# Current Status of Fuel Cell Fault Diagnosis and Lifetime Prediction

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**Abstract:** *Fuel cells (FCs), as an efficient and clean renewable energy technology, face commercialization challenges primarily due to their limited operational lifetime. Prognostics and Health Management (PHM) techniques offer a solution by monitoring FC states and estimating their Remaining Useful Life (RUL), thereby providing decision support for proactive maintenance and extending system lifespan. Current PHM challenges include reliable and rapid fault localization, developing accurate degradation models, and adopting precise, reliable, and cost-effective life prediction methods. This review describes the key steps of PHM for fuel cells, enumerates various fault diagnosis and life prediction methods, and provides a comparative analysis of hybrid prediction approaches. It also summarizes data-driven life prediction methods, including those based on machine learning and signal processing. Finally, future research directions are proposed, encompassing enhancing online fault diagnosis capabilities and improving the accuracy of PHM systems.*

**Keywords:** Fuel cell technology; Prognostics and Health Management; Remaining Useful Life; Fault diagnosis; Hybrid methods; Online monitoring.

## 1. Introduction

The challenges of climate change and energy scarcity demand low-carbon and environmentally friendly energy sources. Proton Exchange Membrane Fuel Cells (PEMFCs) show immense potential in automotive and portable applications due to their high efficiency, environmental friendliness, and relatively low operating temperature (50-90°C) [1]. However, their widespread commercialization is significantly constrained by durability issues and high maintenance costs. However, the durability of PEMFCs in most applications is still far below the desired value and should not be disregarded [2]. FC aging primarily results from electrode corrosion, catalyst agglomeration, and membrane degradation. Understanding and predicting voltage decay trends and identifying causes of performance deterioration are crucial for performance improvement [3, 4]. Therefore, real-time monitoring of PEMFC systems to assess health status, identify fault types, and predict Remaining Useful Life (RUL) is essential for devising appropriate maintenance plans and extending operational life [5-7].

Prognostics and Health Management (PHM) technology, which evaluates internal system states, predicts aging characteristics, and implements corresponding management strategies, has proven effective in enhancing FC durability and reliability [8-10]. PHM must handle system nonlinearities, multiple failure sources, and varied time scales. Compared to model-based methods, non-model-based (e.g., data-driven) approaches represent a newer trend in FC system diagnosis [11]. This paper aims to summarize the application characteristics of non-model-based fault diagnosis methods in the FC domain.

Estimating the RUL of an FC system is central to solving the short lifespan problem, enabling proactive maintenance scheduling [12-14]. RUL prediction techniques are typically categorized into data-driven methods, model-based methods, and hybrid methods [15]. The aging of PEMFC systems involves a complex coupling of various components, physical conditions, and variables. While performance degradation is inevitable, understanding its mechanisms can help minimize the degradation rate [16, 17].

This paper introduces the PHM workflow and its application in fault diagnosis and life prediction, reviews the current state of major methods, and discusses future research trends. Section 2 briefly describes the PHM workflow and application. Section 3 focuses on non-model-based fault diagnosis methods. Section 4 systematically reviews life prediction methods from both model-driven and data-driven perspectives. Section 5 discusses hybrid prediction techniques that integrate multiple approaches.

## 2. Prognostics and Health Management

PHM aims to detect potential equipment faults, diagnose fault types and severity, and predict future health states, thereby reserving time for system maintenance, enabling cost-effective scheduling, and improving equipment availability and reliability [18-20].

### 2.1 Prognostics and Health Management Workflow

A typical PHM framework comprises five steps: data acquisition, data processing, fault diagnosis, prognostics (life prediction), and health management, as shown in Figure 1.



**Figure 1:** PHM architecture

Data Acquisition: Sensors monitor parameters like temperature, voltage, and current in real-time. However, the complexity of PEMFC testing often leads to scarcity of durability data, especially open-source aging datasets [21].

Data Processing: Acquired signals undergo filtering (e.g., LOESS, GWMA) and feature extraction. Common Health Indicators (HIs) include output voltage, power, and polarization curves. Extracting features that accurately

represent degradation remains a research challenge due to the lack of universal aging indicators [22].

