

Review

The Role of Digitalization in the Advancements of Fuel Cell Systems for Sustainable Energy Conversion

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Abstract: Fuel cells have been increasingly considered one of the most advanced energy conversion technologies due to the various advantages they offer in terms of performance and environmental benefits compared to other conventional systems. However, due to their complexity and multi-influencing factors, they face several challenges related to maintenance, optimization, monitoring, and prediction. Owing to these factors, the integration of digitalization technologies into fuel cells has frequently shown a promising approach to overcome such challenges. This paper provides a detailed investigation of the recent advancements in fuel cell digitalization, namely digital twin, machine learning, and IoT, with a focus on the developments carried out in the last 5 years. According to the reported studies, these technologies have been utilized in a wide variety of applications and objectives, including electric vehicles, energy management, fault detection, and predictive maintenance. Through examining the various digitalization technologies, the integration of machine learning into fuel cells is currently the most mature and commonly used technique in comparison to the other investigated digitalization technologies. This paper highlights the viability and pathways of integrating digitalization into various types of fuel cells, such as proton exchange membrane, solid oxide, and microbial fuel cells, for a more sustainable energy conversion and management systems.

Keywords: fuel cells; digital twin; machine learning; internet of things; hydrogen; artificial intelligence

1. Introduction

Fuel cells are considered to be one of the key technologies for electricity generation among clean and efficient energy systems, with high efficiencies and low environmental impact compared to conventional power production techniques [1]. Moreover, it has a wide range of applications, including stationary systems, portable devices, and transportation [2]. The employment of fuel cells in such applications offers various benefits related to sustainability and energy-efficient utilization. For instance, using fuel cells in vehicles generates zero emissions and allows long distances with fast refueling [3].

One of the major topics that requires investigation is the optimization and improvement of membrane production costs and service life [4]. Furthermore, the broad deployment of fuel cells is still limited because of operational challenges, variable performance, and costly system integration and maintenance [5]. To address these challenges, digitalization technologies, such as digital twin (DT) [6], machine learning (ML) [7], and the Internet of Things (IoT) [8], are increasingly being adopted to enhance the design, control, and optimization of fuel cell systems. DT technology provides a real-time virtual representation of the physical fuel cell systems, which enables



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predictive modeling, remote monitoring, and performance optimization [9]. When combined with ML, DT will have the ability to learn from historical and real-time data to identify complex system behaviors [10]. Moreover, IoT expands the functionality of fuel cells by enabling continuous sensing, connectivity, and intelligent feedback control, particularly in distributed or mobile energy environments such as fuel cell electrical vehicles (FCEVs) and off-grid energy harvesters [11,12].

This paper provides a detailed analysis of integrating digitalization technologies in fuel cell systems, with a particular focus on DT, ML, and IoT reported over the last five years. It analyzes the three technologies within a unified framework, assessing their relative maturity, complementary roles, and applications. The study aims to examine the viability of these technologies to address key challenges in fuel cell operation, including performance optimization, real-time monitoring, fault detection, predictive maintenance, and energy management. Moreover, the capabilities and limitations of each technology across different fuel cell types, highlighting the existing technical and economic challenges.

2. Methodology

This section sets out the systematic approach used to identify and appraise the literature analyzed in this paper. A state-of-the-art review methodology was employed to examine the integration of DT, ML, and IoT in fuel cell systems. The purpose of this review is to summarize new development trends, analyze the deployment tactics, and describe technological difficulties in fuel cell technologies.

2.1. Review Framework

The review process is illustrated in Figure 1, which outlines the structured approach: from initial topic definition and keyword formulation to inclusion/exclusion screening and thematic synthesis. Only peer-reviewed journal articles, conference papers, and review studies published in English between 2020 and July 2025 were considered. A total of 175 publications were retrieved from the Scopus database using the following search string: TITLE ((“Machine Learning” OR “Digital Twin” OR “IoT” OR “Internet of Things”) AND “fuel cell*”) AND PUBYEAR > 2019 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “cp”) OR LIMIT-TO (DOCTYPE, “re”)) AND (LIMIT-TO (LANGUAGE, “English”)).

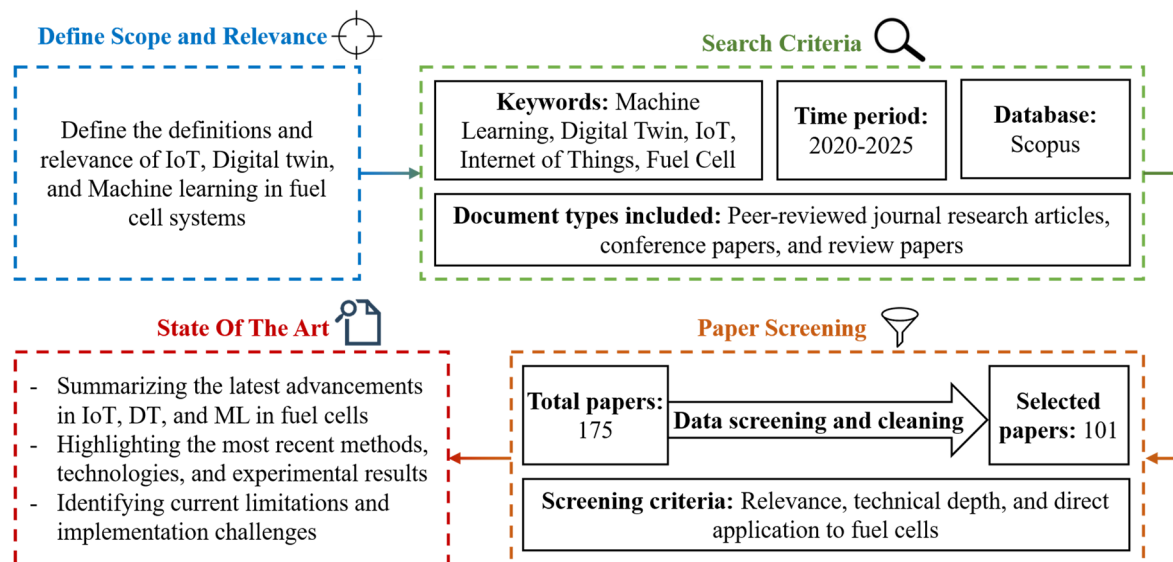


Figure 1. Flowchart of the review methodology.

2.2. Inclusion Criteria and Selection

The retrieved papers went through initial screening to ensure they fit the following inclusion criteria:

- Addressed the application of ML, DT, or IoT in fuel cells.
- Provided technical depth, such as quantitative performance evaluation, model training, or system simulation.
- Presented either experimental results or validated modeling approaches.

Out of the 175 papers initially retrieved, 74 were excluded during screening, leaving 101 studies for in-depth review. These exclusions fell into three broad groups. Approximately 15% were removed because of accessibility issues. The second group, accounting for roughly 40% of the exclusions, was removed because the work addressed

adjacent topics, such as general hydrogen production, water electrolysis, or stand-alone IoT and machine-learning applications, without explicit integration into fuel cell systems. The remaining exclusions were screened out for insufficient technical depth, meaning that they did not report quantitative performance evaluation, model training details, or experimentally or numerically validated results. This screening outcome is summarized in the review flowchart in Figure 1.

All papers were appraised against a consistent set of quality indicators: the clarity of the modeling or experimental methodology, the availability of quantitative validation metrics such as R^2 , root mean square error (RMSE), or accuracy, the size and representativeness of the datasets used, and whether the reported results were validated experimentally or only through simulation. Studies satisfying more of these indicators were given greater weight in the thematic analysis, whereas those offering limited validation or based on small datasets were retained mainly as supporting evidence.

2.3. Thematic Review Method

To synthesize the literature on ML, DT, IoT, and fuel cells, a thematic review was performed by establishing qualitative analysis principles [13]. This method allowed for the identification and interpretation of recurring patterns across 101 selected studies systematically focused on fuel cell digitalization.

The selected papers were grouped into thematic categories based on their core contributions, such as:

- Performance prediction and optimization,
- Fault detection and diagnostics,
- Thermal/flow-field design,
- Real-time control and IoT-based integration,
- Material and catalyst modeling

This thematic classification allowed for a focused, cross-comparative synthesis of technological trends, methods, and future research directions.

3. Digital Twin in Fuel Cells

3.1. Background on Digital Twin

Building on the thematic categorization defined in the methodology, this section presents the first of the three digitalization technologies (digital twin), which most directly mirrors the physical fuel cell system. DT represents the next evolution in simulation technology [14]. It was first defined at the University of Michigan in 2003 as a digital representation of a physical product [15], and was merely utilized as a data acquisition system to collect data throughout the life cycle of a product. Nowadays, DT has developed into a whole integrated system which contains three parts: the physical part, the virtual part, and the connection between them, as shown in Figure 2. DT works by creating a virtual replica of the physical system for optimization and prediction [16]. It can help to adopt the transition aimed at creating more sustainable energy systems [17], particularly when combined with ML, as it gives the capability to emulate patterns that are used to optimize critical parameters [9].

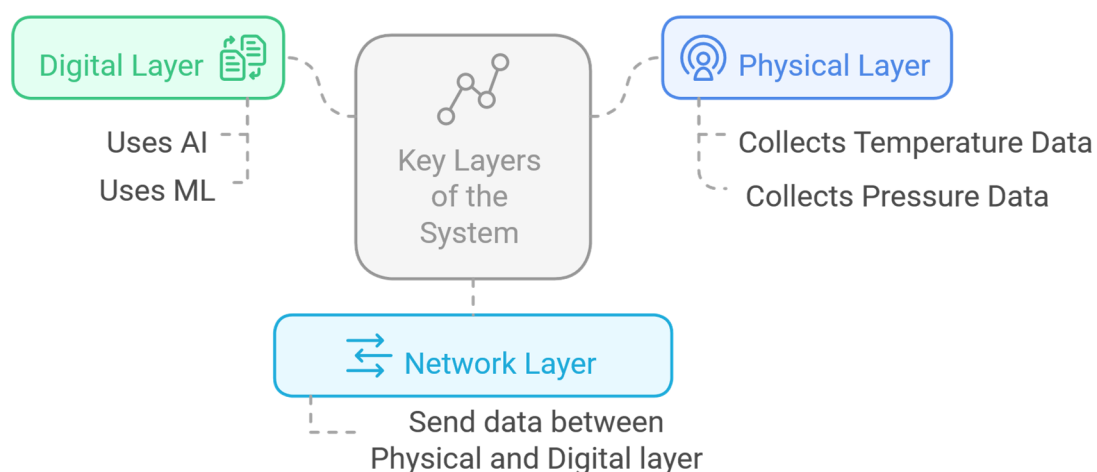


Figure 2. General layout of a digital twin system.

The DT workflow starts by gathering initial data, which is later trained to adapt to real-life models and finally employed to predict and optimize the required scenarios, as illustrated in Figure 3. For example, a loss function called QH-loss teaches the model to make accurate predictions about the lifetime of a fuel cell. After this, the digital layer can be adapted to the real-time data to be ready to estimate the Remaining Useful Lifetime of the fuel cell [18]. The primary aspect of modeling the physical system in a DT is to use simulation tools to construct a virtual replica; this step is called digital backward [19]. DT can be used for multiple objectives; for example, it can simplify and eliminate the excess modeling time and cost associated with conventional simulation models, such as computational fluid dynamics (CFD) [20]. Moreover, DT can be used to maximize the fuel cell power output by simulating the performance cycle of a fuel cell and employing maximum power point tracking (MPPT) algorithms. These algorithms control the fuel cell with optimized parameters derived from the simulation [16]. Nowadays, DT is used in many industries, such as the transportation sector [21], with a wide range of applications.

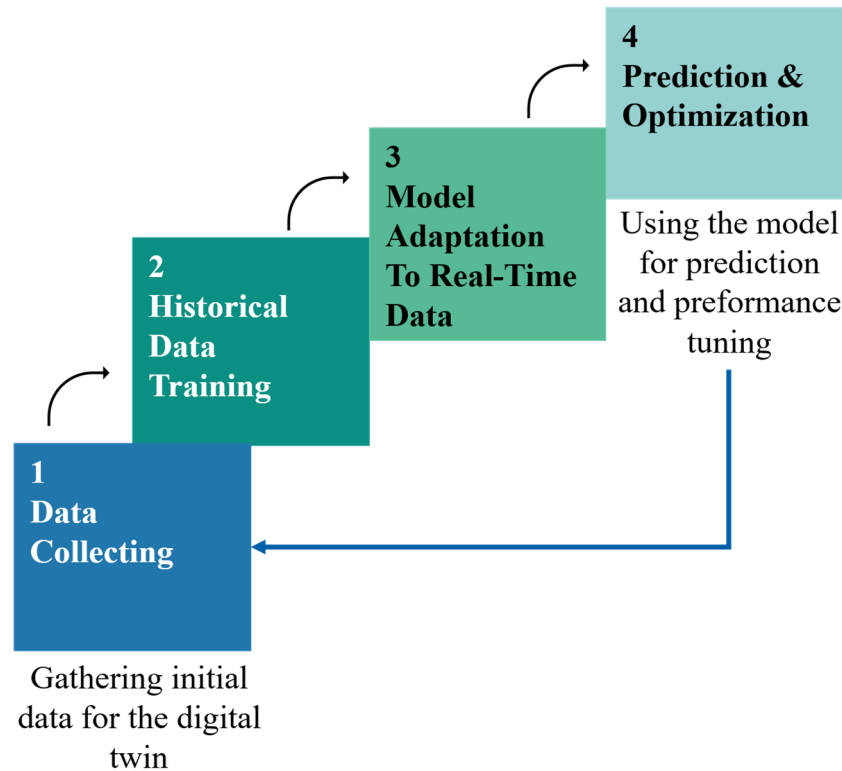


Figure 3. Digital twin workflow.

