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COMPARATIVE STUDY OF ENERGY MANAGEMENT STRATEGIES FOR HYBRID ELECTRIC VEHICLE WITH HYBRID ENERGY STORAGE SYSTEM

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ABSTRACT

This analysis focus on the enhancement of Artificial Neural Networks (ANN) and Fuzzy Logic Controller (FLC) based Energy Management System (EMS) for Hybrid Electric Vehicle (HEV) with hybrid energy storage system (HESS). The EMS plays a vital role in HEVs by enhancing driving range and reducing operational costs. This article explores energy management and optimization strategy for HEV using HESS consisting of a lithium-ion battery pack and an ultracapacitor (UC) pack. The proposed approach employs FLC and ANN to enhance key battery performance metrics, including state of charge, driving range, and lifespan. A parametric comparison with a conventional PID controller is also provided. While battery powered HEV offer high energy density, low environmental impact, and dependable operation, the addition of UC's further improves their ability to manage rapid power demands. Simulink is used to simulate the system's performance and evaluate the effectiveness of each intelligent control method. The results of the comparative analysis highlight the optimal strategy for efficient energy management in HEV.

I. OVERVIEW

EV's deliver notable ecological, engineering, and economic advantages, facilitating a level of integration between energy supply networks and transportation systems that was previously unattainable. This integration is largely enabled by the EV battery, which serves as the primary source of power for propulsion, control circuits, HVAC units, and auxiliary loads. Nevertheless, grid-connected EV charging imposes additional strain on utility infrastructure, especially during times of elevated demand [1]. HEV consist different types of energy sources and power converters, which generally refer to vehicles consisting of an internal combustion engine (ICE) with an electric motor. The general goal to develop HEVs is to reduce fuel consumption and emissions while ensuring drivers power demands by investigating the appropriate EMS. EMS aims to obtain an optimal power split in view of complex driving conditions, as well as to minimize fuel consumption and emissions. It is commonly acknowledged that improvements in the fuel economy of HEVs, and thus the consequent reduction in emissions, depend crucially on their EMS [2].

The main objective of EMS is to instantaneously manage the power flows from the energy converters to achieve the control objectives. In recent years, AI applications have advanced rapidly across research, engineering, and industry. In power electronic systems, various machine learning methods, algorithms that learn from data and improve automatically through experience are especially promising for numerous tasks, including fault diagnosis, predictive maintenance, reliability forecasting, quality control, control design, reverse engineering, advanced modeling and system optimization [3]. EMS can be divided into three categories: rule-based EMSs, local optimization-based EMSs, and global optimization-based EMSs. The classification of energy management such as optimization-based control strategies and rule-based control strategies are introduced according to their mathematical models and the approach commonly used [4].

ANN trained using datasets that could be obtained from simulations, experimental measurements, datasheets, publications, and other sources. In this methodology, the ANNs themselves do not incorporate any explicit physics-based modeling; only the input and output variables retain a clear physical interpretation [5]. However, to compete effectively with traditional multi-objective optimization algorithms and models, machine learning approaches must address several key challenges and avoid common pitfalls. These include ensuring that the models are:

- Accurate and robust
- Versatile and flexible
- Extensible and adaptable
- Capable of providing access to internal data
- Supported by sufficient and high-quality datasets

An ultracapacitor also known as a supercapacitor, is a highly durable energy storage device capable of charging and discharging electrical energy at much faster rates than conventional batteries. Unlike batteries, which store energy through electrochemical reactions, capacitors store energy in an electric field formed between two electrodes. However, traditional capacitors have limited energy storage capacity because they rely solely on the accumulation of electrons, leading to charge repulsion that restricts the total amount of energy that can be stored [6]. The authors in [7] proposed various control strategies for different energy storage systems. In their approach, a hybrid control strategy was implemented to enhance the state of charge (SOC) of the battery through the integration of UC. As a result, the overall driving range of the electric vehicle was improved using FLC. The paper presents a comprehensive Simulink model representing the complete energy management network of an integrated electric vehicle powertrain powered by both a lithium-ion battery and UC. The lithium-ion battery serves as the primary energy storage device, offering fast response characteristics, low self-discharge rate, long cycle life, and high energy density. The authors in [8] proposed comparison of fuzzy logic and neural network in maximum power point tracker for PV systems using various control strategies for PV system.

