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Review

A Comprehensive Analysis of Online and Offline Energy Management Approaches for Optimal Performance of Fuel Cell Hybrid Electric Vehicles

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Abstract: The global impact of hybrid electric vehicles (HEVs) is exponentially rising as it is an emission-free and reliable alternative to fossil fuel-based vehicles that cause enormous negative impacts on the socioeconomic and environmental sectors. Fuel cell hybrid electric vehicles (FCHEV) have been widely considered in the latest research as an energy-efficient, environmentally friendly, and longer-range green transportation alternative. The performance of these FCHEVs, however, is primarily dependent upon the optimal selection of Energy Management Strategies (EMSs) adopted for optimum power split and energy resource management. This research reviews the latest EMS techniques presented in the literature and highlights their working principle, operation, and impact on the FCHEV performance and reliability. This research also highlights the challenges associated with the globalization of FCHEVs and recommends future work and research directions essential for optimal FCHEV performance and commercialization.

Keywords: fuel cell hybrid electric vehicles (FCHEVs); fuel cell (FC); battery; supercapacitor (SC); energy management strategies (EMS); system optimization

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1. Introduction

Automobiles have evolved as a primary mode of transportation and have become an essential requirement for every family. These vehicles majorly operate on fossil fuels for their propulsion and are one of the significant contributors to Greenhouse Gas (GHG) emissions worldwide [1]. Their absolute necessity and environmental concern have compelled the scientific community to consider alternative fuels and automobile structures for a cost-effective, efficient, and green transportation system [2].

Electric vehicles are the most efficient alternative to conventional fossil fuel-based automobiles as they provide efficient performance with the indemnity of cost-effectiveness and environmental safety [3]. The research and development and popularization of various electric vehicles (EVs) are rising worldwide, intending to conserve energy and lower consumption, as well as alleviate the problem of environmental pollution.

Hybrid electric vehicles (HEVs) have been adopted widely in recent years as they offer enormous benefits from the traditional internal combustion engine (ICE) vehicles and can compete with EVs. The adaptation of consumers to hybrid electric vehicles is straightforward as the interface and working of the HEV are much similar to traditional vehicles, and the user is not compelled to adopt something entirely new. This easy adaptability of HEVs makes it easier for customers to shift to buying these vehicles. Moreover, the HEV offers enormous environmental benefits, including less dependence on fossil fuels and very low carbon emissions [4]. The HEVs have lifetime emissions, usually 25 to 30% less than conventional ICE cars [5], whereas the fuel consumption in HEVs is almost 30% less than the traditional vehicles as they can restore energy during braking through a regenerative braking mechanism [6]. This regenerative braking mechanism in the HEVs can save around 70% of the kinetic energy which otherwise is wasted [7]. Similarly, HEVs have better dynamic performance and acceleration experience as they have battery power assistance. HEVs, with the overall benefits of better fuel efficiency, higher performance, and lesser carbon footprint, encourage consumers to adopt this promising technology.

With the maturation of fuel cell (FC) technology, the application of FCs in automobiles has piqued the interest of businesses and academics [8]. The latest literature discusses the adaptation and benefits of FC electric vehicles (FCEVs) in detail [9]. Besides the benefits of FCEVs, fuel cell hybrid electric vehicles (FCHEVs) are one of the most promising future vehicles [10]. The system offers the benefits of reduced waste and low energy consumption due to the direct conversion of fuel into electrical energy by the FCHEV and the utilization of multiple energy resources [11].

The EV industry has developed exponentially as these vehicles provide economic viability, green propulsion, and greater performance flexibility. The sales of electric vehicles worldwide are increasing exponentially. This industry has been booming, especially in the past decade, as global EV sales hit a record 6.9 million in 2021, more than a 101% increase from the past year [12]. Figure 1 depicts global EV sales until 2021. Among the EV's market, China is leading the globe with more than 50% sales of around 3.5 million EVs in China, while Europe, with 2.3 million EV sales, is the second largest EV market.

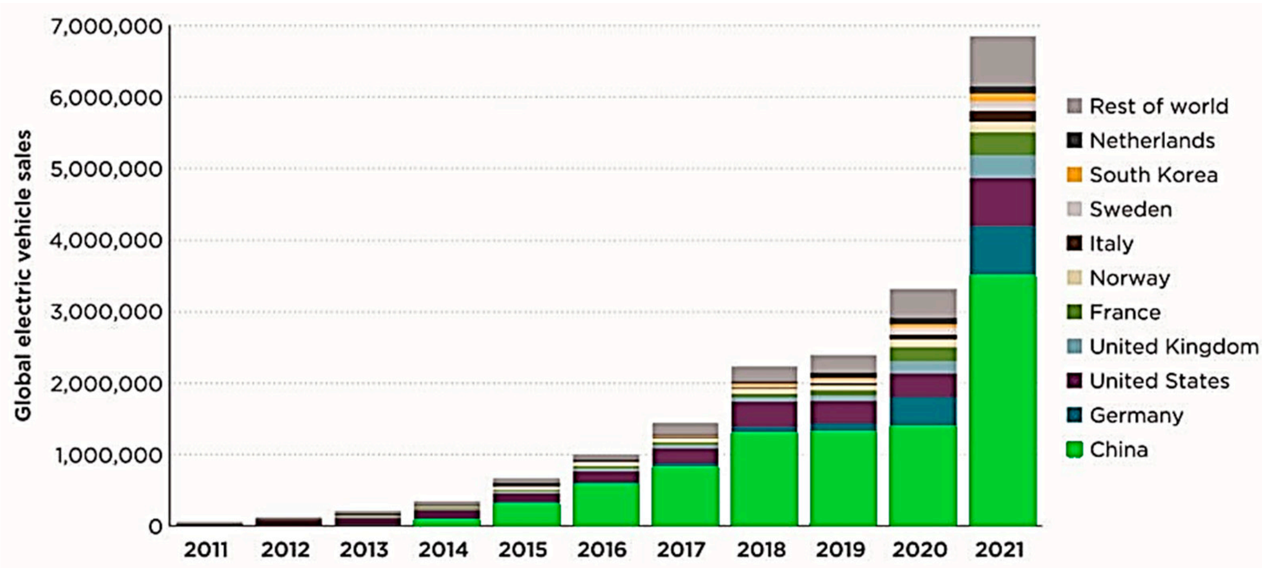


Figure 1. Annual EV sales [12].

Considering increased sales and public interest in EVs, significant research and development institutes and educational institutions are creating cutting-edge technologies to improve EVs' performance, durability, and cost-effectiveness. The expected EV sales in the global automobile market will increase by more than 45% in the upcoming decades, as shown in Figure 2. With so much economic impact, business potential, and environmental benefits, there is an extensive need to further develop this technology through continuous innovation and research [13].

Alongside the exponential growth of the global EV market and the goal of developing green transportation sources, researchers are developing innovative EV types that operate on different energy resources to further enhance the global EV footprint. In this regard, fuel cell electric vehicles (FCEVs) are emerging as a strong candidate in recent years. Figure 3 presents the predicted FCEV market trend [14].

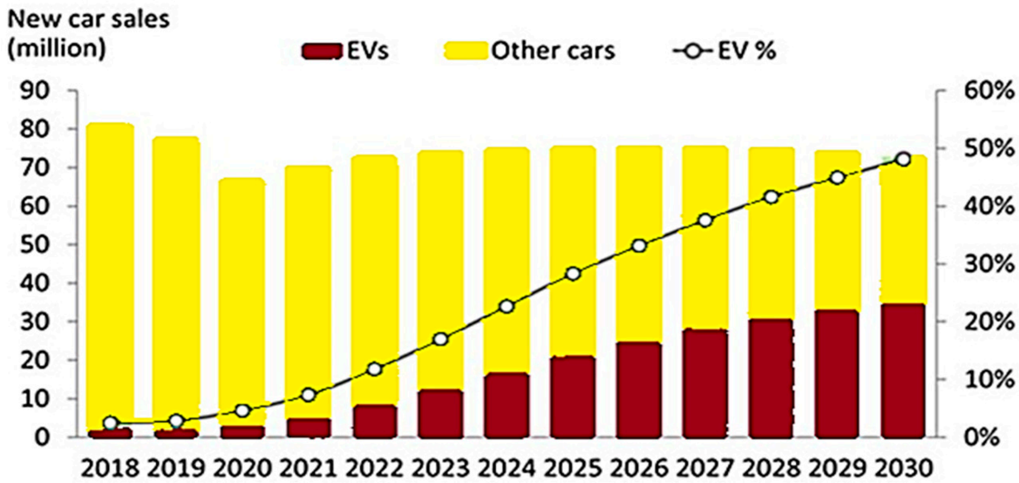


Figure 2. Expected car sales [13].

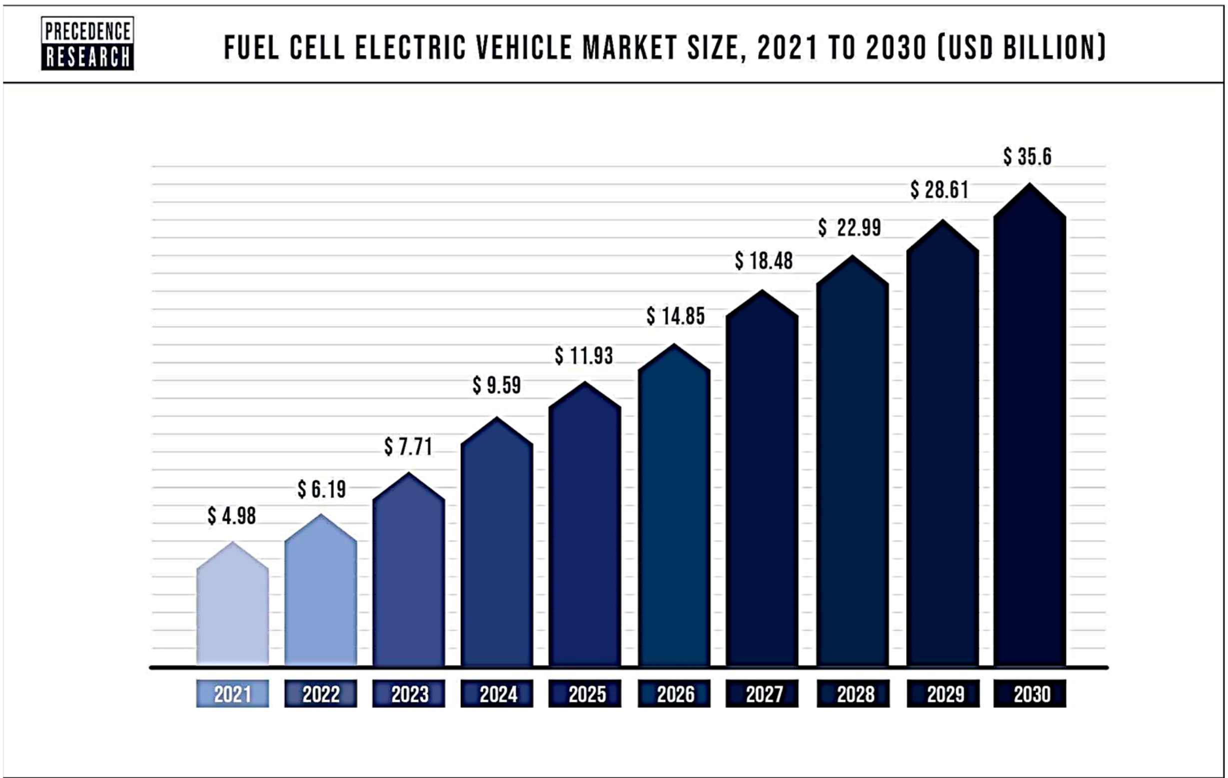


Figure 3. Fuel cell EV market [14].

The FCEV operates on the same principle as other EV types, with a significant difference in the working principle of the power cell, as the FCEV is powered through a fuel cell with or without the combination of any external energy source. Meanwhile, only water and heat are discharged with electrical energy generation, making it one of the cleanest and most energy-efficient power sources for EVs.

