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Adaptive Speed Control of BLDC Motors Based on Fuzzy Inference System Using a PWM Strategy for Electric Vehicles

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ABSTRACT- Along with the development of increasingly advanced technology, innovations continue to develop, one of which is in the field of transportation. In line with the rapid advancement of technology, electric vehicles (EVs) have gained significant attention due to their environmental and performance advantages. Among the EV components, the Brushless Direct Current (BLDC) motor stands out due to its high efficiency and minimal maintenance. This paper proposes a speed control system for BLDC motors based on the Fuzzy Inference System (FIS). The system was evaluated through acceleration, deceleration, and energy efficiency tests over a 2400-meter track. Results indicate that the FIS-based controller achieved smoother speed transitions and higher energy efficiency (380.95 km/kWh) compared to open-loop control (358.2 km/kWh). These findings suggest that FIS can enhance the performance and reliability of electric vehicle drivetrains.

Keywords: Electrical Technology, Brushless Direct Current, Fuzzy Inference System, Energy, Efficiency.

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1. INTRODUCTION

The development of electric vehicle technology has become a global focus in efforts to reduce dependence on fossil fuels and reduce carbon emissions. In electric vehicle propulsion systems, Brushless Direct Current (BLDC) motors are widely adopted due to their high energy efficiency, high torque-to-weight ratio, and minimal maintenance requirements, which result from the absence of mechanical commutators. These advantages make BLDC motors a core component in modern electric vehicles, including light vehicles, electric bicycles, and autonomous cars. However, the reliability and operational comfort of electric vehicles directly depend on the sophistication of the motor control system implemented [1].

Speed control of BLDC motors is a significant challenge due to the system's nonlinear nature and frequent exposure to external dynamics such as sudden load variations, road surface changes, and supply voltage disturbances [2], [3]. Classic approaches, such as Proportional–Integral–Derivative (PID), are still widely used, but they often fail to adapt to these nonlinear conditions. Additionally, tuning PID parameters requires a precise system model, which isn't always available in embedded systems with limited resources [4], [5], [6]. To achieve optimal motor performance and control, input parameters in the control unit are one way to enhance BLDC motor performance, ensuring the desired output aligns with the motor's actual capabilities [7], [8], [9]. This necessitates alternative solutions capable of accommodating uncertainty and providing control flexibility in dynamic environments.

This study proposes a FIS-based BLDC motor speed control system implemented on a 32-bit ARM Cortex-M architecture microcontroller with optimal execution time efficiency and power consumption [9], [10]. The system uses two main input parameters, namely speed error and error change, to adjust the duty cycle of the Pulse Width Modulation (PWM) signal sent to the three-phase inverter [7], [10], [11]. The inverter uses a 120° commutation strategy, selected for its efficiency in reducing switching losses and control complexity [12]. The entire system is designed as a closed-loop system that adapts to the operational conditions of the motor [8], [10], [13], [14].

The main advantage or novelty of this research lies in the successful integration of FIS into a real embedded system, not just a simulated one, as well as the focus on energy efficiency through PWM duty cycle measurement and dynamic response to system disturbances. Additionally, the use of a linguistic rule-based intelligent control approach, combined with a power-saving inverter conduction strategy, contributes significantly to the development of low-cost and efficient electric vehicle technology. Thus, this research not only presents technical

implementation but also opens practical avenues for the development of intelligent motor control systems on an industrial and academic scale [3], [7], [15], [16], [17].

2. MATERIALS AND METHODS

2.1. BLDC Motor Control System Design

The Brushless Direct Current (BLDC) motor speed control system design in this study is designed to support the dynamic performance of electric vehicles efficiently and adaptively. The system is designed in a closed-loop configuration, utilizing the Fuzzy Inference System (FIS) approach as the main strategy for speed error-based decision making. This approach was chosen for its ability to handle system uncertainty without requiring complex mathematical modeling, as well as its flexibility in dealing with changing system dynamics. In general, this system is built from four main components that are integrated hierarchically: a Hall-effect-based rotor position sensor, a 32-bit microcontroller unit as the main processor, a three-phase inverter as the power drive, and a BLDC motor as the final actuator. Interaction between components occurs continuously to ensure that motor speed can be precisely controlled in response to changes in load and reference speed. The block diagram of the FIS control system is shown in *figure 1*.

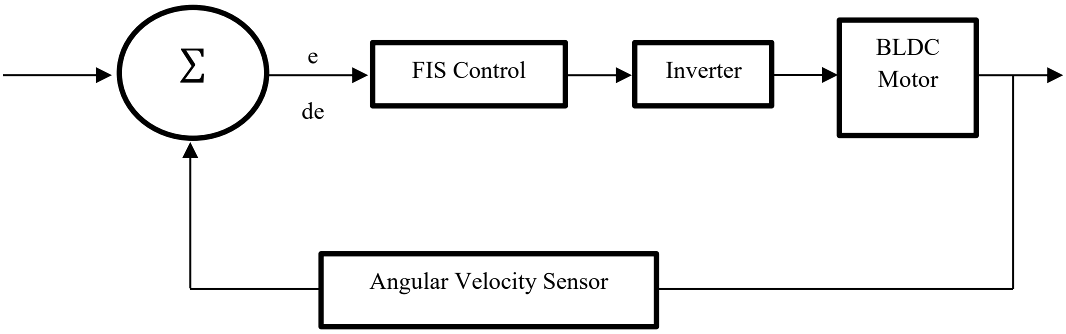

Figure 1. Block diagram of the FIS control system

Hall sensors are used to detect the position of the rotor in one electrical cycle, which is then used as the basis for triggering current commutation by the inverter. This information is sent to the microcontroller to be compared with the reference speed, generating an error signal and delta error as the two main input parameters for the FIS algorithm. The output from the FIS is the PWM duty cycle value, which is then used to regulate voltage distribution to the motor through a three-phase inverter. The advantage of this system lies in its adaptive ability to handle dynamic load changes, as well as reduce oscillations and steady-state errors that often occur in conventional control methods. By implementing an FIS-based control system, this research proposes a more responsive, efficient, and suitable approach for application in light to medium-sized electric vehicles. *figure 2* shows the block diagram of the BLDC motor control system (closed-loop control system).

