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Review Article

Current State, Challenges, Recommendations and Prospects of Machine Learning Application in Fuel Cell Based Hybrid Electric Cars: A Comprehensive Overview

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ABSTRACT

This paper reviews the current progress and outlook of various applications of machine learning techniques in the context of hydrogen fuel cell electric vehicles. Emphasizing the importance of efficient energy management systems, it presents a detailed comparative analysis of recent developments. Key research works on machine learning-based energy management systems are discussed, including the use of the Twin Delayed Deep Deterministic Policy Gradient algorithm, which has demonstrated up to 28% reduction in overall operational costs. Moreover, the review includes machine learning -based energy management systems approaches that account for fuel cell degradation, an area receiving growing attention due to its impact on performance and longevity. Notably, reinforcement learning strategies have achieved improvements in fuel economy of 5.7% and reductions in fuel cell degradation rates by 4.5%. In addition, robust machine learning -based prediction models are highlighted for their effectiveness in data-driven fault diagnosis, contributing to a 13.9% reduction in fuel usage during the Federal Test Procedure 75 Driving Cycle and a 14.32% reduction in the New European Driving Cycle, along with carbon dioxide emissions cut to less than 26.4%. Despite this progress, existing review papers seldom address the use of machine learning for predictive maintenance in the automotive sector, nor do they adequately consider functional safety aspects. This dual gap underscores the novelty and relevance of the present study. Furthermore, this work uniquely explores the integration of machine learning with smart traffic management systems to optimize hydrogen fuel cell electric vehicle operations and critically examines the defies and potential solutions for advancing hydrogen refueling infrastructure. The paper concludes by discussing major ongoing challenges and offering perspectives for future research in this transformative field.

KEYWORDS

Fuel cell electric vehicle, Machine Learning, Efficient energy management system, Predictive maintenance, Fuel economy.

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INTRODUCTION

The transportation industry stands as one of the primary contributors to the generation of detrimental emissions. Indeed, the use of fossil fuels by Internal Combustion Engine vehicles (ICE) leads to significant environmental impacts due to the emission of harmful pollutants and raises growing concerns about the depletion of future resources [1], [2]. To address these issues, numerous automobile manufacturers, including Toyota, Nissan, Fiat, and others, have been actively promoting recent electric automobiles powered by environmentally friendly transportation innovations for several generations, as well as hydrogen-powered fuel cell electric vehicles [3]. Indeed, fuel cell hybrid electric vehicles and hydrogen fuel cell vehicles (FCEVs and FCHEVs) make some contributions to greenhouse gas emissions, making them a viable option for addressing environmental concerns [4].

Fuel cell hybrid vehicles often have fuel cells (FC) as their primary energy source and ultracapacitors or batteries as backup energy sources [5], [6], [7], [8]. Consequently, the function of supplemental power supply remains essential. Ultracapacitor and battery can both be useful as auxiliary energy sources [6], [7]. When there's a strong need for power, batteries can capture extra energy and use it to power the system alongside to fuel cell [9], [10]. Ultracapacitors can provide prompt attention to sudden variations in load requirements thanks to their features of quick dynamical response, rapid recuperation of energy, and enhanced specific power. There are currently three basic system architectures for FC hybrid cars. The initial kind is a hybrid system consisting of batteries and FC. The other type integrates ultracapacitors and fuel cells. The last one was comprised of ultracapacitors, batteries, and FC [11]. One of the more commonly used forms of FCHEVs involves the integration of FC and batteries. This integration is driven by limitations in the rate at which the fuel cell system can adjust its energy output and a need for regenerative braking. As a result, an additional battery storage system is frequently employed to exchange high dynamic power [12], [13], [14], [15], [16]. he hybrid battery can instantly supply the high power needed for the compressor and other Balance of Plant (BOP) components[12], [13], [14], [15], [16]. Therefore, it is not an optional add-on but a core enabling technology for making FCEVs efficient, dynamic, and competitive in real traffic conditions. [12], [13], [14], [15], [16].

Consequently, fuel cell system rated power was reduced to align with an appropriate power value, while to accommodate peak power demands, the rated power of the battery is customized through acceleration and regenerative braking periods. An energy management system that coordinates the interaction between both systems (fuel cells and batteries) is able to optimize hydrogen utilization, respecting different component restrictions [3], [6], [7].

The issue of energy management is crucial. Therefore, it is imperative to employ suitable control strategies encompassing prediction, control, energy management, cell design enhancement and optimization, as well as addressing PEM fuel cell durability and performance in these vehicles [17], [18], [19], [20]. The two papers [16], [17] while focused on microgrids, provide a critical methodological framework directly transferable to FCEV energy management. In [17], [18], [19], [20], a novel control strategies is introduced in and explicitly designed for the FCEV application.

To achieve these objectives, researchers are increasingly focusing on the application of machine learning techniques to enhance fuel cell durability, reduce hydrogen consumption, lower fuel economy costs, and achieve an optimal equilibrium between battery charging and discharging, among other objectives. Moreover, within the automotive sector, maintaining functional safety throughout a product's lifecycle while managing maintenance expenses has emerged as a significant hurdle. An essential strategy to address this challenge involves the implementation of machine learning (ML) for predictive maintenance (PdM) [21], [22]. Another trendy concept in the realm of managing large-scale vehicular traffic issues is the Intelligent Transportation System (ITS), which is designed to ensure safety, efficiency, and sustainability. Machine learning is used with current traffic control systems in ITS to provide real-time strategies for maintaining smooth traffic flow. Furthermore, various optimization techniques have been developed for intelligent traffic police management and deployment [22], [23].

The present review paper deals with various applications of machine learning techniques in the context of hydrogen fuel cell vehicles. To ensure comprehensive knowledge, several articles were inspected through searches conducted on reputable publishers' search engines, encompassing a wide range of sources. Web of Science, Scopus, and IEEE Xplore were among the primary electronic databases that were searched because of their reputation for covering engineering fields. A combination of keywords and Boolean operators specific to the syntax of each database was used in the search approach. Basic searches comprised ("[Fuel Cell Electric Vehicle]", ("[Machine Learning Application]"), and ("[Energy Management System]"), combined with the AND operator to refine the results. The search focused on peer-reviewed journal papers and conference proceedings published in English between 2015 and 2025. An initial screening of titles and abstracts was conducted to find relevant research, after which the full texts of shortlisted publications were retrieved and reviewed for final inclusion based on their relevance to the study's objectives. This procedure resulted in the identification and synthesis of 127 essential papers, which served as the foundation for this evaluation.

This review explores the applications and possibilities of ML in the context of cell modeling and optimization, energy management, system control, and the durability and implementation of PEMFC. The paper focuses also on key challenge areas in fuel cell hybrid electric vehicles (FCHEVs) to the specific Machine Learning (ML) techniques being applied internationally to solve them.

For example, in the field of system health monitoring advanced deep learning architectures like Convolutional Neural Networks paired with Long Short-Term Memory networks (CNN-LSTM) are used to reliably anticipate and diagnose faults and voltage degradation [24]. Simultaneously, Deep Reinforcement Learning (DRL) algorithms have outperformed conventional energy management techniques by adaptively optimizing energy sharing between the battery and fuel cell to optimize hydrogen economy [25], with more recent developments focusing on multi-objective optimization as well as degradation minimization [26]. Above the vehicle level, machine learning is transforming basic materials research; high-throughput experiments are being guided by neural network models and Bayesian optimization to find new, high-performance catalyst materials and membrane electrode assemblies with lower platinum loading [27], [28]. Lastly, enhanced control techniques for essential auxiliaries such as the air compressor and thermal management system are being made possible at the subsystem level by data-driven models [29].

In several studies, ML-based EMS for FCHEVs has been applied to enhance the efficiency of onboard power utilization by distributing energy more evenly, minimizing hydrogen consumption, and preventing fuel cell deterioration [30], [31]. For example, in [32] authors created an optimal energy management approach for FCHEVs based on a classifier fusion algorithm (KNN, SVM, and Naive Bayes) to achieve optimum performance. Individual classifiers, including KNN, Naïve Bayes, and SVM, give accuracy percentages of 92%, 94%, and 96%, respectively. Finally, they reached a precision percentage of 98% after combining these three features. Specifically, RL-based EMS has quickly gained significant attention because it enables efficient solutions to challenging EMS issues by using methods like deterministic policy gradients and deep neural networks. With its adaptability and instantaneous capabilities, reinforcement learning has emerged as a successful method in FCEV EMSs. Significant progress has been achieved since RL algorithms were first used in car EMS, and several researchers are working to alter conventional RL algorithms to address underlying problems. These changes have made it possible to use these algorithms in automobile EMS more successfully. In [33] researchers combined Q-learning with double deep Q-learning to track the necessary SOC references and achieve sufficient fuel efficiency in various driving circumstances. In [34], authors introduced the deep Q network (DQN) algorithm and multiple objectives in the aim to improve the economy of the hybrid system by 16.0 percent. Researchers proposed in [35] the Deep Q-Network with primarily experience with the aim of reducing fuel economy by 0.53 percent; FC degradation reaches 88.73 percent. Compared to the dynamic programming (DP)-based technique, computing efficiency is increased by more than 70%. Scientists [36] suggested in [30] an advanced DRL-based Twin Delay Deep Deterministic Policy Gradient (TD3) to maintain minimal hydrogen usage while reducing FC deterioration. TD3-EMS indicates an improvement in the overall operational cost of up to 28%. Authors [37] developed in [31] a novel RL algorithm that can learn in "multi-steps". Thus, the vehicle's energy efficiency improved from a starting level of 34 percent to 44 percent. For the same driving conditions, energy savings of at least 7.8% were achieved. In [38], researchers exposed a DRL algorithm. As results, the suggested DRL-based EMS's fuel economy improved by an average of 3.63%. The average FC deterioration rate is reduced by 63.49 percent, and EMS's convergence rate has improved by an average of 30.54 percent. In [39], Scientists integrated a DRL-based twin delayed deep deterministic policy gradient algorithm to optimize vehicle-driving costs. As a result, this approach allowed for an increased training efficiency of 54.69%, a greater learning capacity of 36.82%, and 2.45% less than the whole car. More recently, authors [40] presented an EMS based on scalable reinforcement learning in a novel environment (SLNE) to enhance the FC lifespan and reduce fuel consumption. The suggested SLNE-based EMS improves fuel efficiency by about 5%, reduces the rate of fuel cell degradation by around 4.5%, and increases the lifetime of the lithium-ion battery compared to DQN-based EMS [41], [42].