3.2. Applications in Fuel Cell Optimization and Monitoring

Kang et al. [22] highlighted the DT's role in optimizing 25 kw plant-scale solid oxide fuel cells (SOFC) by scaling down the plant to 1 kw, integrating auxiliary components (e.g., methane reformers, downstream burners, and heat exchangers) into the DT. The model was able to predict and optimize the performance of a commercial 25 kW SOFC plant with voltage errors below 5%, reliably guiding safe and stable operation. DTs can also bridge cell-scale CFD and stack-scale simulations for both PEMFCs and SOFCs, compressing compute time from 1–2 days to under a second while maintaining <1% error, as shown in the results of a study by [20]. Similarly, Uralde et al. [16] proposed a DT-based MPPT controller in PEMFCs. The proposed model reduced the Integral of Absolute Error by 67% during startup and by 42.9% during load variations as compared to the conventional sliding mode control.

Zhang et al. [18] found that the DT works more effectively when trained on constant data because it can learn clearer patterns without being affected by sudden changes. DTs can eliminate the need for collecting faulty data by simulating multiple scenarios to collect a large set of data, as shown in [23,24], which helps to reduce cost and improve the accuracy of other frameworks, calculate the RUL of a product, and drive design optimization. DT can be designed to simulate the gas, water, thermal, and electrical interactions within a PEMFC. As shown in Figure 4, several assumptions can be adopted. For example, in [24], gas transport processes can be assumed to follow the ideal gas law.

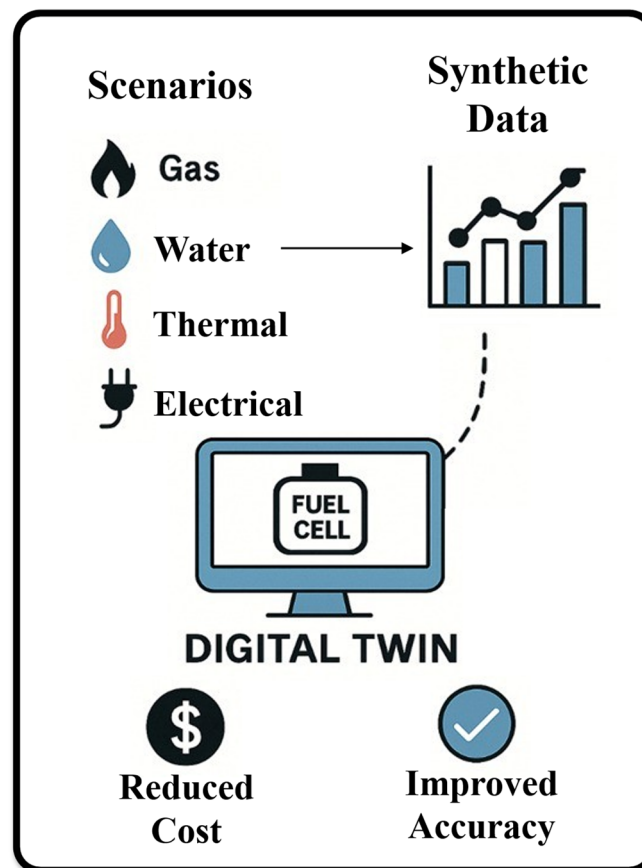


Figure 4. Scenario simulation and digital twin integration for fuel cell optimization.

Autoencoders were also explored as a method with the ability to discover more features by adding noise to the input data and training the model to reconstruct the original noise-free input data. This approach is known as a denoising autoencoder; using this method, the DT will be improved to become more reliable and flexible in many scenarios, as was proposed in [25]. Moreover, the integration of the DT and ML was used by [17] to ensure an accurate ML model that monitors aging, detects potential faults, and replicates electrical efficiency as operational conditions vary. In SOFC, DT parts are designed into an interface to sense the key parameters and run and visualize the optimization results. As shown in Figure 5, the DT framework consists of three main layers: an interface layer, a data processing layer, and an optimization layer, with each layer responsible for sensing, processing, and optimizing system behavior. The system processes data using Python scripts to update the ML models, and the final part uses different optimization algorithms to calculate various strategies based on profit, energy, and environmental impacts. This integration discusses a DT framework that can be used to develop the most accurate DT with the ability to replicate the exact behavior of the SOFC. By reviewing the evaluated models, Extreme Gradient Boosting (XGBoost), random forest (RF), Long Short-Term Memory (LSTM), gradient boosting, Artificial Neural Networks (ANN), Polynomial, and Regression. These models were trained and evaluated based on experimental data collected over 3935 h. In the study, score results were calculated every 500 h to highlight the advantages and disadvantages of each model. The RF model performs exceptionally well, reaching an R^2 score of 0.98 and a mean squared error (MSE) of 0.14 in estimating electric efficiency.

Relying exclusively on stand-alone PEMFCs shortens the system's life cycle because these systems consume all available dynamic current. Therefore, hybrid power systems (HPS) are utilized in [19], with the fuel cell being a crucial component of these systems. HPS architecture typically includes five hierarchical layers: the physical system layer, intelligent sensing terminal, data space layer, platform layer, and application layer, as illustrated in Figure 6. Each layer contributes to prediction and control. To test the DT, an HPS was connected to the electric motor, which powered the vehicle. The fuel cell and battery are the main sources of power for the hybrid vehicle motor. The Markov chain prediction method is employed to forecast the future operational speed of the vehicle. Using a park vehicle for experimentation, DT results for different states of charge simulated that a high state of charge (SOC) can reduce H_2 consumption but slightly increase the fuel cell decay rate.

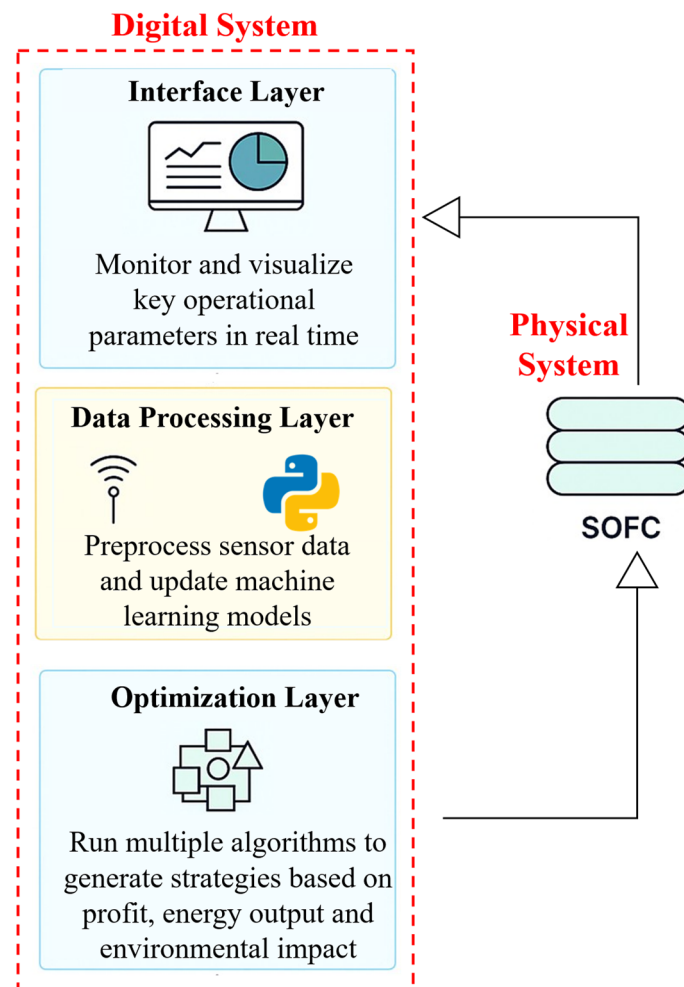


Figure 5. Framework for the integration of digital twin and fuel cell.

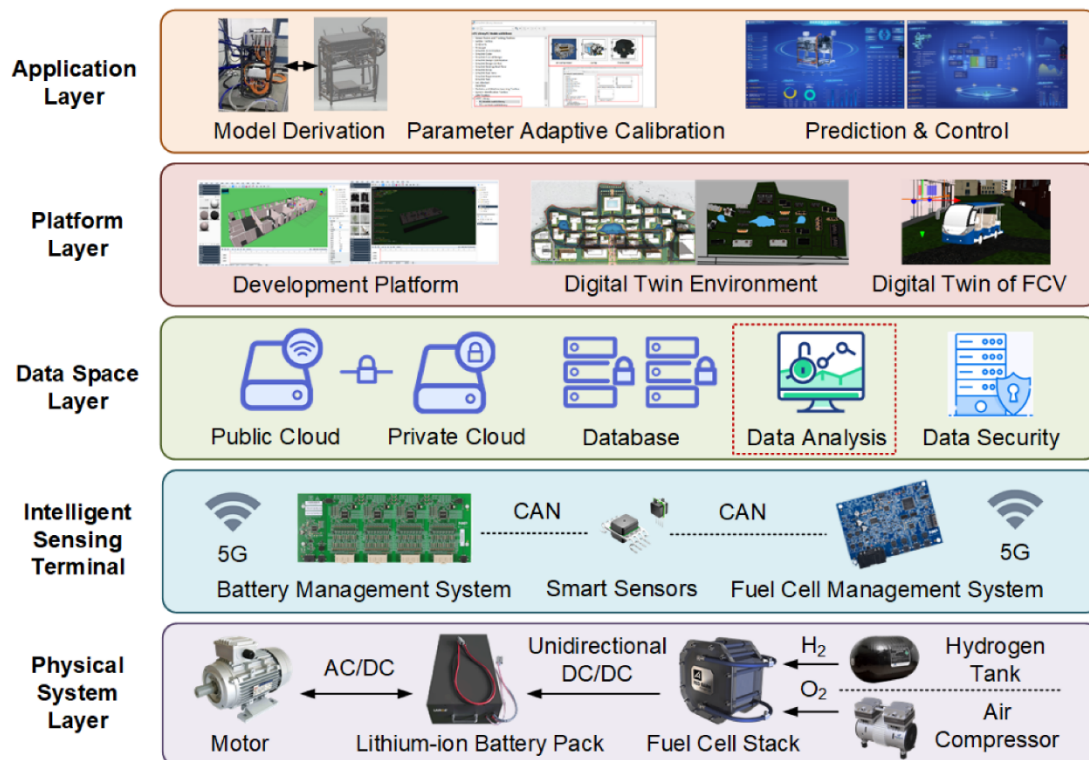


Figure 6. The structure of the edge-to-cloud HPS management system [19]. (Open access).

The fault diagnosis framework proposed in [23] utilized the DT unsupervised to predict faults in PEMFC using different methods based on Unsupervised Domain Adaptation. This approach succeeded in diagnosing nine typical faults in the fuel cell with an accuracy that reached 92.5%.

3.3. Digital twins in Fuel Cell Electric Vehicles

Extending the application of fuel cell technology, a recent case study by [9] developed a DT for a fuel cell electric bus to predict the amount of energy required for the trip. Artificial Intelligence (AI) is modeled to forecast how much gasoline and energy the trip will consume, leveraging the Internet of Vehicles (IoV) and sensors for the hydrogen fuel cell, as illustrated in Figure 7. The bus is 60 feet long and is equipped with four powered wheels and two for steering. IoV is used to extract the acceleration and deceleration of the drive cycle using GPS. A rule-based algorithm III-B3 was developed to manage the power flow along with different models such as RF, Neural Network (NN), and k-Nearest Neighbor (KNN). The NN model showed the best performance for predicting hydrogen consumption with 0.4439% MSE.

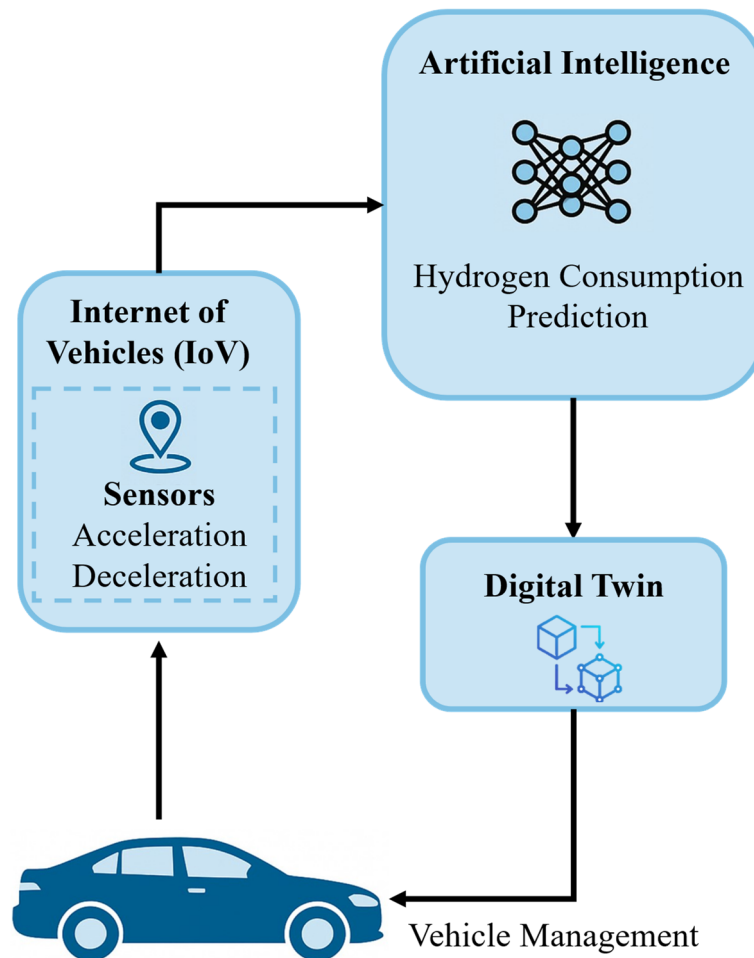


Figure 7. AI-Driven DT for fuel cell vehicle management.