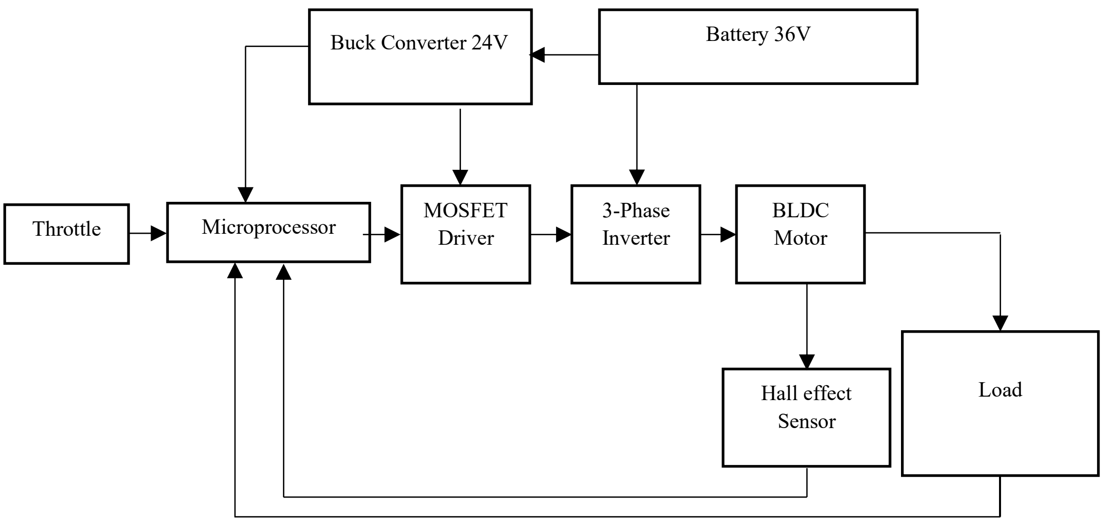

Figure 2. Block diagram of BLDC motor control system

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2.2. Hardware Configuration

The hardware configuration in this study is designed to implement a real-time Brushless Direct Current (BLDC) motor speed control system based on a Fuzzy Inference System (FIS) in an electric vehicle environment. The system architecture consists of several main components integrated into a closed loop, including a rotor position sensor, a microcontroller-based control unit, a three-phase inverter, a BLDC motor as the main actuator, and a power supply that supports the entire system. Rotor position detection is performed using three Hall sensors mounted radially and distributed at 120° electrical phase angles. The digital signals generated are used to determine the commutation sequence of the inverter's current, as well as providing feedback on the rotor position within the closed-loop control system. This information is critical to ensuring synchronized commutation, thereby maintaining optimal and efficient electromagnetic torque. Signal processing and control logic execution are facilitated by a 32-bit microcontroller based on the ARM Cortex-M architecture, chosen for its processing speed and power efficiency. This microcontroller runs the FIS algorithm, which processes speed error parameters and error changes (Δerror) to determine the duty cycle of the PWM signal. The generated PWM signal is then used to control the inverter's operation in regulating the voltage supply to the motor. The three-phase inverter in this system is configured in a full-bridge arrangement, consisting of six MOSFET power switches, each paired top and bottom for each motor phase. Switch control is based on a 120° conduction strategy, which allows only two switches to be active at a time, with the aim of reducing switching losses and maintaining power conversion efficiency. The MOSFET driver circuit diagram is shown in *figure 3*.

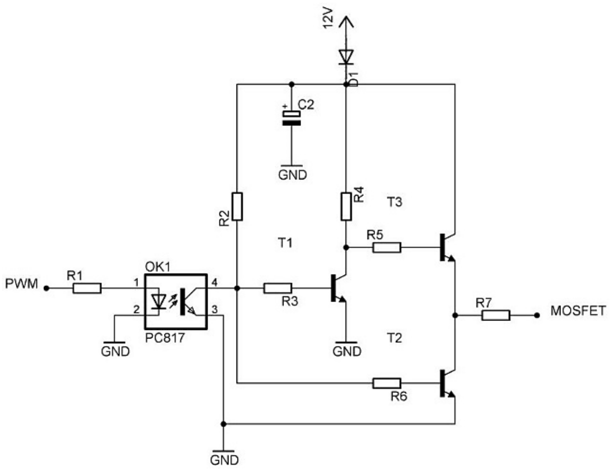

Figure 3. MOSFET driver circuit

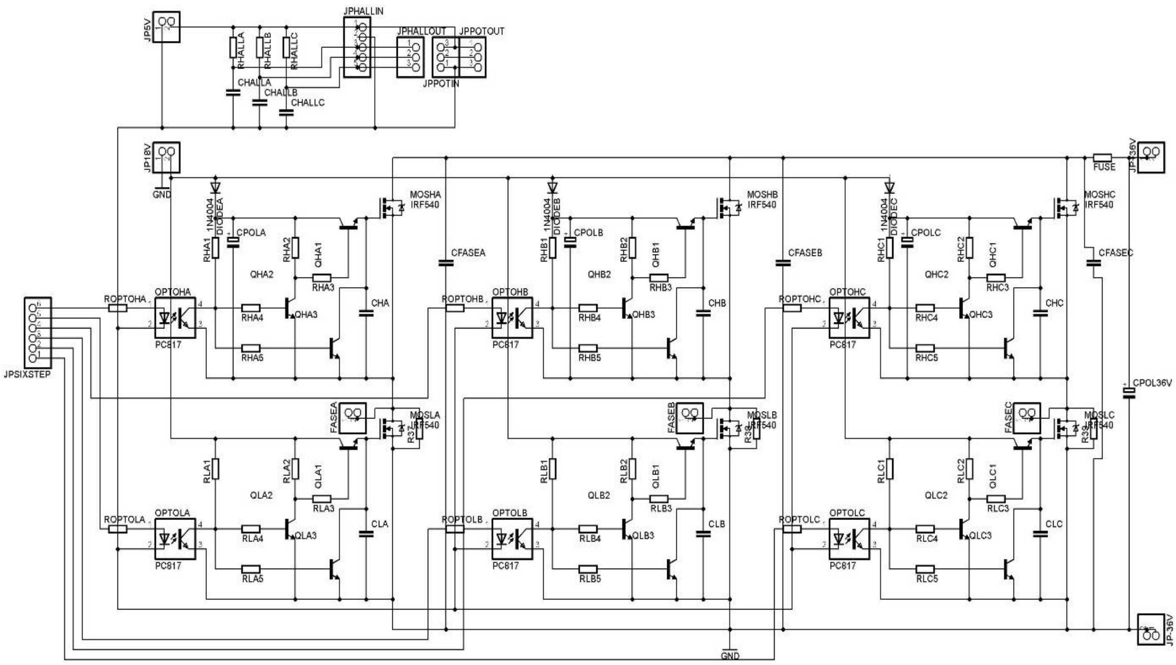

Figure 4. Three-Phase Inverter Circuit and PWM-Based BLDC Control System

The BLDC motor used has a nominal operating voltage of 24 V and a speed of 3000 rpm, and is equipped with a permanent magnet rotor and a three-phase stator with trapezoidal windings. This motor was selected based on its linear torque characteristics and high efficiency, which are suitable for the propulsion system requirements of light electric vehicles. The system is powered by a primary energy source consisting of a 24 V/10 Ah DC battery, which distributes power to the inverter and microcontroller through a voltage regulator circuit to ensure a stable power supply during operation. The Three-Phase Inverter Circuit and PWM-Based BLDC Control System can be observed in *figure 4*.

