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SURVEY

Energy Management in Hybrid Electric and Hybrid Energy Storage System Vehicles: A Fuzzy Logic Controller Review

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ABSTRACT The transportation sector, a significant contributor to carbon dioxide emissions as of 2020, confronts a pressing challenge in mitigating pollution. Electric Vehicles (EVs) present a promising solution, offering a cleaner alternative; however, their limited travel range poses a constraint. Hybrid Electric Vehicles (HEVs) and Hybrid Energy Storage System Electric Vehicles (HESS EVs) emerge as economically feasible compromises. Nonetheless, the effective management of energy and the optimization of power source size remain crucial challenges for both HEVs and HESS EVs. Among various Energy Management Strategies (EMS), the Fuzzy Logic Controller (FLC) stands out for its performance, simplicity, and real-time applicability. This article comprehensively explores the diverse applications of FLC as an EMS in both HEVs and HESS EVs, providing a comparative analysis with other EMS methods and delving into the advantages and challenges associated with each approach. A detailed examination of various FLC types employed as EMS has been conducted, drawing insights from a multitude of references. Each class of FLC EMS is scrutinized, presenting a broad overview of proposed methodologies within each category. By providing this comprehensive information, the article equips readers with foundational knowledge and insights for the continued development of FLC EMS in hybrid electric and hybrid energy storage system electric vehicles.

INDEX TERMS Energy management, hybrid vehicle, electric vehicle, fuzzy logic controller, review.

I. INTRODUCTION

As of 2020, the transportation sector contributes significantly to carbon dioxide emissions, accounting for up to 35% [1]. Embracing electric vehicles (EVs), which produce zero pollutants, emerges as a promising avenue to mitigate pollution in transportation [2], [3], [4]. EVs offer numerous advantages over traditional engine-equipped vehicles, including lower pollution levels, increased efficiency, and abundant energy sources [5]. The primary power source in electric vehicles is a rechargeable battery, restricting the vehicle's travel range due to limited battery capacity. For EVs covering shorter distances, Hybrid Electric Vehicles (HEVs) have proven practical [6], exhibiting minimal emissions compared to conventional Internal Combustion Engine (ICE) vehicles [7]. HEVs employ two or more power sources, commonly combining an engine with a battery.

Unlike EVs, HEVs bypass challenges such as high prices, charging infrastructure limitations, extended charging times, and power interruptions, as revealed in a study by Rajper and Albrecht [8]. HEVs find applicability in underdeveloped countries, as exemplified by Mansour and Haddad, who highlight issues with Lebanon's EV charging infrastructure [9]. They argue that HEVs, requiring no upfront costs and reducing greenhouse gas emissions compared to traditional ICE vehicles, present a pragmatic choice for the average user. This underscores the environmental benefits and practicality of HEVs in regions with inadequate EV charging infrastructure.

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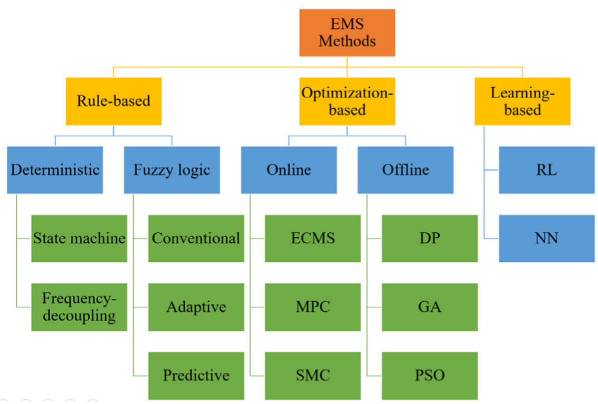

FIGURE 1. EMS classification [25].

A study in Bangladesh by Limon et al. further supports HEVs as a feasible and viable option for emerging nations, contributing to the transition to lower carbon emissions without substantial increases in infrastructure expenses [10].

Within the realm of engine-battery hybrid vehicles, Plug-in Hybrid Electric Vehicles (PHEVs) use a larger capacity battery rechargeable from the grid. Operating primarily in electric mode when the battery has sufficient energy, PHEVs rely on various battery types, predominantly Lithium-ion batteries [11]. While Lithium-ion batteries possess high energy storage density, they exhibit limitations such as low specific power, limited charging and discharging capability, and a short service life [12], [13]. Addressing these shortcomings, an alternative Energy Storage System (ESS) with high power and current capability becomes imperative. Supercapacitors (SC) offer high-power density and extended life, serving as a complementary solution to batteries [14]. According to [15], battery is a high-energy type ESS which enables longer vehicle traveling distance, and SC is the high-power type ESS which can handle high load power in the acceleration phase. Combining the strengths of batteries and supercapacitors, the Hybrid Energy Storage System (HESS) is proposed. The Energy Management Strategy (EMS) for HESS aims to harness the characteristics of supercapacitors, mitigating high current damage to the battery, extending battery life, increasing driving distance, and enhancing energy efficiency [16]. Rimpas et al. assert that implementing HESS in EVs enhances power supply system performance and maximizes battery life by minimizing stress on the battery [17]. The HESS concept was also adopted in the microgrid which combined renewable energy sources and ESS as in [18], [19], and [20].

The EMS plays a crucial role in both HEVs and HESS EVs by efficiently distributing energy from multiple sources [21], [22], [23]. Scholars have proposed various EMS methods, each designed to optimize energy usage. Panaparambil et al. categorize the objectives of EMS into four main goals: reducing pollution and greenhouse effects, ensuring effective and safe source usage to enhance ESS longevity, improving performance, and enhancing fuel and energy efficiency [24]. In the broader context, EMS methods can be classified into three main categories: rule-based, optimization-based, and learning-based as shown in Fig. 1 [25], [26], [27]. Rule-based methods include deterministic and fuzzy-logic approaches, while optimization-based methods encompass online and offline optimization. Learning-based methods leverage Artificial Intelligence (AI) and Machine Learning (ML), such as Neural Networks (NN) and Reinforcement Learning (RL).

