A Review of Fuzzy Logic Controllers for Energy Management in Vehicles with Hybrid Electric and Hybrid Electric and Hybrid Energy Storage Systems

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Abstract: **As a major source of carbon dioxide emissions as of 2020, the transportation sector faces a major obstacle in the fight against pollution. Although electric vehicles (EVs) offer a greener alternative and seem like a promising option, their short range is a drawback. As financially viable alternatives, hybrid electric vehicles (HEVs) and hybrid energy storage system electric vehicles (HESS EVs) stand out. However, efficient energy management and power source size optimization continue to be significant obstacles for both HEVs and HES SEVs.**

The performance, ease of use, and realtime applicabilit y of the Fuzzy Logic Controller (FLC)make it stand ou t among other Energy Management Strategies (EMS). The various uses of FLC as an EMS in HEVs and HES S EVs are thoroughly examined in this article, which al so compares it to other EMS techniques and examines the benefits and drawbacks of each strategy. Using information from numerous sources, a thorough analysis of the different FLC types used as EMS has been carried out. Every FLC EMS class is examined, including a comprehensive summary of suggested approaches within each group. The article gives readers the fundamental knowledge and understanding they need to support the ongoing advancement of FLC EMS in hybrid electric and hybrid energy storage system electric vehicles by offering this thorough information.

1. INTRODUCTION

The transportation industry is responsible for up to 35% of carbon dioxide emissions as of 2020 [1]. Adopting electric vehicles (EVs), which emit no pollutants, appears to be a viable way to reduce transportation-related pollution [2, 3, 4]. Compared to conventional engine-equipped vehicles, EVs have many benefits, such as reduced pollution, enhanced efficiency, and a plentiful supply of energy [5]. Rechargeable batteries are the main power source in electric cars, and because of their finite capacity, they limit the vehicle's range. Hybrid Electric Vehicles (HEVs) have shown themselves to be feasible for EVs traveling shorter distances [6], with lower emissions than traditional Internal Combustion Engine (ICE) vehicles [7]. HEVs use two or more power sources, usually a battery and an engine.

According to a study by Rajper and Albrecht [8], HEVs avoid issues like high costs, restricted charging infrastructure, lengthy charging periods, and power outages that EVs face. As demonstrated by Mansour and Haddad, who draw attention to problems with Lebanon's EV charging infrastructure, HEVs are useful in developing nations [9].

They contend that HEVs are a sensible option for the typical user because they have no up-front fees and emit fewer greenhouse gases than conventional ICE cars. This highlights the advantages of HEVs for the environment and their usefulness in areas with insufficient EV charging infrastructure.

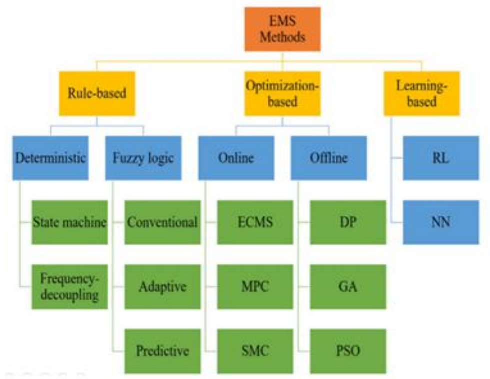


Fig1.EMS CLASSIFICATION

HEVs are a practical and viable choice for developing countries, helping to reduce carbon emissions without significantly raising infrastructure costs, according to a study conducted in Bangladesh by Limon et al. [10].
Plug-in Hybrid Electric Vehicles (PHEVs) are engine-battery hybrid vehicles that employ a greater capacity battery that can be recharged from the grid.

PHEVs use a variety of battery types, mainly lithium-ion batteries, and run mostly in electric mode when the battery has enough energy. Despite having a high energy storage density, lithium-ion batteries have drawbacks such low specific power, restricted capacity for charging and discharging, and a brief lifespan. An alternative Energy Storage System (ESS) with high power and current capabilities is necessary to address these drawbacks. As a supplement to batteries, supercapacitors (SC) provide great power density and long lifespan . According to a battery is a high-energy ESS that allows for a longer vehicle's travel distance, while a SC is a high-power ESS that can manage a high load power during the acceleration phase.

The Hybrid Energy Storage System (HESS), which combines the advantages of batteries and supercapacitors, is suggested. Utilizing the properties of supercapacitors, the Energy Management Strategy (EMS) for HESS seeks to prolong battery life, improve energy efficiency, reduce high current damage to the battery, and increase driving distance . According to Rimpas et al., by reducing battery stress, HESS in EVs improves power supply system performance and extends battery life. The microgrid that integrated ESS and renewable energy sources also embraced the HESS concept.