A DT of fuel cells proved in [26] that the fuel cell auxiliaries impact energy consumption by 28% under standard conditions, increasing to over 40% in winter scenarios, with the fan representing the most significant share. The external air temperature reduced the vehicle range from 430 km to 356 km in winter. Doubling the battery pack can enhance the efficiency and thermal management while increasing the vehicle range. Additionally, Bartolucci et al. [27] used DT to control vehicles in real-time by simulating the use of different control strategies, such as range extenders and fuzzy logic control. A range extender is a traditional strategy that turns on and off when the SOC reaches a certain level, unlike fuzzy logic control, which uses smart thinking to deal with the fuel cell operation, considering when the car needs more power to increase the current of the fuel cell. Implementing these strategies in the virtual car model saves time and money. A comparative analysis is conducted to evaluate the performance of the two control strategies in a fuel cell hybrid electric vehicle virtual replica. Based on the simulation data, the vehicle showed an increase of approximately 30 km compared to the range extender, while

the system efficiency using the range extender was higher than that of the fuzzy logic control by 1.5%. However, fuzzy logic control achieved a higher energy conversion efficiency (71.5% compared to 67.9%). Although the fuzzy logic controller demonstrates slightly lower system efficiency, it saves more hydrogen due to the fact that the range extender method turns on the fuel cell at full power to charge the battery. In turn, consuming more power in order to keep the cooling system working, as observed in Figure 8.

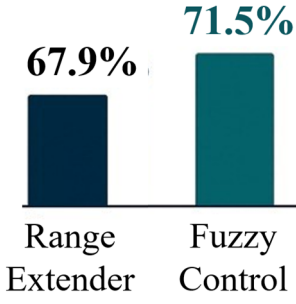
Range Extender Turns fuel cell on/off based on state of charge (SOC).	Fuzzy Logic Control Uses intelligent logic to balance power needs in real time
 Vehicle Range	+30KM
 Energy Conversion	3.6% more energy efficient
Energy Conversion Efficiency	 67.9% 71.5% Range Extender Fuzzy Control

Figure 8. Range extender and fuzzy control performance comparison, data taken from [27].

DT can be enhanced to predict early-stage fuel cell degradation by implementing a hybrid convolutional neural network (CNN)-LSTM model with transfer learning, which can be observed in Figure 9. This approach was used in [28]. The model works well because LSTM captures long-term trends in degradation (e.g., gradual voltage decline), while CNNs identify short-term patterns (e.g., short-term temperature fluctuations). Transfer learning is a technique used to avoid the significant drop in performance when a new task is given by analyzing historical data. It can be seen that through the 200-h test (Trial 1), The RMSE and Mean Absolute Error (MAE) reduced by around 80% and 75%, respectively. This demonstrates how effective and flexible this model can be in many scenarios. Table 1 summarizes the key aspects and applications of DT in fuel cell technologies. The table highlights the advances from a lifecycle modeling concept to a data-driven optimization framework.

Despite these encouraging results, the DT studies surveyed also reveal practical barriers that temper their reported performance gains. Model calibration remains demanding because an accurate virtual replica depends on parameters that drift as the physical cell ages, which requires periodic re-identification rather than a one-off fitting step. Data availability is a recurring constraint: high-fidelity twins need long, well-instrumented operating histories that are costly to obtain, which is precisely why several of the reviewed works rely on simulated fault data instead of measured data. Real-time deployment is further limited by the computational load of coupled multi-physics models, so the sub-second inference times reported above are typically achieved only after significant model-order reduction or surrogate modeling. Recognizing these calibration, data, and latency constraints is important for interpreting DT results realistically, and from a sustainability standpoint, it clarifies that the efficiency and lifetime gains attributed to DTs are only realizable where the supporting data infrastructure can be maintained across the full service life of the system.

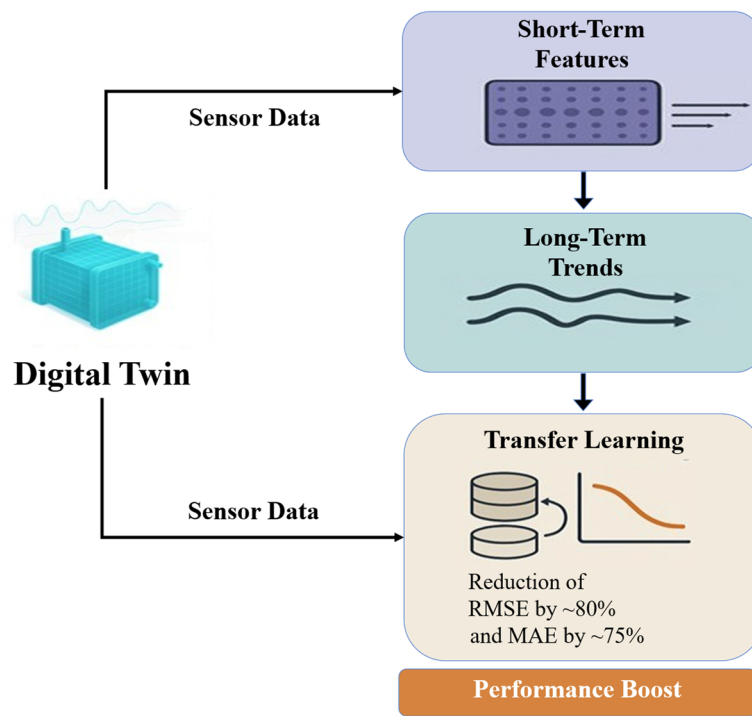


Figure 9. Hybrid CNN-LSTM digital twin, data from [28].

Table 1. Key aspects and applications of digital twin in fuel cell technologies.

Aspect	Description	Reference(s)
Initial Definition of DT	DT was first defined in 2003 comprising a physical asset, its virtual replica, and their connections.	[15]
Sustainability Transition	Enables transition toward more sustainable energy systems.	[17]
ML Integration & Optimization	Combines with ML to emulate patterns and optimize critical parameters.	[9]
Lifecycle Data Collection	Originally used to collect data across a product's entire lifecycle.	[15]
Self-Adaptive DT & RUL Estimation	Transfer-learning-based DT using a QH-loss function for training on historical data, then adapting to real-time data to predict remaining useful life.	[18]
Digital Backward Modeling	"Digital backward" step: use simulation tools to build detailed virtual replicas of physical systems.	[19]
MPPT for Fuel Cell Power	Uses MPPT algorithms within a DT to maximize fuel cell power: achieved 67% improvement in error at startup and 42.9% during load changes.	[16]
CFD-Scale Integration	DT links unit-scale CFD simulations to stack-scale models, cutting computation times from days to seconds with <1% deviation.	[20]
Scenario Simulation for Data Generation	Simulates multiple scenarios (e.g., gas, water, thermal, electrical interactions under ideal-gas assumptions) to generate large, fault-free datasets.	[23,24]
DT Framework for SOFC Optimization	Integrates interface sensors, Python-based data processing, ML models (XGBoost, RF, LSTM, etc.), and denoising autoencoders for aging, fault, and efficiency.	[17,25]
Plant-Scale SOFC Optimization	Scaled down 1 kW model of a 25 kW SOFC plant (including reformers, burners, exchangers) predicts performance with <5% voltage error.	[22]
HPS Integration with DT	In a hybrid power system driving a vehicle, DT coupled with Markov-chain speed prediction shows that high SOC reduces H ₂ use but slightly raises fuel cell decay.	[19]
Fault Diagnosis Framework	Unsupervised domain adaptation within DT diagnosed nine PEMFC fault types with 92.5% accuracy.	[23]
Fuel Cell Electric Bus DT	DT of a 60-ft H ₂ fuel-cell bus uses IoV data and rule-based + ML models (RF, NN, KNN); NN achieved the best hydrogen-consumption prediction (0.4439% MSE).	[9]
Control Strategies in Hybrid Vehicles	Virtual comparison of range-extender vs. fuzzy logic control in a DT hybrid vehicle: fuzzy logic yields +30 km range; range-extender has 1.5% higher efficiency.	[27]
Auxiliaries & Environmental Impact	DT shows fuel cell auxiliaries account for 28% of energy use; winter ambient drops range from 430 km to 356 km; doubling battery packs improves range & thermal management while increasing the vehicle range.	[26]
Degradation Prediction	Hybrid CNN-LSTM DT with transfer learning captures short- and long-term aging patterns, reducing RMSE by ~80% and MAE by ~75%.	[28]

As evidenced by the DT studies reviewed, the development of predictive and adaptive behavior within a DT occurs through knowledge of the virtual replica and the ML models that are included as part of the DT. All of the above predictive capabilities, including degradation prediction for abnormal use and normal operating conditions, prediction of hydrogen consumption based upon input variables, diagnosis of faults within a fuel cell, and optimization of operational parameters when applied in real time with test data, were achieved by using data-driven algorithms (CNN-LSTM, NN, and XGBoost) located inside the DT. Therefore, DT and ML provide complementary functions for the digitalization of fuel cells. DT provides a structured, physics-based environment and a real-time connection to the physical fuel cell system, while ML provides the ability to learn how to turn data from multiple sensor streams into useful predictions for real-world applications such as diagnostics and control. Thus, the use of ML as a surrogate for achieving the predictive function of the DT allows researchers and engineers to overcome many of the limitations associated with DT integration.

4. Machine Learning in Fuel Cells

ML is a subset of AI that allows computers to discover significant relationships between inputs and outputs by analyzing training datasets. It is mainly categorized into three learning paradigms: supervised learning, unsupervised learning, and reinforcement learning [29]. ML-based approaches are gaining increasing attention because of their advantages, including quick computational time, reliability in complex computations, and adaptability to varying sample sizes [30].

The most widely used models in PEMFC research concentrate on supervised, unsupervised, or semi-supervised learning, as shown in Figure 10. Supervised learning, which relies on labeled datasets to perform tasks such as regression and classification. In contrast, unsupervised learning works without labeled data and is primarily used to uncover hidden structures or groupings within the data through clustering techniques. Semi-supervised learning integrates a small quantity of labeled data with a larger pool of unlabeled data. This integration is beneficial when comprehensive annotation is not feasible. Choosing the right learning type depends on the characteristics of the data and the specific objectives [31].

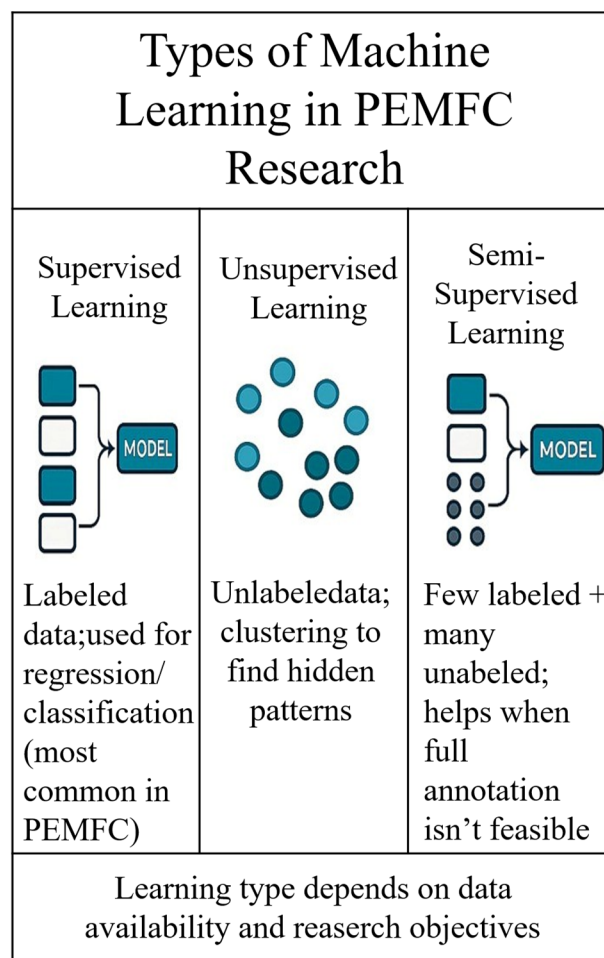


Figure 10. Machine learning types.

ML and deep learning have facilitated significant advancements in PEMFCs [32]. These advancements focus on multiple areas, including fuel cell design, material choice, correlations, system control with fuel cell, power management, and monitoring of the operational health of the fuel cell.

