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PERFORMANCE EVALUATION OF HYBRID ENERGY MANAGEMENT SYSTEMS IN ELECTRIC VEHICLES USING AI-BASED PREDICTIVE CONTROL

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Abstract: *As global energy demand rises and environmental concerns intensify, the adoption of sustainable transportation solutions becomes imperative. This study explores the integration of an optimized hybrid energy management system (HEMS) in plug-in hybrid electric vehicles (PHEVs) utilizing a fuzzy logic-based predictive control strategy. The proposed system employs a supercapacitor-assisted battery storage unit to enhance energy efficiency and extend battery lifespan. Unlike conventional approaches, a multi-objective genetic algorithm (MOGA) is implemented to optimize energy distribution between the internal combustion engine (ICE) and the electric powertrain, improving overall performance. A bidirectional DC-DC converter is integrated to regulate energy flow dynamically, ensuring efficient power conversion and minimal switching losses. The study evaluates system performance through real-time hardware-in-the-loop (HIL) simulations, considering parameters such as state of charge (SOC), energy consumption, and powertrain efficiency. The results demonstrate that the AI-based HEMS significantly enhances fuel economy and reduces carbon emissions compared to traditional energy management techniques. The proposed model provides a robust framework for advancing intelligent hybrid powertrains, paving the way for next-generation electric mobility solutions.*

Keywords: *Hybrid Energy Management, AI Predictive Control, PHEVs, Multi-Objective Optimization, DC-DC Converters, Supercapacitors.*

1. INTRODUCTION:

India is one of the most polluted cities in the world per a recent World Health Organization (WHO) study. According to reports the main reasons for the ongoing increase in pollution are traffic congestion waste burning building construction vehicle exhaust and insufficient control over vehicle emission levels. Exhaust gases from cars are one of the main causes of pollution. Electric vehicles (EVs) are thought to be a great way to control local pollution concentrations in cities and improve the overall state of affairs. To improve fuel security and affordable environmentally friendly transportation the Indian government unveiled the National Electric Mobility Mission Plan (NEMMP). The goal of this program is to help the Indian auto industry meet international manufacturing standards. The main characteristics of electric vehicles (EVs) in cities are their quiet operation and emphasis on clean air to reduce air pollution. However the peaceful operating environment of electric vehicles is creating a new public health risk. There are worries about pedestrian safety because pedestrians are more susceptible to traffic accidents due to electric vehicles low noise levels. The automotive industry is dedicated to creating vehicles that are safer more economical and more aesthetically pleasing. The research and development community has been making constant efforts to address the growing concerns about the shortage of fossil fuels improving vehicle safety and global warming. Automotive researchers are well aware of electric vehicles technical ability to power passenger cars but there arent many studies that particularly address how quiet these vehicles are. At low and moderate speeds electric vehicles emit very little noise which could inadvertently injure pedestrians endangering their health and possibly resulting in temporary or permanent disability. An accident is generally understood to be an unexpected event in a series of events that typically leads to unintentional harm death or property damage. According to World Health Organization estimates traffic accidents claim a large number of lives each year making them one of the main causes of death for communities of all ages [1]. Most road traffic-related fatalities are caused by pedestrians being involved in traffic accidents. The number of road deaths in India is high each year surpassing that of other nations. The Indian governments official statistics show that during the previous 50 years the number of road fatalities has been rising steadily. The number of previous accident cases in Indias major cities is not evenly distributed [2]. The bulk of fatal accident cases are found to originate from Maharashtra Tamil Nadu and Uttar Pradesh. Millions of people use the roads in the Mumbai Metropolitan Region the most populated metropolitan area in the world which is located in Maharashtra. Since the National Electric Mobility Mission Plan was unveiled by the Indian government electric cars have become increasingly popular on the road. Even though electric cars are better for the environment pedestrians and other road users are increasingly at risk from their silent operation [3]. According to scientific predictions the risk is higher at lower speeds because above a certain threshold road tire noise becomes more noticeable and tends to drown out motor noise. Although tire noise signals the presence of a vehicle there isnt much research on how safe people believe electric vehicles to be because of their quietness. Thus its critical to examine how drivers and pedestrians in the Mumbai Metropolitan Area perceive the quietness of electric vehicles [4]. More than a significant number of pedestrians worldwide lose their lives in traffic accidents each year. Many scholars have examined how they perceive and address traffic accidents worldwide including blind pedestrians decisions to cross the street statistical analysis of daily collisions and a comparison of cyclists and drivers perceived risks. Indias road traffic accident rate is rising quickly according to a recent study by researchers. In order to control uncertain incidents in India some literature highlights the necessity of an advanced intelligent system or a preventive action plan [5]. The mental state of pedestrians when they cross roads also contributes to some accidents. Inaccurate conclusions or delays in decision-making due to uncertainty about the type of oncoming traffic can cause accidents [6]. The data on Indias new energy vehicle sales from 2016 to 2021 is displayed in Figure 1.