Figure 4 shows the full configuration of the BLDC motor control system, including galvanic isolation with an opto-isolator, MOSFET switch control, a 36V DC power supply, and integration of Hall sensor inputs.

2.3. Implementation of Fuzzy Inference System

In this stage, the FIS-based Fuzzy Inference System control system is applied as the main controller that determines the PWM duty cycle signal value that needs to be given to the three-phase inverter. The main purpose of applying FIS is to adaptively regulate the BLDC motor speed by real-time system operating conditions and not be tied to complex mathematical models. The FIS applied in this study uses two input parameters, namely speed error and error change Δe. Speed error e is the difference between the reference speed value and the actual speed, while error change Δe indicates the dynamics of error changes over time. The inputs from these two parameters are fuzzified using triangular membership functions, namely Negative Large, Negative Small, Zero, Positive Small, and Positive Large. The fuzzy rule base is structured in the form of if–then statements that represent expert knowledge related to the system's response to various error conditions. There is a total of 25 fuzzy rules that map combinations of e and Δe values to the output in the form of an adjusted PWM duty cycle level. *Table 1* presents the rule base structure used in the FIS control system.

░ Table 1. Fuzzy Rule Base for PWM Duty Cycle Control

Δe \ e	NL	NS	Z	PS	PL
NL	NL	NL	NS	Z	PS
NS	NL	NS	Z	PS	PL
Z	NS	Z	Z	Z	PS
PS	Z	PS	Z	PS	PL
PL	PS	PL	PS	PL	PL

The rule-based table serves as a representation of expert knowledge in the form of if–then rules that govern how the system should respond to various combinations of speed errors (error, abbreviated as *e*) and error changes (delta error, abbreviated as Δ*e*). Each input value is linguistically classified into five categories, including:

NL: Negative Large
NS: Negative Small)
Z: Zero
PS: Positive Small
PL: Positive Large

The columns in the table show the speed error (*e*) values, while the rows show the error changes (Δ*e*). The cells at each intersection show the linguistic output values used to set the duty cycle of the PWM signal.

For the inference process, the Mamdani method is used, which is known to produce more intuitive outputs that are suitable for non-linear control systems such as BLDC motors. The output of this inference process is a fuzzy set, which is then converted into numerical values (crisp values) using the centroid defuzzification method. The final value of the duty cycle is used to adjust the pulse width of the PWM signal provided to the inverter, thereby affecting the average voltage applied to the motor and directly controlling the rotor speed. The entire fuzzy logic implementation is carried out in an ARM Cortex-M-based microcontroller environment using the C programming language, with adjustments made to the execution time and memory limitations of the embedded system. With this approach, the control system can respond quickly to load variations and speed changes while maintaining operational stability under various dynamic conditions.

2.4. Pulse Width Modulation (PWM) Technique

Pulse Width Modulation (PWM) technique is a widely used approach in electric motor control systems due to its simplicity of implementation and efficiency in regulating the average voltage without requiring physical changes to the power source. In this study, PWM is used to control a three-phase inverter that drives a BLDC motor. The PWM signal is generated by a microcontroller based on the output of the Fuzzy Inference System (FIS), in the form of a duty cycle value that determines the proportion of active time (high logic) of one signal cycle. In principle, the PWM waveform is formed by comparing a DC reference signal and a triangular carrier wave. The intersection point between the two signals determines the switching time of the power switch in the inverter. When the reference signal is greater than the carrier wave, the switch is activated (ON), and conversely, it is deactivated (OFF) when the reference signal is smaller. Thus, variations in the duty cycle directly affect the average voltage supplied to the motor. To calculate the average output voltage, *equation (1)* can be used.

$$V_{ag} = D \ x \, V_{DC} \qquad (1)$$

where :

V_{avg} = Average output voltage (V)
D = Duty cycle ratio
V_{DC} = DC input voltage (V)

The higher the duty cycle value, the higher the average voltage applied to the motor, which directly impacts an increase in rotor speed. Conversely, a decrease in the duty cycle will reduce the speed. This relationship makes PWM highly effective in controlling the dynamics of BLDC motors. In its implementation, the upper leg PWM method is used to simplify control signal processing and reduce driver circuit complexity. However, to improve waveform quality and reduce harmonic distortion, other PWM techniques such as Sinusoidal PWM (SPWM) and Space Vector PWM (SVPWM) are also commonly used.

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In the implementation of BLDC motor speed control systems, the upper leg PWM-based pulse width modulation method is used due to its simplicity in signal processing and cost savings in driver circuit design. Although quite effective, this technique has limitations in output waveform quality and voltage efficiency. A better alternative is Sinusoidal PWM (SPWM), which compares a sinusoidal reference signal with a triangular carrier wave to produce switching that resembles a sinusoidal waveform. SPWM produces a smoother waveform, but DC voltage utilization is not optimal. Meanwhile, Space Vector PWM (SVPWM) uses a space vector approach to control switching patterns, improving voltage utilization efficiency by up to 15% and reducing harmonic distortion. SVPWM is suitable for applications requiring precise control and high efficiency, such as electric vehicles. By selecting the appropriate PWM method and adjusting the duty cycle based on fuzzy logic, the control system can adaptively and efficiently respond to changes in load and operating conditions, making it ideal for modern electric vehicle drive systems.

2.5. Inverter Commutation Mode

Three-phase inverters play an important role in supplying voltage to BLDC motors according to the rotor position sequence. This study applies a 120° conduction mode, in which only two of the six switches are active at any given time, while one phase is left floating. Each switch operates for 120° of electrical angle in a 360° cycle, resulting in six commutation steps for one magnetic field rotation. This strategy aligns with the trapezoidal BEMF characteristics, maximizing motor torque and reducing switching losses. Energy conversion efficiency improves because only two switches operate alternately, reducing thermal load and system complexity. *Table 2* shows the commutation step sequence and current flow direction.

