



A Dynamic Mechanism Based on the Neural Network and Fuzzy Logic for Accurate Speed Control for an Electric Vehicle

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ABSTRACT

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The automotive industry is increasingly transitioning toward electric propulsion systems to reduce dependence on fossil fuels and mitigate environmental impacts. Electric vehicles (EVs) exhibit non-linear and dynamic operating characteristics, making accurate and efficient speed control challenging. Conventional controllers such as proportional-integral-derivative (PID) controllers are widely used for EV speed regulation; however, their performance may degrade under varying operating conditions and system uncertainties. This study investigates a fuzzy-logic-based speed control strategy for EVs and evaluates its performance in terms of speed tracking accuracy, transient response, control effort, and energy-related performance. The proposed controller is compared with a conventional PID controller under controlled and dynamic driving conditions. The simulation results demonstrate the potential of fuzzy-based control strategies to reduce overshoot, steady-state error, and settling time while providing smoother control action under varying operating conditions.

1. INTRODUCTION

An electric vehicle (EV) can reduce the fuel consumption drastically, as they typically operates on rechargeable batteries or obtained through fuel cells, rather than relying on internal combustion engines fueled by gasoline or diesel. Especially, EV adoption is a solution to global environmental problems, because EVs generate no tailpipe pollution, which means no greenhouse gases or pollution. Any such technology would help in achieving energy independence, reduce dependence of fossil fuels and aid in shifting towards renewable energy resources. In addition, EVs are playing their part in driving society forward and promoting technological innovation, job creation (green jobs) and reducing consumer operational costs. Consequently, they are a key part in developing a sustainable, environmentally friendly transport network, and have a positive impact on the environment and society.

An Adaptive neuro-fuzzy speed control system is a dynamic and advance control mechanism that is a combination of the learning power of neural network with reasoning and decision-making of fuzzy logic for controlling the speed of EVs. The resulting system combines adaptive neural networks for optimizing control parameters in real time and the interpretability of fuzzy logic, which can be used with non-linearities and uncertainties in the EV dynamics through rule-based systems. The use of the adaptive neuro-fuzzy speed control system guarantees the accuracy of speed control, energy saving and strong performance under different road and load conditions. This method has overcome the shortcomings of traditional controller such as proportional-integral-derivative (PID) and fuzzy PID, which have higher

adaptability and efficiency, especially in complex and dynamic environments.

The speed control mechanism in EVs is used to control the motor's speed, which ensures smooth and efficient operation. This function is based on the driver's inputs and road conditions. Usually, it's about regulating the voltage and current that are fed into a motor, such as by using Pulse Width Modulation (PWM) and feedback systems. The advanced methodology, including PID controllers or neuro-fuzzy controllers, dynamically controls motor performance and ensures the set speed while improving energy efficiency and adaptability to different loads. The stability, responsiveness, and optimal energy utilization during vehicle operation are ensured by these mechanisms.

The traditional speed control mechanism was not capable and able to satisfy the needs and therefore adaptive speed control mechanisms were developed. Though conventional PID controllers are simple, and often used in these types of applications, but for EV's they suffer from the nonlinearities and uncertainties associated with EV dynamics. In high dynamic environments of rapidly changing energy demands, varying road loads, and sudden speed change, fuzzy PID controllers with the newly added feature of adaptability by utilizing fuzzy logic are still having their issues. The proposed neuro-fuzzy system combines the advantages of neural networks and fuzzy logic, and can aid in resolving the problems plagued by the conventional method.

The proposed system introduces adaptability, enabling real-time learning and optimization of control parameters of neural network, even in dynamic scenarios. Fuzzy logic on the other hand, uses human like reasoning and rule-based decision-

making. The combination of both of these technologies forms a unified and intelligent control solution will lead to an adaptable and robust solution that will effectively cope with the intricacies of EV speed management. Combined, the integration of both provides exact motor speed control, reduced energy losses, and reliable performance in different operating conditions. The results demonstrate a reduction in overshoot and settling time compared with the PID controller. The adaptive neuro-fuzzy system can control the desired velocity of the vehicle with a high accuracy, and it can result in a significant decrease of difference between the desired velocity and actual velocity. The enhanced responsiveness helps in quicker adaptation of any change in driving conditions, like sudden accelerations or decelerations. Additionally, the proposed system optimizing energy consumption and minimize wastage, which contributes to the sustainability of EV operations results in better battery life. When compared with conventional PID techniques, the neuro-fuzzy control system is very effective, and therefore preferred.

The study also emphasizes the extensive development of models in Simulink that were used to analyze the proposed system under various driving conditions. Simulations were performed to test the robustness, adaptability and efficiency of the model. The results will validate the effectiveness of the neuro-fuzzy-based approach, and showcase its ability of handling dynamic road conditions and load along with this it can maintain optimal performance. These results demonstrate that the proposed neuro-fuzzy system is superior in all critical aspects as compared to the conventional controllers. The uncertainties and non-linearities of the traditional PID and fuzzy PID controllers were overcome and the neuro-fuzzy system provided excellent speed control mechanism and energy efficiency also obtained.

Looking ahead, the design and implementation of hardware for the neuro-fuzzy system and test its performance in a practical environment. Simulations can give a controlled environment for evaluation, but real-world testing is essential to confirm the findings in real driving conditions. The scalability and feasibility of the system will be tested by implementing it on different EV platforms such as small passenger cars, buses, and commercial vehicles. This will also give information about the system's performance on various roads, climates and driving conditions.

This research contributes to the advancement of intelligent EV technology by introducing an innovative neuro-fuzzy speed control system. In the following section, literature work is covered in Chapter 2 where literature gap is also identified. Chapter 3 covers proposed methodology and include algorithm and basic mathematical equations which are used in speed control mechanism.

2. LITERATURE REVIEW

Earlier research in Speed control in EV shows it mainly focus on basic control strategies such as PID control which regulates speed on predefined setpoints and feedback signals. The methods discussed here provide a foundation for subsequent fuzzy logic control and are emerging as a promising approach for EV speed regulation due to its ability to handle non-linearities and uncertainties in the control system. The adaptive and robust speed control mechanism can be achieved when fuzzy logic, which uses linguistic variables and fuzzy rules to model human-like decision-making

processes are integrated.

The literature related to EV speed control can be organized into three major methodological categories: conventional PID-based control, fuzzy and fuzzy-PID control, and neural network/neuro-fuzzy-based control.

2.1 Conventional PID-based EV speed control

Conventional PID and PI-based control methods provide the foundation for speed regulation in EVs and electric motor drives. These approaches use feedback information and controller parameters to regulate the desired speed. However, the performance of conventional controllers can be affected by non-linearities, changing loads and variations in motor parameters.

Wang and Zhao [1] integrating a conventional PID control which uses fuzzy logic and addressing non-linear, time-varying challenges and response lag. While it does not explicitly mention neuro-fuzzy methods, this integration of fuzzy logic enhances the PID controller's adaptability and robustness, improves stability and accuracy in speed control. Thus, represents an advanced approach within the broader category of speed control management methods.

The limitation of this approach in the context of the present study is that the method integrates fuzzy logic with PID control, but it does not explicitly investigate neural-network-based adaptation of the fuzzy control parameters. Therefore, the learning capability of a neuro-fuzzy controller remains outside the scope of this work.