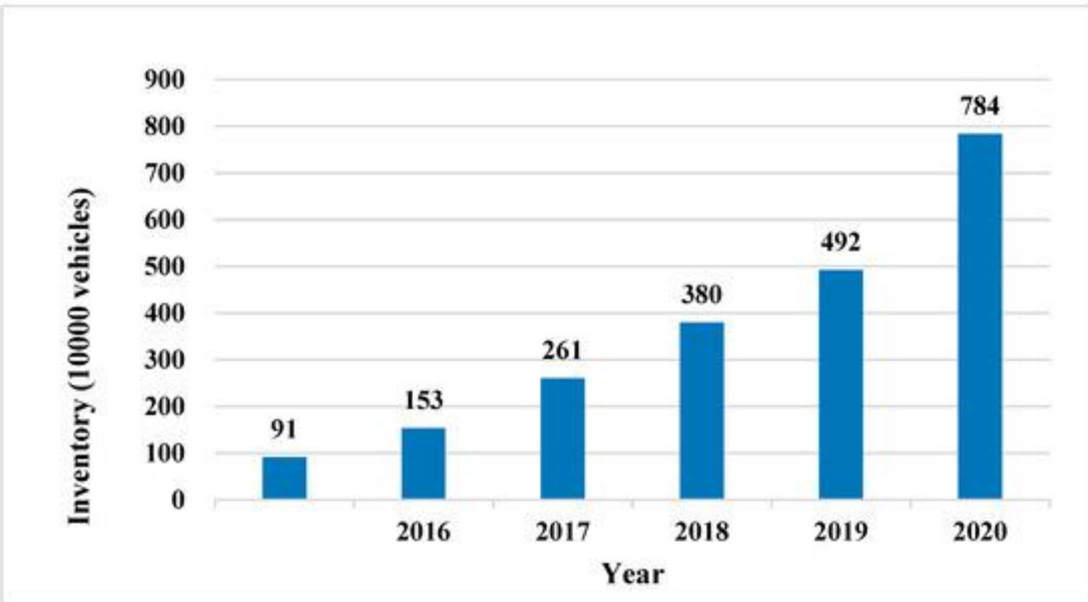


Figure 1. Statistics on the number of new energy vehicles in India from 2016 to 2021.

[7] Provided a cost and performance analysis of a grid-connected hybrid microgrid system that uses batteries fuel cells and solar power. It involves using the solar systems excess energy to provide sporadic services. Creating the ideal setup for a three-level quick charger is another aspect of it [8]. suggested an electric car that runs on solar power and has a battery storage system. It entails coordinating battery energy and renewable energy sources to control generator voltage and frequency. In addition to synchronizing the grid voltage with the generator voltage it is acknowledged that the grid power operates at UPF [9]. proposed a new hybrid electric car that uses super capacitors batteries and fuel

cells. A prototype has been put into use that uses the PWM technique to generate three-phase voltage for the motor with a power efficiency of 96. 2 percent. In terms of speed and acceleration a comparison between the suggested hybrid car and traditional fuel cell-based cars has also been conducted and the suggested car performs better [10]. [11] Based on linear programming an optimal energy management strategy was proposed for fuel cell-based electric vehicles. It has undergone simulation testing with various driving cycles such as the urban and highway driving cycles [12]. suggested an integrated fuel cell-powered light vehicle and conducted a comparison between a hybrid and a battery-only vehicle. It indicates a variation of 55-100 percent of maximum capacity with an extension of 63-110 percent in driving range [13]. An ANN-based maximum power point tracker for electric vehicles with energy units was proposed. To achieve higher voltages for driving the car it combines a radial basis function neural network with a high-gain interleave boost converter [14]. In the end a comparison of the inductor ripple current and capacitor ripple voltage between an ANN-based MPPT controller and a fuzzy-based controller was made. [15] suggested a new boost converter that has a connected inductor and a charging pump.