By effectively distributing energy from various sources, the EMS is essential to both HEVs and HESS EVs. Numerous EMS techniques have been presented by academics, all aimed at optimizing energy use. According to Panaparambil et al., EMS aims to reduce pollutants and greenhouse impacts, ensure safe and efficient source consumption to extend ESS lifespan, improve performance, and increase fuel and energy economy.
three main categories: rule-based, optimization-based, and learning-based as shown in Fig. 1. Rule-based methods include deterministic and fuzzy-logic approaches, while optimization-based methods encompass online and offline optimization Learning-based approaches, such neural networks (NN) and reinforcement learning (RL), make use of artificial intelligence (AI) and machine learning (ML).
Researchers like and have conducted a review study on the EMS in hybrid cars. Both of them, however, cover a wide range of EMS utilized in hybrid cars rather than concentrating on any one EMS technique. Low-pass filtering (LPF) , model predictive control (MPC), equivalent consumption minimization strategy (ECMS), and reinforcement learning (RL) are among the EMS techniques that are reviewed in certain publications. However, as far as the authors are aware, there isn't a single publication that examines and discusses fuzzy logic controllers (FLCs) as EMS in the Scopus database. After the deterministic rule-based approach, FLC is one of the most popular EMS techniques, according to the Scopus database from 2019 to 2023. Thus, the review of the FLC EMS utilized in both HEVs and HESS EVs will be the main objective of this study.

Based on a thorough analysis of literature from the Scopus database, this study focuses on the use of the Fuzzy Logic Controller (FLC), a real-time and useful EMS technique. By (1) reviewing the basic ideas and architecture of FLC and its use in HEVs and HESS EVs, (2) talking about the difficulties and restrictions that FLC in EMS is now facing, and (3) suggesting potential avenues for future research, the essay seeks to make a contribution.

The purpose of the material provided here is to help researchers who work with HEV and HESS EV energy management choose the best FLC EMS technique.
Following that, there is a thorough analysis of FLC in EMS, a comparison of FLC EMS with alternative approaches, a discussion of the difficulties, constraints, and upcoming advancements, and a conclusion.

II. REAL-TIME EMS

Optimizing the performance of electric vehicles (EVs) and hybrid electric vehicles (HEVs) with hybrid energy storage systems (HESS EVs) requires a real-time energy management strategy (EMS). Real-time energy distribution balancing is a challenging process that is frequently impacted by computing limitations. This section will cover a variety of real-time EMS techniques, with an emphasis on fuzzy logic control (FLC).

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 1. EMS methods comparison based on structural complexity

In a research comparing fuzzy-based EMS with alternative techniques, Panday and Bansal took into account the need for previous information, computing time, solution type, and structural complexity . According to the findings, which are compiled in Table 1, FLC performs similarly to Model Predictive Control (MPC) across the first three criteria. Though not required, FLC does require prior knowledge, which can improve its outcomes. MPC is more dependent on the system model in contrast. Furthermore, Xu et al. compared the performance of several EMS techniques, assigning scores according to real-time performance, computational time, fuel economy, computational burden, and realization degree, as shown in Fig. 2

Fuzzy and other rule-based approaches scored highest overall, despite worries about their low fuel Combining optimization strategies with rule-based approaches can help overcome this restriction. Additional comparisons in demonstrate FLC's higher performance over ECMS, MPC, Proportional-Integral (PI), and deterministic rule-based approaches.

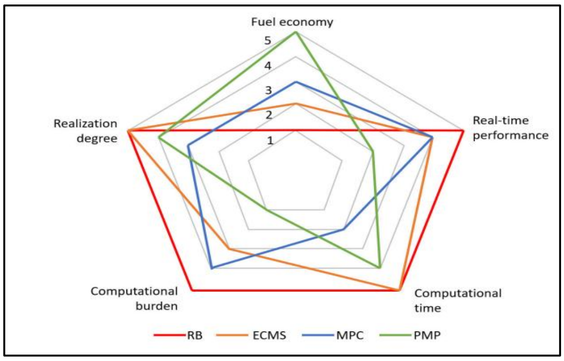


FIGURE 2. EMS performance comparison

The fact that its performance differs from MPC's shows how contextual the comparison is Dynamic Programming (DP) is a standard in EMS evaluations, despite being limited to simulations because of its intricate structure. After comparing the FLC's performance to that of a traditional rule-based EMS in a Toyota Prius, Montazeri and Mahmoodi came to the conclusion that the suggested FLC cut emissions and fuel consumption by about 10% .

The benefits of FLC are outlined in Table 3, along with the parallels and discrepancies between it and MPC and deterministic rule-based approaches. Deterministic rule-based techniques and FLC are both straightforward, inexpensive, resilient, and easy to design. They do, however, have several disadvantages in common, such as poor fuel efficiency and subpar performance. In contrast, MPC provides near-optimal solutions, high accuracy, and predictive capability; nonetheless, the system model has a significant impact on how well it performs.