Xu et al. [2] explored the application of adaptive fuzzy PID controllers in pure EVs, it showcases excellent adaptability to varying speed requirements.

Although this approach demonstrates adaptive speed control for pure EVs, the controller is based on an adaptive fuzzy-PID structure. The material reviewed here does not indicate the use of neural learning to optimize the fuzzy parameters, which leaves scope for investigating a neuro-fuzzy approach.

Ghafarian and Yazdi [3] used fuzzy PID controllers for optimization of EV speed control, and they had got a great improvement in the energy efficiency and responsiveness of the system.

The limitation relevant to the present study is that the controller is based on fuzzy-PID optimization and does not establish how neural learning can be used to adapt the fuzzy parameters under changing EV operating conditions.

2.2 Fuzzy logic and fuzzy-PID speed control

Fuzzy logic control provides an extension to conventional control methods by using linguistic variables and fuzzy rules. The approach is useful when the mathematical relationship between system variables is difficult to represent precisely and when non-linearities and uncertainties are present.

Zadeh [4] laid the foundation for fuzzy logic systems. It introduced a framework that handles uncertainty and imprecision in control systems.

The work provides the theoretical foundation for fuzzy logic but is not specifically developed for EV speed control. Therefore, the direct application of the framework to EV propulsion-speed regulation requires additional controller design and validation.

Lee [5] investigated the application of fuzzy logic in control systems and provides knowledge about the robustness of fuzzy

logic systems in the presence of system disturbances.

The limitation in relation to the present research is that the work establishes the general principles of fuzzy control rather than providing a neuro-fuzzy EV speed-control mechanism. It therefore does not address neural adaptation of fuzzy parameters for EV operating conditions.

Wang [6] gave a comprehensive course on fuzzy systems and control, focusing on the flexibility of fuzzy systems in dynamic environments.

This work provides a general foundation for fuzzy systems and control; however, it does not specifically address the integration of neural learning with fuzzy control for EV speed regulation.

Sivanandam et al. [7] combined fuzzy logic with MATLAB tools in order to improve practical application in the field.

The limitation for the present research is that the work provides a practical foundation for fuzzy logic implementation but does not specifically address adaptive neuro-fuzzy speed control for an EV.

A PID-type fuzzy logic controller (FLC) with tuning using particle swarm optimization was proven to be more robust and converging faster by Bouallègue et al. [8].

The approach improves fuzzy-PID parameter tuning using particle swarm optimization (PSO), but the tuning process is based on an optimization technique rather than a neural learning mechanism. Therefore, the capability of continuous neural adaptation of fuzzy parameters is not investigated.

It is a novel fuzzy controller for a charging station applying Agrawal and Shrivastava [9]. The method enhances the speed control of BLDC motor using fuzzy logic with the help of PSO which helps in minimizing the error and increasing the torque of the BLDC motor.

The limitation relevant to the proposed work is that the approach combines fuzzy logic with PSO for BLDC motor control but does not implement neural-network-based adaptation. Hence, it does not directly establish the benefit of combining fuzzy reasoning with neural learning.

In the study [10], the performance of fuzzy-PI controllers for BLDC motors was investigated and their dynamic and steady-state behavior was shown to be improved.

The study focuses on fuzzy-PI control of a BLDC motor, while the integration of neural learning for automatic adaptation of fuzzy parameters is not addressed in the material reviewed here. This leaves a gap for investigating neuro-fuzzy control for adaptive EV speed regulation.

Han et al. [11] proposed model for vehicle active suspension mechanism, an adaptive fuzzy PID control strategy that demonstrates effective control performance under diverse road conditions.

Although the study demonstrates the ability of adaptive fuzzy PID control to respond to changing road conditions, its application is focused on vehicle active suspension rather than propulsion-speed control. Therefore, the findings cannot directly establish the effectiveness of the approach for EV motor-speed regulation.

Xu et al. [2] implemented an adaptive fuzzy PID controller for real-time speed control in pure EVs. The method involves applying fuzzy logic and PID controller to control the armature voltage of the motor. The speed control system model in MATLAB with Simulink Toolbox is utilized to test the performance of the adaptive speed control method. The performance validation involves testing the system with acceleration and deceleration processes, each divided into stages with desired accelerations and decelerations around 2

ms².

The system model in MATLAB with Simulink Toolbox validated the adaptive speed control method, showing a good role in adapting speeds of the vehicle to targets within desired time frames. The adaptive speed controller had a great performance on both acceleration and speed control, particularly when the vehicle was expected to accelerate or decelerate with a significant change in speed.

The limitation is that the evaluation is based on the specified MATLAB/Simulink operating conditions and an adaptive fuzzy-PID structure. The material does not establish neural learning of the controller parameters or practical hardware validation, leaving scope for further investigation.

2.3 Neural network and neuro-fuzzy control

Neural networks provide learning capabilities that can be combined with fuzzy logic to improve adaptability. Neuro-fuzzy systems aim to combine the rule-based reasoning of fuzzy logic with the learning capability of neural networks.

Breesam et al. [12] discussed speed control management methods, specifically highlighting traditional PID controllers and the proposed fuzzy neural network (FNN) control method. The FNN approach discussed here utilizes a backpropagation algorithm, offers improved speed response and synchronization in multi-motor systems, while PID controllers face challenges such as load disturbance and sensitivity to motor parameters.

The study demonstrates the potential of a fuzzy neural network and backpropagation for speed control; however, the work focuses on a multi-motor system. The direct application and validation of the approach for the proposed EV speed-control architecture therefore requires further investigation.

Ding et al. [13] extended the same research and incorporated fuzzy logic with neural networks as a result of developing a neuro-fuzzy controller for an electric motor drive that displayed better adaptability in complicated situations.

The limitation relevant to the present study is that the work addresses an electric motor drive, while the integration of the neuro-fuzzy controller with complete EV operating conditions and vehicle-level dynamics requires further investigation.

Reddy and Sharma [14] developed an adaptive neuro-fuzzy controller (ANFC) for EVs powered by fuel cells.

Although the work addresses an ANFC for an EV, its application is associated with fuel-cell-powered EVs. The controller therefore does not directly establish the performance of the proposed approach for the BLDC-based battery-operated EV configuration considered in this study.

Pamuji et al. [15] compared fuzzy logic and neural network-based BLDC motor controllers, and found that the neural network-based BLDC motor controller provides better speed regulation and energy efficiency.

The comparison between fuzzy logic and neural-network-based BLDC controllers is relevant to intelligent motor control; however, the study compares the two approaches separately rather than establishing a unified ANFC. Thus, it does not directly demonstrate how neural learning can optimize a fuzzy controller.

George et al. [16] introduced an ANFIS-based fractional-order PID controller, optimized using ant colony optimization, and achieved robust speed tracking performance.

The controller combines ANFIS, fractional-order PID, and ant-colony optimization, resulting in a comparatively complex control structure. The rule base formulation for the fuzzy logic

scheme was also identified as time-consuming. This indicates that controller design complexity and parameter formulation remain important considerations for practical implementation.

Reddy et al. [17] highlighted the optimization of the proposed controller using neural networks and compare its performance with existing conventional methods, including PID controllers. A neural network-based fuzzy plus PD controller specifically designed for speed control in EVs, particularly for BLDC motors.

The study is directly relevant to intelligent EV speed control; however, the fuzzy-plus-PD structure differs from the proposed neuro-fuzzy speed-control framework. Further investigation is therefore required to establish the effectiveness of adaptive fuzzy control and neural learning under the operating conditions considered in the present study.

