Journal of Operation and Automation in Power Engineering

vol. 12, no. Special Issue, Dec. 2024, Pages: 53-63

http://joape.uma.ac.ir

Research Paper

Designing an Energy Management Control System in Hybrid Vehicles Using an Optimized Fuzzy Method

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***Abstract*— *Improving fuel efficiency and enhancing the dynamic performance of hybrid electric vehicles are critical challenges in modern powertrain control design. This paper proposes a novel optimized fuzzy logic-based energy management strategy specifically developed for a Class B HEV. The main objective is to reduce fuel consumption and emissions while ensuring effective power distribution among key drivetrain components. The study introduces a two-stage methodology: first, an optimal sizing of the powertrain components—internal combustion engine, electric motor, and battery—is achieved using a genetic algorithm, ensuring the most efficient configuration for vehicle performance. Second, three different energy management strategies are implemented and compared: a conventional rule-based control, a standard fuzzy logic controller, and the proposed optimized fuzzy controller. Simulation results demonstrate that the optimized fuzzy strategy significantly improves fuel economy and emission performance compared to the other methods. Specifically, it achieves up to 20% better fuel efficiency than the rule-based controller while maintaining smooth power transitions. The study also highlights the impact of component sizing on control effectiveness, reinforcing the advantage of co-optimization of both sizing and control logic. The findings suggest that integrating intelligent optimization techniques such as GA with fuzzy control logic provides a superior approach to energy management in HEVs. This makes the proposed method a promising solution for next-generation hybrid vehicle applications aiming for both environmental sustainability and high performance.*

Keywords—Hybrid electric vehicle, energy management strategy, fuzzy logic controller, genetic algorithm, powertrain optimization, fuel efficiency, emissions reduction.

1. Introduction

The rapid growth of global transportation demands has intensified concerns regarding fuel consumption, environmental pollution, and energy sustainability. As fossil fuel reserves deplete and greenhouse gas emissions continue to rise, the transportation sector faces mounting pressure to adopt cleaner and more efficient technologies. Hybrid Electric Vehicles (HEVs), which integrate traditional internal combustion engines with electric propulsion systems, have emerged as a promising transitional solution toward fully electrified transportation. However, designing and optimizing HEVs remain complex challenges due to the presence of multiple power sources, the need for efficient energy management strategies, and the variability of real-world driving conditions. This study contributes to this evolving field by exploring advanced energy management techniques aimed at enhancing HEV performance while reducing environmental impact.

1.1. Research motivation

Demand and supply of energy, global warming, and sustainability have posed tremendous challenges to the world [1]. The harmful emissions from conventional vehicles, which operate using fossil fuels and internal combustion engines (ICEs), are major contributors to these global issues [2]. To address this, the transportation sector must transition to cleaner energy sources. Although Electric Vehicles (EVs) offer a promising alternative,

Received: 04 Apr. 2025
Revised: 03 Jul. 2025
Accepted: 10 Jul. 2025
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DOI: 10.22098/JOAPE.2024.17112.2334

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their limited driving range and lengthy charging times restrict their practical implementation [3].

Hybrid Electric Vehicles (HEVs), which combine ICEs with electric power sources, offer a balanced solution by reducing fuel consumption while maintaining conventional vehicle functionality [3]. These vehicles typically use the ICE as the main power source and a battery as a secondary source [4]. Among available technologies, proton exchange membrane batteries have gained attention due to their low operating temperatures, compact size, and high power density [5]. However, their slow dynamic response requires support from secondary energy storage systems. Advanced fuzzy-based control frameworks, such as parallel fuzzy PID mechanisms, have shown strong potential in managing complex, nonlinear systems like microgrids by delivering adaptive and robust dynamic responses through optimization techniques [6]. These findings further support the suitability of intelligent fuzzy controllers in HEVs, where similar control challenges arise due to the multi-source energy architecture and dynamic operating conditions. Lithium-ion batteries, despite being costly, are widely adopted for their superior energy and power density, making them highly suitable for automotive applications [7].

1.2. Literature review

A recent review on energy management in HEVs and HESS EVs underscores the effectiveness of Fuzzy Logic Controllers (FLCs) due to their simplicity, performance, and real-time capability [8]. It also highlights various FLC types and their applications, supporting the need for continued advancement in optimized FLC-based strategies. Another recent review emphasizes the broad applicability of Fuzzy Logic Controllers (FLCs) across various subsystems in electric, hybrid, and fuel cell vehicles, highlighting their adaptability, robustness, and effectiveness in scenarios where mathematical modeling is challenging. The study also notes the importance of optimization algorithms for fine-tuning FLC parameters for maximum performance [9]. Although primarily focused on electromagnetic compatibility (EMC), recent research into surrogate models has demonstrated the critical role of sampling strategies in improving simulation accuracy for uncertainty analysis and optimization tasks. These insights are also relevant to HEV control design, where surrogate modeling can support efficient parameter tuning and system optimization under complex, uncertain driving conditions [10]. Recent advances in energy management strategies for hydrogen fuel cell electric vehicles (HFCEVs) highlight the limitations of rule-based controls in handling complex, multi-objective systems—challenges also relevant to HEVs. The study emphasizes the potential of artificial intelligence (AI)-based algorithms, including hybrid and reinforcement learning methods, to enhance performance and cost-effectiveness, offering insights applicable to HEV control system optimization [11]. The identified limitations of rule-based systems in HFCEVs parallel challenges in HEVs, particularly in managing complex, multi-objective control tasks. AI-based methods, especially reinforcement learning and hybrid algorithms, are presented as promising alternatives for enhancing energy management performance—an approach that aligns with ongoing efforts to optimize HEV control strategies [12].

Fuzzy Logic Controllers (FLCs) have emerged as suitable solutions for HEV energy management. Optimized FLCs, in particular, can provide rapid responses without depending on historical data, although their design complexity requires careful analysis [5]. Control strategies for HEVs generally fall into two categories: predictive and real-time. Predictive methods involve forecasting future driving conditions using dynamic programming, while real-time methods rely on empirical rule-based algorithms, particularly fuzzy logic [13]. Despite their practicality, rule-based fuzzy controllers often face challenges such as sensitivity to parameter tuning and limited adaptability [14, 15]. Emerging strategies, such as equivalent fuel consumption minimization, combine predictive techniques with real-time adaptability to overcome these limitations [4, 17]. This paper builds upon such predictive control strategies, using a genetic algorithm (GA) to optimize fuzzy parameters in a hierarchical control structure. In terms of data-driven approaches, research has extensively examined driving behavior and traffic conditions to inform HEV design. Studies in [1, 2] have developed regional driving cycles based on real-world data, a practice also adopted in Iran where satellite tracking systems have enabled the construction of local driving cycles through statistical analysis. Research in [13, 18, 19] has applied genetic algorithms to optimize power management strategies in HEVs and plug-in HEVs, offering valuable insight into performance comparisons between different architectures. A related study applies Teaching–Learning-Based Optimization to tune fuzzy controllers in hybrid energy storage systems, improving energy efficiency and system dynamics [20]. While [21] systematically reviews the application of artificial intelligence algorithms in hybrid electric powertrain control, focusing on broad architectures and future prospects, our work specifically implements and evaluates a GA-optimized fuzzy controller within a real-time hierarchical EMS, with experimental comparisons under realistic driving conditions.. Although similar in integrating rule-based, fuzzy, and genetic algorithms, their focus is primarily on power-split configurations. In contrast, our study targets parallel HEVs and uniquely compares rule-based, fuzzy, and genetic-fuzzy strategies under real driving conditions using a unified evaluation framework. A particle swarm optimization (PSO)-based fuzzy logic controller was developed to manage a lithium-ion battery–ultracapacitor hybrid energy storage system (HESS) in EVs, focusing on minimizing battery stress and thermal load to improve lifespan [22]. While their approach targets battery health under temperature constraints, our work emphasizes broader system-level efficiency in HEVs through a comparative evaluation of multiple control strategies enhanced by genetic optimization. In summary, existing literature demonstrates significant progress in the application of intelligent energy management strategies for EVs and HEVs, particularly through fuzzy logic and optimization techniques. However, most prior studies focus on either specific vehicle architectures or isolated control strategies. This highlights a gap in comprehensive, comparative evaluations under realistic driving conditions. Our work addresses this by integrating rule-based, fuzzy, and genetic-fuzzy methods into a unified framework tailored for parallel HEVs, enabling a holistic assessment of control performance and energy efficiency. Table 1 provides a comparative summary of recent studies related to energy management strategies in hybrid and electric vehicles. It highlights the scope, methodologies, optimization approaches, and contributions of each work in relation to our proposed method. This structured comparison clarifies the novelty of our study in employing genetic algorithm optimization within a fuzzy logic control framework, validated under real-world driving conditions for a parallel HEV architecture.