A review study about the EMS in hybrid vehicles has been done by some researchers such as [28] and [29]. However, both of these do not focus on specific EMS methods but discuss a lot of EMS used in hybrid vehicles. Some studies do indeed review EMS methods such as low-pass filtering (LPF) [23], model predictive control (MPC) [30], [31], [32], equivalent consumption minimization strategy (ECMS) [26], and reinforcement learning (RL) [33]. On the other hand, as the authors know in the Scopus database, no article discusses and reviews Fuzzy Logic Controller (FLC) as EMS. Based on the Scopus database between 2019 to 2023, FLC is one of the most used EMS methods after the deterministic rule-based method. Therefore, this study will focus on reviewing the FLC EMS used in both HEVs and HESS EVs.

This study, rooted in a comprehensive review of literature from the Scopus database, specifically focuses on the application of a real-time and practical EMS method: Fuzzy Logic Controller (FLC). The article aims to contribute by (1) Reviewing the fundamental principles and architecture of FLC and its application in HEVs and HESS EVs, (2) Discussing current challenges and limitations associated with FLC in EMS, and proposing future research directions. The information presented herein is intended to assist scholars involved in the energy management of HEVs and HESS EVs in selecting the most suitable FLC EMS method.

The subsequent sections delve into the comparison of FLC EMS with other methods, a detailed review of FLC in EMS, a discussion on challenges, limitations, and future developments, and finally, a conclusion.

II. REAL-TIME EMS

Real-time Energy Management Strategy (EMS) plays a crucial role in optimizing the performance of Hybrid Electric Vehicles (HEVs) and Electric Vehicles (EVs) with Hybrid Energy Storage Systems (HESS EVs). Balancing the energy distribution in real-time is a complex task, often influenced by computational constraints. In this section, various real-time EMS methods, with a particular focus on Fuzzy Logic Control (FLC), will be discussed.

Panday and Bansal conducted a study comparing fuzzy-based EMS with other methods, considering structural complexity, computational time, type of solution, and the requirement for a priori knowledge [34]. The results, summarized in Table 1, indicate that FLC exhibits similar performance to Model Predictive Control (MPC) in the first three criteria. However, FLC requires a priori knowledge, although not mandatory, which can enhance its results. In comparison, MPC is more reliant on the system model. Additionally, Xu et al. conducted a performance comparison of

TABLE 1. EMS methods comparison based on [34].

Methods	Structural complexity	Computational time	Type of Solution	Requirement of a priori knowledge
Fuzzy Logic Controller (FLC)	N	S	G	Y
Genetic Algorithm (GA)	Y	M	G	N
Particle Swarm Optimization (PSO)	N	M	G	N
Equivalent Consumption Minimization Strategy (ECMS)	Y	S	L	N
Pontryagin's Minimum Principle (PMP)	N	S	L	Y
Dynamic Programming (DP)	Y	M	G	Y
Model Predictive Control (MPC)	N	S	G	N
Stochastic DP (SDP)	Y	M	G	N
Neural Network (NN)	Y	S	G	Y

TABLE 2. Quantitative comparison of FLC-EMS with some methods.

No	Ref	Criteria	FLC	Det. RB	DP	ECMS	MPC	PI
1	[36]	L/100 km	**12.84**			12.95		
2	[37]	L/100 km	**22.1**	25.43	19.95			
3	[38]	Efficiency (%)	73.4		78.7		**76.6**	
4	[39]	Integral Square Error (ISE)	**0.45**					0.52
5	[40]	Life cycle cost (0.1$/km)	**5.5**	5.7			5.7	

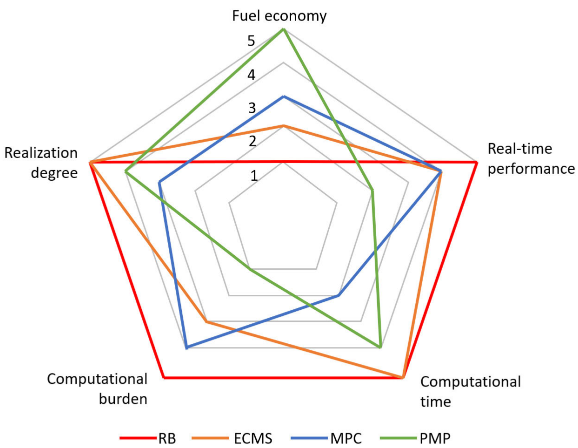

FIGURE 2. EMS performance comparison redrawn from [35].

various EMS methods, scoring them based on fuel economy, real-time performance, computational time, computational burden, and realization degree, as illustrated in Fig. 2 [35]. Rule-based methods, including Fuzzy, received the highest total score, despite concerns about poor fuel economy. This limitation can be addressed by combining rule-based methods with optimization techniques. Further comparisons in Table 2 highlight the superior performance of FLC over deterministic rule-based methods, ECMS, MPC, and Proportional-Integral (PI). Its performance compared to MPC varies, indicating the contextual nature of the comparison. Dynamic Programming (DP), although restricted to simulations due to its complex structure, serves as a benchmark in EMS evaluations. Montazeri and Mahmoodi evaluated FLC's performance against conventional rule-based EMS in a Toyota Prius, concluding that the proposed FLC reduced fuel consumption and emissions by approximately ten percent [41].

Table 3 summarizes the advantages of FLC, highlighting its similarities and differences with deterministic rule-based methods and MPC. Both FLC and deterministic rule-based methods are simple, easy to design, robust, and have low computational costs. However, they share drawbacks such as low fuel economy and performance that fall short of global optimality. In contrast, MPC offers high accuracy, predictive capability, and near-optimal solutions, but its performance heavily depends on the system model.