Fault Diagnosis: Processed data is analyzed to determine system health status, identify fault types, and pinpoint causes, relying on historical data from various health states.

Prognostics (Life Prediction): This core step predicts future system health and RUL based on current degradation levels and future operating scenarios, providing a basis for maintenance strategies [23, 24].

Health Management: Based on diagnostic and prognostic results, reasonable maintenance and replacement plans are formulated to enable preventive actions before failures occur.

## 2.2 Application and Significance of PHM in FCs

The primary goals of PHM are fault diagnosis and prediction. Applying PHM to FCs enables real-time performance monitoring, rapid fault identification, and RUL prediction. Studies show PHM-based health management can significantly enhance the durability of automotive fuel cells, e.g., extending lifespan by up to 95.4% [25]. By extracting HIs that characterize degradation trends, RUL prediction average relative accuracy can exceed 99%. Figure 2 shows the increasing trend in PHM-related journal publications over the past decade. Figure 3 illustrates a complete FC PHM workflow.
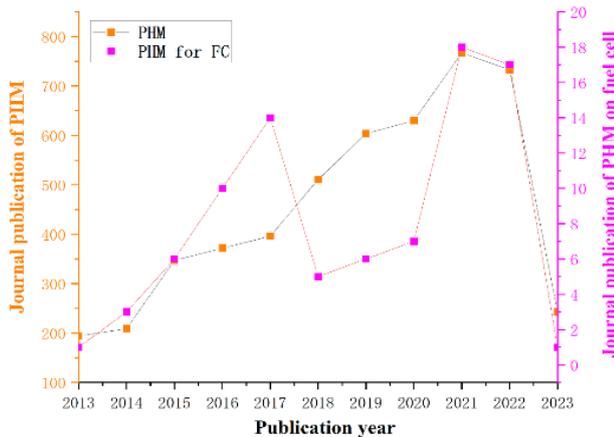


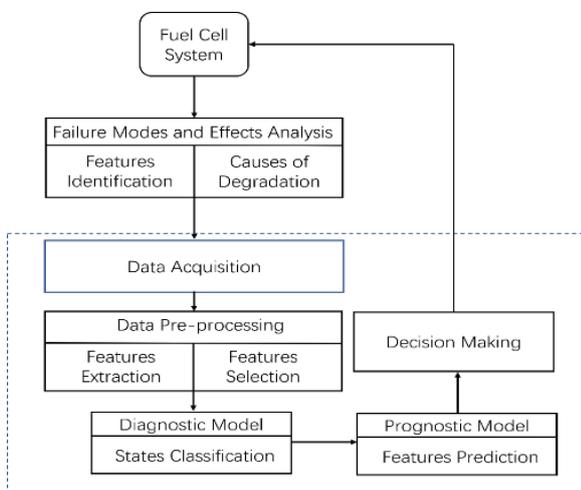**Figure 2:** Number of journal publications on PHM using the Web of Science database.



**Figure 3:** PHM workflow for a FC

# 3. FC Fault Diagnosis

Fault diagnosis is the foundation of PHM, aiming to identify potential issues by monitoring and analyzing performance metrics. This section discusses statistical-based, signal processing-based, and other diagnostic techniques.

### 3.1 Statistical-Based Methods

These methods employ multivariate statistical analysis to handle large amounts of correlated data. Accuracy depends on data quality and modeling.

Principal Component Analysis (PCA): A common dimensionality reduction technique that transforms original data into new uncorrelated variables while retaining maximum information [26]. PCA is widely used in PEMFC fault detection due to its simplicity and efficiency, e.g., for analyzing variable correlations, monitoring stack status, and detecting gas supply faults. However, PCA may perform poorly in nonlinear processes and risk information loss [27].

Fisher Discriminant Analysis (FDA): Another classic dimensionality reduction method that maximizes inter-class distance and minimizes intra-class distance to find optimal linear discriminants for classification. Techniques like Variable-Weighted FDA (VW-FDA) [28], sequential use of FDA and Directed Acyclic Graph Support Vector Machine (DAGSVM) [29] and applying FDA to 2D image data converted from 1D voltage signals have proven effective in extracting discriminative features and reducing computational costs. FDA typically outperforms PCA in classification but its linear nature may limit performance in nonlinear systems [30].