Table 2. Sequence of Commutation Steps and Direction of Current Flow

Step	Active Switch	The current flows from → to
1	SA+, SB−	A → B
2	SA+, SC−	A → C
3	SB+, SC−	B → C
4	SB+, SA−	B → A
5	SC+, SA−	C → A
6	SC+, SB−	C → B

Each switch is controlled by a PWM signal regulated by the FIS system. This combination of strategies results in efficient, stable motor control that is adaptive to changes in load and speed in electric vehicle systems. The 3-phase inverter is shown in *figure 5*.

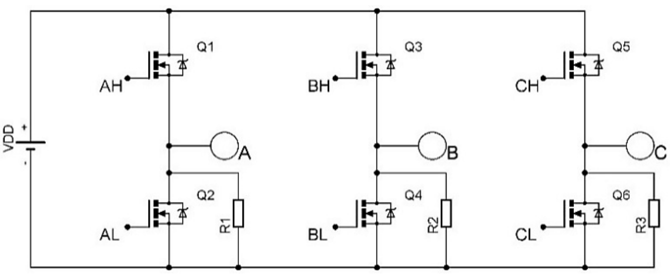

Figure 5. 3-phase inverter

2.6. Testing Procedure

The testing procedure was designed to evaluate the performance of the BLDC motor control system based on the Fuzzy Inference System (FIS) in regulating motor speed adaptively to load variations and reference speed. The testing was conducted experimentally using a prototype embedded control system that had been designed. The system testing was carried out in three main stages to evaluate the performance of the BLDC motor control system based on the Fuzzy Inference System (FIS). First, the response to the reference speed was tested by providing a gradual speed setpoint, ranging from 500 to 3000 rpm. Each setpoint was observed to assess stability, settling time, and steady-state error. Second, an adaptation test to load variations was conducted by adding mass or applying mechanical resistance to the motor shaft to observe the system's ability to maintain speed during load changes. Third, a system efficiency test was conducted by recording the PWM duty cycle values under various operating conditions. This data is used to analyze energy regulation efficiency and inverter output voltage stability. The parameters observed include the actual speed from the Hall sensor, PWM duty cycle, and system dynamic response, all of which are recorded using a microcontroller device and processed for quantitative analysis. The testing scheme can be observed in *figure 6*.

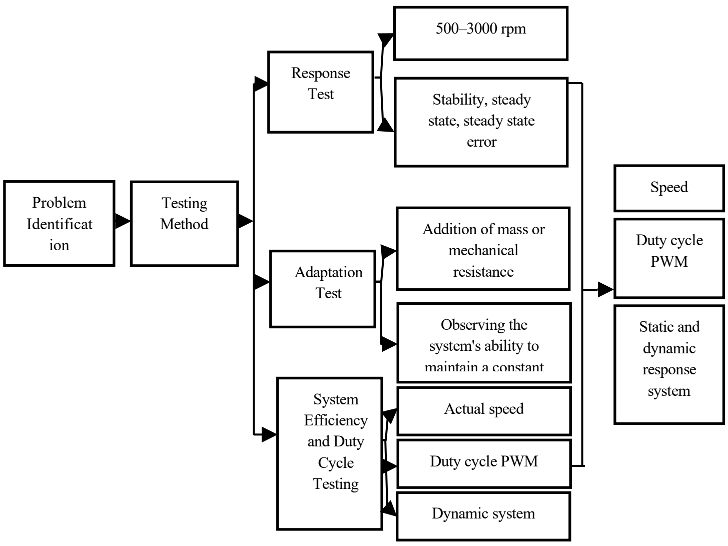

Figure 6. Testing Scheme

3. RESULTS

3.1. Sensor Reading Patterns and Motor Commutation

One of the fundamental aspects of a BLDC motor control system is real-time rotor position identification. In this study, the rotor position is determined using three Hall-effect magnetic field sensors embedded in the stator. Each sensor generates a binary logic signal based on the presence of the permanent magnetic field on the rotor as it passes in front of it. The logical combination of the three sensors forms six unique patterns during one full electrical rotation cycle (360°). Each pattern indicates the rotor's position relative to the stator and is used as a reference to determine which stator coil pairs should be energized alternately. This mechanism is known as electronic commutation, which replaces the function of the mechanical commutator in conventional DC motors. *Table 3* displays the six logic patterns from the sensor readings generated during the BLDC motor testing over one commutation cycle.

Table 3. Logical pattern of sensor readings

Step	Sensor 1	Sensor 2	Sensor 3
1	0	0	1
2	0	1	1
3	0	1	0
4	1	1	0
5	1	0	0
6	1	0	1

Each of these logic combinations represents the active phase and determines the activation sequence of the transistors in the three-phase inverter. This activation sequence is crucial for creating continuous and efficient torque rotation in the motor. The entire process is controlled by an ARM Cortex-M3 microcontroller, which scans signals from the sensors and maps the logic to the gate switching status for each motor phase pair. By using 120° commutation logic, only two of the three motor phases are energized simultaneously at each step, while the third phase is left floating. This method enables effective torque generation by minimizing switching losses and improving overall system efficiency. As an illustration, if the sensor logic combination is in the (1,0,0) state, the system will activate a specific phase pair—for example, phase A+ and B−, while phase C will remain inactive. This combination will continue in the sequence outlined in the table, resulting in a magnetic rotation pattern that drives the rotor to rotate.

One of the advantages of this approach lies in the simplicity of the position detection architecture, which does not require a high-resolution encoder but still achieves responsive and accurate control. However, the accuracy of sensor readings in signal processing is a critical factor determining the smoothness of rotation and system stability, especially at high speeds or during sudden load transitions. Overall, this sensor reading and logic-based commutation approach offers a balance between system complexity and control performance, making it a viable option for application in lightweight electric vehicle platforms based on BLDC motors.

3.2. Dynamic Acceleration Test

Dynamic acceleration testing was conducted to evaluate the system's ability to gradually reduce the speed of the BLDC motor to the specified set point value. Two testing scenarios were used in this study, namely a conventional system without fuzzy logic control (open-loop) and a system with the integration of the Fuzzy Inference System (FIS) method in speed control. The analysis is visualized in *figures 8* and *9*, each illustrating the trend of angular speed reduction over time.