ANNs are one of the most effective approaches to ML techniques [33]. ANNs can learn, categorize data, generalize findings, and predict variable values. They accomplish this through their memory retention, developed during the training phase, and their ability to adjust to new inputs [34]. Implementing a comprehensive 4E (energy, exergy, economic, and environmental evaluations) analysis is essential for evaluating a system's effectiveness and identifying the best thermodynamic cycles to improve performance [35]. An ML model can also be trained to replace density functional theory [36].

4.1. Performance Prediction and Management

4.1.1. Energy Management and Real-Time Control

Recent studies have increasingly focused on energy management and real-time control strategies to enhance the dynamic performance of fuel cell systems by implementing ML with these systems. Yewale et al. [37] investigated a microbial fuel cell (MFC) that operates under a multiple model-based control strategy that utilizes five ML-based model-switching algorithms: Recursive Bayesian Approach, weighted kNN, Gap Metric Approach, Multi-model Weighted Algorithm, and Hotelling T^2 Strategy. These algorithms work together to dynamically select the most effective local controller. Findings reveal that weighted kNN significantly surpasses the other methods, achieving a 65% reduction in average settling time compared to a single linear controller and enhancing key performance metrics, such as an 85% decrease in integral control effort. Furthermore, the weighted kNN-based multiple model-based controller showcases strong resilience to disturbances and noise, confirming its effectiveness for precise control of power and temperature in continuous MFC systems.

One method that has received some attention for computing optimal feedback control for a hydrogen gas reformer in PEMFC for electric vehicles is reinforcement learning that is used in [38], more precisely, policy iteration. The dynamics of the reformer are complicated and are described by a high-dimensional nonlinear system with 10 differential equations, with the fuel cell current as a major disturbance. The duality problem is cast as a zero-sum differential game, and it is demonstrated that optimal control can be achieved in a small number of iterations. It shows that including the disturbance in the control model yields better performance compared to methods that do not consider the disturbance, which may result in up to 2% in error.

Hossain et al. [39] introduced an advanced hybrid model and demonstrated its improved ability to predict electricity output from MFCs. These models performed automatic hyperparameter optimization within a Bayesian Algorithm, effectively circumventing the limitations of conventional trial-and-error tuning. The study showed that the Bayesian Algorithm (BA)- Support Vector Regression (SVR) model outperformed traditional response surface methodology (RSM) and BA-Boosted regression tree across several performance metrics (R^2 , MAE, RMSE, Mean Absolute Percentage Error (MAPE)), achieving an R^2 greater than 0.99 and improving performance by over 90%.

Al Hajri et al. [33] trained an LSTM model, which involved multiple ML algorithms such as Radial Basis Function NN, Back Propagation NN, and Adaptive Neuro-Fuzzy Inference System, while establishing a self-improving feedback loop by using IoT data to enhance the model. This model was trained to enable switching between different energy sources based on forecasted consumption and energy efficiency. The model has managed to source the required energy by using 60% of solar energy, 30% wind energy, and 10% of hydrogen fuel cells in real-time.

A new concept of the MPPT technique was presented by Dandil et al. [40]. The technique used Linear Regression (LR) and Support Vector Machine (SVM) to enhance the efficiency and dynamic response of PEMFCs. Results were compared to the conventional MPPT technique and demonstrated a substantial improvement in performance for the proposed model. Comparative simulation results revealed that the proposed ML-based tracking method demonstrates substantial improvements in performance compared to conventional MPPT techniques. Additionally, it was demonstrated that the suggested approach significantly increased the average efficiency for both the perturb and observe and Incremental Conductance techniques, with the LR-based method exhibiting the best performance in efficiency and tracking speed.

The capabilities of ML were investigated by Gürbüz et al. [41] in increasing the operation of Plant Microbial Fuel Cell (PMFCs), which generate energy from plants and microorganisms. Using data from 229 observations from 51 studies to utilize principal component analysis, SHapley Additive exPlanations (SHAP), and a decision tree approach to uncover the most prominent drivers of power output. The temperature, natural light, soil support, and some plant families of particular mention Poaceae (grass family), were the factors with the strongest impact. The decision tree revealed nine optimal configurations for high power, especially those using wastewater with

sodium bicarbonate and excluding graphite plate cathodes. The study showed that ML helped uncover key conditions for maximizing energy production in PMFCs.

The fuel cell purge process consists of three phases; the first phase is known as the slow rise phase, during which water is expelled from the fuel cell. The second phase, the fast rise phase, starts once the water is expelled. During this phase, water evaporates from the membrane, resulting in an increase in high-frequency resistance. The final phase is the membrane equilibrium phase, where the membrane's water content stabilizes with the purge gas [42]. Current research efforts concentrate on expediting the slow rise phase and refining the fast rise phase to augment the efficacy of the purge process. Shi et al. [43] applied ML using the PSO-SVR- Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm, which can optimize the shutdown purge strategy. The PSO-SVR algorithm is employed to forecast the shutdown purge simulation data, while the NSGA-II algorithm focuses on multi-objective optimization. A two-dimensional multiphase CFD model was used to simulate shutdown purge scenarios. Based on the simulation results, PSO-SVR was trained to predict 2,117,220 sets of mapping relationships that are being optimized by NSGA-II, which resulted in 35 optimal solutions; the RMSEs are below 5%, demonstrating the model's strong fit.

4.1.2. Hybrid Energy Systems Integration

Recent advancements in ML have significantly enhanced the understanding and optimization of fuel cell-based hybrid energy systems. For instance, in [44], a SOFC combined with a supercritical CO₂ cycle was optimized using a gray wolf algorithm and ANN, achieving 73.8% energy efficiency.

In [45], an SOFC with Compressed Air Energy Storage was optimized using regression-based ML methods achieved R² values exceeding 98%, resulting in high efficiency and reduced emissions. Another study by Gholamian et al. [46] demonstrated that combining SOFCs with bottoming cycles like the Stirling engine can significantly improve system efficiency and reduce emissions. Building on this, the authors presented an integrated energy system that connected a SOFC with a Stirling engine and vanadium chlorine cycle for the co-production of electricity and hydrogen. By the combination of gray wolf optimization with TOPSIS decision-making method, an efficiency of 81% was achieved under minimum energy production costs. The results indicated that the fuel cell temperature and the fuel utilization per membrane can improve the power and economic performance significantly.

Zhou et al. [47] introduced a new type of MCFC technology, the MCFC-type supercritical CO₂ recovery system. It is a highly efficient power and cooling solution derived from biomass. The author addressed the lack of utilization of MCFCs as opposed to SOFC, even though both technologies have similar benefits with regard to high efficiency and low emissions. The system integrated biomass conversion techniques, such as anaerobic digestion or gasification with a supercritical CO₂ cycle that serves as the bottoming cycle. By using the MATLAB-based ML methods, multi-objective optimization was used to minimize emissions and the levelized cost of product by increasing efficiency in parallel. The results of a parametric study showed that current density, fuel utilization factor, cell temperature, and pressure ratio play an important role in system performance. In particular, efficiency decreases to 52% when the cell voltage falls, and current density rises. Furthermore, 7% decrease in the net power output was obtained due to a rise in the fuel utilization factor. The optimized solution of the study resulted 56.5% in exergy efficiency, 0.35 ton/MWh emission, and a total cost equal to \$0.11/GJ, representing a promising potential for this hybrid system for sustainable energy production.

4.1.3. Real-Time Estimation and Diagnostics

ML-based real-time parameter estimation enables accurate circuit diagnostics and fault detection in fuel cells under dynamic operating conditions. Ghorbani and Vijayaraghavan [48] developed an ML model to create a virtual hydrogen sensor system for detecting fuel starvation in SOFC. ANN achieved an accuracy of 97.5%. Furthermore, GBDT was used by Chen et al. [49]. The model was trained on CFD-generated data, validated experimentally, and compared with LR, KNN, SVM, Decision Tree, Bagging, RF, Extremely Randomized Trees, and Adaboost. GBDT achieved the highest accuracy (R² = 0.896 in simulation, 0.910 in experiments).

A computationally efficient approach to learning equivalent circuit models of fuel cell parameter values from ML-based inverse models is proposed in [50]. The authors used SVM Regression, Least Squares SVM, and GPR to predict model parameters directly from the Electrochemical Impedance Spectroscopy (EIS) data. By learning from synthetic datasets generated from the forward model, these inverse models can quickly determine the parameter values with minimal computation, thus enabling on-site, real-time, low-cost diagnosis with embedded systems. The method demonstrated faster and more stable performance than conventional descending methods. The GPR and SVM models performed stably even in the presence of noise.

In [51], the authors trained physics-informed DNNs as reduced-order models for SOFC-based natural gas fuel cell systems, cutting prediction error from ~10% to under 5%. Through the inclusion of these models into Institute for the Design of Advanced Energy Systems, the method lowers prediction errors and decreases computation costs for system optimization, which leads to more efficient system optimization. The usability and accessibility are also enhanced with open-source GUI. Moreover, the detrimental permeation of N₂ from cathode to anode in PEMFCs causes a 28.9% performance loss. Addressing nitrogen crossover by using ML models achieved near-perfect accuracy, $R^2 > 0.97$ [52].

4.1.4. Energy Management in Fuel Cell Vehicles

Hydrogen fuel cells are being widely used in vehicles. Recent studies have increasingly focused on optimizing the real-world performance of hydrogen vehicles [53]. For example, Peksen [54] developed a hybrid approach based on Multiphysics simulation, design of experiments, and ML to forecast fuel consumption peaks in hydrogen FCEVs. The hybrid approach comprised fuel cells, battery, electric motor, and thermal balance, and was simulated for the New European Driving Cycle. To create training data, various parameters, including fuel cell power, the initial SOC of the battery, and vehicle weight, were used. Four separate ML models were constructed and validated: LR, stepwise LR, GPR, and a feedforward NN. The stepwise LR model performed best with < 1% prediction error. The proposed technique allows for the quick and accurate prediction of FCEV fuel economy peak and to drive FCEV in real-time optimization.

In [55], an energy management strategy for fuel cell hybrid buses was developed using NNs to predict the global average fuel cell power based on driving cycle features, and an LSTM network to optimize real-time power distribution. This combination reduces hydrogen consumption by 0.58–0.36%, outperforming a commercial rule-based strategy that consumed 0.96–1.80% more in both driving cycle.

A new method called driving condition recognition was introduced by Ji et al. [56] to be used in trucks. It combined prediction and ML to recognize driving conditions more quickly and accurately. The method used a Markov Chain to predict short-term speed changes and a Learning Vector Quantization NN to classify the type of driving. This helps the fuel cell manage energy better in real time. This method succeeded in lowering fuel cell power fluctuations by 30.4% and cutting hydrogen use by 1.2%, which improves fuel efficiency and extends the life of the fuel cell system.

In [57], a diagnostic prognostic system capable of predicting the electric part failures in IGBT modules used in electric/hybrid/fuel cell vehicles is presented. When subjected to heat and mechanical stress, such modules can be damaged, resulting in issues including wire-bond lift-off and solder joint decay. Based on MATLAB Simulink simulations, the system was developed to follow key parameters related to the behavior changes of the module during degradation. Processing of this data and predicting the failures is based on the KNN algorithm. In case of a noticeable deviation, a warning is generated, and maintenance can be carried out on time. The presented approach is efficient, economical, and applicable to real-time operation on vehicles and has been well verified by simulations and hardware experiments.

Shojaeefard and Raesi [53] developed an ML model using AMESim software to compare the performance of gasoline direct injection and FCVS, optimizing the essential cycle parameters like average speed, peak speed, and braking time. Driving patterns and paths decreased NO_x production in the engine by 52% and energy consumption by 38%.

Liu et al. [58] proposed a complete model-free online optimal control of PEMFC by using a fixed-weight Recurrent Neural Network (RNN). With this architecture, the design does not require the need for recursive least squares-based weight updates, which reduces implementation complexity while ensuring finite-time convergence and control stability. Moreover, the approach is systematically evaluated in Hardware-in-the-Loop tests and shows advantages over existing methods with better tracking performance as well as robustness against real-world parameter variations such as nonlinear and multi-parameter disturbances, which have not been considered in previous works.

Song et al. [59] proposed an ML-assisted energy management strategy for fuel cell hybrid electric vehicles to enhance safety, durability, and efficiency. Using a deep deterministic policy gradient algorithm, the power distribution between the fuel cell and lithium-ion battery is optimized to minimize thermal risk and system degradation. Results showed that the proposed method reduces peak battery temperature by 10.52% and lowers overall driving costs by up to 0.1258 \$/km, while maintaining battery charge within safe limits.

4.1.5. Methodological Challenges and Alternative Perspectives

Despite significant progress, the application of ML in fuel cell research faces methodological challenges that shape strategic directions for improving performance, material efficiency, and development workflows. Ding et al. [60] stated that effectively providing higher power density with less utilization of precious metals, which can be done using ML, has become the most important goal pursued by researchers. Ding et al. [31] give a holistic view of how ML methods are changing PEMFC science and development at diverse levels. The authors rigorously analyzed the way in which ML techniques are affecting the transition from conventional trial-and-error-based experimental methods to data-driven optimization methods that result in substantial reductions in both experimental and computational costs. The study explored narratives that systematically consider ML in the overall PEMFC ecosystem, including predicting active electrocatalysts at the nanoscale to avoid expensive calculations employing density functional theory. By acting as a surrogate model, ML automatically extracts hidden rules from experimental datasets and theoretical predictions that are hard to recognize, in turn allowing researchers to be guided throughout the Multiphysics and multiscale world of PEMFCs, which has, over time, hampered optimization. Although many technological and economic challenges, such as the costly manufacturing process, the need for platinum, and intricate Multiphysics processes, are reported in their review, it is pointed out that the ML technique could solve these interlinked problems through efficient multi-parameter optimizations.