FCHEVs with Proton Exchange Membrane Fuel Cells (PEMFCs) can work with no charging constraint while having a more extended driving range than battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) [15]. A PEMFC benefits from being clean and ecologically benign and having a rapid start-up and refilling time [16]. A PEMFC, on the other hand, is unable to recover the electric energy of motor brake feedback due to its relatively soft output profile and limited dynamic response capabilities. As the FCs have slower dynamics, their response to rapid acceleration and deceleration is inadequate, and its effect on the FC lifespan is also detrimental [17]. As a result, super capacitors or batteries are required as an energy storage technology for balancing energy, providing rapid energy demands, and storing excess energy available during regenerating braking and excess power generation by the FCs [18]. Compared to most traditional power systems, batteries and supercapacitors regulate energy to flow better and are typically advantageous in increasing vehicle efficiency [19]. However, proper resource management in FCHEVs is critical to achieving optimal performance and system efficiency.

Furthermore, fuel cells are commonly employed in hybrid power systems that combine multiple energy sources. It can help to minimize hydrogen consumption, lower the size of fuel cells, and improve the economics of hybrid power systems. FC-based hybrid systems are commonly employed in transportation equipment such as unmanned aerial vehicles (UAVs), trams, and FC hybrid automobiles. This fact demonstrates that hydrogen energy is becoming increasingly significant in transportation. As a result, it is critical to focus on developing innovative and affective EMSs for optimal FCHEV performance.

EMSs are crucial to the performance and efficiency of any hybrid electric vehicle [20]. Their primary purpose, particularly in FCHEVs, is to distribute power between different energy sources while achieving primary objectives: first, decreasing hydrogen use or limiting equivalent energy consumption and, second, prolonging fuel cell life, which also implies boosting the hybrid system's economics [21]. These two optimizations' aims are essential to various energy management systems.

Several different types of EMS techniques for the performance enhancement of FCHEVs can be mainly categorized into two major types. The first category contains the offline EMS techniques in which the system design objectives are primarily achieved through rule-based approaches. The rule-based technique is the offline EMS that is most widely discussed in the literature. This technique necessitates collecting the fuel cell's power map to determine the most efficient operating range. According to the power system status, it may also modify the power distribution of the fuel cell and the energy storage system (battery or supercapacitor). However, it has several drawbacks, including parameters impacted by the test operating settings, a lack of flexibility for diverse operating conditions, and suboptimal control outcomes [22].

Moreover, the offline EMS techniques are not applicable in real-time as they require prior information about the entire driving cycle. The computational complexity of finding optimal solutions through these techniques is also high [23]. Offline EMSs also include global optimization-based EMS techniques with the primary objective of an optimal power split among the onboard energy resources. Rule-based EMS techniques often integrate with these optimization techniques to further enhance their capabilities.

Online EMS techniques, on the other hand, consist of instantaneous optimization as well as predictive and learning-based EMS techniques. The online EMS techniques are more favorable for real-time optimum energy management as they can deliver optimum performance without prior information about the driving cycles [24]. Model predictive Control (MPC) is among the most researched of predictive online EMS techniques, while learning-based EMSs are also becoming popular. The primary concept of a learning-based online EMS is to leverage massive data sets of real-time and historical information to train the strategy's parameters to achieve optimal control [25]. Regardless of the energy management technique used, optimization consists of two objectives: optimizing energy consumption through optimal resource management and prolonging the life of fuel cells and other components.

The dynamic nature of energy demand and supply are well incorporated by the EMS techniques through optimal load current distribution among the available energy resources. The load current is distributed among the energy resources in accordance with the power and energy densities. If the system has two energy resources such as FC and battery, then the FC handles the normal load current requirements while the battery compensates for the dynamic current requirements. Moreover, if the designed FCHEV has three energy resources in the form of FC, battery, and supercapacitor (SC), then the FC considers the slower dynamical load current requirements while the battery and SC handle the medium-range and transient load current requirements, respectively. The performance of FCEVs can be optimized by integrating the system with the more reliable, fast, and efficient EMS techniques.

This research work is intended to first elaborate on the latest topologies of FCEVs in the literature, as they can have different types of energy sources, degrees of hybridization, and other topologies related to their design and operation. All kinds of FCEVs, especially the FCHEV with multiple energy resources, depend highly on efficient and intelligent EMSs for optimal performance. This research presents the latest EMS techniques available in the literature to enhance the FCHEV performance and provides an overview of their effect on FCHEV performance and overall reliability. This study can be considered a research direction for researchers to study the latest literature and choose the best-suited FCEV topology and EMS techniques. The research contributions and novelties of this research work are highlighted below.

- Provides a state-of-the-art understanding of the FCHEVs infrastructure and their topologies.
- Discusses the latest EMS techniques presented in the recent research publication and critically analyzes their functionality and their pros and cons related to their contributions towards optimum resource management.
- Provides an in-depth review of the latest research contributions in the domain of EMS implementation in FCHEVs and elaborates on the challenges associated with their practical implementation.
- Discusses the most critical issues and challenges in the globalization of FCHEVs and proposes their adequate solutions.

Section 2 elaborates on the latest FCEV configurations in the literature and provides their advantages and disadvantages. Section 3 provides a state-of-the-art review of the EMSs adopted in the newest literature and elaborates on them by dividing them into two broad categories regarding their offline and online utilization status. It also provides inside knowledge of offline EMSs and elaborates on their working principles. Section 4 highlights the online EMSs adopted in the literature, explains their functionality and performance, and highlights the advantages and superiority of one over the other. Section 5 presents the challenges and issues associated with FCHEV globalization, and Section 6 provides a conclusion and recommendation to enhance the FCHEV's performance and commercialization.

2. FCEV Configurations and Power Train Topologies

Fuel cells are frequently combined with various auxiliary energy sources to power hybrid electric vehicles. Supercapacitors (SCs), batteries, solar PV (SPVs), superconducting magnetic energy storage (SMES), and flywheels are examples of supplementary power sources. Batteries and SCs are the most often employed supplementary energy sources. Batteries are simple to install, need little upkeep, and are inexpensive. As a result, fuel cell/battery hybrid electric cars are extensively produced and the most popular topology. An SC is a storage device used to improve dynamic responsiveness. When the load fluctuates rapidly, it can deliver load or recover energy immediately. Other supplementary energy storage devices are used less frequently than batteries and SCs.

Other energy resources are also affective in delivering the required energy potential but have some shortcomings. SMESs are energy storage devices with high power output but poor energy density. Solar PV is a nonpolluting, sustainable power-generating technology; however, its energy generation is unpredictable due to solar irradiation. Mechanical energy is stored in the flywheel when torque is applied to it. When the system requires more power, the flywheel may convert mechanical energy into electrical energy and supply it to the system. It requires strict security and is widely used in electric systems.

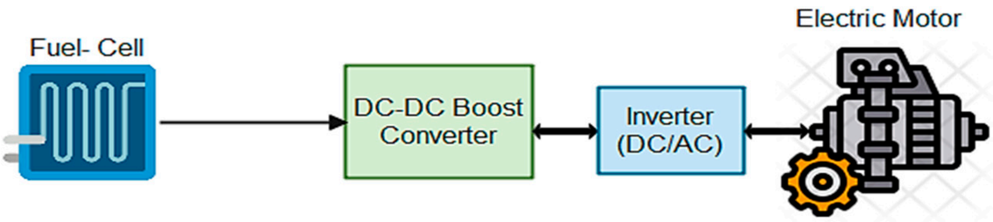
Regarding energy resources, the FCEV can be considered to have six types: FC only, FC-Battery, FC-SC, FC-Battery-SC, FC-SC-Battery-PV, and FC-Other. All of these energy resources are of different types and require the integration of power converters for integration with the overall system structure. The pictorial representation of these FCEV configurations is presented in Figure 4.

The first topology, as shown in Figure 4a, depicts that only a single power source in the form of FCs drives the EV. The connection of the FC with the DC-DC boost converter and inverter stabilizes the DC output from the FC and converts the DC power into AC for the electric motor. This simple configuration has the advantage of more straightforward implementation and is commonly favorable under low-speed requirements. However, any transient load fluctuations can affect the FC lifespan, and the kinetic energy during braking also goes to waste.

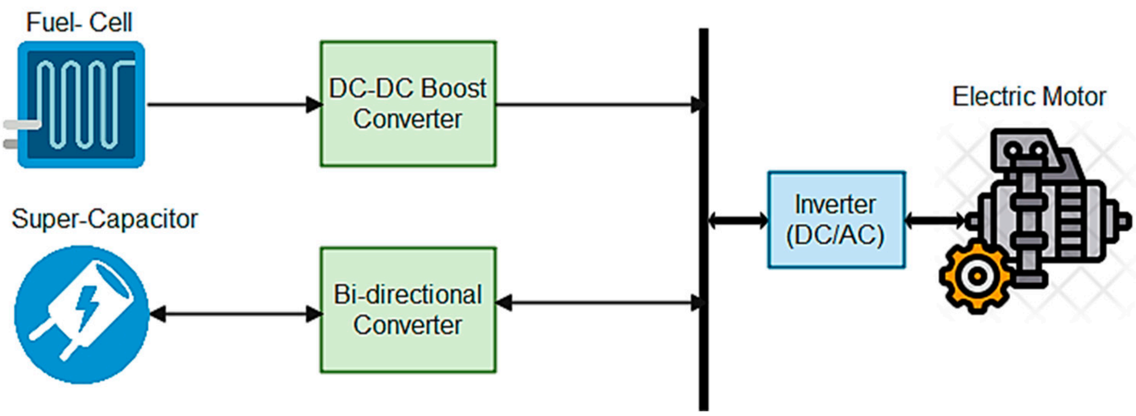
Topology Figure 4b considered in this research consists of the FC and SC energy resources. Here, the integration of SC benefits in handling the transient load fluctuations and enables the system to restore kinetic energy during braking through the bi-directional converter. Similarly, Topology Figure 4c depicts battery utilization along with the FC. This topology can deliver a more extended driving range because of the battery's high energy density and can also handle the regenerative braking phenomenon.

Topology Figure 4d comprises three energy resources where the battery and SC are integrated with the FC to further enhance the system design efficiency. This configuration has faster system design dynamics because of the SC while having a higher range because of high battery energy density. This topology is also favored for the electrifications and energy management of aircrafts as well as offering numerous design benefits [26]. This system prioritizes the energy restored from the regenerative braking in recharging the battery and SC according to the system requirements and conditions.

Figure 4e presents the topology of integrating solar PV with the other available energy resources. The purpose of solar PV integration is to recharge the auxiliary energy resources during the daytime operation of the FCHEV. This configuration can further enhance the driving range of the vehicle and can deliver more efficient overall system performance.

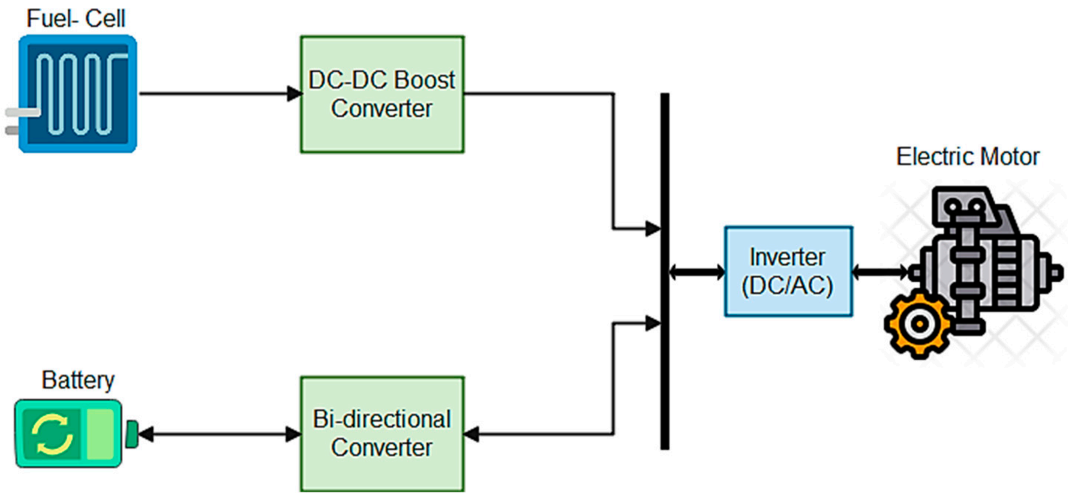


(**a**)



(**b**)

