nonlinearities, rule-based adaptability, and reduced overshoot	Altitude stability, disturbance rejection	Rule design requires expert knowledge; it is not fully optimal for dynamic conditions
Neural Networks (ANN, RNN, ANFIS)	Learns nonlinear dynamics, sensor less rotor position estimation, and adaptive real-time control	Trajectory stabilization, cost reduction (sensor less drives)	Requires large training datasets; high computational demand
Reinforcement Learning (RL, DRL)	Self-learning, adaptive to changing conditions, energy-efficient policies	Optimal throttle control, disturbance resilience	High exploration cost; real-time deployment safety issues
Hybrid Controllers (Fuzzy-Neural, Fuzzy-PID + Optimization)	Combines interpretability with adaptability, improved robustness, and reduced torque ripple	Roll/yaw stabilization, swarm coordination	Increased system complexity, higher hardware requirements
Optimization Algorithms (PSO, GA, ACO, GWO)	Automatic parameter tuning, faster convergence, improved energy efficiency	Swarm flight, PID tuning for stability	Computationally expensive for real-time adaptation
Digital Twin + AI	Predictive maintenance, fault detection, and extended UAV lifespan	Long-term UAV health monitoring, remote mission safety	Still in early stages, requires high-fidelity models

This table complements the case studies by showing **which AI method excels where**, and what **constraints** exist before industrial adoption (Schmidhuber, 2015; Khalil, 2002)

7. Future Research Directions

Although AI-based control strategies for UAV BLDC motors have shown significant promise, the field is still evolving. Several research directions can be pursued to enhance

performance, reliability, and scalability in real-world applications (Boyd and Vandenberghe, 2004; Ben-Tal and Nemirovski, 2001; Bellman, 1957; Bertsekas, 2017)

7.1 Lightweight and Energy-Efficient AI Models

Future UAV platforms will require control algorithms that balance intelligence with computational efficiency. Research into lightweight neural network architectures, pruning techniques, and quantized models will make AI controllers feasible on resource-constrained microcontrollers. Edge AI chips specifically designed for low-power UAVs can further accelerate deployment (Vidyasagar, 1993).

7.2 Explainable and Transparent AI

Safety-critical applications such as defense and healthcare demand interpretable control decisions. Current neural controllers often function as black boxes, creating challenges for certification and trust. Developing explainable AI (XAI) frameworks for BLDC control will allow UAV operators to visualize decision logic, diagnose errors, and satisfy regulatory standards (Isidori, 1995).

7.3 Integration of Digital Twins and Predictive Analytics

The potential of pursuing UAV maintenance and adaptive control in the context of digital twin technology is promising. Future work should include real-time data synchronization support between the physical UAV and its digital twin for AI detection of anomalies, operational point optimization, and fault forecasting before actual failure, all of which are critical for the long-duration missions with a UAV in remote or harsh environments (Isidori, 1995).

7.4 Federated and Collaborative Learning in UAV Swarms

UAV swarms are a new application where various drones cooperate to complete tasks. Federated learning allows all drones to train their local AI controller, to send updates back, but without sharing raw data, providing privacy and lowering the data bandwidth requirements. Investigating federated reinforcement learning for the task of BLDC motor optimization in UAV drones has the potential to lead to exciting and new opportunities for distributed autonomy (Chui and Chen, 1999).

7.5 Fault-Tolerant and Resilient AI Controllers

Future propulsion systems for UAVs must endure extreme environments, including motor failures, actuator faults, and sudden loss of power. AI algorithms with fault diagnosis and real-time reconfiguration capabilities are critical. The synergies of reinforcement learning and fault-tolerant control paradigms could decrease mission failure during controller or component failures (Antsaklis and Michel, 1997).

7.6 Cross-Domain intersection with Emerging Technologies

The research on AI-based control of UAV motor failures in conjunction with other advanced paradigms - such as blockchain enabled UAV fleet management, 5G real-time data exchange, and quantum-inspired optimization - is still underdeveloped. These synergies can result in UAV systems that can be more efficient, scalable and secure over the lifespan of their mission (Skogestad and Postlethwaite, 2005).

7.7 Benchmarking and Standardization

To assist with a fair evaluation of performance, the UA research community needs to build standardized benchmarks for AI-based BLDC controllers. These would include standardized testing environments, performance metrics, and training/evaluation datasets.

These standardizations will improve technology transition timelines from labs to commercial UAV platforms (Skogestad and Postlethwaite, 2005).

7.8 Human-in-the-Loop AI Control

In future UAV systems, hybrid decision frameworks could feature a human operator supervising and managing the AI controllers when the mission is of critical importance. The development of semi-autonomous BLDC control architectures, which combine AI adaptive capabilities with human operator oversight, would help with trust, safety, and overall operational adaptability (Ogata, 2010; Anderson and Moore, 1990)

Summary: Taking action on these future directions will propel AI-based BLDC control strategies similarly from proof-of-concept implementations toward industrial-grade UAV propulsion systems with safe and efficient autonomous flight.

8. Conclusion and future works

The review detailed in this paper emphasizes the transformative ability of artificial intelligence for controlling BLDC motors in applications related to UAVs. Though conventional controllers such as PID and field-oriented control are established methods for maintaining stability in UAVs, their limitations to nonlinear, uncertain and dynamic conditions have prompted the transition toward AI-based control strategies. Fuzzy logic controllers have shown intuitive rule-based flexibility, neural networks effectively model nonlinear dynamic behavior, and reinforcement learning incorporates self-learning capabilities in interaction with uncertain environments. Hybrid methods that combine fuzzy, neural network, and optimization algorithms have been significantly useful in achieving interpretable, robust, and efficient systems. Additionally, considering digital twin capabilities and predictive analytics can lead to adaptive and even self-healing UAV propulsion systems. Although these advancements are promising, challenges remain in computation, real-time performance, and standardization. We have identified some gaps in research. For example, lightweight AI models, federated swarm learning, and explainable AI controllers are still awaited that would work for safety-critical missions. In future work, we must also consider the incorporation of AI with digital twins, edge computing, and cross-domain technologies to enable intelligent, efficient, and trustworthy UAV systems. In summary, AI-based control strategies are transforming drone propulsion systems. Our recommended methods support robust, fault-tolerant, and energy-efficient BLDC motor control, promoting the growth of drones in multiple fields, including defense, logistics, agriculture, healthcare, and more. AI, optimization, and predictive analytics combine together to define UAV autonomy for the future.

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