In [61], a novel approach was developed, namely the experimental design paradigm to efficiently discover improved cathodes for Protonic Ceramic Fuel Cell. Contrary to trial-and-error or ML, the experimental design paradigm requires fewer experiments and smaller data sets. With limited test conditions and only 32 experiments, a superior material was obtained, and the excellent prospect for the operation of long-term, efficient, and durable fuel cells was shown.

Smart Prediction of Advanced Research is a novel ML methodology that was developed by Rui et al. [62] to accurately forecast the performance and durability of PEMs used in fuel cell applications. The study identified key factors such as testing conditions, humidity effects, material properties, and membrane thickness and their influence on durability. Thinner membranes enhanced performance but compromised durability, whereas higher ceria content increased durability at the expense of performance. This methodology enabled quicker, more cost-effective PEMs design without the need for extensive laboratory testing.

A further methodological barrier concerns the limited interpretability of the most powerful ML models. While architecture, such as LSTM and CNN, delivers high predictive accuracy for degradation and fault detection, they operate largely as black boxes, which is a significant obstacle to industrial adoption, where operators must be able to justify maintenance or control decisions. Within the surveyed literature, the more transparent studies address this by pairing predictions with post-training explanation tools: SHAP was used to rank the physical parameters driving power output and cathode behavior, turning opaque models into a source of design insight. However, such tools remain only partially satisfactory for fuel cell applications, since SHAP and comparable methods explain statistical correlations rather than electrochemical causation, can be unstable for strongly coupled multi-physics inputs, and are still rarely applied to the time-series deep learning models that dominate prognostics. Wider and more careful use of interpretability methods is therefore needed before complex ML models can be trusted in safety-critical fuel cell deployment.

The limitations provide a rationale for explainable AI, tools that let the user see which inputs or features contribute to a model's output, as a new direction in development rather than an optional add-on. The only instance of interpretability seen in the reviewed studies was SHAP, and only in a couple of cases. Increasing the number of explainable methods used would offer two other benefits. An instance-level approach would give operators the ability to justify each individual fault or degradation alert generated by the predictive model. In complex multi-physics systems, where many features are interrelated, a causal approach would help separate genuine physical drivers from statistical correlations in the data. Extending such methods to the time-series models that currently dominate prognostics would make ML predictions more transparent and support their use in safety-critical fuel cells.

4.2. Fault Detection and Diagnostics

Fault detection and diagnostics are important for ensuring safety and avoiding the shutdown of fuel cells. Recent studies have used ML to predict and diagnose abnormalities and to enhance early fault detection, such as hydrogen leaks. An ML system to localize and detect hydrogen leaks was developed by Zhao et al. [63]. The system produced input data for two ML models: an ANN and a K- dynamic time warping (DTW) algorithm. The ANN operated on single-point-in-time sensor data, whereas K-DTW used time series information. The ANN predicted the unseen leak locations with an accuracy of 78.4%, and K-DTW classed leak positions accurately at the rate of 87.5%. These results highlighted the promise of ML to improve safety in hydrogen vehicle scenarios.

Le et al. [64] developed a simulation-informed machine-learning approach to diagnose failure modes in SOFC stacks using EIS by examining three different failure types: fuel maldistribution, delamination, and oxidant crossover. In the fuel maldistribution failure, one cell in a 6-cell stack receives significantly less hydrogen fuel than the others, leading to increased fuel utilization, hydrogen depletion, and elevated gas concentration impedance at low frequencies. For delamination, loss of electrochemically active area in the center of a cell was modeled, which increases both the ohmic and activation resistances. In the oxidant crossover model, a leakage was simulated to allow oxygen to flow from the cathode to the anode.

Zaveri et al. [65] applied an ML method of predicting dehydration and flooding in a fuel cell by analyzing real-time Relative Humidity can reduce the size of data before entering it into the training model. The objective of this method is to increase speed, reduce training time, and avoid overfitting by simply removing redundancies. The primary parameters that influence the fuel cell are current density, followed by voltage. SVR provides a higher accuracy in predicting fuel cell performance depending on dehydration and flooding than decision tree, RF, and ANN, and enables fast Relative Humidity-based fault detection (Low represents dehydration; high Relative Humidity implies flooding). This approach replaces costly diagnosis (e.g., neutron radiography) and also provides real-time monitoring, and is possibly scalable by analyzing larger datasets in the future.

Vairo et al. [66] investigated advanced monitoring systems to monitor hydrogen leakages. A physics-informed ML framework was developed, which combines gradient-boosted decision trees with CFD simulations to detect anomalies such as internal hydrogen crossover. By combining impedance spectra (real and imaginary) with the current-voltage (I-V) data, this hybrid model achieved an F1 score of 0.99 for leak, safe accuracy, macro average, and weighted average.

In [67], ML has proved its strong potential in diagnosing faults in fuel cells; 18 faults were diagnosed accurately in PEMs; these faults were in the thermal management system, first cooling line, second cooling line, air supply system, and water management system. Demonstrating that ML can effectively detect a wide range of faults across different system components. Table 2 summarizes the diagnostic target, and the ML model was used to identify abnormality across different fuel cell types.

Table 2. Diagnostic targets and accuracy of ML models across different fuel cell types.

Reference	Fuel Cell Type	Diagnostic Target	ML Model	Accuracy
[63]	PEMFC	Hydrogen leak localization	ANN, K-DTW	ANN = 78.4%, K-DTW = 87.5%
[68]	HT-PEMFC	Internal structural shifts due to acid leaching	ML segmentation	Validated via imaging
[64]	SOFC	Fuel maldistribution, delamination, and oxidant crossover	Simulation-informed ML	Detailed mode-specific insights
[65]	PEMFC	Dehydration and flooding	SVR, decision tree, RF, ANN	SVR highest, RMSE= 0.4309
[66]	PEMFC/SOFC	Hydrogen crossover	GBDT + CFD	F1 score = 0.99
[67]	PEMFC	18 system faults	NN, RF	High (18 faults diagnosed)

4.3. Lifetime Prediction and Maintenance

Durability is a key factor restricting the widespread use of fuel cells. The main cause of fuel cell life degradation is gas starvation [69]. Accurate health state predictions can enhance their safety and longevity. Fuel cell aging results in changes to voltage, internal resistance, and other indicators, as well as a reduction in the electrochemically active area [70]. Degradation can increase fuel cell consumption by more than 15%, which increases the need for ML to minimize these effects [71].

Raeesi et al. [72] found that DNN has the best accuracy in the prediction of fuel cell output voltage compared to RNN, LSTM, and Bidirectional- LSTM. Moreover, GPR, SVM, and ANN were utilized to predict the State of Health (SOH) of a PEMFC under dynamic load conditions, using a dataset of 1000 h for model training. training models on raw sensor data (such as voltage, current, pressure, and temperature) to anticipate voltage degradation. Furthermore, another study by Nagulapati et al. [73] used a 50:50 training-to-testing data split. Results indicated that GPR attained the highest accuracy, evidenced by an RMSE of 0.0071 with 70% of the data used for training, while SVM and ANN showed lower performance, with RMSE values of 0.0290 and 0.0372, respectively. Notably, ANN's performance decreased with larger data volumes due to its sensitivity to noise.

Dhaked et al. [29] used LR, SVM, Decision Trees, and RF to predict the performance and degradation of the fuel cell by predicting the voltage. Utilizing input parameters such as system current, temperature, hydrogen pressure, and electronic load to forecast output voltage, among all models. RF and decision trees demonstrated superior predictive performance, achieving 0.998 R^2 scores and an average precision above 0.98.

The remaining life of a fuel cell was determined in [74] by capturing the multi-scale variations in cell performance through the integration of Variational Mode Decomposition, which reveals critical degradation

patterns, and an Improved WOA-optimized Back Propagation Neural Network (BPNN) that identifies the nonlinear relationships within data. This combined approach significantly enhanced prediction accuracy, providing a robust framework for extending the operational life and efficiency of fuel cells in real-world applications.

Moreover, Hong et al. [70] used an LSTM trained with different proportions of training data ranging between 40% and 90%, while the rest of the data percentage was used for validation. Results showed that increasing the training proportion reduced prediction errors. In [75], the combination of LSTM NETWORKS (F-LSTM for EIS and T-LSTM for IV) with dynamic EIS can predict SOFC degradation. This model decreases EIS testing time by more than 50% through low-frequency impedance prediction. This approach allows for cost-effective, mechanism-independent prognostics for fuel cells and batteries.

Another contribution by Manesh et al. [76] in MFC is the use of deep learning techniques to extract a comprehensive performance relationship that enhances health monitoring in wastewater recovery by providing quantifiable metrics for treatment efficiency and system longevity, which offers a practical framework for optimizing biological wastewater treatment systems. The research achieved 73% chemical oxygen demand removal efficiency and extended the operational time by 74 days.

A framework for PEMFC health status analysis by Zhang et al. [77] was proposed to enhance the durability by combining electrochemical degradation modeling, particle filtering, and specifically using the Transformer deep learning model as the primary ML algorithm. After 3750 h of experimentation, degradation was noted, with the electrochemically active surface area (ECSA) decreasing by 29%, leakage current rising exponentially to 5.75 A m^{-2} , ionic impedance nearly doubling from $5.22 \text{ } \Omega$ to $10.28 \text{ } \Omega$, and reduced mass transport capacity due to morphological changes. The framework effectively predicted voltage degradation for 1000 h under various operating conditions, with average errors below 4%, surpassing previous studies in long-term prediction accuracy. Table 3 summarizes the papers that used ML models for predictive maintenance and degradation prediction while showing the input data, best performance metric, and the key findings.

Table 3. Summary of key machine learning models for predictive maintenance and degradation prediction.

Reference	ML Model(s) Used	Input Data	Prediction Target	Best Performance Metric	Key Findings
[72]	DNN, RNN, LSTM, Bidirectional- LSTM	Voltage, load current	Output voltage	DNN outperformed others (qualitative)	DNN showed the highest prediction accuracy among the tested networks
[73]	GPR, SVM, ANN	Voltage, current, temperature, pressure	SOH/voltage degradation	RMSE GPR: 0.0071; SVM: 0.0290; ANN: 0.0372	GPR is most accurate; ANN is sensitive to noise and data volume
[29]	LR, SVM, Decision Trees, RF	System current, temperature, H_2 pressure, and electronic load	Output voltage	RF & Decision Trees: High R^2 , Low Error	RF and tree models achieved superior performance
[75]	F-LSTM, T-LSTM (LSTM + DEIS)	EIS, IV curves	SOFC degradation	More than 50% reduction in EIS testing time	Enables mechanism independent, fast SOFC prognostics
[74]	VMD + IWOA-optimized BPNN	VMD components from sensor data	RUL	Improved prediction accuracy (qualitative)	Captures nonlinear degradation patterns and enhances lifespan modeling
[77]	Transformer + Particle Filtering	Voltage, ECSA, impedance, leakage current	Voltage degradation	Avg. error < 4% over 1000 h	ECSA decreases 29%; impedance nearly doubled; highly accurate under dynamic conditions

4.4. Materials and Process Optimization

4.4.1. Catalyst Layer and Electrochemical Material Optimization

Catalyst layer and electrochemical material optimization in fuel cells rely on capturing complex performance dependencies. Lou et al. [78] proposed a hybrid data-driven and physical model based on XGBoost with a physical PEMFC framework, which was used to predict the fuel cell performance and perform quantitative sensitivity analysis of cathode catalyst layer parameters as seen in Figure 11. This method quantified the relative importance of several key parameters, including agglomerate radius, Pt loading, and catalyst composition, and their non-linear effects on performance characteristics. They also employed multi-objective optimization tools and a genetic algorithm, which increased peak power and limited current densities by 9.96% and 10.47%, respectively. At the same time, it decreased platinum loading by 28% and balanced performance with cost. It also highlighted that thermal stability in the PEMFC is of high relevance by taking temperature uniformity into account as an optimization target. This unified approach represents a departure from the general trend of predicting design parameters to an explicative and interpretable methodology based on predictive modeling for fuel cell components.