III. FUZZY LOGIC CONTROLLER EMS

Fuzzy Logic Controller (FLC) is widely used as an Energy Management Strategy (EMS) in HEVs and HESS EVs. Two sides classify FLC as an EMS controller. One side classifies it as conventional fuzzy (also known as basic or traditional), adaptive fuzzy, and predictive fuzzy [21], [42], [43], [44]. On the other side, the conventional fuzzy is replaced by an optimized fuzzy while the rest two are the same [25], [45]. Since the conventional and optimized fuzzy have a significant difference in method and results, they differentiate in this review. Furthermore, the adoption of predictive fuzzy has only been used by a few scholars. Hence, it is named a combination which means combining FLC EMS with other EMS methods. Finally, the FLC EMS in this review is classified as conventional, optimal, adaptive, and combination.

A. CONVENTIONAL FLC

The conventional FLC method serves as the foundational approach in energy management strategy (EMS), utilizing inputs to the FLC to produce desired outputs through fuzzy reasoning. This method requires applying available knowledge or expertise to design fuzzy memberships and rules [46]. Numerous configurations of conventional FLC EMS have been proposed in the literature, catering to different vehicle architectures.

TABLE 3. The advantages and disadvantages of FLC, Deterministic, and MPC as EMS.

No	EMS Methods	Advantages	Disadvantages	References
1	FLC	1. Robustness 2. Adaptive 3. Good with model uncertainties and state variation 4. No dependency on the overall mathematical model 5. Computational efficiency 6. Low complexity	1. Different cycle needs different control parameter 2. Performance far from global optimum 3. Dependent on membership function 4. Optimal control is not guaranteed 5. Designers need skillful knowledge of the problem	[21][25][38][46][48]
2	Deterministic	1. Simplicity 2. Easy to design 3. Robust 4. Low computation	1. Low fuel economy 2. Requirement in special driving situations 3. Sub-optimal solution 4. Not accurate	[24][25][46][48][49]
3	MPC	1. Adaptability and high predictive capability 2. Less computational burden 3. Solution close to global optimum 4. Ability to tackle constraints in the control action. 5. High-accuracy online application 6. No need for full cycle info	1. Require prior cycle information 2. Depend on prediction accuracy 3. Performance heavily relies on model accuracy	[24][25][50][51][52]

For Hybrid Electric Vehicles (HEVs), the conventional FLC EMS has been applied by various researchers. Suhail et al. conducted a comparative study between FLC and ANFIS, with both employing two inputs (battery State of Charge - SoC and engine speed) and one output (battery power) [47]. ANFIS demonstrated superior results, outperforming FLC with a small SoC drop. Singh et al. utilized a Mamdani-type FLC with inputs of torque demand, battery SoC, and brake demand, resulting in improved fuel economy by 50.56% according to simulation and Hardware-in-the-Loop (HIL) testing [53]. Similarly, Ma et al. employed Mamdani-type FLC with inputs of required torque and battery SoC, demonstrating a 13.3% reduction in fuel consumption compared to the logic-threshold method [54].

In various HEV configurations, such as through-the-road hybrid vehicles (TTR HEVs) and fuel cell extended-range vehicles, conventional FLC has proven effective. Sabri et al. applied FLC-based EMS in a TTR HEV, achieving a 62% reduction in fuel consumption compared to rule-based EMS [22]. Narwade et al. compared FLC and Neural Network (NN) EMS for a two-wheeler TTR parallel HEV, with NN EMS demonstrating superior performance based on total energy consumed [55]. Geng et al. proposed FLC EMS in a fuel cell extended-range vehicle, demonstrating improved performance in terms of acceleration time and total mileage [56].

Researchers have extensively employed conventional FLC as an Energy Management Strategy (EMS) in Fuel-cell vehicles, exemplified by studies such as [57], [58], [59], and [60]. Lin et al. applied FLC EMS in a hybrid Fuel Cell and Supercapacitor Electric Vehicle (FCHEV), introducing switching control to safeguard the Supercapacitor (SC) within a defined operational range [57]. Additionally, a moving average filter was implemented to reduce charge rates and protect the Fuel Cell (FC). The Mamdani-type FLC, manually designed with rules, utilized delta-power and SC State of Charge (SoC) as input, producing an output scaling factor for FC power. In comparison with PI and power follower control, this approach demonstrated a remarkable 13.15% and 9.18% reduction in fuel consumption, respectively. Song et al. similarly adopted FLC EMS in an FCHEV combining FC and battery components [58]. Utilizing Hardware-in-the-Loop (HIL) testing, they concluded that, compared to power follower control, FLC EMS exhibited superior adaptability to varying driving conditions. Shen et al. proposed FLC EMS for a hybrid fuel-cell and battery system, incorporating a unique Variable Structure Battery (VSB) to substitute a bidirectional DC converter for the battery [59]. The conventional FLC, with inputs of power demand, FC power, and battery SoC, yielded FC delta-power as the output, showcasing the ability to smooth FC power and maintain high efficiency. Authors in [60] proposed FLC EMS in FC-battery EV in combination with model predictive direct torque control (MPDTC) as motor speed control. The FLC uses the Mamdani type to input battery SoC and load power. Whereas the output is a power reference for the fuel cell. They conclude

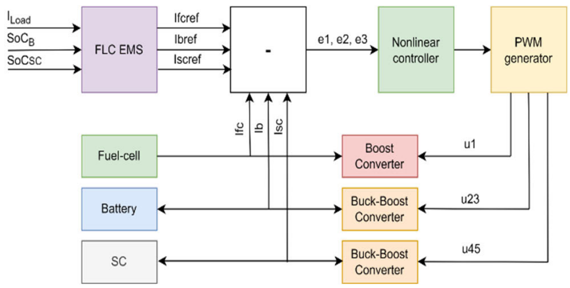

FIGURE 3. Conventional FLC-EMS redrawn from [65].