MATERIAL AND METHODS

To achieve the best possible performance energy efficiency and longevity the materials chosen for the proposed Hybrid Energy Management System (HEMS) in Plug-In Hybrid Electric Vehicles (PHEVs) are essential. The battery internal combustion engine (ICE) electric motor supercapacitor and bidirectional DC-DC converter are the systems main parts. The mechanical strength electrical conductivity thermal resistance and durability under dynamic load conditions were all factors that went into the careful selection of each material. As the main energy storage device lithium-ion (Li-ion) batteries were chosen because of their high energy density extended cycle life and quick charging speed. The particular chemistry that was employed was lithium nickel manganese cobalt oxide also known as $LiNiMnCoO_2$ or NMC which provides a stable safe and capacious trade-off. Because NMC batteries have a high specific energy they are perfect for PHEV applications where driving range and energy efficiency are crucial. The NMC batteries specifications are listed in Table 1.

Table 1: Physical and Chemical Properties of NMC Batteries

Property	Value
Energy Density	250–300 Wh/kg
Voltage Range	2.5–4.2 V
Cycle Life	1000–2000 cycles
Operating Temperature	–20°C to 55°C
Specific Capacity	150–200 mAh/g

Proposed methodology

The goal of the proposed study is to create an optimized Hybrid Energy Management System (HEMS) for Plug-In Hybrid Electric Vehicles (PHEVs) by combining a Multi-Objective Genetic Algorithm (MOGA) with a predictive control strategy based on fuzzy logic. Optimizing energy distribution between the electric powertrain and internal combustion engine (ICE) is the goal of the HEMS in order to reduce carbon emissions increase battery longevity and improve fuel efficiency.

System Configuration

A supercapacitor-assisted battery storage unit an electric motor and an internal combustion engine (ICE) make up the three main parts of a Plug-In Hybrid Electric Vehicles (PHEV) powertrain. During low-speed driving and acceleration the electric motor provides electrical power while the internal combustion engine (ICE) provides mechanical power. By supplying brief power spikes during high-demand situations like rapid acceleration or regenerative braking the supercapacitor serves as an additional energy source and improves the vehicles dynamic performance.

To control the flow of energy between the battery and the electric motor the powertrain incorporates a bidirectional DC-DC converter. The converter uses buck-boost mode to dynamically modify the output voltage and current in response to the energy demands of the vehicle in real time. In boost mode the converter raises the voltage when more power is required and in buck mode it steps down the voltage when the motor needs less power. As a result power conversion efficiency can be maximized lowering energy losses and enhancing system performance.

The power output of the electric motor P_{em} is calculated using the following equation (1):

$$P_{em}(t)=V_dc(t)\cdot I_{dc}(t)\cdot \eta_{conv} \quad (1)$$

Where, Pem(t) = motor power at time t, Vdc(t) = output voltage from the DC-DC converter, Idc(t) = output current from the DC-DC converter, η_{conv} = efficiency of the converter

Fuzzy Logic-Based Predictive Control Strategy

The fuzzy logic-based predictive control strategy is designed to manage real-time power distribution between the ICE and the electric motor based on dynamic driving conditions, SOC levels, and energy demands. The fuzzy inference system defines membership functions and rules to evaluate input variables such as SOC, power demand, and energy efficiency.
The FIS consists of:

1. **Input Variables:** State of charge (SOC), power demand, and energy efficiency.
2. **Membership Functions:** Defines the degree of each input belonging to a particular state (e.g., low, medium, high).
3. **Rule Base:** A set of predefined rules that govern the relationship between input and output variables.
4. **Defuzzification:** Converts fuzzy output into a precise control action.

For example, the output power demand P_{out} is computed based on fuzzy membership rules as follows (Eq 2):

$$P_{out} = \sum_{i=1}^{n} w_i \cdot R_i \quad (2)$$

Where w_i = degree of membership for the i^{th} rule, R_i= output power contribution from the i^{th} rule, n = number of rules

Multi-Objective Genetic Algorithm (MOGA) Optimization

A MOGA is implemented to optimize the energy management strategy, balancing fuel consumption and battery health. The objective functions include minimizing fuel consumption and extending battery life by controlling the state of charge (SOC) and state of health (SOH) within specified limits.