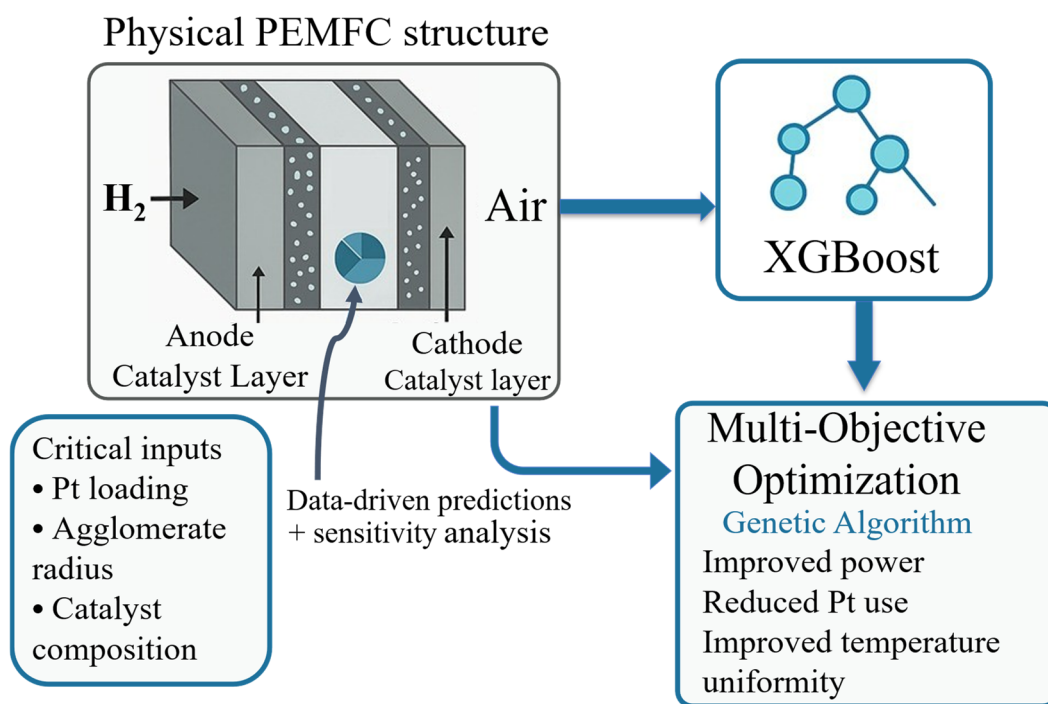


Figure 11. Optimizing PEMFC catalysts.

Park et al. [79] provided a catalyst design procedure that uses ML to weed out potentially effective and affordable electrocatalysts in the vast ternary alloy market. The ML-based catalyst screening model attributed structural stability, catalytic efficiency, and economic efficiency as important factors. It screened 10 and 37 candidates from more than three thousand candidate materials for each fuel cell cathode and anode. $Cu_3Au@Pt$, as experimentally confirmed ternary core-shell catalyst offered a performance higher than Pt but with a more cost-effective approach.

Zhou et al. [80] developed a new ML-integrated methodology for hydrogenation alloy design, in particular, single-phase C14-Laves type intermetallic compounds. Using a new dataset with 234 alloy compositions, this work combined general (magpie descriptors) and specific chemical information to train ML models. SVM was the best learning model for the prediction of pressure-dependent properties, while gradient boosting decision trees (GBDT) obtained the best performance in the prediction of hydrogen storage capacity. It was proven that the MeanIonicChar value and Fe content were the most important parameters affecting hydrogen capacity. The scientists developed and tested an alloy, $Ti_{0.9}Zr_{0.12}Mn_{1.2}Cr_{0.55}(VFe)_{0.25}$, which matched other calculated properties and acted efficiently in fuel cell conditions. The study reported on a data-driven and structurally guided approach to design advanced materials for hydrogen storage and fuel cell applications.

In a study by Rohilla et al. [81], ML was employed to predict and optimize the proton conductivity of sulfonated polyimide-based PEM. Decision tree classifiers and RF regressors were applied to a dataset of 81 sulfonated polyimide monomers. The ML models facilitated the rationalization of key structure-property relationships (sulfonate group molar content, double bond content, molecular weight, aromaticity, and fluorination) that influence proton transport and were able to provide clear design rules while differentiating high and low conductivity materials. The classification accuracy reached as high as 88.9%. This study demonstrated the predictive ability of ML for polymer design and illustrated that ML can extract actionable insights, which could dramatically speed up the discovery of high-efficiency and lower-cost polymer electrolyte membrane candidates for fuel cell applications.

The catalyst layer is regarded as a pivotal component of PEMFCs, with a significant impact exerted on both performance and durability [82]. In [83], the RF regression was combined with a mesoscopic pore-scale model to analyze the relationship between factors affecting the high-temperature-PEMFC (HT-PEMFC) cathode catalyst layer's pore structure, mass transfer, and its corresponding electrochemical properties, such as structure and property relationship. The findings highlighted the outstanding capability of the RF model in forecasting potential variations while effectively capturing overall trends and relationships.

Çolak [34] used two different ANN models to estimate the electrochemical parameters of the ammonia molten carbonate fuel cell (MCFC) using ML. Two distinct ANNS models are developed to estimate current

density and voltage values based on three different input parameters, given that the variables influencing both parameters are different. These models demonstrated outstanding accuracy in forecasting, with approximately 1.37% variation in current and 0.44% for voltage.

Kim et al. [84] used 6 ML models (LR, decision tree, RF, multi-layer-perceptron, SVM, and XGBoost) based on the sci-kit-learn open-source code to predict and optimize the behavior of a protonic ceramic fuel cell. Compared to other models, XGBoost achieved the best performance. Feature-importance analysis using a SHAP analysis was successfully conducted to specify the impact of each variable. Co, Ba, and Pr significantly influenced the cathode, whereas zirconium (Zr), yttrium (Y), cerium (Ce), and ytterbium (Yb) had the most pronounced effect on the electrolyte. Furthermore, in [85], sixty samples were used to train and compare seven ML models, including linear, second-order polynomial, SVR, KNN, gradient boosting trees, RF, and an ANN for direct methanol fuel cells (DMFC). The study found that the ANN can facilitate thorough planning of experiments by optimizing synthesis and testing conditions in advance. This optimization, in turn, should lead to better resource allocation for materials, equipment, and labor in future experimental efforts involving similar systems.

4.4.2. GDL and Microstructure Modeling

One of the critical components in PEMFC is the GDL, which is responsible for facilitating mass and heat transport. Enhancing the GDL can improve the efficiency and durability of the fuel cell. Wang et al. [86] integrated a detailed multi-physics model with ML surrogate models, RSM, and ANN for multi-objective optimization of deformed GDL of PEMFC. The ANN model improved current density by 20.8% and reduced oxygen distribution variance by 74.6%, while significantly cutting computational cost. Moreover, the ANN was found to be superior compared to RSM, provided that it receives sufficient data as input. Similarly, Omongos et al. [87] applied ML to optimize the GDL design. The ML achieved high predictive accuracy with R^2 scores of approximately 95% for six out of seven key properties and around 90% for GDL–Microporous Layer contact resistance, while cutting computation time from 3–4 h to just 3 s.

Topological data analysis can be employed to examine the minute structures within SOFCs by converting them into specialized images that illustrate their shapes and connections. These images can be utilized alongside deep learning models to forecast fuel cell performance. This method captures essential features of the microstructures more effectively than conventional image-based techniques and performs well even with limited training data. Altogether, this strategy demonstrates potential for enhancing the prediction of fuel cell performance and creating improved electrodes. In order to construct and validate their model, Szemer et al. [88] created a database of more than 500 synthetic SOFC microstructures by applying a cellular automata approach. Each microstructure was first transformed into nine persistence diagrams that reflected 0th, 1st, and 2nd-order topological invariants in three phases, which were then represented as high-resolution persistence images. These images were used as input to a specially designed NN model with three branches. By fine-tuning the image resolution as well as weight function settings, optimal model performance with an MSE of 3.3×10^{-5} and R^2 score of 0.983 was achieved. The model showed good accuracy, even with training data consisting of just 100 microstructures. This model offers a promising strategy for linking electrode microstructure to electrochemical performance. Figure 12 illustrates the overall workflow, from microstructure preprocessing to topological representation and NN-compatible input.

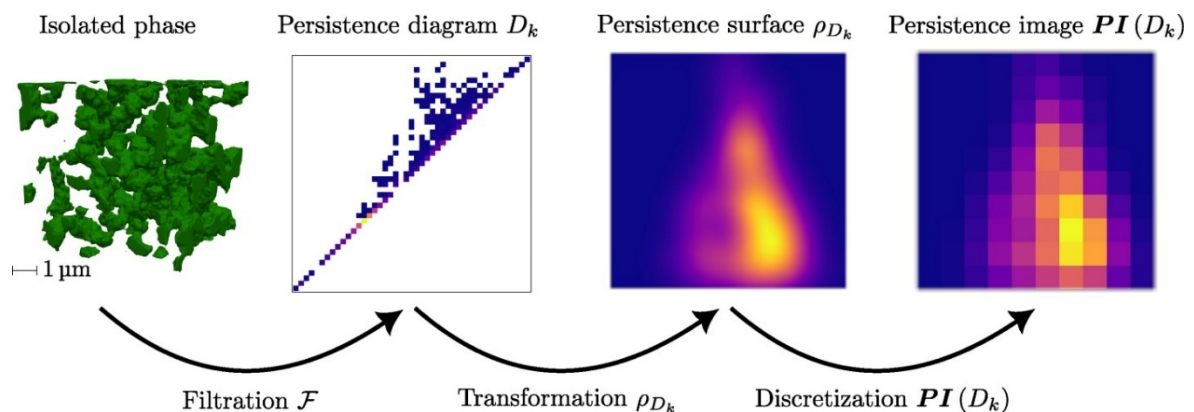


Figure 12. A Topological Data Analysis Pipeline for Converting SOFC Microstructures into Persistence Images [88]. (Open access).

4.4.3. Manufacturing, Coating, and Process Optimization

ML has also been applied to manufacturing, coating, and process optimization of fuel cells. In [89], to print thick layers (at least 500 μm) without bubbles for fuel cell seals by testing 25 UV-curable adhesives, an ML model was developed to measure properties like viscosity, surface tension, and adhesive recovery after movement. The model achieved over 88% accuracy. The results indicated that a higher thixotropy index made the adhesive more printable.

In [90], the anti-corrosion performance of diamond-like carbon coatings on metallic bipolar plates in PEMFC is modeled to predict the performance of the coating, since traditional ways are time-consuming and costly, XGBoost and ANN were employed. ANN outperformed XGBoost in all cases, achieving R^2 values above 0.98 for corrosion current density and above 0.99 for impedance predictions. The results demonstrated that ML models offer a promising tool for optimizing metallic bipolar plate coatings in PEMFC applications.

Shin et al. [91] used ML to optimize the co-firing process for metal-based SOFC. These cells combine metal substrates, such as cermet layers arrayed like an anode, cathode, and electrolyte. The co-firing process must meet two requirements: It must ensure that one layer does not bend due to another's shrinkage, and it must avoid developing any cracks between layers. The authors used two ML models, RF and NN, to forecast issues like shrinkage, bending, and pore size at different process parameters. The authors found that the RF model gave a better forecast result and was able to identify key factors, such as sintering temperature, pore-former amount, or decreasing temperature by examining spatial relationships between each of the layers with ML methods.

4.4.4. Flow-Field Design and Thermal Optimization

Flow field and thermal optimization require critical prediction in fuel cells, pressure drop due to water slugs in fuel cells can be predicted using ML models. ANN, logistic regression, and SVM were tested to characterize the two-phase flow in PEMFC. A recent study by Chauhan et al. [92] used a charge-coupled device camera while a pressure transducer measured the liquid-gas two-phase flow pressure drop. The results indicated that ANN achieved the highest accuracy with a score of 95%, followed by SVM at 80% and logistic regression at 63%. Another study by Santamaria et al. [93] found that the accuracy of the decision tree can be improved if used with lower airflow rates, as the liquid phase becomes dominant because lower airflow has reduced air turbulence, which allows the liquid to settle, leading to improved accuracy.

A study by Li et al. [94] developed the Improved Twin Delayed Deep Deterministic Policy Gradient (ITD3) algorithm to fine-tune a PID controller, aiming for optimal thermal management in PEMFC. This approach has improved thermal stability by reducing temperature overshoot, shortening response time, and eliminating steady-state error. In addition, [95] used a hybrid PEMFC model which combines a first-principles 1D dynamical model and an ANN in order to predict the membrane equilibrium water content. This method provides for the data-driven calibration of physico-chemical relationships using conveniently measured system outputs, thereby improving model-based control strategies without invasive membrane characterization.

A ML-driven 3D (consider the flow field designs, which enable them to capture the large heterogeneity across the catalyst layer surface and achieve higher precision) +1D (heterogeneity in the thickness direction at the cost of a several magnitudes longer computing time) hierarchical model for PEMFC is presented in [96] to increase the accuracy across a broad spectrum of operating conditions without affecting the computational costs, combining a 3D model covering the gas diffusion layers (GDL) and gas channels with an NN. The proposed framework achieved very high accuracy with an RMSE of 0.17% and a maximum error that doesn't exceed 3%.

A study by Wei et al. [97] developed a smart thermal management system for PEMFC using deep reinforcement learning, combining energy and thermal control in a two-layer system to improve fuel efficiency and protect the battery's health. Using the deep deterministic policy gradient algorithm, the cooling system is adjusted to meet temperature needs. This experiment proved that this system could track temperature more accurately than fuzzy logic control.

Furthermore, a helical baffle flow field was proposed by Liu et al. [98] to optimize the flow-field geometry. The model was sampled with optimal latin hypercube sampling and trained with a back-propagation Bayesian-regularized ANN, while optimizing via genetic algorithms. The optimized design was able to improve drainage performance by 7.8%.

4.4.5. Multi-Objective Optimization and System-Level Modeling

System-level modeling combined with multi-objective optimization enables coordinated improvement of fuel cell performance across interacting design and operating parameters. Zhou et al. [99] presented an ML-based approach to optimize fuel cell powertrains. By utilizing global sensitivity analysis, the authors identified five

critical design factors in energy efficiency. Partial optimization with these variables resulted in 17.78% energy savings, which is slightly lower than the 19.62% improvement achieved with the fully optimized solution.

