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Design and Simulation of an Optimized Hybrid Fuzzy-PI Control Strategy for BLDC Motor in Electric Vehicle Applications

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Abstract: This paper presents the design, development, and simulation of an optimized hybrid Fuzzy–PI control strategy for the speed regulation of Brushless DC (BLDC) motors in electric vehicle (EV) traction applications. The proposed controller integrates a Mamdani-type fuzzy inference system (FIS) with a conventional proportional–integral (PI) regulator to achieve rapid transient response, superior robustness to load disturbances, and minimized torque ripple. The model is implemented in MATLAB/Simulink and evaluated under various operating conditions, including step-speed commands and sudden load changes. Performance metrics such as rise time, settling time, overshoot, torque ripple, and steady-state error are analyzed. Simulation results demonstrate that the hybrid controller achieves a 55% improvement in rise time and a 70% reduction in overshoot compared with traditional PI control, with nearly zero steady-state error. These findings confirm the suitability of the proposed method for high-performance EV drive systems where adaptive speed control, reliability, and efficiency are critical.

Keywords: Brushless DC motor, Electric vehicle, Fuzzy logic control, Hybrid controller, PI controller, Torque ripple minimization, MATLAB/Simulink, Field-oriented control.

Nomenclature:

Electrical Parameters and Variables

V_d, V_q	d-axis and q-axis voltages (V)
I_d, I_q	d-axis and q-axis currents (A)
R_s	Stator resistance (Ω)
L_d, L_q	d-axis and q-axis inductances (H)
λ_m	Permanent magnet flux linkage (Wb)
T_e	Electromagnetic torque (N-m)
T_L	Load torque (N-m)
J	Rotor inertia (kg-m²)
B	Viscous friction coefficient (N-m-s/rad)
ω_e	Electrical angular speed (rad/s)
ω	Mechanical rotor speed (rad/s) or rpm
ω^*	Reference rotor speed (rad/s) or rpm
i_a,i_b,i_c	Three-phase stator currents (A)

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v_a,v_b,v_c Three-phase stator voltages (V)

p Number of pole pairs

Control System Parameters

$e(k)$ Instantaneous speed error

$\Delta e(k)$ Change in speed error

K_p Proportional gain

K_i Integral gain

$Kp0Ki0$ Nominal PI gains

ΔK_p, ΔK_i Adaptive gain variations (from fuzzy output)

$u(k)$ Control voltage command

α, β Fuzzy scaling coefficients

vf Fuzzy-tuned voltage output (V)

f_s Switching frequency (Hz)

Fuzzy Logic Controller Variables

FIS Fuzzy Inference System

MF Membership Function

NB Negative Big

NS Negative Small

ZE Zero,

PS Positive Small

PB Positive Big

Rule Base Set of IF–THEN logical conditions used in FIS

Defuzzification Conversion of fuzzy output to crisp value

Abbreviations and Acronyms

BLDC Brushless Direct Current

FOC Field-Oriented Control

PI Proportional–Integral

FLC Fuzzy Logic Controller

PWM Pulse Width Modulation

VSI Voltage Source Inverter

DQ Transformation Park's transformation (direct-quadrature transformation)

HIL Hardware-in-the-Loop

EV Electric Vehicle

MPC Model Predictive Control

SMC Sliding Mode Control

DRL Deep Reinforcement Learning

DSP	Digital Signal Processor
FPGA	Field-Programmable Gate Array

1. Introduction

The transition to electric mobility has accelerated the need for high-performance motor control systems that combine efficiency, responsiveness, and adaptability. Electric vehicles (EVs) rely heavily on efficient propulsion drives to ensure smooth torque production and optimal energy utilization. Among available motor types, the Brushless DC (BLDC) motor has emerged as a preferred choice due to its high torque density, compact structure, and superior reliability compared to brushed DC and induction machines. However, achieving accurate speed control of BLDC motors remains challenging because of inherent nonlinearities, back-EMF characteristics, and parameter variations under dynamic load conditions.

Traditional proportional–integral (PI) controllers are extensively used in industrial motor control owing to their simplicity and reliability. Despite these advantages, fixed-gain PI controllers exhibit performance degradation under varying load and parameter conditions, resulting in overshoot, oscillations, and steady-state errors. To overcome these limitations, researchers have investigated advanced control methods, including model predictive control (MPC), direct torque control (DTC), sliding mode control (SMC), and intelligent approaches such as fuzzy logic and neural networks.