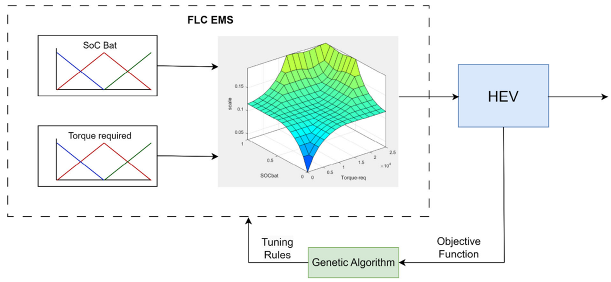

FIGURE 4. Optimal FLC EMS redrawn from [75].

that the proposed EMS method can keep the battery SoC under safe limits.

In the context of Electric Vehicles (EVs) equipped with Hybrid Energy Storage Systems (HESS), Keskin and Urazel introduced FLC EMS for EVs with batteries and Supercapacitors (SCs), considering battery degradation [61]. This Mamdani-type fuzzy system, designed manually, utilized power demand, battery SoC, and SC SoC as inputs, generating power allocation for the battery as the output. Comparative analysis with battery-only and logic threshold methods indicated the proposed FLC EMS as more effective in reducing peak current while ensuring minimum battery SoC usage. A similar approach was adopted by [62] considering the effects of motor control.

Conventional FLC was also deployed in configurations involving three power sources which are FC, battery, and SC, as evidenced by studies such as [63] and [64]. Kamoona et al. utilized a dual-level controller EMS, employing FLC and Artificial Neural Network (ANN) in high-level control, and a Proportional-Integral (PI) controller tuned by Particle Swarm Optimization (PSO) in low-level control [63]. The FLC, with inputs of load power and battery State of Charge (SoC), produced FC power reference, subsequently used to train ANN for EMS. Comparisons in low-level control demonstrated nearly identical results between FLC and ANN. Similarly, authors in [64] presented an EV structure with a direct connection of SC, emphasizing its high efficiency for SC charge, acting as an energy buffer, and contributing to a 13.54% increase in fuel efficiency, as validated through experimental testing. Some studies combined conventional FLC with traction motor control, as exemplified by [65], [66], and [67]. In [65], the FLC received inputs of load current, battery SoC, and SC SoC, producing reference currents for FC, battery (B), and SC, depicted in Fig. 3. The Sliding Mode Control (SMC) method was employed to regulate the converters of FC, B, and SC. The proposed method claimed a 29% reduction in hydrogen consumption. In [66], inputs of the Vehicle Dynamics Controller (VDC), Vehicle Speed Controller (VSC), and motor current were utilized, with outputs being battery and SC power references. The control utilized the PI algorithm and SMC in motor control, showcasing fast and high performance under various speeds and system dynamics. A concept similar to [66], with a change in motor control to Backstepping-Direct Torque Control (BS-DTC), was proposed by [67].

B. OPTIMAL FLC

In contrast to conventional FLC, which requires expert knowledge for designing membership functions and rules, the optimized or optimal FLC method employs optimization techniques to enhance performance. This approach addresses the time-consuming nature and non-guaranteed optimality of conventional FLC. Researchers, such as those in [68] and [69], have demonstrated that optimization methods can improve FLC EMS's efficiency compared to conventional approaches. The configuration of optimal FLC shares similarities with conventional FLC, differing primarily in the utilization of optimization methods to find optimal memberships and/or rule bases for the fuzzy system.

Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are the most employed optimization methods for fine-tuning FLC EMS based on the literature. Researchers, such as Jia et al. applied PSO to optimize a series FLC (SFLC) for hybrid Fuel Cell (FC) and battery systems, achieving mileage improvements [70]. Tifour et al. optimized Sugeno-type FLC using PSO for hybrid FCHEVs, showcasing improvements in fuel economy and overall efficiency [71].

GA has also been extensively used in optimizing FLC EMS. Wang et al. utilized GA to optimize fuzzy membership functions, aiming to minimize energy loss [72]. Similarly, authors in [73] employed GA to optimize FLC for a hybrid fuel cell vehicle, enhancing fuel economy, vehicle performance, and optimal energy distribution. Eckert et al. utilized GA to optimize FLC EMS for Electric Vehicles (EVs) with battery and Supercapacitors (SC), achieving efficient HESS configurations [74]. They use three objective functions which are minimize HESS mass, maximize driving range, and maximize performance. After simulation testing, they concluded that the HESS configuration is more efficient using a smaller SC with a high-capacity battery.

Fig. 4 illustrates an optimal FLC EMS proposed by [75], showcasing the integration of GA for enhanced performance. Ye et al. conducted a comparative study between various FLC-based EMS methods, including FLC, FLC-GA, FLC-PSO, and Dynamic Programming (DP) as a benchmark, applied to EVs with battery and SC [74]. The results indicated that FLC-GA exhibited lower and more stable peak currents compared to FLC-PSO, with only a 0.6% deviation compared to DP. Table 4 provides an overview of some improved PSO and GA methods used to optimize FLC EMS. Other opti-

TABLE 4. Some PSO and GA improvement method to Optimize FLC EMS.

No	Ref	Opt. Method	Remark
1	[75]	Non-sorted Genetic Algorithm (NSGA)	Combine for optimal EMS and HESS sizing
2	[78]	Chaotic improved generalized particle swarm optimization (CIGPSO)	Fuzzy type-2, offline optimization Better in reducing energy consumption compared to conventional and multi-objective PSO
3	[79]	Iterative modified PSO (IMPSO)	Fuzzy type-2, online optimization using the cloud system Better in reducing battery loss compared to rule-based and conventional FLC
4	[80]	Chaos-enhanced accelerated particle swarm optimization (CAPSO)	Back-to-back competitive learning mechanisms (BCLM) to select the best of two FLCs used. The best FLC will continue to work while the others will be trained with CAPSO. Improve fuel economy compared to rule-based and conventional FLC
5	[81]	Improved quantum-GA (IQGA)	Reduce fuel consumption by 5.17% compared to conventional FLC

mization methods are also used to optimize FLC for example Differential Evolution Algorithm (DEA) [76], rule-learning from Dynamic Programming [77], etc.