Briceno-Mena et al. [100] presented a novel integrated ML, few-shot transfer learning, and derivative-free optimization strategy to get improved performance characterization of HT-PEMFCs. In this context, because there are a limited number of experimental data resources, NNs are pre-trained using simulations that follow knowledge-based models, followed by training on small samples of real datasets. Extrapolation is handled by a kNN approach to identify out-of-distribution predictions in order to perform safe optimization. The constructed surrogate exhibits good representation of important system dynamics, with multi-objective optimization of fuel cell design, through which are identified the base levers towards increasing performance: Oxygen stoichiometry, temperature, and ionomer conductivity.

Alibeigi et al. [101] utilized a combination of 3D modeling, RSM, and AI techniques, including deep neural networks (DNN), SVR, and Gaussian process regression (GPR) for prediction and optimization of maximum power and current density at the optimum node of the HT-PEMFC. Additionally, optimization algorithms such as the whale optimization algorithm (WOA), grasshopper optimization algorithm (GOA), firefly algorithm, and genetic algorithm were integrated to identify optimal operating conditions. The DNN model demonstrated the highest accuracy, with a MAPE of 0.81%, outperforming SVR (0.83%) and GPR (2.24%). Most optimization results showed errors below 8%, with the DNN-GOA and SVR-GA combinations achieving the lowest errors, confirming the strong potential of AI-assisted optimization in HT-PEMFC performance enhancement.

Zhou et al. [102] developed an LSTM with genetic algorithms to optimize fuel cell operational parameters. Experimental results demonstrated an increase of 6% for the maximum net output power of the system, and system efficiency consistently exceeded 55%.

In [103], Multi-generation systems were integrated with PEMFC. During peak solar energy usage, geothermal energy can be integrated with solar energy in the Brayton and Organic Rankine Cycles, humidification-dehumidification desalination, and PEM Electrolyzers to produce electricity, fresh water, and hydrogen. The generated hydrogen is stored and used at night to power the fuel cell, which extends nighttime operation from 8 to 14 h and reduces hydrogen consumption per hour from 286.38 kg to 102.27 kg. This change consequently affects power output and efficiency, with XGBoost providing the most accurate predictions.

5. Internet of Things in Fuel Cells

While the DT and ML sections focused primarily on modeling and prediction, this section addresses the IoT, which provides the sensing and connectivity layer that supplies both technologies with the real-time data they depend on. The IoT represents a transformative technology on a daily basis, from household appliances to industrial machinery [104]. It was first recognized by Kevin Ashton in 1999 in the context of supply chain management [105]. Additionally, IoT and ML can improve power production, storage, and consumption by providing real-time monitoring and predictive analysis. Hybrid systems powered by IoT, taking readings from a multitude of types of sensors and applying ML to process those readings, can fine-tune energy generation to leverage real-time environmental conditions and consumption patterns [33].

IoT comprises three layers as shown in Figure 13. These layers are: the perception layer, the network layer, and the application layer. The perception layer is responsible for data acquisition, processing, and automatic control. It includes various sensors, RFID, two-dimensional codes, and intelligent devices. The network layer connects the perception layer with the application, using wired and wireless methods to transmit data stably and securely. It relies on mobile communication networks, the internet, and users' private networks. The application layer focuses on processing information and facilitating human-machine interaction. It manages data sent from the network layer, processes it, and displays it via software interfaces [106]. Many controllers are being used in IoT to collect and send data from the sensor to the cloud. One of the most used controllers is the Raspberry Pi, which is being used with IoT devices in many research projects for its low cost, flexibility, and affordability [107].

Beyond this three-layer description, the architecture of IoT systems for fuel cells deserves closer attention, since it directly shapes which monitoring and control functions are feasible. At the perception layer, fuel cell deployments rely on heterogeneous sensing of voltage, current, temperature, pressure, humidity, and gas concentration, often combined with embedded controllers such as Raspberry Pi or ATmega-class microcontrollers. The network layer is where the most consequential design choices are made: short-range protocols such as Wi-Fi and Bluetooth offer high bandwidth but limited coverage and relatively high power draw, whereas low-power wide-area technologies such as LoRa are better suited to distributed or off-grid fuel cell nodes at the cost of lower data rates. Application-layer communication in the reviewed studies is dominated by lightweight publish-subscribe protocols, particularly MQTT, feeding cloud platforms such as ThingSpeak for visualization and analytics.

Recognizing these architectural and protocol-level trade-offs is essential because latency, bandwidth, and energy budgets ultimately determine whether an IoT layer can support only periodic monitoring or also real-time, closed-loop control of the fuel cell.

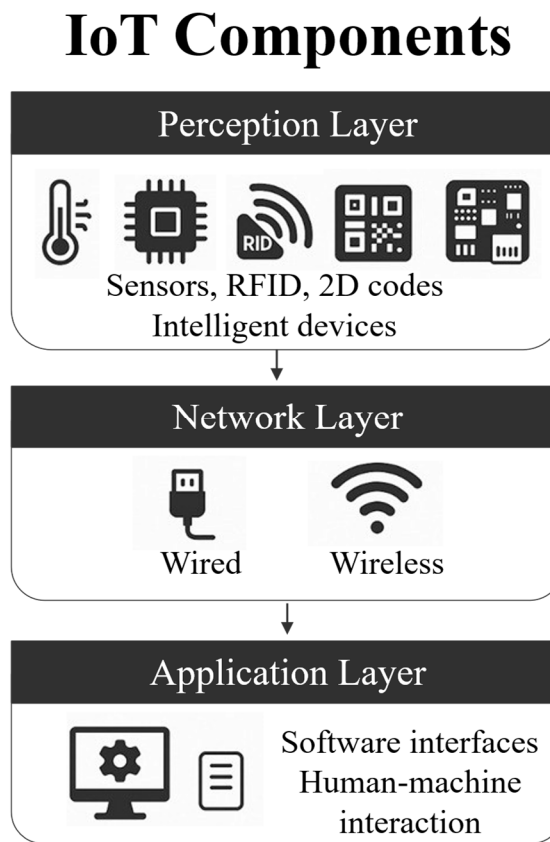


Figure 13. Internet of things layers.

5.1. Self-Sustaining Power Solutions for IoT

Energy harvesting is becoming crucial because IoT power sources are becoming an important issue for the sake of eliminating batteries [108] and providing uninterrupted, eco-friendly power during grid outages or disasters while minimizing reliance on finite resources [107]. IoT sensors have very high energy demands; therefore, MFCs [12], Sediment MFC [109], and PMFC [110] have been deployed to power IoT applications in remote locations such as farms and other off-grid environments.

Exploring alternative methods for electricity generation in IoT devices, a study was conducted by [111] to design a Microfluidic MFC powered by *Shewanella putrefaciens*, integrating with an IoT cloud framework, which allowed for the simultaneous real-time monitoring of six Microfluidic Paper-based MFC, sending data every 20 s using the MQTT protocol to the ThingSpeak cloud platform. The system's ability for continuous, battery-free energy harvesting was verified through remote access via web interfaces and smartphone apps, making it suitable for low-power IoT applications in remote locations. Moreover, Shabani et al. [112] engineered a self-sustaining water quality sensing system, in which the MFC produced power while also serving as a chemical oxygen demand sensor. A low-power SVR model-based platform has been developed, which inputs voltage signals from the MFC to get the chemical oxygen demand level quantification with high accuracy ($R^2 = 0.94$). This design does not require any batteries or external power, making it perfect for remote, real-world use. The applicability of the device was verified by natural pond water, which exhibited reliable performance and a possible way to environmentally friendly, IoT approachable monitoring system

A recent study by Li et al. [12] adopted a self-sustaining environmental monitoring system with the PMFC, voltage booster circuit, and IoT to increase the power generation of PMFC. Even though PMFC generates continuously and costs less than solar energy, it still doesn't generate as much electricity as solar energy. The self-sustaining environmental monitoring system IoT network consists of several nodes, each featuring its own PMFC power generator, booster circuits, sensors, and microcontroller units. Each node is capable of environmental monitoring using its individual microcontroller units and sensors. Furthermore, every node comes with a LoRa

module for communication, enabling low-power transmission throughout the system. The proposed system showed that it can sustain itself with minimal maintenance required.

Another study presented in [113] designed power management units using a microwatt-powered ultra-low-power energy harvester, a supercapacitor, and a tailored microcontroller to facilitate efficient energy management. Integrating power management units into a real-time IoT, which is powered by a laser-ablated reduced graphene oxide (rGO) based aluminum–air (Al–air) fuel cell, demonstrates a self-sustaining energy solution for low-power IoT applications. To power an IoT device using a low-voltage input source, a boost DC/DC converter is necessary. A basic voltage-doubler converter is taken into consideration. Berlitz et al. [108] replaced one capacitor in a voltage-doubler Switched-Capacitor Converter with an MFC, creating a switched fuel-cell converter that holds a high efficiency of more than 95% with a peak of 97.25%. The switched fuel-cell operates more effectively than the Switched-Capacitor Converter counterpart when considering the life of the coin battery.

Figure 14 illustrates a typical self-sustaining PMFC-powered IoT monitoring architecture. The system integrates a PMFC with a voltage booster, environmental sensors, a low-power microcontroller (ATmega328), and a wireless communication module (Wi-Fi or LoRa). Data collected from the environment is transmitted in real time to a cloud platform or smartphone interface, enabling continuous, off-grid environmental monitoring without the need for batteries or external power sources [113].

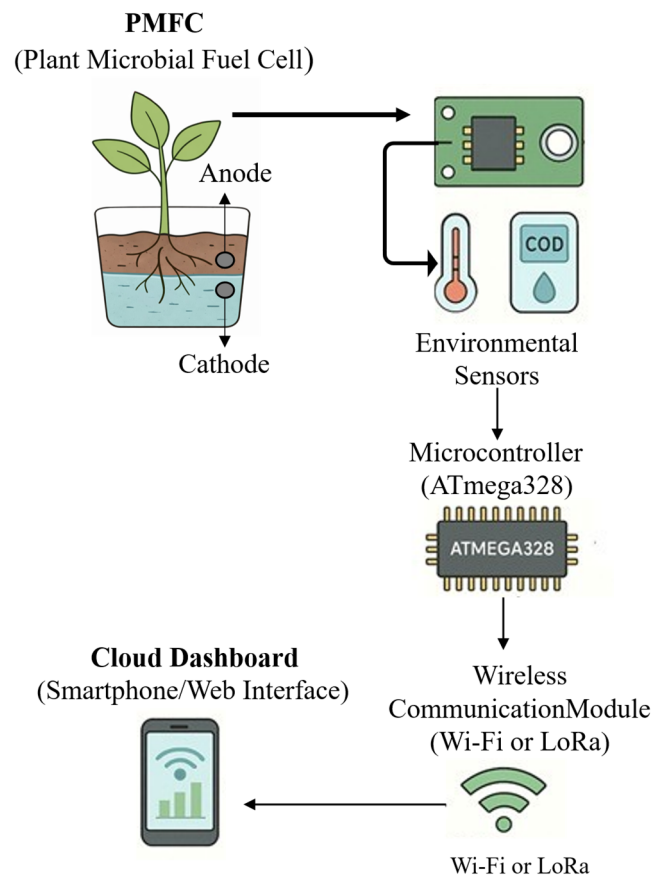


Figure 14. Architecture of a self-sustaining PMFC-powered IoT monitoring system.

5.2. IoT in Fuel Cell Applications and Sustainability

IoT has many applications for fuel cell vehicles, such as enhancements in efficiency, safety, and sustainability. Through real-time data analysis, efficiency can be improved by optimizing hydrogen production, delivery, and consumption. Sensors can also detect increases in temperature and leaks, allowing for prompt corrective actions to enhance operational safety. The energy management system is essential for sustainability by incorporating IoT technology into the hydrogen production process and minimizing the dependence on fossil fuels to reduce emissions [114].

IoT has a significant role in FCEVS, especially autonomous vehicles, which can transmit the location, direction, and route of the ride to optimize the most efficient fuel consumption [115]. The PEM fuel cell system showed better performance, cost-effectiveness, and sustainability than batteries, confirming its potential for eco-

friendly IoT applications [107]. Furthermore, DMFCs are suitable for IoT applications, operating for 3600 h and experiencing three faults, which were fundamentally resolved [116].

A strong case study was introduced by [117] to design an IoT-enabled MFC that cleans wastewater and produces electricity as a byproduct. Three different filtering materials were tested to filter the water: Jhama brick, brick surkhi, and rubber tire fragments, using IoT sensors to monitor voltage, current, and power density in real-time. Jhama brick outperformed the others in pollutant removal, while rubber tire fragments achieved the highest power density but lagged in wastewater treatment efficiency. The treated water was reused to grow hydroponic plants, enhancing sustainability. The IoT gathers real-time data to identify the optimal material, sending this information to a cloud server via Wi-Fi to alert users about issues such as biofilm decay or clogged media, enabling quick responses. The model effectively produced bioenergy from wastewater and eliminated a large number of contaminants under continuous monitoring. The study highlighted the potential of IoT-enabled MFCs for sustainable wastewater treatment and energy generation.