The paper presents a comprehensive Simulink model representing FLC can deliver more power than the neural network controller and can give more power than other different methods.The concept of EV evolved through the integration of various energy storage technologies, including batteries, UCs and fuel cells (FCs). Subsequent advancements in EV technology led to the development of HEVs, which combine multiple energy sources to improve efficiency and ensure a continuous power supply during vehicle operation [9],[10]. The primary objective of this paper is to enhance the SOC of the energy storage system, thereby extending the driving range of the HEV. The operation of the HEV is managed using ANN, FLC and other effective control methods [11]. This approach enables real-time supervisory control, and the obtained results are compared with those of a conventional PID controller [12]. The paper is organized as follows: Section 1 overview of the research topic. Section 2 details the system description. The FLC for hybrid system is described in Section 3. ANN controller explained in Section 4. Evaluation and discussion of results are presented in Section 5, and the paper concludes in Section 6. This structured approach ensures a comprehensive understanding of the development and implementation of FLC and ANN controller for HEV system, addressing key challenges and highlighting the advancements over traditional control methods.

II. SYSTEM ARCHITECTURE

This Integrated system comprises a Battery-UC connected to loads, including an EV. The key energy sources in this hybrid setup are the Battery and UC to facilitate the integration of these sources, dc–dc converters are employed.

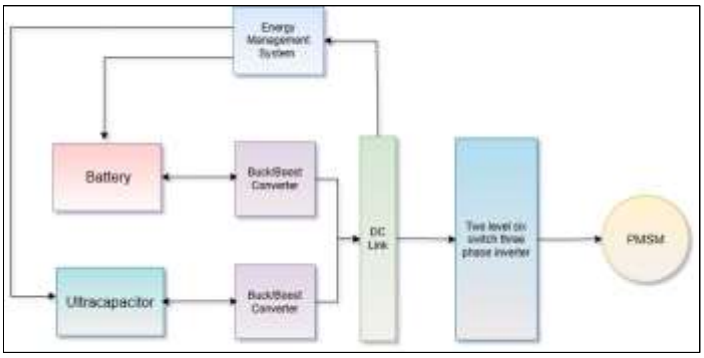


Figure 1: Electric Vehicle Connected Hybrid System.
Source: Authors, (2026).

This arrangement allows for efficient conversion and management of electrical power between the Battery-UC hybrid source and Electric vehicle, contributing to a comprehensive and well-integrated hybrid energy system [13]. From Figure 1 the Buck/Boost converter linked to the Battery array serves as an optimal power tracking controller. UC is connected to the Buck/Boost converter and these two systems commonly connected to DC link. DC link is connected to the Two level six switch three phase inverter which is connected to the PMSM and connected to the wheels of an electric vehicle. At the condition of starting of vehicle it requires full acceleration then both Battery and UC will work, after reaching to accelerated point for smooth operation battery will works and UC will charge [14]. At the condition of regenerative braking three phase converter will work like a rectifier and battery charges. EMS plays a key role in maintaining SOC of the battery. By maintaining Duty ratio of the DC link voltage, we can improve the SOC of vehicle battery. This can be done by using FLC and ANN which is used to control the battery SOC. Where PID controller also used in electric vehicle for maintaining SOC and to improve battery range but Fuzzy controller and ANN gives better performance which will be compared in the results section.

