

Comparative Analysis of Energy Management Strategies for a Hybrid Electric Vehicle in Urban Transportation: A Case Study

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Abstract— The present study provides a comprehensive overview of energy management strategies (EMS) in urban transportation, with a focus on their application in emerging electric vehicle (EV) technologies, particularly hybrid electric vehicles (HEVs). It presents a comparative analysis of global optimization methods—such as particle swarm optimization (PSO) and genetic algorithms (GA)—and rule-based approaches, including fuzzy logic and Boolean logic. The objective is to evaluate their effectiveness when the electric motor (EM) and internal combustion engine (ICE) operate in hybrid mode, using key performance indicators (KPIs) derived from MATLAB simulations. By determining the most suitable operating mode—whether to use the EM, the ICE, or both—the system aims to optimize energy use, enhance driver experience, reduce ICE dependency and fuel consumption, and support environmental sustainability. The study also explores the potential of emerging technologies like artificial intelligence (AI) and machine learning (ML) to further improve EMS decision-making.

Keywords: Optimization, Rule based, energy management strategies, hybrid electric vehicle, artificial intelligence, decision-making.

I. INTRODUCTION

Electric mobility is changing how people and goods move around the world. The sector is growing fast, from electric cars to public transport systems [1, 2]. Many countries are adopting more electric vehicle (EV) technologies. For example, in Norway, 95% of all new car sales were EVs in February 2025.

EV technologies offer a range of advantages, including the reduction of air pollution and greenhouse gas emissions, contributing to cleaner and healthier urban ecosystem [3, 4]. They also present lower fuel and maintenance expenses, leading to long-term financial savings. Additionally, the convenience of charging at home minimizes the need for frequent trips to gas stations [5]. Despite these benefits, challenges persist, as many countries continue to face issues, particularly concerning charging infrastructure [6-8]. Developing a widespread and robust charging network is crucial to overcoming these obstacles to adoption. In countries where infrastructure is still developing, the approach is to prioritize the promotion of hybrid electric vehicles (HEVs) as an initial phase in the transition process, rather than concentrating mainly on fully EVs or battery electric vehicle (BEVs) [9].

From another perspective, HEVs require an effective energy management strategy (EMS) to regulate energy flow between different power sources. The primary goal is to enable optimal

decision-making that balances vehicle performance, driver experience, and environmental impact by minimizing fuel consumption and reducing emissions.

In this vein, we perform a comparative evaluation of two distinct EMS strategies: global optimization methods, such as particle swarm optimization (PSO) and genetic algorithms (GA), among others, and rule-based techniques, including fuzzy logic and Boolean logic.

The primary objective is to assess the effectiveness and impact of these strategies particularly in hybrid mode operation, focusing on various Key Performance Indicators (KPIs) such as fuel consumption, CO₂ emission reduction, and CPU computational time, among others. Additionally, we evaluate the integration of emerging technologies to enhance their performance.

A. Outline of the present paper

The organization of the present paper is as follows: Section II offers a broad overview of HEV technologies. Section III delves into the energy management strategy: importance and need. section IV features a case study: comparative analysis. Section V includes the discussion and performance evaluation. In Section VI, future perspective of learning based techniques is explored. Finally, Section VII provides a summary of the overall conclusions.

II. HYBRID ELECTRIC VEHICLES: OVERVIEW

The integration of EV technologies into road transport is regarded as a promising approach to decreasing fossil fuel consumption and reducing emissions, while enhancing the global energy mix through the vehicle to Grid (V2G) concept. This encompasses various EVs, including plug-in electric vehicles (PEVs), and plug in hybrid electric vehicles (PHEVs). However, inadequate charging infrastructure may cause consumer doubt about PEV range. As shown in Fig. 1, HEVs achieved the highest adoption rate among new cars in Europe during Q1 2025, highlighting their appeal as a bridge between conventional vehicle (CV) technology and PEVs/BEVs [10]. This trend stems from consumer demand for fuel efficiency and range flexibility, along with wider availability and lower upfront costs compared to BEVs. Government incentives and hybrid technology advances have driven their adoption, positioning HEVs as a top alternative in the EU's automotive market. As a result, this study concentrates mainly on HEV technology. HEVs do not require

plugging in, making them a potentially attractive long-term solution if targeted marketing strategies and purchasing policies are implemented to scale up the urban transition.

HEV technology is mainly composed of an internal combustion engine (ICE) and one (or more) electric motor (s), as well as a storage system (e.g. battery, fuel cell, and so on). Different energy sources can function either alternately or simultaneously to minimize fuel consumption and CO₂ emissions.