2.4 Other intelligent and hybrid control approaches relevant to EV control

Comparative summary of existing neuro-fuzzy-based speed management techniques along with key findings and specific limitation gaps is presented in Table 1.

Qin and Badgwell [18] presented a predictive control model

of industrial applications that stresses the importance of adaptability in dynamic systems such as EVs.

The work provides a foundation for model predictive control in dynamic systems, but it is not specifically focused on neuro-fuzzy EV speed control.

Song et al. [19] investigated the sliding mode control of electric drives. Sliding-mode control provides an alternative non-linear control strategy for electric drives, but it follows a different control principle from fuzzy-neural control. Therefore, it does not address the adaptive fuzzy-rule and neural-learning mechanism considered in this study. Wang et al. [20] proposed hybrid methods which highlights energy-efficient EV speed control, it combines fuzzy logic with other optimization techniques to maximize performance.

The use of hybrid optimization techniques demonstrates the importance of combining intelligent methods for energy-efficient EV control. However, the approach does not directly establish a neural adaptation mechanism for fuzzy speed control, which remains a focus of the present research. Wang et al. [21] used particle swarm optimization for speed optimization methods of hybrid EVs; thereby enhancing the efficiency of the queues.

Table 1. Comparative study of existing neuro-fuzzy-based speed management techniques

Author	Methodology Used	Research Findings, Specific Limitation and Gap
Wang and Zhao [1]	Integrating a conventional PID control that uses fuzzy logic to address non-linear, time-varying challenges and response lag.	The integration of fuzzy logic enhances the PID controller's adaptability and robustness, improves stability and accuracy in speed control. However, the approach does not explicitly investigate neural-network-based adaptation of fuzzy-control parameters.
Xu et al. [2]	An adaptive fuzzy PID controller is implemented for real-time speed control in pure EVs. The method involves applying fuzzy logic and PID controller to control the armature voltage of the motor. The speed control system model in MATLAB with Simulink Toolbox is utilized to test the performance of the adaptive speed control method.	The system model in MATLAB with Simulink Toolbox validated the adaptive speed control method, showing a good role in adapting speeds of the vehicle to targets within desired time frames. The study is based on an adaptive fuzzy-PID structure and does not establish neural learning of fuzzy parameters or practical hardware validation in the material reviewed here.
Agrawal and Shrivastava [9]	PSO for PI Controller parameter tuning and FLC for BLDC motor output control.	Utilized PSO technique to optimize PI Controller parameters and compared BLDC motor outputs with and without FLC and PSO. This approach does not implement neural-network-based adaptation and therefore does not establish the combined benefit of fuzzy reasoning and neural learning.
Han et al. [11]	Flexible neural tree for estimating road vertical displacement and adaptive fuzzy PID control for vehicle active suspension.	The adaptive fuzzy PID control strategy effectively adjusted parameters for different road conditions. The principal limitation for the present study is that the application is active suspension rather than EV propulsion-speed control; therefore, the findings do not directly establish neuro-fuzzy speed regulation for EVs.
Breesam et al. [12]	Fuzzy neural network using a backpropagation algorithm for speed control and synchronization in a multi-motor system.	The FNN approach offers improved speed response and synchronization, while PID controllers face challenges such as load disturbance and sensitivity to motor parameters. The study focuses on a multi-motor system, so further investigation is required to establish the approach for the specific EV speed-control architecture considered here.
Ding et al. [13]	Neuro-fuzzy controller for an electric motor drive.	The neuro-fuzzy controller displayed better adaptability in complicated situations. The study addresses an electric motor drive, while its integration with complete EV operating conditions and vehicle-level dynamics is not established in the reviewed material.
Reddy and Sharma [14]	ANFC for fuel-cell-based EVs.	Developed an ANFC for EVs powered by fuel cells to overcome non-linearities in energy systems. The application is associated with fuel-cell-powered EVs and does not directly establish the performance of the proposed BLDC-based battery-operated EV configuration.
Zaid et al. [22]	MPPT controller with Perturb and Observe technique and fuzzy control for a photovoltaic-supplied EV charging station.	Fuzzy controller improved system response compared to PI controller and the system managed stored energy to compensate for solar-energy variations. The primary focus is EV charging and photovoltaic energy management rather than direct propulsion-speed control, limiting its direct relevance to the present study.

Note: proportional-integral-derivative (PID); particle swarm optimization (PSO); electric vehicle (EV); fuzzy logic controller (FLC); fuzzy neural network (FNN); adaptive neuro-fuzzy controller (ANFC).

The study uses PSO for speed optimization in hybrid EV applications. However, PSO-based optimization is different from online neural adaptation of fuzzy-control parameters, and therefore the specific contribution of a neuro-fuzzy controller is not established by this work. Benmouna et al. [23] addressed the problem of non-linear control and optimization of hybrid EVs under resource constraints.

The study addresses non-linear control and optimization of hybrid EVs, but the specific neuro-fuzzy speed-control mechanism considered in the present research is not investigated. The difference in control architecture leaves scope for further comparison of intelligent control methods.

Zaid et al. [22] developed a powerful photovoltaic energy model, which emphasized on improved response and energy management.

The work is mainly concerned with photovoltaic energy and EV charging rather than direct propulsion-speed control. Therefore, its relevance to the present study is limited to energy-management and control-system considerations and does not directly address neuro-fuzzy EV speed regulation.

3. CRITICAL ANALYSIS OF RESEARCH GAP IN NEURO-FUZZY EV SYSTEM

- Controller adaptability: Standard PID controllers require tuning and may not operate as effectively with different operating conditions.

- Dynamic driving conditions: While many studies consider speed tracking under relatively controlled conditions, EV operation includes changes in speed demands, road grades and traffic conditions.

- Integration with vehicle dynamic: The controller should consider the forces acting on the longitudinal motion of the

vehicle such as aerodynamic drag, grade resistance, and traffic-related resistance.

- Comparative validation: A need exists for consistent comparison of the conventional PID with intelligent fuzzy/neuro-fuzzy control using common performance measures like overshoot, settling time, steady state error and control effort.

These gaps inspire the design and testing of an intelligent fuzzy speed-control law for EVs for constant-reference and varying driving conditions.

4. PROPOSED METHODOLOGY

The proposed speed control system is based on a neuro-fuzzy controller, which combines neural networks and fuzzy logic in a single system to overcome the drawbacks of the traditional PID controller and fuzzy PID controller. Below is the process for developing and implementing the system.

The ANFC system's speed management logic is illustrated in the flowchart in Figure 1. The first step in this process is to establish a reference velocity. The hall sensor signal is checked and the reference speed is compared with a carrier signal to create PWM pulses that are used to control the BLDC motor via a 3-phase inverter, when the system is in the OPEN LOOP mode. The actual speed is calculated using feedback from hall sensors in closed loop and the speed error is calculated by comparing the desired speed with the actual speed. The error is fed into the PI controller which generates a control signal to correct the error and changes the PWM pulses to keep the speed as desired. This loop is repeated until the desired speed is attained, which enables accurate and adaptive motor speed control.