To improve the optimality in the unknown drive cycle and to add the robustness of the optimal FLC, researchers combine some driving cycles in the training step as in [82]. They combine three drive cycles and apply optimization using the Genetic Simulated Annealing Algorithm (GASA). The cooling load is also considered in this study. Finally, they conclude that the proposed method is better than rule-based and adaptive-ECMS (A-ECMS). The same concept was used by [83] with the NSGA-III optimization method.

The optimization method besides optimizing FLC, can be used to find the optimal HESS sizing. The component size in both HEV and HESS EVs is important since it affects the vehicle mass, performance, and price. Herrera et al. combined two FLCs for EMS in a hybrid bus, utilizing GA multi-objective optimization to achieve optimal sizing and operation of the Energy Storage System (ESS) [84]. The simulation testing shows that the proposed method can reduce the daily operational cost and fuel consumption by up to 15% and 19%, respectively. Silva et al. use the same concept with an interactive adaptive weight genetic algorithm (i-AWGA) [85]. From the cost analysis, they conclude that the proposed system can reduce up to 63.59% of the cost-to-autonomy ratio. Whereas authors in [86] expand the study using a dual-HESS system with FLC EMS optimized by i-AWGA. The vehicle structure is it has front and rear propulsion systems in front and rear wheels respectively. Three FLC EMS are employed, one for power sharing between front and rear propulsion, whereas two others for each HESS. Compared with a similar EV with a single HESS and optimized under the same driving conditions, dual HESS can increase driving range and battery life by up to 19.57% and 22.88%, respectively.

C. ADAPTIVE FLC

In the realm of Energy Management Strategy (EMS), Fuzzy Logic Controllers (FLC) exhibit adaptability within operational ranges but face limitations dictated by factors like membership limits. Recognizing the need for tailored rules for different driving profiles, the adaptive FLC as EMS emerges. This section delves into the four categories of adaptive FLC: Powering-Braking-Based, Road-Condition-Based, Driving-Conditions-Based, and Online-Based, illustrated in Fig. 5.

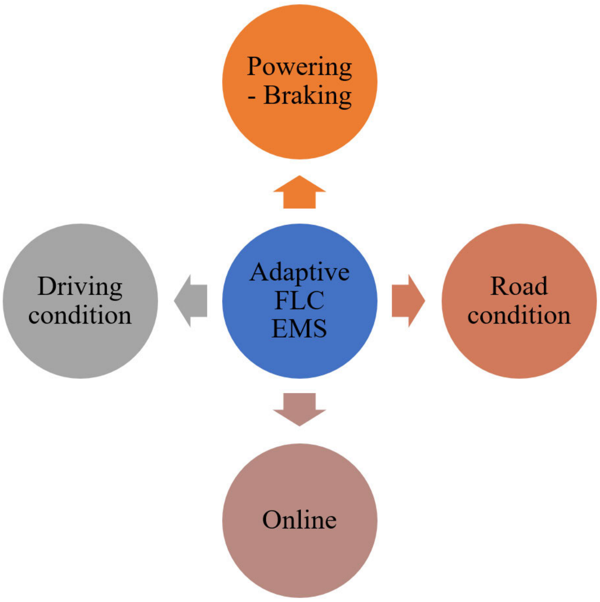

FIGURE 5. Adaptive FLC EMS classification.

One approach involves distinct fuzzy matrix rules for powering and braking conditions, depicted in Fig. 6. Authors in [87] employ FLC-charge and FLC-discharge controllers for Electric Vehicles (EVs) with hybrid battery and Supercapacitors (SC), dynamically distributing power based on load power, battery SoC, and SC SoC. This adaptive scheme, utilizing particle filters for battery SoC estimation, enhances performance by minimizing charge and discharge currents. Lu, et al. implement dual FLCs for powering and braking in a hybrid battery-flywheel system, optimizing the scaling factor for battery power [88]. Xu et.al. extends this concept to parallel hybrid engines and batteries, using a double FLC EMS to distribute powering and braking torque efficiently [89]. The study incorporates Genetic Algorithms (GA) to optimize FLC rules, demonstrating performance comparable to Dynamic Programming (DP) and surpassing rule-based and single-FLC methods. Additionally, Zhang et al. introduce two distinct fuzzy rules for charge and discharge modes,

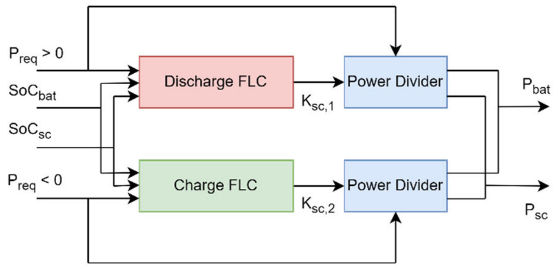

FIGURE 6. Adaptive FLC EMS: powering-braking-based [87].

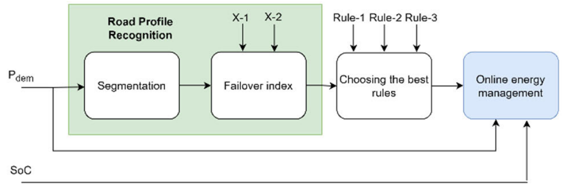

FIGURE 7. Adaptive FLC-EMS proposed by [92].

enabling efficient power provision during discharge and smooth battery charging during regenerative braking [16]. Simulation results highlight superior energy consumption metrics compared to rule-based and conventional fuzzy approaches in terms of Energy Consumption (kJ) by 2.4% and 1.28% respectively. The same concept as in [16] is also used by [90]. Whereas [91] combines this Adaptive-FLC mechanism with MPC in a hierarchical coordinated EMS. They conclude that this structure improves the performance including time response, error reduction, and stability.