III. FUZZY LOGIC CONTROLLER EMS

A common Energy Management Strategy (EMS) in HEVs and HESS EVs is the fuzzy logic controller (FLC). FLC is categorized as an EMS controller by two parties. Conventional fuzzy, also referred to as basic or traditional, adaptive fuzzy, and predictive fuzzy are the classifications made by one side.
Conversely, an optimized fuzzy takes the place of the conventional fuzzy, while the other two remain unchanged. This review distinguishes between the conventional and optimized fuzzy because of their notable differences in methodology and outcomes. Furthermore, only a small number of academics have adopted predictive fuzzy. Because of this, it is called a combination, meaning that FLC EMS is combined with other EMS techniques. Lastly, the FLC EMS in this review is categorized as combination, adaptive, optimum, and conventional.

A. CONVENTIONAL FLC

The traditional FLC method is the cornerstone of energy management strategy (EMS), employing fuzzy reasoning to generate desired outputs from inputs to the FLC. This approach necessitates designing fuzzy memberships and rules by utilizing existing knowledge or experience
The literature has proposed a wide variety of standard FLC EMS designs to accommodate various vehicle layouts.
Many researchers have used the traditional FLC EMS for Hybrid Electric Vehicles (HEVs). In a study comparing FLC and ANFIS, Suhail et al. used two inputs (engine speed and battery state of charge, or SoC) and one output (battery power) . With a slight SoC dip, ANFIS outperformed FLC and showed better performance. Simulation and Hardware-in-the-Loop (HIL) testing showed that Singh et al.'s use of a Mamdani-type FLC with inputs of torque demand, battery SoC, and brake demand increased fuel efficiency by 50.56%. Similarly, Ma et al. used the Madani-type FLC with inputs for battery SoC and necessary torque, showing a 13.3% decrease in fuel consumption over the logic-threshold approach.
Conventional FLC has shown promise in a variety of HEV configurations, including fuel cell extended-

range cars and through-the-road hybrid vehicles (TTR HEVs). When FLC-based EMS was used in a TTR HEV, Sabri et al. were able to reduce fuel usage by 62% in comparison to rule-based EMS . Nar wade and associates. evaluated Neural Network (NN) EMS against FLC for a two-wheeler TTR parallel HEV, finding that NN EMS performed better in terms of total energy used. A fuel cell extended-range vehicle with FLC EMS was proposed by Geng et al., who showed enhanced performance in terms of acceleration time and total mileage.

As demonstrated by studies like researchers have widely used conventional FLC as an Energy Management Strategy (EMS) in fuel-cell cars. By using switching control to protect the Supercapacitor (SC) within a certain operating range, Lin et al. implemented FLC EMS in a hybrid Fuel Cell and Supercapacitor Electric Vehicle (FCHEV). A moving average filter was also used to lower charge rates and safeguard the fuel cell (FC). By using delta-power and SC State of Charge (SoC) as inputs, the Mamdani-type FLC, which was manually built using rules, produced an output scaling factor for FC power. Fuel consumption was significantly reduced by this method compared to PI and power follower control, by 13.15% and 9.18%, respectively. FLC EMS was also used by Song et al. in an FCHEV that combined battery and FC components. Through Hardware-in-the-Loop (HIL) testing, they came to the conclusion that FLC EMS was more adaptable to changing driving conditions than power follower control. In order to replace the battery with a bidirectional DC converter, Shen et al. designed FLC EMS, a hybrid fuel-cell and battery system that incorporates a special Variable Structure Battery (VSB). With power demand, FC power, and battery SoC as inputs, the traditional FLC produced FC delta-power as the output, demonstrating the capacity to retain high efficiency while smoothing FC power. FLC EMS in FC-battery EV was suggested by the authors along with model predictive direct torque control (MPDTC) for motor speed control. The FLC inputs battery SoC and loads power using the Mamdani type. On the other hand, the output serves as the fuel cell's power reference. They get to the conclusion that the suggested EMS technique can maintain the battery SoC within acceptable bounds.

Keskin and Urazel presented FLC EMS for EVs with batteries and supercapacitors (SCs), taking battery degradation into account, in the context of EVs fitted with hybrid energy storage systems (HESS) . This manually developed Mamdani-type fuzzy system generated power allocation for the battery as its output by using power demand, battery SoC, and SC SoC as inputs.

When compared to battery-only and logic threshold techniques, the suggested FLC EMS was found to be more successful in lowering peak current while maintaining the lowest possible battery SoC use took a similar tack when examining the consequences of motor control.