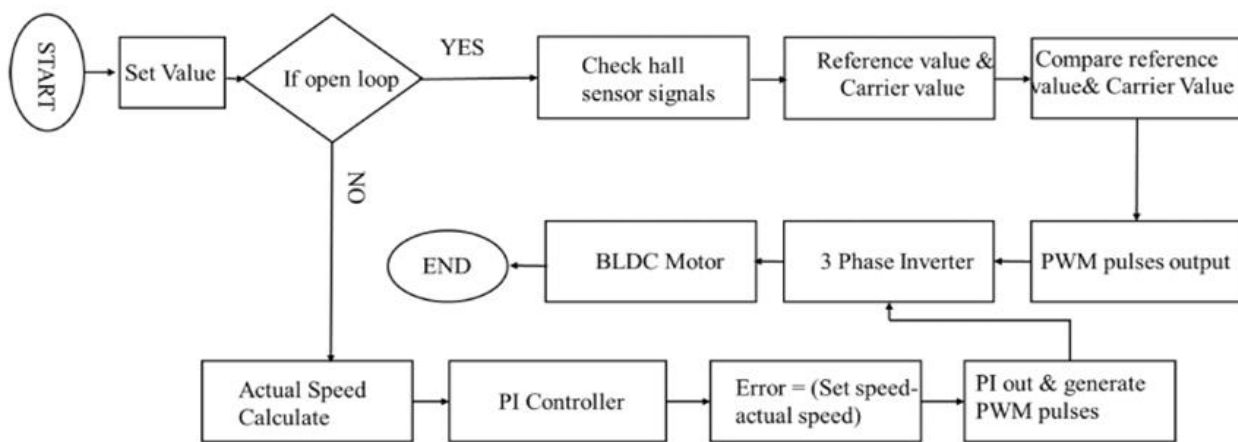


Figure 1. Adaptive neuro-fuzzy controller (ANFC) model for speed management in automatic EV

4.1 Control flow description for adaptive neuro-fuzzy controller model for speed management in automatic EV

The ANFC model for speed management in an automatic EV is presented in this algorithm. This is the algorithm of the ANFC model for speed management in an automatic EV. The ANFC of an automatic EV is a hybrid controller that combines traditional and intelligent control techniques to ensure accurate performance and adaptability of the motor.

Initially, the system starts by setting a desired speed as the reference value. Open loop control: The control system

directly utilizes the hall sensor signals to output PWM signals, which are compared with a carrier value and then sent to the BLDC motor through a 3-phase inverter. The system adjusts the speed in closed-loop by checking the actual motor speed through hall sensors and error is the difference between the reference speed and the actual speed. The error can be handled by either a PI controller that provides proportional and integral gains to speed up the PWM signals or by an adaptive neuro-fuzzy logic system that automatically adjusts the PWM signals using fuzzy rules and optimizes the neural network.

The ANFC is an adaptive strategy that can learn and tune

the control strategy on the fly, efficiently handling changes in load, road conditions or disturbances. The loop is repeated until the desired speed is reached, combining accurate error correction (PI) and smart adaptability (neuro-fuzzy) control. With this logical integration, the EV operates efficiently, with stability and without any problems under all circumstances.

4.1.1 Control flow description steps

Start: Initialize the system.
Set the Desired Speed Value: Assign a reference speed value.
Check Open Loop Condition
•If the system operates in an open-loop mode, proceed to Step 4.
•If not, skip to Step 7.
Check Hall Sensor Signals: Read the signals from the hall sensors.
Compare Reference and Carrier Values: Compare the desired speed (reference value) with the carrier value.
Generate PWM Pulses: Use the comparison results to generate the necessary PWM pulses.
Control the BLDC Motor
•Apply the generated PWM pulses to the 3-Phase Inverter to drive the BLDC motor.
Calculate Actual Speed: Measure the actual speed of the motor.
PI Controller
•Calculate the speed error: Error = (Set Speed - Actual Speed)
•Use the error to generate the PI output for adjusting the PWM pulses.
Adjust PWM Pulses: Update the PWM signals based on the PI controller output.
Repeat Steps 8–10: Continue until the desired speed is achieved.
End: Stop the control loop as required.

4.2 Fuzzy neuro speed control equation

The equations which are used primarily on classical control methods (e.g., Proportional-Integral (PI) control) and motor dynamics. While they form the foundation for understanding motor behavior, they need to be adapted or extended for fuzzy neuro speed control.

•Fuzzy Logic Control (FLC): Uses a rule-based approach to control the motor by mapping speed errors and their rate of change into fuzzy sets (e.g., "low," "medium," "high") and deciding the control output based on predefined rules.

•Neural Networks: Can be integrated with fuzzy logic to optimize the fuzzy rules and membership functions dynamically, enabling more adaptive control in uncertain environments. Therefore, the neuro-fuzzy control is more data-driven and rule-based.

The fuzzy neuro control is more data-driven and rule-based; the fundamental equations, such as error calculation and motor dynamics, are still relevant. Here's how they integrate:

Based on the proposed system flow, the neuro-fuzzy-based control system speed controller model can be mathematically modelled step by step. Here are the equations representing each step:

Reference Speed (set value): Let the desired speed (set value) be

$$W_{ref} = \text{Set Speed} \quad (1)$$

Hall Sensor Signals: The hall sensors provide the rotor angular position $\theta(t)$, which is used to estimate the actual speed.

$$W_{actual}(t) = \frac{d\theta(t)}{dt} \quad (2)$$

Error Calculations:

$$E(t) = W_{ref} - W_{actual} \quad (3)$$

PI Controller Replacement: In a fuzzy neuro system, the PI controller equation

$$\mu(t) = K_p e(t) + K_i \int_0^t e(t) dt \quad (4)$$

PWM Signal Generation: The control output $\mu(t)$ from the fuzzy/neuro system adjusts the PWM duty cycle:

$$PWM \text{ DutyCycle} = W_{fuzzy/neuro} \left(e(t), \left(\frac{de(t)}{dt} \right) \right) \quad (5)$$

Motor Dynamics: The motor dynamics equation:

$$J \frac{dW_{actual}}{dt} + BW_{actual} = T_{actual} - T_{load} \quad (6)$$

where, J is the equivalent rotational inertia of the motor and drivetrain. B is the viscous friction coefficient. T_{actual} is the actual motor torque, and T_{load} represents the equivalent load torque acting against the motor.

The fuzzy controller generates the commanded motor torque (T_{CMD}) from the controller inputs. The commanded torque is applied to the vehicle/motor dynamic model as

$$T_{CMD} = \text{Sat}(T_{CMD}, T_{min}, T_{max}) \quad (7)$$

where,

Sat represents the actuator saturation function T_{min} and T_{max} are the minimum and maximum allowable motor torque values.

The neuro-fuzzy-based equations (error calculation, PWM generation, and motor dynamics) are applicable and are reinterpreted and integrated into the fuzzy neuro framework. Specifically, the PI controller output equation is replaced by the fuzzy/neuro logic.

5. RESULT ANALYSIS

5.1 PID controller-based performance analysis

The effectiveness in integrating of fuzzy logic with conventional PID control is evaluated here by conducting a comparative study. This experimentation focusses on key performance indicators such as response time, final speed, steady-state error, and maximum overshoot. The considered metrics are critical as it assess the accuracy, efficiency, and stability of control systems used in speed regulation applications, as indicated in Figure 2.