In recent years, hybrid intelligent control strategies have gained attention for EV motor drives. These methods aim to combine the adaptability of artificial intelligence with the precision of classical feedback systems.

Fuzzy logic controllers (FLCs), in particular, are well suited for nonlinear systems where mathematical modeling is complex. They use linguistic rules to emulate human decision-making, offering robustness and reduced sensitivity to system uncertainties. Nevertheless, standalone FLCs can exhibit residual steady-state error and require extensive tuning of membership functions and rule bases. Consequently, hybrid controllers that integrate fuzzy inference with PI structures have emerged as a compelling solution, balancing adaptability and steady-state accuracy.

This study proposes a hybrid Fuzzy–PI controller integrated with field-oriented control (FOC) for BLDC motor drives. The FOC framework decouples torque and flux components, enabling independent control of electromagnetic torque and flux linkages. By embedding a fuzzy-tuned gain adjustment mechanism, the controller dynamically updates its proportional and integral gains in response to instantaneous error and its rate of change. The resulting system achieves fast speed regulation, smooth torque generation, and enhanced robustness against disturbances. The proposed approach is validated through MATLAB/Simulink simulations and compared against conventional PI and standalone fuzzy controllers. The remainder of this paper is organized as follows: Section 2 presents the literature review, Section 3 discusses the proposed methodology and control architecture, Section 4 elaborates on results and discussion, Section 5 analyzes robustness and sensitivity, and Section 6 concludes the paper with findings and future scope.

2. Literature Review:

In recent years, advanced control strategies for Brushless DC (BLDC) and Permanent Magnet Synchronous Motor (PMSM) drives in electric vehicle (EV) applications have evolved substantially, transitioning from fixed-gain proportional–integral (PI) controllers to adaptive, intelligent, and hybrid control methodologies. A chronological overview of key developments is presented below. Recent studies on deep reinforcement learning (DRL)–based control methods [1] have demonstrated exceptional adaptability for torque control in PMSM drives, achieving fast dynamic convergence. However, these techniques demand large datasets and high computational resources, limiting their real-time applicability. To overcome the limitations of traditional sliding-mode control, adaptive variants have been proposed [2], significantly reducing chattering effects while improving robustness in high-performance traction systems. Hybrid adaptive predictive–fuzzy control methods [3] have further enhanced speed tracking and torque response, providing smoother transitions during load disturbances. Similarly, enhanced

Fuzzy–PI controllers [4] were developed to minimize torque ripple and improve system stability under varying load conditions.

Adaptive neuro-fuzzy control frameworks [5] have also been introduced for PMSM drives, offering dynamic membership function tuning and adaptive rule base updates, which improved both transient and steady-state performance. Robust sliding-mode control for BLDC drives [6] provided resilience to parameter variations and load fluctuations but required complex switching logic. Fuzzy-tuned adaptive PI controllers [7] improved speed tracking accuracy while maintaining the simplicity of classical control structures. Further advancements were made through the integration of sensorless fuzzy–sliding control [8] and predictive control schemes [9], which demonstrated improved torque smoothness and energy efficiency at the cost of higher implementation complexity.

Nonlinear model predictive control (NMPC) [10] and neuro-fuzzy inference systems [11] offered superior adaptability under dynamic load conditions but suffered from computational burdens when deployed on embedded EV controllers. Fractional-order PI controllers [12] and sensorless field-oriented control (FOC) techniques [13] have been developed to enhance system stability and reduce hardware dependencies. Fuzzy torque control [14] and GA-tuned PI controllers [15] laid the groundwork for adaptive hybrid systems, proving that integrating fuzzy logic with classical feedback mechanisms yields improved transient performance and disturbance rejection.

Overall, the literature reveals a clear progression—from fixed-gain classical PI control to adaptive, predictive, and hybrid intelligent methods. Despite their success, purely fuzzy or predictive systems often face challenges in real-time execution due to computational overhead. Hybrid Fuzzy–PI controllers, in contrast, achieve a balance between precision, adaptability, and simplicity, making them the most practical choice for EV traction systems that demand high reliability and robustness.