1.3. Gap challenge

Despite the progress in HEV control systems, existing fuzzy controllers often lack the flexibility needed for diverse, real-world driving conditions due to their reliance on static rule sets. Optimized fuzzy systems offer improvements but face implementation challenges in real-time environments. Additionally, there is a lack of unified frameworks that combine optimal component sizing with adaptive control strategies under realistic operating scenarios.

Most prior works focus either on control algorithm development or component optimization in isolation. Few have conducted comprehensive performance evaluations comparing rule-based, fuzzy, and genetic-fuzzy controllers using the same testbed. Addressing these gaps is essential to develop an integrated, efficient, and real-time-capable HEV control strategy.

Table 1. Comparison of recent studies on energy management strategies for HEVs and EVs.

Ref.	Year	Method / Strategy	Vehicle Type / Architecture	Optimization Used	Real Driving Conditions	Comparative Analysis	Contribution Focus
[8]	2024	FLC Review	HEV, HESS	No	No	No	Review of FLC in hybrid systems
[9]	2024	FLC Review	HEV, EV, FCV	No	No	No	Broad FLC applicability and tuning discussion
[10]	2024	Surrogate modeling for EMC	EV	Yes (sampling strategy)	No	No	Simulation enhancement for EMC-related models
[11]	2024	AI/Hybrid EMS for HFCEV	HFCEV	AI-based (Hybrid, RL)	No	No	AI for EMS in complex systems
[12]	2024	AI review for HEV EMS	HEV	AI-based (Reinforcement learning)	No	No	Intelligent techniques review
[13]	2024	ANFIS-based Predictive EMS	Heavy HEV	Adaptive FIS, Prediction	No	No	Predictive EMS with adaptive horizon
[14]	2024	Wavelet + Real-time EMS	HESS EV	Wavelet Transform	No	No	Time-frequency-based real-time control
[15]	2022	HESS EMS Review	EV	No	No	No	Review of Li-ion + SC EMS architectures
[16]	2024	FLC Review for HEV/HESS	HEV, HESS	No	No	No	Robustness and real-time capability of FLC
[17]	2024	GA-Optimized FLC for FCHEV	FCHEV	Genetic Algorithm	No	No	GA-based tuning for FLC
[18]	2020	Multi-objective GA-FLC	EV, HESS	Genetic Algorithm	No	No	Dual energy source EMS with GA optimization
[19]	2003	Policy Review	HEV programs	No	No	No	U.S. DoE + PNGV policy perspective
[20]	2024	TLBO-Optimized FLC for HESS	EV	Teaching–Learning-Based Optimization	No	No	TLBO algorithm for fuzzy EMS
[21]	2025	AI-Based Control Strategies (Review)	Hybrid Electric Vehicles (HEVs)	Various AI Algorithms (e.g., RL, NN, GA, etc.)	Yes	Yes	Comprehensive review of AI control methods for HEVs
[22]	2024	PSO-Optimized FLC for HESS	EV	Particle Swarm Optimization	No	No	Battery lifespan and thermal management
This Work	–	Rule-Based, FLC, GA-Optimized FLC	Parallel HEV	Genetic Algorithm	Yes	Yes	Unified comparison, real driving cycles, parallel architecture

1.4. Novelty and main contributions

This study introduces a novel and integrated energy management framework for parallel hybrid electric vehicles (HEVs), which uniquely combines intelligent control with powertrain component optimization. The primary contributions of this research are as follows:

1) **Hybrid fuzzy-GA control strategy:** A key innovation is the development of an optimized fuzzy energy management system, in which the fuzzy controller's parameters—typically tuned through expert knowledge—are automatically fine-tuned using a genetic algorithm (GA). This hybrid design enhances the system's adaptability and decision-making efficiency under varying driving conditions.
2) **Integrated component sizing and control:** Unlike most prior studies that treat powertrain sizing and energy management as separate problems, this work proposes a co-optimization approach in which major powertrain components are sized concurrently with the tuning of the control strategy. This ensures better synergy between hardware configuration and software control.
3) **Comparative evaluation of control strategies:** A detailed comparative analysis is conducted across three strategies: conventional rule-based, basic fuzzy, and the proposed GA-optimized fuzzy controller. The performance is assessed in terms of fuel consumption, emission levels, and dynamic response, using realistic driving cycles and validated against Euro 6 emission standards.
4) **Real-world applicability:** The proposed strategy is applied to a Class B HEV model and tested under standard driving cycles, demonstrating a significant improvement in fuel economy (up to 20% compared to rule-based) while ensuring compliance with strict emissions regulations.

Despite its advantages, the proposed method involves higher computational cost due to the optimization layer, which may limit its real-time applicability without sufficient processing resources. Moreover, the system's performance was validated on a simulation platform; future work will be needed to confirm these results in hardware-in-the-loop (HIL) or full vehicle implementations. Overall, this research fills a critical gap in the literature by unifying optimal sizing and intelligent control into a practical and high-performance energy management strategy for HEVs.

1.5. Paper organization

The remainder of this paper is structured as follows: Section 2 presents the methodology, including the genetic algorithm-based component sizing, fuzzy control system design, and development of the hybrid genetic-fuzzy strategy. Section 3 provides the results and discussion, encompassing simulation outcomes, performance comparisons, and sensitivity analyses of various control approaches. Finally, Section 4 concludes the study by summarizing key findings, discussing current limitations, and suggesting directions for future research.

2. HEV Model

In order to enhance the performance and robustness of the fuzzy logic controller (FLC) in managing the complex energy demands of hybrid electric vehicles (HEVs), optimization techniques are essential. Traditional fuzzy controllers, while effective, may not always deliver optimal performance across a range of driving conditions, fuel consumption, or emissions. This is particularly true when considering dynamic and highly variable factors such as battery state-of-charge (SoC), engine load, and vehicle speed. Genetic algorithms (GA) provide a powerful, adaptive optimization approach capable of tuning the fuzzy controller's membership functions and rule base, thereby refining its performance in real-world scenarios. In the following section, we delve into the specific optimization framework employed in this study, detailing the GA-based method used to optimize the fuzzy controller and its components.