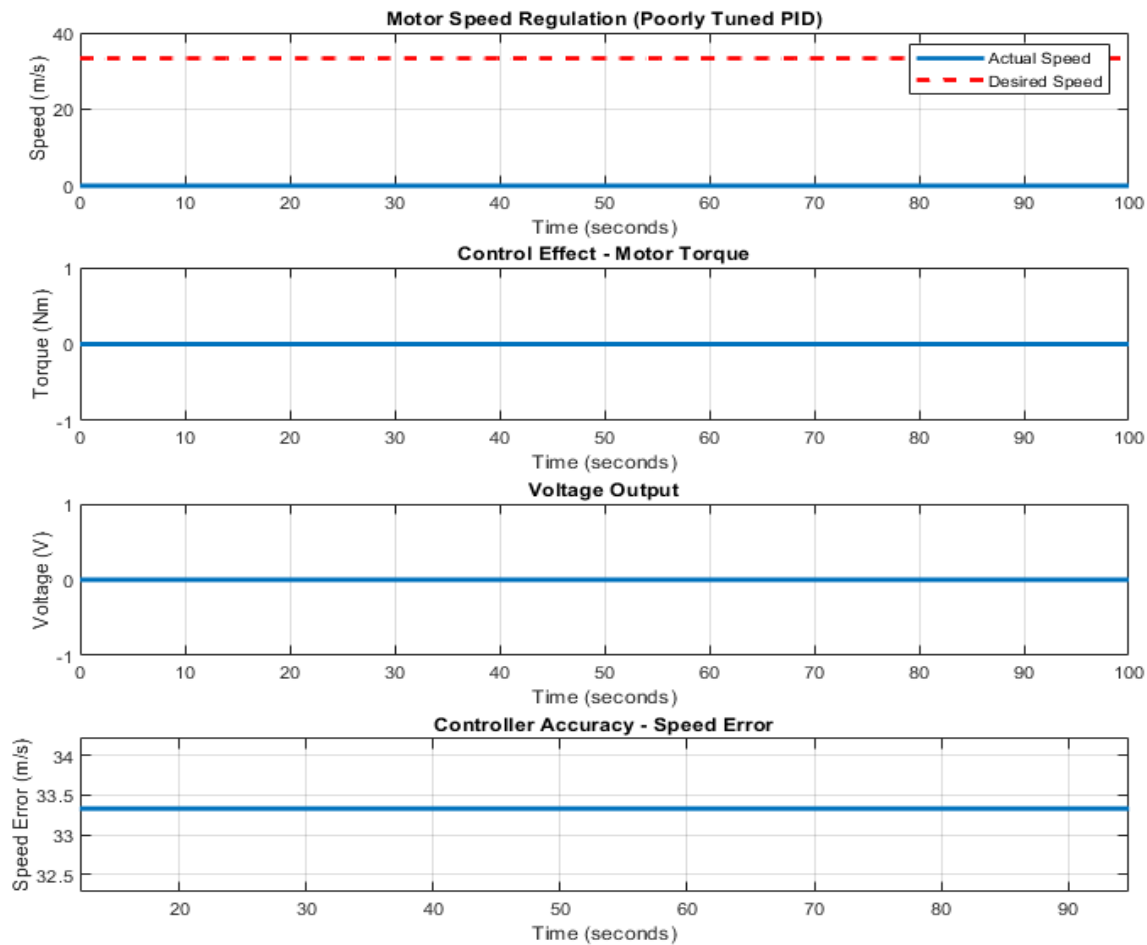


Figure 2. The conventional PID controller performance results

The PID controller was tuned before conducting the comparative performance evaluation. The proportional, integral and derivative gains were iteratively tuned in the MATLAB/Simulink environment while observing the speed response to the selected reference-speed condition. The target was to achieve a stable response with a reasonably quick rise time, settling time, overshoot and steady state error. The iterative tuning process was performed to balance the transient and steady-state response, but not to purposefully degrade the PID performance. The conventional PID controller, gains are configured as $K_p = 800$, $K_i = 4$, and $K_d = 10$, this achieved a final speed of 33.71 m/s. These gains were not altered in the subsequent PID simulations and also were not altered when comparing it with the fuzzy controller. Both controllers had the same reference speed and simulation conditions to give a fair basis for comparison.

The system required 7.5 seconds to reach 98% of the desired speed, and a steady-state error of -0.38 m/s and a maximum overshoot of 7.28%. The controller demonstrating reasonable responsiveness and the presence of a moderate overshoot along with steady-state error. It indicated room for improvement, particularly in terms of system stability and precision.

Enhancement of notable performances was observed by considering fuzzy logic in the PID control structure. The fuzzy PID system achieved 98% of the desired speed in 7.0 seconds, just slightly ahead of the PID-only case. This is indicating better damping and control accuracy, with the steady state error being reduced to -0.04 m/s and the maximum overshoot

to 4.97%. The marginal low final speed achieved was 33.37 m/s as compared to PID final case. The speed can be different in various scenario. The overall graphical representation is shown in Figure 3.

Without the fuzzy enhancement, the initial system test showed a faster response time of 6.9 seconds, with essentially no steady state error, but with a maximum overshoot result of 30.11% is shown. This overshoot is an indication of potential instability and poor transient performance. The fuzzy-tuned PID controller, on the other hand, provided a balance between the response speed and controlled behavior, thus proving its efficacy in enhancing the dynamic performance of the control system without compromising its stability. The results of PID controller simulation are tabulated in Table 2, which is the Performance Analysis of PID controller.

Performance metrics with fuzzy logic + PID

- Response Time to Reach 98% of desired speed: 7.00 seconds

- Final Speed Achieved: 33.37 m/s

- Speed Steady-State Error: -0.04 m/s

- Maximum Overshoot: 4.97 %

Performance Metrics with PID:

