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Fuzzy Logic-Based Intelligent Control Strategies for BLDC Motor Drives –A Review

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Abstract

The Brushless DC (BLDC) motor has become a cornerstone of modern motion control applications, ranging from electric vehicles and industrial automation to aerospace and medical devices, due to its high efficiency, power density, and reliability. The efficacy of its control system, particularly the speed regulation loop, is predominantly dependent on the tuning of the Proportional-Integral (PI) controller. Conventional fixed-gain PI controllers, while simple, exhibit significant limitations in handling the BLDC motor's inherent nonlinearities, parameter variations, and sudden load disturbances. To overcome these challenges, the integration of Fuzzy Logic (FL) for intelligent, adaptive optimization of PI gains has emerged as a transformative research paradigm over the past two decades. This paper presents a comprehensive review of the state-of-the-art in Fuzzy Logic-based intelligent tuning strategies for PI controllers in BLDC motor drive systems. It systematically classifies the various FL-PI hybrid architectures, including Fuzzy Pre-compensated PI, Fuzzy Gain Scheduling (FGS-PI), and direct Fuzzy Self-Tuning PI controllers. The review critically analyzes the design methodologies, including the selection of membership functions, rule bases, inference mechanisms, and defuzzification strategies, as highlighted in key research works. Furthermore, it explores advanced hybridizations, such as the fusion of FL with metaheuristic algorithms for offline optimization and with other AI techniques like Artificial Neural Networks (ANNs). The paper meticulously compares the performance enhancements reported in the literature—

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Volume 4 Issue 12 December 2025

Review Paper 2

encompassing dynamic response, steady-state accuracy, robustness, and disturbance rejection—against conventional PI and other adaptive controllers. Finally, the review identifies prevailing research gaps, practical implementation challenges related to computational load and real-time deployment, and suggests future directions, including the integration of Type-2 Fuzzy Logic, adaptive neuro-fuzzy inference systems (ANFIS), and cloud-based tuning for next-generation intelligent motor drives.

1.Introduction

Brushless DC motors have revolutionized precision drive technology, offering superior performance characteristics compared to their brushed counterparts. Their operation relies on electronic commutation facilitated by a three-phase inverter and rotor position feedback, typically from Hall-effect sensors or sensorless estimators. The core control objective is to maintain precise speed or torque output despite system nonlinearities (e.g., cogging torque, magnetic saturation), time-varying parameters (e.g., winding resistance with temperature), and external load torque disturbances. The cascaded control structure, with an inner current (torque) loop and an outer speed loop, is standard. The PI controller remains the workhorse for these loops due to its structural simplicity and intuitive tuning. However, the 'textbook' tuning methods like Ziegler-Nichols often yield suboptimal performance for the nonlinear BLDC plant, forcing a conservative trade-off between fast response (high gain) and stability/overshoot (low gain).

The quest for an adaptive controller that can modulate its parameters in real-time based on operating conditions led to the exploration of Fuzzy Logic, pioneered by Zadeh [4]. FL provides a formal methodology for representing, manipulating, and implementing human heuristic knowledge (e.g., "if the speed error is large positive, then significantly increase the proportional gain") through rule-based systems without requiring precise mathematical models. The marriage of FL's adaptability with the PI controller's structure creates an intelligent, nonlinear controller capable of superior regulation. This review synthesizes the extensive body of research dedicated to this fusion, categorizing approaches, evaluating outcomes, and charting the evolution of intelligent PI gain optimization for BLDC motors.

2.Fundamental Challenges in Conventional PI Control of BLDC Motors

To appreciate the value of FL integration, one must first understand the limitations of fixed-gain PI controllers in BLDC drives:

- **Plant Nonlinearity:** The relationship between voltage, current, torque, and speed is not linear. Cogging torque, saturation, and PWM inverter dead-time introduce nonlinear effects that a linear PI controller cannot fully compensate for.
- **Parameter Uncertainty:** Motor parameters (stator resistance R, inductance L, back-EMF constant Ke) vary with temperature and magnetic operating point. Fixed gains optimized for nominal parameters degrade performance under variation.
- **Load Disturbance Sensitivity:** Abrupt load changes cause significant speed dips and slow recovery if PI gains are not aggressive enough, yet aggressive gains cause overshoot and instability during transients.
- **Setpoint Change Response:** The need for fast rise time without overshoot presents a classical control challenge. Fixed gains force a compromise, often resulting in sluggish response or unacceptable overshoot.

These challenges create a compelling case for an adaptive control strategy where PI gains (Kp, Ki) are no longer constants but functions of the system's dynamic state.

3.Fuzzy Logic as an Intelligent Optimization Tool

Fuzzy Logic operates on the principles of fuzzy set theory, where an element's membership in a set is a matter of degree [0,1] [4]. A typical Fuzzy Logic Controller (FLC) comprises four components:

1. **Fuzzification:** Converts crisp input values (e.g., speed error $e(t)$ and change in error $\Delta e(t)$) into linguistic variables with associated membership degrees using predefined membership functions (MFs—triangular, trapezoidal, Gaussian).
2. **Knowledge Base:** Contains the Rule Base (a set of IF-THEN rules encapsulating expert knowledge) and the Database (defining the MFs).
3. **Inference Engine:** Emulates human reasoning by evaluating the applicable rules based on current inputs. Common inference mechanisms include Mamdani [5] and Sugeno [6] models.