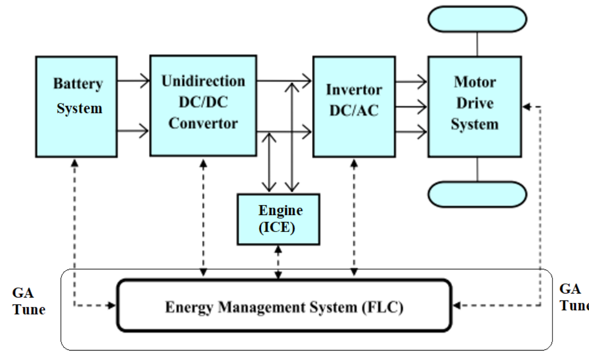

Fig. 1. Optimized FLC in HEV dynamics.

2.1. Sizing

HEV powertrains are a lot more intricate in comparison with conventional vehicles and it is mainly due to the fact that their powertrains are composed of a variety of constituents such as electric motors, state-of-the-art controllers, electrical converters, and energy storage systems besides the typical components like ICEs, transmissions, and so forth. The complexity of HEV powertrains has made them as one of the hottest topics in the area of HEV development. Needless to say, operational efficiency and the price of a HEV powertrain is heavily influenced by the selected configuration and the powertrain parameters need to be adjusted in the right way so that they can meet the preferred performance. In this study, a parametric design approach is utilized to estimate the size of prime components which are electric motor, ICE, and battery. The sole employment of parametric design definitely will not result in an optimum estimation of the components size and it needs further investigation by means of optimization algorithms. The applicable optimization algorithms for the component sizing of the HEVs can be grouped into three broad categories of gradient-based versus derivative free, local versus global, and deterministic versus stochastic. In the process of a HEV development, the vehicle performance and fuel economy are usually perceived as the main objectives which normally involve a lot of local minima and can be noisy and discontinuous. Gradient-based approaches trace the local minima by the utilization of derivative data and the crucial complication of local methods is also that they are not capable of delving into the whole search domain and as a result they cannot find the global minima. On the contrary, Derivative-free methods such GA, divided rectangles (DIRECT) [18], and so on can be viewed as efficient global algorithms since they investigate the entire search space to discover the global minima. It is worthy of mention that the major disparity between DIRECT and other mentioned methods like GA is that DIRECT is deterministic but GA is stochastic which makes them eminently suitable for dealing with the existed noise and discontinuity of the objective function. This system consists of a series of stages, in each of which all parts are working simultaneously in parallel. This system fails when all components of a given stage fail. The fuzzy mathematical model of this structure is as follows [23]:

$$\max \tilde{R}_s(t, n_1, n_2, \ldots, n_N) = \prod_{i=1}^{N} \left\{1 - \left(1 - \tilde{R}_i\right)^{n_i}\right\} = \prod_{i=1}^{N} \left\{1 - \left(1 - e^{-\tilde{\lambda}_i t}\right)^{n_i}\right\} \tag{1}$$

$$\tilde{C}_s(t, n_1, n_2, \ldots, n_N) = \sum_{i=1}^{N} \tilde{C}_i n_i \leq \tilde{C} \tag{2}$$

$$\tilde{W}_s(t, n_1, n_2, \ldots, n_N) = \sum_{i=1}^{N} \tilde{W}_i n_i \leq \tilde{W} \tag{3}$$

$$n_i \geq 0, \text{ integer} \quad \text{for } i = 1, 2, \ldots, N \tag{4}$$

In this work, the parametric sizing procedure is conducted for finding the appropriate size of components by means of GA and the results are further compared profoundly in the succeeding sections. The procedure of the GA in control strategy has been illustrated in Fig. 2.

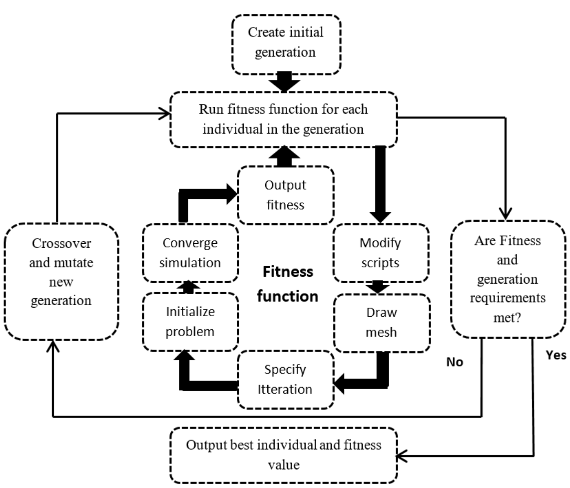

Fig. 2. GA flowchart.

In current research, Partnership for the Next Generation of Vehicles constraints, discussed in [19], are incorporated into the objective function formulation as penalties so as not to sacrifice the vehicle performance while trying to reach higher fuel economy. In order to integrate the above optimization algorithms into the measurement process formulation, an objective function is required. The objective function in this study aims to optimize the energy management of a hybrid electric vehicle (HEV) system. It incorporates fuel consumption, emissions, and penalties for violating system constraints, ensuring that the HEV performs optimally while respecting the vehicle's performance constraints.

A) Detailed formulation of the objective function [24]

$$F(x) = F_c + F_e - \sum_{i=1}^{N_{con}} \alpha_i C_i(x) \tag{5}$$

Where:

F(x) is the total objective function.

F_C is the fuel consumption, typically measured in liters per 100 km (L/100km) or equivalent fuel economy.

F_e is the emission function, which includes the emissions of nitrogen oxides (NOx), carbon monoxide (CO), and hydrocarbons (HC).

α_i is the penalty factor for the i-th constraint .

$C_i(x)$ is the penalty function corresponding to the i-th constraint.

N_{con} is the total number of constraints imposed on the system.

B) Detailed descriptions of parameters

1) Fuel consumption F_c :

Fuel consumption is a critical performance metric and is typically modeled as a function of the energy split between the internal combustion engine (ICE) and the electric motor (EM) [25]:

$$F_c = \int_{t_0}^{t_f} \frac{P_{ICE}(t)}{E_{fuel}} dt \tag{6}$$

Where:

$P_{ICE}(t)$ is the power delivered by the internal combustion engine at time t.

E_{fuel} is the energy content of the fuel, typically given in Joules per liter (J/L).

2) Emissions F_e :

Emissions F_e are typically computed as a function of engine power, driving conditions, and fuel consumption. A simple model can be [26]:

$$F_e = \sum_{i=NOx,CO,HC} \int_{t_0}^{t_f} E_{emission}(P_{ICE}(t), speed(t), load(t))dt \tag{7}$$

Where:

$E_{emission}$ is the emission factor for each type of pollutant (NOx, CO, HC), which can be modeled as a function of engine power $P_{ICE}(t)$, vehicle speed speed (t), and load load (t).