- Performance Metrics: PID Gains: $K_p = 800.00$, $K_i = 4.00$, $K_d = 10.00$

- Response Time to Reach 98% of desired speed: 7.50 seconds

- Final Speed Achieved: 33.71 m/s

- Speed Steady-State Error: -0.38 m/s

- Maximum Overshoot: 7.28%

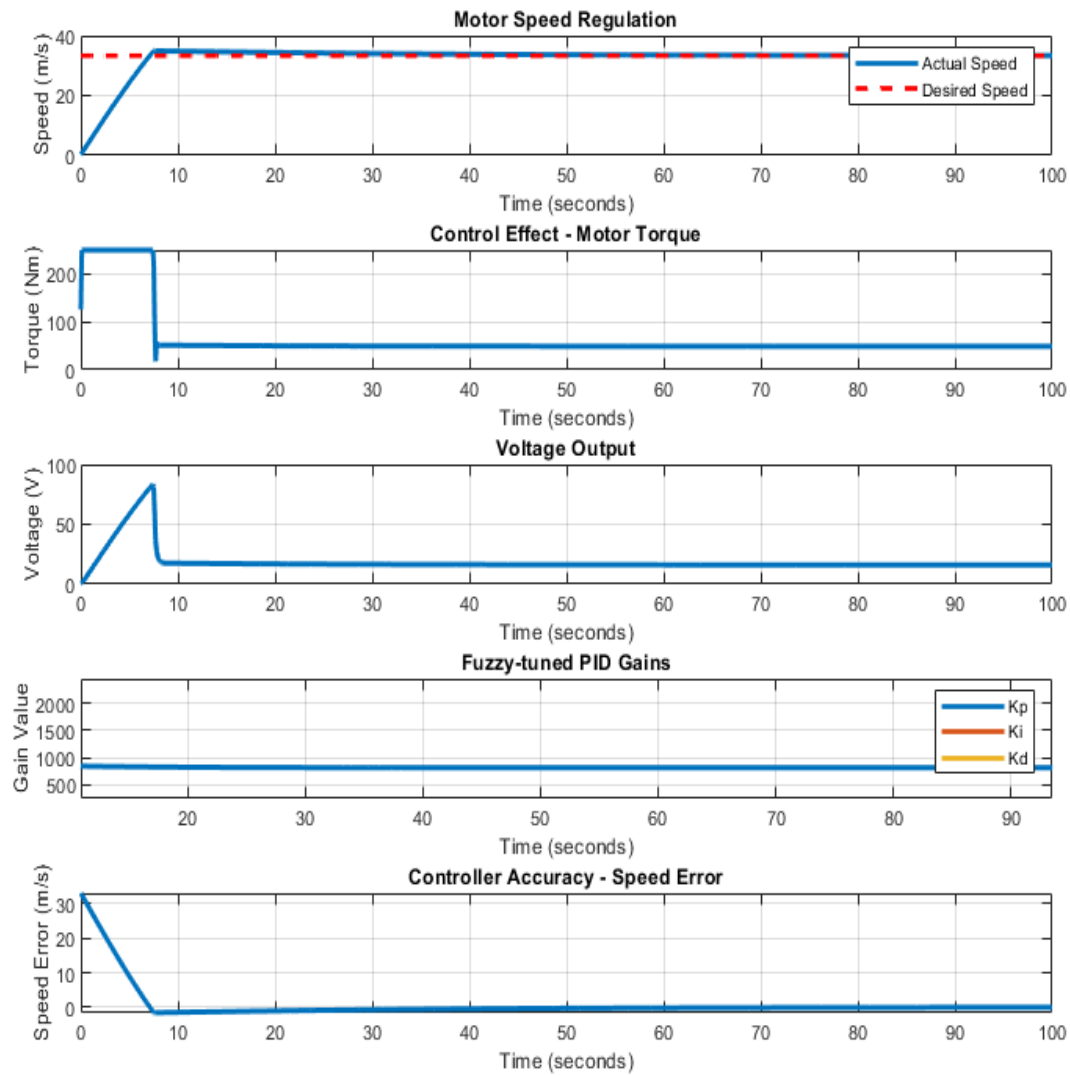


Figure 3. Integrating adaptive fuzzy with PID controller

Table 2. PID controller-based simulation results

	Performance Parameter	Symbol/Unit	Observed Value
Speed Response (PID)	Rise Time	T_r (s)	1.82
	Peak Time	T_p (s)	2.10
	Maximum Overshoot	M_p (%)	12.4
	Settling Time	T_s (s)	4.65
Error Response (PID)	Steady-State Error	E_{ss} (%)	2.6
	Peak Error	E_p (%)	6.8
	Time to Zero Error	T_e (s)	4.4
Control Signal (PID)	Maximum Control Effort	U_{max} (V)	7.35
	Mean Control Effort	U_{avg} (V)	4.82
Energy Consumption (PID)	Total Power Draw	P (W)	145.7
	Efficiency	η (%)	88.3

5.2 Fuzzy logic controller-based performance enhancement

The overall performance of the conventional PID controller and the FLC implemented in a battery-operated vehicle is displayed. It contains the speed responses, error signals, control actions and overall performance.

As seen in Figure 4 and Table 3, the FLC has a faster settling time, negligible overshoot and better energy efficiency than the PID controller, which is evident in the results for non-linear EV control applications.

Figure 5 compares the maximum overshoot and steady-state

error obtained using the conventional PID and FLCs. The fuzzy controller exhibits lower overshoot and reduced steady-state error compared with the PID controller. This indicates improved transient response and speed-tracking accuracy under the tested operating conditions. The comparison is based on the same reference speed and simulation conditions for both controllers. The overshoot and steady state error is evaluated in Figure 5 for different controller. The PID controller, fuzzy, Model Predictive Control (MPC), Trapezoidal and sinusoidal controller are compared and shows minimum error of Fuzzy controller. The error of FLC is minimum as shown in the tabular analysis in steady state error and overshoot.