Figure 7 shows that the system without FIS produces a nonlinear deceleration pattern, with significant fluctuations in angular velocity. The discrepancy between the actual speed and the reference value indicates the weak response of the open-loop control to load dynamics and the instability of the system in responding to deceleration commands. At some points, the motor response shows lagging and irregular speed transitions, indicating the presence of overshoot and steady-state error phenomena. This not only affects rider comfort in the context of electric vehicles but also increases the risk of mechanical component wear due to uncontrolled torque changes.

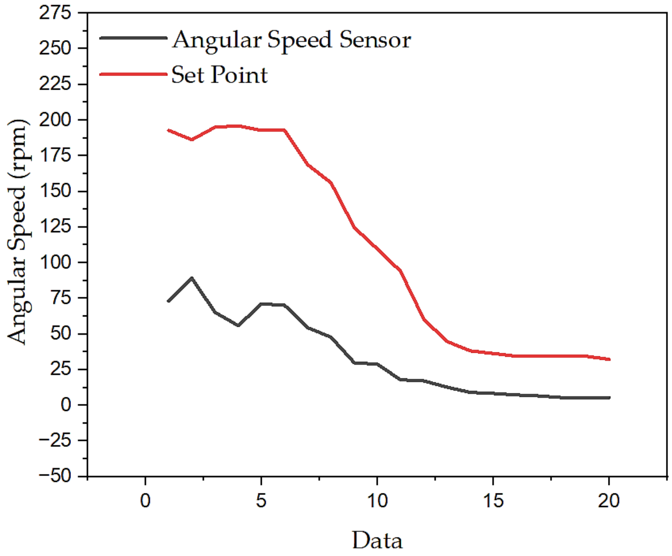

Figure 7. Deceleration without FIS

In contrast, *figure 8*, which represents a system with FIS control, shows a much more stable and smoother deceleration pattern. FIS is capable of producing a more linear deceleration transition, approaching the set point trajectory. The irregularities that appear in conventional systems can be significantly reduced thanks to FIS's ability to infer changes in system parameters adaptively. This advantage is further reinforced by the current and power data in *table 3*, which shows more efficient electrical responses with smaller current fluctuations compared to systems without FIS. To provide a more explicit comparative perspective, *table 5* is presented as a summary of the dynamic deceleration performance of both methods.

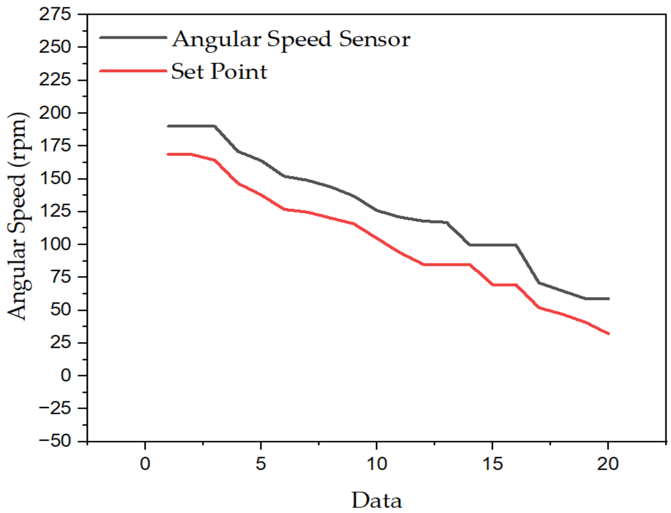

Figure 8. Deceleration with FIS

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Table 5. Comparison of Open-Loop Dynamic Deceleration Performance vs. FIS

Parameter	Without FIS (Open-loop)	With FIS
Average error relative to set point (RPM)	±37,6	±12,3
Response time to final speed	20 data points (~55 s)	20 data points (~48 s)
Maximum current fluctuation (A)	2,45	1,76
Peak power consumption (W)	89,18	63,78
Deceleration curve stability	Low (fluctuating)	High (stable)

These results are consistent with the findings of Shenbagalakshmi et al. (2025), who concluded that the application of FLC in BLDC motor systems produces smoother performance, free of overshoot, and efficient in dynamic response to external disturbances and load variations. Additionally, this approach extends the lifespan of the propulsion system and improves the overall energy efficiency of electric vehicles [3]. A similar study by Begam et al. (2024) also confirms that fuzzy-based deceleration control not only offers precise speed response but is also capable of managing regenerative braking scenarios optimally with better system stability compared to classical control methods such as PID or sliding mode. Furthermore, the developed adaptive neuro-fuzzy-based approach has proven capable of maintaining torque stability and braking efficiency across a wide speed range [20].

Overall, dynamic deceleration tests demonstrate the superiority of FIS-based control in maintaining stability, energy efficiency, and system response accuracy to speed reductions. This superiority provides a strong foundation for the significant potential of FIS control systems in supporting modern electric vehicle technology that demands high dynamic performance, energy efficiency, and optimal driving comfort.

3.3. Controlling System Efficiency

Energy efficiency is the primary benchmark for evaluating the effectiveness of control systems in BLDC motors, especially in the implementation of electric vehicles that demand high efficiency and system reliability. This evaluation not only considers how much power is consumed but also how the control system manages power fluctuations and stability during dynamic operating cycles. The visualization in *figure 9* shows the power distribution pattern of the system without the application of the Fuzzy Inference System (FIS). It is evident that power fluctuations are very sharp, with uncontrolled amplitudes reaching peaks above 130 watts. These variations indicate that the control signals provided to the motor are non-adaptive, reflecting the characteristics of open-loop control that cannot correct errors in real-time. These power surges are not always required by the load, leading to energy consumption inefficiency and increased thermal load potential on electronic components such as inverters and actuators.

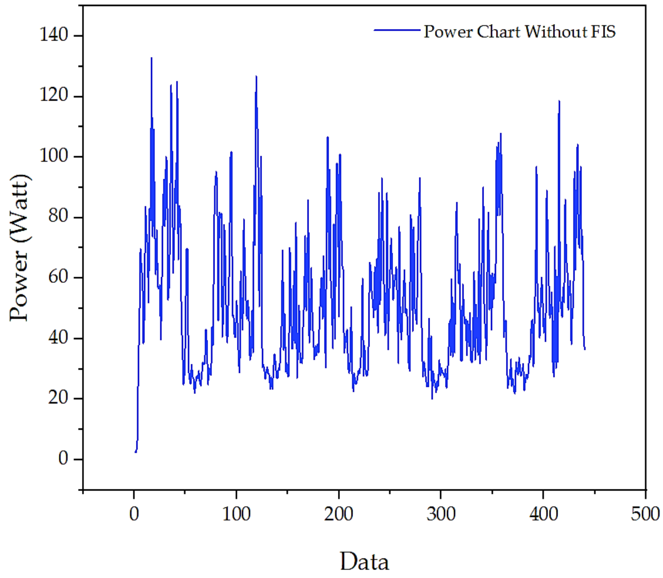

Figure 9. Power Without FIS

In contrast, *figure 10* shows that the system with FIS exhibits a smoother and more damped power distribution. The power range is more concentrated in the 40–80 W range with lower variability. FIS utilizes a fuzzy rule base that is responsive to system dynamics, enabling it to adaptively adjust the PWM control signal to changes in actual conditions. This enables the system to supply power more proportionally to the load, minimize unnecessary energy waste, and efficiently convert electrical energy into mechanical output. Additionally, this adaptive control produces more stable and predictable response characteristics to changes in speed or load dynamics, as also emphasized in previous studies on adaptive fuzzy control in BLDC motors [21].