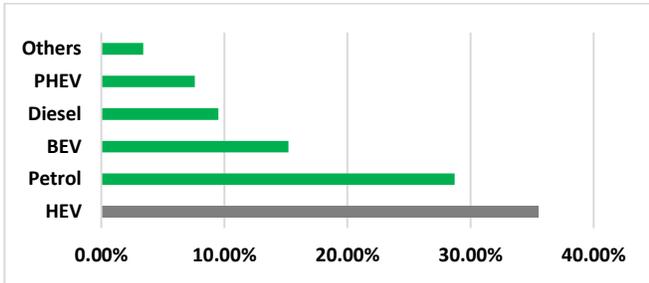


Figure 1. New EU Car Registrations By Power Source, Q1, 2025.

This operation depends on various factors, including road conditions (such as inclines and declines), weather conditions (like rain and wind), and driving situations (such as speeding up and slowing down). Additionally, HEV technologies are divided into various architectures: series, parallel, and power-split. Each type has its own unique features, advantages, and drawbacks.

III. ENERGY MANAGEMENT STRATEGY: : IMPORTANCE AND NEED

To boost the efficiency and performance of HEVs, EMS are crucial in managing the energy flow between the ICE and the battery that powers the traction system, particularly the EM. This management not only optimizes performance and efficiency but also affects battery lifespan. Additionally, it helps reduce fuel consumption and CO₂ emissions, offering consumers a balanced range and environmental protection [11]. EMS in general can be classified into different categories based on different criteria such as real-time Applications (online and offline, development, application domain (research, industry), type of problem (stochastic, deterministic) [12]. In this study we will focus on the following classification: optimization based, rule based and learning based techniques as presented in Fig. 2.

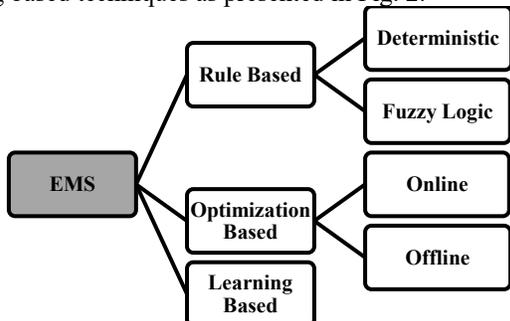


Figure 2. EMS for HEV technology.

Optimization based involves determining the best solution to a given problem by identifying the values of decision variables that yield the highest or lowest possible outcomes for one or more objectives. Large-scale optimization challenges related to EV technologies involve numerous decision variables, making them particularly complex. Over time, a variety of strategies have been employed to address these optimization challenges: economic, ecological, and operational/system enhancement [13]. These objectives encompass a wide range of criteria and parameters, including, but not limited to, fuel consumption, emissions reduction, powertrain and charging station design, charging costs, battery charging and discharging processes, and comfort. Figure 3 illustrates the general optimization search process.

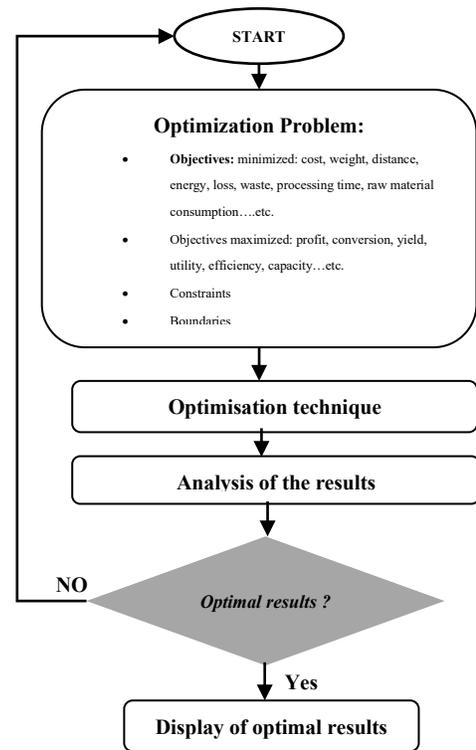


Figure 3. General Optimization search process.