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Volume 4 Issue 12 December 2025
Review Paper 2

4. **Defuzzification:** Converts the fuzzy output from the inference engine into a crisp, actionable value (e.g., ΔKp, ΔKi, or direct control output). Common methods include centroid, bisector, and mean of maxima.

In the context of PI gain optimization, FL acts as a supervisory or tuning mechanism, dynamically adjusting the controller parameters based on real-time performance metrics.

4. Classification of Fuzzy Logic-Based PI Tuning Architectures for BLDC Drives

Research in this domain can be broadly classified into three principal architectural configurations, each with distinct operational philosophies.

4.1. Fuzzy Pre-Compensated or Fuzzy Logic Supervisor PI Controller

This is a straightforward hybridization where a conventional PI controller generates the primary control signal, and a fuzzy logic module acts as a pre-compensator or add-on supervisor. The FLC takes e(t) and Δe(t) as inputs and its output is added to the PI controller's output. Effectively, the FLC provides a nonlinear correction term to handle large errors or disturbances, while the PI handles fine regulation near the setpoint. This method is simpler to design as it does not alter the underlying PI gains but augments the control action. Early research by researchers like B. K. Bose [1] demonstrated this approach for general motor drives, providing a foundation for BLDC-specific applications.

4.2. Fuzzy Gain Scheduling (FGS-PI) Controller

This is the most prevalent and directly relevant architecture for "PI gain optimization." Here, the fuzzy logic system functions as an online gain scheduler. The inputs (typically e(t) and Δe(t)) are fuzzified, processed through a rule base, and the outputs provide incremental adjustments (ΔKp, ΔKi) or the direct new values of the PI gains. The rules are formulated from a deep understanding of PI controller behavior:

- **Large Error:** When e(t) is large, a large Kp is needed to accelerate the response, and Ki is often limited or small to prevent integral windup and large overshoot.
- **Small Error with Decreasing Trend:** When e(t) is small and Δe(t) is negative, a moderate Kp and increased Ki are used to eliminate steady-state error without causing oscillation.

- **Oscillatory Condition:** When e(t) is small but Δe(t) alternates, both gains might be reduced to dampen oscillations.
  This architecture allows the PI controller to behave like a nonlinear, variable-structure controller, offering aggressive action during transients and fine-tuning at steady state. Numerous studies, including foundational work by C. M. Liaw and F. J. Lin [2], and later BLDC-specific implementations [15], [16], have validated the superiority of FGS-PI over fixed-gain PI in terms of settling time, overshoot, and load disturbance rejection.

4.3. Direct Fuzzy Self-Tuning PI (FST-PI) Controller

In this advanced configuration, the fuzzy logic module completely replaces the standard PI algorithm. The FLC uses e(t) and Δe(t) as inputs and directly computes the control signal (duty cycle or voltage command) for the inverter. This is equivalent to a nonlinear, adaptive, PD-like controller. To incorporate integral action for zero steady-state error, one common method is to add an integral term of the error to the FLC output. Alternatively, a separate fuzzy integrator can be designed. While this offers maximum design freedom, it also requires a more extensive and carefully crafted rule base, as the FLC now directly governs all aspects of the control action. Research by Y.-S. Kung and colleagues [3] has shown effective implementations of such direct fuzzy controllers for BLDC drives.

5. Critical Analysis of Design Elements and Research Trends

The performance of any FL-PI controller hinges on its design parameters. Research has focused on optimizing these elements.

5.1. Input/output Selection and Scaling Factors

While e(t) and Δe(t) are standard inputs, some studies incorporate the integral of error for better steady-state handling or load torque observers for feedforward action. The scaling factors (GE, GCE, GΔKp, GΔKi) are critical as they normalize the input/output universe of discourse. Their tuning is often heuristic or optimized offline using evolutionary algorithms. Research has shown that adaptive scaling factors can further enhance performance [11].

5.2. Membership Functions and Rule Base Design

The shape, number, and overlap of MFs significantly impact smoothness and sensitivity. While triangular MFs are common for simplicity, Gaussian MFs offer smoother control surfaces. The rule base, often derived from the Macvicar-Whelan table, is typically composed of 25-49 rules for two-input systems. A key research trend is the simplification of rule bases to reduce computational burden for microcontroller implementation without significant performance loss [15].