Bayesian Network (BN): A probabilistic graphical model (Directed Acyclic Graph) describing variable dependencies and inference. In PEMFC diagnosis, BNs can diagnose fault causes based on observed effects [31]. Using probabilistic methods (e.g., K2, MCMC) to quantify dependencies among sensor-monitored variables yields diagnostic results consistent with original faults [32]. Static discrete BNs have also been applied to Solid Oxide Fuel Cell (SOFC) systems [33]. BNs help understand variable relationships and are widely applicable.

The classification of the statistical methods used is shown in the following subsections and Table 1.

**Table 1:** Classification of statistics-based diagnostic methods

| Method | Year | Index | Online/Offline | Ref. |
|---|---|---|---|---|
| MCSKPCA + WT | 2011 | Corresponding time responses | — | [26] |
| PCA + PE | 2019 | Voltage | On | [27] |
| FDA + VW | 2009 | FDA-based discriminative features | — | [28] |
| FDA + DAGSVM | 2015 | Individual cell voltages | On | [29] |
| PCA | 2011 | Voltage | — | [30] |
| Bayesian + K2 + MCMC | 2008 | Output voltage and electric current | On | [31] |
| Bayesian + K2 + MCMC | 2007 | Voltage, temperature, hydrogen pressure | On | [32] |
| Discrete Bayesian | 2012 | Voltage and current | — | [33] |
| PCA + multi-sensor signals | 2017 | PCA-based health indictor | On | [34] |
| KFDA + SVD | 2016 | SVD-based features | — | [35] |

## 3.2 Signal Processing-based Approach

Fast Fourier Transform (FFT): An efficient algorithm converting time-domain signals to the frequency domain. It analyzes Electrochemical Impedance Spectroscopy (EIS) data to assess health [36], diagnoses dynamic behavior by analyzing dominant frequencies of voltage drops [37], and analyzes fractional-order model resistance via FFT-EIS to reflect degradation [38].

Wavelet Transform (WT): Decomposes signals into different frequency components, offering better time-frequency localization. Both Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) are used for PEMFC diagnosis. CWT with Extended Kalman Filter (EKF) estimates stack impedance in real-time [39]. DWT with Multi-Resolution Analysis extracts information from Open Circuit Voltage spectra to determine State of Health (SOH) [40]. WT is also used for detecting air supply issues and diagnosing water management faults [41].

**Table 2:** Signal-based diagnosis methods.

| Method | Year | Signal | On-line/ Offline | Ref. |
|---|---|---|---|---|
| FFT+EIS | 2022 | Battery voltage and current | On | [36] |
| EFD+HT | 2022 | Battery voltage | — | [37] |
| FFT+EIS+FOM | 2023 | Battery voltage and current | On | [38] |
| CWT+EKF | 2014 | Battery voltage and current | On | [39] |
| DWT-MRA | 2014 | Output voltage | — | [40] |
| WT-EIV | 2020 | Voltage fluctuation | On | [41] |
| CWT+MRMR+ MIQ+KNN | 2014 | Stack voltage | On | [42] |
| FFT | 2017 | Stack voltage and cathode/anode voltage drop | Off | [43] |
| WT | 2016 | Stack voltage and cathode/anode voltage drop | — | [44] |

## 3.3 Additional Diagnostic Techniques

Acoustic Emission (AE): Captures and analyzes elastic waves generated by displacements and stress changes within the FC, particularly sensitive to water management issues [45].

External Magnetic Field Detection: Based on the principle that faults alter current and magnetic fields. Non-invasively monitors magnetic field distribution changes via sensors placed around the system to assess health and detect faults (e.g., gas leaks) [46].

Fault Scenario Testing: Determines optimal operating parameters by conducting fault operation tests under various scenarios. For instance, using Artificial Neural Networks (ANN) combined with 3D models to locate faults within different FC regions [47].

Sensor Selection Techniques: Utilizing multi-sensor information fusion provides richer fault information, as different failure mechanisms may affect different sensors. Sensor selection helps ensure reliable diagnosis without extensive physical modeling and enables early degradation detection [48].