Rule-based techniques rely on predefined rules and logic to make decisions such as Fuzzy logic and Boolean logic. Numerous research papers explore optimization techniques aimed at boosting EV technology efficiency and performance. These encompass strategies and algorithms designed to enhance vehicle operational efficiency and energy consumption. The authors in [14] examined EMS optimization for fuel cell hybrid electric vehicles (FCHEVs) through genetic algorithms (GAs). They emphasized the importance of effective EMS in enhancing system performance, reducing hydrogen consumption, and prolonging fuel cell lifespan. The authors highlighted GA benefits in addressing multi-objective optimization challenges and balancing cost, energy use, and component durability in hybrid power systems. By examining optimization methods, they sought to enhance energy utilization efficiency and guide optimal

control strategies for FCHEVs, advancing clean energy solutions in transportation.

Others in [15] discussed creating multi-objective optimal EMS for parallel HEVs, focusing on improving fuel economy, electric system efficiency, and battery lifespan. They developed two strategies: one for fuel consumption and electrical efficiency, and another to extend battery life. They used a multi-objective GA to optimize control inputs for pre- and post-transmission drivetrain configurations. Results showed notable battery performance improvements, particularly in pre-transmission setup, while maintaining fuel consumption compared to a baseline rule-based strategy. They proposed that incorporating battery longevity into energy management could enhance vehicle performance across driving cycles.

Other research efforts have highlighted the success of logic-based EMS in EV technologies. The authors in [16] proposed an EMS for dual-source electric vehicles, using Fuzzy logic control to optimize energy allocation between a PEM fuel cell and Li-ion battery across driving conditions. Their goal was to boost efficiency, reduce fuel consumption, and maintain propulsion power by managing energy flow from power sources. The EMS was validated using three driving cycles—New York City, Worldwide Harmonized Light Vehicles Test Procedure, and Urban Dynamometer Driving Schedule—and addresses PEM fuel cell challenges like slow dynamic response by enabling cooperation between energy sources. Simulation outcomes confirm the EMS's efficacy, with fuzzy logic enabling optimal energy distribution among PEMFC stack, Li-ion battery, and traction system. They provided a vehicle modeling framework considering forces impacting vehicle dynamics.

Moreover, researchers in [17] conducted a study on fuzzy logic-based EMS for hybrid fuel cell electric ships to reduce hydrogen consumption and improve efficiency. They assessed control-based, optimization-based, and Fuzzy logic methods, concluding that fuzzy logic strategy surpasses others by managing power distribution and minimizing fuel consumption during river journeys under diverse conditions. They emphasized Fuzzy logic techniques' potential in optimizing hybrid propulsion systems for marine applications. With advancements in machine learning (ML) and artificial intelligence (AI), learning-based techniques are increasingly utilized today [18].

In the following section, a comparison between rule based techniques and Global Offline Optimization techniques will explore the effectiveness of EMS strategies during hybrid mode operation in HEV with parallel architecture.

IV. CASE STUDY: COMPARATIVE ANALYSIS

A. Background

In this section a comparative study between different EMS techniques will be presented taking into consideration the case of HEV with parallel architecture and specifically we will take in consideration the Hybrid mode where the ICE and EM are working simultaneously as presented in Fig. 4.

The overall system of the studied vehicle included a permanent magnet synchronous machine (PMSM) with 4.5 kWh power, which is linked to the Lithium ion battery (250V) by means of a conversion system composed of a DC/AC converter. This converter is, in turn, linked to an intermediate DC bus, and an inverter. Besides, the parallel HEV includes an ICE (32.5 Nm), which is linked to the continuous variable transmission (CVT) and the reduction gear [13].

Essential stages in a vehicle EMS framework start with the association of the vehicle model and control, which involves integrating powertrain components and system design using MATLAB/Simulink Software. Following this, parametric settings are adjusted to fine-tune performance. The driving cycle is then selected, specifically the New European Driving Cycle (NEDC), with particular parameters outlined in Table I. These inputs are essential for the core EMS process, where the operational flowchart takes into account vehicle speed and battery SOC, as shown in Fig. 5. The general flowchart outlines the various modes of the control strategy employed: electric, thermal, hybrid, regenerative, and no transmission.

TABLE I. NEDC CYCLE PARAMETERS.