III. FUZZY CONTROLLER FOR HYBRID SYSTEM

The battery charge controller block is responsible for regulating the charging and discharging processes of the battery while the EV is in operation. It receives the error in DC link voltage and the change in this error as inputs, and based on a predefined set of fuzzy rules, it generates a duty ratio as the output. By continuously monitoring the DC link voltage and its rate of change, the HEV can achieve optimized and intelligent energy management [15], [16]. Through the application of PWM techniques, the controller maintains and adjusts the SOC of the battery, thereby enhancing the vehicle's driving range. The FLC plays a crucial role in managing various converters and has recently been employed for regulating the SOC of batteries in HEV. The controller's performance depends on multiple system variables, making it essential to effectively coordinate all parameters in response to changes in battery conditions. In this context, the FLC proves to be an optimal solution, demonstrating strong capability in maintaining the desired SOC and improving overall energy management efficiency [17]. The design of the FLC primarily involves the careful selection of input and output variables, along with the definition of appropriate membership functions [18]. These membership functions are used in the max–min composition process and combined using logical AND/OR rules to generate the controller's output. This approach ensures that the output accurately represents the system's dynamic behavior based on the defined input variables and control rules.

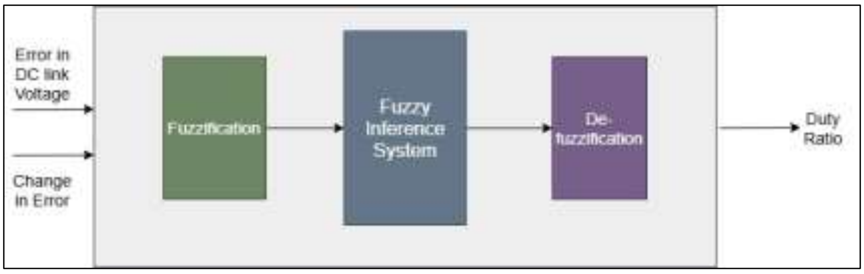


Figure 2: Working of Fuzzy logic controller for HEV.
Source: Authors, (2026).

Figure 2 illustrates the working principle of the FLC. The controller receives two input variables: the error in the DC link voltage and the change in this error. The process begins with fuzzification, where the fuzzifier converts these crisp input values into corresponding fuzzy sets. Next, the fuzzy inference system (FIS) applies a set of predefined fuzzy rules to evaluate the fuzzified inputs and generate an intermediate fuzzy output. Finally, this output is passed through the defuzzification stage, which converts it back into a crisp value representing the duty ratio, serving as the final control signal for the system.

III.1 MEMBERSHIP FUNCTIONS

The input is classified into 7 types that are negative big (NB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM) and positive big (PB) [19]. Error in dc link voltage value in range between -200 to +200. Similarly, the change in error input function also 7 membership functions for each input. The range is taken -1 to +1 and the duty ratio output function also 7 membership function and range taken between -100 to +100. Table 1 presents the rule-based approach for managing various input value ranges in the fuzzy charge control system.

Table 1: Rule strategy for Duty ratio.

Duty Ratio		**Error**						
		NB	**NM**	**NS**	**Z**	**PS**	**PM**	**PB**
Change in Error	**PS**	Z	PS	PM	PB	PB	PB	PB
	PM	NS	Z	PS	PM	PB	PB	PB
	PB	NM	NS	Z	PS	PM	PB	PB
	Z	NB	NM	NS	Z	PS	PM	PB
	NS	NB	NB	NM	NS	Z	PS	PM
	NM	NB	NB	NB	NM	NS	Z	PS
	NB	NB	NB	NB	NB	NM	NS	Z

Source: Authors, (2026).

IV. ANN CONTROLLER FOR HYBRID SYSTEM

ANNs have become increasingly popular and are now among the most commonly used learning algorithms for identifying complex relationships within datasets. In this paper, ANN is utilized to improve the estimation of the battery's SOC [20]. Due to their strong processing capabilities, ANNs can deliver highly satisfactory results, particularly in complex pattern recognition problems. The principle of an ANN is inspired by the structure and function of the human brain. In a biological brain, a large number of neurons are interconnected, forming a network that processes inputs received from sensory receptors. Similarly, in ANN, artificial neurons are interconnected, with each neuron belonging to a specific layer within the network [21]. From figure 3 the general architecture of the ANN used in this work consists of three layers input layer,hidden layer and the output layer. Each neuron in one layer is connected to all neurons in the subsequent layer through weighted connections. The process begins when neurons in the input layer receive input values and pass them to the neurons in the hidden layer. The hidden layer processes these values, and its number of layers defines the depth of the network. Finally, the output layer generates the final output of the network. During this process, each neuron applies a mathematical operation that combines the weighted sum of its inputs through an activation function, enabling the ANN to perform nonlinear transformations and learn complex mappings between inputs and output [22], [23].