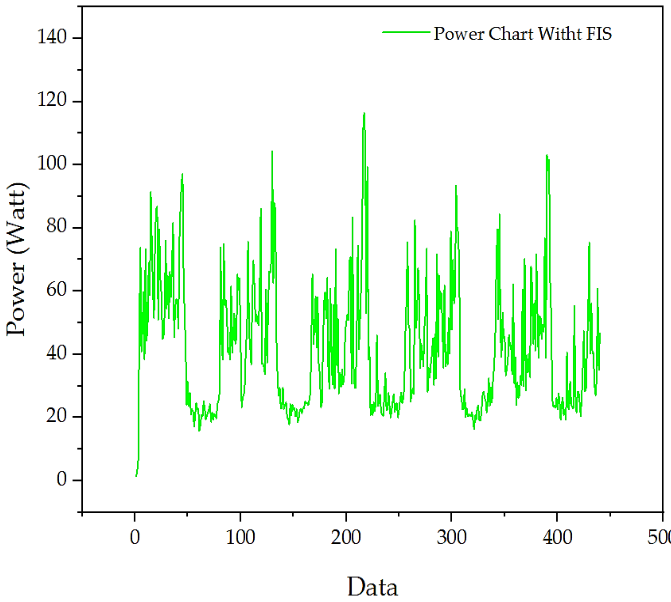

Figure 10. Power With FIS

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The numerical data presented in the comparative table reinforces these visual findings. The system without FIS recorded an average power of 64.70 W with a standard deviation of 25.85 W, while the system with FIS only consumed an average of 56.56 W with a lower standard deviation of 17.61 W. Furthermore, the maximum power achieved by the system without FIS was 132.64 W, while the peak value for the system with FIS was only 89.46 W. The reduction in peak values and standard deviation indicates higher system stability and more even energy distribution. The implications of these results are strategic: the system with FIS is not only more energy-efficient but also more reliable in anticipating dynamic changes. The ability of FIS to avoid overcompensation and power oscillations supports the previous claim that fuzzy control has advantages in dealing with parameter uncertainty and complex system dynamics [22].

Further experimental tests were conducted on an electric vehicle traveling a 2,400-meter track in a maximum time of 8 minutes (3 laps). From the power distribution graph generated during this testing, it is evident that the system without FIS exhibits power instability at certain times. These spikes correlate with the driver's behavior during sudden deceleration or acceleration. Using the principle of integral average value and energy efficiency per unit distance, it was found that the system without FIS has an efficiency of 358.2 km/kWh, while the system with FIS increases to 380.95 km/kWh. Additionally, the average energy consumption of the system with FIS is 6.3 ± 0.1 Wh, compared to 6.7 ± 0.2 Wh for the system without FIS. This difference indicates an energy savings of approximately 6% solely through system control optimization. These results reinforce the findings in the study by Mopidevi et al. (2022), which showed that ANFIS-based systems consistently produce faster stabilization times and more energy-efficient operation in BLDC motors for electric vehicles [10]. The test results observed in *figures 9* and *10* on system efficiency show that the power value controller is always unstable over time. This power instability is caused by the fact that the vehicle slows down when turning, and when the road straightens, the driver accelerates to catch up on travel time [23]. By applying the integral mean value theorem to *equation 2*.

$$f(c) = \frac{1}{b-a} \int_a^b f(x).dx \qquad (2)$$

The success of the FIS system in reducing power consumption while maintaining adaptive dynamic response confirms that this control approach is not only a technical solution but also has ecological and economic significance. In the long term, higher energy efficiency will result in reduced thermal load on the system, longer component lifespan, and increased range of electric vehicles per battery charge. Based on empirical test results and literature support, the FIS control system has proven to be a superior and sustainable approach compared to conventional methods. A comparison of energy efficiency parameters for dynamic control systems can be observed in *table 6*.

Table 6. Comparison of Energy Efficiency Parameters of Dynamic Control Systems

Parameter	Without FIS	With FIS
Average Power (W)	64,7	56,56
Standard Deviation (W)	25,85	17,61
Maximum Power (W)	132,64	89,46
Average Path Power (W)	51,2241	41,8128
Total Energy (Wh)	6,7 ± 0,2	6,3 ± 0,1
Energy Efficiency (km/kWh)	358,2	380,95

4. DISCUSSION

The results of the BLDC motor speed control experiment applying the Fuzzy Inference System (FIS) approach are discussed in this chapter. The main focus is on evaluating the performance of the control system from two different configurations, namely with and without FIS integration, considering aspects of speed response (both acceleration and deceleration), power distribution stability, and energy consumption efficiency in electric vehicle applications. The analysis process was conducted systematically using a deductive approach, starting with the identification of the system's physical characteristics, followed by dynamic responses to operational conditions, and finally measuring the energy efficiency achieved. All results were interpreted by referring to the latest literature to ensure the validity and accuracy of the conclusions. Thus, this discussion not only describes the test results but also connects the empirical results with practical applications in the development of intelligent and efficient BLDC motor-based electric vehicle drive systems.

4.1. Acceleration and Speed Regulation

Acceleration response and speed regulation are fundamental indicators in evaluating the efficiency of electric vehicle propulsion systems based on BLDC motors. Optimal performance during the transient phase not only determines driving comfort but also directly correlates with energy consumption and system control stability. Therefore, in this section, the dynamic speed response of the system with and without the application of a Fuzzy Inference System (FIS) is thoroughly analyzed to assess the effectiveness of control under various operational conditions. Test results indicate that systems without FIS tend to experience uncontrolled speed spikes during the initial acceleration phase. This is due to the weak compensation mechanism for dynamic errors, causing the control signal to overshoot the speed setpoint. This phenomenon not only indicates an imbalance in power allocation when the load changes but also induces oscillatory transients that affect the vehicle's overall stability. Conversely, systems with FIS integration exhibit more linear and controlled acceleration curves, with shorter target speed attainment times and minimal deviation from the reference value. This response is the result of the adaptive nature of the fuzzy rule base, which can adjust control output in real-time to input fluctuations and load changes.