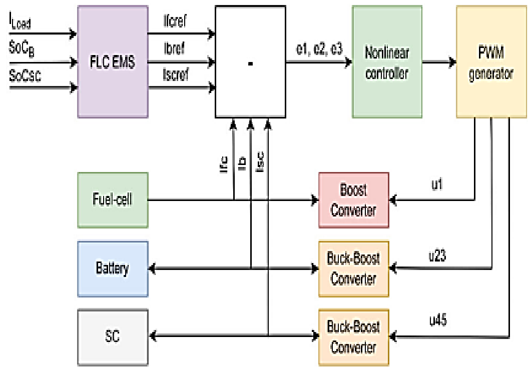


FIGURE 3. Conventional FLC-EMS

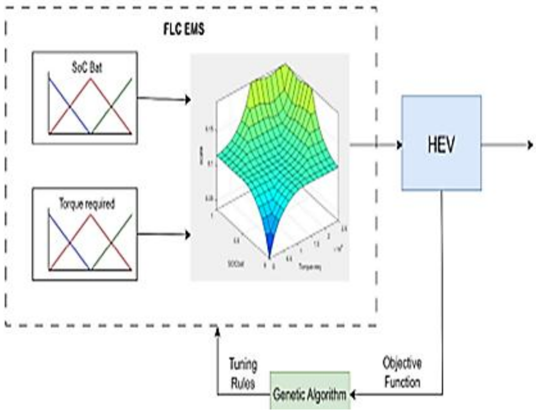


FIGURE 4. Optimal FLC EMS

As demonstrated by research like conventional FLC was also used in setups including three power sources: FC, battery, and SC. In their dual-level controller EMS, Kamoona et al. used a proportional-integral (PI) controller adjusted by particle swarm optimization (PSO) for low-level control and FLC and an artificial neural network (ANN) for high-level control . With load power and battery State of Charge (SoC) as inputs, the FLC generated an FC power reference, which was then utilized to train an ANN for EMS. Low-level control comparisons showed that FLC and ANN produced outcomes that were essentially comparable. Similar to this, the authors of demonstrated an EV structure with a direct connection of SC, highlighting its excellent SC charge efficiency, serving as an energy buffer, and helping to achieve a 13.54% gain in fuel economy, which was confirmed by experimental testing. Some investigations, such those integrated traction motor control with traditional FLC.

Reference currents for FC, battery (B), and SC are shown in Fig. 3 after the FLC received inputs of load current, battery SoC, and SC SoC. The converters of FC, B, and SC were controlled using the Sliding Mode Control (SMC) technique. According to the suggested approach, hydrogen consumption was reduced by 29%. The Vehicle Dynamics Controller (VDC), Vehicle Speed Controller (VSC), and motor current were used as inputs, while the battery and SC power references were used as outputs. The control demonstrated quick and excellent performance under a range of speeds and system dynamics by using the PI algorithm and SMC in motor control suggested a similar idea but with Backstepping-Direct Torque Control (BS-DTC) in place of motor control.

B. OPTIMAL FLC

The optimized or optimal FLC approach uses optimization techniques to improve performance, in contrast to standard FLC, which necessitates experts to build membership functions and rules. The time-consuming nature and unproven optimality of traditional FLC are addressed by this method. When compared to traditional methodologies, researchers like those have shown that optimization techniques can increase FLC EMS's efficiency. The main way that optimal FLC and conventional FLC differ from one another is in how optimization techniques are used to determine the best memberships and/or rule bases for the fuzzy system.

Based on the literature, the most popular optimization techniques for enhancing FLC EMS are Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Scientists like Jia et al. improved mileage by using PSO to optimize a series FLC (SFLC) for hybrid fuel cell (FC) and battery systems . Tifour et al. demonstrated increases in fuel economy and overall efficiency by optimizing Sugeno-type FLC for hybrid FCHEVs using PSO.

GA has also been widely applied to FLC EMS optimization. In order to reduce energy loss, Wang et al. used GA to optimize fuzzy membership functions. In a similar vein, scientists in used GA to optimize FLC for a hybrid fuel cell vehicle, improving vehicle performance, fuel efficiency, and the best possible energy distribution. In order to achieve effective HESS configurations, Eckert et al. used GA to optimize FLC EMS for Electric Vehicles (EVs) with batteries and Supercapacitors (SC). They employ three objective functions: performance, driving range, and HESS mass minimization. They came to the conclusion that the HESS arrangement, which uses a smaller SC with a high-capacity battery, is more efficient after simulation testing.

An ideal FLC EMS suggested is shown in Fig. 4, demonstrating the incorporation of GA for improved performance. Ye et al. compared several FLC-based EMS techniques for EVs with batteries and SC, including FLC, FLC-GA, FC-PSO, and Dynamic Programming (DP) as a benchmark. The findings showed that FLC-GA had peak currents that were lower and more consistent than FLC-PSO, deviating from DP by just 0.6%. An overview of certain enhanced PSO and GA techniques for FLC EMS optimization is given in Table 4. FLC is also optimized using other optimization techniques, such as rule-learning from dynamic programming the Differential Evolution Algorithm (DEA) etc.

Researchers incorporate some driving cycles in the training step, as to increase the optimality in the unknown drive cycle and to boost the resilience of the optimal FLC.They apply optimization using the Genetic Simulated Annealing Algorithm (GASA) and combine three drive cycles. This analysis also takes the cooling burden into account. Ultimately, they come to the conclusion that the suggested approach outperforms both rule-based and adaptive ECMS (A-ECMS) used the similar idea to the NSGA-III optimization technique.