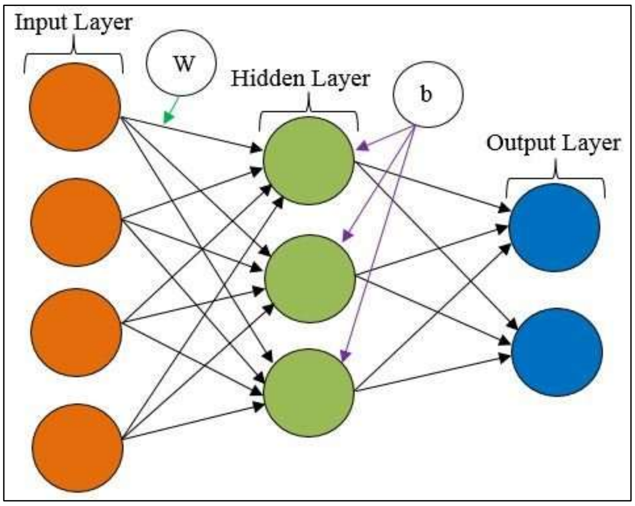


Figure 3: Architecture of ANN.
Source: Authors, (2026).

In this application, ANN is an effective method for improving SOC estimation, which requires modeling a nonlinear function. The hidden layers in an ANN learn to map the relationships between inputs and outputs, enabling the network to represent both linear and nonlinear functions.

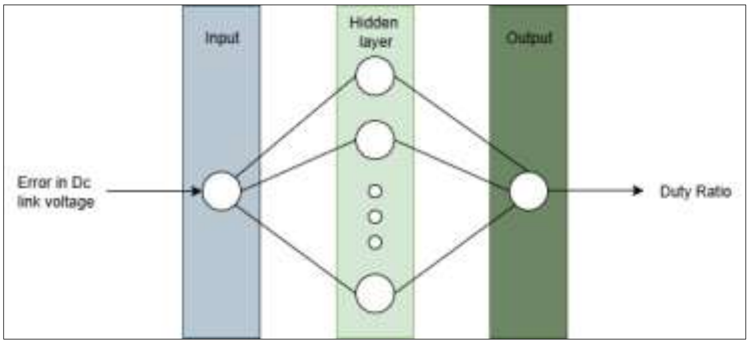


Figure 4: ANN based SOC controller.
Source: Authors, (2026).

V. RESULTS AND DISCUSSIONS

The key advantage of such systems is their adherence to precise rules, ensuring execution within the specified rule limits. Utilizing the dc link voltage battery SOC can enhance, enabling the hybrid mode for longer-distance travel. The Simulink model used to simulate PID controller, FLC and ANN controller is represented in Figure 5 and Figure 6.