For cell model and optimization, the prediction of fuel cell voltage, membrane hydration level, and membrane resistance is accomplished using support vector machine regressor (SVR) algorithms [43]. Results indicate that SVR is beneficial for modeling fundamental regressions as it significantly reduces the computational load without sacrificing accuracy and achieves an R-squared value of less than 0.99 for each predicted variable. Concerning predictive maintenance using machine learning for fuel cell vehicles [21], [22], the SVM model's accuracy ranged from 98.5% for the fuel system to 96.6% for the ignition and cooling systems, with the fuel system showing the highest accuracy. Regarding the machine learning-based traffic management system [23], [30], [31], simulation results showed OS-ELM performed better than the other approaches in computational precision and effectiveness. In fact, it was predicted that daily energy savings of up to 12.2% could be achieved. Finally, this paper critically discusses the perspectives of developing machine learning strategy based on a hydrogen fueling stations for FCHEV production and storage.

While several studies have explored the applications of machine learning (ML) in fuel cell hybrid electric vehicles (FCHEVs), focusing on cell modeling and optimization [37], energy management [39], system control [35], and the durability and implementation of PEMFC [36],[38], key areas remain underexplored. In particular, the use of ML for predictive maintenance (PdM) of automotive components, as well as the integration of functional safety considerations throughout the product lifecycle, are seldom addressed in literature. Yet, managing maintenance costs while ensuring functional safety poses a significant challenge in FCHEV systems. This paper offers a focused review of ML applications specifically tailored to FCHEVs, setting it apart from broader reviews in the automotive domain. Key contributions include an in-depth analysis of reinforcement learning (RL)-based energy management systems, ML-driven predictive maintenance strategies, and deep learning approaches for processing complex datasets relevant to FCHEVs [44], [45]. In addition, this review examines the role of ML in supporting the development and optimization of hydrogen fueling infrastructure, outlining promising directions for future research and deployment in the FCHEV landscape [46], [47].

The importance of ML in various transport applications and more generally in Industry 4.0 is rising, due to the ongoing energy transition; however, this implies novel hazards that are possibly faced by ML. In fact, the ML models' sensitivity to adversarial assaults [48] poses serious safety issues, since malicious perturbations can cause severe system failures. Furthermore, the inherent opacity of complex models requires an emphasis on explainability to foster confidence and enable debugging, particularly in safety-critical applications [49]. This is exacerbated by the issue of out-of-distribution detection, which needs models to consistently manage the unpredictable character of real-world settings and recognize when they are unclear [50]. On the other hand, the energy transition necessitates the development of new technologies such as large-scale hydrogen storage and battery systems, both of which pose previously unidentified safety challenges and hazards in their manufacturing, handling, and storage [50]. In recent years, several deep learning (DL)-based FD/D algorithms have evolved for fault detection and diagnosis of induction motors [51], allowing autonomous feature engineering and learning and therefore reducing the disadvantages of classic ML-based methods. Finally, the data-driven nature of these systems raises issues about security and privacy in industrial IoT ecosystems, necessitating solutions such as federated learning to safeguard critical operational data [52]. Therefore, the pursuit of ML performance must be intrinsically linked with the development of robust, interpretable, and secure systems to avoid these dangers and ensure trustworthy adoption.

To highlight the originality of this work, a comparative analysis was carried out against several existing review papers in the field. This comparison, summarized in Figure 1, identifies the thematic areas treated in prior studies and clearly emphasizes the exclusive contributions of the present review.

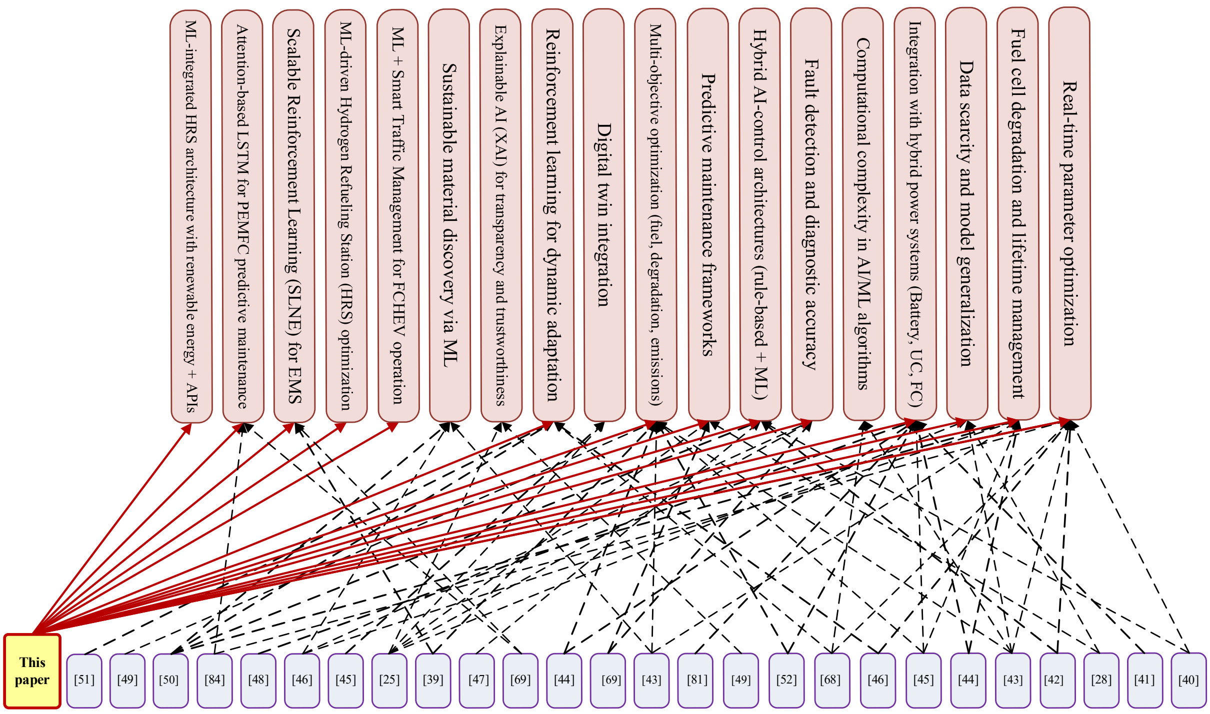

Figure 1. Mapping of Addressed Topics in Prior Reviews and the Novelty of This Study

This comprehensive review is structured to provide a systematic analysis of the integration of machine learning (ML) in fuel cell hybrid electric vehicles (FCHEVs). To guide the discussion and delineate the scope of this work, the paper is designed to answer the following specific research questions (RQs):

RQ1: what is the current state-of-the-art in applying ml techniques for the core functions of FCHEVs, such as energy management, fault diagnosis, FC modeling and performance and smart traffic management?

RQ 2: what are the most significant technical and practical challenges hindering the widespread deployment of ml in this domain?

RQ 3: based on the identified challenges, what are actionable recommendations for researchers and industry practitioners to overcome these barriers?

RQ 4: what are the promising future research directions and prospects for next-generation ML algorithms (e.g., deep reinforcement learning, transfer learning) to enhance the performance and durability of FCHEVs?

The paper is structured into three sections, beginning with an overview of machine learning applications in fuel cell electric vehicles. It proceeds to provide a concise examination of ML methods in the context of FCHEVs, and then an exposition of the exploration of ML applications for FCHEVs especially in energy management system, fuel cell degradation, modeling and performance, FC vehicle diagnostics and maintenance, fuel efficiency and emissions, advances in driver assistance systems, safety technologies and smart traffic management. Finally, the paper concludes by offering remarks and outlining the future research scope.

MACHINE LEARNING APPLICATIONS IN FUEL CELL ELECTRIC VEHICLES

After the preceding section's general review of machine learning's function in fuel cell hybrid electric cars, it is crucial to examine the particular algorithmic techniques that make these applications possible. Therefore, this section methodically analyzes the machine learning methods used in the area.

Searching on Machine Learning Methods

ML is an artificial intelligence (AI) whose its approaches can be categorized into four distinct categories based on the types of data that need to be forecasted, as seen in **Figure 2** **[53]**, **[54]**.

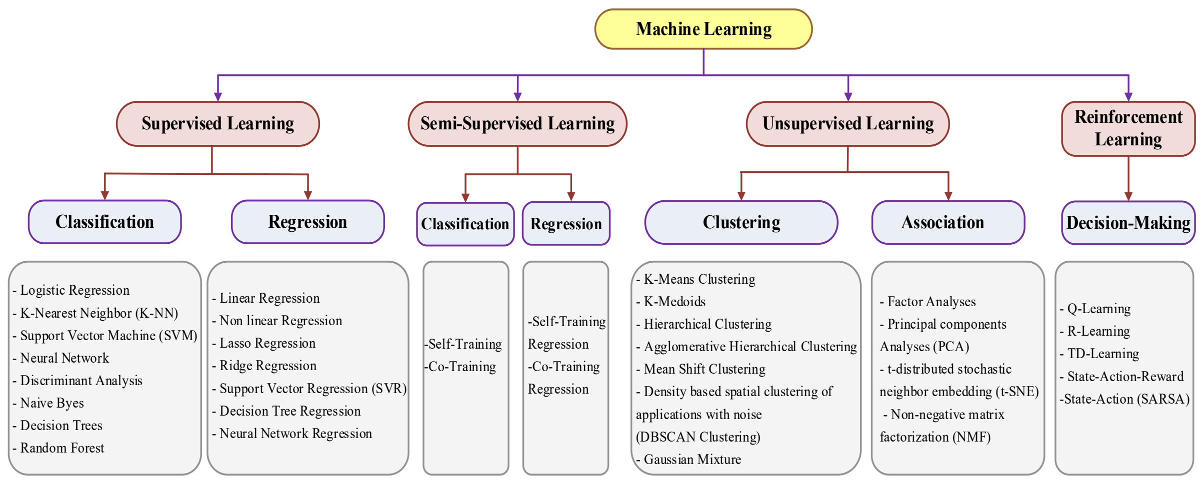

Figure 2. Machine learning techniques

Supervised learning. In this technique, the software's propensity to predict the output data relates to the labeled data and specified variables. In this approach, the output, input, and data are defined. Regression and classification are the two main problems under supervised learning. Some well-known regression methods in this domain include regression trees, polynomial regression, non-linear regression, and linear regression, among others. Several popular methods for classification consist of K-Nearest Neighbor (KNN), Neural Network, Naive Bayes, Random Forest, Decision Trees, Logistic Regression, Support Vector Machines (SVM), Linear Discriminant Analysis, and Linear Classifiers.

Unsupervised learning. This technique develops tagged data by combing datasets for any significant relationships. The preset output is derived from trained data that can forecast or suggest further data. Unlike supervised learning, unsupervised machine learning doesn't require a human to monitor the model in real time [55]. Thus, it may be further divided into two categories: clustering and association. Algorithm examples include autoencoders, PCA, DBSCAN, and K-means clustering. Applications include recommendation engines, anomaly detection, and market segmentation.