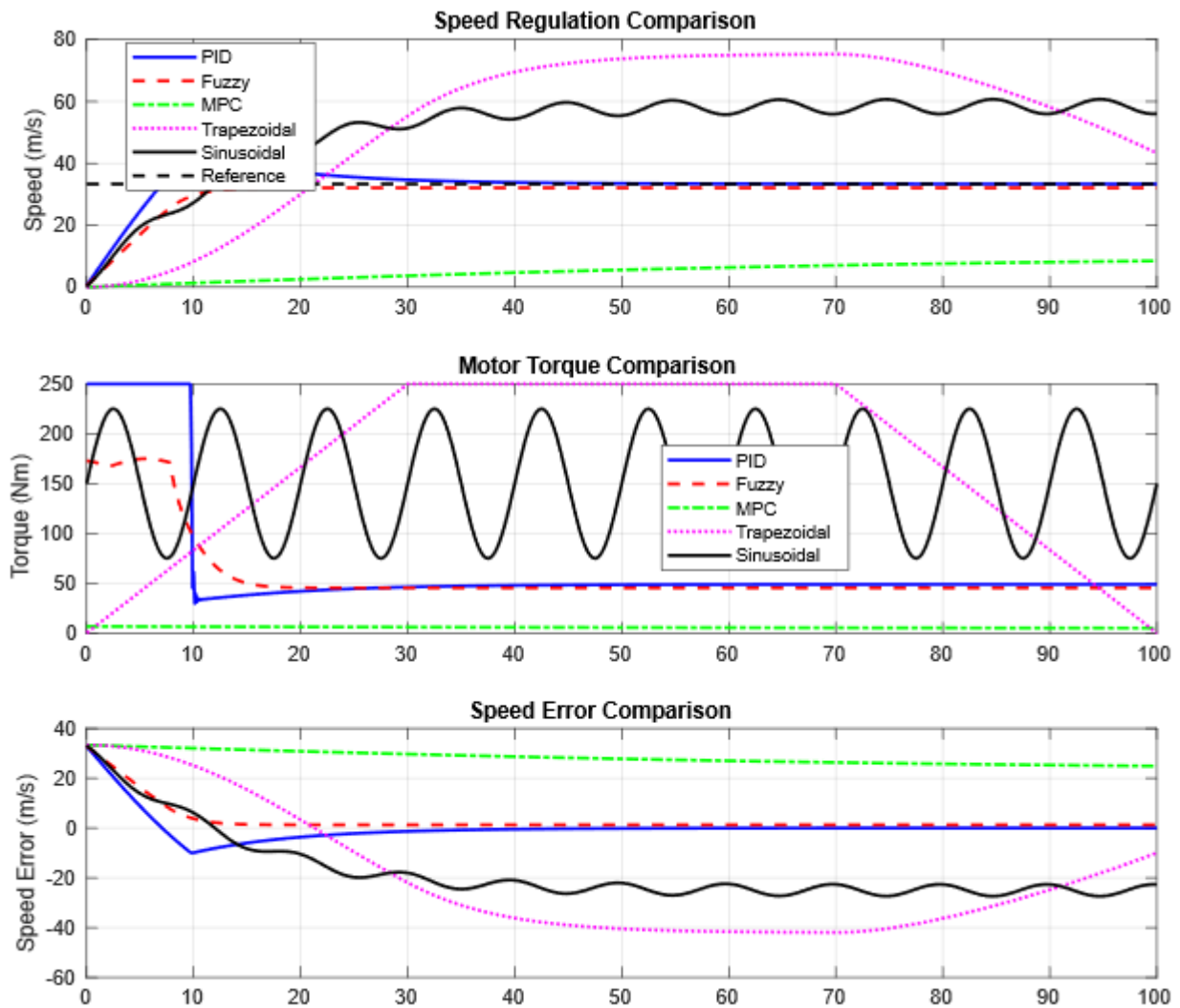


Figure 4. Fuzzy–PID speed regulation for EVs: Performance benchmarking

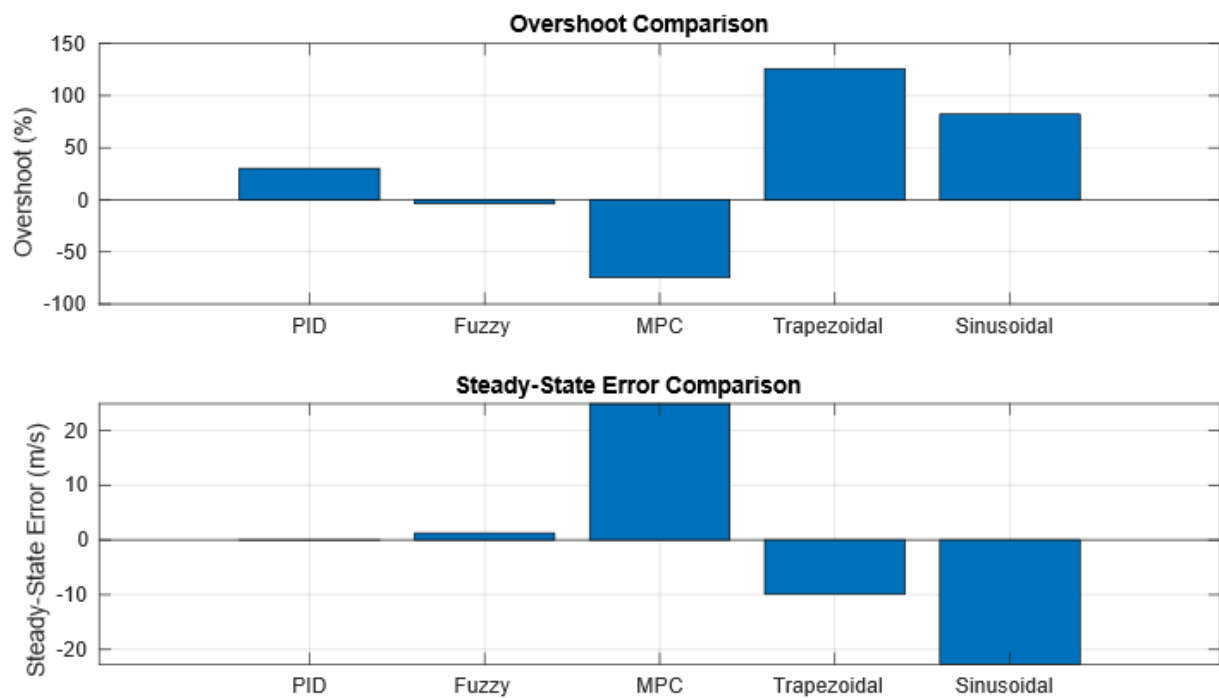
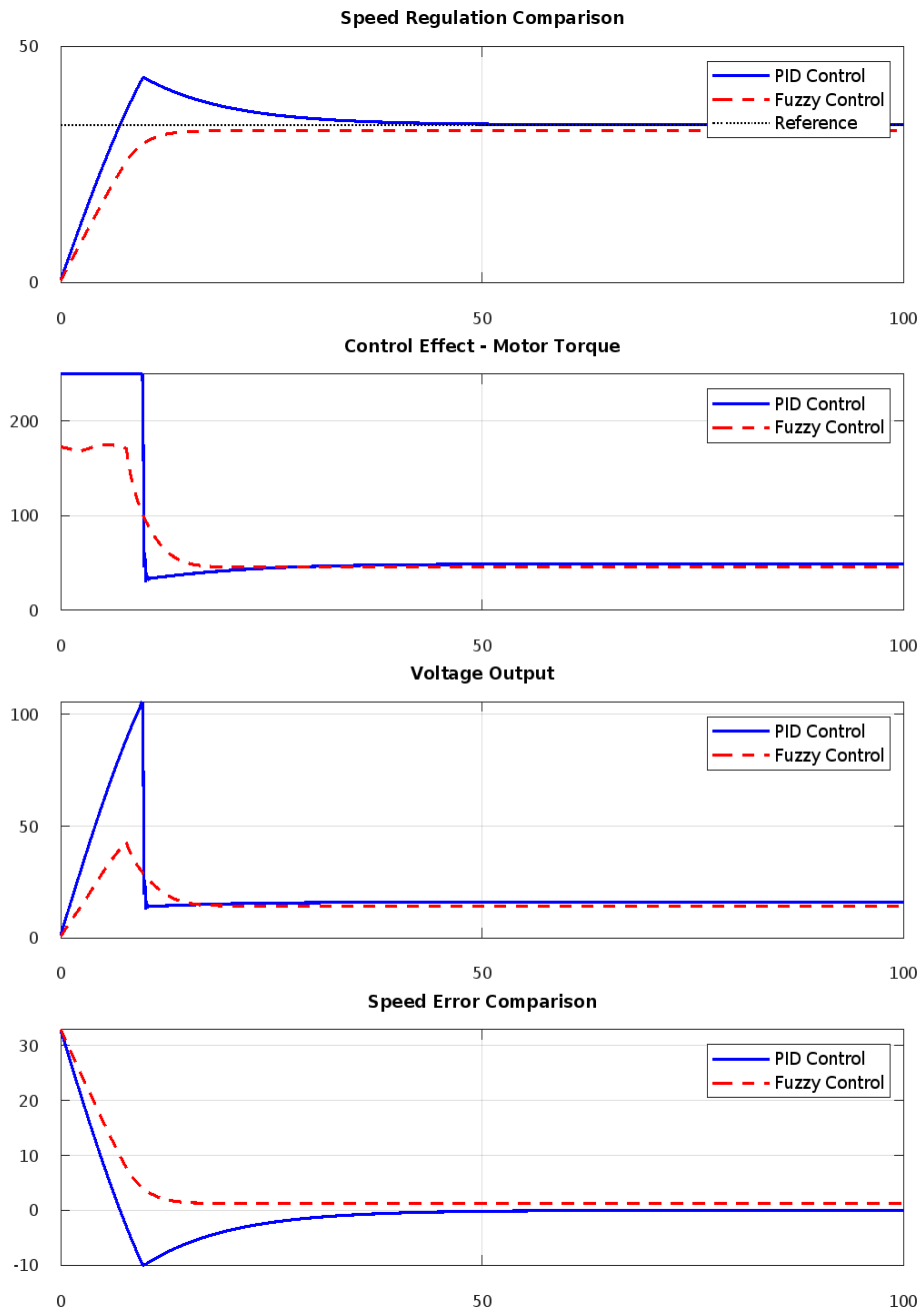