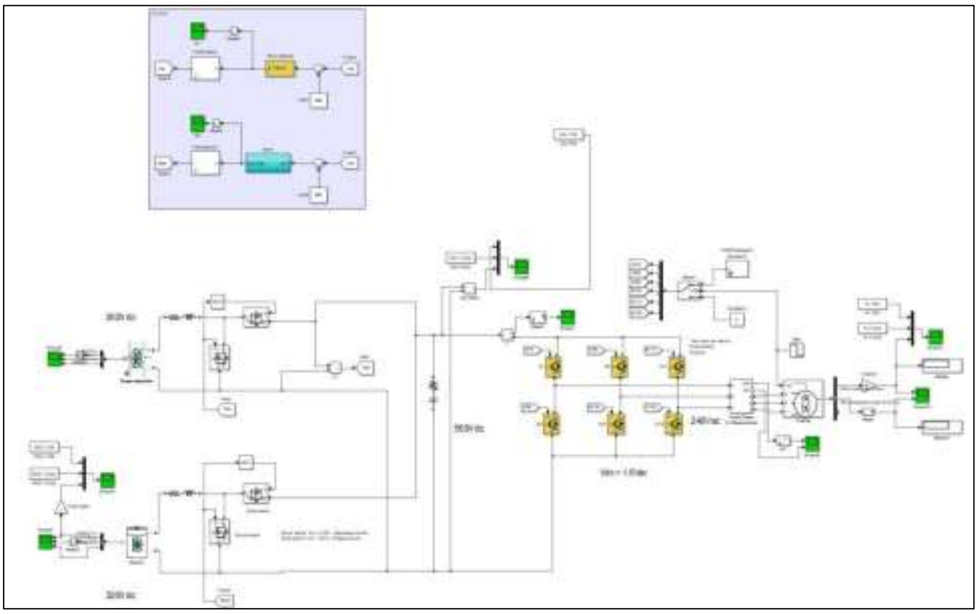


Figure 5: Simulink Model of Hybrid System.
Source: Authors, (2026).

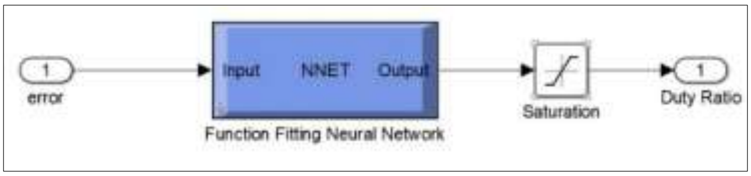


Figure 6: ANN controller of Hybrid System.
Source: Authors, (2026).

The preceding section's model is simulated and the results are provided in the following two conditions, that are:

- At starting condition and
- At braking condition

At starting condition both battery and UC discharges and three phase converter works as a rectifier which is connected to the PMSM drive. From 0 sec to 4 sec considered as the starting and normal driving of the vehicle. Braking applied at 4 sec then motor works like a generator and three phase converter works as an inverter then battery stores energy by using regenerative braking method. From Figure 7 the SOC curve of battery with PID controller is initially at 100% and gradually decreases to 99.892% up to braking condition of 4 sec. At the time of braking condition, the motor will work as a generator and charges the battery from 4 sec to 5 sec from 99.892% to 99.896%. With FLC the SOC curve of the battery is initially at 100% and gradually decreases to 99.946% up to braking condition of 4 sec. At the time of braking condition, from 4 sec to 5 sec battery charges from 99.946% to 99.952%. With ANN controller the SOC curve of battery is initially at 100% and gradually decreases to 99.922% up to braking condition of 4 sec. At the time of braking condition, from 4 sec to 5 sec battery charges from 99.922% to 99.928%. we can conclude that by using FLC battery SOC maintained smoothly and driving range also increases at the end.

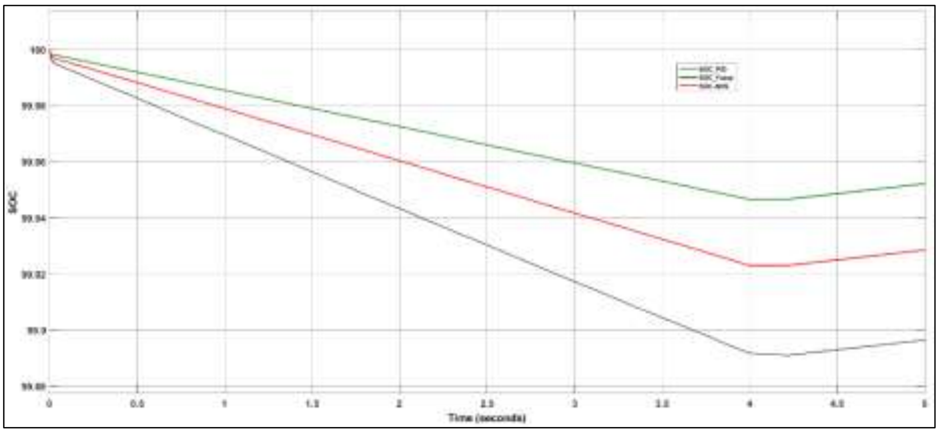


Figure 7: Battery SOC using PID and Fuzzy controller.
Source: Authors, (2026).