Figure 4. *Cont.*



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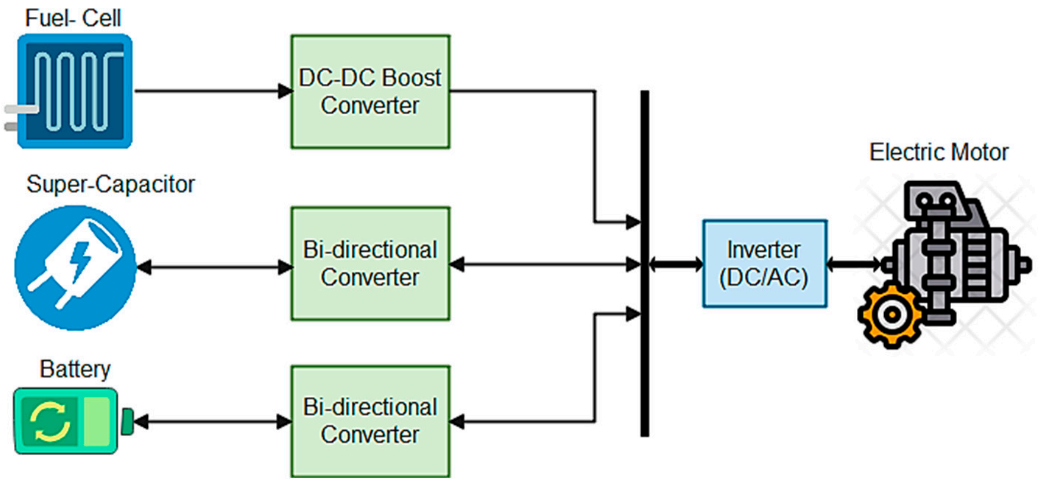

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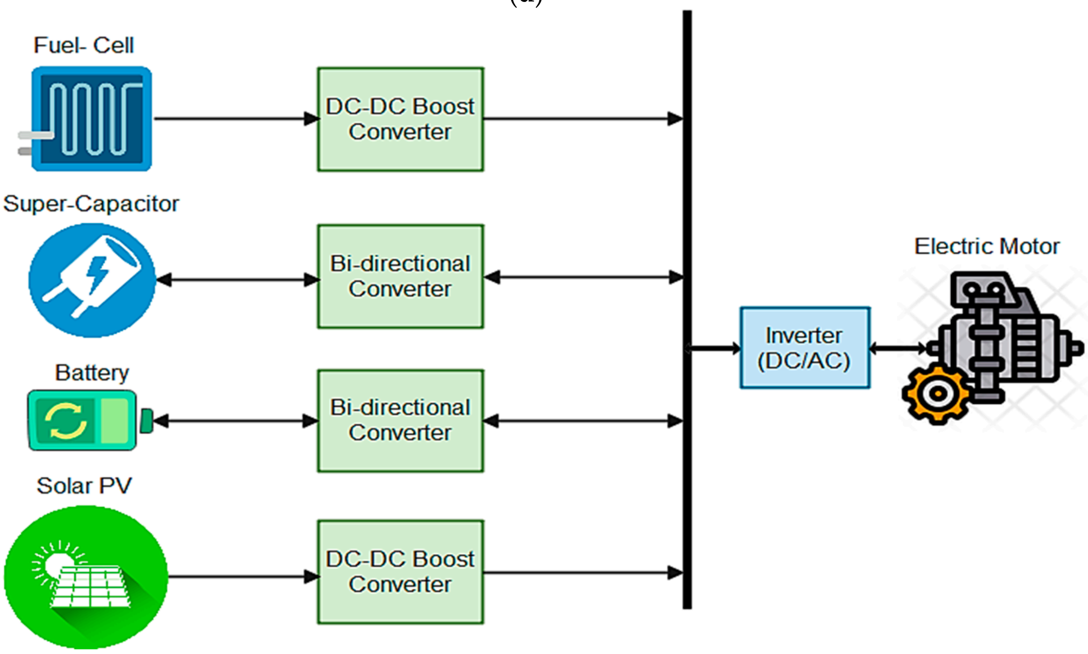

(**e**)

Figure 4. FCEV power source configurations: (**a**) FC only; (**b**) FC-SC; (**c**) FC-Battery; (**d**) FC-SC-Battery; (**e**) FC-SC-PV-Battery.

The first configuration is of FC only, with only a single power source. The FC is connected with the DC-DC boost converter to stabilize the output, as it does not support any reverse flow of current. This output is then connected to a DC-AC inverter to convert the DC power generated from the FC to the AC to operate the power train AC electric motor. The second configuration contains the FC with SC to support the transient power requirements and to store the excess energy through the bi-directional converter. The third configuration consists of an FC with a battery. The battery is connected to a DC-DC bi-directional converter to provide energy during demand and to restore it during deceleration. The battery delivers moderate instant power requirements and prolongs the FC lifespan.

The fourth configuration consists of the FC-SC-Battery configuration. This configuration has the advantage that the FC handles the regular load demand. The battery takes up the moderate load current while the SC delivers the transient load current during the running and startup conditions. These energy resources complement each other under current conditions and deliver better financial and performance results than the previous configurations through the utilization of EMS techniques.

The fifth configuration involves the addition of solar panels along with other energy resources. Solar panels can provide energy during daytime to recharge the battery and SC and can affect the fuel efficiency and reliability of the EV. Table 1 highlights the significant constituents, merits, and demerits of each FCEV HPS configuration

Table 1. Major FCEV configurations and their characteristics.

Ref#	FCEV Configuration	Merits	Demerits
[27]	Fuel Cell Only	• Easier implementation • Simple control design	• Excess energy goes wasted • Higher fuel requirements
[17]	FC-SC	• Ability to handle high transient currents • Offers longer FC lifespan • Ability to store excess energy	• Cannot provide energy for a long time • Higher capital cost
[28]	FC-Battery	• Offers longer FC lifespan • High energy density • Excess energy can be recovered through regenerative braking	• Limited battery lifetime • Low power flow control flexibility • Cannot handle high transient current
[29]	FC-SC-Battery	• Ability to handle all types of slow to high transients' current requirements • Excess energy is fully recovered • Better fuel efficiency • Better DC bus voltage stability • High energy density as well as high power density availability • Faster system response to dynamics	• Complex control requirements • Challenging to achieve system stability • Higher capital cost
[30]	FC-SC-Battery-PV	• High energy and power density availability • On the way, battery and SC charging by solar • Better FC fuel efficiency • Longer FC, SC, and battery lifespan	• Complex control implementation • Challenging to achieve DC bus voltage stability

The FC's green energy provides a competitive perspective on the vehicle market, functioning as an adequate substitute for internal combustion (IC) engines [31]. BEVs now have lower manufacturing costs than FCEVs in both the small and intermediate classes in the green energy category [32]. As a result, the light-duty and heavy-duty vehicle market for fuel cell electric vehicles look to become very promising by 2030, accounting for half of the current competitive categories [33].

Recently, different vehicle manufacturers have developed automobiles based on this FCEV technology. The USA is the largest consumer of FCEVs as there are around 15,000 in California State where there is the largest hydrogen fueling station network. Europe and Asia Pacific are the other two big FCEV markets rising exponentially. China is the largest market share for FCEVs in the Asia Pacific region, while South Korea has the second largest market share, as shown in Figure 5.

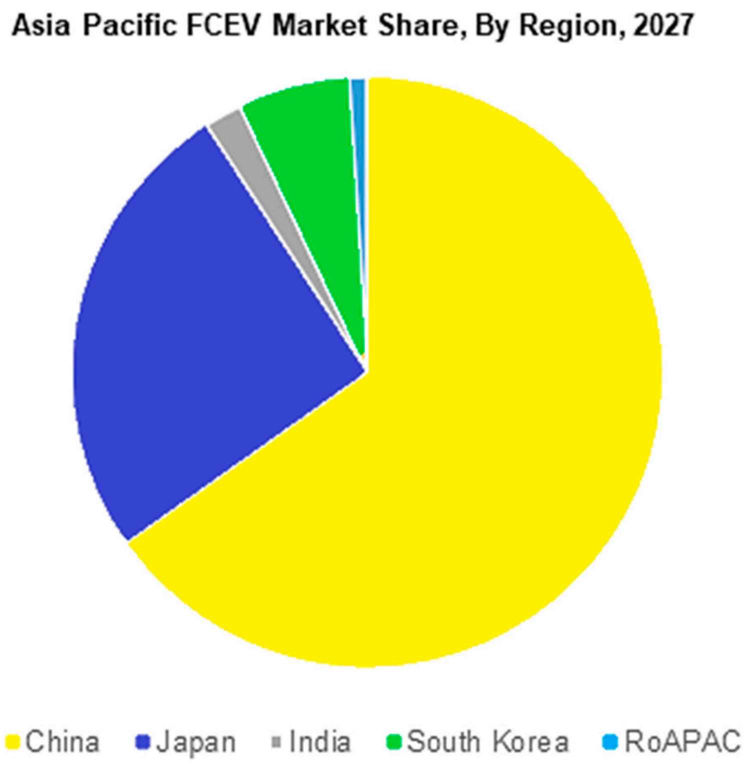

Figure 5. Asia Pacific FCEV market [34].

The competitive market trend from the recent past has motivated several manufacturers to develop their vehicles with this technology, and Toyota leads the others in this domain. Table 2 presents the FCEVs developed by different manufactures, their specifications, and the overall system design summary. It can be seen that no manufacturer has considered SC as the energy source, and there is a potential for integration of SC with the FC and battery to enhance the FCEV performance and fuel efficiency further.

Table 2. FCHEV model summaries.

Ref	Model	Vehicle Power (hp)	FC Stack Power	Plug-In (y/n)	Hydrogen Tank Capacity (kg)	Battery Capacity (kWh)	Range (Km)	0 to 100 km/h
[35]	Toyota Mirai 2022	182	172	n	5.6	1.24	646	9.1
[36]	Honda Clarity 2021	174	103	y	5.46	1.7	579	9.7
[37]	Hyundai NEXO 2022	161	95	n	6.3	1.56	611	9.2
[38]	PEUGEOT e-Expert	100	45	y	4.4	10.5	400	-
[39]	Mercedez Benz GLC F-CELL	211	-	y	4.4	13.5	478	-
[40]	Hyundai ix35	133	-	n	5.46	-	594	12.5
[41]	Citroën ë-Jumpy Hydrogen	134	45	n	4.4	10.5	400	-

Durability and affordability are the primary obstacles that vehicle industry developers confront when enhancing FCEVs and growing worldwide sales volumes [42]. When more than one energy source is examined, the primary difficulties impeding global manufacture and development of this technology are a lack of effective control and energy management systems. The appropriate power distribution across energy resources, carefully considering the capabilities and limits of each energy source, can significantly increase the durability and viability of such technology. Optimal EMS approaches may ensure optimal system performance and, as a result, deliver the FCEV revolution to the market much sooner than envisaged.

The following study covers the most recent EMS techniques examined in the literature to improve FCEV performance, dependability, and durability.

3. Energy Management Strategies for Optimal FCEV Performance

The performance of FCEVs is very much dependent upon the selection of appropriate EMS techniques. These EMS techniques are responsible for the most critical system design objectives: optimal resource management, system durability, and hydrogen fuel efficiency. Figure 6 presents the primary design objectives of EMSs. Current vehicle manufacturers must design and develop effective energy management systems to increase the performance of fuel cell hybrids. Mainstream energy management methods are now being employed to enhance hybrid cars' energy consumption and component durability performance. The critical task in terms of energy usage is to minimize hydrogen use. In comparison, durability depends upon the focus on avoiding the deterioration of fuel cells, batteries, and SCs.