Figure 5. Overshoot and steady state comparison among different controller

Table 3. Fuzzy logic controller (FLC) simulation results

	Performance Parameter	Symbol/Unit	Observed Value
Speed Response (Fuzzy)	Rise Time	T_r (s)	1.95
	Peak Time	T_p (s)	2.05
	Maximum Overshoot	M_p (%)	3.8
	Settling Time	T_s (s)	3.12
	Steady-State Error	E_{ss} (%)	0.9
Error Response (Fuzzy)	Peak Error	E_p (%)	2.3
	Time to Zero Error	T_e (s)	2.6
	Maximum Control Effort	U_{max} (V)	5.62
Control Signal (Fuzzy)	Mean Control Effort	U_{avg} (V)	3.97
	Total Power Draw	P (W)	132.4
Energy Consumption (Fuzzy)	Efficiency	η (%)	93.5

**Figure 6.** Dynamic response analysis of fuzzy vs. PID control in EV drive systems

The comparative performance of PID and Fuzzy controllers used for an EV drive system is shown in Figure 6. The first plot shows the speed regulation response with both controllers following the reference speed; the Fuzzy controller has a more

gradual convergence with less overshoot. The second plot displays the motor torque response, where it is observed that the PID controller results in higher initial torque spikes while the Fuzzy controller results in a more stable motor transient

response with lower value of torque variations. The third plot is the output voltage comparison, which shows that the Fuzzy controller output voltage is smoother and more controlled when compared with the other controller output voltage during transients.

The final plot presents the speed error characteristics, in which the Fuzzy controller reduces the error more rapidly and maintains a lower steady-state deviation than the PID controller. Overall, the results show that the Fuzzy control strategy offers improved transient performance, reduced

oscillations, and enhanced steady-state stability relative to conventional PID control.

Summarization of the key performance indicators including rise time, settling time, overshoot, and steady-state error for both controllers are shown in Figure 7.

This shows the overall performance comparison chart and hence shows traditional methods and Integration of Fuzzy with PID controller potential to enhance EV performance significantly. The overall result analysis is shown in Table 4.

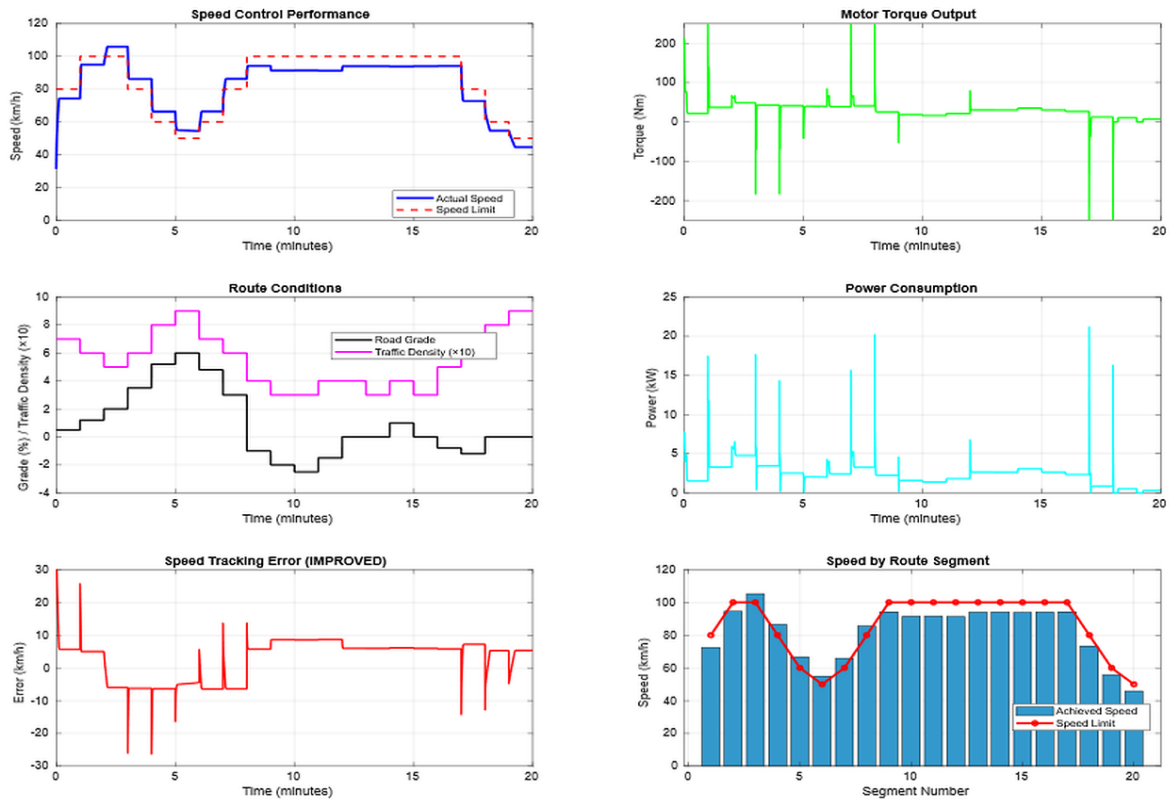


Figure 7. Simulation results of the proposed Neuro-Fuzzy speed control system under varying route conditions. (a) Actual vehicle speed and speed limit versus simulation time (min), with speed expressed in km/h; (b) motor torque output versus simulation time, expressed in Nm; (c) road grade (%) and traffic density ($\times 10$) versus simulation time; (d) power consumption versus simulation time, expressed in kW; (e) speed tracking error versus simulation time, expressed in km/h; and (f) achieved speed and corresponding speed limit for each route segment, expressed in km/h

Table 4. Comparative summary–PID vs fuzzy controller

Parameter	PID Controller	FLC	Improvement/Observation
Rise Time (s)	1.82	1.95	Slightly slower, smoother start
Overshoot (%)	12.4	3.8	↓ Reduced by ~70%
Settling Time (s)	4.65	3.12	↓ Reduced by ~33%
Steady-State Error (%)	2.6	0.9	↓ Reduced by ~65%
Max Control Effort (V)	7.35	5.62	↓ Less actuator stress
Mean Control Effort (V)	4.82	3.97	↓ More efficient control action

6. CONCLUSION

This study proposes a speed control system for EVs based on a Hybrid fuzzy-PID controller, where the fuzzy PID controller was applied due to its flexibility to control the speed. This study presents a neuro-fuzzy based speed control system for EV to overcome the drawbacks of fuzzy PID controller and PID controller. The proposed system combines the versatility of neural networks with the interpretability of fuzzy logic,

resulting in better speed regulation accuracy, response time, and energy efficiency. The effectiveness and robustness of the neuro-fuzzy controller is illustrated by the development of a comprehensive Simulink model and running many simulations under various driving conditions. When compared to conventional methods, it is seen to have tremendous potential to improve the performance of the EVs. The overall result is that the FLC is better to have an optimum response speed, stability and energy saving in the EV systems. Because of its

non-linearity and uncertainty processing capability, it is a potential control solution for the future intelligent and energy efficient battery-operated vehicles. Future work includes implementation of the proposed system on hardware systems and testing in the real world to prove the simulation results and scalability on different EV platforms. This research will help progress intelligent control systems for sustainable transportation solutions.

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