Parameters	Values
Distance (m)	11023
Mean speed(m/s)	33.6
Duration(s)	1180

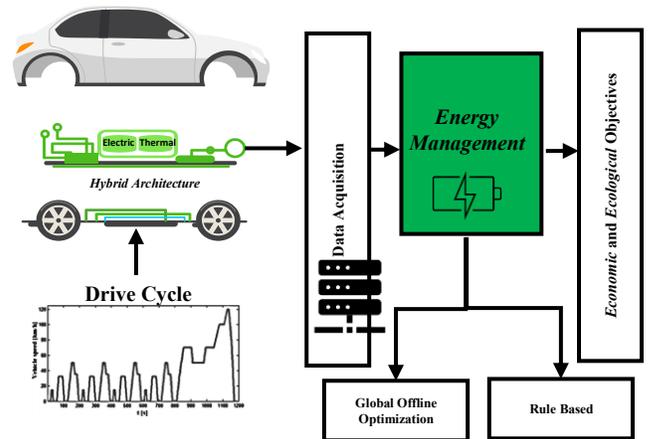


Figure 4. Adopted EMS Strategies.

B. Simulation Results

To assess the effectiveness and accuracy of the various proposed EMS methods, the outcomes were examined using the NEDC cycle depicted in Fig. 6. In this section, our simulations concentrated on the vehicle's hybrid mode, where both the EM and ICE are employed to drive the HEV concurrently during the period from 1014 seconds to 1160 seconds. As shown, the model's speed aligns with the reference speed.

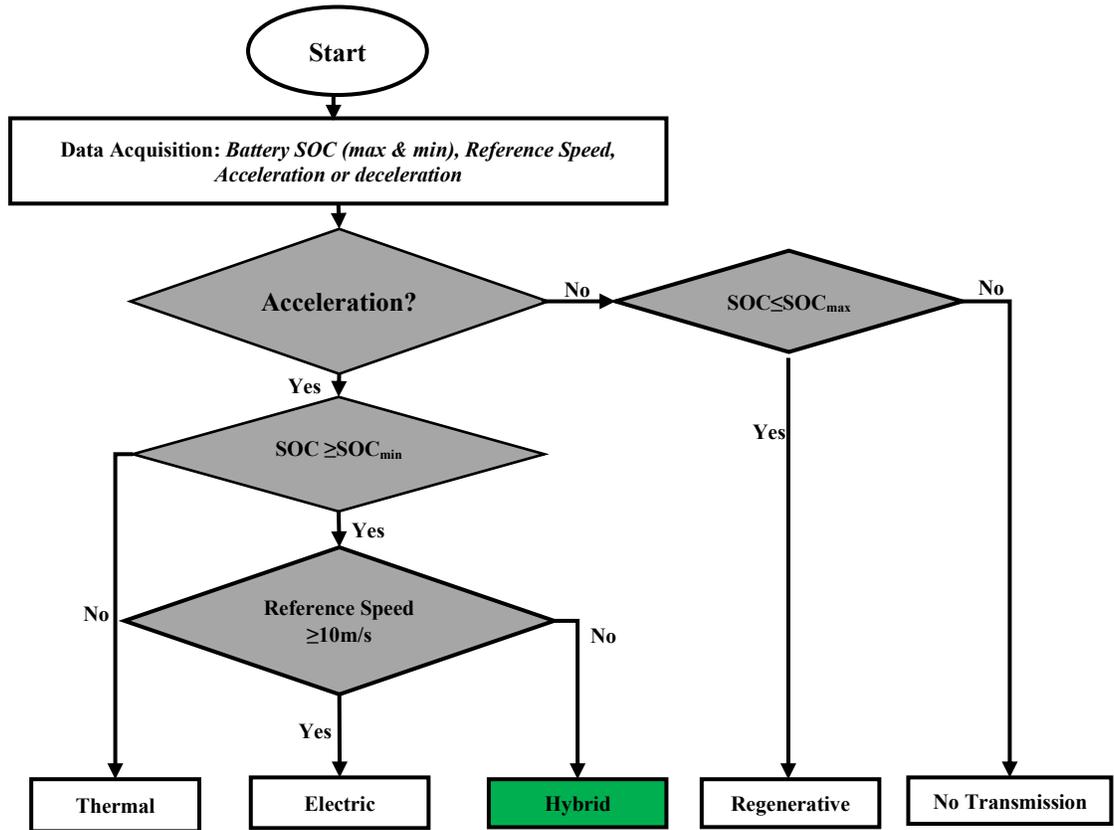


Figure 5. Flowchart of the management of the HEV operation.

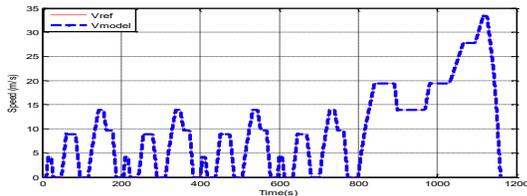


Figure 6. NEDC cycle speed.

