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Review

Fault Detection for PEM Fuel Cells via Analytical Redundancy: A Critical Review and Prospects

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Abstract: Decarbonization of the transport sector could be achieved through fuel cell technology. The candidature of this technology is motivated by its high current density and lack of emissions. However, its widespread deployment is restrained by durability and reliability constraints. During normal operation, the fuel cell system supplies stable power to the load. Contrarily, when it is operated under faulty conditions, the system's output power deteriorates, leading to low durability. It is therefore of paramount importance to ensure that the system is operated in a non-faulty condition. In this paper, we provide a critical review of the analytical-redundancy-based fault diagnosis methods for proton exchange membrane fuel cells (PEMFCs). An in-depth analysis of the various methods has been presented in terms of accuracy, complexity, implementability, and robustness to aging and dynamic operating conditions.

Keywords: PEMFC; fault detection; analytical redundancy; prognosis and health management; durability and reliability; fault diagnosis tool; model-based; operating conditions; review

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1. Introduction

Burning fossil fuels such as coal, oil, and natural gas in the energy and transport sectors has a significant impact on global emissions. In addition, the health and environmental problems brought on by the use of fossil fuels are becoming more and more significant. Fortunately, the negative effects of burning fossil fuels can be reduced with the help of renewable energy sources and electric vehicles [1,2].

Over the decades, fuel cell technology has been considered one of the promising candidates for clean energy generation. The technology varies according to the nature of the electrolyte, fuel, catalyst, and operating temperature. PEMFCs are the fastest-growing type of fuel cells due to their relatively light weight and low operating temperature. They are therefore the leading fuel cell technology used in transport applications, including cars, buses, and trucks. The technology suffers from insufficient durability, which affects its widespread commercialization. For efficient performance, the membrane electrolyte of the system must be operated under optimal conditions. Conversely, faulty operating conditions worsen its performance and reduce its life. Prognosis and health management for PEMFCs are thought to be a panacea to these problems. Thus, they have been given tremendous attention by the research and industrial communities. The idea is to proactively maintain the fuel cell in its healthy state by deploying an algorithm that is capable of detection and isolation of faults.

Fault detection can broadly be divided into residual-based and non-residual-based methods. Residual-based methods are also called analytical redundancy methods. In these methods, residuals are generated by comparing some fault indicators from the real system with the nominal values from a model. A fault is said to be detected when the residuals go above a certain threshold. Contrarily, in non-residual-based methods, a fault is detected directly by monitoring the evolution of the fault indicators. Concerning the inherent variations of PEMFC voltage due to load fluctuations, a non-residual approach could lead to many false alarms and missed detections. Therefore, residual-based methods outperform non-residual-based methods in terms of reliability and efficiency [3]. After successful fault detection, additional steps could be set up to identify the type, location, and severity of the fault. This step is known as *fault isolation*.

In [4], a review of model-based detection methods for PEMFC is presented. The methods are compared in terms of some chosen criteria, including complexity, accuracy, genericity, and implementability. This review, however, requires updating and improvement, with some more challenging criteria such as robustness to aging and dynamic operating conditions. In addition, in [5], model-based prognosis for PEMFCs under a specific case of automotive load cycling is presented. The review is limited to papers related to predicting the remaining useful life (RUL) of the PEMFC to apply preventive maintenance. While some publications, such as [6–10], present a general review of fault diagnosis for PEMFCs comprising both model-based (residual generation) and data-driven approaches, several others provide a review of a specific category. Fault diagnoses associated with pressure drop are reviewed in [11–13], where a comprehensive investigation of the effects of pressure drop, estimation methods, and diagnostic methods are summarized. However, these reviews are limited to only water-management-related faults, which of course are not the only faults occurring in the system.

The main goal of this paper is to critically summarize recent advances in the fault detection of PEMFCs using analytical redundancy techniques. In addition, the review will also summarize the various input variables used for the diagnosis, various faults considered, merits/demerits of each method, implementability issues, limitations, and the way forward with respect to improving the durability and reliability of PEMFCs.