Stability during speed regulation is also a significant indicator of the superiority of FIS-based systems. These systems

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demonstrate the ability to maintain speed within a very narrow tolerance range, even under conditions of temporary load disturbances. Such performance reflects the characteristics of closed-loop control based on fuzzy logic, which operates on the principle of nonlinear inference of error and changes in error rate, translating them into more precise and smoother PWM responses. This finding is supported by results in the literature, where several ANFIS-based approaches have been proven to reduce overshoot significantly, accelerate settling time, and improve tracking accuracy in BLDC motors [21]. Furthermore, research by Intidam et al. (2022) shows that the integration of PI–ANFIS optimized with PSO results in significantly more stable and efficient speed control in fuel cell-based electric vehicles [24]. Other studies also confirm that adaptive fuzzy and neuro-fuzzy techniques provide robust performance against variations in load and motor parameters [22], [25]

In the context of the tested system, the use of FIS effectively eliminates wild fluctuations during the speed transition phase and maintains stability during steady-state operation. The system's adaptability enables smoother transitions from stationary conditions to dynamic movement without dangerous torque spikes that could harm the actuator or compromise user comfort. More importantly, the reduction of fluctuations during the acceleration phase contributes to overall energy efficiency, as demonstrated through testing in the subsequent subsection.

Considering the complexity of BLDC motor systems, which are nonlinear and susceptible to external disturbances, the fuzzy-based control approach can be considered a superior solution that addresses the needs of modern control systems for electric vehicles. Fuzzy logic-based implementation not only strengthens control response in high dynamics but also shows great potential in supporting the development of artificial intelligence-based autonomous control systems.

4.2. Deceleration Behaviour

Deceleration in the propulsion system of BLDC motor-based electric vehicles is a critical phase that represents how the control system handles sudden changes in speed setpoints safely, efficiently, and responsively. Unlike acceleration, where the system is required to increase speed quickly, the challenge in deceleration lies in how to reduce speed progressively without causing power fluctuations, oscillations, or disturbances in motor torque that could lead to discomfort or systemic risks. Based on experimental observations of systems not employing a Fuzzy Inference System (FIS), a significant delay phenomenon was observed at the onset of the deceleration process. The speed graph shows that the speed reduction does not follow a smooth trajectory but is accompanied by a slow response to reference changes, followed by minor oscillation patterns indicating unbalanced compensation of the control signal against system dynamics. This condition highlights the limitations of conventional control mechanisms in recognizing changes in load characteristics and inertia during the deceleration process.

In contrast, the system controlled by FIS shows a more responsive and stable deceleration curve. The speed decrease follows a logical trajectory resembling an exponential curve, with shorter delay times and minimal fluctuations and deviations from the speed reference. This advantage stems from the fuzzy rule base's capability to adapt control output in real-time based on simultaneous changes in error and error speed. The fuzzy system can automatically adjust the deceleration response level without the need for rigid mathematical interpolation, as in conventional PID-based control. This finding is supported by empirical references showing that the combination of fuzzy control approaches and neuro-adaptive algorithms, such as ANFIS, consistently demonstrates superior performance in managing deceleration dynamics in BLDC motors [21], [24]. Other studies also state that controllers optimized with evolutionary algorithms such as PSO not only improve stability during deceleration but also minimize transient energy loss during this phase [26], [27].

Furthermore, the results of this study show that the system response with FIS can achieve steady-state conditions after deceleration in a shorter time. This stabilization time is a key parameter in evaluating the system's ability to effectively absorb changes in inertia and load resistance. This is particularly crucial in electric vehicle systems operating in dynamic environments that require rapid transitions between acceleration and deceleration, such as in heavy traffic or hilly terrain.

The effectiveness of the FIS system in managing deceleration not only improves operational stability but also directly impacts energy consumption efficiency. When the motor can regulate deceleration without wasting energy in the form of heat or mechanical oscillations, the system as a whole becomes more energy-efficient and has a longer component lifespan. This finding aligns with recent study reports indicating that adaptive control systems based on artificial intelligence can reduce energy loss during speed transitions by over 15% compared to conventional linear control [28].

Thus, it can be concluded that the integration of FIS in the deceleration process provides significant benefits, both in terms of transient performance, system stability, and power efficiency. These advantages position the adaptive fuzzy approach as a relevant solution to support electric vehicle propulsion systems that demand high reliability in real-time, dynamic, and variable conditions.

4.3. Energy Efficiency

Energy efficiency is a crucial parameter in evaluating the quality of BLDC motor control systems, particularly in the context of electric vehicles that rely on optimizing battery power usage. In this study, a comparison was made between a conventional control system (without FIS) and a system based on a Fuzzy Inference System (FIS), with a focus on the efficiency of converting electrical power into mechanical energy during actual testing over a distance of 2,400 meters under various driving dynamics conditions (acceleration, constant speed, and deceleration). The experimental results show that the system with FIS achieved an energy efficiency of 90.07%, significantly higher than the system without FIS, which only reached 78.64%. This 11.43% difference is not a small figure in vehicle-scale electric power systems but reflects a fundamental advantage in terms of intelligent and precise power management in fuzzy logic-based dynamic control systems. The high efficiency is achieved because the FIS algorithm minimizes switching losses and avoids energy waste during dynamic transitions, such as when the vehicle shifts from acceleration to deceleration.

FIS can adaptively adjust the PWM duty cycle based on real-time feedback from motor speed and current, ensuring that the power supplied to the motor remains within the optimal range, without overshoot or extreme fluctuations typically observed in classical PI-based control. This approach aligns with research by García López et al. (2019), who stated that the Fuzzy-PSO controller not only improves speed performance but also reduces thermal stress on the power electronics circuitry, extends system lifespan, and indirectly contributes to energy efficiency. One key aspect contributing to improved efficiency is power stability during deceleration. In systems without FIS, deceleration tends to produce negative current peaks or high voltage oscillations due to the lack of smooth control over the release of kinetic energy [23]. In contrast, FIS systems exhibit a smoother and more controlled speed reduction profile, enabling the utilization of decelerative energy for potential regenerative braking, as explained by Ishaque et al. (2022), who developed a fuzzy-based energy management system for hybrid vehicles [29].