Figure 8 shows dc link voltage of PID controller, fuzzy and ANN controller. Using an ANN controller reduces ripples more effectively than a fuzzy controller. By minimizing ripples in the DC-link voltage, the voltage error is decreased and the SOC is improved.

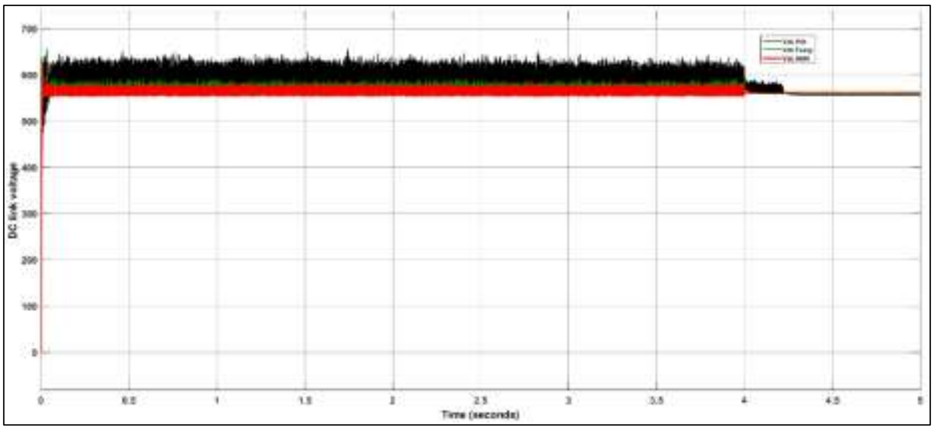


Figure 8: DC link voltage of PID, Fuzzy and ANN controller.
Source: Authors, (2026).

Figure 9 shows the speed characteristics of PID, FLC and ANN controller, where the simulation implemented with same speed and torque parameters but there is a smooth operation with Fuzzy and ANN controller.

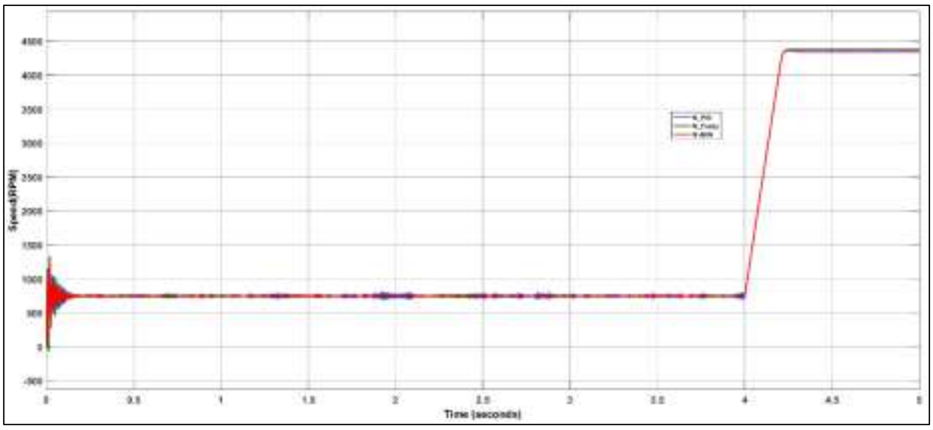
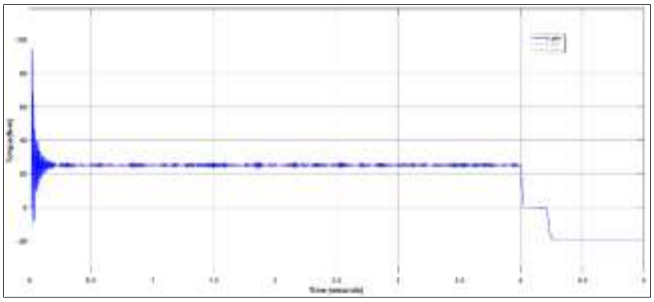
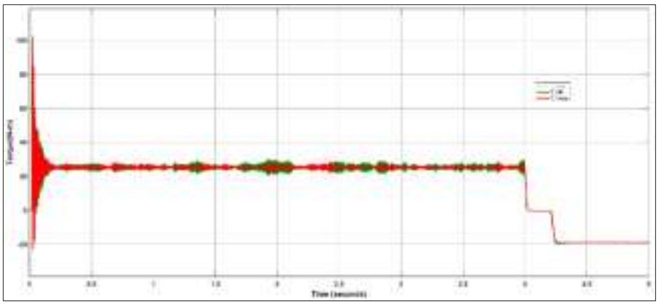