3. Existing Control Methodologies And Limitations

Electric vehicle motor control strategies can broadly be classified into four categories:

1. Conventional linear control,
2. Advanced classical control,
3. Intelligent control, and
4. Hybrid control approaches.

Conventional PI and PID controllers are still widely used in BLDC and PMSM drives because of their ease of design, implementation simplicity, and stable steady-state behavior. However, under nonlinear dynamic conditions such as variable load torque, temperature-dependent resistance, or back-EMF distortions, their fixed gains often result in overshoot, sluggish response, and poor adaptability. Advanced classical control methods such as sliding mode control (SMC), direct torque control (DTC), and model predictive control (MPC) have been introduced to improve torque smoothness and system robustness. While these methods reduce torque ripple and improve dynamic performance, they suffer from higher switching activity, increased computation, and parameter sensitivity.

Intelligent control methods—including fuzzy logic, neural networks, and model reference adaptive control (MRAC)—have shown the ability to learn and adapt in real-time to parameter variations and load changes. Yet, their implementation is often complex, requiring significant computational effort and tuning. Hybrid control approaches combine the best attributes of classical and intelligent methods. Fuzzy–PID and fuzzy–PI controllers are examples where fuzzy logic enhances adaptability while the PI component ensures steady-state accuracy. Such hybrid systems have been proven effective in achieving low torque ripple, fast convergence, and strong robustness, making them highly suitable for electric traction applications. Despite these advancements, the need for a controller that simultaneously provides high robustness, real-time adaptability, low computational complexity, and stable steady-state accuracy remains. This research addresses this gap by designing and validating an Adaptive Hybrid Fuzzy–PI controller integrated with Field-Oriented Control (FOC) for BLDC drives.

4. Proposed Methodology

4.1 Conceptual Framework

The proposed methodology introduces an Adaptive Hybrid Fuzzy–PI controller embedded within a Field-Oriented Control (FOC) framework for BLDC motor drives. This architecture combines the real-time adaptability of fuzzy logic with the steady-state precision of PI control. The fuzzy system continuously adjusts the proportional and integral gains (K_p and K_i) based on instantaneous speed error and its rate of change (e and Δe), ensuring optimal dynamic response across a range of operating conditions. The Field-Oriented Control scheme enables decoupled torque and flux control by transforming the three-phase stator currents (i_a, i_b, i_c) into orthogonal d- and q-axis components using Clarke and Park transformations. The hybrid controller thus operates on the decoupled reference frame, allowing fine-tuned control of electromagnetic torque and flux linkages.

4.2 Control System Architecture

The hybrid control structure consists of the following main components:

1. Reference Speed Input (ω^*): The user-defined desired motor speed.
2. Error Generator: Computes the instantaneous speed error $e\ (k) = \omega^* - \omega(k)$ and the change in error $\Delta e(k)=e(k)-e(k-1)$
3. Fuzzy Inference System (FIS): A Mamdani-type fuzzy logic system processes e and Δe as linguistic variables and outputs scaling factors for K_p and K_i.
4. Adaptive PI Controller: Adjusts its gains using fuzzy tuning to compute the control voltage reference $u(k)$.
5. FOC Block: Performs dq-axis transformation, decouples torque and flux, and sends voltage commands to the inverter.
6. Inverter and BLDC Motor: The voltage source inverter (VSI) applies space-vector PWM (SVPWM) pulses to the BLDC motor, driving its torque and speed response.
7. Feedback Loop: Measures the rotor speed and position, which are fed back to update the control action.