3) Penalty function $C_i(x)$:

Each constraint $C_i(x)$ represents a limitation on the vehicle's operation. Common constraints include limits on the battery's state of charge (SOC), power output of the engine, and vehicle acceleration [27]. For example:

C) SOC constraint

$$C_{SOC}(x) = |SOC(t) - SOC_{target}| \tag{8}$$

Where $SOC(t)$ is the state of charge at time t and SOC_{target} is the target SOC value for optimal battery operation.

D) Power constraints [28]

$$C_{power}(x) = |P_{total}(t) - P_{\max}| \tag{9}$$

Where $P_{\text{total}}(t)$ is the total power demand at time t and $P_{\max}$ is the maximum allowable power output of the system.

The penalty factor α_i determines how heavily each constraint is penalized if violated. These factors are chosen based on the relative importance of each constraint in the overall optimization.

2.2. Proposed energy management control strategy

The proposed energy management strategy for the hybrid vehicle aims to optimally distribute the required torque between the internal combustion engine (ICE) and the electric motor (EM), ensuring efficiency while satisfying driving conditions and minimizing fuel consumption and emissions. The control system uses a fuzzy logic approach, where two primary inputs are used: the driver's requested torque and the battery's state of charge (SOC).

The system follows a Mamdani-type fuzzy inference model, in which the inputs are fuzzified and processed through a rule-based decision-making system. The output, ICE torque, is then defuzzified to provide a crisp value, which dictates how much torque should be provided by the ICE. The remaining required torque is supplied by the electric motor.

The fuzzy controller is structured as follows:

1. Inputs:

o *Driver's Requested Torque* (T_{req})*:* The torque demand from the driver is normalized between 0 and 1.

o *Battery State of Charge (SOC):* The battery's charge level is normalized, with 0 indicating a low charge and 1 representing a full charge.

2. Fuzzification:

o Both inputs are divided into fuzzy sets: Low, Medium, and High. This process converts the crisp inputs into fuzzy values that reflect their degree of membership in each set.

3. Inference engine:

o A rule base, consisting of expert-designed fuzzy rules, is used to process the fuzzified inputs and determine the ICE torque required. The fuzzy inference system evaluates the inputs to generate a fuzzy output.

4. Defuzzification:

o The fuzzy output is defuzzified using the center of gravity method, providing a crisp value for the ICE torque.

5. Output:

o The defuzzified output represents the ICE torque, and the remaining torque is supplied by the electric motor.

The general equation representing the fuzzy controller is [29]:

$$T_{ICE} = f_{fuzzy}(SOC, T_{req}) \tag{10}$$

Where:

- T_{ICE} is the output torque from the internal combustion engine,
- SOC is the battery state of charge,
- T_{req} is the driver's requested torque.

The fuzzy controller is designed using a Mamdani-type inference system to manage the energy distribution between the internal combustion engine (ICE) and electric motor (EM). In the design of the fuzzy-based energy management control system for hybrid electric vehicles (HEVs), the selection of inputs such as the load demand (driver's requested torque) and the battery state of charge (SOC) is essential for optimizing system performance. These inputs were chosen based on their direct impact on the operation and energy distribution within the HEV.

1. Load demand: The load demand, represented by the driver's requested torque, is a critical input as it determines the amount of power needed from the system at any given moment. The energy management system must respond to these demands by appropriately distributing the workload between the internal combustion engine (ICE) and the electric motor (EM). Incorporating this input allows the controller to manage energy flow efficiently and ensure that the vehicle meets the required performance without unnecessary fuel consumption or emissions.

2. Battery state of charge: The SOC provides essential information about the remaining energy in the battery and is crucial for determining when the battery should be charged or discharged. By including this input, the controller can avoid overcharging or deep discharging, which could lead to reduced battery life. The SOC helps balance the power split between the ICE and the electric motor, ensuring that energy from the battery is used optimally and that the vehicle maintains the desired performance levels without depleting the battery too quickly.

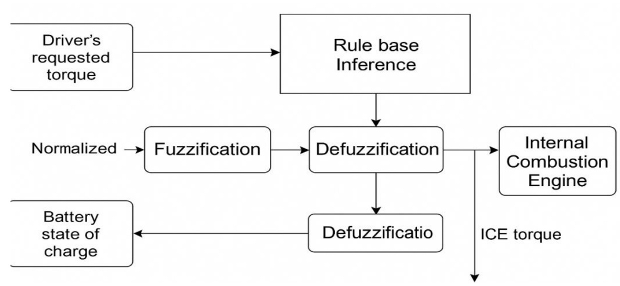

Fig. 3. Structure of the fuzzy controller for energy management in HEVs.

As shown in Fig. 3, the controller receives two normalized inputs: the driver's requested torque and the battery's state of charge (SOC). These inputs pass through fuzzification modules where they are mapped to linguistic variables. Based on a predefined rule base (Table 1), the inference mechanism determines the appropriate output torque command for the ICE. The defuzzification module then converts the fuzzy output into a crisp value that defines the ICE torque, while the remaining torque required is fulfilled by the electric motor. The controller is robust, adaptable, and capable of handling nonlinearities in real-time operating conditions.

Each of the inputs and outputs has three membership functions and the controller has a total of nine fuzzy rules. To manage the energy flow in the HEV efficiently, a fuzzy rule-based decision table is developed using expert knowledge and trial-and-error tuning. The fuzzy system utilizes two inputs: the normalized driver torque demand and the battery SOC, each divided into three fuzzy sets: Low, Medium, and High. The output of the fuzzy controller is the normalized torque to be provided by the internal combustion engine (ICE), also categorized into Zero, Low, Medium, and High based on the operating condition. The full rule base is presented in Table 2.

Table 2. Fuzzy rules.

Battery SOC	Driver torque request	Engine torque output
Low	Low	Medium
Low	Medium	High
Low	High	High
Medium	Low	Low
Medium	Medium	Medium
Medium	High	High
High	Low	Low
High	Medium	Low
High	High	Medium

To manage the energy flow in the HEV efficiently, a fuzzy rule-based decision table is developed using expert knowledge and trial-and-error tuning. The fuzzy system utilizes two inputs: the normalized driver torque demand and the battery SOC, each divided into three fuzzy sets: Low, Medium, and High. The output of the fuzzy controller is the normalized torque to be provided by the internal combustion engine (ICE), also categorized into Zero, Low, Medium, and High based on the operating condition. The full rule base is presented in Table 2.

The requested torque is normalized to a number between 0 and 1, where 0 represents zero torque, 0.5 represents the optimal torque calculated for the combustion engine based on the engine speed at the current moment, and 1 is the maximum torque that can be provided by the combustion engine at this moment. To normalize the requested torque at any moment, this torque is compared with the optimal torque of the combustion engine at any moment. It should be noted that the optimal torque of the combustion engine - the number 0.5 - changes at any moment. Similarly, the battery charge level is normalized to a number between 0 and 1, where 0 represents the minimum allowable charge level of the batteries and 1 represents the maximum allowable charge level of the batteries. The number 0.5 also corresponds to the target charge level value.

In order for the battery pack and the vehicle to perform optimally, a target value for the battery charge level is defined here. For a specific battery, this target value can be determined using the battery charge and discharge graph. This target value should be chosen so that it is close to the minimum charge and discharge resistance values. For example, the charge and discharge resistance curves for a lead-acid battery used in a hybrid vehicle are shown in Fig. 4. For this battery, the target value for battery charge can be considered to be 0.65.