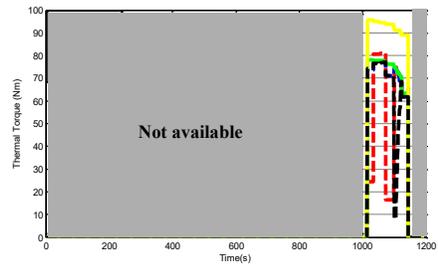


Figure 8. Optimized Thermal Torque.

- *Optimization Based*

In this subsection, the global optimization algorithms employed include PSO, Fmincon, APSO, GA, and Convex algorithm. Figure 7 illustrates the electric vehicle torque for all the algorithms examined. Meanwhile, the results for the thermal vehicle torque are shown in Fig. 8.

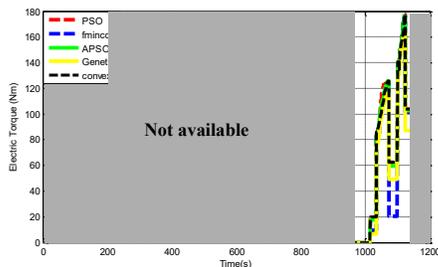


Figure 7. Optimized Electric Torque.

To gain a clearer insight into the variations in optimization torques during the time interval of [1014 s, 1160 s], Fig. 9 illustrates the SOC profiles of the Lithium battery for the different EMS in the aforementioned parallel HEV. It is observed that the SOC reduction for different algorithms is influenced by the HEV's electricity usage and the rise in electric torque.

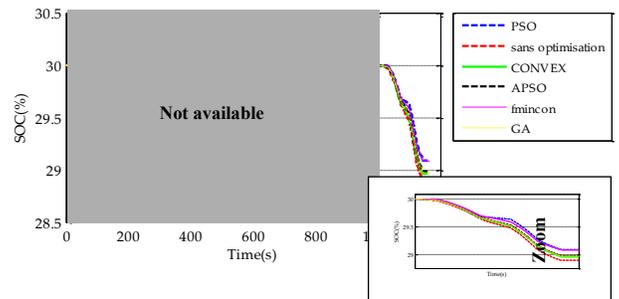


Figure 9. Lithium ion Battery SOC evolution.

- *Rule Based EMS*

Figure 10 compares the electric torque evolutions using Boolean and Fuzzy logic methods. With fuzzy logic strategy, the electromagnetic torque of the PMSM motor is smaller than Boolean logic, which affects the battery charge and discharge modes.

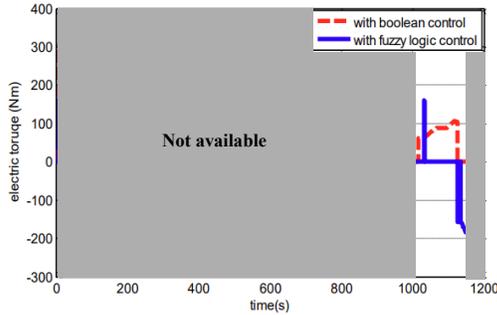


Figure 10. Electric Torque.

Fig.11 illustrates the comparison of thermal evolution during the NEDC cycle in the initial test using both approaches. It is evident that the results from the fuzzy logic are significantly smaller than those from the logic method.

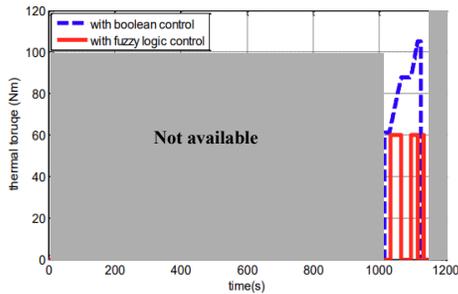


Figure 11. Thermal torque.

Figure 12 illustrates the changes in SOC values when applying two different control methods: the fuzzy logic and Boolean logic control strategies, during the NEDC driving cycle.

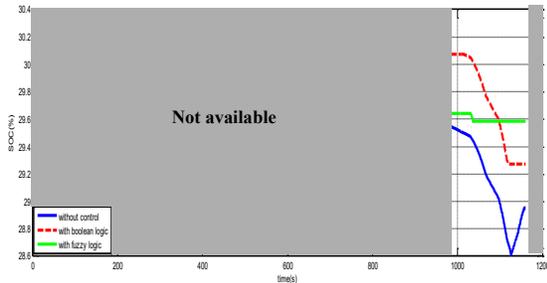


Figure 12. Lithium ion SOC evolution.