Semi-supervised learning. Semi-supervised learning is an algorithm that combines the first two techniques. Although the algorithm may freely examine the information independently and gain more understanding of the data set, it labels training data [54].

Reinforcement learning. The Reinforcement learning (RL) methodology continuously improves its model by gathering feedback from past iterations in a loop, unlike supervised and unsupervised learning methods. As a result, after the model is created from training and test data, it does not approach an indefinite endpoint. In fact, Q-Learning, R-Learning and TD-Learning algorithms are employed in reinforcement learning. The method will be detailed in the next section because it is frequently utilized in research papers for control and energy management systems in vehicles [21], [56].

Machine Learning Applications for Fuel Cell Electric Vehicle Energy Management System

A FC vehicle's energy management system (EMS) is a crucial operational necessity. As mentioned in [57], the FCEVs have a choice of two to three power sources, including FCs, batteries, and UCs. The best source for the time and amount of energy needed is chosen by the EMS. Because of its quick start-up, it may be presumed that the battery satisfies all short-duration pulse energy needs for quick acceleration. However, fuel cell systems offer a more reliable and long-lasting source of energy. These systems are operated gently to produce the energy required to prevent harm. The EMS must actually make quick decisions based on information from the car and the driver [58].

In this context, one of the learning-based energy management systems for FC cars is reinforcement learning. For FC vehicles, RL algorithms with modest or large data inputs are frequently used in EMS, which are:

- The Q-Learning method for fuel cell hybrid automobiles is proposed in several research papers [58], [59] with the aim of reducing hydrogen and fuel consumption and obtaining optimum FC efficiency while taking into account the FC lifetime. In [59], a Q-learning algorithm with dual reward functions is exposed in order to lessen the strain on the system and ensure secure and steady FCHEV operation. This approach makes use of a three-level effectiveness enhancement that was put to the test in an experiment. Results have shown reduced hydrogen and fuel consumption. Then, a hierarchical energy management approach based on RL data-driven FCHEV is suggested in [59]. An association of both Q-learning and Markov decision algorithms is developed in this study. The results demonstrate optimum FC efficiency, reduced computational time, and fuel consumption savings, which were evaluated under experimental conditions. After that, an efficient Q-learning-based reinforcement learning technique is analyzed in, which takes into account the FC lifetime. The method's performance time proved its adaptability for real-time EMS, especially with three different drive cycle sources under variable conditions.

- The Q-network algorithm, designed for energy management control in FC hybrid automobiles, is proposed in some papers in order to minimize hydrogen usage and improve fuel cell lifetime [60], [61], [62]. In [62], the authors introduced a multi-objective DQN algorithm to reduce hydrogen usage and enhance fuel cell lifetime. The results of the proposed DQN algorithm demonstrate significant improvements in convergence speed, fuel consumption, and durability when compared with the Q-learning algorithm. Additionally, the DQN algorithm is utilized in **[60]** in untrained situations and unknown driving environments. The outcomes reveal a substantial decrease in the amount of hydrogen consumption compared to differential privacy (DP) -based methods which present an increasingly important tool in deep learning. In **[61]**, the authors aimed to minimize hydrogen usage and assess the adaptability of the algorithm. Furthermore, FC Hybrid buses adopt a deep reinforcement learning (DRL) technique based on DQN, as developed in **[63]**. The results show around 3.7 percent and 5.7 percent rise in the usage of hydrogen compared to EMSs, whose methods are DP- and RL, respectively.

- The DDPG method for energy management is proposed in the context of fuel cell hybrid cars in order to reduce fuel consumption and extend FC lifetime in FCHEVs. In **[64]**, a DDPG is developed in order to achieve control over energy management. The algorithm enhanced the control effect by utilizing the FCs' efficiency features. In this work, the authors attempted to increase the computational effectiveness of DDPG. The outcome demonstrates an optimal adaptive energy management method with stable convergence. In **[65]**, DQL (Deep Q-Learning) and DDPG methods are designed to reduce fuel consumption and extend FC lifetime in FCHEVs. In this study, the DDPG algorithm was assessed for four different drive cycle sources using a multi-objective reward operation that took into account fuel economy and energy fluctuation. The DDPG approach proves that it is adaptable for multi-cycle usage compared to deep reinforcement learning. Further, in **[36]**, a DDPG algorithm is applied with the aim of regulating the battery SOC and assisting with energy consumption in various drive cycle sources. In **[37]**, authors suggested a DDPG approach for energy allocation according to acceleration, the battery's SOC, and car speed to enhance fuel consumption. Increased FC durability and reduced hydrogen consumption are revealed by the results. It's also important to remember that the DDPG strategy is affected by unsteady training compared to the other mentioned.
- The Twin Delayed DDPG TD3 algorithm, applied to fuel cell cars, is proposed in several research papers. For example, in (Habib, 2024), this approach is more reliable and economical. The disadvantage of this algorithm is its lengthy learning period, which makes it unsuitable in real-time vehicle EMS. In addition, the TD3 algorithm for intelligent transportation systems is recommended for various automobile configurations to offer agents other beneficial signals related to the environment.

To conclude, DQN operates more effectively than Q-learning algorithms. Despite DQN's tendency to overestimate Q-function values, the results demonstrate superior convergence compared to Q-learning. The outcomes show that the energy management system based on DQN is more flexible than the other mentioned. The TD3 technique is necessary to maximize hydrogen use using an RL-based approach.

Table 1 provides a list of machine learning-based EMS algorithms employed in FCHEVs where reinforcement learning, including deep RL, Q-learning, and deep reinforcement learning (DRL), is the most often employed machine learning approach in EMS. Each cited study in this table has been divided into one of the three groups listed below : i) Real Driving Conditions (RDC) for research utilizing data from on-road vehicle tests, ii) Laboratory/Test Bench (Lab) for research projects that use data from component test benches, and iii) Simulation/Model (Sim) for research projects that do not use physical hardware validation and instead depend solely on simulation models (such as Simulink). The same applies to the following tables (**Table 2** and **Table 3**).

Researchers are employing RL approach in EMS in order to achieve minimal computing costs, optimum fuel cell efficiency, and economical energy use **[66]**.

For example, in [67], a new learning-based robust model predictive control (LRMPC) energy management system according to ML approaches for a 4WD FCEV is introduced. The state observer built within the LRMPC can accurately reflect SOC changes using the fundamental ML techniques in the supposed LRMPC. In [68], model-based reinforcement learning was applied to fuel cell electric car energy management to minimize hydrogen fuel use. The results of the fuel consumption simulations demonstrate that the suggested method uses less fuel than the rule-based approach. Then, in [69], a novel learning approach by enhancing the value of fuzzy rules-based energy management approaches for hybrid electric cars supplied by fuel cells is presented to decrease hydrogen use and maintain continuous battery operation. In various publications [33], [34], [38], [70], [71], Q-learning is recommended as a way to lower fuel usage in FCHEVs. The suggested technique tracks the related SOC references and delivers acceptable fuel efficiency in a variety of driving situations.

The study [71] reveals an independent Q-learning (IQL)-based EMS, a multi-agent reinforcement learning algorithm, in the same setting. Its goal is to decrease the amount of hydrogen used and preserve the battery's state of charge (SOC). The generalization and fault-safe operating capabilities of this method are other advantages.

The deep reinforcement learning approach for EMS is largely used in the literature to mainly optimize vehicle driving costs and suppress system degradation. These papers propose optimum power control using deep reinforcement learning with the goal of reducing the total amount of hydrogen consumed and battery and fuel cell deterioration.

The DRL algorithms used in these papers are Deep Q-Networks [34], [34], [35], [38], TD3 [36], [39] and DDPG [34], [38], [64], [65], which are applied in EMS to reduce hydrogen consumption and suppress system degradation.

After that, an efficient energy management approach by combining SVM, KNN, and the Naive Bayes technique is created in this work [32]. By combining these proposed techniques, the performance accuracy of the optimization approach is improved. Moreover, these individual classifiers, including KNN, Naïve Bayes, and SVM, give accuracy percentages of 92%, 94%, and 96%, respectively. An accurate percentage of 98% was achieved after combining these three features.

More recently, a scalable reinforcement learning-based energy management approach for fuel cell electric cars in a new area (SLNE) was created in this study [40]. The suggested SLNE-based EMS improves fuel efficiency by about 5%, reduces the rate of fuel cell degradation by around 4.5%, and increases the lithium-ion battery's lifetime in comparison to the DQN-based EMS. In contrast to current learning algorithms and improved methodologies, suggested energy management techniques based on RL may attain high computational effectiveness, decreased fuel cell energy changes, and optimal FCHEV fuel economy.

From the reviewed works presented in Table 1, it can be observed that the primarily commonly employed ML technique in EMS is RL, particularly deep RL, employing various approaches. Generally, in the different applications discussed in the review, machine learning-based EMS is applied to enhance the efficiency of onboard power utilization by distributing energy more evenly, minimizing hydrogen consumption, and preventing fuel cell deterioration.

Researchers are paying increased attention to RL-based EMS due to its advantages over competing methods, such as Q-learning, which is suggested as a means to reduce fuel consumption in FCHEVs, and deep reinforcement learning optimizes vehicle driving costs and mainly suppresses system degradation based on algorithms as follows: DQN, TD3, and DDPG. In order to enhance fuel cell efficiency, the reinforcement learning algorithm is currently experiencing a number of improvements in algorithm development.

Table 1. Overview of the works considered for the FCHEV's energy management strategy based on machine learning techniques

Ref	Application	ML Method research	Objectives	Approach	Data Set	Validation Environment	Results and Performance
[38]	FCEV	New hybrid degradation model of PEMFC: -Extreme Learning Machine (ELM) -Genetic Algorithm (GA).	-build each sub-waveform degradation model.	PEMFC wavelet analysis	Real-data analysis from three PEMFCs from three FCEVs	Comprehensive simulations on a modeled fuel cell hybrid vehicle system over various driving cycles.	PEMFC APE (Absolute Percent Error) degradation model < 2%.
[72]	Transportation Electrification	A specific PEMFC failure detection technique combines: Evidence theory of Dempster-Shafer (D-S) and the Extreme Learning Machine (ELM)	-improve test accuracy and running speed -reduce the duration of the training -solve data-driven diagnosis of failures problems	The PEMFCs model of failure diagnosis is created using both of: -online sequential ELM method. -kernel ELM algorithm	Real data from 3 PEMFCs in 3 FCEVs -data fusion	Software simulation on a modeled fuel cell hybrid vehicle system, using standard driving cycles for validation.	-average recognition rate 98.70% -operation time 0.2011 s
[73]	FCEV	FC degradation model based on ML machine learning techniques	-evaluate the degradation MODEL impacts in FC stack about the fuel usage of the hydrogen fuel-cell buses		a real driving cycle for Victoria City in Canada's British Columbia -dynamic simulation since operating condition	Simulation environment under various driving cycles.	-The other buses' fuel use is the lowest, but this one has increased by more than 24%.
[74]	hydrogen passenger vehicles	degradation PEMFC model based on machine learning algorithms	-solve FC degradation by robust prediction techniques -reduce fuel consumption and total emission	Simcenter Amesim software with real-time dynamic simulation capability is used to calculate: -fuel use and FC deterioration -engine efficiency	- FTP-75, a new European driving cycle	Hardware-in-the-Loop (HiL) / Laboratory (Lab)	-In FTP-75 and New European Driving Cycles, fuel consumption increased by 14.32% and 13.9%, respectively, with deteriorated PEMFC. -When compared to PEMFC without degradation, FC is expected to generate 26.4% greater CO2 emissions.