2. The Proton Exchange Membrane Fuel Cells (PEMFC)

2.1. Working Principle of PEMFC

The PEMFC operates based on electro-catalytic reactions occurring in the membrane electrode assembly (MEA). These reactions involve the oxidation of hydrogen at the anode and the reduction of oxygen at the cathode. A catalyst facilitates the breakdown of hydrogen atoms into protons and electrons. The protons move across the membrane to the cathode, while the electrons travel through an external circuit since they cannot pass through the membrane. At the cathode, the protons combine with oxygen to form water, generating heat as a by-product. The membrane acts as a conductor for protons while providing electronic insulation. To ensure efficient proton transport, particularly in low-temperature PEMFCs, adequate humidification of the membrane is necessary. Thus, maintaining a steady minimum water content in the electrolyte is crucial [14].

$$H_{2(g)} \rightarrow 2H^+ + 2e^- \quad (1)$$

$$\frac{1}{2}O_{2(g)} + 2H^+ + 2e^- \rightarrow H_2O_{(g,l)} \quad (2)$$

$$H_{2(g)} + \frac{1}{2}O_{2(g)} \rightarrow H_2O_{(g,l)} + \text{heat} + \text{electricity} \quad (3)$$

The reactions at the anode and cathode can be represented as Equation (1) and Equation (2), respectively. The overall reaction can be described by Equation (3). For efficient performance of the PEMFC, operating conditions must be maintained at their nominal states. These operating conditions are regulated using other subsystems such as humidifiers, controllers/regulators, and compressors. Each subsystem has to ensure a specific function. For example, thermal management is handled by the cooling subsystem. Power management is handled by the electrical power converter and control unit. The humidification system saturates the hydrogen and air with water before their use in the fuel cells. It also manages the product water that results from the fuel cell's reaction. Some fuel cell power plants combine humidification and stack cooling systems.

2.2. Major of Faults in PEMFCs

An abnormal condition or defect that may cause a failure at the component, equipment, or sub-system level is referred to as a fault. The following are the major fault scenarios occurring in a PEMFC system.

2.2.1. Water Management Faults

The water produced in PEMFCs must be evacuated continuously or periodically using a water management system. If the water evacuation rate is slower than the water production rate, excess water will accumulate, leading to a *flooding fault*. The channels or the gas diffusion layer (GDL) may be clogged, thereby preventing oxygen from reaching the catalyst layer. In both cases, insufficient reactants over the active surface area result in poor performance of the PEMFC [15].

Conversely, when the water evacuation rate is faster than the water production rate, membrane dehydration or a *drying fault* occurs. This causes degradation of the membrane and increases ohmic losses. Drying faults mostly occur on the anode side since water is created on the cathode side. Thus, for optimal performance of the PEMFC, the water management system must be in a non-faulty condition. This aims to ensure a proper balance between water production and evacuation rates.

2.2.2. Cooling System Faults

The fuel cell reaction temperature is controlled by the cooling system, which also provides source heat to humidify the reactant gases. When the cooling system is faulty, this could lead to *over-heating* or *over-cooling* in the stack. While over-cooling of the stack encourages flooding and carbon corrosion, over-heating encourages membrane dehydration. It also favors the acceleration of parasitic reactions, creating chemical substances responsible for a chemical attack on the membrane [16].

2.2.3. Supply System Faults

Controlled amounts of hydrogen and air are supplied continuously to the stack using their individual supply systems. When the fuel supply system is faulty, a hydrogen starvation fault occurs. Hydrogen starvation in PEMFCs is responsible for the corrosion of carbon support, leading to the loss of active area and decreases in performance. Oxidant starvation faults occur when the air supply system is faulty. This decreases the cathode active surface, which causes performance degradation [17].

Other fault scenarios occurring in the PEMFC include poisoning faults, sensor faults, short-circuit faults, and actuator faults.

3. Analytical Redundancy Methods for Fault Detection in PEMFC

Analytical redundancy is an efficient method of detecting faults in a complex system. As depicted in Figure 1, a model is developed to estimate some features or indicators that are essential for fault detection. These features are considered as the nominal output of the system. They are then compared with the actual measurements from the real system. Measurements from the real system depend on the actual condition of the system. When the system is in a normal condition, the outputs from the system and the model are theoretically equal. Thus, zero residuals would be generated. However, when the system is in a faulty condition, the outputs of the model and the system differ. In this case, non-zero residuals would be generated, and a fault would be detected. These nominal models can be developed using white-box, black-box, or grey-box methods.

3.1. White-Box Methods

White-box methods are used to simulate the behavior of the PEMFC to produce the required nominal features for fault detection. They exploit the use of the physical, thermal, electrochemical, and fluidic equations such as Nernst–Planck, Butler–Volmer, and Fick's equations. White-box methods can be divided into three.