In addition to optimizing FLC, the optimization method can be applied to determine the ideal HESS dimensions. Because it influences the vehicle's mass, performance, and cost, component size is crucial for both HEVs and HESS EVs. Herrera et al. used GA multi-objective optimization to integrate two FLCs for EMS on a hybrid bus, resulting in the Energy Storage System (ESS) operating and scaling optimally [84]. According to simulation tests, the suggested approach can save fuel consumption and daily operating costs by up to 19% and 15%, respectively. The same idea is applied by Silva et al. using an interactive adaptive weight genetic algorithm (i-AWGA).The suggested solution can lower the cost-to-autonomy ratio by up to 63.59%, according to the cost study. The investigation is expanded by the authors in utilizing a dual-HESS system with FLC EMS optimized by i-AWGA. The front and rear wheels of the vehicle are equipped with propulsion systems, respectively. There are three FLC EMS used: two for each HESS and one for power sharing between front and rear propulsion. When compared to a comparable EV with a single HESS and optimized for the same driving circumstances, dual HESS can improve battery life and driving range by up to 22.88% and 19.57%, respectively.

C. ADAPTIVE FLC

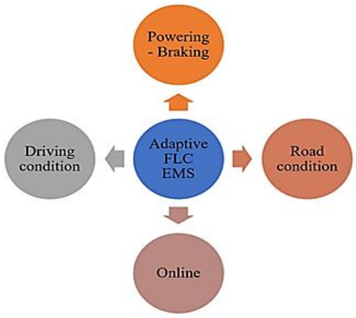


FIGURE 5. Adaptive FLC EMS classification

Fuzzy Logic Controllers (FLC) in the context of Energy Management Strategy (EMS) demonstrate flexibility within operational ranges, although they are constrained by elements such as membership limits. As EMS develops, the adaptive FLC acknowledges the necessity for customized regulations for various driving profiles. The four types of adaptive FLC are examined in this section: Fig. 5 shows the powering-braking-based, road-condition-based, driving-conditions-based, and online-based models.

One method, shown in Fig. 6, uses separate fuzzy matrix rules for braking and powering conditions. For electric vehicles

(EVs) with hybrid batteries and supercapacitors (SC), the authors in use

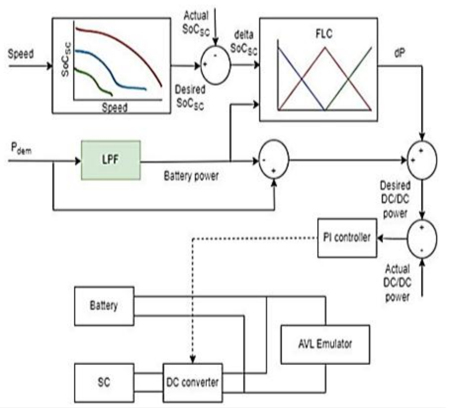


FIGURE 6. Adaptive FLC EMS: powering-braking

FLC-charge and FLC-discharge controllers, which dynamically distribute power based on load power, battery SoC, and SC SoC. By reducing charge and discharge currents, this adaptive system improves battery performance through the use of particle filters for SoC estimate.In order to maximize the scaling factor for battery power, Lu et al. use multiple FLCs for braking and powering in a hybrid battery-flywheel system . By employing a twin FLC EMS to effectively distribute powering and braking torque, Xu et al. expand this idea to parallel hybrid engines and batteries.

The study optimizes FLC rules using Genetic Algorithms (GA), outperforming rule-based and single-FLC approaches and showing performance on par with Dynamic Programming (DP). Furthermore, Zhang et al. present two unique fuzzy rules for charge and discharge modes, which allow for smooth battery charging during regenerative braking and effective power providing during discharge. The simulation findings demonstrate better energy consumption metrics by 2.4% and 1.28%, respectively, as compared to rule-based and traditional fuzzy techniques in terms of Energy Consumption (kJ) also makes use of the same idea . In contrast, creates a hierarchical coordinated EMS by combining this Adaptive-FLC technique with MPC. They draw the conclusion that this structure enhances performance in terms of stability, error reduction, and time response.

Suggests the adaptable FLC based on the road circumstances, which is shown in Fig. 7. The road conditions are divided into three profiles: highway, road, and urban. By segmenting power demand, this method uses Genetic Algorithms (GA) to optimize fuzzy rule sets offline while dynamically adjusting to driving conditions. The same idea is put out who use neural networks (NN) to recognize driving cycles. Zhang et al. optimize FLC rules using GA . The suggested adaptive FLC exhibits versatility across a range of driving cycles by improving stability and consuming less gasoline. Additionally, the authors use FLC to modify the power distribution between the battery and supercapacitor and a Contour Positioning System (CPS) to determine route slope. Performance improvements in an electric vehicle's (EV) hybrid energy storage system (HESS) are confirmed by simulations.

A multimode-FLC (MFLC) for a hybrid tractor is introduced by the authors , who modify fuzzy rules in response to predetermined operational (driving) conditions. By employing fuzzy C-means (FCM) for operational condition identification, MFLC can reduce power usage by up to 13% when compared to thermostat control strategy (TCS). Furthermore, highlights data-driven approaches, making use of actual driving data to forecast routes and maximize fuel economy. Fuel savings of up to 16% in residential neighborhoods are confirmed by the simulation.