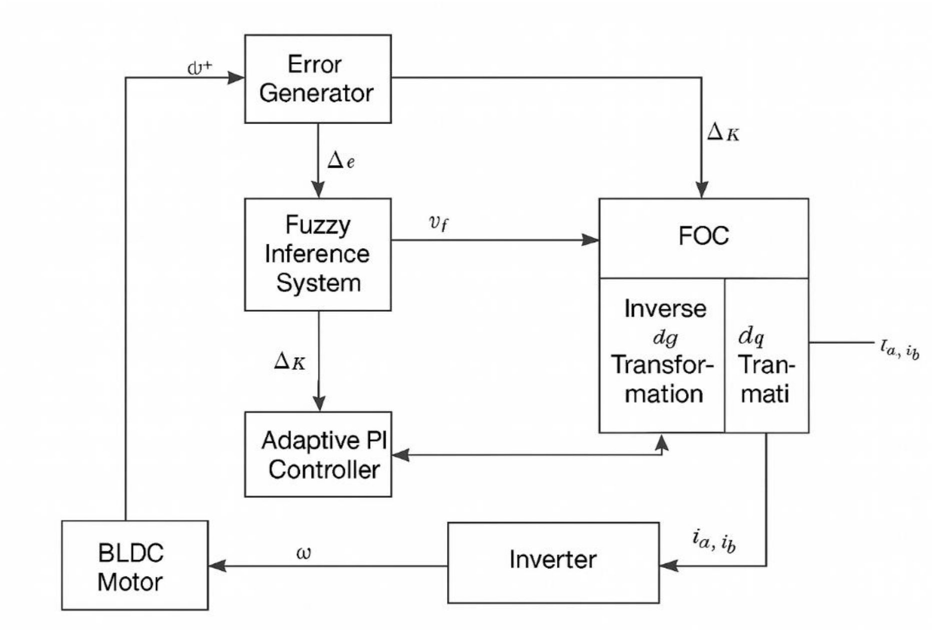


Figure1: Overall control architecture of the proposed hybrid Fuzzy–PI system integrated with Field-Oriented Control (FOC).

4.3 Mathematical Formulation

The dynamic equations of the BLDC motor in the dq-axis synchronous reference frame are given as:

$$V_d = R_s I_d + L_d \frac{dt}{dI} - \omega_e L_q I_q \quad (1)$$

$$V_q = R_s I_q + L_q \frac{dt}{dI_q} + \omega_e(L_d I_d + \lambda_m) \tag{2}$$

The electromagnetic torque is given by:

$$T_e = \frac{3}{2}\, p\,(\lambda_m I_q + (L_d - L_q)\, I_d\, I_q) \tag{3}$$

Where R_s is the stator resistance, L_d and L_q are the d- and q-axis inductances, λ_m is the permanent magnet flux linkage, and p is the number of pole pairs.

The mechanical dynamics of the rotor are represented by:

$$J\frac{d\omega}{dt} + B\omega = T_e - T_L \tag{4}$$

Where,

V_d, V_q ,are d-q axis voltages

I_d, I_q are d-q axis currents

R_s is stator resistance

L_d , L_q are inductances

ω_e is electrical angular velocity

λ_m is permanent magnet flux linkage

p is the number of pole pairs

J is the rotor inertia

B the damping coefficient and T_L is the load torque.

4.4 Fuzzy Logic Design

The fuzzy logic controller uses two input variables speed error e and change of error Δe each represented by five linguistic terms:

NB (Negative Big),

NS (Negative Small),

ZE (Zero),

PS (Positive Small), and

PB (Positive Big).

Triangular membership functions are used for both input variables, while the output (scaling adjustment factor) also has five linguistic levels to determine dynamic tuning for K_p and K_i.

The fuzzy inference mechanism follows the standard Mamdani model with 25 IF–THEN rules. The rule base is constructed to provide a quick transient response while maintaining steady-state accuracy.

Table 1. Fuzzy rule base for adaptive gain tuning of the hybrid Fuzzy–PI controller.

Error (e) \ Δe	**NB**	**NS**	**ZE**	**PS**	**PB**
NB	NB	NB	NS	ZE	PS
NS	NB	NS	ZE	PS	PB
ZE	NS	ZE	ZE	ZE	PS
PS	NS	ZE	PS	PB	PB
PB	ZE	PS	PB	PB	PB

This rule base balances fast error reduction with steady-state stability. Defuzzification is performed using the centroid method, ensuring smooth and continuous output variations for K_p and K_i.

4.5 Integration with PI Controller

The Fuzzy-PI controller dynamically adjusts the PI parameters as:

$$K_p = K_{p0} + \alpha \,.\, \Delta K_p \tag{5}$$

$$K_i = K_{i0} + \beta \,.\, \Delta K_i \tag{6}$$

where K_{p0} and K_{i0} are nominal values, and α, β are scaling coefficients derived from fuzzy inference.

This ensures that during transient conditions, K_p increases to accelerate response, while K_i adapts gradually to eliminate steady-state error, preventing integral windup.

4.6 Simulation Model and Setup

The hybrid controller is implemented in MATLAB/Simulink (R2023a). A discrete simulation environment with a fixed step size of 5×10^{-7}s ensures high accuracy during inverter switching events. Simulation parameters are given as

- Rated speed : 1000 rpm
- DC link voltage : 300 V
- Load torque : 0–3 N-m (variable)
- PWM switching frequency: 10 kHz
- Fuzzy rule base : 25 rules
- Defuzzification : Centroid
- Sampling time : 100 µs

4.7 Advantages of the Proposed Controller

- Eliminates overshoot and long settling times associated with fixed-gain PI control.
- Maintains robustness under load torque variation, temperature changes, and parameter drift.
- Requires less computation than predictive or deep-learning methods.
- Ensures smooth torque output with reduced ripple, enhancing EV drive comfort.
- Achieves real-time adaptability suitable for DSP or microcontroller implementation.