The adaptive FLC based on the road conditions is proposed by [92] depicted in Fig. 7. The road conditions, are categorized profiles into urban, road, and highway. This approach employs Genetic Algorithms (GA) to optimize fuzzy rule sets offline, dynamically adapting to driving conditions by segmenting power demand. The same concept is proposed by [93], [94], and [95] leverage Neural Networks (NN) for driving cycle recognition. Zhang et al. utilize GA to optimize FLC rules [94]. The proposed adaptive FLC reduces fuel consumption and enhances stability, showcasing adaptability across diverse driving cycles. Moreover, the authors in [96] incorporate a Contour Positioning System (CPS) to determine route slope, utilizing FLC to adjust power distribution between the battery and supercapacitor. Simulations confirm performance enhancements in a Hybrid Energy Storage System (HESS) for Electric Vehicles (EVs).

Authors [97] introduce a multimode-FLC (MFLC) for a hybrid tractor, adjusting fuzzy rules based on predefined operational (driving) conditions. Operational condition recognition using Fuzzy C-means (FCM) enables MFLC to achieve up to a 13% reduction in power consumption compared to thermostat control strategy (TCS). Additionally, [98] emphasizes data-driven methods, utilizing real driving data to predict roads and optimize fuel efficiency. The simulation validates fuel savings of up to 16% in residential districts. Furthermore, Hussan et al. adopt FLC for voltage regulation in a hybrid system with fuel cells, batteries, and supercapacitors [99]. Classifying rules based on driving conditions like normal, acceleration, deceleration, uphill, and downhill, the proposed FLC outperforms Proportional-Integral (PI) and Sliding Mode Control (SMC) methods in voltage regulation, energy management, and reference tracking.

The last, online adaptation is proposed by [100] which uses the FLC Sugeno type as EMS for a hybrid tram of battery and SC. The weighting rule of FLC is optimized using a hyper-spherical search algorithm online; therefore, its weight dynamically changes. Through the simulation, they validate that the proposed method can reduce the battery peak current by 31.02% and increase the tram mileage by 22.45% compared to FLC with a fixed weight scheme.

D. COMBINATION

The FLC EMS also combined with other methods to improve its performance. This part is divided into three combinations: FLC and frequency decoupling, FLC and NN, and others. More details about each will be discussed in this part.

1) FLC AND FREQUENCY DECOUPLING

The frequency decoupling mostly combined with FLC for EMS is a low-pass filter (LPF) and wavelet transform (WT). Zhang and Li present an experimentally validated system for semi-active battery-supercapacitor EVs, as depicted in Fig. 8 [101]. The LPF segregates low-frequency power for the battery and high-frequency power for the supercapacitor. The FLC regulates power distribution based on State of Charge (SoC) discrepancies, exhibiting a reduction in battery capacity size by up to 78.62%. Similarly, [102] integrates FLC and LPF, managing SC State of Charge (SoC) and power ratios. High-Frequency power is directed to the supercapacitor, achieving battery degradation assurance, and validating the proposed HESS architecture through Hardware-in-the-Loop (HIL) simulations. In the fully active parallel topology of EVs with batteries and SCs, [103] and [104] leverage FLC combined with LPF, showcasing a reduction in battery RMS current and optimal SC utilization. Fuzzy Type-2 EMS, incorporating LPF, is also explored by [105] and [106], highlighting the ability to handle fuzzy rule uncertainties.

Combining FLC with Wavelet Transform (WT) yields improved performance in [107], [108], and [109]. Wang et al. employ a Mamdani-type FLC with three inputs, achieving optimal power allocation for batteries through WT-RB [107]. Simulations and Hardware-in-the-Loop (HIL) tests confirm superior efficiency, improving by up to 14.89%. Authors in [108] utilize a three-layered approach, optimizing Hybrid Energy Storage Systems (HESS) parameters based on driving cycles, segmenting low and high-frequency power demands through WT, and distributing power through FLC-EMS. The integrated EMS minimizes energy consumption by 6.54% compared to WT-based-only systems, demonstrating extended battery life. Moreover, [109] proposes a two-step EMS employing adaptive LPF based on FLC and a power-sharing algorithm based on WT and FLC. The adaptive LPF utilizes FLC for cut-off frequency adjustment, providing power to SC, while the remaining power is directed

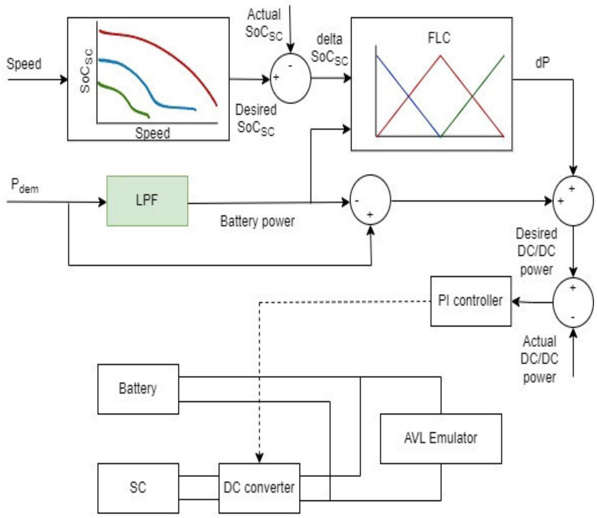

FIGURE 8. FLC combined with LPF proposed by [101].

to the second step where WT and FLC distribute power to FC and battery. Simulation and experimental results exhibit a 7.94% reduction in fuel consumption compared to the Equivalent Consumption Minimization Strategy (ECMS).