Fuel Cell Degradation Model-Based Machine Learning Techniques

One of the major issues concerning hydrogen FC cars is FC degradation, a problem that can be addressed through reliable prediction methods such as machine learning. Models of fuel cell degradation developed in the literature can effectively solve databased fault diagnosis problems. These models have a significant impact on fuel efficiency and overall emissions. In [38], a novel hybrid PEMFC degradation model utilizing an Extreme Learning Machine (ELM) and Genetic Algorithm (GA) for FCEV is proposed. In [72], ELM and Dempster-Shafer evidence theory are used to create a new failure diagnosis approach for PEMFC systems to improve test accuracy and shorten the training time. Then, in [73], Fuel cell degradation model is applied to enhance the performance of the bus. The effects of the FC stack's deterioration model on the fuel consumption of hydrogen-fueled buses are assessed using machine learning techniques. In [74], the evaluation of a deteriorated PEMFC stack for hydrogen-powered passenger automobiles using ML techniques in actual driving situations is introduced by the authors. An overview of the studied publications relating to using machine learning techniques-based fuel cell degradation models for FCHEVs is presented in Table 2.

Table 2. List of the reviewed works that utilize machinelearning techniques-based fuel cell degradation models for FCHEVs.

Ref	ML Method	Objectives	Application	Approach	Data Set	Results and Performance	Validation Environment
[67]	Learning-based robust model predictive control (LRMPC)	Suitable power distribution between several energy sources.	4WD (Wheel D) FCEV	- ML techniques with high regression accuracy and outstanding generalization ability are taught offline: -To build the precise state observer for SOC.		-Optimal control effect in potential energy savings - LRMPC has significant real-time application capabilities.	Real Driving Conditions (RDC) as it utilizes real-world operational data for validation.
[68]	Model-based RL (MBRL)	- Reduce hydrogen fuel consumption –ensure FC and battery efficiency	Internal FC electric vehicle powertrain	- RL is carried out in the context of the driving cycle profile to improve the control policy.	Model developed as the learning process proceeds using input from experiences through standard driving cycles	-Average fuel usage decreased by 5.7% compared to the rule-based technique.	do not present primary validation
[70]	RL: -Q-Learning -python	- Achieve power allocation FC and lithium batteries -reduce fuel usage -keep battery SOC constant.	FC/Battery HEV	Application of Q-Learning to: -Reduce Fuel Consumption and Ensure Battery Sustainability	New European drive cycle	- Effectiveness of Proposed method verified	simulated hybrid electric vehicle model in a software environment
[75]	RL	-Improve batteries lifetime -Minimizing the battery SOC variation.	Fuel Cell/Battery Hybrid Electric Vehicle	Autonomously learn the optimal policy in real time through interaction with the on-board hybrid energy system.		Energy system efficiency improved	simulated "rough pavement constraints" within a software-defined environment
[33]	RL: - Q-learning (QL) - Double QL algorithm (DQL)	Optimization plan for PHEVs' internal energy distribution.	Powertrain transmission type	-Establishing the speed predictor using the Q-learning (QL) technique -Double QL approach to develop an efficient offline controller that achieves the ideal power distribution SOC -a novel speed predictor is proposed, to create the bi-level energy management method.		-The suggested solution tracked the necessary SOC references -while achieving sufficient fuel efficiency in various driving circumstances.	Simulation environment (Simulink) for validation
[76]	Fuzzy rule value reinforcement learning	- Consider reducing hydrogen usage -continue running on battery power. - respond to changes in driving conditions and FC degradation.		Using a fuzzy inference system, it is possible to: -approximate the state-action value function. -allows the creation of a continuous state and/or action space.		-The proposed method effectiveness to solve energy management issues is verified. -Faste and smooth convergence as well as strong environment change	Validated on a simulated fuel cell hybrid electric vehicle model running standard driving cycles.

Ref	ML Method	Objectives	Application	Approach	Data Set	Results and Performance	Validation Environment
						resistance are confirmed	
[71]	Multi-agent RL : Independent Q-learning algorithm	-Maintain battery SOC -Minimize hydrogen consumptio n	FCHEV	Fuel cell system with multiple stacks (MFCS) algorithm using numerous fuel cell stacks with low power (FCSs).	(IQLS) learned offline in a well-establishe d model setting,	-Good generalizatio n and the capacity for fault-tolerant operation.	Simulation (Sim) due to validation within software models using standard driving cycles.
[59]	RL	Realize: -a low cost ofcomputati on -a maximum FC efficiency -economics of energy usage.	FC/battery/UC hybrid electric cars	Structure of hierarchical power splitting used: - to reduce the size of a huge state-action range using an adaptive fuzzy filter.	Based on testing data for numerous driving cycles and traffic scenarios, a power splitting scheme was developed.	-High computing effectiveness, -Low power fluctuation, -Optimal fuel economy of FCHEV are achieved.	do not present primary validation
[34]	DRL : - Using the deep Q network algorithm and multiple objectives	-Reduce your use of hydrogen -suppress system deterioratio n	Fuel Cell/battery Hybrid Powertrain	Synergistic approach: -Compares optimal power management and battery size at the same time.		- The most cost-effective sizing parameters are found. -The economy of the hybrid system is increased by 16.0 percent using a synergistic method.	Sim: fuel cell hybrid powertrain model built in MATLAB/Simulin k.
[35]	DRL : Deep Q-Network	Achieve: -fuel economy -FCs degradation -hydrogen consumptio n reduction	Fuel cell hybrid electric car	Deep Q-Network with first and foremost experience Replay is intended to minimize hydrogen consumption -The objective function incorporates the deterioration of FCs.	UDDS driving cycle	-Fuel economy reduces by 0.53 percent. -FCs degradation reaches 88.73 percent. -Degradation of FCs is effectively suppressed. -Compared to the DP-based technique, the computing efficiency is increased by more than 70%.	FCHEV longevity is developed and tested using a high-fidelity simulation model of the vehicle powertrain.
[34], [38]	RL with -Three main RL algorithms are applied Q-learning, deep Qnetwork and deep deterministic policy gradient -Multi-objectiv e control	Achieve: -fuel economy -fuel cell longevity according to the FC deterioratio n theory	FC hybrid vehicles	Three common RL algorithms are used in order to enhance EMS's functionality.		-The performances of RL-based EMS were assessed and achieved. -FCHV fuel economy, FC durability, and the EMS adaptability are verified.	Comprehensive simulations on a modeled fuel cell hybrid vehicle system over various driving cycles.
[64], [65]	DRL: DDPG	-Reduce overall travel expenses -Increase the DFC's durability.	Dual-stack fuel cell (DFC) and battery logistics vehicle	EMS working with the DDPG and APF function: –artificial potential field (APF) to ensure the upkeep of SOC and the effectiveness of DFC		-Efficient at adjusting to the dynamic price changes of different energy sources -Advantageo	Laboratory (Lab) based on its focus on experimental PEMFC optimization.

Ref	ML Method	Objectives	Application	Approach	Data Set	Results and Performance	Validation Environment
				-DDPG, leveraged to support the distribution of power among different energy sources		us to lower overall travel expenses and prolong the life of the DFC	
[36]	DRL-TD3	-Reduce the amount of hydrogen used and the expense of FC aging -Achieve a good balance between battery charging and discharging	FC hybrid railway vehicles	Advanced DRL method based TD3 to obtain a promising EMS	-Model for online aging estimation of fuel cells. -Real measured speed profiles	Battery charging is achieved by TD3-EMS. -Maintaining minimal hydrogen usage whereas reducing FC deterioration. -TD3-EMS indicates an improvement in the overall operational cost of up to 28%.	The validation is performed on a detailed simulation model of a railway vehicle powertrain.
[37]	RL -'model-free' predictive EMS	- Allows the energy management control policy to be continuously improved online.	Off-highway linked electric vehicle	A novel RL algorithm that can learn in "multi-steps" (Sum-to Terminal, Average-to-Neighbor Recurrent-to-Terminal) to permit the EMS online optimization and control policy for the rest of one's life.	Online optimization	-Vehicle's energy efficiency improved, which, after 5 hours of 35-step instruction, went from a starting level of 34 percent to 44 percent. -The forecast horizon length was extended by 71% (in real-time computing, from 35 to 65 steps with a 1-second interval); -For the same driving conditions, energy savings of at least 7.8% were achieved.	Real Driving Conditions (RDC) collected from an electrified off-highway vehicle.
[38]	DRL	-To improve FC durability ased on a FC degradation model. -optimize the control's real-time performance -improving fuel economy	FC hybrid buses (FCHBs)	-DRL algorithm is limited to increase fuel economy -Experience Replay with Prioritization (PER) use to enhance DRL algorithm's convergence performance.		-An improvement of suggested DRL-based EMS's fuel economy by an average of 3.63% -The average FC deterioration rate is reduced by 63.49 percent. -The suggested DRL-based EMS's	Comprehensive simulations on a modeled fuel cell hybrid vehicle system over various driving cycles.