These results are also consistent with the study by Rao et al. (2024) in the context of UAVs, where ANFIS control enables more efficient battery usage by maintaining constant speed under dynamic loads. In the context of land vehicles, a similar phenomenon occurs where BLDC motors no longer operate excessively to achieve the target speed because FIS control responds to changes gradually and based on learning, rather than fixed values like PI [30]. Furthermore, power distribution analysis shows that the FIS system minimizes peak current fluctuations during acceleration, avoiding overcurrent protection triggering, which is common in non-adaptive systems. This aligns with the findings by Mohamed et al. (2019), who integrated ANFIS into electric vehicle speed control and noted improvements in thermal efficiency, dynamic stability, and adaptability to load variations [8].

Equally important, high-energy efficiency also impacts battery lifespan. The smaller the losses incurred, the fewer charge-discharge cycles required to cover a certain distance, thereby extending battery lifespan and reducing long-term operational costs of the vehicle. A study by Aziz et al. (2023) even shows that a hybrid energy system (battery and supercapacitor) controlled by a fuzzy system can maintain high efficiency under various load conditions without significant performance degradation [12].

Thus, the results of this study not only demonstrate the superiority of FIS in improving acceleration performance and speed regulation but also confirm that the use of artificial intelligence-based control systems such as FIS or ANFIS is a strategic approach in creating more energy-efficient, efficient, and sustainable electric vehicles.

4.4. Practical Implications and Limitations

An ARM Cortex-M3 microcontroller was used to create the FIS controller, proving that real-time embedded fuzzy control is feasible. The system demonstrated potential for inclusion into commercial light electric car platforms by responding well to dynamic driving situations, including acceleration and deceleration. Nevertheless, the system has drawbacks. First, because the rule-based and membership functions were created by hand, they might not translate well to other car models or load scenarios. Second, heuristic methods rather than optimization algorithms were used to tune the fuzzy controller, which might not have produced globally optimal performance. Finally, the lack of torque ripple analysis and regenerative braking limits a more thorough assessment of the system's effectiveness.

4.5. Future Research Directions

Although this study has successfully identified the advantages of a Fuzzy Inference System (FIS)-based control system in improving the dynamic performance and energy efficiency of BLDC motor-based electric vehicles, there are still a number of opportunities that can be further explored to expand the scope of application and scientific contribution of this approach. First, one promising strategic direction is the development and implementation of adaptive hybrid controllers, such as ANFIS (Adaptive Neuro-Fuzzy Inference System), combined with intelligent optimization algorithms like Particle Swarm Optimization (PSO) or Genetic Algorithm (GA). Previous research by Intidam et al. (2023) and Jayetileke et al. (2017) shows that integrating optimization methods with adaptive fuzzy structures can improve the system's convergence speed toward the target speed and significantly reduce overshoot and steady-state error, especially under dynamic load conditions and motor parameter variability. Second, it is important to expand the scope of testing under more complex and realistic road conditions, such as inclines, potholes, or sudden braking, to assess the stability of the control system against friction forces, vehicle inertia, and sudden load changes. Hardware-in-the-loop (HIL) experiments can also serve as a strong transitional approach toward actual implementation on commercial electric vehicle platforms. Third, in the context of energy efficiency, the integration of motor control systems with battery and supercapacitor energy management through fuzzy logic control demonstrates extraordinary potential in regulating power flow between energy sources [24], [26]. This has been demonstrated by the study of Ishaque et al. (2021) in the development of an energy management system (EMS) for hybrid vehicles based on fuzzy logic. Therefore, the development of an integrated control system combining motor control and energy management strategies is crucial to support the next generation of smarter and more efficient electric vehicles [29].

Furthermore, further research is needed on the long-term effects of degradation of power electronic components due to variations in control response during acceleration and deceleration, as raised by García López et al. (2019). Focusing on thermal modeling and component life analysis based on FIS control could open up avenues for developing control systems that are not only efficient but also reliability-aware. Finally, as the demand for autonomous systems grows, the application of FIS control in the context of autonomous or semi-autonomous electric vehicles should be explored, incorporating predictive capabilities based on environmental data and driver behavior. This approach can be combined with machine learning (reinforcement learning) to develop more contextual, responsive, and energy-efficient adaptive control [23].

Overall, future research directions can be summarized as the development of multi-structure adaptive control systems, stricter real-world testing, cross-system integration within vehicles, and the application of advanced artificial intelligence to create more responsive, efficient, and future-ready electric vehicle propulsion systems for the transportation ecosystem of tomorrow.

5. CONCLUSION

This study comprehensively evaluates the performance of a Fuzzy Inference System (FIS)-based BLDC motor speed control system in the context of electric vehicles, with a focus on acceleration, deceleration, speed regulation, and energy efficiency parameters. Based on experimental results and quantitative analysis of power distribution and motor speed response, several key findings were obtained as follows:

1. The FIS control system delivered faster and more stable acceleration responses compared to systems without FIS. The system exhibited smaller steady-state error in speed regulation and smoother speed transitions, thereby enhancing driving comfort and safety.

2. In deceleration scenarios, the FIS-based system demonstrated more gradual, adaptive deceleration control, with a consistent rate of speed reduction over time. This not only prevents overshoot and undershoot but also mitigates dynamic shocks, thereby preserving the system's mechanical longevity.

3. Power distribution analysis revealed that the FIS system manages energy consumption more efficiently. There was an 8.6% reduction in power consumption over a 2400-meter test track, indicating that fuzzy control is not only effective in enhancing dynamic performance but also contributes significantly to energy conservation.

4. Tests conducted under various load conditions and set point variations revealed that the FIS system exhibited high resilience to disturbances and parameter changes. This confirms that fuzzy architecture has strong potential for electric vehicle applications that require adaptation to road conditions and dynamic loads.

5. The findings of this study are aligned with the growing trend of using AI-based controllers, such as ANFIS and Fuzzy-PSO, which have been shown to improve performance across various electric vehicle and drone platforms. These results provide a foundation for the broader integration of intelligent control systems, particularly in autonomous and hybrid electric vehicles (HEVs).

Overall, the FIS control system offers an effective and efficient solution for controlling the speed of BLDC motors in electric vehicles. Its advantages in terms of dynamic response, energy efficiency, and adaptability to external conditions make it a highly competitive alternative to conventional controllers. With further development, this approach has the potential to become a core element in the control architecture of next-generation electric vehicles.

Conflicts of Interest: The authors declare no conflict of interest.

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