It is vital to choose the best method for fault diagnosis based on the specific application circumstances because each of the different diagnostic techniques has its own benefits and drawbacks. Table 3 provides a detailed summary of the results.

**Table 3:** Review of additional diagnostic technologies.

| Method | Year | Fault Type | Online/ Offline | Ref. |
|---|---|---|---|---|
| External Magnetic Field | 2019 | State of Health | — | [46] |
| 3D Fault Sensitive Model + ANN | 2022 | Flooding and Drying | Off | [47] |
| Sensor Selection Technique | 2014 | Various System Faults | On | [48] |
| Acoustic Emission | 2008 | Flooding and Drying | On | [49] |
| Electrochemical Noise | 2015 | Flooding and Drying | On | [50] |
| Superposition Principle | 2017 | Cell Stack Defects | On | [51] |

Life prediction is another core PHM component. End-of-life is often defined as when stack maximum power drops to 90% of rated power [52]. Prediction methods are categorized into model-based and data-based approaches, as shown in Figure 4.
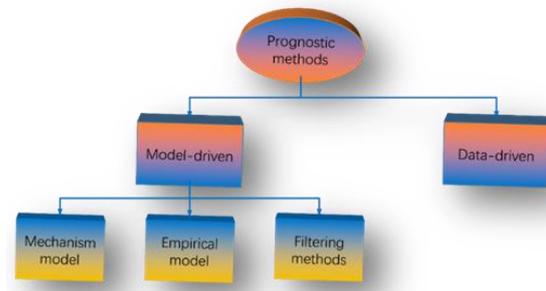


**Figure 4:** Classification of prognostic methods

Model-driven methods rely on understanding load conditions, material properties, and degradation mechanisms, building mathematical models to predict RUL.

Mechanistic Models ("White-Box Models"): Built on internal electrochemical, fluid dynamic, and thermodynamic principles. Examples include studying platinum dissolution/deposition via potential cycling [53], simulating active surface area loss using multi-scale modeling [54, 55], and proposing prediction methods based on multi-physics aging models [51]. Mechanistic models offer clear physical meaning and interpretability but are difficult to develop quickly and may not cover all degradation scenarios. Table 4 summarizes mechanistic model-based methods.

**Table 4:** Classification of prognostic methods by mechanism models

| Research object | Year | Evaluation method | Operating state | Ref. |
|---|---|---|---|---|
| Physical degradation phenomena | 2017 | Multiphysical ageing model | Steady state | [48] |
| Platinum dissolution and deposition | 2006 | Simulated equivalent active surface area loss | Dynamic state | [53] |
| Performance loss of the PEMFC | 2016 | Simulated equivalent active surface area loss | Dynamic state | [54] |
| Maximum service life of FCs for vehicle applications | 2019 | Maximum service/nonlinear lifetime prediction formulas | Steady and dynamic states and real conditions | [56] |
| Performance loss of the PEMFC | 2020 | Operando current density distribution measurements and electrochemical characterization techniques | Steady and dynamic states | [57] |

Empirical/Semi-Empirical Models: Based on external system behavior and statistical knowledge, correlating measurable parameters (e.g., temperature, pressure) with output characteristics. Semi-empirical models incorporate mechanistic equations, making parameters easier to obtain. Examples include online updating of semi-empirical model parameters [58], establishing life prediction models based on load profile eigenvalues [59], and using optimization algorithms like Whale Optimization Algorithm (WOA) for parameter determination [60]. A Voltage Prediction Model (VPM) incorporating a recovery factor accurately predicted PEMFC degradation curves [61]. Table 5 summarizes empirical model-based methods.

Particle Filter (PF): Suitable for state estimation in nonlinear, non-Gaussian systems. It uses Sequential Importance Sampling to represent probability distributions with particles, estimating the system's Probability Density Function (PDF)

and fault probabilities [63]. PF compares different voltage degradation models, achieving RUL prediction accuracy over 95% [64]. Adaptive PF (APF) addresses challenges like dynamic operating conditions and recovery effects by introducing self-healing factors or mitigating sample impoverishment, improving accuracy and efficiency [65].