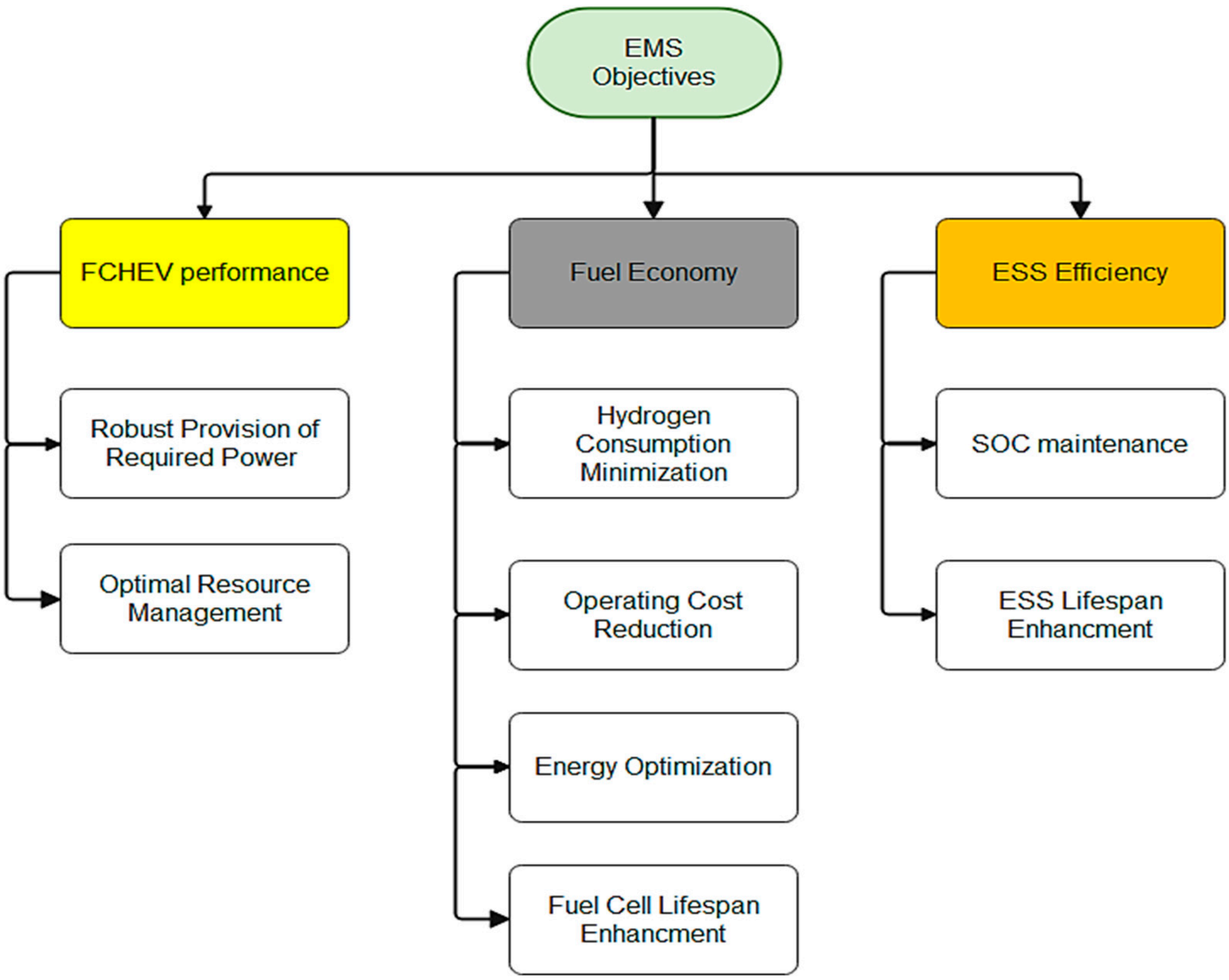

Figure 6. EMS primary design objectives.

Reduced costs and improved power system durability of the FCHEV are required to compete with the HEV [20]. One of the most significant issues facing PEMFCs before the large-scale commercialization of FCHEVs is how to devise effective EMSs for the power system to achieve improved performance by lowering hydrogen consumption and enhancing PEMFC lifespan. This section discusses major EMS strategies employed in the latest literature to achieve these optimization objectives. Each EMS technique has merits, demerits, and implication challenges, which are also addressed here.

Different EMS classifications are present in the literature that define the EMS techniques according to different design perspectives. In this research work, the EMS techniques for the FCEV are classified according to two major categories: offline and online EMS techniques. This classification of EMS techniques is developed by considering different parametric conditions involved in designing and operating EMS techniques. The offline EMS techniques consider the rule-based and the global optimization-based EMSs and depend on the driving cycle considered in the study. Driving cycles are historical driving data developed by considering different driving conditions and behaviors for EV performance testing. The online EMS strategies include real-time optimization-based, learning-based, and predictive EMS techniques for FCEV performance enhancement. Figure 7 presents the categorization of EMS techniques presented in this research work.

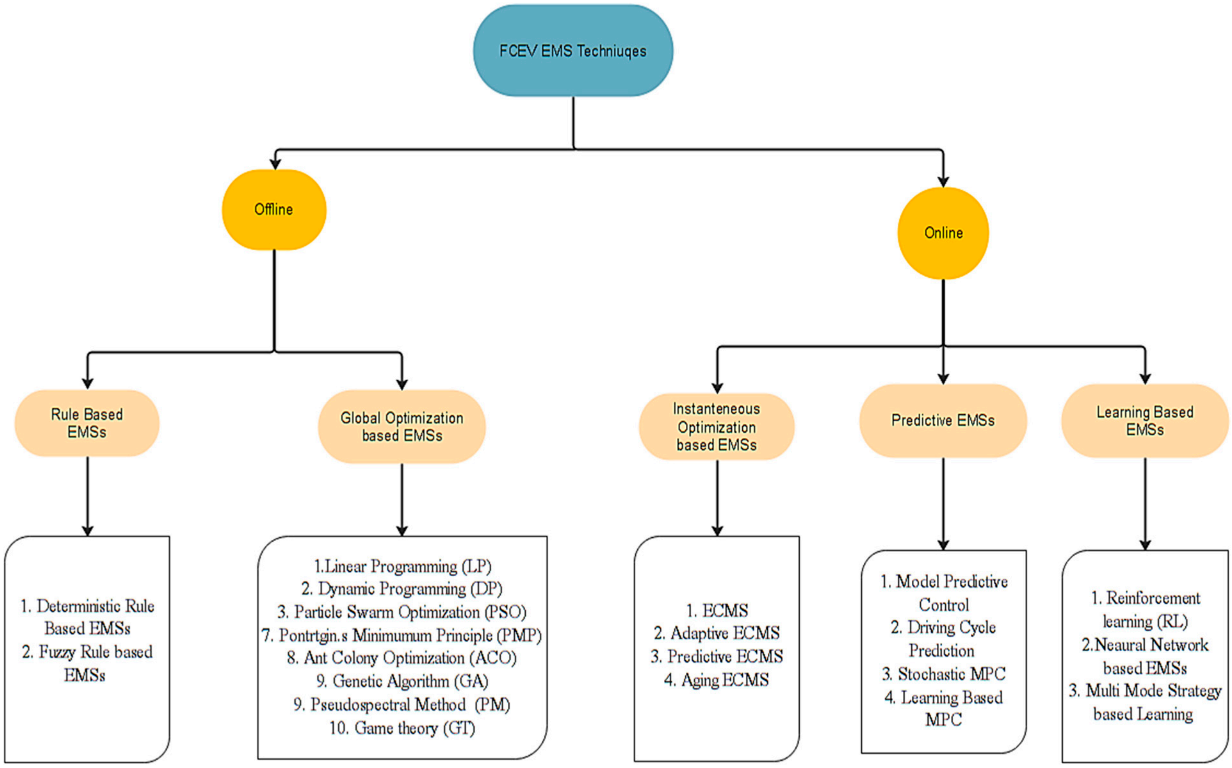

Figure 7. Categorization of EMS techniques.

3.1. Offline EMS

The offline EMSs consist of the conventional rule-based EMSs as well as the global optimization-based EMSs. The rule-based EMSs perform the primary objective of optimal resource management through some predefined set of rules and conditions. These rule-based approaches have good performance, but other offline EMS techniques, including the global optimization-based EMSs, have better overall performance. Despite having better performance, the global optimization-based EMS is not directly applicable to real-world electric vehicles because of their complexity and the requirement of complete prior knowledge of the driving conditions and the driving cycle.

3.1.1. Global Optimization-Based EMSs

The global optimization-based EMSs deliver efficient performance by seeking global optimum solutions. However, they are not practicable in actual system designs as they depend on future system values and are noncausal. These types of optimization-based EMSs are usually integrated with other techniques to attain better performance and viability. Linear programing-based EMS design is a commonly used global optimization technique during offline system design. Linear programing is an optimization technique that linearizes the problem to find the optimal solution according to the described cost function. LP, like any other optimization approach, has advantages and disadvantages. The main benefit is that a solution is guaranteed if the problem is stated correctly, and the region of feasible likely solutions is convex, while solving times are frequently short when compared to other optimization techniques. However, if the data size is too huge and there is a substantial percentage of equations to solve, the system may experience memory challenges, longer processing times, and convergence issues.

Dynamic programing (DP) is a widespread and efficient approach for addressing multistage optimization problems, as it can effectively cope with design limitations and deliver optimal solutions. As an offline optimization approach, dynamic programing can provide an optimal global solution for a given driving cycle; however, it cannot be directly implemented in an actual automobile EMS since future driving situations cannot be forecasted. DP also suffers from a substantial processing time necessary to solve the ideal issue of determining the first control input in a feasible area from the future state. As the dimension of the system states expands, so does the computational overhead. However, it may be used as a guideline to determine the operating parameters resulting in optimal fuel use worldwide. Its optimization aims to discover the appropriate power distribution order between the fuel cell and the external energy sources (battery and SC) by which the designed system can deliver the highest fuel efficiency. Equation (1) presents the definition of the objective function:

$$\text{Obj} = min \sum_{t=0}^{T} \left\{ m_H(i) + \left[SOC_{bat}(i) - SOC_{ref}(i) \right]^2 + \left[SOC_{UC}(i) - SOC_{ref}(i) \right]^2 \right\} \quad (1)$$

Here, $m_H(i)$ represents the hydrogen fuel consumption where as SOC_{bat}, SOC_{UC}, and SOC_{ref} represent the existing and reference SOC of the battery and SC, respectively. The DP performs the optimization process to minimize this objective function to achieve the global optimum results under some defined constraints related to the fuel consumption and battery and SC SOC limitations. The latest literature works where LP and DP approaches are considered are presented in Table 3, along with their description and limitations.

Several research works also consider the Particle Swarm optimization (PSO)-based EMS technique for optimal component sizing and resource management. This technique for optimal power train sizing generally optimizes the operation of other EMS techniques to increase their performance and overall impact in achieving the system design objective. The PSO algorithm defines and programs the optimal problem's control variable as a large number of particles with two properties: location and velocity. Each particle's location reflects a potential control policy. According to their present velocity, the particles can migrate to a new position from their existing position. The velocity of a particle is defined by the particle's personal best location and the particle swarm's global best position. This metaheuristic EMS can be easily implementable while requiring fewer system parameters. The summary of the latest research works related to PSO-based EMSs, along with their description and limitations, is presented in Table 4.

Table 3. Summary of the latest literature related to LP- and DP-based EMSs.

Literature	EMS Technique(s)	Description	Limitations
Huang, Yongyi, et al. [43]	LP, ROEMS	EMSs are compared for fuel economy and load change control, and the ROEMS gives better performance.	Simulation is provided without any hardware support.
Meng, Guangzhao, et al. [44]	MILP	MILP-based EMS was adopted to minimize the hydrogen fuel in the FCHEV. Cost savings of up to 30% were achieved.	Hardware implementation is not considered.
Du, Changqing, et al. [45]	Rule-based EMS with DP	Rule-based EMS is optimized with DP to enhance FCHEV performance.	Simulation is provided without any hardware experimental setup; challenges and future scope are not explained.
Hui-ce, Yang, et al. [46]	DP	DP-based EMS is proposed for optimal resource management and increasing fuel economy.	Only two power sources are considered, and the results are not verified through hardware implementation.
Hou, Shengyan, et al. [47]	Bi-Loop DP and CP	Bi-loop DP-based EMS provided better performance as compared to CP in the case of energy management as well as battery size optimization.	Simulation is provided without any hardware experimental setup; challenges and future scope are not explained.
Lee, Heeyun, et al. [48]	DP, RL	Both EMS approaches are compared for fuel economy, and the performance of stochastic DP is competitive with RL to get optimal results.	Hardware experimental verification not performed; challenges and future scope not explained.
Liu, Yanwei, et al. [49]	MDDP	MDDP is used to perform optimal resource management and component sizing. MDDP reduced fuel consumption by 3.1% while durability increased by 1.08%.	Simulation is provided without any hardware experimental setup; challenges not explained.
Bao, Shuyue, et al. [50]	MDDP	MDDP with adaptive adjustments is utilized for energy saving in the FCHEV structure, and the proposed EMS can deliver a fuel consumption reduction of around 3.2%.	Hardware experimental verification not performed; challenges and future scope not explained.

Table 4. Summary of the latest literature related to PSO-based EMSs.