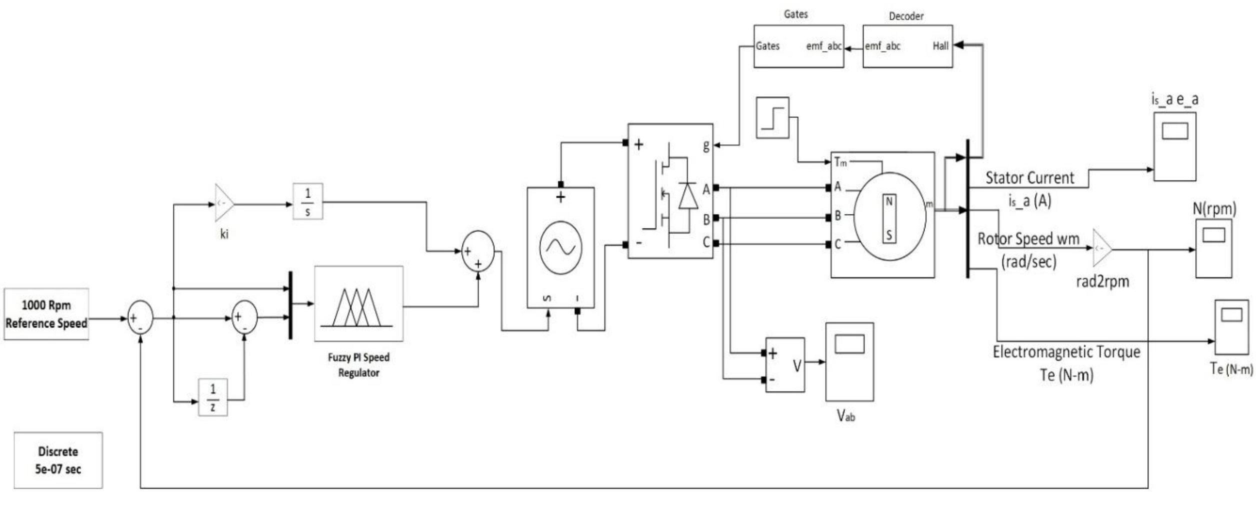


Figure 2. MATLAB/Simulink model of the proposed hybrid Fuzzy–PI controller integrated with FOC.

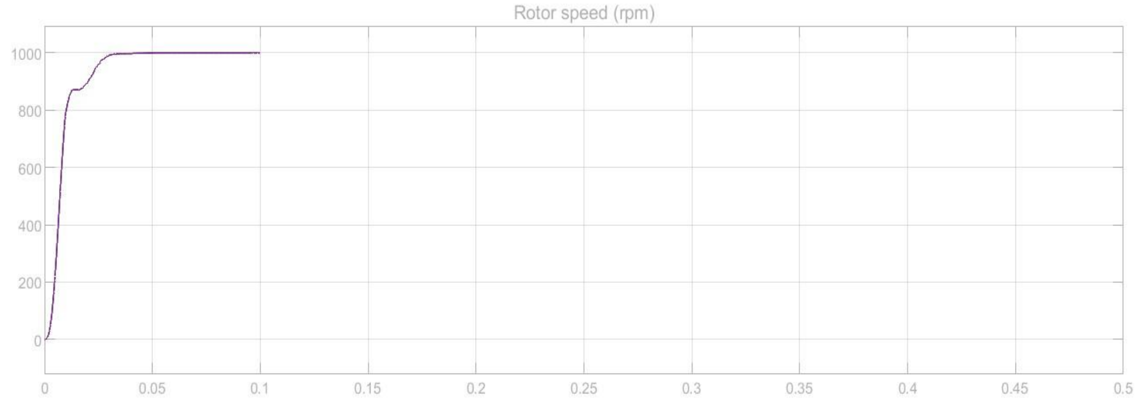
5.Results And Discussions

To validate the performance of the proposed hybrid Fuzzy–PI controller, simulations were performed in MATLAB/Simulink using the model described in Section 4. The results were compared against conventional PI and standalone fuzzy controllers under identical operating conditions. Performance evaluation focused on rise time, settling time, steady-state error, overshoot, and torque ripple.