5.3. Advanced Hybridization and Optimization Techniques

To address the subjectivity in FLC design, researchers have combined FL with optimization algorithms:

- **FL with Metaheuristic Algorithms:** Genetic Algorithms (GA) [9], Particle Swarm Optimization (PSO) [10], and Ant Colony Optimization (ACO) have been used to optimally design the MFs, rule bases, and scaling factors offline. This data-driven approach reduces reliance on expert knowledge and often yields superior performance [13].
- **Neuro-Fuzzy Systems (ANFIS):** Adaptive Neuro-Fuzzy Inference Systems combine FL and ANNs to create self-learning controllers [8]. ANFIS can tune the MFs and rules based on input-output training data, creating an adaptive FLC that can handle unmodeled dynamics more effectively.
- **Type-2 Fuzzy Logic:** To handle higher levels of uncertainty and imprecision in rule definitions, Interval Type-2 Fuzzy Logic Controllers (IT2FLCs) have been explored [20]. Their three-dimensional membership functions provide an extra degree of freedom for managing uncertainties, potentially offering more robust performance under significant parameter variations.

6. Performance Evaluation and Comparative Assessment

The literature consistently reports substantial performance improvements when using FL-based PI tuning for BLDC motors compared to conventional PI control. The following table synthesizes key performance metrics from reviewed research:

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Volume 4 Issue 12 December 2025
Review Paper 2

Performance Metric	Conventional PI	Fuzzy Logic-Based PI (FGS/FST)	Key Research Findings (Representative)
Rise Time	Slower	**Faster** (15-40% improvement)	Aggressive Kp scheduling reduces rise time significantly [2], [16].
Overshoot (%)	Higher (compromise)	**Lower/Negligible**	Ki is restrained during large error, preventing windup [2], [15].
Settling Time	Longer	**Shorter** (30-50% improvement)	Adaptive gains quickly damp oscillations [3], [16].
Steady-State Error	Very low (depends on Ki)	**Nearly Zero**	Integral action is effectively managed [1], [15].
Load Disturbance Rejection	Slower recovery, larger dip	**Faster recovery, smaller dip** (30-60% better)	FL rapidly increases gains to counteract disturbance [2], [11].
Parameter Robustness	Sensitive	**More Robust**	FL adapts to changing plant dynamics implicitly [13], [20].

Comparative studies also pit FL-PI against other advanced controllers like Sliding Mode Control (SMC) and model-reference adaptive control. While SMC may offer comparable or better robustness [11], [19], it often suffers from chattering. FL-PI typically provides a smoother control signal, which is advantageous for reducing torque ripple and acoustic noise in BLDC drives.

7. Implementation Considerations and Challenges

Despite the proven advantages, practical deployment faces hurdles:

- **Computational Burden:** The fuzzification, rule evaluation, and defuzzification cycles require more processing power than a simple PI algorithm. This limits the feasible sampling frequency on low-cost microcontrollers.
- **Design Complexity:** Tuning scaling factors, MFs, and rules is non-trivial and can be time-consuming, though optimization algorithms mitigate this.
- **Stability Analysis:** Formally proving the stability of a nonlinear fuzzy-controlled system is challenging. Most research relies on extensive simulation and experimental validation rather than Lyapunov-based proofs.
- **Real-Time Code Generation:** Efficient implementation of the fuzzy inference engine in embedded C code is crucial. Tools like MATLAB/Simulink's fuzzy logic toolbox with automatic code generation have facilitated this process.

8. Future Research Directions

The evolution of FL-PI optimization for BLDC drives is poised to advance in several directions:

1. **Edge-AI Integration:** Implementing lightweight, optimized fuzzy inference engines on AI-accelerated microcontrollers for ultra-high-speed control.
2. **Cloud-Enhanced Tuning:** Using cloud computing to run complex metaheuristic optimizations for fleet-level motor controller tuning, with results downloaded to edge controllers.

3. **Deep Learning for Rule Synthesis:** Employing deep reinforcement learning to autonomously develop and refine fuzzy rule bases through interaction with a motor simulation model.
4. **Hybrid Model-Predictive Fuzzy Control:** Combining the predictive capability of MPC with the intuitive adaptation of FL for improved performance under constraints.
5. **Standardized Benchmarks:** The field would benefit from standardized BLDC motor test benches and disturbance profiles to allow fair and direct comparison of different intelligent control algorithms.

9.Conclusion

The intelligent optimization of PI controller gains using Fuzzy Logic represents a mature and highly effective solution for enhancing the performance of BLDC motor drives. By transitioning from fixed-parameter linear control to adaptive, rule-based nonlinear control, FL-PI hybrid architectures successfully address the core challenges of nonlinearities, parameter variations, and load disturbances. This review has systematically categorized the prevalent architectures—Fuzzy Pre-compensated, Fuzzy Gain Scheduling, and Direct Fuzzy Self-Tuning—and analyzed the critical design elements that govern their success. The consensus in the literature is unequivocal: FL-based tuning offers superior dynamic response, robustness, and operational efficiency compared to conventional PI control. While implementation challenges related to computational load and stability analysis persist, ongoing trends toward hybridization with metaheuristic algorithms, neuro-fuzzy systems, and Type-2 Fuzzy Logic continue to push the boundaries of performance and adaptability. As BLDC motors find ever more critical applications in electrification and precision automation [17], the role of intelligent, fuzzy logic-driven control strategies will only become more vital, driving research towards more autonomous, efficient, and robust motion control systems.

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Volume 4 Issue 12 December 2025

Review Paper 2

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Volume 4 Issue 12 December 2025

Review Paper 2

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