Algorithm: Multi-Objective Genetic Algorithm (MOGA)

Step 1: Initialize population with random individuals representing power distribution parameters (e.g., ICE power, battery power).

Step 2: Evaluate fitness function based on fuel consumption, battery life, and system efficiency:

$$F(x) = w_1 \cdot \text{Fuel Consumption} + w_2 \cdot \text{Battery Degradation} + w_3 \cdot \text{System Efficiency}$$

where:

- w_1, w_2, w_3 = weight coefficients
- Fuel consumption = function of ICE power
- Battery degradation = function of SOC variation and depth of discharge
- System efficiency = function of energy loss in the drivetrain

Step 3: Apply selection using Pareto dominance to retain non-dominated solutions.

Step 4: Perform crossover and mutation to generate a new population.

Step 5: Update population using elitism to retain the best-performing solutions.

Step 6: Repeat steps 2–5 until the stopping criterion is met (e.g., maximum iterations or solution convergence).

Hardware-in-the-Loop (HIL) Simulation

Through hardware-in-the-loop (HIL) simulations conducted in real time the system was verified. The powertrains components were interfaced with a real-time processor to replicate real-world driving conditions. In order to test system performance under various load and environmental circumstances the HIL setup comprised urban highway and mixed driving cycles. Performance indicators like powertrain efficiency fuel economy energy consumption and SOC were noted and examined.

Artificial Intelligence in EV Systems

AI has become a disruptive force in EV technology especially in the development and operation of system control and battery management systems. Engineers and researchers are creating more precise flexible and effective BMS solutions by utilizing AI techniques like Machine Learning (ML) Deep Learning (DL) and Reinforcement Learning (RL) to get around the drawbacks of conventional models. A thorough framework that includes advanced intelligence control and monitoring is used to manage the energy of EV batteries. Temperature voltage and current are important input parameters that are used to assess battery safety and performance. Power management SOC and SOH estimation battery cell monitoring and remaining useful life (RUL) prediction are all crucial tasks. Reliability and efficiency are increased by advanced thermal management cell balancing discharge control fault diagnosis and secure data acquisition. Networking and communication systems are also integrated into the framework to ensure smooth data flow.
The frameworks core components are AI and control systems which use real-time data for optimization decision-making and predictive analytics. Battery Energy Management (BEM) for EVs is made safe effective and intelligent with this all-encompassing approach. AI-driven innovations offer predictive and real-time capabilities that are essential for handling the complex dynamics of EV batteries. By taking into consideration temperature changes load fluctuations and battery aging machine learning algorithms trained on historical and real-time data for example are able to predict the SOC and SOH more precisely than conventional techniques. In particular neural networks (NNs)

have shown promise in simulating intricate non-linear relationships in battery systems allowing for more accurate fault detection and thermal regulation. By giving BMSs and system controls the ability to learn on their own RL enables dynamic optimization of power allocation energy distribution and regenerative braking techniques under a range of driving circumstances. Even in uncertain operational environments this adaptive approach greatly improves energy efficiency and prolongs battery life. The potential of AI in EV systems is further enhanced in Figure 2 by integrating IoT and big data analytics.