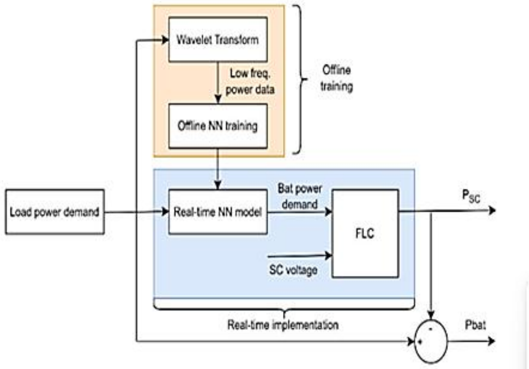


FIGURE 7. Adaptive FLC-EMS proposed

Additionally, Hussan et al. use FLC to control voltage in a hybrid system that combines supercapacitors, batteries, and fuel cells. The suggested FLC performs better than the Proportional-Integral (PI) and Sliding Mode Control (SMC) approaches in voltage regulation, energy management, and reference tracking when rules are categorized according to driving circumstances such as normal, acceleration, deceleration, uphill, and down hill.Suggests the final online adaption, which employs the FLC Sugeno type as EMS for a battery-and-SC hybrid tram. FLC's weight fluctuates because its weighting method is optimized online utilizing a hyper-spherical search algorithm. They confirm through the simulation that, in comparison to FLC with a fixed weight scheme, the suggested approach can boost tram mileage by 22.45% and decrease battery peak current by 31.02%.

D. COMBINATION

In order to enhance its performance, the FLC EMS also integrated other techniques. There are three combinations in this section: FLC and NN, FLC with frequency decoupling, and others. In this section, each will be covered in more detail.

I.FLC AND FREQUENCY DECOUPLIN

The wavelet transform (WT) and low-pass filter (LPF) are the frequency decoupling methods typically used in conjunction with FLC for EMS. controlling power distribution based on State of Charge (SoC) disparities. In a similar manner, controls SC State of Charge (SoC) and power ratios by integrating FC and LPF. The supercapacitor receives high-frequency power, guaranteeing battery deterioration and confirming the suggested HESS. Hardware-in-the-Loop (HIL) testing and simulations verify increased efficiency of up to 14.89%. The authors of [108] employ a three-layered strategy, dividing low- and high-frequency power demands using WT, allocating power using FLC-EMS, and optimizing Hybrid Energy Storage Systems (HESS) characteristics based on driving cycles.

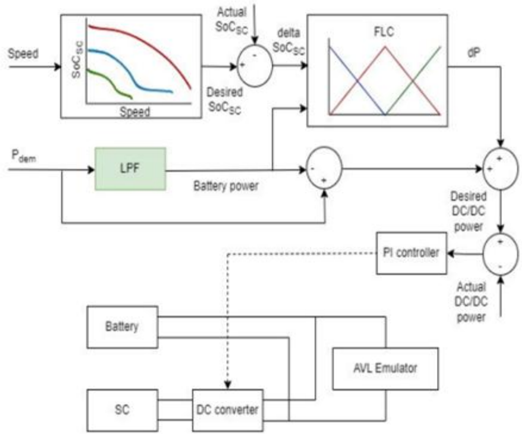


FIGURE 8. FLC combined with LPF

When compared to WT-based-only systems, the integrated EMS reduces energy consumption by 6.54%, exhibiting longer battery life. Additionally, [109] suggests a two-step EMS that uses a power-sharing algorithm based on WT and FLC as well as adaptive LPF based on FLC. The second stage, where WT and FLC distribute power to FC and battery, receives the remaining power from the adaptive LPF, which uses FLC for cut-off frequency adjustment and supplies power to SC. Fuel consumption is reduced by 7.94% in comparison to the Equivalent Consumption Minimization Strategy (ECMS), according to simulation and experimental data.

II.FLC AND NN (ANFIS)

Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which combine learning capabilities with fuzzy logic flexibility, are the consequence of the combination of FLC and Neural Networks (NN).

The authors of provide examples of how ANFIS is used in EMS for parallel hybrid electric vehicles (EVs) and hybrid electric buses. Reference trains ANFIS for EMS in a hybrid electric bus using iterative Dynamic Programming (DP), outperforming ECMS and rule-based techniques in simulations and experiments.

Through simulations and HIL testing, the authors of teach ANFIS to simulate ECMS as EMS for a hybrid bus, demonstrating lower fuel usage than ECMS itself. In contrast, Gao et al. train ANFIS for a parallel hybrid EV with a DC-motor traction motor using logic threshold EMS, improving simulation test results.

In order to improve kinetic energy usage using ANFIS EMS, the authors in suggest a special HESS EV setup. Battery, SC, and FC are the ESSs that are utilized. To enhance the energy absorption of regenerative braking, a DC generator is mounted on the front wheels. According to the simulation, this system's efficiency with ANFIS EMS can reach 98.2%.