Ref	ML Method	Objectives	Application	Approach	Data Set	Results and Performance	Validation Environment
						convergence rate has improved by an average of 30.54 percent. -The suggested DRL-based EMS's adaptability is validated On a novel driving cycle.	
[39]	DRL -twin delayed deep deterministic policy gradient algorithm-based (TD3)	-Optimize vehicle driving cost	FC hybrid electric bus (FCHEB)	A novel EMS - To properly make use of the FCHEB's economic potential, the strategy framework must incorporate the restrictions of battery aging and FC power variance.	Actual driving conditions gathered as training data.	TD3-based EMS compared (DDPG)-based EMS has : -increased training efficiency by 54.69%, -36.82% greater capacity for learning, -2.45% less than the whole car -Operating expenses validating the effectiveness of the proposed strategy.	Fuel cell hybrid buses is developed and tested using a simulation platform (ADVISOR, Simulink).
[32]	Classifier Fusion Technique: SVM, KNN, and the Naive Bayes	Achieving optimal performance	FCHEV	- To create an efficient energy management approach - To develop a better performing EMS		- Individual classifiers including KNN, Naïve Bayes, and SVM, give accuracy percentage of 92%, 94% & 96% respectively. - Finally, an accurate percentage of 98% was achieved after combining these three features.	Energy management is developed and validated through simulations conducted in MATLAB/Simulink using standard driving cycles.
[43]	Scalable reinforcement learning in novel environment (SLNE)	Enhancing the FC lifespan and reducing The fuel consumption	FCEVs	- To improve fuel efficiency -- To reduce the rate of fuel cell degradation increase the lifetime of the lithium-ion battery		The suggested SLNE-based EMS improves fuel efficiency by about 5%, reduces the rate of fuel cell degradation by around 4.5%, and increases the lifetime of the lithium-ion battery compared to DQN-based EMS.	Laboratory (Lab), the model is developed and validated using extensive experimental data obtained from a laboratory test bench

Modeling and Performance for Fuel Cells with a Polymer Electrolyte Membrane Using Machine Learning Techniques

Machine learning techniques are widely employed in the fields of chemistry and materials science to explore novel material characteristics and create materials for future generations [77], [78], [79]. Concurrently, understanding the basic principles of PEMFCs is vital for advancing technologies that enhance fuel cell performance and reduce costs. This understanding is crucial in the development of various aspects of FC design, including durability, and dynamic operation. This section delves into these components and discusses their significance in fuel cell technology. This section consider recent trend toward the development of physics-informed Machine-Learning model to predict performance and aging of fuel cells, prevent anomalies and possible hydrogen leakage and implement automated safe-operation system with AI-Driven Early Warning.

Machine learning for durability and performance. The application of ML in this domain primarily focuses on two critical, interconnected aspects:

ML for Performance Prediction: The utilization of PEMFC modeling, driven by machine learning and requiring no prior expertise, offers a range of significant advantages, particularly in understanding the intricate interplay of linked electrochemical and transport processes within PEMFC function. This approach simplifies the simulation process substantially, accommodating even those processes for which the underlying physical mechanisms are not fully elucidated. Despite these advantages, there is a concern: since it operates without a physical representation, its effectiveness in scenarios beyond the scope of the test data set might be compromised. To address this limitation, a promising solution involves the development of a combination of models, integrating both physical processes and ML techniques. By embedding physical processes into ML, FC efficiency, especially in complex conditions, can be substantially enhanced. A recent proposal in the literature suggests the integration of physics-informed neural networks, as demonstrated by the authors in [40]. Successfully incorporating fundamental physics into each component of PEMFC through deep learning represents a significant challenge, but it holds the key to achieving the desired design objectives.

ML for durability: PEMFC that remains reliable throughout its lifetime is essential to industrialization. Therefore, it is necessary to estimate the state of health (SoH), remaining useful life (RUL), and PEMFCs durability by analyzing the data generated by control units [43], [80]. In this context, the FC cell voltage presents a crucial indicator of the output parameter in machine learning because it provides an essential measure of FC performance. Recently, machine learning has been used for predicting FCs SoH and durability, which can mostly be categorized as model-driven and database-driven approaches.

The former approach is computationally costly since it relies on physical or semi-empirical models. In research, both types of methods are studied for RUL and SoH prediction, encompassing several studies comparing different algorithms. The following paragraph will provide examples of various machine learning approaches used for PEMFC's features and prognostics. In [81], a hybrid method that combines an auto-regressive integrated moving average (ARIMA) with an LSTM-RNN is introduced for predicting fuel cell state of health. When combined with ARIMA, LSTM enables effective long-term degradation prediction, allowing for the tracking of degradation trends. The model is evaluated using experimental datasets from two PEMFCs that have aged, showing promise in aiding the design of management strategies and predicting performance prior to experimental testing. In [82], a PEMFC RUL prediction technique based on deep neural networks (DNN) and sparse auto encoders (SAE) is proposed. SAE is employed to automatically extract prediction characteristics, while the DNN is used for RUL prediction. To reduce noisy data, a Gaussian-weighted moving average filter is chosen. Compared with experimental data points, this model prediction shows an accuracy of up to 99.68%. Moreover, the model is able to predict RUL under dynamic conditions.

Machine learning for fuel cell modeling. Several machine learning approaches are employed to create models using data for PEMFC's internal states and performance aspects. For example, in [83], machine learning is applied to improve the power density of high-temperature PEMFCs (HT-PEMFC) through its tools for fast and efficient exploration of wide search areas. The ML framework is predicated on a methodology for data analysis and a semi-empirical 0-D model of HT-PEMFC polarization behavior, leading to dimension reduction and clustering based on density. This study demonstrates pathways surpassing 1 W cm^2 in HT-PEMFC. Then, in [84], the prediction of fuel cell voltage, membrane hydration level, and membrane resistance is accomplished using support vector machine regressor (SVR) algorithms and artificial neural networks under various operating conditions. The authors consider two different sets of data: a 1-D computational fluid dynamics model with reduced dimensions and a physics-based semi-empirical model. Results indicate that SVR is beneficial for modeling fundamental regressions as it significantly reduces the computational load without sacrificing accuracy. As for the artificial neural network with the dropout strategy, it achieves an R-squared value of less than 0.99 for each predicted variable.

The Emergence of Physics-Informed Machine Learning for Robust Modeling. The development of Physics-Informed Machine Learning (PIML) is a noteworthy and promising trend to overcome the limits of purely data-driven models [85]. Through physics-based loss functions or specialized network architectures, this paradigm integrates fundamental physical laws (such as conservation laws, thermodynamics, and electrochemical principles) into a data-driven algorithmic model based on a computational model of the SOFC system and a gradient-boosted decision tree. This method improves predicted accuracy in situations when data is noisy or limited, enforces physical consistency, and increases model generalizability beyond training data conditions all of which are especially beneficial for complicated fuel cell systems [86]. For safety-centric predictive tasks, such as the precise prediction of performance decline (aging) and the deployment of reliable AI-driven early warning systems, PIML application is essential. For example, by identifying patterns that defy established physical limitations, PIML models may be taught to identify abnormalities and stop dangerous operational deviations, including those that result in hydrogen leaking [85]. As recent research has shown, this is crucial for building automated safe-operation systems in critical applications like as marine transport [85] and serves as a foundation for the next generation of predictive health management in FCHEVs [86].

Machine learning for fuel cell Vehicle Diagnostics and Maintenance

In the automobile sector, maintaining functional safety while minimizing maintenance costs has become a significant concern. Predictive maintenance (PdM) has emerged as a key strategy to achieve this goal. Maintenance efforts, which include fixing errors or implementing preventive steps, are aimed at keeping a system operating in its designated mode. There are various methods to categorize maintenance strategies; however, the following three are frequently used: PdM, or predictive maintenance, as well as corrective and preventive maintenance [87]. This review focuses on predictive maintenance.

Industrial equipment reliability and health are shown in real time through predictive maintenance, which gathers information from a range of system sensors, adding to the complexity of the process. Four phases are used to develop this maintenance strategy: receiving information from the system's numerous sensors, then preprocessing the data, followed by the diagnosis and prognosis of faults, and finally making a decision about the maintenance plan. Diagnostics and the prognosis of faults are two areas of study that have caught the interest of both academia and industry. The main objective of diagnostics is to locate, recognize, and separate a defect that has occurred. Typically, there are two essential processes in error diagnosis: the selection and extraction of features and the classification of faults. Prognostics are focused on tracking changes in a system's operating characteristics during its typical operational cycle. It enables us to calculate the RUL of the equipment and anticipate failures before they happen. Typically, it is carried out in three major steps: prediction of the machinery RUL, distinction of the health stage (HS), and health indicator (HI).

Data collected from the physical world may now be gathered and analyzed thanks to machine learning and artificial intelligence methods [21]. Several methods are identified for predictive maintenance [22]: physical modeling strategy, knowledge-based approach, data-driven approach, and digital twin approach. Regarding the automotive and transportation sectors, this section attempts to give a survey of the literature on recently developed methods as potent instruments for predictive maintenance. Machine learning algorithms that are powered by data must effectively analyze enormous amounts of both historical and real-time data coming from various sources (sensors and computers). Therefore, a machine learning algorithm's performance is significantly impacted by data preparation. The key ML concepts that apply to PdM are summarized in the following paragraph.

The two primary approaches that make up the key machine learning techniques for predictive maintenance are the supervised learning, in which the modeling data set contains information about the occurrence of failures; the unsupervised learning, in which only process information is available and no historical maintenance data is available; and the semi-supervised learning. Predictive maintenance uses the following tried-and-true machine learning approaches in an operational setting:

- Classification algorithms that reflect groupings of the item under observation with normal and bad health status
- Regression algorithms
- Clustering techniques utilizing anomaly detection algorithms

<u>Condition-based predictive maintenance using statistics.</u> A key development of this approach is condition-based predictive maintenance, which relies on statistical analysis of real-time data.

- Statistical predictive maintenance: In statistical PdM, as exposed in [88], data from several cars in a shared backend is employed instead of data that is connected to a single automobile's state. Big data techniques are also discussed. Examples involve details on preceding maintenance, age, driving distance, and kind of automobile features, as well as fleet feedback data.

- Condition-based predictive maintenance: Condition-based PdM, in contrast to statistical PdM, employs operational data from individual cars to determine the overall system state or the status of one or more components. According to this approach, a maintenance decision associated with the component may be made [88]. Fault detection is an essential method for failure prediction. Early fault detection can prevent it from spreading, enabling actions to be taken before failures occur. Thus, anomaly detection or classification is a common method for achieving condition-based PdM. Generally speaking, depending on data and label availability, supervised, semi-supervised, and unsupervised learning methods can be applied.

The essential vehicle parts for which conditional based PdM has been performed are presented in **Figure 3**.