Literature	EMS Technique(s)	Description	Limitations
Tifour, Benali, et al. [51]	Fuzzy EMS with PSO	Fuzzy-based EMS integrated with PSO is proposed for optimal resource management, and results show that the performance of the proposed EMS with PSO is enhanced.	Hardware experimental verification not performed; challenges and future scope not explained.
Abdelqawee et al. [52]	Hybrid JS/PSO/BAT	PI controller with optimized design parameters from the hybrid JSPSOBAT optimization technique is used for resource management and optimal system sizing.	Simulation is provided without any hardware experimental setup; challenges not explained; only one driving cycle is considered for verification.
Perez Davila et al. [53]	PSO	The PSO is utilized to optimally select the parameters for the rule-based single and multilevel EMSs. The results reveal that the vehicle range is enhanced by 9 and 12% for both the EMSs under PSO optimization.	Hardware experimental verification not performed; challenges and future scope not explained.
Gu, Hao, et al. [54]	Fuzzy with PSO	Fuzzy-based EMS with rules optimized through PSO is proposed to find the optimal sizing of energy elements and for optimal resource management. Results reveal that the vehicle range is increased by 4.7 to 5.9% under different driving cycles, whereas fuel degradation is reduced by 21.4% to 19.8%.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.

Table 4. *Cont.*

Literature	EMS Technique(s)	Description	Limitations
Gim, Juhui et al. [55]	DP, PSO	DP-based EMS is proposed for analyzing the allowable current limit of FC, and then the modulation ratio of the FC current is determined through PSO for proper FC utilization.	Simulation is provided without any hardware experimental verification

Pontryagin's Minimum Principle (PMP) is an offline global optimization technique that delivers a set of optimization conditions to solve the optimal control problem. It constrains the system design variables to a finite boundary of defined conditions to achieve the design objectives of lesser fuel consumption and auxiliary source(s) SOC maintenance. The only limitation in implementing this EMS technique is that the PMP can only deliver optimal results when the entire driving cycle information is priorly available and accessible. The effectiveness of this technique can be further enhanced by considering the adaptive PMP approach. This adaptive approach adjusts the system control parameters to increase the fuel consumption minimization and the overall impact of the EMS approach on the system performance. The flowchart of PMP for the FCHEV application is presented in Figure 8. Table 5 summarizes recent research work related to PMP.

Table 5. Summary of the latest literature related to PMP-based EMS.

Literature	EMS Technique(s)	Description	Limitations
Hou, Daizheng, et al. [56]	PMP	A PMP-based adaptive EMS with Taguchi robust design (TRD) method is adopted for optimal control of FCHEV, resulting in an 18% of fuel economy improvement.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Huangfu, Yigeng, et al. [57]	PMP	An optimal PMP-based EMS is proposed, and the results are compared with the state machine EMS strategy. Fuel consumption was reduced by 10%, while the FC stress decreased by around 40%.	Challenges and future scope not explained.
Wei, Xiaodong, et al. [58]	PMP	Pi Controller with PMP EMS is proposed and compared with the ECMS-based EMS. PMP-based EMS delivered better fuel economy and energy conservation.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Liu, Yonggang, et al. [59]	PMP	EMS rules upgradation with PMP for improving FCHEV fuel economy.	Challenges and future scope not explained.

Ant Colony Optimization (ACO) technique is another offline metaheuristic optimization method to solve complex engineering problems such as optimal resource management in FCHEVs. In this technique, artificial ants are developed to find the optimal path for solving the given problem by incrementally building solutions on the weighted graph. The ant's pheromone model inspires solution exploitation. This model helps develop a priority listing of the energy resources in the EVS and then zooms in on the optimal solution by reducing the solution search space after every iteration. This technique is often integrated with other methods to find the optimal design parameters for better results in a short computational time and with a lower cost.

The genetic algorithm (GA)-based EMS technique is also considered in several research works for optimal resource management and overall optimized system performance. The GA is an evolutionary algorithm inspired by the natural evolutionary process developed to solve complex optimization problems. It is favored because of its high convergence rate and lower complexity in solving the optimal resource management problem in FCHEVs. This technique works by solving an objective function in the presence of some defined constraints to find optimal system design parameters or to update the existing variables in such a way that the global minimization of the objective function is achieved. The GA flowchart is presented in Figure 9. Table 6 summarizes the latest research work related to ACO and GA.

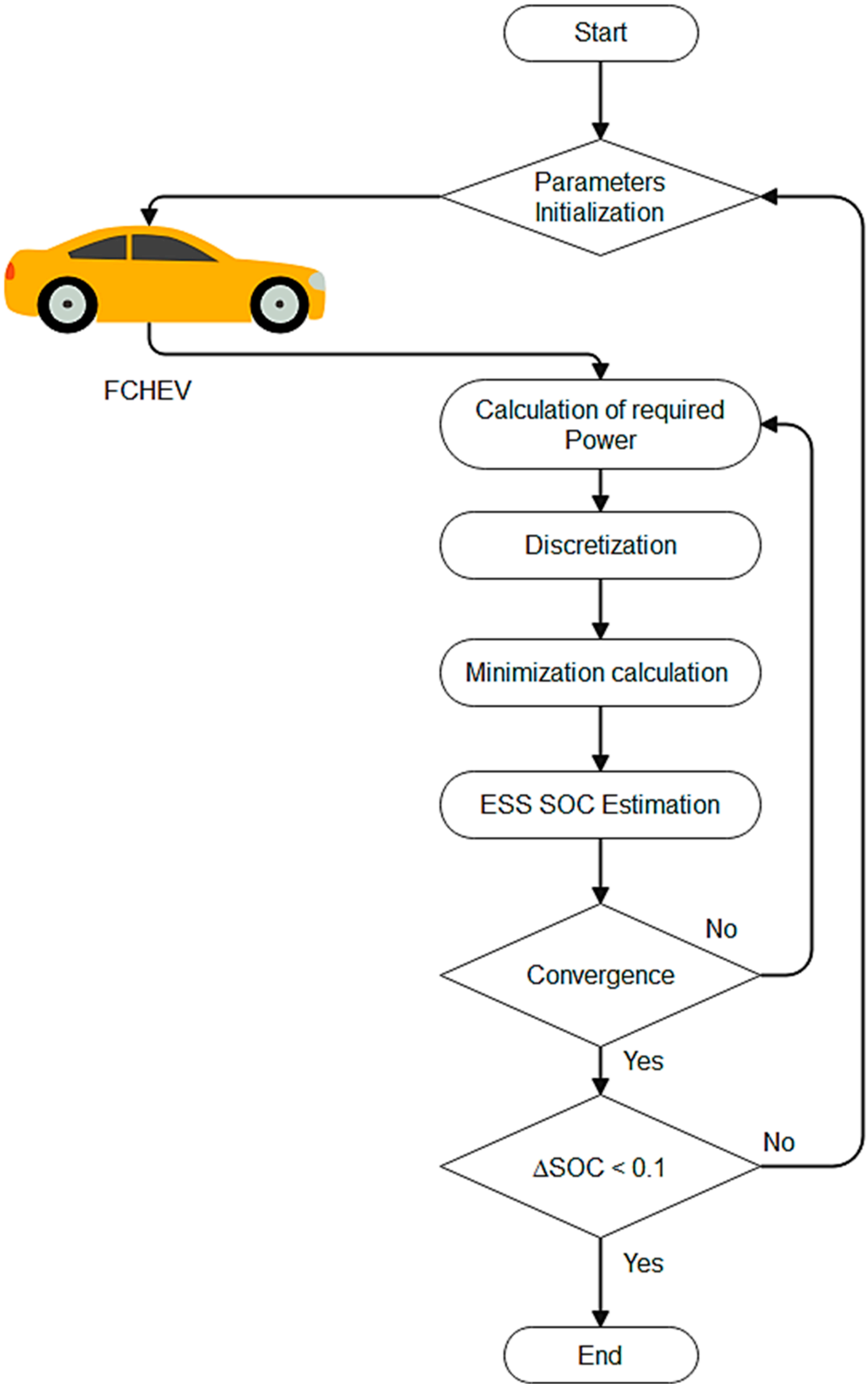

Figure 8. PMP flowchart.

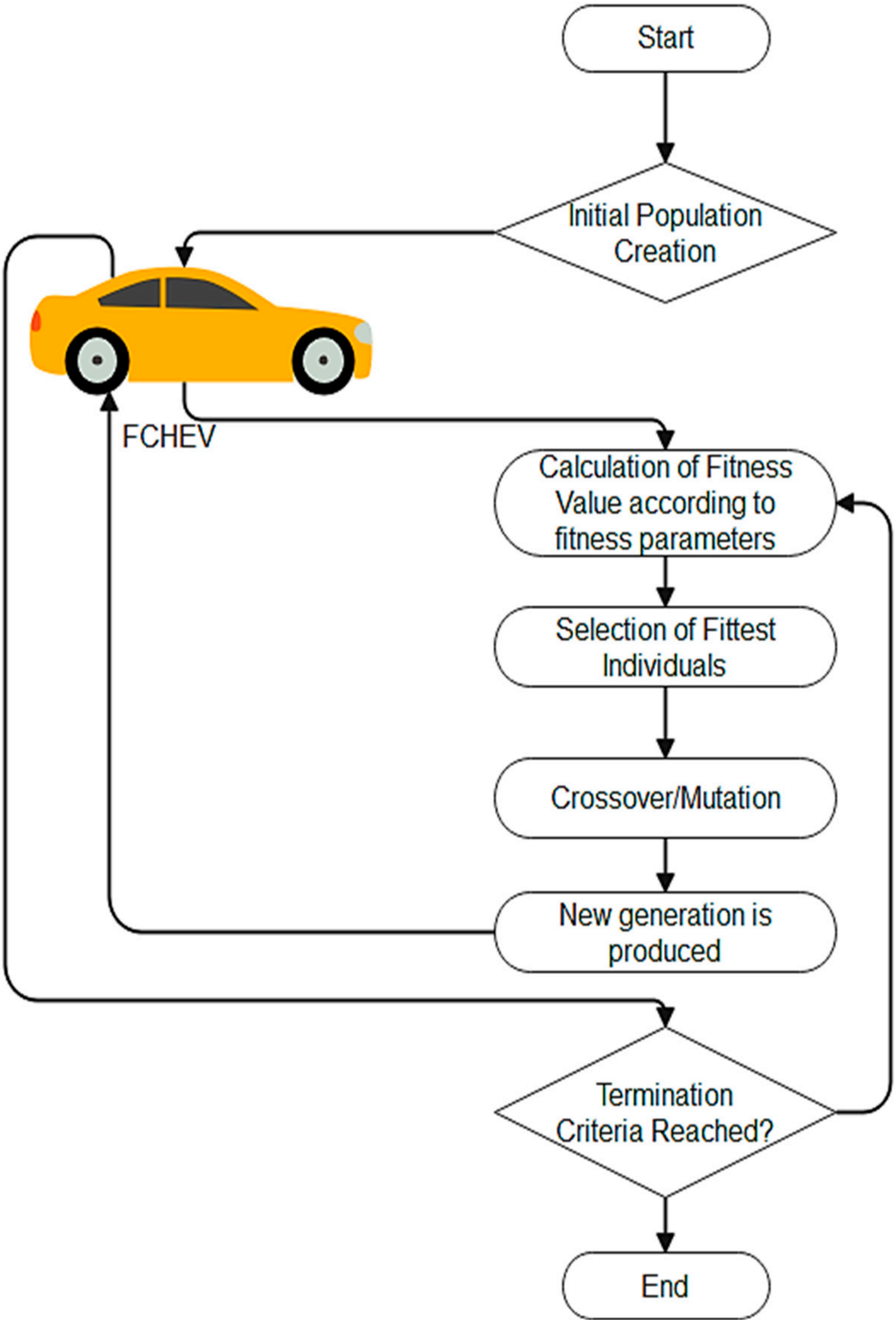

Figure 9. GA with FCHEV flowchart.

The pseudospectral method (PM) is another global optimization approach considered in some research articles to solve optimization problems. This technique can solve the energy management problem by discretizing and transforming it into a nonlinear programing problem and can work as a direct numerical method. The original problem is discretized using pseudospectral methods, resulting in a nonlinear programing problem. This problem is then quantitatively addressed using a sparse nonlinear programing method to yield an approximate optimum solution.

Table 6. Summary of the latest literature related to ACO- and GA-based EMSs.