III OTHER APPROACHES

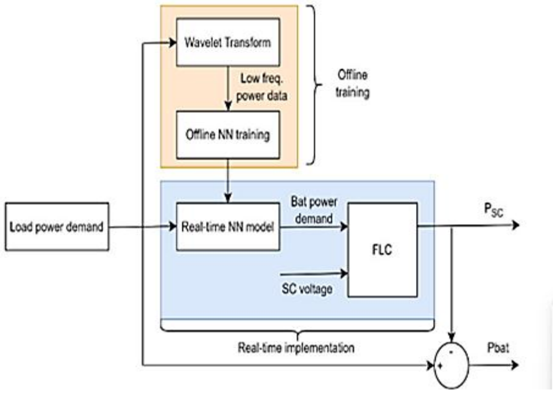


FIGURE 9. Combined-FLC EMS

In Fig. 9 , Zhang et al. combine Wavelet Transform (WT), neural networks (NN), and the best FLC EMS for hybrid battery and SC vehicles. PSO optimizes FLC membership functions, NN processes real-time application data, and WT extracts battery power demand. According to experimental testing, the suggested approach improves regenerative braking energy recovery by 44.22% and lowers battery life costs by 18%. Guo et al. create a hybrid FC and battery EV by combining FLC with Reinforcement Learning (RL) . In Hardware-in-the-Loop (HIL) simulations, the suggested Fuzzy-Reinforce employs Policy Gradient Reinforcement Learning (PGRL), exhibiting stability, speed, and reduced hydrogen consumption in comparison to conventional RL. Matignom et al. create an integrated EMS by combining learning-, rule-, and optimization-based EMS techniques. The suggested approach achieves performance that is comparable to ideal offline strategies by utilizing fuzzy rule-based techniques, online Pontryagin's minimal principle (PMP) optimization, and fuzzy C-means for driving pattern recognition. This wide range of hybrid strategies demonstrates how FLC can be used in conjunction with other methods to optimize EMS for a variety of hybrid and electric vehicle applications.

IV. DISCUSSION AND FUTURE DEVELOPMENT

The EMS in HEV and HESS EV has distinct functions. FLC EMS designs accommodate a variety of operating modes and energy sources in Hybrid Electric Vehicles (HEVs), which combine electric powertrains with conventional engines. Optimising energy use under dynamic driving situations and guaranteeing smooth power source transitions are challenges. FLC EMS handles the complexities of controlling energy from batteries and supercapacitors in Hybrid Energy Storage Systems of Electric Vehicles (HESS EV), which primarily concentrate on electric propulsion. High-frequency load demands and maintaining the lifespan of responsive but aging ESS components, such as batteries and fuel cells (FC), present challenges.

V. FLC EMS PERFORMANCE INSIGHTS

Four main strategies are recognized for the use of FLC EMS: combination, optimum, adaptive, and conventional. Traditional FLC uses fuzzy logic of the Mamdani type and is manually tuned. The output—power reference for Energy Storage Systems (ESS)—is determined by inputs, most commonly load power and State of Charge (SoC).

Optimization techniques like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), also referred to as optimal FLC, are widely used to get around tuning issues and produce ideal outcomes. Numerous aim functions are also employed, including boosting mileage, cutting fuel consumption, cutting energy use, cutting energy loss, etc.

The ideal FLC EMS, which is adjusted according to the particular driving cycle, cannot provide the best results in other drive cycles due to the unpredictable drive cycle. The adaptive FLC EMS is suggested as a solution to this problem. Scholars offer many adaptive methods. Four categories—powering-braking-based, road-condition-based, driving conditions-based, and online-based—are used to group this review. See the section on adaptive FLC for further information. The powering and braking are affected by the state of the road and the driver. Consequently, both driving condition-based and road condition-based can be accommodated by the appropriate powering-braking-based option. However, if the infrastructure is available, the online method is the most effective.

Combining FLC with another technique is the final option. Thus, the researcher has offered numerous combinations of FLC approaches. The majority of them, as far as the authors can tell, work in tandem with frequency decoupling techniques like LPF and WT. Low response ESS like FC and batteries age because power sharing or energy management from FLC cannot handle high-frequency loads. In order to help distribute load power into the appropriate ESS with the load power frequency, frequency decoupling is added. For ANFIS, FLC can also be combined with NN. It can be trained as a fuzzy inference. The implementation of highly computational EMS, like DP and ECMS, is also made possible by the ANFIS. Lastly, a combination of the frequency decoupling method, optimization algorithm, adaptive mechanism, and FLC is also available.

The results of optimal FLC are superior to those of standard FLC. But because it depends on the track, it can be difficult to execute consistently across different tracks. Adaptive FLC successfully addresses this constraint by dynamically modifying fuzzy rules. The classification of FLC and its advantages and disadvantages in applications for HEVs and HESS EVs are shown in Fig. 10.