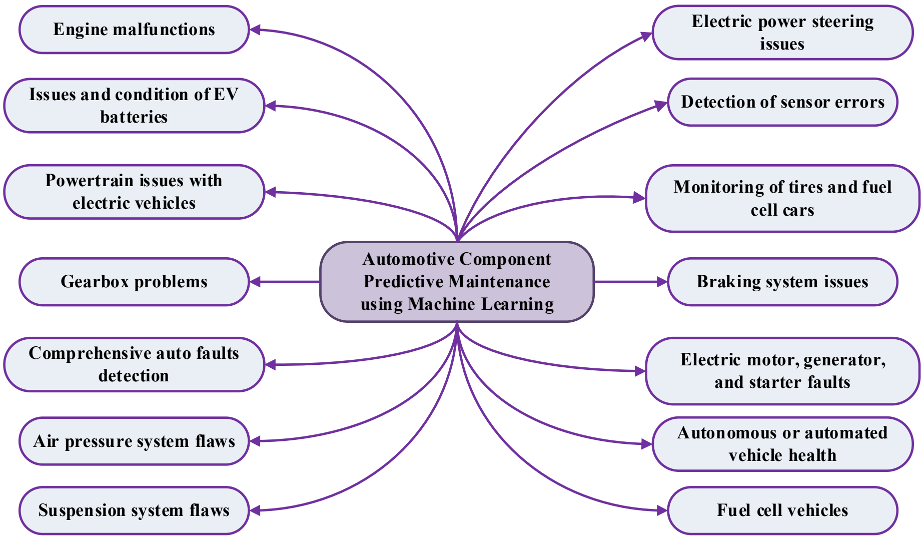

Figure 3. Automotive component predictive maintenance research using Machine Learning

Primary use case for machine learning-based predictive maintenance in automotive systems. The automotive applications for ML-based PdM are primarily categorized into two key domains:

- *Application for Fuel Cell vehicles*

Predictive maintenance using machine learning for fuel cell vehicles is discussed in **[89]**, where the authors utilized an Artificial Neural Network (ANN) to categorize water management faults. The authors developed a mathematically designed Artificial Neural Network system. These ANNs successfully classified and located 9 simulated cells with defects related to drying and flooding. As discussed in **[90]**, the authors developed LSTM networks and Gated Recurrent Units (GRUs) to forecast the FC's terminal voltage as a function of load current and degradation. To achieve this, the authors tested a PEMFC for its ability to sustain long-term dynamic loads. During the last test stage, the attention-based LSTM yielded the best prediction results, with an estimation coefficient reaching up to 0.89.

- *Application for automobile components*

In this section, the focus is on predictive maintenance for automobile components using machine learning techniques. The research in this area is categorized into several subfields based on their primary application cases, as outlined in **Table 3**.

In general, selecting the best machine learning algorithm for predictive maintenance requires conducting tests, considering various options, and adjusting parameters. It relies on several parameters, considering the particular problem, the data's nature, and appropriate settings. Numerous comparisons between different machine learning techniques can be found in the literature. For example, researchers in **[100]** estimated the SoC of lithium-ion batteries using the following six machine learning algorithms: ensemble boosting, ensemble bagging, support vector machine, linear regression, Gaussian process regression (GPR), and artificial neural networks. Following this comparison, the suggested ANN and GPR strategies demonstrated high performance, outperforming other methods with a mean absolute error of 85%. In terms of SoC projections, ANN and GPR could contribute to developing an optimal battery management system for electric cars. In **[100]**, Random Forest, SVM, Decision Trees, and k-Nearest Neighbors were the four classifiers compared. The SVM classification exhibited the greatest efficiency across four functional systems, with results indicating high accuracy. The SVM model's accuracy ranged from 98.5% for the fuel system to 96.6% for the ignition and cooling systems, with the fuel system showing the highest accuracy. Across the four operating systems, the SVM classifier consistently performed the best, achieving accuracies of

96.6%, 98.7%, 98%, and 96.6%. Additionally, a study in [101] demonstrated the viability of applying various ML techniques, such as Gaussian Processes (GP), Support Vector Machines, several kinds of Artificial Neural Networks, and Random Forest, as classifying predictions for fault identification jobs. For defect identification in turbo petrol engine systems, the authors used datasets for training and testing obtained from standardized driving cycles produced using a simulation testbed. The Random Forest approach yielded the best results, as its minimum accuracy, 0.88539, was greater than the Support Vector Machine approach's second-highest accuracy of 0.806120. Furthermore, the accuracy of all techniques can be improved by applying a low pass filter to the outputs.

Table 3. Overview of automotive component predictive maintenance research using machine learning: top use cases

References	Validation Environment	Use case	Machine learning method
[91]	do not present primary validation	Faults in engines	ANN revision
			Logistic regression and residual selection.
[92]	Laboratory (Lab): test bench in a laboratory setting, with experimental results		LSTM and CNN, SVM of one class, random forest, and logistic regression
[93]	Simulation (Sim) through software simulation in MATLAB/Simulink. and Laboratory (Lab)		ANN
[94]	Laboratory (Lab)	Batteries for SoH EVs	ELM vs. ANN
			LSTM
		Battery issues with EVs	-random forests
		EV powertrain issues	k-NN, SVM, ANN variation
		Detection of all car faults	Ensemble of classifiers for one and two classes
		Air pressure system flaws	ANN, CNN, LSTM
[95]	Physical fuel cell test station using a Scribner Associates test station, making this a laboratory-based study.	Problems with gearboxes	Deep hybrid belief networks
[96]	do not present primary validation	Suspension system flaws	ANN, CNN, NARX
[97]	Real Driving Conditions (RDC) provided by an automotive manufacturer.		SVM
[97]	Real Driving Conditions (RDC) provided by an automotivemanufacturer.	Brake system errors	SVM, ANN, Hoeffding trees, and best initial trees
		Steering system flaws	Rough set theory, deciduous trees, SVM, k-NN, and an ANN variation
[89]	Simulation (Sim) / Computational Screening	Defect detection for sensors	ANN and ELM-based autoencoders
[90]	do not present primary validation	Fuel cell automobiles	LSTM with attention and GRU (gated recurrent unit)
[98]	Laboratory environment.	Mechanism of starting an engine	Multinomial regression models combined
[99]	Simulation (Sim) via FASTSim and Laboratory (Lab)	Automated SoH vehicles	CNN

Machine Learning for Fuel Efficiency and Emissions

Energy usage is significantly influenced by transportation, and driving habits have a significant impact on how much gasoline cars consume. In the literature, there are many articles dealing with fuel consumption prediction, engine performance optimization for better fuel efficiency, and emissions control using machine learning. For example, in [102] authors present a Multi-Linear Regression (MLR) in machine learning to demonstrate the weighted effect of independent variables. According to [103], a reinforcement learning algorithm is proposed to utilize road altitude data for the intended route, training deep neural networks with the aim of creating a fuel-efficient speed profile for autonomous cars. This demonstrated technique, based on neural networks, can be trained to develop effective strategies for improving fuel efficiency even on uncharted routes. Consequently, it increased fuel efficiency by 8% over a straightforward grid search method. In [104], to maximize fuel efficiency across the fleet, the model proposed by the authors can be quickly tailored for every single car and connected to the group. The method employed is a data synthesis strategy applied to a distance approach as opposed to the usual time frame. The results suggest that, for routes comprising both bicycle paths on city streets and highways, fuel consumption may be predicted with a coefficient of 0.91 and a peak-to-peak percentage error of less than 4% within a 1-kilometer window. In [105], the effectiveness of experimental results for a dual fuel compression ignition (CI) engine running on hydrogen and diesel was assessed using machine learning regression models. In this work, in order to assess different emissions such as hydrocarbons (HC), oxides of nitrogen (NO), carbon dioxide (CO), and smoke, factors such as hydrogen concentration, engine load, diesel intake, speed, and equivalency ratio were taken into account. The following performance measures were used: coefficient of correlation, relative absolute error, mean absolute error, root mean squared error, and root relative squared error. In [106], the authors introduced two types of ML methods to evaluate the use of naturalistic driving data in determining how fuel-efficient a driver performs. The results show that the suggested approach can successfully establish a link between driving style and fuel usage at the macro and micro levels, making it possible to forecast the features of fuel consumption from beginning to end. These predictions could subsequently be used in innovative driver assistance technologies. Additionally, in [107], fuel economy maxima in NEDCs (New European Driving Cycles) for FC electrical cars were examined. Traditional Multiphysics analysis, experiment design, and machine learning are effectively blended in a novel way to accelerate the delivery and analysis of data that precisely estimates the peak fuel usage in FC electric cars. The findings from the trained and verified models are extremely precise, with less than 1% inaccuracy.

And in [108], two machine learning models were created and used for two light car chassis emission tests and a truck Real Driving Emissions (RDE) test. The methodology presented in the research and the created digital twins' model accurately predicted immediate and cumulative fuel usage, even for test cycles that were different from those used to train the model.

Advances in Driver Assistance Systems, Autonomous Vehicles, and Safety Technologies

Automated vehicles represent a significant advancement in road safety, aiming to mitigate the predominant cause of accidents: human error. Advanced Driver Assistance Systems (ADAS) have a crucial role in this paradigm shift. ADAS, encompassing features such as automated park assistance systems, adaptive cruise control, lane departure warning, front collision warning, automotive night vision, driver monitoring systems, and anti-lock brake systems, significantly enhances driver safety. These systems leverage data from diverse sources, including Light Detection and Ranging (LIDAR) technology, radar systems, and cameras, to provide comprehensive situational awareness [109].

In parallel, the development of autonomous vehicles is underpinned by sophisticated infrastructure. A multifaceted architecture, as outlined in [59], integrates IoT layer processing, cloud computing, fog computing, and machine learning. This framework not only supports the operation of autonomous cars but also forms the foundation for their intelligence and connectivity.

Furthermore, in the domain of automated vehicle movement and operation, reinforcement learning has emerged as a promising methodology. By combining perceptual planning with reinforcement learning techniques, the movement of automated vehicles becomes more nuanced and contextually aware. Deep learning neural networks, augmenting traditional machine learning methods, amplify the benefits of these advancements, heralding a future where travel is both safer and more efficient [109].

Distractions are a common cause of auto accidents, often exacerbated by factors such as variable message signs (VMSs) that demand extra attention, leading to distraction on the road. This section explores developments in autonomous vehicle technology and safety measures implemented through machine and reinforcement learning, as discussed in the literature:

- For Autonomous Vehicles (AV) safety, authors in [109] build machine learning models utilizing data from the European HyTunnel project's tests for predicting the effects of hydrogen emissions in enclosed spaces. Additionally, the project presented in [110] aims to develop a prototype of a machine learning-based Variable Message Sign (VMS) reading system, a technology that is currently underutilized, particularly in this area. As a result of the research, a prototype Advanced Driver Assistance System for interpreting various message signs has been acquired. The system operates using RetinaNet, a neural network built on ResNet50, with an average accuracy of 0.703. On the other hand, the authors in [111] propose the implementation of Advanced Driver Assistance Systems using a combination of machine and deep learning algorithms. As a result, this approach reduces the complexity and size of the vehicle's sensors.
- For Safety requirements and challenges with autonomous automobiles, accidents and deaths can be the consequence of human error elements like poor judgment, distractions, and fatigue. Thus, autonomous vehicles (AVs) have the potential to increase vehicle safety by lowering the number of traffic accidents and driving errors caused by people. To minimize human errors in driving, enhance security, and optimize the movement of traffic, modern technologies are used by AV, including GPS, Electronic Control Units, 3D mapping, path planning, and LiDAR sensors [23]. The challenging assignments for AV, in which security and safety require major research efforts. Security for AV focuses on protecting the automobile from intentional incidents, whereas safety for AV guards against unintentional collisions [63]. A multisensory AV system can anticipate potential threats and respond appropriately. In such situations, AV could evade the incident or accident by altering course. The integration of modern technologies like AI/ML, IoT, and big data analysis makes these capabilities feasible. In [23], [63], the authors discussed accident problems identified through machine learning techniques and highlighted the detrimental and unanticipated behavior of insufficient artificial intelligence systems. The authors listed several research issues and categorized them specifically under unintended risks. Several critical challenges related to autonomous vehicles have been classified as open issues, including the treatment of data as the equivalent of oil in AVs. AVs often accumulate petabytes of data, posing challenges in parallelizing training procedures with storage resources.