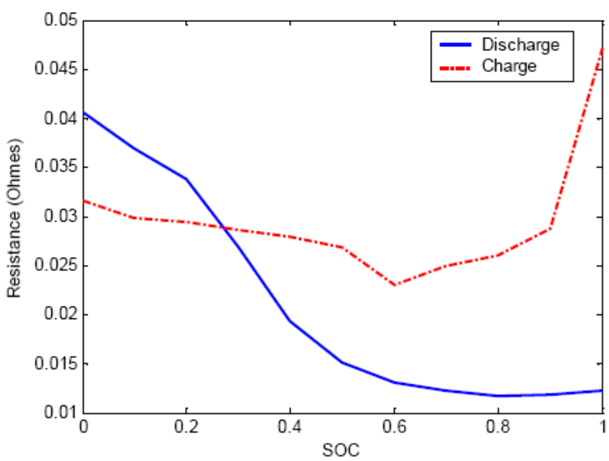

Fig. 4. Charge and discharge of battery (lithium ion).

Because the output of the fuzzy controller is also the torque of the combustion engine, the output membership functions here are exactly the same as the first input membership functions, i.e. the requested torque. The initial membership functions are shown in Fig. 5.

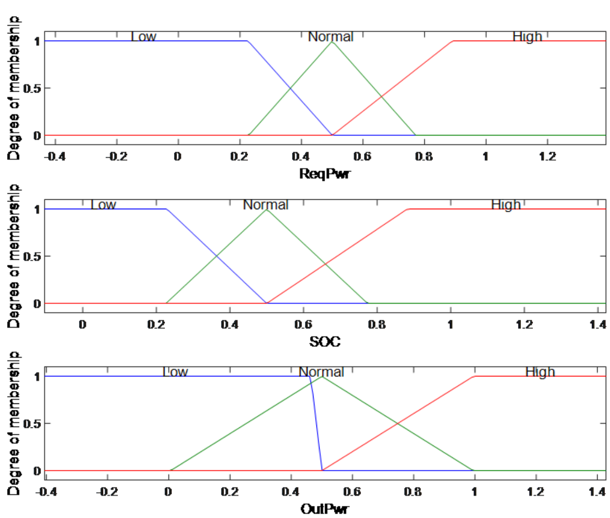

Fig. 5. Optimized fuzzy rules by GA.

2.3. Fuzzy controller optimization using genetic algorithm

To enhance the performance and robustness of the fuzzy logic controller used in the HEV energy management system, we adopt a Genetic Algorithm (GA)-based optimization method. This approach ensures that the membership functions and, if desired, the fuzzy rule base are adaptively optimized to minimize fuel consumption and emissions while preserving the vehicle's performance constraints.

A) Optimization framework

The GA employed in this study is a stochastic, population-based, global optimization technique inspired by the principles of natural selection and genetics. It is particularly effective for solving complex, nonlinear, and discontinuous problems such as tuning fuzzy logic controllers for hybrid vehicles.

The optimization process involves the following key steps:

1. Initialization:

o The population is initialized with a set of chromosomes. Each chromosome encodes a potential solution, i.e., a set of parameters that define the fuzzy controller's membership function shapes (e.g., triangular or trapezoidal), positions, and optionally rule base weights.

o Chromosomes are represented as real-valued vectors where each gene corresponds to a breakpoint or slope of a membership function.

2. Evaluation:

o Each chromosome is decoded into a fuzzy controller.

o The HEV model is simulated under a standard driving cycle (e.g., FTP).

o The objective function is computed for each candidate controller, evaluating fuel consumption, emissions, and constraint violations.

3. Objective function [30]:

$$F(x) = w_1.\ Fuel\ Consumption+ \\ w_2.\ Emissions + \sum_{i=1}^{n} \gamma_i.Penalty_i(x) \tag{11}$$

• w_1 and w_2 are weights for fuel consumption and emissions.

• γ_i is the penalty factor for violating constraint i.

• Constraints include limits on battery SOC, engine torque, and vehicle performance.

B) Constraints include

• Maintaining battery SOC within allowable bounds:

$$SOCmin \leq SOC(t) \leq SOCmax \tag{12}$$

• Ensuring ICE torque stays within operational limits.

• Satisfying torque demand to maintain drivability.

These constraints ensure that the optimized controller not only minimizes fuel consumption and emissions but also preserves system safety and performance.

4. Selection:

o A tournament selection or roulette wheel method selects the best-performing chromosomes based on fitness scores.

5. Crossover and mutation:

o Crossover combines parts of two parent chromosomes to produce new offspring.

o Mutation introduces random changes to genes, ensuring diversity and exploration of the search space.

6. Convergence check:

o The algorithm proceeds for a predefined number of generations or until improvements fall below a set threshold.

o Convergence behavior is monitored via changes in best fitness values across generations.

7. Output:

o The best solution found defines the optimized fuzzy membership functions (Fig. 5) and optionally an improved rule base.

o This controller is implemented for final simulations and result analysis.

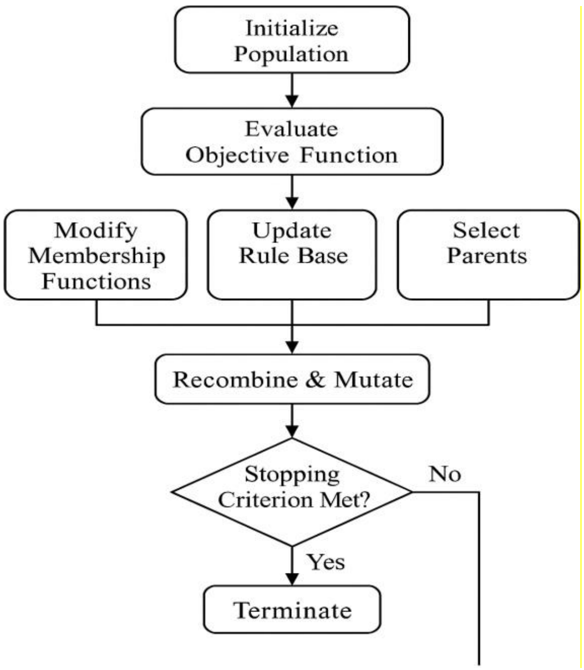

Fig. 6. Genetic algorithm-based optimization of fuzzy controller.

C) GA encoding details

A detailed flowchart illustrating the GA-based fuzzy controller optimization process is presented in Fig. 6.

• Each fuzzy input and output (e.g., Torque Request, SOC, ICE Torque Output) is initialized with basic triangular functions. During GA optimization, the position of breakpoints (e.g., centers, spreads) of these functions are encoded into the chromosome. GA adjusts these parameters to improve control performance.

• In a more advanced version, rule weights or even rule selection (binary on/off genes) can be encoded. This allows GA not only to tune the shapes of membership functions but also to evolve or simplify the fuzzy rule base, leading to better generalization and reduced rule complexity.

2.4. Integration of the GA-optimized fuzzy controller in HEV energy management

To effectively manage the power flow between the internal combustion engine (ICE) and the electric motor (EM) in hybrid electric vehicles (HEVs), the proposed controller is embedded within a hierarchical energy management system (EMS). The controller is optimized using a Genetic Algorithm (GA), ensuring adaptive performance under varying driving conditions and load demands.