FUTURE DIRECTIONS: FLC EMS will be developed with an emphasis on combination, adaptable, and optimal forms. Even if the adaptable form can adjust to a wide range of circumstances, it still needs a lot of rules. As a result, a high processor specification is needed. Enhancing both the optimal and combination FLC EMS is the answer. Any novel optimization technique that can handle multi-objective functions and perform more effectively can be used to improve the optimal FLC. Similar to the adaptive FLC but using fewer criteria, the optimal FLC can also be taught with a large number of drive cycles to become optimal in the majority of drive cycles. When combined with another technique, FLC EMS performance can be enhanced without appreciably increasing computation time.

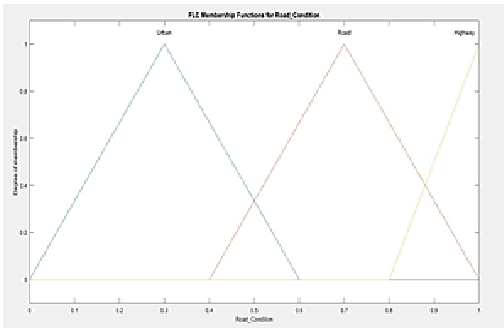
Opportunities to improve FLC EMS are presented by developments in communication paradigms, especially Vehicle-to-Everything (V2X) technologies. Vehicle-to-device (V2D), Vehicle-to-infrastructure (V2I), Vehicle-to-grid (V2G), Vehicle-to-pedestrian (V2P), Vehicle-to-network (V2N), and Vehicle-to-vehicle (V2V) subsystems are all included in V2X [119]. By lowering processing burdens and guaranteeing that FLC EMS is continuously updated with the best outcomes, utilizing V2X can enable real-time optimization. In terms of calculation time, this can resolve the adaptive FLC issue.

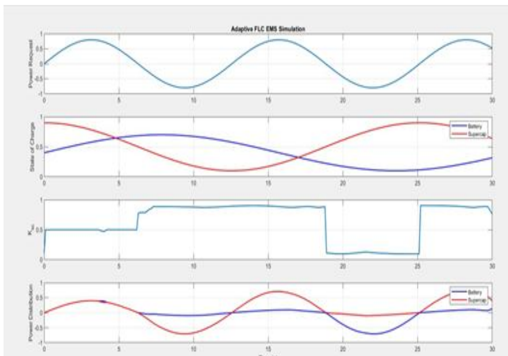
Future advancements might look into how V2X and FC EMS technologies can work together to give cars real-time traffic updates and operational status communication. Increased fuel economy, decreased component damage, and improved energy efficiency are all possible outcomes of such integration. It becomes increasingly important to overcome hardware implementation issues as research advances. Validating FLC EMS designs in real-world situations requires bridging the gap between simulation, Hardwarein-the-Loop (HIL) methods, and full-scale prototypes.

VI.RESULTS

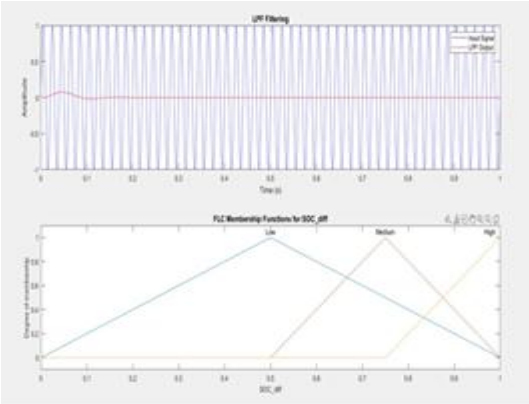
I.ADAPTIVE FUZZY LOGIC CONTROLLER FOR EV POWER MANAGEMENT

This MATLAB implementation demonstrates an adaptive Fuzzy Logic Controller (FLC) that optimizes power distribution in electric vehicles (EVs) based on varying road conditions and power demands. The system uses fuzzy logic to make intelligent decisions about how to allocate power resources efficiently





II.HYBRID ENERGY MANAGEMENT SYSTEM WITH WAVELET TRANSFORM, NEURAL NETWORK, AND FUZZY LOGIC CONTROL



VII. CONCLUSION

The flexibility and efficiency 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) are highlighted in this review, in conclusion. Certain advantages and disadvantages of the conventional, optimum, adaptive, and combination FLC approaches are shown by analysis. Despite its complexity, the adaptive technique provides track-independent adaptability and improved performance, the optimal method shines in particular cases but lacks diversity, and the standard method is straightforward but unsatisfactory. When it comes to FLC limits, particularly those related to frequency constraints, the combination approach shows potential. For academics examining energy management in EVs, particularly with FLC, this review is an invaluable resource. In order to enhance Hybrid Energy Storage Systems (HESS), future research should concentrate on real-world performance evaluations and the practical application of FLC.and support environmentally friendly transportation options. It is essential to comprehend the subtleties of various vehicle architectures in order to influence the development of electric and hybrid vehicle technologies in the future. There is great potential for developing effective and environmentally friendly transportation solutions with the ongoing improvement of FLC methodologies.

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