2) FLC AND NN (ANFIS)

The fusion of FLC and Neural Networks (NN) results in Adaptive Neuro-Fuzzy Inference Systems (ANFIS), combining learning capabilities with fuzzy logic adaptability. Authors in [110], [111], and [112] exemplify ANFIS application in EMS for hybrid electric buses and parallel hybrid Electric Vehicles (EVs). Reference [110] employs iterative Dynamic Programming (DP) to train ANFIS for EMS in a hybrid electric bus, demonstrating superiority over ECMS and rule-based methods in simulations and experiments. Authors of [111] train ANFIS to mimic ECMS as EMS for a hybrid bus, showcasing lower fuel consumption than ECMS itself through simulations and HIL testing. Whereas Gao et al. utilize logic threshold EMS to train ANFIS for a parallel hybrid EV with a DC-motor traction motor, achieving improved performance in simulation tests [112]. Authors in [113] propose a unique HESS EV configuration to increase kinetic energy utilization with ANFIS EMS. The ESS used are FC, battery, and SC. The DC generator is added to the front wheels to increase the regenerative braking energy absorption. The simulation shows that this system with ANFIS EMS gives an efficiency of up to 98.2%.

3) OTHER APPROACHES

Fu et al. employ GA to optimize the membership function of FLC-EMS for a hybrid FC, battery, and ultra-capacitor system, considering fuel economy and FC lifespan [114]. The combination with LPF and WT results in a 4.4% reduction in hydrogen consumption compared to conventional FLC-EMS. Yang et al. combine FLC optimized by PSO, and wavelet transform for a hybrid tramway [115]. Utilizing PSO to tune FLC membership functions, coupled with wavelet

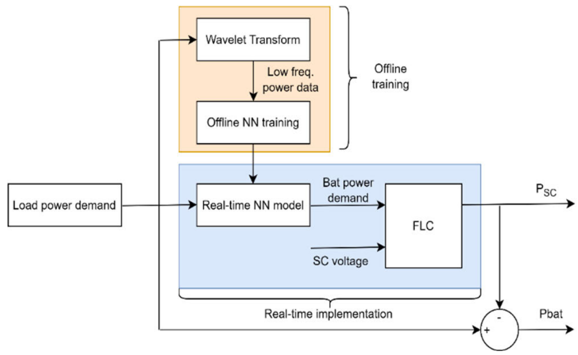

FIGURE 9. Combined-FLC EMS redrawn from [116].

transforms, the proposed method reduces operational costs by up to 5.19%. Zhang et al. integrate Wavelet Transform (WT), Neural Networks (NN), and optimal FLC EMS for hybrid battery and SC vehicles, depicted in Fig. 9 [116]. WT extracts battery power demand, NN processes real-time application data, and PSO optimizes FLC membership functions. Experimental testing concludes that the proposed method reduces battery life costs by 18% and enhances regenerative braking energy recovery by 44.22%. Guo et al. combine FLC with Reinforcement Learning (RL) in a hybrid FC and battery EV [117]. The proposed Fuzzy-Reinforce utilizes Policy Gradient Reinforcement Learning (PGRL), demonstrating stability, speed, and lower hydrogen consumption compared to traditional RL in Hardware-in-the-Loop (HIL) simulations. Matignom et al. synthesize learning-based, rule-based, and optimization-based EMS strategies into an integrated EMS [118]. Utilizing Fuzzy C-means for driving pattern recognition, fuzzy rule-based methods, and online Pontryagin's minimum principle (PMP) optimization, the proposed strategy achieves performance close to optimal offline strategies. This diverse spectrum of hybrid approaches illustrates the versatility and adaptability of FLC in combination with other techniques to optimize EMS for various hybrid and electric vehicle applications.

IV. DISCUSSION AND FUTURE DEVELOPMENT

There are different functionalities of EMS in HEV and HESS EV. In Hybrid Electric Vehicles (HEVs), where both conventional engines and electric powertrains coexist, FLC EMS designs cater to diverse operational modes and energy sources. Challenges include ensuring seamless transitions between power sources and optimizing energy utilization in dynamic driving conditions. In Hybrid Energy Storage Systems of Electric Vehicle (HESS EV), with a primary focus on electric propulsion, FLC EMS navigates the intricacies of managing energy from batteries and supercapacitors. Challenges involve addressing high-frequency load demands and preserving the lifespan of responsive but aging ESS components like Fuel Cells (FC) and batteries.

A. FLC EMS PERFORMANCE INSIGHTS

In the application of FLC EMS, four predominant approaches are identified: conventional, optimal, adaptive,