As illustrated in Fig. 7, the controller receives key real-time input signals including:

• Torque demand from the driver,
• Battery state of charge (SOC),
• Vehicle speed and other dynamic variables.

These inputs are processed by a fuzzy inference system, whose membership functions and rules have been optimized offline using GA. The output of this system determines the optimal power distribution strategy, balancing energy from the ICE and EM to:

• Minimize fuel consumption,
• Protect battery life by maintaining SOC within limits,
• Maintain smooth and responsive vehicle performance.

The GA-based tuning allows the fuzzy controller to surpass conventional rule-based strategies by providing:

• Better adaptability to nonlinear system dynamics,
• More efficient fuel usage under various driving cycles,
• Greater robustness to uncertainties and driving pattern variations.

This integrated control strategy is implemented within a modular EMS framework that dispatches the computed commands to the powertrain actuators in real-time. The hierarchical structure also allows room for predictive modules or learning-based enhancements in future implementations.

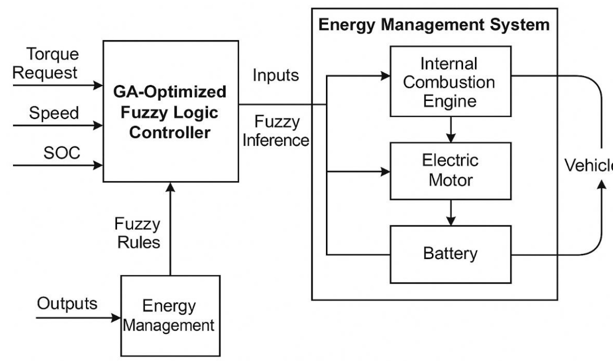

Fig. 7. Energy management system.

3. Results

One of the main variables affecting the performance of hybrid vehicles is the battery charge level during the actual driving cycle and its rate of change, because the rate of change, in addition to the amount of battery use, is also an indicator of the battery health. Therefore, in Fig. 8, the changes in the battery charge level before and after optimization are combined. As can be seen, the lower line graph, which is the changes after optimization, has a steeper slope than the upper line graph, which indicates that more battery consumption has been used after optimization. This difference implies that the fuzzy-genetic controller, considering that it has optimized for a distance of 20 km, which is less than about 80 km, has used more battery power based on its objective function to reduce both fuel consumption and pollutants.

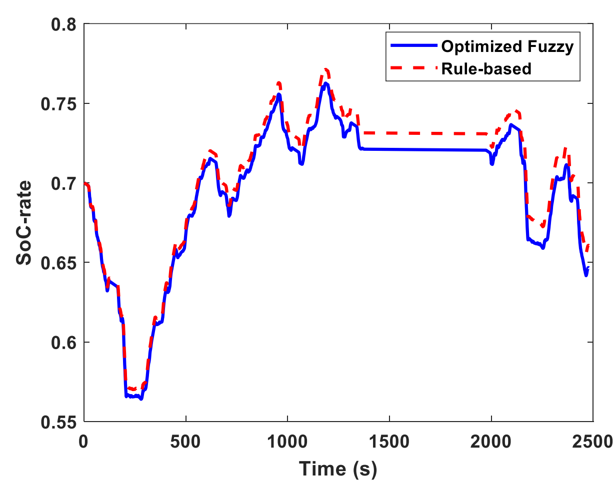

Fig. 8. SoC rate of battery.

The battery SoC trend in Fig. 9 indicates a more aggressive but controlled use of battery energy in the optimized controller. The sharper decline in SoC reflects that the fuzzy-genetic controller relies more on the electric motor, reducing demand on the ICE and improving overall efficiency. Despite the steeper slope, the SoC remains within operational limits, ensuring long-term battery health while enabling better fuel economy.

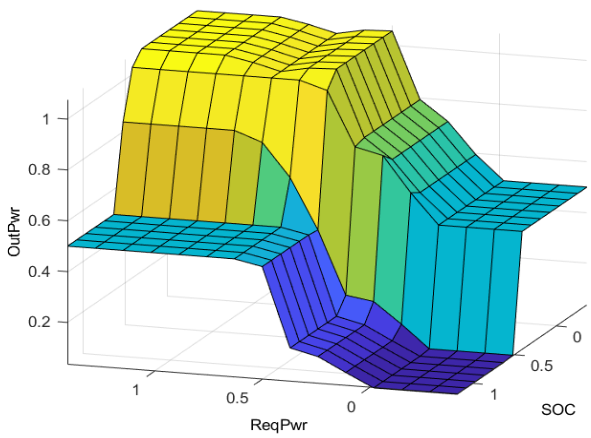

Fig. 9. Power-SoC variation.

First, the performance of the combustion engine and the energy loss in the two optimal and rule-base fuzzy machines are compared in Fig. 10. As can be seen in the Fig. 10, by using optimized fuzzy, the amount of power loss in the combustion engine is reduced by about 20%, which can also lead to a reduction in fuel consumption and pollution.

The fuel consumption in the two cases is plotted in Fig. 11, which shows that the fuel consumption performance of the optimal fuzzy system is improved by up to 15% compared to the rule-base control system. As shown in the figure, the maximum instantaneous fuel consumption is 6.2 and 4.3 liters per 100 km for the rule-base and optimal fuzzy systems, respectively, which represents a reduction in instantaneous fuel consumption of up to 31%. These improvements reflect the optimized controller's ability to more efficiently balance power demand between the ICE and the electric motor based on dynamic driving conditions.

In addition to reducing fuel consumption, the optimized control strategy minimizes unnecessary ICE activation and operates the engine closer to its efficiency zone more consistently. This smoother energy management not only improves fuel economy but also extends the lifespan of engine components by reducing abrupt transitions. To demonstrate the characteristics of the control strategy of hybrid electric vehicles, the simulation is performed in a hybrid operating mode. In this simulation, it is assumed that 30% of the electrical energy in the battery is lost during conversion to mechanical energy and reaching the wheels. Also, the size conditions of the electric motor and the combustion engine are assumed to be 23% and 68%, respectively. The operating mode considered in this simulation is the hybrid mode of the combustion engine, which means that the combustion engine produces the most power with respect to its optimal limit in the charging state, and the vehicle controller commands the optimal power of the combustion engine. The remaining power is also provided by the electric motor.

The fuel consumption, pollutant emissions, and dynamic performance of the vehicle for all three cycles and when using the original and optimized controllers are shown in Table 3. By examining Table 3, it can be seen that the optimized controller is superior to the original controller in terms of fuel consumption, pollutant emissions, and dynamic performance.

As summarized in Table 3, the optimized fuzzy-genetic controller consistently outperforms both the conventional and rule-based fuzzy controllers across multiple performance indicators:

- **Fuel consumption:** Reduced by up to 15% on average.
- **Power loss in ICE:** Decreased by 20%.
- **Acceleration (0–97 km/h):** Improved by ∼19%.
- **Battery SOC usage**: More dynamic but maintained within safe thresholds.