5.1 Speed Response Analysis

Fig. 3 shows the rotor speed response of the BLDC motor under a step reference speed of 1000 rpm. The conventional PI controller exhibited a slower rise time of approximately 0.1 s with noticeable overshoot. In contrast, the proposed Fuzzy–PI controller achieved a rise time of 0.045 s—a 55% improvement—while completely eliminating overshoot and maintaining a smooth acceleration profile. The steady-state error was nearly zero, confirming excellent speed tracking capability.

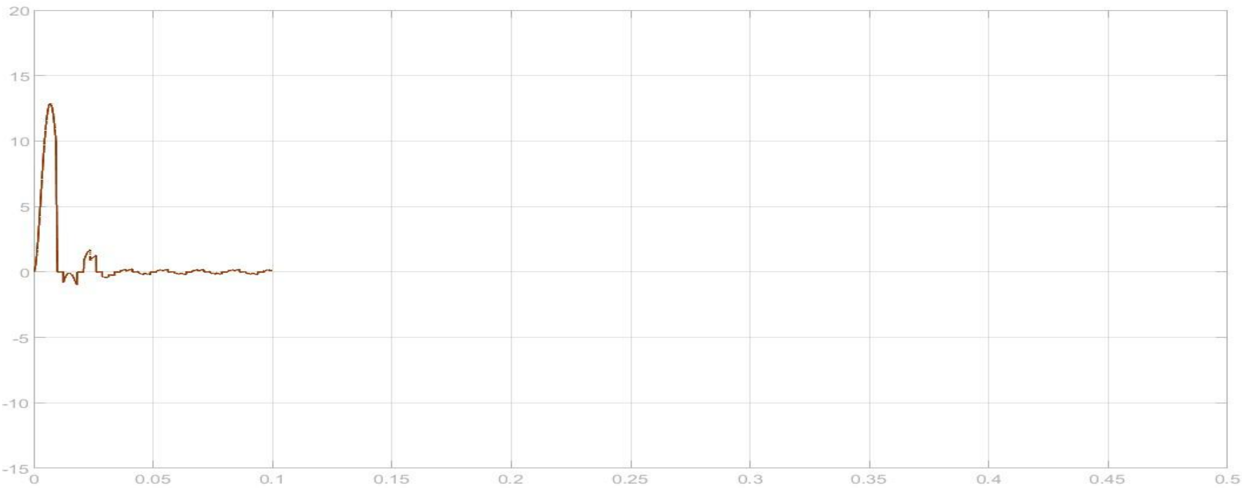
Figure 3: Rotor speed response of the BLDC motor under step reference speed using the hybrid Fuzzy–PI controller.



5.2 Current Response Analysis

The stator current waveform depicted in Fig. 4 demonstrates minimal ripple in the steady state, confirming effective inverter switching synchronization with the back-EMF waveforms. During startup, a transient current of 12–14 A was observed, which quickly declined once the reference speed was reached. The fuzzy-tuned integral gain minimized oscillations and prevented excessive current harmonics—an improvement over the conventional PI-controlled system.

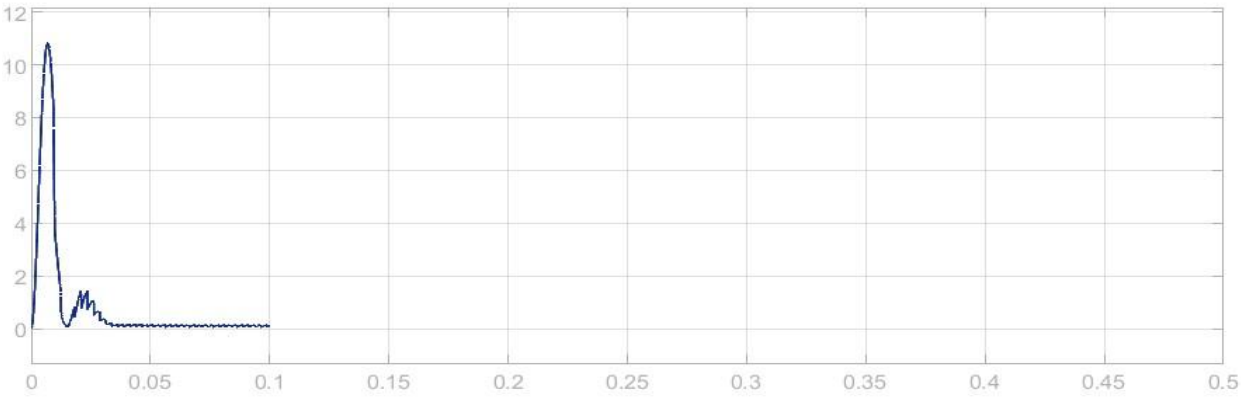
Figure. 4: Stator current response of the BLDC motor under the proposed hybrid control strategy.