Figure 9: Speed characteristics of PID, Fuzzy and ANN controller.
Source: Authors, (2026).

Figure 10 shows the torque characteristics of PID, FLC and ANN controller, where the simulation implemented with same speed and torque parameters but ripples reduced with FLC and ANN controller. At the braking condition torque to the negative condition and battery charges using inverter.



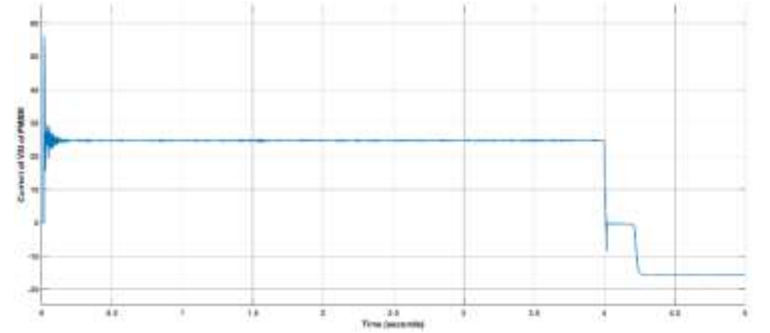
(a)



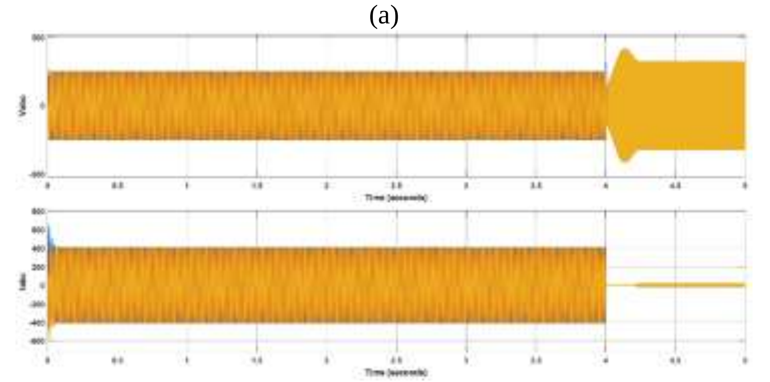
(b)

Figure 10: (a) Torque characteristics of ANN controller and (b) Torque characteristics of PID and Fuzzy controller.
Source: Authors, (2026).

Figure 11 shows the DC link current and Vabc and Iabc of VSI of PMSM. At braking condition current goes to the negative peak.