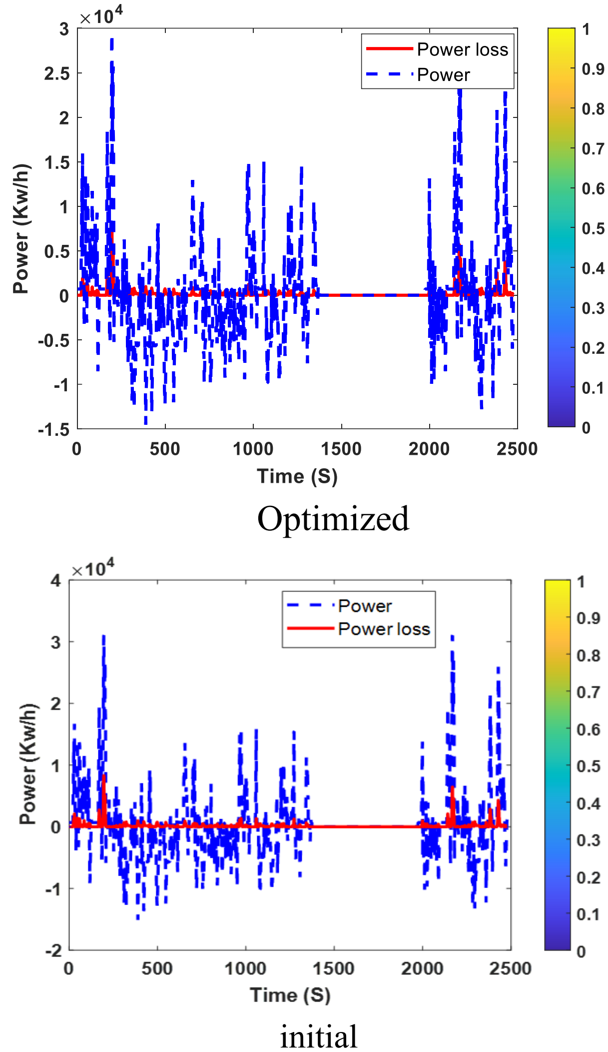

Fig. 10. Power and loss rates by initial and optimized strategy.

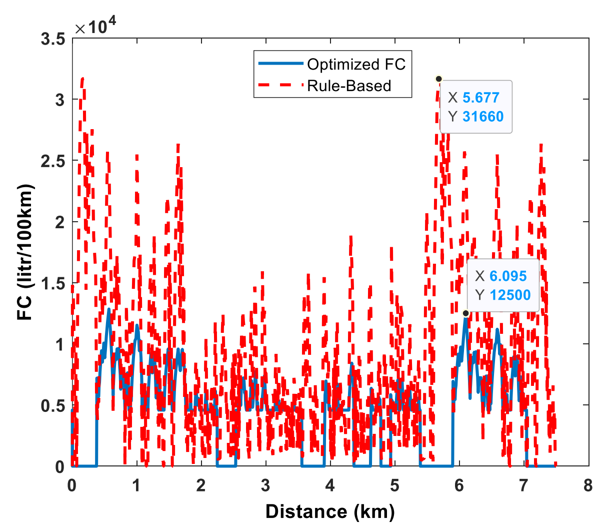

Fig. 11. Fuel consumption rate.

- **Emissions:** All major pollutants (HC, CO, NOx) reduced.

These results confirm the improved energy management capabilities of the optimized controller while maintaining

Table 3. Fuel consumption, pollutant emissions, and dynamic performance of a hybrid vehicle with a fuzzy controller.

	FTP cycle			
Variables	**Conventional**	**Rule base**	**Optimized**	**Units**
Objective	2.134	1.676	1.467	-
Fuel consumption	5.785	5.0841	4.3456	L/100 km
HC	0.349	0.319	0.298	g/km
CO	0.9520	1.1079	0.922	g/km
NOx	0.2750	0.1902	0.1603	g/km
Grade ability	5.295	6.563	6.465	-
Time 0–97 km/h	12.83	10.33	10.38	sec
Time 64–97 km/h	7.04	5.28	5.22	sec
Time 0–137 km/h	34.68	21.88	22.19	sec
Maximum speed	151.3	153.48	152.98	km/h
Maximum acceleration	4.951	4.950	4.948	m/s^2
Distance traveled in 5 seconds	49.18	51.83	50.43	m

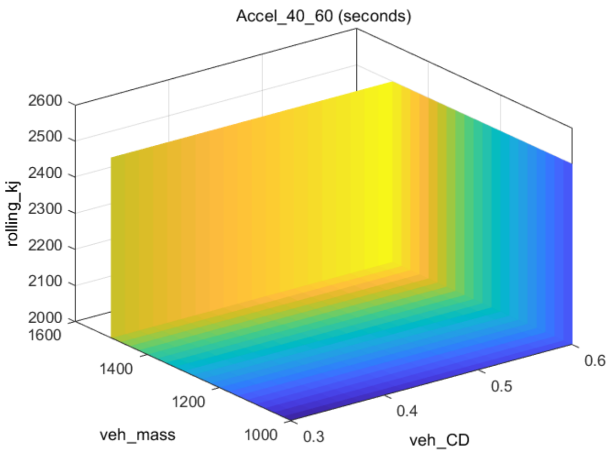

Fig. 12. Acceleration rate.

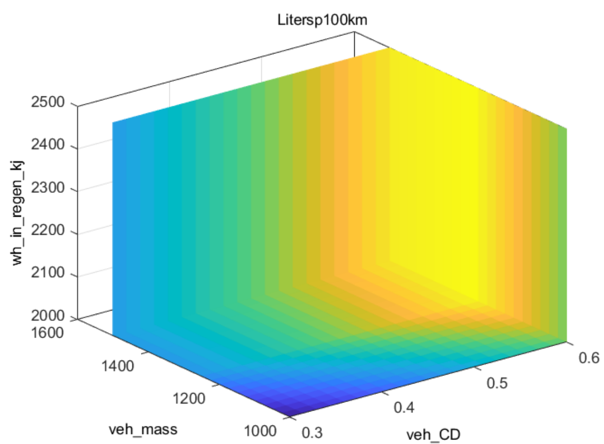

Fig. 13. Fuel consumption rate.

compliance with Euro 6 standards and ensuring stable vehicle dynamics.

The results show that the optimal control strategy performs better than the rule-based one in reducing fuel consumption and emissions. Also, the performance of the hybrid vehicle improves with increasing the initial charge. The simulation results clearly show the positive effect of optimization in reducing fuel consumption and emissions. As the results show, with proper optimization of a conventional hybrid vehicle, fuel consumption and emissions can be reduced by an average of 19% and 15%, respectively, in real driving cycles.

Given that the designed fuzzy-based controller can better utilize

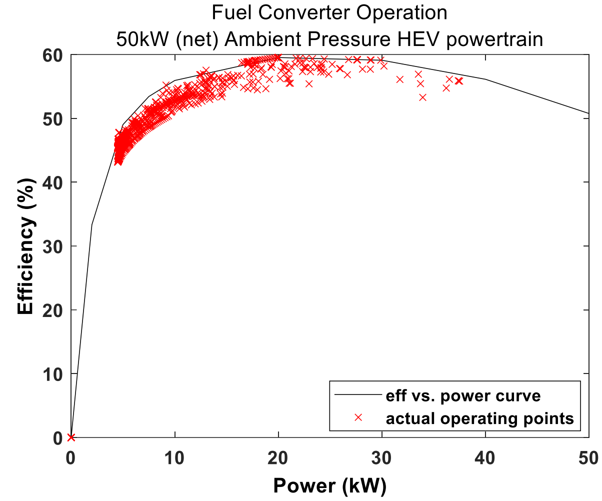

Fig. 14. Fuel converter operation.