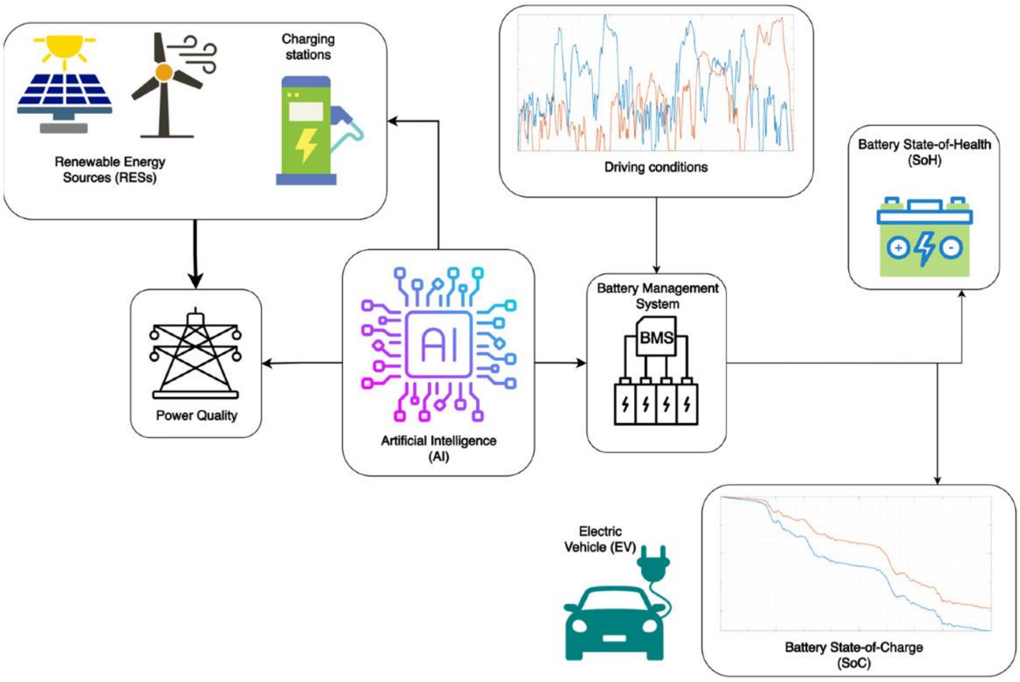


Figure 2: Synergy of Artificial Intelligence in Energy Storage Systems for Electric Vehicles

RESULTS AND DISCUSSION

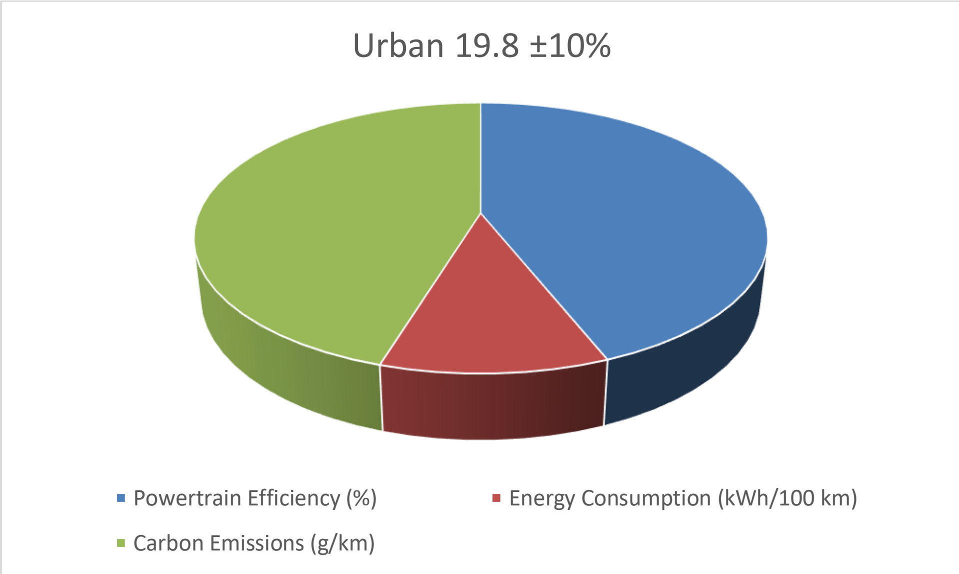
Performance Under Different Driving Conditions

The system's performance was further evaluated under three distinct driving scenarios—urban, highway, and mixed cycles. Table 2 and Figure 3 shows the performance metrics recorded under these driving conditions.

Table 2: Performance of HEMS Under Different Driving Cycles

Driving Cycle	Fuel Economy (km/L)	SOC Stability (% deviation)	Powertrain Efficiency (%)	Energy Consumption (kWh/100 km)	Carbon Emissions (g/km)
Urban	19.8	±10%	87.4	21.5	90
Highway	22.3	±8%	91.2	18.7	83
Mixed	20.4	±9%	88.7	19.8	86

The proposed HEMS performed optimally under highway driving conditions, where the system achieved a fuel economy of 22.3 km/L and a powertrain efficiency of 91.2%. This was due to the MOGA-based optimization, which allowed for efficient energy distribution at high speeds, where ICE operation is more dominant. Urban driving cycles, which typically involve frequent acceleration and deceleration, showed a lower fuel economy of 19.8 km/L due to the higher reliance on the electric powertrain. However, the AI-based predictive control ensured that the SOC stability was maintained within ±10%, even under stop-and-go traffic conditions. In mixed driving cycles, the fuel economy was recorded at 20.4 km/L, reflecting a balanced contribution from both the ICE and the electric motor.