Smart Traffic Management

Urban traffic congestion has become a significant issue. Traditional traffic management techniques do not effectively regulate traffic and lack proper human resource management, leading to increased traffic congestion and road infractions.

For addressing serious vehicle, traffic issues on a large scale, Intelligent Transportation Systems (ITS) offer solutions that enhance safety, effectiveness, and sustainability. ITS utilizes machine learning in collaboration with existing traffic control systems to create real-time plans and ensure a smooth flow of traffic. Many researchers have achieved outstanding results by employing various optimization strategies for the deployment and control of intelligent traffic systems.

In the realm of intelligent transportation systems, a comprehensive classification of the areas of application as: smart cities (Emergency vehicle, Pollution prevention, Navigation, Smart parking, Traffic optimization), traffic management (Traffic optimization, Police scheduling, Traffic Light control) and safety (Vehicle tracking Accident prevention) where in ITS is actively employed. In significant smart cities, ITS plays a pivotal role, offering diverse functions, most notably in traffic management and safety. These components, supported by research **[112]**, form the backbone of seamless vehicular movement in urban landscapes. A range of ITS applications, including parking guidance, weather reporting systems, early collision termination systems, variable speed limits, emergency vehicle alarm systems, pollution controls, automated traffic enforcement, and even dynamic bridge management, facilitates this seamless movement. Additionally, the traffic management applications within the ITS framework encompass vital aspects such as emergency vehicle routing, ensuring traffic regulations, accident prevention, and faster traffic clearance. These integrated technologies collectively enhance the efficiency and safety of urban transportation systems, ensuring a smoother and more secure experience for commuters.

In this section, a traffic management system based on machine learning is analyzed, aiming to ensure the efficient utilization of human resources, time, money, and fuel to create sustainable smart cities **[113]**. For instance, in **[114]** researchers have focused on modern strategies for optimizing signal processes, with Reinforcement Learning being a major approach under scrutiny. Gradient Boosting Regression Tree (GBRT) and reinforcement learning were integrated to decrease state complexity and latency, respectively. The results demonstrated that the suggested control technique significantly reduces waiting delays and state-space complexity. Additionally, authors in **[115]** introduced a systematic approach to address challenging prediction issues, emphasizing energy efficiency. In order to determine which recurrent and sequential neural network was the most efficient in terms of computation time and prediction accuracy, the case study compared four different neural network architectures: long short-term memory, gated recurrent units, online sequential extreme learning machine (OS-ELM), and recurrent neural networks. The outcomes showed OS-ELM performed better than the other networks in computational precision and effectiveness. Using real traffic data in a simulation, it was predicted that daily energy savings of up to 12.2% could be achieved.

CHALLENGES IN APPLYING MACHINE LEARNING FOR FUEL CELL ELECTRIC VEHICLE

Among the many obstacles to the integration of Machine Learning in FCHEVs, data concerns stand out as the most important. The following subsections delves into the core of these barriers, beginning with a critical evaluation of the data requirements, with a particular emphasis on the dimensionality and reliability of the input data.

Data Requirements and Challenges for Machine Learning for Fuel Cell Electric Vehicle

The selection of input variables is a crucial design factor that presents two constraints. First, the number directly determines model complexity and computational load and kind of features, thus dimensionality reduction is frequently necessary to lessen the curse of dimensionality. Second, the precision, sampling rate, and signal-to-noise ratio of the source data—which is frequently obtained from automotive-grade sensors functioning in challenging conditions—determine the model's predicted accuracy and dependability in the actual world. Therefore, an ideal framework must strike a compromise between the practical limitations of data collection and computational complexity. A list of common input variables and related data challenges for machine learning in FCHEVs is shown in **Table 4**.

Table 4. Common Input Variables and related data challenges for machine learning in FCHEVs

Application field	Typical Input Variables	Source of data	Important Data Challenges
Energy Management	Fuel cell efficiency map, GPS/traffic data, battery SOC, power demand, and H_2 tank level	Cloud, , Sensor, Maps	Variety of data; dependability of outside data (traffic forecasts, for example); and requirement for real-time processing.
Fuel Cell Prognostics	Temperature, pressure, voltage, current, H_2 purity, and historical loading	Physical Sensor	Sensor noise, linked features, high dimensionality, and the necessity of feature selection to prevent over fitting.
Fault Diagnosis	Voltage/current ripple, acoustic data, temperature gradients, gas composition	Microphone, Sensor	Class imbalance (limited examples of faults); high-frequency data necessitates substantial processing and storage.

Dimensionality and Reliability of Input Data

The practical limitations of direct sensor readings for important system states provide a substantial barrier to real-world deployment of machine learning models in FCHEVs. Due to sensor cost, reliability, or the intrusive nature of measurement, many factors that are crucial for optimum control, prognostics, and health management are either impossible or prohibitively expensive to monitor directly under actual driving conditions. This means that inferring these values from existing, correlated data requires the use of soft sensors and state estimation techniques. The table below (**Table 5**) outlines significant unmeasurable variables, their influence on system functioning, and the principal methodologies used for their estimate, showing a critical area where model-based and data-driven approaches must work together for successful application.

Table 5. Key Unmeasurable Variables and Estimation Approaches in FCHEVs

Unmeasurable Variable		Impact on System Performance and Health	Common Estimation Techniques
PEMFC Membrane Hydrations		-Directly affects durability, efficiency, and proton conductivity. -Flood and dehydration both significantly decrease performance.	• Data-driven soft sensors employing stack voltage, current and temperature • High-Frequency Resistance (HFR) Measurement • Adaptive Kalman Filter
Battery	**State of Health (SOH)**	Vital for estimating the maximum power limitations and residual energy capacity, which has a direct effect on lifetime and energy management strategy (EMS).	• The combination of model-based and data-driven methodologies • Machine Learning regression on impedance/voltage properties • Coulomb counting and differential voltage analysis
	State of Charge (SOC)	Vital for controlling high-power transients and maximizing the effectiveness of regenerative braking. Temperature and current have a significant influence on voltage-based SOC.	• Hybrid models that combine electrical and thermal dynamics • Recursive Least Squares (RLS) for parameter identification • Adaptive Kalman Filter
Catalyst Degradation State		Increases activation losses and causes irreversible voltage decline by decreasing electrochemical active surface area (ECSA).	• Machine learning models trained on voltage transient data • Voltage loss decomposition mrthods • Model-based observers (Extended Kalman Filter)
Precise Internal Temperature Gradients		Degradation of the battery and FC is accelerated by local hot areas. Effective thermal control is essential for longevity and safety.	• Neural networks trained on surface temperature data • Nonlinear observers • Distributed thermal models with lumped parameter inputs

Therefore, the accuracy and resilience of the underlying estimating techniques inextricably link to the performance of any ML-based application. Future research should thus concentrate on the co-development of integrated frameworks that combine robust state estimation with sophisticated ML control and diagnostics, assuring dependability under the noise, uncertainty, and dynamic situations of real-world driving.

PERSPECTIVES

As remarks, regarding the EMS area, reinforcement learning-based EMS is suggested due to its benefits over other techniques as mentioned above, in particular deep RL, using various approaches. In general, in the different applications exposed in the review, machine learning based EMS is performed to increase the efficiency of all onboard power utilization by distributing energy more evenly, using less H2, and avoiding FC deterioration. Reinforcement learning-based EMS is receiving greater attention from researchers due to its benefits over other techniques, such as: 1) Q-learning is suggested to reduce FCHEV's fuel usage; 2) DQN suppresses system degradation; 3) DRL optimizes the vehicle driving cost.

As to the use of machine learning for predicting performance, it may be extended to deep learning to fuel cell performance by including pertinent physics.

Respecting FC vehicle diagnostics and maintenance, attention-based LSTM could provide the best prediction results for predicting FC's output voltage based on load current and degradation. In addition, the ANN and GPR strategies outperformed previous approaches and produced high performance. With regard to SoC projections, GPR and ANN may support creating an ideal battery management system for electrical cars. For Driver Assistance and Safety, basic ML methods are not immediately used due to the geographical and temporal nature of the data. A complicated and nonlinear dataset is appropriate for deep learning-based algorithms.

As perspectives, a machine learning strategy based on a hydrogen fueling stations (HRS) for fuel cell hybrid electric vehicle (FCHEV) production and storage is proposed [116], [117]. The proposed station based on renewable energy sources (REs) is composed of four primary blocs: REs, hydrogen storage tank, alkaline electrolyze, and grid-connected component, as seen in Figure 4.