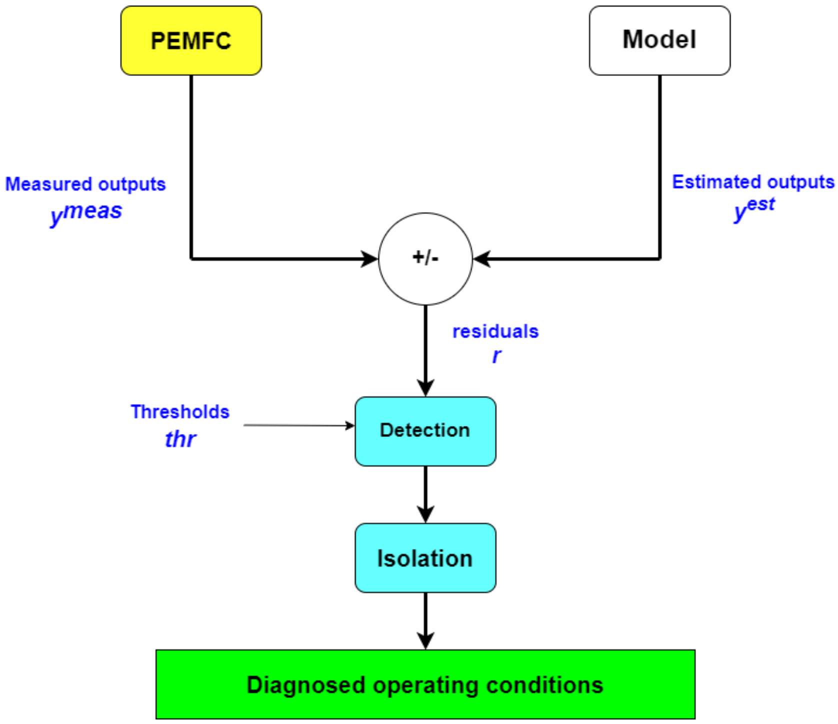

Figure 1. Analytical-redundancy-based fault diagnosis.

3.1.1. Parametric Identification Method

This involves developing a nonlinear model of the fuel cell whose output variables depend on some parameters. These unknown parameters are then identified and obtained using numerical search. Pukrushpan et al. have developed a nonlinear physics-based model of a PEMFC in [18]. The model is used to predict the stack voltage as a function of the load current and the operating conditions. These operating conditions include cell temperature, air pressure, oxygen partial pressure, and membrane humidity. Pukrushpan's model has been modified and adopted for fault detection [19]. In the proposed work, the sensitivity of a residual to fault is a transfer function that describes the effects of a given fault on the residual. The merit of the proposed method is that it does not require knowledge of the fault magnitude to provide a diagnosis. However, neither the fault detection model nor the isolation algorithm is validated with experimental data, as they are all simulated in MATLAB/Simulink. In addition, the proposed method is not robust to aging and dynamic operating conditions. Other similar literature that adopts the Pukrushpan model for fault diagnosis of some pre-defined fault scenarios can be found in [20,21].

An electrical equivalent model of a PEMFC for fault diagnosis of PEMFCs has been presented in [22]. The proposed method provides a global model of the PEMFC such that each subsystem is represented by its electrical analogy to predict stack voltage and gas dynamics via parametric identification. Three fault scenarios (flooding, drying, and membrane deterioration) are considered in the proposed method and are validated experimentally. The authors show that flow resistance indicates the presence of excess water in the stack, but it is not enough to identify the source of the fault. However, the model does not take into account liquid water in the diffusion layer. In addition, aging and dynamic operating conditions are not considered in the proposed approach.

In [23], a static circuit-based model of a PEMFC is developed for fault detection. In this approach, the stack output voltage can be estimated by subtracting the voltage losses due to the activation process, diffusion, and ohmic resistance from the theoretical voltage source. Parametric identification is used to determine the optimized values of unknown parameters of the model using a built-in optimization function of MATLAB. Experimental data acquisition was performed on a stack with three cells, an active area of 100 cm^2, and a current density of 1 A/cm^2, using the current sweep method, in which voltage and current are measured, filtered, and then optimized. As the work considers the aging process, data from both healthy and damaged fuel cells are recorded to identify the parameters for predicting the model output. It is observed that the membrane resistance at the beginning of life (BOL) or healthy state is recorded to be 0.0012 Ω, while it is 0.00155 Ω in a non-healthy state, indicating a significant increase. The effect is shown on the polarization curve, where the voltage drop due to aging is identified. However, more fault indicators must be estimated for accurate fault detection.