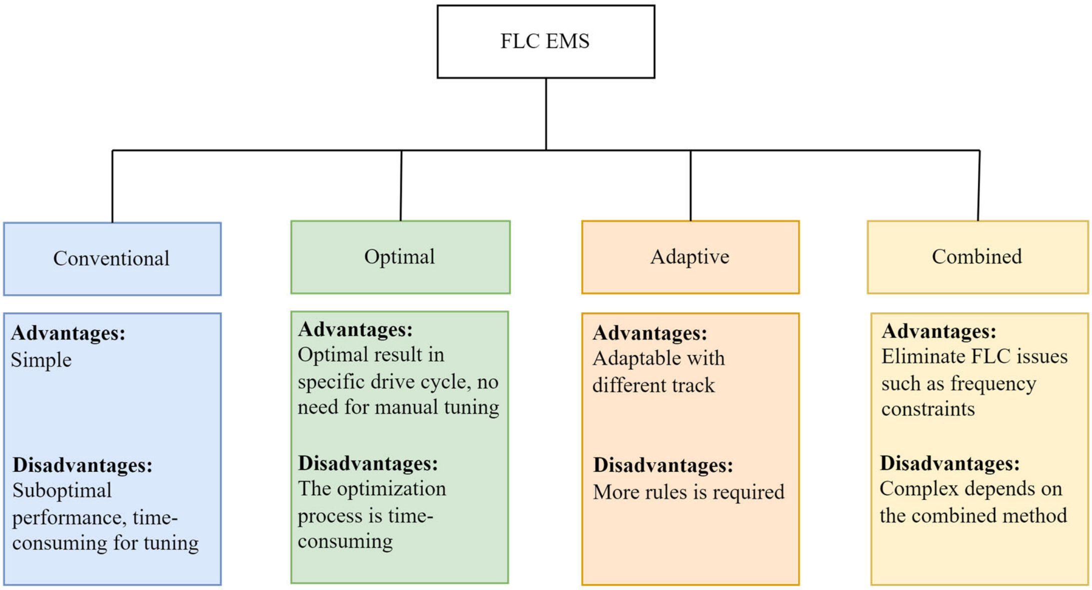

FIGURE 10. **FLC EMS classification.**

and combination. Conventional FLC relies on manual tuning, predominantly using Mamdani-type fuzzy logic. Inputs, often load power and State of Charge (SoC), dictate the output—power reference for Energy Storage Systems (ESS). To overcome tuning challenges and achieve optimal results, optimization methods like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are frequently employed known as optimal FLC. There are also a lot of objective functions used such as increasing mileage, reducing fuel consumption, reducing energy consumption, reducing energy loss, etc.

The unpredictable drive cycle makes the optimal FLC EMS which is tuned based on the specific driving cycle cannot give optimal results in different drive cycles. To handle this issue, adaptive FLC EMS is proposed. Different adaptive method is proposed by scholars. This review is categorized into four classes which are: powering-braking-based, road-condition-based, driving conditions-based, and online-based. For more details, see the adaptive FLC section. The road condition and driving condition have an impact on the powering and braking. Therefore, the right choice of powering-braking-based can accommodate both road-condition-based and driving condition-based. Whereas the online mechanism is the best one if the infrastructure is available.

The last way is by combining FLC with another method. In this way, there is a lot of combination of FLC methods proposed by the researcher. Most of them, which the authors can find are in combination with frequency decoupling such as LPF and WT. Power sharing or energy management from FLC cannot handle high-frequency load which affects the aging of low response ESS such as FC and battery. Therefore, the frequency decoupling is added to help distribute load power into the right ESS with the load power frequency. Another combination of FLC is with NN to form ANFIS. Which is a fuzzy inference that can be trained. The ANFIS also used to accommodate the realization of high computational EMS such as DP and ECMS. Finally, there is also a combination of FLC, optimization algorithm, adaptive mechanism, and frequency decoupling method.

In contrast to conventional FLC, optimal FLC yields superior outcomes. However, it's tracking-dependent, making consistent performance challenging across various tracks. Adaptive FLC, by dynamically altering fuzzy rules, tackles this limitation effectively. Fig. 10 illustrates the categorization of FLC and highlights its benefits and drawbacks in HEVs and HESS EVs applications.

B. FUTURE DIRECTIONS

The development of FLC EMS will be focused on optimal, adaptive, and combination forms. In the adaptive form, although can adapt to many conditions, it requires a lot of rules. Therefore, it requires a high specification of the processor. The solution to solve it is to improve the optimal and combination FLC EMS. The optimal FLC can be improved with any new optimization method that can perform more powerfully and accommodate multi-objective functions. The optimal FLC also can be trained with a lot of drive cycles to make it optimal in most of the drive cycles which can perform like the adaptive FLC but with fewer rules. The combination with another method also can improve FLC EMS performance without significantly increasing its computational time.

Advancements in communication paradigms, particularly Vehicle-to-Everything (V2X) technologies, present opportunities for enhancing FLC EMS. V2X encompasses Vehicle-to-Vehicle (V2V), Vehicle-to-Device (V2D), Vehicle-to-Infrastructure (V2I), Vehicle-to-Grid (V2G), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Network (V2N) subsystems [119]. Leveraging V2X can facilitate real-time optimization by reducing computing loads and ensuring FLC EMS is continually updated with optimal results. This can solve the adaptive FLC problem regarding the computational time.

Future developments could explore synergies between FLC EMS and V2X technologies, allowing vehicles to communicate operational status and receive real-time traffic updates. Such integration holds promise for achieving enhanced energy efficiency, reduced fuel consumption, and minimized component damage. As research progresses, addressing challenges in hardware implementation becomes crucial. Bridging the gap between simulation, Hardware-in-the-Loop (HIL) techniques, and full-scale prototypes are essential to validate FLC EMS designs in practical scenarios.

V. CONCLUSION

In summary, this review highlights the adaptability and effectiveness of the Fuzzy Logic Controller (FLC) as an Energy Management Strategy (EMS) for Hybrid Electric Vehicles (HEVs) and Hybrid Energy Storage Systems Electric Vehicles (HESS EVs). The analysis of conventional, optimal, adaptive, and combination FLC methods reveals specific strengths and limitations. The conventional method is simple but suboptimal, the optimal method excels in specific scenarios but lacks versatility, and the adaptive method, despite its complexity, offers track-independent adaptability and enhanced performance. The combination method shows promise in addressing FLC limitations, especially concerning frequency constraints. This review is a valuable resource for researchers exploring energy management in EVs, particularly with FLC. Future research should focus on practical FLC implementation and real-world performance assessments to advance Hybrid Energy Storage Systems (HESS) and contribute to sustainable transportation solutions. Understanding the nuances of different vehicle architectures is crucial for shaping the future of electric and hybrid vehicle technology. The continuous refinement of FLC methodologies holds significant promise for achieving efficient and eco-friendly transportation solutions.

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