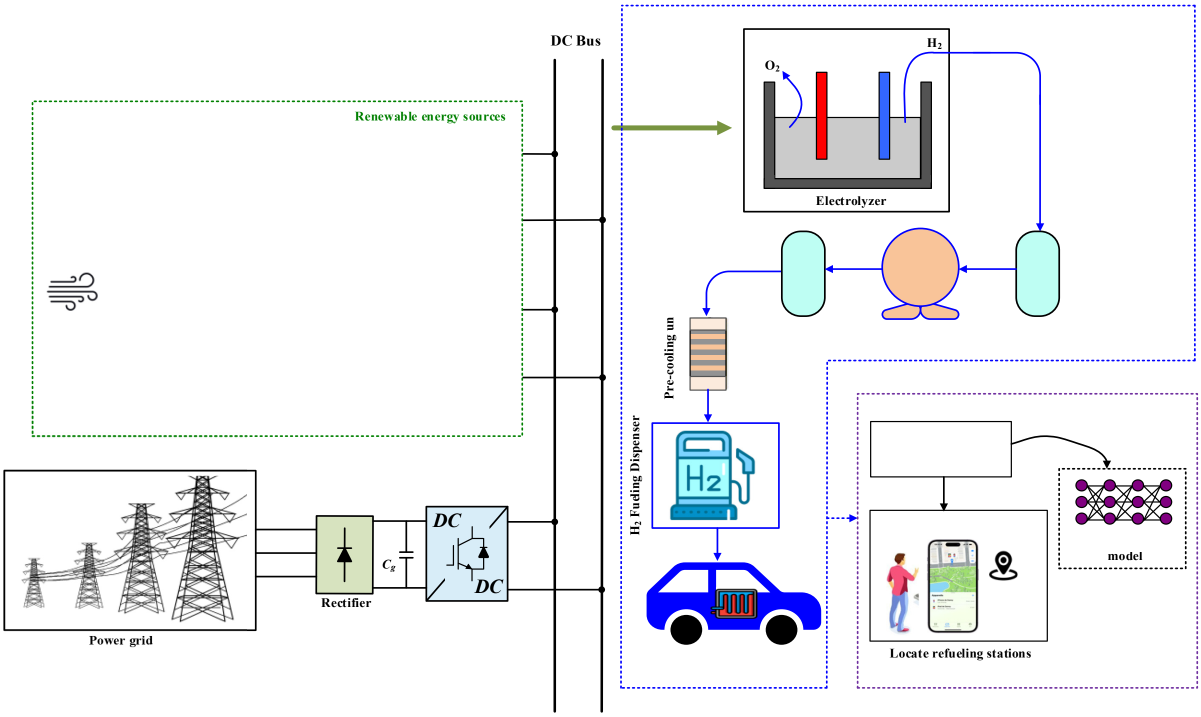

Figure 4. Renewable energy sources powered the hydrogen refueling station

The principal elements employed when transitioning from producing to delivering hydrogen are as follows: An on-grid photovoltaic and wind power system is designed to drive water electrolysis plant to produce hydrogen for an improved FC electric vehicle. The purification unit, compressor, storage tank, gas boosters, cooling unit, safety devices, mechanical and electrical systems, and dispensers are all parts of the hydrogen production chamber that are also implemented [53], [116]. Then, a compressor is utilized to raise the station's tanks' hydrogen gas pressure from low to high in order to prevent overheating and overfilling while recharging the quick storage [117]. Besides, pre-cooling unit and dispenser are integrated. Hydrogen needs to cool down before being refueled since it can overheat if it is refueled directly [117].

This proposed study offers an attractive solution to reduce hydrocarbon fuel consumption. Therefore, in order to reduce cost and enhance system reliability, an efficient operation algorithm based on hydrogen energy demand estimate is investigated for directly hydrogen fueling stations [118], [119]. For instance, an optimization technique based on harmony search for the most efficient possible size of a hydrogen storage system-based solar/wind power generating system is needed in order to optimize reliability and decrease cost. This paper shows that the proposed method can first decrease the storage tank [102], electrolyze ratings configuration for HRS [103], and second decrease the hydrogen energy unit [120], [121], [122].

HRS and their optimal location strategies can be discussed in upcoming works [109]. In fact, optimization strategies and methods based on machine learning approaches can be used to locate hydrogen fuel refueling stations [110]. A machine learning model can be employed for urban areas by simulating and forecasting refueling behavior using data (**Figure 4**). The model gap is significantly dependent on big data sets, which can be improved in future projects [123], [124], [125], [126].

Machine learning techniques are recommended for process categorization and prediction. Monitoring hydrogen refueling stations guarantees both operational safety and compliance with the necessary refueling performance standards. The fueling process was traditionally controlled by table-based or dynamic control techniques. The primary performance goal of the mechanism for fueling and the state of charge (SOC) are to be predicted using machine learning techniques, according to this study.

Finally, numerous researchers have explored reinforcement learning techniques in various hybrid electric powertrain applications. However, their applicability to FCHEV is still evolving. A promising avenue for future research is to conduct in-depth examinations of energy management systems utilizing reinforcement learning.

FCHEV's machine learning system will be able to analyze vehicle behavior to predict potential failures, providing a solution that minimizes costs associated with unscheduled downtime, increases asset longevity, and improves efficiency during operations. To achieve these goals, it is imperative to explore cutting-edge algorithms and machine learning methods designed to meticulously monitor the car and its operations. This opens the door to future advancements and innovations.

CONCLUSION

This research explores the use of machine learning in fuel cell hybrid electric vehicles applications. This research’s highlights and conclusions can be synthesized as follows: design of cells and enhancement, system management, and operation health monitoring are developed to ensure both durability and performance. Then, the integration of an effective Energy Management System is suggested for meeting load requirements while optimizing power sources in FCHEVs. A comprehensive comparative study is provided, highlighting the advantages and challenges. In literature, attention has been given in RL-based EMS due to its advantages over competing methods. In the reviewed works, RL is proposed to reduce fuel consumption in FCHEVs. The average fuel usage decreased by 5.7% compared to the rule-based technique. On the other hand, it optimizes the vehicle driving cost and mainly suppresses the system degradation based on the following algorithms: i) Deep Q-Networks presents an increasing economy of hybrid system by 16.0%, the FC degradation reached 88.73%, and the computational efficiency increased by more than 70% and ii) TD3-based EMS indicates an improvement in overall operational cost up to 28%.

Solutions for these challenges are explored, paving the way for future research endeavors. In fact, fuel cell degradation is a significant challenge faced by hydrogen FC vehicles. Robust prediction techniques based on machine learning are presented as effective solutions for data-based fault diagnosis. These models have significant influence on fuel consumption and overall emissions. These models play a pivotal role in reducing fuel usage by 13.9% in the Federal Test Procedure FTP-75 Driving Cycle and 14.32% in the NEDCs, and overall emissions by generating less than 26.4% CO2 emissions. For driver assistance and safety, a complicated and nonlinear dataset is appropriate for deep learning-based algorithms.

Finally, this paper has identified several challenges and suggested future research directions. This comprehensive overview has delineated the significant potential of ML in advancing FCHEV technology; however, it also unveils critical research gaps that must be bridged to transition from laboratory simulations to real-world deployment. The most prominent experimental gap is the scarcity of high-quality, publicly available datasets encompassing diverse driving conditions, fuel cell aging profiles, and fault scenarios, which severely limits the training robustness and benchmarking of ML models. Furthermore, a significant knowledge gap exists in the integration of physics-based models with data-driven ML, particularly for explaining the 'black-box' decisions of complex algorithms and ensuring their predictions adhere to thermodynamic and electrochemical principles. This is crucial for safety-critical applications like predicting hydrogen leakage or cell failure. Finally, there is a pronounced gap in standardized validation protocols for comparing the real-time performance, computational efficiency, and durability of different ML strategies under identical conditions. To address these gaps, future research must prioritize: (1) the creation of open-source data initiatives and digital twins for robust testing; (2) the development of explainable AI (XAI) and hybrid physics-informed ML models to enhance trust and generalizability; and (3) the establishment of universal benchmarking standards to evaluate the real-world viability and longevity of ML-driven energy management and prognostic systems. Pursuing these directions will be pivotal in achieving the safe, efficient, and widespread commercialization of AI-enhanced fuel cell vehicles.

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Abbreviations

A
AC Alternating Current
ADAS Advanced Driver Assistance Systems
AE Autoencoder
AI artificial intelligence
AFCs alkaline fuel cell
ANNs Artificial neural networks
APE Absolute Percent Error
APF artificial potential field
APU auxiliary power units
ARIMA Auto-Regressive Integrated Moving Average
AV Autonomous Vehicles
B
BDC bidirectional converter
FCHBs FC hybrid buses
FCV fuel cell vehicle
FCs Fuel Cell system
FTP Federal Test Procedure
G
GBRT Gradient Boosting Regression Tree
GP Gaussian Processes
GPR Gaussian Process Regression
GRU Gated Recurrent Units
GNN gray neural network
GBR Gradient Boosted Regression
GA Genetic Algorithm
H
HC hydrocarbons
P
PAFCs Phosphoric acid fuel cells
PCA Principal Component Analysis
PdM Predictive maintenance
PEMFCs Polymer Electrolyte Membrane Fuel Cell
PER Prioritized Experience Replay
PFSA Perfluorosulfonic Acid
PvM Preventive maintenance
Q
QL Q-Learning
R
RD The data types are Real Data
RDC Real Driving Conditions
RDE Real Driving Emissions

BOP Balance of Plant
C
CI compression ignition
CO Carbon dioxide
CNN Convolutional Neural Network
D
DBSCAN Density-Based Spatial Clustering of Applications with Noise
DC direct current
DDPG Deep Deterministic Policy Gradient
DFC Dual-stack fuel cell
DFT density functional theory
DL Deep learning
DMSC dual metal site
DNN deep neural networks
DP Differential privacy
DQL Deep Q-Learning
DQL double QL algorithm
DQN Deep Q-network
DRL Deep Reinforcement learning
D-S Dempster-Shafer
DT Decision tree EBa Ensemble bagging
E
ELM Extreme Learning Machine
EMS Energy Management System
ESN Echo State Network
EVs electric vehicles
F
FCHEVs fuel cell hybrid electric vehicles
FCEVs fuel cell electric vehicles
HI health indicator
HS health indicator
HT-PEMFC High-temperature PEMFCs
HRS hydrogen refueling stations
I
IoT Internet of Things
IQL independent Q-learning
ITS Intelligent Transportation Systems
K
k-NN k-nearest neighbors
L
Lab Laboratory/Test Bench
Lidar Light Detection and Ranging
LRMPC learning-based robust model predictive control
LR Linear regression
LSTM Long short-term memory
LSTM-RNN long-short-term memory recurrent neutral network
M
MBRL model-based RL
MCFCs Molten carbonate fuel cell
MFCs multi-stack fuel cell system
MLR Multi-Linear Regression
ML Machine Learning
N
NARNN nonlinear autoregressive neural network
NEDCs New European Driving Cycle
NMF non-negative matrix factorization
O
ORR Oxygen Reduction Reaction
OS-ELM online sequential extreme learning machine
RQ Research Question
RF Random Forest
RL Reinforcement learning
R&D research and development
RNN Recurrent neural network
RtF Run-to-failure
RUL remaining useful life
REs Renewable energy sources
S
SAE sparse autoencoders
SARSA State Action-Reward-State-Action
SD Synthetic Data
Sim Simulation/Model
SOC state of charge
SOFCs Solid oxide fuel cell
SOH state of health
SVM Support vector machine
SVR vector machine regressor
T
TD3 Twin Delay Deep Deterministic Policy Gradient
t-SNE t-distributed stochastic neighbor embedding
U
UAV Unmanned Aerial Vehicle
UC ultracapacitors
UDC unidirectional converter (buck or boost converter)
UDDS Urban Dynamometer Driving Schedule
V, W
VMSs variable message signs
WD wheel D

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