6. Analysis of Digitalization Trends in Fuel Cell Research

This section provides a quantitative view of the surveyed literature and maps how the studies divide across the three digitalization technologies and fuel cell types, aiming to show where research effort has been concentrated and where it stays thin. Figure 15 shows how the reviewed studies are divided across the three digitalization technologies. ML appears in 74 studies, DT comes second with 14 studies, and IoT third with 13 studies. The gap between ML and the other two is wide, and it matches the maturity gap noted in the earlier sections. ML benefits from a large existing toolbox, lower data infrastructure needs, and clear validation metrics such as R^2 , RMSE, and accuracy that map well onto fuel cell tasks. DT and IoT remain smaller in count because each needs more upstream investment, such as calibrated physical models for DT, and sensing and connectivity hardware for IoT.

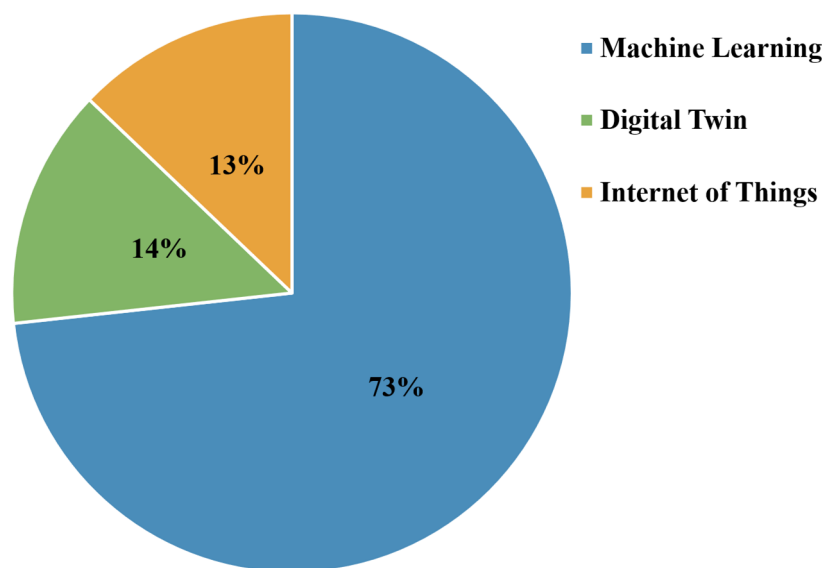


Figure 15. Distribution of reviewed studies across digitalization technologies.

Figure 16 regroups the same 101 studies by fuel cell type. PEMFC dominates with 60 studies, counting both standard and high-temperature (HT-PEMFC) variants. SOFC accounts for 13 studies, MFC for 10, and an “Others” category covers the remaining 18, which groups less common types such as DMFC, MCFC, protonic ceramic fuel cell, and undefined types. The dominance of PEMFC mirrors its standing in the wider fuel cell market. Its low operating temperature, fast start-up, and use in vehicles produce long and well-instrumented duty cycles that ML and DT methods need. SOFC and MFC attract fewer digitalization studies for different reasons, including that SOFC operates at high temperatures and serves stationary cogeneration applications, where instrumented data campaigns are slow and expensive to run, while MFC stays at lab scale with low power output and unstable voltage, which makes large training datasets hard to build. The 18 papers under “Others” show that researchers also explore less mature cell chemistries, but coverage there is shallow and split across several types.

Figure 17 disaggregates the 74 ML studies identified in Figure 15 according to the model employed. The totals sum to 141 rather than 74 because a number of the studies benchmark two or more algorithms against one another on the same task. ANN are the most frequently reported, with 35 occurrences, followed by SVM/SVR and gradient

boosting with 18 each, and RF and decision tree with 12 each. KNN and LR jointly occupy the sixth position with 8 occurrences each, ahead of GPR at 6, and LSTM, logistic regression, and MLP at 4 occurrences each.

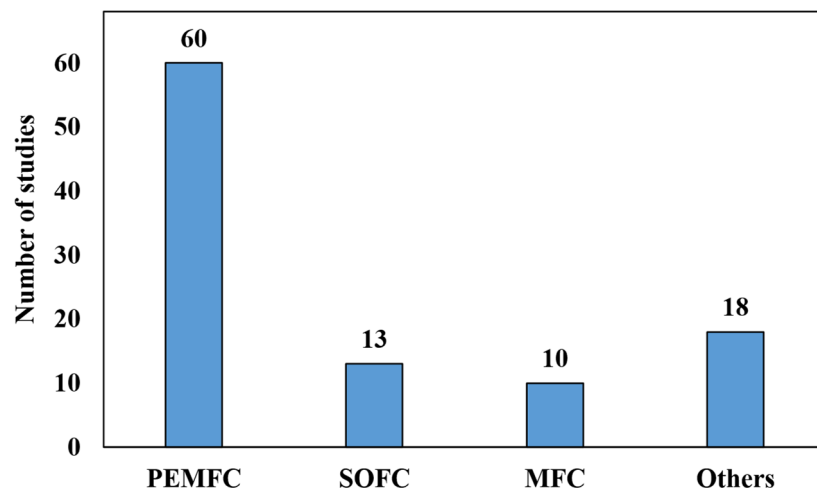


Figure 16. Distribution of reviewed studies across fuel cell types.

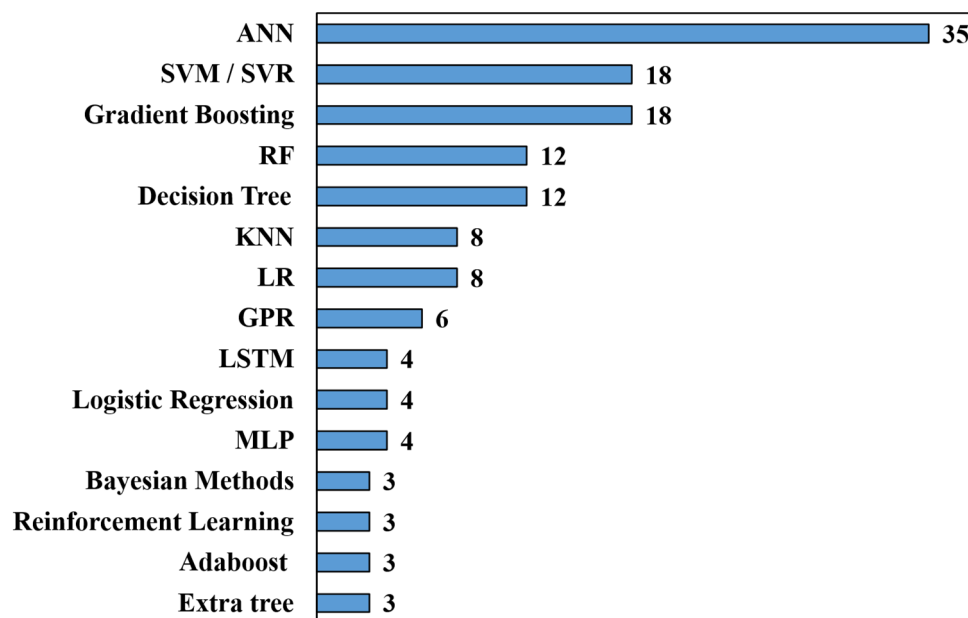


Figure 17. Distribution of ML models.

As seen in Figure 17, the list is dominated by classical and shallow learning algorithms. ANN, SVM/SVR, gradient boosting, RF, decision tree, KNN, and LR collectively account for 111 (~79%) of the 141 occurrences, reflecting their suitability for sequential degradation and prognostic tasks. The prevalence of SVM/SVR and ANN is consistent with the data regime that characterises fuel cell research, in which datasets are typically small to moderate in size. Both exhibit favourable training efficiency, robust generalization, and tolerance to heterogeneous input descriptors. The continued presence of tree-based and probabilistic methods, namely RF, decision tree, XGBoost, GBDT, and GPR, can be attributed to their interpretability and uncertainty quantification, which permit a direct mapping between model outputs and physically meaningful operating parameters such as platinum loading, cell temperature, and oxygen stoichiometry.

Drawing the three technologies together, a critical comparison shows that they differ markedly in maturity and in the evidence supporting them. ML is the most mature, not simply because it appears most often in the literature, but judged against concrete criteria: the breadth of validated applications, the consistency of reported accuracy, and the availability of quantitative metrics. Across the fault-detection studies surveyed, ML models repeatedly reach accuracies in the high-80% to near-99% range, with ensemble and gradient-boosting methods, such as GBDT and XGBoost, and ANN-based models among the strongest performers, while regression-oriented tasks such as remaining-useful-life and degradation prediction frequently report R^2 values above 0.95. DTs occupy an

intermediate position: they deliver the largest computational savings, compressing simulations from days to seconds with reported deviations below 1-5%, but these gains rest on a smaller body of work and on case-specific calibration. IoT is also a valuable as an enabling data layer but rarely evaluated against quantitative performance targets. A clear limitation of the current literature, and of this review, is that these metrics are not directly comparable because studies differ in fuel cell type, dataset size, operating conditions, and reporting conventions; a standardized benchmarking effort is needed before a fully meta-analytical comparison becomes possible.

7. Conclusions

This paper provided an analysis of the strategic application of DT, ML, and IoT technologies in fuel cell optimization, development, and commercialization. Based on the research conducted in the past five years, it is evident that digitalization has transcended concept demonstration and is increasingly serving the performance enhancement, fault diagnosis, lifetime prediction, and system-level integration of fuel cell technologies. A quantitative analysis of the 101 reviewed studies highlights clear trends and varying maturity levels across current digitalization research. ML is the most dominant technology, featured in 73% of the literature. In contrast, DT and IoT represent a smaller share of the research, accounting for 14% and 13%, respectively.

Specifically, ML has been applied to predict performance, optimize control, model degradation, and energy management. In fact, data-driven models supplement expensive physics simulations, facilitating expedited design cycles and real-time influence. Concurrently, DT has demonstrated strong potential in connecting real-world fuel cell systems to their digital replica counterparts in virtual worlds, and such bridges the possibility for online monitoring, predictive maintenance, and condition-based optimization at both the component level and system level. Through the integration of ML, the features of DT can be further enhanced in terms of adaptability, reduced dependency on fault data, and better accuracy during dynamic operation. IoT technologies have shown a distinct and enabling role in terms of instant, distributed data acquisition and connection. In addition to typical monitoring activities, IoT-enabled fuel cells (especially microbial and plant) have demonstrated the potential for self-sustaining power solutions for remote sensing and environmental monitoring. These applications illustrate the wider sustainability implications of fuel cell–IoT convergence beyond transportation and stationary power.

Promising directions for future work include interpretable and physics-effective ML models, scalable DT systems architecture, and efficient IoT devices. More attention to real-world validation, cross-platform data sharing, and long-term operational studies will be necessary in order to move digitalization of fuel cell technology from the lab into industry and commerce. A recurring gap across all three technologies is the distance between reported performance and real-world implementation. Many of the surveyed models achieve high accuracy on controlled experimental or simulated datasets, yet relatively few are validated on long-duration field data, across multiple cells, or under the variable conditions encountered in service. Furthermore, to address the dominance of classical ML models, future research must expand the application of deep learning architectures beyond isolated prognostic tasks, while simultaneously advancing physics-informed interpretability to ensure these models can be trusted in safety-critical decisions.

Author Contributions

A.M.N: writing—original draft preparation, writing—reviewing and editing, data curation, visualization; M.M.: writing—original draft preparation, writing—reviewing and editing, investigation, conceptualization; A.A.: writing—original draft preparation, writing—reviewing and editing, supervision, methodology. All authors have read and agreed to the published version of the manuscript.

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Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT and Grammarly to rephrase sentences and enhance language. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

List of Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
ANN	Artificial Neural Network
BA	Bayesian Algorithm
BPNN	Back Propagation Neural Network
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Network
DEIS	Dynamic Electrochemical Impedance Spectroscopy
DMFC	Direct Methanol Fuel Cell
DNN	Deep Neural Network
DT	Digital Twin
DTW	Dynamic Time Warping
ECSA	Electrochemically Active Surface Area
EIS	Electrochemical Impedance Spectroscopy
FCEV	Fuel Cell Electric Vehicle
GBDT	Gradient Boosting Decision Tree
GDL	Gas Diffusion Layer
GOA	Grasshopper Optimization Algorithm
GPR	Gaussian Process Regression
HPS	Hybrid Power Systems
IoT	Internet of Things
IoV	Internet of Vehicles
ITD3	Improved Twin Delayed Deep Deterministic Policy Gradient
IWOA	Improved Whale Optimization Algorithm
KNN	k-Nearest Neighbor
LR	Linear Regression
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MBP	Metallic Bipolar Plate
MCFC	Molten Carbonate Fuel Cell
MFC	Microbial Fuel Cell
ML	Machine Learning
MPPT	Maximum Power Point Tracking
MSE	Mean Squared Error
NN	Neural Network
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
PEM/PEMFC	Proton Exchange Membrane (Fuel Cell)
PMFC	Plant Microbial Fuel Cell
RF	Random Forest / Random Forest Regressor
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RSM	Response Surface Methodology
SHAP	SHapley Additive exPlanations
SOC	State of Charge
SOFC	Solid Oxide Fuel Cell
SOH	State of Health
SVM	Support Vector Machine
SVR	Support Vector Regression
WOA	Whale Optimization Algorithm
WTW	Well-To-Wheel
XGBoost	Extreme Gradient Boosting

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