Literature	EMS Technique(s)	Description	Limitations
Hu, H., et al. [60]	ACO	Fuzzy EMS rules upgradation with ACA for optimal system performance regarding fuel consumption and battery and SC SOC fluctuation.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Min, D., et al. [61]	GA	GA-optimized neural network-based EMS reduces the FCHEV fuel consumption by 33%.	Experimental validation and future scope are not discussed.
Yuan, H.-B., et al. [62]	GA	GA-optimized rule-based EMS realized optimal fuel consumption reduction as compared to DP-based EMS.	Simulation work is provided without any hardware experimental verification; challenges and future scope are not explained.
Wang, C. et al. [63]	GA	GA-optimized fuzzy EMS performance in the case of fuel consumption is better than the nonoptimized fuzzy EMS, with the energy economy going as high as 40%.	Experimental validation and future scope are not discussed.
Fu, Z. et al. [64]	GA	Frequency decoupling EMS with GA-optimized fuzzy is considered for the FCHEV energy management that delivered a near-optimal performance in the case of fuel economy.	Challenges and future scope not explained.
Yang, H. et al. [65]	GA	GA-optimized fuzzy EMS improves the FCHEV fuel efficiency and increases FC lifespan.	Experimental validation and future scope are not discussed.
Zhao, Z. et al. [66]	GA	GA-optimized fuzzy EMS decreased fuel consumption by about 8% with considerable extension in the FCHEV driving range.	Simulation work is provided without any hardware experimental verification; challenges and future scope are not explained.

Another global optimization technique utilized for energy management is game theory. This multiobjective optimization technique solves problems by analyzing the forecasted and actual performance of the parameters involved in the game. Game theory is not a mechanism for finding an otherwise inaccessible issue solution; instead, it promotes strategic thinking to resolve the problem. In particular, the game theory model incorporates time into the decision-making process and offers a distributed, self-organizing, and self-optimizing solution to a problem through competing for objective functions. This technique can provide adequate resource distribution among HEVs, and the overall impact of this EMS technique is satisfactory. Table 7 highlights the latest work related to PM and GT.

Table 7. Summary of the latest literature related to PM- and GT-based EMSs.

Literature	EMS Technique(s)	Description	Limitations
Liu, Y. et al. [67]	PM	PM-based EMS is considered for optimal resource sizing and FC lifespan enhancement.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Jiansheng, L. et al. [68]	PM	A cloud computing center utilizes PM for optimal resource management in FCHEVs and delivers better resource management with an extended FC lifespan.	Experimental verification not presented; challenges and future scope not explained.
Liu, H. et al. [69]	PM	PM is employed for power distribution among energy resources in FCHEVs.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.

Table 7. *Cont.*

Literature	EMS Technique(s)	Description	Limitations
Sun, Z. et al. [70]	GT	GT-based optimal EMS is compared with four different EMS techniques. The GT EMS reduced hydrogen fuel consumption by about 6.8%.	Challenges and future scope not explained. Experimental verification not presented.
Zhang, Q. et al. [71]	GT	Prediction-based GT EMS was adopted for optimal power distribution and fuel economy improvement. EMS saved around 7.4% of the hydrogen fuel.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Li, J. et al. [72]	GT	With adaptive driving pattern prediction, GT EMS is considered for fuel and economic cost reduction. The EMS improved fuel economy by 81% with a 76% reduction in economic parameters.	Experimental setup with hardware setup is not considered.

3.1.2. Rule-Based EMSs

Rule-based energy management systems are easier to incorporate in embedded controllers, allowing them to be widely used in engineering [73]. It has also been established that basic rule-based controllers can produce effective control outcomes because of their flexibility and more accessible adaptation capability [74]. In general, rule-based EMSs may be carried out by establishing logical rules based on the features and mode of operation of the HEV system. The rules are developed using an "if-then" architecture based on the battery SOC, operator power demand, and vehicle velocity. With these rules in place, the power split may be carried out to meet the driver's power requirements while maintaining the SOC within a specified range. This technique is based on logical concepts and local constraints rather than previous knowledge of the driving cycle. The control settings cannot be tweaked since there is no future information on the driving cycle, making it less sensitive to changing driving conditions.

Deterministic rule-based EMS strategies are simple to implement, have satisfactory results, and are extensively used in the latest literature to achieve the primary design objective. The deterministic rule-based EMS approach depends upon some predefined set of rules to mainly achieve the optimal power split objective in the FCHEV design [22]. Optimal resource management is necessary to reduce hydrogen fuel consumption and sustain the battery's State of Charge (SOC). The designing of these EMSs majorly considers the respective driving cycle for defining the rules to achieve optimal performance.

The basic control rules considered for the FCHEV majorly consider the type and number of energy resources to define the rules. The most important objectives considered while defining rules are to conserve FC power by reducing fuel consumption and to sustain the SOC of the external energy resources, which are either battery, SC, or their combination. Several research works have considered the rules-based approach to develop the EMSs for their system.

Fuzzy logic control (FLC)-based EMS strategies are also very commonly implemented to achieve the objectives of proper resource management. The fuzzy rules are based on shared human logic about process control and EMS implementation. The fuzzy set of rules is majorly developed by considering famous logical reasoning approaches such as the Mamdani and Takagi–Sugeno methods. Fuzzy logic is majorly derived through some linguistic rules based on common logic. These rules and the membership functions assigned to the system variables are devised to achieve the resource management objectives optimally.

Fuzzy-based EMS approaches are further classified according to the type of fuzzy EMS approach considered in the research work. Fuzzy logic control can be of many different types according to the defined fuzzy rules, their membership functions, and the defuzzification approaches considered. Fuzzy rules can be deterministic, such as the one described earlier, or adaptive. The adaptive fuzzy EMS approach can learn from the process data by adapting to newer fuzzy rules and adjusting the membership functions to optimize the overall fuzzy system results.

The rule-based EMS effectively achieves the system design objectives of optimal resource management and hydrogen fuel reduction. However, in the latest research, these rule-based EMS techniques are frequently adopted with global optimization techniques to achieve better and more robust performance. Some research contributions update the rules of the deterministic rule-based EMSs and fuzzy EMS rules by adopting optimization algorithms and other adaptive techniques [75]. Table 8 depicts the latest research works considering the simple rule-based EMS and the advanced rule-based EMSs integrated with other optimization techniques to enhance the performance and overall system response.

Table 8. Summary of the latest literature related to rule-based EMSs.

Literature	EMS Technique(s)	Description	Limitations
Yujie W. et al. [76]	Rule-based EMS	Considered the rule-based EMS approach to perform resource management in FCHEVs that decreases hydrogen consumption.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Yuan, H.-B. et al. [77]	GA-optimized rule-based EMS	Rule-based EMS is considered for optimal resource management.	Lacks the explanation of challenges and future scope of the work.
Song, Y. et al. [78]	FLC	The proposed EMS reduced the FCHEV fuel consumption by 17.9%.	Lacks experimental verification of results.
Peng, H. et al. [79]	Adaptive rule-based EMS	The proposed EMS with DP enhanced the fuel economy and increased the FC and battery lifetime.	Lacks the explanation of challenges and limitations; experimental verification of results not performed.
Xu, Y. et al. [80]	Rule-based EMS	Rule-based EMS is considered for optimal resource management.	Lacks experimental verification of results.
Ferrara, A. et al. [81]	Rule-based EMS	Rule-based EMS is considered for optimal resource management and lowering the global system cost.	Lacks the explanation of challenges and limitations; experimental verification of results not performed.
Luca, R. et al. [82]	Mutative FLC (MFLC)	MFLC EMS was adopted to assess charge-sustaining ability, FC degradation limitation, and fuel economy enhancement.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Wang, Y. et al. [83]	GA-optimized FLC	FLC EMS with GA-based optimization delivers around 40% fuel economy with an extended FC lifespan.	Lacks experimental verification of results.
Hu, X. et al. [84]	GA-optimized FLC	FLC EMS with GA-based optimization with AI-based prediction control was adopted to improve fuel economy and system economics.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Jafari, H. et al. [85]	Modified FLC	Modified FLC enhanced the fuel economy by 2.9% while reducing the FC degradation.	Lacks experimental verification of results.
Wenguang, L. et al. [86]	Wavelet-FLC	Wavelet-FLC extracted near-optimal power from FC and reduced fuel economy and system cost.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Hoai-An, T. et al. [87]	Adaptive FLC	The proposed EMS increased the FC stack efficiency by 53% with around 21% fuel consumption reduction.	Lacks experimental verification of results.

Table 8. *Cont.*

Literature	EMS Technique(s)	Description	Limitations
H Fallah, G. et al. [88]	Type 2-FLC	This EMS delivers reliable performance with increased hydrogen fuel economy and FC degradation limit.	Hardware experimental verification not performed; challenges and future scope not explained.
Jili, T. et al. [89]	Q-Learning-based FLC	Q-learning-based FLC with GA optimization is adopted for optimal demand power distribution, delivering around a 6.9% increase in fuel economy.	Lacks experimental verification of results.
H Fallah, G. et al. [90]	Observer-based Type 3-FLC	Observer-based Type 2FLC EMS delivers reliable performance with increased hydrogen fuel economy and FC degradation limit.	Lacks experimental verification of results; challenges and future scope not explained.

4. Online EMS

Online EMSs are driven by local optimization and can be used in real-time control. Among these strategies, instantaneous optimization EMSs can reduce immediate fuel usage at each instant without previous information of the entire driving cycle and only produce local optimum results. EMSs that apply immediate optimization include the robust control (RC) equivalent consumption minimization strategy (ECMS) and the adaptive ECMS (A-ECMS). Other online EMS techniques include predictive EMS techniques such as Model Predictive Control (MPC), stochastic MPC, and learning-based MPC. At the same time, other online EMS techniques may include the machine-learning techniques such as supervised and unsupervised learning and reinforcement learning approaches. Learning-based EMSs primarily use training data to update system configurations to enhance flexibility in changing driving situations.

Online energy management techniques provide local optimization without requiring prior knowledge about the driving conditions and behaviors. The real-time implementation of the online EMSs comes with the drawback of utilizing more computational power than the offline EMSs. Moreover, the mathematical calculations involved in their computation are also more complex than the offline EMSs. However, the optimization results under online EMSs are considered more realistic and are more likely to be practically implementable. Online EMSs can be categorized into three primary forms such as instantaneous, predictive, and learning-based EMSs.

4.1. Instantaneous Optimization-Based EMSs

Instantaneous EMS techniques perform resource management for each energy source at each instant. They perform the optimal load distribution and other deliverables without prior knowledge of the driving cycle and have the advantage of being robust and practically feasible. These instantaneous EMSs involve adaptive and nonadaptive EMS techniques: namely, the equivalent energy consumption minimization strategy (ECMS) and adaptive ECMS. The fuel efficiency and overall system performance under instantaneous EMS techniques are generally higher than the rule-based EMSs, but with the limitation that these EMSs can only provide local optimum results.

ECMS is a global optimization technique that considers the minimization of instantaneous fuel consumption by the FCHEV at each instant. It minimizes fuel consumption by adjusting a factor known as the equivalent factor (EF) [91]. This EF is the relation between the power consumption by the auxiliary energy resources, either battery, SC, or both, in the form of equivalent hydrogen fuel consumption and the primary power demand. The EF in most of the research works is found through an iterative process, as the performance of the ECMS EMS is mainly dependent upon the value of it. Optimal EF will result in near-optimal resource distribution and fuel consumption minimization. Equation (2) represents the main relationship of the ECMS for FCHEVs.

$$\dot{m}_{eqv} = \dot{m}_{FC} + K_{bat}\,\dot{m}_{bat} + K_{SC}\dot{m}_{SC} \quad (2)$$

Here, $\dot{m}_{eqv}$ represents the combined hydrogen consumption and $\dot{m}_{FC}$ is the hydrogen consumption by the FC. $\dot{m}_{bat}$ and $\dot{m}_{SC}$ are the equivalent hydrogen consumption considered for the battery and SC, whereas K_{bat} and K_{SC} represent the penalty coefficients for battery and SC, respectively.