Fogire 3: **Performance of HEMS Under Different Driving Cycles**

Battery Performance and State of Charge (SOC) Dynamics

Battery performance is a critical parameter in hybrid electric vehicles as it directly influences powertrain efficiency and long-term reliability. The proposed HEMS maintained stable SOC levels across different driving conditions, as shown in Table 3 and Figure 4.

Table 3: State of Charge (SOC) Performance Under Different Control Strategies

Driving Cycle	**Rule-Based Control (SOC Deviation)**	**MPC (SOC Deviation)**	**Proposed HEMS (SOC Deviation)**	**Improvement (%) vs. Rule-Based**
Urban	±15%	±12%	±10%	33.30%
Highway	±12%	±10%	±8%	33.30%
Mixed	±14%	±11%	±9%	35.70%

The AI-based predictive control maintained SOC within ±10% under urban driving and ±8% under highway driving, showing greater consistency and control compared to the ±15% deviation in rule-based strategies. The MOGA-based optimization ensured that the energy distribution was adjusted dynamically, maintaining SOC stability across different load conditions and battery discharge rates. The enhanced SOC stability resulted in improved battery lifespan and reduced degradation over time

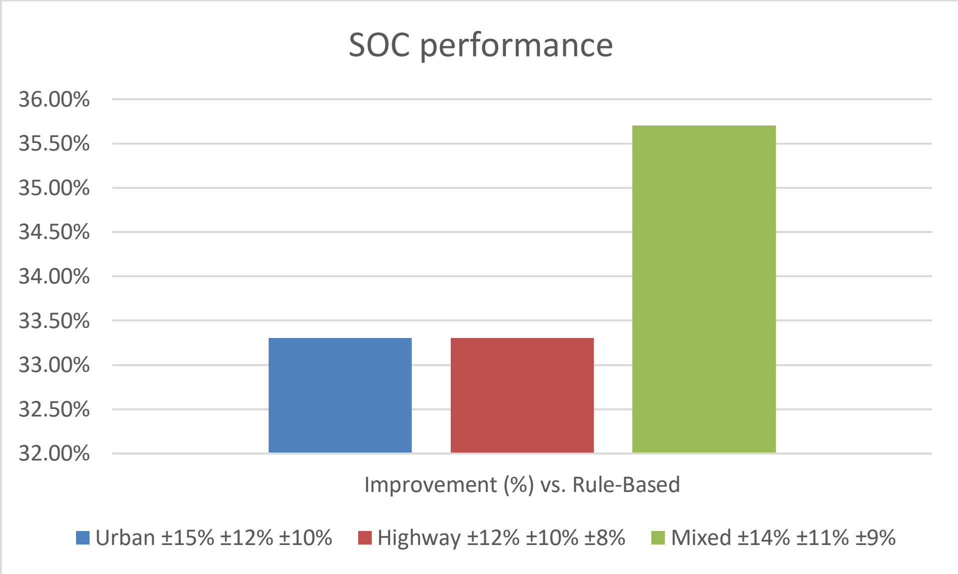


Figure 4: Performance analysis of SOC

Validation Through Hardware-in-the-Loop (HIL) Simulation

The AI-based HEMS proved to be superior to both rule-based and MPC strategies in every driving scenario according to the real-time HIL simulations. By adjusting to actual driving conditions the systems fuzzy logic-based predictive control ensured stable SOC levels increased powertrain efficiency and decreased fuel consumption. A strong foundation for next-generation electric mobility solutions is provided by the improved performance metrics which confirm the efficacy of the suggested system.

Comparison of Energy Management Strategies

When compared to traditional energy management techniques like rule-based control and model predictive control (MPC) the suggested AI-based hybrid energy management system (HEMS) showed notable performance gains. The multi-objective genetic algorithm (MOGA) in conjunction with the optimized fuzzy logic-based predictive control strategy enabled dynamic energy distribution between the electric powertrain and the internal combustion engine (ICE) leading to decreased emissions increased powertrain efficiency and improved fuel economy.