Kalman Filter (KF): Provides efficient recursive least-squares solutions. Extended Kalman Filter (EKF) estimates time-varying parameters representing aging and degradation rates [66]. Unscented Kalman Filter (UKF) combined with voltage degradation models predicts PEMFC life under real operating conditions with low average relative error (e.g., 2.03%). Adaptive UKF (AUKF) and Frequency-Domain KF (FDKF) further enhance prediction performance and computational efficiency [67-69]. The filtering-based prediction methods are shown in Table 6.

**Table 5:** Classification of prognostic methods by empirical-based models

| Research purpose | Year | Evaluation method | Operating state | Ref. |
|---|---|---|---|---|
| Improving performance of fuel cell vehicles | 2014 | ARLS + ANOVA + Semiempirical model | Dynamic state | [58] |
| Estimating of the degradation rate of the cell voltage | 2017 | Voltage degradation model with ageing and load profiles | Steady and dynamic states | [59] |
| Developing precise PEMFC models | 2019 | WOA + semiempirical model | Steady and dynamic states | [60] |
| Predicting the degradation trends of PEMFCs | 2021 | VPM with recovery factor + ERDM | Steady state and real condition | [61] |
| Estimating of PEM FC lifetime | 2015 | Residual lifetime estimation formula | Real condition | [62] |

**Table 6:** Classification of prognostic methods by filtering-based methods

| Research purpose | Year | Evaluation method | Operating state | RE | Ref. |
|---|---|---|---|---|---|
| Calculating the probability of fault conditions in real-time | 2009 | FDI module + PF | — | — | [63] |
| Estimating the remaining useful life before failures occur | 2014 | APF | Steady state | 5% | [65] |
| Estimating the state of health and predicting the RUL | 2016 | EFK + LM optimization method | Dynamic state | — | [66] |
| Tracking the damage variable throughout the degradation process | 2020 | UFK + prognostic-oriented ageing model | Dynamic state | — | [67] |
| Predicting the degradation of PEMFCs in the frequency domain | 2021 | FDKF + Voltage degradation model | Steady and quasi-dynamic states | 1.8% 3% | [69] |
| Estimating the RUL of PEMFCs | 2014 | APF with self-healing factors | Steady and dynamic states | 5% | [70] |
| Developing precise PEMFC models | 2020 | APF + self-evaluation method | Steady and dynamic states | 6.82% | [71] |
| Estimating the voltage degradation trends of PEMFCs in FCEVs | 2017 | UFK + voltage degradation model | Real condition | 2.03% | [72] |

**3.4 Data-Based Prediction Methods**

Data-driven methods avoid reliance on complex physical models by learning patterns and correlations from historical data.

Adaptive Neuro-Fuzzy Inference System (ANFIS): Combines neural networks and fuzzy logic for complex nonlinear problems. ANFIS predicts output voltage trends [73]. ANFIS with Fuzzy C-Means (FCM) and Particle Swarm Optimization (PSO) shows promise for short-term prediction [51]

Extreme Learning Machine (ELM): A Single-hidden Layer Feedforward Network with randomly generated input weights, offering high learning efficiency and strong generalization. ELM variants (e.g., SW-ELM, ELM-AE-FEBLS) demonstrate good accuracy and robustness in PEMFC degradation prediction [74-76].

Support Vector Machine (SVM): Widely used for

classification and regression, providing predictions and confidence intervals. SVM predicts PEMFC V-I and P-I curves [77]. Relevance Vector Machine (RVM), a Bayesian extension, yields sparser models and lower computational requirements, outperforming SVM in battery SOH and RUL prediction [77].

Long Short-Term Memory Network (LSTM): An RNN variant addressing vanishing/exploding gradients via gating mechanisms, excelling at time series and long-term dependency modeling. LSTM and its variants (e.g., G-LSTM, Bi-LSTM) are widely used for long and short-term PEMFC aging prediction, achieving high accuracy (e.g., $R^2 > 99\%$) [78-82].

Echo State Network (ESN): A novel RNN with an input layer, sparsely connected reservoir, and output layer. ESN is used for long and short-term PEMFC prediction [83, 84]. Enhanced versions with moving weight matrices or Markov chains improve prediction performance under dynamic loads [85-87].