The adaptive ECMS is closely related to the conventional ECMS with the addition that the utilization of some adaptive controls tunes the EF under this configuration. The optimal tuning of the EF can provide optimal hydrogen fuel consumption while considering the correct auxiliary energy sources SOC, real-time prediction of the power train, and the driving cycle while keeping the SOC under some predefined limits. Adaptive ECMS has better overall performance and is more reliable than nonadaptive ECMS. Different adaptive controls, such as adaptive PI, are integrated with the ECMS to enhance the ECMS performance. A predictive ECMS is also present in some latest research work that works by adjusting the EF through some predictive approach. In this approach, the first step involves calculating demanded power according to the predicted velocity over the prediction horizon. The EF is then adjusted through adaptive laws for optimal power resource management. Table 9 summarizes the latest research on ECMSs, adaptive, predictive, and other improvements of ECMS-based EMSs.

Table 9. Summary of the latest literature related to ECMS and adaptive ECMS EMSs.

Literature	EMS Technique(s)	Description	Limitations
Fu, Zhumu, et al. [92]	ECMS	ECMS adopted for near-optimal power allocation among the energy resources to increase fuel efficiency and FC lifespan.	Lacks experimental verification of results.
Zhou, Bin, et al. [93]	Aging ECMS	Aging ECMS adopted to improve battery aging with little fuel economy penalty.	Hardware experimental implementation and future scope not explained.
Kwon, Laeun, et al. [94]	Degradation ECMS	The proposed EMS is adopted for optimal resource management while improving global system cost by 34%.	Fuel economy and the FC lifespan decreased.
Li, Huan, et al. [95]	Adaptive ECMS	The adaptive ECMS decreases FC fuel consumption by more than 2% with decreased FC degradation.	Challenges and future scope not explained.
Lin, Xinyou, et al. [96]	Predictive ECMS	The proposed EMS decreases fuel consumption by 4.35 while increasing FC lifespan and system durability.	Challenges and future scope not explained.
Lin, Xinyou, et al. [97]	SQP-ECMS	The proposed EMS delivered near-optimal results related to fuel economy and FC and battery lifespan enhancement.	Challenges and future scope not explained.
Moghadari, Mohammadreza, et al. [98]	ECMS	ECMS-based EMS is adopted for maximizing the fuel efficiency of the FC. Results depict that the ECMS is a close match with DP EMS besides being online.	Hardware experimental verification and future scope not explained.
Li, Cheng, et al. [99]	Adaptive ECMS	The proposed EMS under less computation power reduced the hydrogen consumption by up to 10% with lesser battery SOC deviation.	Hardware experimental verification and future scope not explained.

4.2. Predictive EMS Techniques

The predictive EMS techniques utilize the previous and currently available data to perform optimal demand power distribution among the energy resources. They usually predict the future output response by examining and manipulating the available information and require prior driving cycle information for optimal performance. The more accurate the provided driving cycle information, the more optimal the resource management they would provide. Many factors, such as driving behavior, traffic, and vehicle conditions, affect the accuracy of the predicted cycle. Therefore, the performance of the predictive EMS techniques is highly dependent upon the prediction accuracy. As a result, additional surrounding information must be successfully evaluated to increase prediction accuracy. The ideal control input is obtained by reducing performance indices such as hydrogen fuel consumption and the additional source's SOC maintenance over a specific time horizon and adapting effectively to changing driving circumstances. As a result, researchers are increasingly using predictive EMSs to achieve the system design objectives in FCHEVs. Equation (3) represents the optimal cost function for the FCHEV with FC, battery, and SC as three energy resources. This cost function tends to be minimized under some predefined constraints, as presented in Equation (4). Equation (5) shows the $\varepsilon(SOC_{BAT,SC})$ where SOC_0 represents the initial SOC of the energy resources.

$$J = \int_{k}^{k+t_p+H_s} F(t, u(t))dt + \mu\varepsilon(SOC_{BAT,SC}) \tag{3}$$

$$\left\{ \begin{array}{c} T_{mot}^{min} \leq T_{mot} \leq T_{mot}^{max} \\ w_{mot}^{min} \leq w_{mot} \leq w_{mot}^{max} \\ I_{bat}^{min} \leq I_{bat} \leq I_{bat}^{max} \\ I_{SC}^{min} \leq I_{SC} \leq I_{SC}^{max} \\ P_{FC}^{min} \leq P_{FC} \leq P_{FC}^{max} \\ SOC^{min} \leq SOC_{SC,bat} \leq SOC^{max} \end{array} \right\} \tag{4}$$

$$\varepsilon(SOC_{BAT,SC}) = \int_{k}^{k+t_p+H_s} (SOC(t+t_h) - SOC_0)^2 \tag{5}$$

Here, F represents the prediction horizon related to hydrogen fuel consumption, $u(t)$ is the control input vector, μ represents the penalty factor integrated with the SOC, k is the current simulation time, t_p and H_s are the sizes of the prediction horizon and controller time step, respectively, T_{mot} and w_{mot} represent motor torque and speed, respectively, I_{bat} and I_{SC} are battery and SC currents. P_{FC} and $SOC_{SC,bat}$ represent the FC power and the SOC of the battery and SC, respectively.

4.2.1. Driving Cycle Prediction

Forecasting the driving cycle is crucial for EMSs, particularly predictive EMSs. The primary problem with EMSs is that power is shared within a predefined typical driving cycle, which cannot achieve ideal fuel economy due to the diversity of the driving cycles. Many unpredictable elements exist, particularly in metropolitan conditions, making it difficult to predict the critical driving cycle for FCHEV energy management. Driving cycle prediction can be accomplished through velocity prediction (VP), Pattern Recognition (PR), traffic flow modeling, intelligent transportation systems, and artificial intelligence. The performance of the driving cycle prediction technique directly impacts the performance of the EMS applied to the FCHEV. Table 10 presents the latest research work comprising driving cycle prediction EMS approaches.

4.2.2. Model Predictive Control

Another predictive EMS approach is the Model Predictive Control (MPC) which creates a model for calculating future system response by analyzing the previous and current system variables. It is a widely used method to perform optimal resource management in real-time. It is a practical approach to dealing with systems with multivariable control problems such as FCHEV. It involves predicting future system responses through online optimization while considering historical and future input and output data. Figure 10 presents the basic working principle of the MPC in the case of an FCHEV. MPC implication in the case of FCHEVs is suitable because the FCHEV structure is complex and has multiple control variables. Additionally, MPC is favorable for examining the FCHEV performance in real-time applications.

Table 10. Summary of the latest literature related to driving cycle prediction EMSs.

Literature	EMS Technique(s)	Description	Limitations
Lin, Xinyou, et al. [100]	Velocity Prediction-based EMS	Neural network-based velocity prediction EMS reduced fuel consumption by 17%, promising optimal FCHEV performance.	Hardware experimental verification and future scope not explained.
Zhou, Yang, et al. [101]	Predictive EMS	Velocity Forecast and MPC-combined EMS provided optimal resource management with a 12% hydrogen consumption reduction	Lacks experimental verification of results.
Zhou, Yang, et al. [2]	Predictive EMS	A fuzzy C-means velocity prediction and MPC-combined EMS provided optimal resource management with a 3.79% hydrogen consumption reduction.	Hardware experimental verification and future scope not explained.
Zhou, Yang, et al. [102]	Speed Prediction EMS	The real recurrent neural network-based speed predictive EMS improved the FCHEV fuel efficiency and extended FC lifetime.	Lacks experimental verification of results.

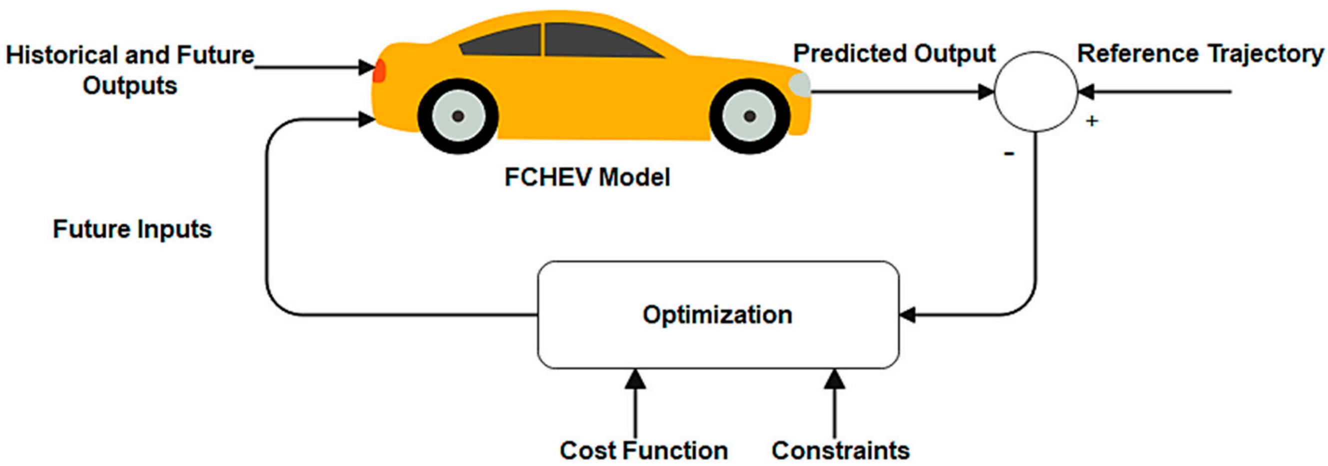

Figure 10. MPC flowchart for FCHEV.

MPC, along with various latest scientific variations, such as linear MPC, nonlinear MPC, adaptive-MPC, Stochastic MPC (SMPC), learning-based SPMC, are considered in the latest literature for optimal energy management in FCHEVs. These different types of MPCs provide optimal performance by integrating the latest stochastic and machine-learning approaches to enhance the MPC performance and deliver more realistic results. Learning techniques are integrated with MPC to adjust the optimization problem's parameters and enhance performance. Table 11 highlights the latest research work consisting of MPC and the latest MPC advancements for optimal resource management in FCHEVs.

4.3. Learning-Based (LB) EMS Techniques

Most modern EMS approaches rely on prediction algorithms or predefined criteria. However, they have limited adaptation to real-time driving situations and cannot deliver the optimal solution for actual driving conditions. The learning-based EMSs can compensate for these shortcomings and have the benefit of not requiring a model and are capable of learning the optimal strategy independently in real time. LB techniques have the real advantage of self-learning and adaptive capability for adjusting the system variables in a way to obtain the optimal performance. However, these EMS techniques require a large amount of real data to train the learning-based EMSs. The learning-based EMSs majorly involve reinforcement learning (RL), neural networks, multimode strategy-learning vector quantization (LVQ), and supervised and unsupervised learning EMSs. These EMSs also involve a large amount of mathematical support and calculations to train the learning EMSs so that the required optimal performance can be achieved from it. Table 12 highlights the latest research work consisting of LB EMSs for performance enhancement of FCHEVs.

Table 11. Summary of the latest literature related to MPC-based EMSs.

Literature	EMS Technique(s)	Description	Limitations
Zhou, Yang, et al. [103]	MPC	With more than 94% accuracy, the current EMS reduced the FC power transients with a 2% decrease in fuel consumption.	Hardware experimental verification and future scope not explained.
Jia, Chao, et al. [104]	A-MPC	A-MPC-based EMS reduced hydrogen consumption as well as FC current fluctuation.	Hardware experimental verification and future scope not explained.
Pereira, Derick, et al. [105]	Nonlinear MPC	The proposed EMS provided better fuel efficiency while operating FC in its efficient region.	Lacks experimental verification of results; challenges and future scope not explained.
Anbarasu, Arivoli et al. [106]	Dynamic MPC	Optimal resource management, FC power fluctuation, and fuel consumption minimization are performed.	Hardware experimental verification and future scope not explained.
Ma, Yan, et al. [107]	S-MPC	The proposed EMS reduced fuel consumption by 6% while maintaining the SOC of additional energy resources.	Lacks experimental verification of results; challenges and future scope not explained.
Zhou, Yang, et al. [108]	MPC	FC lifespan with this EMS increased to 14% with the least computational power and time consumption.	Lacks experimental verification of results.

Table 12. Summary of the latest literature related to learning-based EMSs.