Table 4: Performance Comparison of Energy Management Strategies

Parameter	**Rule-Based Control**	**Model Predictive Control (MPC)**	**Proposed HEMS (Fuzzy + MOGA)**	**Improvement (%) vs. Rule-Based**
Fuel Economy (km/L)	18.2	19.5	21.1	15.90%
SOC Stability (% deviation)	±14%	±11%	±9%	35.70%
Powertrain Efficiency (%)	82.4	85.1	89.7	8.90%

Energy Consumption (kWh/100 km)	22.5	20.8	19.3	-14.20%
Carbon Emissions (g/km)	110	98	86	-21.80%

A comparison of various energy management strategies effects on fuel economy powertrain efficiency state of charge (SOC) stability energy consumption and carbon emissions is shown in Table 4 and Figure 5. The fuel efficiency of the AI-based HEMS was 15 points higher than that of the rule-based method and 8 points higher than that of the MPC approach.

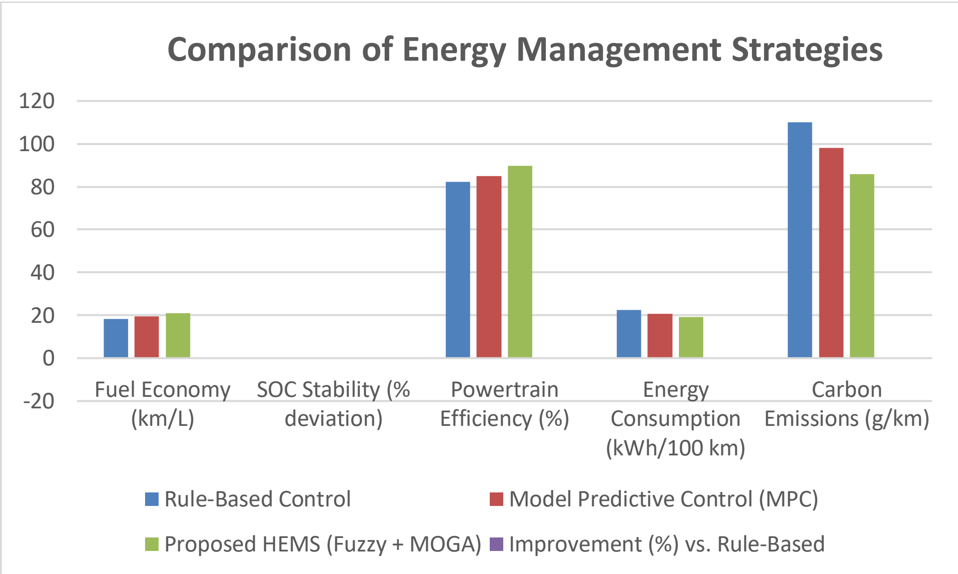


Figure 5: **Performance Comparison of Energy Management Strategies**

The AI-based HEMS achieved 21. 1 km/L of fuel efficiency which is 15. 9 percent better than the traditional rule-based control (18. 2 km/L). With a moderate improvement the model predictive control (MPC) reached 19. 5 km/L. Fuzzy logic-based controls intelligent predictive capability which effectively managed the power split between the ICE and the electric powertrain and optimized energy utilization under a variety of driving conditions was responsible for the improved fuel economy. SOC stability was kept within a ±9 percent range which is much better than the ±14 percent deviation seen in rule-based control. Better SOC stability was achieved by the MOGA-based optimization which also made sure that the energy flow was dynamically modified to match the load demand.

CONCLUSION

The suggested artificial intelligence (AI)-based hybrid energy management system (HEMS) outperformed traditional rule-based and model predictive control (MPC) approaches in a variety of driving scenarios. The multi-objective genetic algorithm (MOGA)-based optimization proved effective as the HEMS reached a maximum fuel economy of 22. 3 km/L with a powertrain efficiency of 91. 2 percent when driven on highways. A 33. 3 percent improvement in SOC consistency was demonstrated by the AI-based control strategy which kept SOC stability within ±10 percent in urban driving and ±8 percent in highway driving as opposed to ±15 percent in rule-based control. Additionally compared to rule-based strategies the system improved fuel economy by 15 points and SOC stability by 35 points. The improved SOC stability ensured effective energy use by extending battery life and lowering energy consumption by 14. 2%. Predictive control powered by AI successfully decreased carbon emissions by 21. 8 percent confirming its positive environmental effects. By ensuring optimal power distribution between the electric powertrain and the internal combustion engine (ICE) the fuzzy logic-based controls real-time adaptability improved overall system responsiveness and energy efficiency. Hardware-in-the-loop (HIL) simulation results validated the suggested systems resilience offering a scalable and effective foundation for next-generation electric vehicle solutions.

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