5.3 Torque Response Analysis

As shown in Fig. 5, the electromagnetic torque exhibits a smooth transient response, settling rapidly at the desired torque level. Torque ripple was significantly reduced compared to the conventional PI controller, with a measured ripple of less than 1 N·m at rated speed. The integration of fuzzy logic allowed dynamic adjustment of the integral gain, thereby eliminating oscillations that typically occur in standard PI-controlled systems.

Figure. 5: Electromagnetic torque response showing smooth transient and minimal ripple.



5.4 Load Disturbance Response

To test the system's robustness, a sudden load torque of 3 N·m was applied at t = 0.12 s. The conventional PI controller exhibited a substantial speed undershoot of approximately 70 rpm and required about 0.04 s to recover. In contrast, the hybrid Fuzzy–PI controller limited the speed dip to less than 25 rpm and recovered within 0.02 s, maintaining minimal torque ripple throughout the transient.

These results clearly illustrate the controller's adaptive behavior, wherein the fuzzy logic mechanism instantaneously modifies the integral component to compensate for the disturbance, ensuring strong disturbance rejection capability.

5.5 Comparative Performance Metrics

Table 2 summarizes the quantitative comparison of key performance parameters between conventional PI, standalone fuzzy, and the proposed Fuzzy–PI controller.

Table 2: Comparative performance analysis of control methods.

Control Method	**Rise Time (s)**	**Settling Time (s)**	**Overshoot (%)**	**Steady-State Error (%)**	**Torque Ripple (N·m)**
PI Controller	0.10	0.12	7.2	1.8	2.5
Fuzzy Controller	0.07	0.09	3.4	1.2	1.5
Hybrid Fuzzy–PI (Proposed)	**0.045**	**0.08**	**0**	**0.1**	**<1.0**

The results confirm that the proposed controller offers superior transient and steady-state performance across all metrics.

6. Sensitivity and Robustness Analysis

To assess the robustness of the proposed system, several sensitivity tests were conducted under varying motor and control parameters.

6.1 Parameter Variation Test

The motor parameters—stator resistance, inductance, and back-EMF constant—were varied by ±20% from their nominal values. The hybrid controller maintained stable operation with only minor fluctuations in speed (<2%) and torque (<3%), demonstrating strong parameter insensitivity.

6.2 Load Torque Variation

The speed response when the load torque was increased from 1 N-m to 3 N-m. The controller exhibited negligible speed drop and a recovery time of less than 0.02 s, confirming rapid adaptation.

6.3 Noise Immunity Test

To evaluate disturbance rejection, Gaussian noise was injected into the speed feedback signal. The hybrid controller effectively filtered out noise without introducing oscillations, maintaining a smooth torque output.

6.4 Comparative Robustness Index

A robustness index (RI) was calculated as:

$$RI = \frac{\Delta\omega_{max}}{\omega^{*}} \times 100$$

where $\Delta\omega_{max}$ is the maximum deviation from the reference speed. The hybrid controller achieved an RI of 2.3%, compared with 6.8% for PI and 4.1% for fuzzy control, clearly indicating superior robustness.

7. Conclusion

This paper presented an optimized hybrid Fuzzy–PI control strategy integrated with Field-Oriented Control (FOC) for BLDC motor drives in electric vehicle applications. The integration of fuzzy logic with the PI controller allowed dynamic adaptation of control gains, improving both transient and steady-state performance. Simulation results revealed that the proposed method achieved a 55% improvement in rise time, complete elimination of overshoot, and a reduction in torque ripple to less than 1 N-m compared with conventional controllers.

The robustness evaluation demonstrated that the controller maintained high stability under sudden load disturbances and parameter variations. These characteristics make the hybrid Fuzzy–PI controller a promising candidate for implementation in real-time EV drive systems using DSP or FPGA-based control platforms. Future work will focus on hardware-in-the-loop (HIL) validation and experimental verification on a prototype BLDC motor test bench.

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