Literature	EMS Technique(s)	Description	Limitations
Reddy, Praveen, et al. [109]	RL	The proposed EMS improved the battery lifespan and system power losses by minimizing the battery SOC variations.	Hydrogen fuel consumption increased. Hardware implementation not explained.
Tang, Xiaolin, et al. [110]	RL	The RL-based EMS performs better in computational efficiency and SOC maintenance than the DP-based EMS.	The fuel efficiency of the FCHEV decreases with this EMS; hardware implementation is not explained.
Yang, Duo, et al. [111]	RL	RL-based EMS reduced FC degradation and improved the fuel economy by 6%.	Lacks experimental verification of results; challenges and future scope not explained.
Guo, Xiaokai, et al. [112]	Dueling Double Deep Q network-RL	With less computational burden, the proposed EMS delivered better fuel efficiency and extended FC lifespan.	Challenges and future scope not explained.
Zhang, Yuxiang, et al. [113]	Dual Reward Q-Learning	Reduced FC aging and increased fuel efficiency and overall system efficiency enhanced by 52%.	Lacks explanation of challenges and future scope.

It can be observed that both online and offline have their respective benefits and limitations that should be considered before their consideration. Several research publications considered these EMS methodologies and justified their point of utilization. However, most of the research works did not perform the experimental hardware verification of their results. The experimental verification of any proposed system configuration or the EMS technique is necessary to determine whether the proposed approach is practically viable. If a proposed technique does perform satisfactorily under an experimental setup, then future research directions related to the practical implementation of the proposed technique can be investigated. Hardware implementation setup clarifies that the proposed system is efficient under the actual system design environment and is ready for practical implementation.

However, there are several design and implementation challenges in the hardware implementation of some experimental work that hinders the researchers from carrying out the implementation. The very first issue is the hardware and the system design interfacing of the power electronic components as they contain several switching and hardware testing components. The proper interfacing between the hardware design and software will ensure proper results [114]. The other major challenge is the limited processing power and frequency of the available hardware components [115]. This limitation in the processing power of the hardware components causes irregularities and other malfunctioning that deviates the results obtained through hardware setup from the simulation work. Hardware implementation of simulations also face the challenge of troubleshooting as the designed hardware test bench can face some issues related to any design component and integration. The troubleshooting of such issues become a very tough process and requires a lot of expertise and design experience [114].

The hardware experimental data can also help the researchers and the manufacturing units to directly integrate any proposed technique with the actual FCHEV configuration without any extra validation study.

4.4. Standalone EMS Techniques

A few EMS techniques considered in recent publications do not come under the category of online and offline EMS techniques but are rather known as standalone techniques. These standalone EMS techniques have a small contribution towards the performance enhancement of FCHEVs, and their real impact on overall system performance is minimal. Table 13 presents the standalone EMS techniques considered in the recent literature.

Table 13. Standalone EMS techniques.

Literature	EMS Technique(s)	Description	Limitations
Ke song et al. [116]	Degradation Adaptive EMS	Developed EMS considering the fuel cell health degradation as the input to optimize power input. The fuel efficiency of the FC increased by around 2.9%.	Simulation is provided without any hardware experimental verification; challenges and future scope are not explained.
Wang, Tianhong, et al. [117]	Maximum efficiency range identification (MER)	MER-based EMS is proposed for hydrogen consumption minimization and optimal resource management.	Lacks explanation of challenges and future scope. Experimental verification was not performed.
Wei, Xiaodong, et al. [118]	Modified alternating direction method of multipliers (ADMM)	ADMM utilized for the energy management of FCHEV received over 20% fuel savings.	Experimental verification not performed; lacks explanation of challenges and future scope.

5. Challenges and Issues Related to FCHEV Globalization

Various considerations in terms of configurations, power trains, energy resources, and other design dynamics are required to form an optimum FCHEV. The current FCHEV market is growing exponentially but faces various design and development issues and challenges whose resolution is necessary for its global impact and acceptance. Internal combustion engine cars and battery electric vehicles are the major competitors of the FCHEV, and their performance and efficiency should be comparable to these as well.

5.1. Optimized EMSs Integration

A vehicle's first and foremost requirement is its optimal performance in the sense of power allocation among the available energy resources in such a way that the power demand is optimally satisfied. Many of the latest research contributions have considered various EMS techniques to be integrated with the FCHEV for optimal power allocation and SOC control delivery. All of the techniques have their benefits but lack in some aspects, making their implementation in real-time applications a bit challenging and computationally expensive. Table 14 presents the comparative analysis of the frequently used EMS techniques in the form of pros and cons. It can be estimated that the optimal EMS strategy selection under current development is complex, and some trade-offs need to be considered.

Table 14. Comparative analysis of the frequently used EMS techniques.

EMS Type	Classification	Pros	Cons
Offline EMSs	Rule-based	• Simple implementation • Better flexibility • Simple design	• Less productive in achieving optimal power resource management • Not flexible in dealing with transients
	Global Optimization-based EMSs	• Can provide optimal performance • Relative higher accuracy • Comparatively lesser computational expenses	• The real-time implication is difficult • Computational efficiency is highly dependent upon the initial set of values • A large amount of data is required to get optimal performance • Requires complete historical data
Online EMSs	Instantaneous Optimization-based EMSs	• Can provide near-optimal performance in case of hydrogen fuel efficiency • Can provide accurate performance indices related to SOC and others • Support real-time implementation	• High computational expenses • Have problems in data acquisition • Large mathematical support required • Higher computational power required • Higher computational expenses
	Predictive EMSs	• Can provide optimal energy resource management • Can perform optimal constraints satisfaction • Robust	• Complex functionality • Require large data for optimal training • System model requirement • A higher number of control variables
	Learning-based EMSs	• Provide near-optimal performance in case of fuel efficiency and SOC maintenance • Higher performance accuracy	• Complex implementation • Comparatively higher computational expenses • Difficult to train • Time-consuming • Difficult algorithm selection

5.2. *Hydrogen Availability and Storage*

The commercialization of FCHEVs on a global scale can be an alternative to fossil fuel EVs and can be a competitive transportation with numerous advantages over other transportation sources. However, the fuel with which FCHEVs work is not commonly produced or available in the form that is suitable for FCHEV application. Table 15 presents various ways of generating hydrogen presented in the latest literature. However, there is a need for extensive research work to find a cost-effective, efficient, and long-lasting solution for hydrogen availability.

The hydrogen generated in most of the processes cannot be directly utilized in the FCHEVs, as they require hydrogen at some specific pressurized condition to increase the energy density of hydrogen. In the same context, the next challenge would be the storage of the hydrogen at extremely high pressure with extremely low-temperature conditions, so that the hydrogen energy density can be increased while the hydrogen tank size can be decreased. This solution can help store a large amount of hydrogen fuel in a smaller space and ensure a more extended vehicle driving range in return.

Table 15. Means of hydrogen production.

Resource	Process	Outcome
Natural Gas	Methane steam reforming with or without CO_2 capture.	
Coal	Gasification with or without CO_2 capture.	
Biomass	Gasification without CO_2 capture.	
Renewable Energy Electricity Grid Energy	Electrolysis.	Hydrogen
Ethanol	Reaction with high-temperature steam.	
Solar	High-temperature water splitting.	
Microbes	Water consumption by microbes in sunlight.	

5.3. Safety and Environmental Concerns

Hydrogen, the primary energy resource in FCHEVs, is the reason for consumers' most significant safety concern. Hydrogen is a highly flammable and explosive gas that requires storing at high-pressure conditions in FCHEV applications. Hydrogen also reacts with oxygen and is highly flammable and explosive in that case as well. There is a potential threat in the form of an explosion in the hydrogen storage facility in the vehicle, which can source severe health and safety issues. Another concern in the FCHEV design is the hydrogen tank placement, which is usually placed at the rear end of the vehicle. This configuration at times of sudden collision can also be a safety concern; there is an extensive need to look for secure and highly trustable hydrogen storage options so that the passenger safety concern can be majorly mitigated.

Hydrogen, if produced through renewable energy resources, is a green alternative to fossil fuel, as it does not generate any GHG emissions during its application in FCHEVs. However, the primary hydrogen production at the industrial scale is through methane steam reforming or partial oxidation. These mass hydrogen production techniques generate a large amount of carbon monoxide, which is highly hazardous to the environment. As most of the hydrogen production is through processes that are hazardous to the environment, there is an extensive need to shift towards renewable energy-based, nonpollutant methods for hydrogen generation to provide the claimed emission-free hydrogen transportation.

5.4. Economic and Societal Issues

Fuel cells are the primary energy source in FCHEVS but are the most expensive ones. Their capital cost has a significant share in the FCHEV costs that are available in the market. The FCs preferred in FCHEVs are the expensive proton exchange membrane FCs compared to other energy resources such as batteries and SC. Research is required to develop such FCs that are cost-effective, small, and have higher energy efficiency.

FCHEVs have enormous benefits over their competitors in the form of ICEs and BEVs as they have emission-free propulsion and wider driving ranges than any other EV types. However, before the FCHEVs are present in the market, there is a definite need to install hydrogen refueling infrastructure independent from the giant oil and gas industry partners as they can influence customer preferences. Broad infrastructure development of hydrogen refueling stations with consumer incentives would be necessary before the macro involvement of FCHEVs in society.

5.5. Other Challenges

Other challenges in the performance enhancement and globalization of FCHEVs may include the integration of advanced multiobjective algorithms with the optimal EMS techniques. The multiobjective algorithms can provide efficient performance from the same EMS techniques. These algorithms may include the advanced nonsorted and droop control-based genetic algorithm, reactive search, PSO-Grey Wolf optimization, strength Pareto algorithm, deep learning algorithms, and other AI- and machine learning-based multiobjective algorithms [119]. The implementation of these algorithms can be made possible through a proper scientific and technical assessment of the system design. These algorithms, when integrated with either offline or online EMS techniques, will enhance the efficiency and reliability of the EMSs.

However, the optimal performance of any evolutionary multiobjective algorithms depends upon some factors. The first most important thing is the optimal parametric tuning and the selection of effective parameter values will depict the performance of the algorithm [120]. There also can be issues of nonconvergence of the algorithm to the global optimum and being stuck with local optima. This is a reason that the implementation of the algorithms in the sensitive systems should be done more carefully [121]. Thus, the optimum performance of multiobjective algorithms depends upon the right selection of tuning parameters and the global convergence of the solutions to achieve the desired output.

Other major challenges may include the challenges related to water, air, and thermal management of the fuel cells. The fuel cell lifespan, system durability, and public awareness can be some other potential challenges as well. The FCHEVs may also face the challenge of high cost depreciation in the first years as the technology is not common and the public is still reluctant to use them. Similarly, there are very few manufacturers in the field, so the user has few options for buying FCHEVs. Overall, this technology is still under development and requires consistent research and development efforts to receive global acceptance and public consent.

6. Conclusions and Recommendations

FCHEV's efficiency and optimal performance depend on the EMS technique deployed. Therefore, it is essential to develop and utilize optimal EMS techniques to enhance the performance and cost-effectiveness of FCHEVs. This research investigated the latest power train infrastructure and highlighted their advantages and issues. It then formed a detailed analysis regarding the advancements in developing the offline and online EMSs for FCHEV application. This paper evaluated different EMSs' functionality and reviewed their impact on the FCHEV's performance regarding hydrogen fuel economy and SOC maintenance. However, most of the latest research works only considered simulation-based analysis without supporting their study with experimental hardware implementation. Thus, such EMSs must be developed to deliver optimal simulation performance and have satisfactory outcomes in real-time applications. The FCHEVs globalization depends on some significant factors that must be addressed immediately.

- To increase the overall FCHEV performance, effectiveness, and economic stature, further investigation should be performed to integrate and combine advanced EMS techniques with the latest multiobjective algorithms. This development, with proper management, will enhance the fuel economy, reliability, and cost-effectiveness of FCHEVs.
- There is an extensive need to decrease the costs of manufacturing FCHEVs and their supporting infrastructure. Developing cost-effective FCs with higher energy efficiency and compact size can revolutionize this technology.
- The experimental verification of all the simulation results should be included in the discussion so that the proposed optimal system performance can be achieved in real-time application as well.
- Advanced, emission-free, effective, and robust hydrogen production and storage techniques should be developed to make this technology environmentally friendly and safe. Optimized hydrogen tank size and location should be evaluated to enhance safety and overall vehicle size.
- Proper hydrogen refueling infrastructure with user incentives should be developed to encourage the hassle-free purchase and daily life operation of FCHEVs.

Addressing these recommendations can deliver the optimal performance of FCHEVs, and exponential growth in sales and market presence is expected. At the same time, the selection of optimal EMSs should be made after analyzing the pros and cons of each method, as concluded in Table 13. The FCHEVs with optimal EMSs integrated with advanced FC infrastructure can revolutionize the automobile industry with real emission-free, cost-effective, reliable, and long-range transportation sources.

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