The battery's SOC is lower when controlled by Boolean logic compared to Fuzzy logic. Specifically, the SOC values are 29.2751% with Boolean logic and 29.509% with fuzzy logic at the end of the NEDC driving cycle. This variation in SOC values under both control methods enhances the effectiveness of battery discharge, ensures stable operation, and extends battery life span.

V. PERFORMANCE EVALUATION

Following a brief summary of the case study results and an explanation of the different techniques employed for HEV energy management, this section will delve into a general performance assessment based on several KPIs. The comparative findings can guide interested users in selecting the most suitable technique aligned with their predetermined goals as depicted in Fig. 13. The KPIs primarily focus on:

- *Fuel consumption economy,*
- *CO2 emission reduction,*
- *CPU computational time,*
- *The enhancement of charge-sustaining operations.*

Each indicator is scored on a scale ranging from 3, representing very good performance and marked in red, to 1, indicating acceptable performance and shown in blue as depicted in Fig. 13.

EMS Technique	Fuel_Consumption	CO2_Emission	CPU	Battery_Charge
PSO	2	2	2	3
GA	1	1	1	1
Fuzzy logic	3	3	2	3
Fmincon	3	3	3	3
Convex	2	2	1	1
Boolean Logic	2	2	3	3
APSO	2	2	1	1

Figure 13. EMS Techniques VS Evaluation Criteria.

The simulation results demonstrate the effectiveness of all techniques in reducing fuel consumption, CO2 emissions, and improving battery SOC. Despite concerns about computational time, rule-based methods like Fuzzy achieved the highest score. Fmincon excelled across all criteria, surpassing both optimization-based and rule-based techniques. Each method has advantages and disadvantages. Rule-based techniques are praised for simplicity and user-friendliness, while optimization algorithms rely on tuning parameters that need precise setting. The question remains: are these techniques ready for deployment in online environments, where extensive data analysis is required for real-time decisions? The following section will examine the effectiveness of ML and AI for future online applications, highlighting benefits and drawbacks based on research findings.

VI. FUTURE PERSPECTIVE: LEARNING BASED TECHNIQUES

For future online application of EMS in HEV technology, AI and ML will enhance decision making with more informed

decisions in real-world systems. Researchers are addressing this in studies. In [19], authors analyzed EMS for hybrid fuel cell electric ships, focusing on minimizing hydrogen consumption for passenger vessels during river trips. They compared five approaches: control-based, optimization-based, deterministic rule-based, and fuzzy logic strategies. Results show fuzzy logic rule-based strategy outperforms others, achieving 63.67% reduction in hydrogen use compared to rule-based deterministic strategy, and 66.78% compared to optimization-based approach. This strategy effectively manages energy distribution between fuel cell and storage systems. Future work should implement fuzzy logic strategy in real-time, incorporating AI to improve performance in hybrid marine propulsion systems. In [20], authors reviewed and presented an EMS roadmap for HEVs, emphasizing ML, computer vision, cloud computing, and swarm intelligence in optimizing vehicle efficiency. They highlighted current EMS approaches and discussed how reinforcement learning and deep learning enable adaptive, predictive energy management. They emphasized integrating these technologies to address challenges in data requirements, computational complexity, cybersecurity, and infrastructure limitations, aiming toward EVs and sustainability. In [21], authors presented a hierarchical reinforcement learning-based energy management strategy for fuel cell hybrid electric vehicles that manages power distribution among fuel cells, batteries, and ultracapacitors. Using fuzzy filtering to decouple power demand, the method reduces high-dimensional state-action space for learning. It integrates ECMS to optimize fuel consumption while ensuring real-time applicability. Simulation results show this approach achieves computational efficiency, maintains stability, and improves fuel economy compared to conventional methods.

VII. CONCLUSION AND FUTURE WORK

Efficient energy management is essential for sustainable urban transportation in HEVs that bridge conventional and electric systems. This study compared EMS, examining global optimization techniques like PSO and GA, and rule-based methods like fuzzy logic and Boolean logic. Using KPIs including fuel consumption, CO₂ emissions, CPU time, and charge-sustaining performance, results show strengths and trade-offs of each approach. While both strategies show promising outcomes, integrating AI and ML presents an opportunity to enhance real-time EMS decision-making. Future research will focus on using these systems to improve adaptability, efficiency, and sustainability in real-world driving conditions.

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