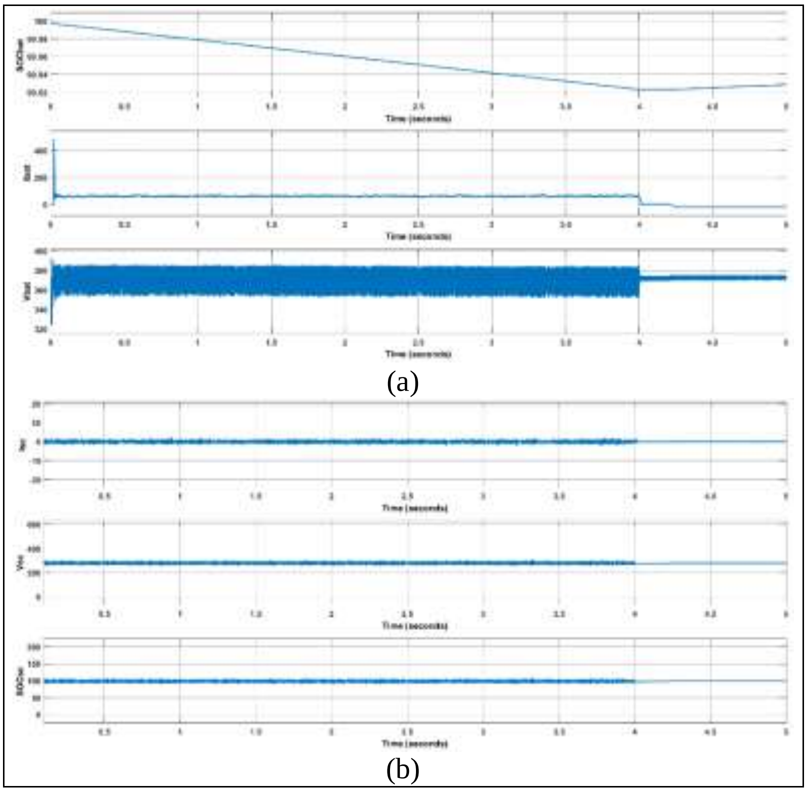
(a)



(b)

Figure 11: (a) DC link Current of PMSM and (b) V_{abc} and I_{abc} of VSI of PMSM.
Source: Authors, (2026).

Figure 12 indicates Battery and UC SOC, voltage and current waveforms with ANN controller.



(a) (b)

Figure 12: SOC, current and voltage with ANN controller of (a) Battery (b) Ultracapacitor.
Source: Authors, (2026).

Table 2 below presents a comparison of various parameters between the PID, FLC and ANN controller.

Table 2: Comparison of various parameters using different Energy management systems.

Parameter	**Battery Controller**		
	PID	**ANN**	**FLC**
Time(sec)	5	5	5
Initial SOC%	100	100	100
Final SOC%	99.896	99.928	99.952
SOC drop	Sharp	Small	Small

Source: Authors, (2026).

The findings indicate that the FLC and ANN controller are more advanced and precise systems, grounded on the input/output data pairs of the system. The objectives of the study were fully met, with simulation results confirming that the fuzzy controller can improve SOC more effectively than the ANN controller. These outcomes not only validate the potential of FLC for real-world battery control applications but also provide a more comprehensive benchmark for future controller evaluations.

VI. CONCLUSIONS

The PID controller regulates the battery SOC, optimizing it for extended driving ranges. Meanwhile, the Fuzzy Logic Controller utilizing input output data pairs, further enhances SOC management. To enable a comprehensive comparison, advanced optimization techniques including the PID, FLC and ANN controllers were implemented and evaluated. Simulation results reveal that the PID controller maintained the battery SOC at 99.89% by the end of the drive cycle, though minor drops occurred during acceleration phases. The ANN controller achieved a slightly higher SOC of 99.92%, while the fuzzy controller, employing a triangular membership function, sustained an even higher SOC above 99.952% at the end of the drive cycle. This outcome highlights the superior capability of the fuzzy controller in preserving SOC stability, maintaining approximately 99.952% even after a 5-second drive.

It can be concluded that the implementation of ANN and Fuzzy controllers enhances battery performance, improving the SOC stability and enabling HEV to achieve longer driving ranges. Overall, both the ANN and FLC approaches significantly enhanced battery performance, improving SOC stability and thereby extending the vehicle's operational range. The study demonstrates how integrating machine learning techniques with traditional power electronic control models can effectively improve battery management and overall system efficiency an advancement particularly relevant for EV applications. As HEV continue to shape the future of transportation, this work underscores the importance of intelligent, energy-efficient control systems that support the shift toward sustainable mobility.

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