**Table 7:** Classification of neural network prediction methods

| Method | Year | RMSE | MAPE | $R^2$ | Operation condition | Length of time | Ref. |
|---|---|---|---|---|---|---|---|
| EANFIS + FCM | 2019 | 0.0216 | 0.0641 | 0.9957 | Steady and quasi-dynamic states | 1000 h | [51] |
| ANFIS | 2014 | 0.01 | 0.2455 | 0.8891 | Steady and quasi-dynamic states | 1000 h | [73] |
| SW-ELM | 2016 | — | — | 0.42 | Steady and dynamic states | 2850 h | [74] |
| SW-ELM | 2017 | <0.018 | — | — | Steady state | — | [75] |
| ELM-AE-FEBLS | 2023 | 9.02e−02 | 3.31e−04 | — | Steady and quasi-dynamic states | 1155 h | [76] |
| RVM | 2014 | 0.002149 | — | 0.9995 | Steady state | — | [77] |
| LSTM | 2018 | 0.1238 | 0.0025 | — | Steady state | 10000 h | [78] |
| G-LSTM | 2018 | 0.0040 | 0.0013 | — | Steady, quasi-dynamic and dynamic states | 10000 h | [79] |
| LSTM-RNN | 2019 | 0.003 | — | — | Steady state | 1154 h | [80] |
| S-LSTM | 2020 | 0.0036 | 0.0633 | — | Steady and quasi-dynamic states | 991 h/1016 h | [81] |
| BILSTM-AT | 2020 | 0.0024 | — | — | Steady states | 591 h | [82] |
| ANOVA-ESN | 2017 | — | 0.0097 | — | Steady state | 1700 h | [84] |
| ESN | 2020 | 0.098 | — | — | Dynamic state | 5000 h | [85] |
| MWM-ESN | 2020 | 0.00552 | 0.00357 | — | Steady state | 1000 h | [86] |
| Markov-ESN | 2021 | 0.0192 | — | — | Steady state | 500 h | [87] |
| Multi–step–ahead RVM | 2016 | 0.2244 | 0.0068 | 0.9296 | Steady state | 400 h | [88] |

# 4. Hybrid Approaches Based on Multiple Data Drivers

Hybrid methods combine the strengths of multiple techniques to overcome the limitations of single methods, becoming a research hotspot in RUL prediction.

## 4.1 Hybrid Approach Based on Multiple Data-driven Methods

Fusion of Multiple Neural Network Methods: Combining Random Forest (RF) and Convolutional Neural Network (CNN) to predict I-V polarization curves, reducing unnecessary experiments [89]. Fusing Bi-LSTM, Bidirectional Gated Recurrent Unit (Bi-GRU), and ESN outperforms single data-driven methods under both static and dynamic conditions [90]. Combining CNN and RNN enhances prediction performance [91, 92].

Neural Networks with Statistical Methods: Combining Analysis of Variance (ANOVA) with ESN improves accuracy by identifying influential parameters [93]. Bayesian Regularized Neural Network (BRNN) optimizes PEMFC parameter extraction before RNN training, enhancing stability and accuracy. LASSO regression optimizes ESN inputs by eliminating non-critical variables, improving prediction accuracy [94].

Neural Networks with Signal Processing Methods: Using wavelet analysis to decompose raw voltage signals before feeding into networks like GMDH or ELM enables direct processing of highly fluctuating data and improves prediction [95-97]. Hilbert-Huang Transform and Adaptive Brownian Bridge-based Aggregation (ABBA) with GRU are used for HI extraction and life prediction under dynamic loads [98].

Overall, a hybrid strategy based on various data-driven approaches can enhance the precision, resilience, and comprehensive performance of prediction or modelling, better handling massive amounts of data and complicated data structures. By utilizing the advantages of various approaches,

more thorough and dependable analytical results can be produced, offering stronger support for applications and decision-making. The classification of data-driven hybrid-based methods is summarized in Table 8.