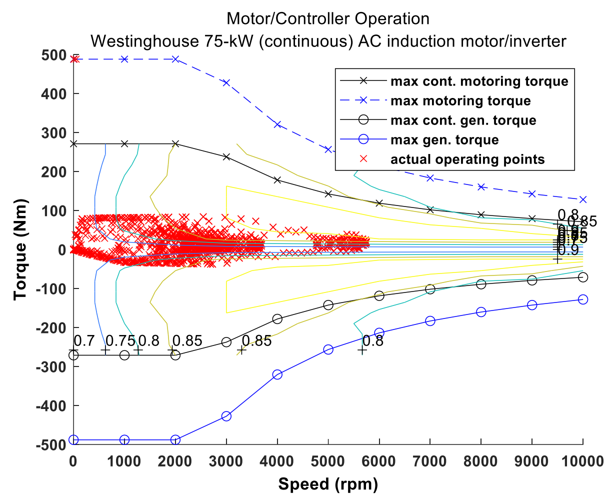

Fig. 15. Electric motor operation.

the conceptual communication capabilities between different parts of the vehicle, this problem does not exist in the simulation implemented with the rule-based supervisory controller and the battery charge level is maintained at a desirable level, which indicates the desirable performance of the proposed control method.

The performance of the ICE and the EM of the hybrid vehicle is compared in Figs. 14 and 15. The operating points of the ICE and the EM are in the optimal performance area by using a higher charge level, which reduces fuel consumption and emissions while meeting the longitudinal dynamic needs of the vehicle. The operating points of the internal combustion engine and the electric motor are in the optimal performance area by using optimization. Fig. 14 illustrates the operating points of the internal combustion engine (ICE), showing that under the optimized fuzzy-genetic controller, the ICE remains within its high-efficiency zone for longer durations compared to the rule-based approach. This concentrated operation near optimal conditions reduces fuel consumption and emissions while minimizing frequent on/off switching, which helps improve mechanical reliability and ride comfort. The smoother distribution of ICE power output also reflects more stable and efficient torque generation, avoiding excessive fluctuations seen in the rule-based method. In Fig. 15, the electric motor (EM) operation demonstrates more deliberate and efficient usage under the optimized strategy. The EM is primarily engaged during low-load or transient phases, operating closer to its optimal efficiency regions. This complementary behavior ensures a more balanced energy split between the ICE and EM, reducing reliance on the engine in inefficient zones. The resulting control effort is smoother and more coordinated, improving energy efficiency and dynamic response while maintaining compliance with Euro 6 emission standards.

The operating pattern of the internal combustion engine (ICE), shown in Fig. 15, indicates that with the optimized controller, the ICE operates within its high-efficiency zone for longer durations and experiences fewer on/off cycles. While explicit engine switching data was not logged numerically, the reduced variation in power output and smoother power transitions suggest a decrease in engine on/off frequency. This contributes to improved fuel efficiency, reduced mechanical wear, and lower overall noise and vibration levels. Overall, these figures confirm that the optimized controller not only improves energy distribution between the ICE and EM but also leads to more stable and efficient system performance across various driving conditions., which reduces fuel and pollution while meeting the longitudinal dynamic needs of the vehicle.

In terms of control effort, the optimized fuzzy-genetic controller demonstrates a more coordinated and efficient distribution of torque between the ICE and electric motor, with fewer abrupt changes in power commands. Compared to the rule-based controller, which relies on fixed rules and often leads to more frequent switching and adjustment, the optimized controller exhibits smoother transitions and reduced control activity. This not only improves energy efficiency but also enhances passenger comfort and system durability.

Also, simulation values show that the hybrid electric vehicle meets the Euro 6 emission standards in the FTP cycle in all traffic conditions. Considering the traffic conditions with slow and dense traffic and air pollution problems, if hybrid electric vehicles are used, more of the benefits of these vehicles can be enjoyed, which in addition to saving fuel consumption can play a very significant role in reducing pollutants. The fuzzy-genetic controller can have a significant impact on reducing fuel consumption and pollutants compared to the rule-base controller. However, the problem is that the fuzzy controller can be implemented on the hybrid electric vehicle in real-time and instantaneously, while the fuzzy-genetic controller cannot work instantaneously.

4. CONCLUSION

In this study, an enhanced fuzzy-genetic control strategy was proposed and implemented for optimal energy management in hybrid electric vehicles (HEVs). The controller integrates fuzzy logic with genetic algorithm (GA)-based optimization to tune membership functions and, optionally, the fuzzy rule base, with the primary aim of reducing fuel consumption and pollutant emissions while preserving vehicle dynamic performance and battery health. Simulation results across real-world driving conditions, particularly the FTP cycle, demonstrated the significant effectiveness of the proposed approach when compared to conventional and rule-based fuzzy controllers. Key findings include:

- **Fuel consumption:** The optimized fuzzy-genetic controller reduced fuel consumption by up to 15% compared to the rule-based controller (from 5.0841 to 4.3456 L/100 km), and up to 25% when compared to a conventional control strategy.
- **Pollutant emissions:** Emissions of key pollutants were significantly reduced:
  o Hydrocarbons (HC): from 0.319 g/km (rule-based) to 0.298 g/km (optimized)
  o Carbon monoxide (CO): from 1.1079 g/km to 0.922 g/km
  o Nitrogen oxides (NOx): from 0.1902 g/km to 0.1603 g/km
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  o Nitrogen oxides (NOx): from 0.1902 g/km to 0.1603 g/km
- **ICE efficiency:** Power loss in the internal combustion engine was reduced by approximately 20%, contributing to both fuel savings and lower pollutant emissions.
- **Battery management:** The battery state of charge (SoC) exhibited a more dynamic but still controlled usage pattern. The optimized controller employed more aggressive electric motor usage while keeping the SoC within safe operational boundaries, promoting long-term battery health.
- **Vehicle dynamics:**
  o Acceleration from 0–97 km/h improved by nearly 19%, from 12.83 seconds to 10.38 seconds.
  o Maximum speed and gradeability remained effectively unchanged, indicating no compromise in performance.
  o Electric motor and ICE operation remained within high-efficiency regions more consistently in the optimized controller scenario, confirming smoother and more energy-efficient torque distribution.

Moreover, the proposed controller proved capable of maintaining compliance with Euro 6 emission standards across all tested driving scenarios, highlighting its practicality for real-world application in urban environments. Despite these advantages, the fuzzy-genetic controller presents a limitation in terms of real-time applicability, as the GA-based optimization cannot adapt instantaneously. However, once the controller parameters are optimized offline, they can be implemented in real-time via a lookup table or embedded logic, mitigating this challenge to some extent. In conclusion, the proposed fuzzy-genetic controller not only outperforms conventional and rule-based controllers in key performance areas but also offers a more intelligent and adaptive framework for managing power flow in HEVs. This makes it particularly well-suited for urban driving cycles characterized by frequent speed changes and variable power demands.

Future research could focus on integrating real-time adaptability into the optimization process through online learning techniques or hybrid metaheuristics. Additionally, incorporating the driving cycle as a dynamic input in the fuzzy cognitive map structure could allow for context-aware control adjustments, further enhancing energy management efficiency. Testing the proposed controller under real-world traffic conditions and with varying vehicle configurations would also be valuable in validating its robustness and generalizability.

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