**Table 8:** Classification of data-driven hybrid-based methods

| Method | Year | Healthy indictor | RMSE | Operation condition | Ref. |
|---|---|---|---|---|---|
| RF+CNN | 2021 | I-V polarization curve | 0.0221 | Dynamic | [89] |
| Bi-LSTM-GRU +ESN | 2022 | Voltage | 0.0235 | Steady-state and dynamic | [90] |
| Bi-RNN +CNN | 2023 | Voltage | 0.00258 | Steady-state | [92] |
| CEEMD+CNN +LSTM | 2023 | Voltage | 1.8005 | Real condition | [91] |
| ANOVA-ESN | 2008 | Mean cells voltage | — | Steady-state | [93] |
| LASSO-ESN | 2021 | Voltage | 0.0145 | Steady-state and dynamic | [94] |
| W-GMDH | 2017 | Voltage | 0.0010 | Steady-state and dynamic | [95] |
| WGA-ELM-Sig | 2019 | Voltage | 0.1184 | Real condition | [96] |
| ABBA-GRU | 2023 | Voltage | — | Dynamic | [98] |
| BRNN-MhAs | 2021 | I-V data | — | Steady-state and dynamic | [99] |
| W-NARX | 2021 | Voltage | — | Steady-state quasi dynamic and real condition | [100] |

## 4.2 Hybrid Approach Based on Data-driven and Model-driven Methods

Data with Filtering Methods: Combining PF with LSTM uses LSTM predictions as observations for PF, addressing PF's lack of measurement updates during prediction and significantly improving accuracy [95]. Combining LSSVM with Random Process Filtering (RPF) uses LSSVM predictions to update RPF observations, effectively merging both advantages [101]. Combining AEKF with NARX neural network captures irreversible degradation trends and dynamic behavior respectively [102]. Data with Mechanistic Models: Using a Physical Aging Model (PAM) to remove non-smooth trends, then ARIMA and TDNN to handle linear and

nonlinear components, enhances prediction robustness [103]. Combining EKF with LSTM uses EKF for parameter identification in training and LSTM for predicting voltage and aging parameters, accurately forecasting degradation under dynamic conditions [104].

Data with Empirical/Semi-Empirical Models: Combining empirical voltage models with NARNN predicts long-term degradation trends with better accuracy than ARIMA [105]. Using ANFIS and AUKF with semi-empirical voltage degradation models enables more precise long-term predictions [97]. Extracting HIs via degradation behavior models and predicting with ABBA-LSTM yields high-confidence RUL predictions under dynamic conditions [106]. Hybrid models combining Semi-Empirical Models (SEM) and Data-Driven Models (DDM) leverage DDM's short-term accuracy and SEM's long-term stability, reducing prediction volatility [38].

This section describes a series of hybrid methods for FC lifetime prediction in recent years, leading to a new trend for lifetime prediction. Hybrid methods for FC lifetime prediction are intended to improve the prediction accuracy and robustness by fusing several different methods. Hybrid methods based on multiple data-driven methods include the fusion of multiple neural network methods, neural network methods, statistical methods, and neural network and signal processing methods. These approaches combine several data processing and analysis methods to increase the forecast precision and accuracy. These methods fully exploit the advantages of the data characteristics while considering the physical characteristics of the system. With these hybrid methods, FC lifetime prediction can be more accurate, reliable, and practical. The classification of the data-driven and model-driven hybrid approaches is summarized in the following Table 9.

**Table 9:** Classification of data-driven and model-driven hybrid approaches

| Method | Year | Health indictor | RMSE | Operation condition | Ref. |
|---|---|---|---|---|---|
| Semiempirical models + DDM | 2023 | Cell voltage | 0.8144(V) | Quasi-dynamic state | [38] |
| Semiempirical models + ANN/SVR | 2022 | Cell voltage, membrane resistance and hydration | <0.035 | Dynamic state | [47] |
| PF + LSTM | 2020 | Cell voltage | 0.0042 | Steady state | [67] |
| Empirical models + ANFIS+AUKF | 2019 | Cell voltage | 0.0097 | Steady and quasi-dynamic states | [97] |
| PF + LSTM | 2017 | Cell voltage | 0.0072 | Steady state | [95] |
| RPF + LSSVM | 2018 | Cell voltage | 0.0644 | Steady state | [101] |
| AEKF + NARX | 2020 | Cell voltage | — | Steady state | [102] |
| PAM + ARMA + TDNN | 2018 | Cell voltage | 0.0073 | Steady state | [103] |
| SG+LSTM | 2021 | Cell voltage | 0.0041 | Real condition | [104] |
| Physical model + EKF + LSTM | 2021 | Cell voltage and EKF-based HI | 0.0110 0.0216 0.0317 | Steady, quasi-dynamic and dynamic states | [104] |
| Empirical model + NARNN | 2017 | Cell voltage | 0.2352 | Steady state | [105] |
| Physical model + ABBA-LSTM | 2022 | HI based on variable width partitions | — | Dynamic state | [106] |
| Empirical models +ABBA-LSTM | 2022 | Equivalent internal resistance and voltage | — | Dynamic state | [106] |
| Empirical models+ multistep ESN | 2022 | Time-varying variable $\alpha(t)$ | 0.051 | Dynamic state | [107] |

## 5. Conclusion and Prospects

This paper first introduces the workflow of the PHM system and its application in the FC field. Subsequently, a systematic and detailed review of the two key steps of PHM, fault diagnosis and prediction, is presented. In fault diagnosis, statistical and signal processing-based methods are the main technical methods. These methods can be applied to the fault diagnosis of each component of a FC and can be combined with other methods for comprehensive analysis. In lifetime prediction, model-driven and data-based methods have different advantages and disadvantages, Model-driven methods can more accurately and reliably reflect the degradation behaviour of a FC system, with higher accuracy and higher performance. While these methods can reflect the degradation behaviour of FC systems more reliably and with high accuracy and interpretability, due to the complexity of FC systems, it is difficult to establish a degradation model quickly, and these models cannot cover many degradation situations. Data-driven approaches can compensate for this deficiency; however, they lack prediction reliability and depend on the quality and quantity of the data. Therefore, an appropriate method should be chosen according to the actual needs. Other prediction methods, such as error-corrected grey prediction models, condition spectrum extraction methods, and similarity-based prediction methods, can be used for specific objectives and operating conditions. In addition, hybrid approaches based on the integration of multiple single prediction models will be important areas of focus in the future; these approaches can exploit the advantages of different methods, enhance the robustness and efficiency of prediction models, and improve the accuracy and reliability of predictions. Although research on FC fault diagnosis and lifetime prediction has made some progress, there are still several challenges and problems. For example, FC lifetime prediction is affected by many factors, such as the operating environment and operation mode. The interactions between these factors are complicated, and it is difficult to establish an accurate degradation trend model. In addition, considering the safety of commercialized applications, the capacity and accuracy of FC lifetime prediction need to be improved even further. The following directions can be considered for further in-depth exploration in subsequent studies:

Increasing the number of dimensions of fault identification features: The accuracy and dependability of fault diagnosis

and prediction can be enhanced by increasing the number of dimensions of fault identification features. Usually, the greater the number of dimensions of fault features is, the better the ability to identify and predict faults. This approach allows more features to offer more information and more accurately reflect the status and changes in the system.

Improving the robustness and reliability of predictive models: The prediction results can be impacted by factors such as sensor noise, ambient changes, and load variations during the measuring procedure. Enhancing the model dependability can lower model errors and uncertainties and increase the prediction accuracy, while enhancing the model robustness can increase the model resilience to disruptions and adapt to dynamic and complex settings. For systems that require long-term operation, such as FCs, accurate model predictions are particularly crucial since only accurate predictions can ensure that the right maintenance steps are performed to increase system longevity and operational effectiveness.

Enabling online long-term forecasting: Online FC life prediction can help operators and maintenance staff make better maintenance plans and decisions to increase the reliability and efficiency of FCs while also lowering the cost of maintenance and replacement parts, as well as downtime and repair expenses.

Combining the use of multiple input features: FC lifetime prediction involves a variety of input features, such as voltage, current, and temperature. Numerous prediction methods can be combined with these features for integrated learning and analysis, and the correlations between various features can be fully utilized to increase the predictability and accuracy.

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