The authors of [14] focus on the monitoring of flooding and drying of a PEMFC using electrochemical impedance spectroscopy (EIS). This method is used to study the response of ac impedance measurements as a function of the inlet gas relative humidity. The fuel cell's impedance can be predicted after parametric identification. Similarly, in [24], EIS has been used together with acoustic emission measurements to provide an electrical equivalent circuit model for diagnosing flooding and drying faults in PEMFCs. Moreover, in [25], extensive EIS measurements have been conducted on a high-temperature PEMFC for detecting FC poisoning faults. Different temperatures, currents, and concentrations of CO, CO_2, and H_2O in the anode gas are used to measure the impedance. An equivalent circuit is fitted to the spectrum at each operating point, and an analysis to pinpoint the various impedance-regulating mechanisms is carried out. When changing the operating conditions under pure H_2, the trend observed generally demonstrates good agreement with the findings from the literature. Despite the prospects of EIS in the detection of water management faults, however, it is difficult to implement online, as it requires a special intrusive device for the measurement. Moreover, residuals based on EIS alone are insufficient for tackling not only the severity of the water management faults but also other faults occurring in the system.

Motivated by the fact that neither the stack output voltage nor the EIS characterization can singlehandedly provide sufficient detection of the major faults in the PEMFC, the thesis work of Julian in [26] combines estimation of the stack voltage and high-frequency impedance. The methodology employed a multiphysics model called MePHYSTO-FC, which is developed in the CEA [27]. The model predicts the nominal stack voltage, while the EIS estimates the high-frequency membrane resistance. An additional machine learning algorithm is then developed to classify several faults in the system. The proposed method is robust to aging phenomena. However, the main drawback of the method lies in the complexity of the model, which needs to be reduced for online implementation. For model order reduction, a trade-off must be made between accuracy level and complexity. In addition, as only platinum dissolution is considered to model the stack aging phenomenon, another possible type of degradation, such as carbon corrosion, could be considered. Moreover, the work is not able to handle dynamic operating conditions.

3.1.2. Observer-Based Method

An observer is a reduced-order model corrected with closed-loop measurements in order to handle model uncertainty and variation of operating conditions. Thus, it could be closer to implementability than a pure open-loop model such as the parametric identification approach. Observer-related models are used to estimate the faultless output of the model and then compare it with the system measurements to obtain residuals. However, since a linearized model of a complex system such as PEMFC is not suitable for fault diagnosis, linear parameter varying (LPV) observers are used instead of Luenberger observers. However, some observers, such as unscented Kalman observer (UKO) and the sliding-mode observers, are able to deal with non-linearity in the PEMFC.

In [28], an interval LPV observer is used to deal with variations of parameters with the operating conditions while maintaining the model's linear structure. The suggested approach also addresses the issue of robustness against modeling uncertainty, which includes unknown parameters whose values are interval-bounded. Relative fault sensitivity analysis (RFS) analysis is used for isolating the faults considered. The four predefined faults considered are the speed sensor fault, sudden change in oxygen ratio, offset in stack voltage, and offset in the supply manifold pressure sensor. Stack temperature is assumed to be constant. The work has been improved in [29] by considering a temperature perturbation of the system instead of it being a constant parameter. Adaptive thresholds produced using interval observers are used to address the robustness issue. Nevertheless, the authors make further improvement in [30], by considering perturbations on the system due to atmospheric temperature and pressure. The model, whose outputs are the stack voltage, oxygen excess ratio, and compressor motor speed, was obtained using Jacobian linearization. Five different sets of fault scenarios are defined and implemented. They include a sudden increase of friction in the mechanical part of the compressor, degradation of the cells due to toxicants, hydrogen leak in the anode, and air leak in the cathode manifold. The work has been further enhanced by the inclusion of the Tagaki–Sugeno interval observer, which models uncertainty in a bounded context, in [31]. The model was decoupled into sub-models, which are used to generate four residuals from four model outputs. Six different faults are considered, primarily sensor faults in the work, and then isolated using a fault signature matrix. However, these works have been considering additive faults on various sensors, thus lacking a proper representation of the major faults taking place in the PEMFC.

A robust observer-based fault diagnosis for the PEMFC air-feed system is also presented in [32]. The goal is to detect a sudden air-leak fault in the air supply manifold. The proposed observer is designed based on the modified super-twisting sliding mode observer (ST-SMO). It consists of two nonlinear and two linear terms. The observer can estimate not only the states but also the fault signals, in the presence of external disturbances. Once the sliding motion is achieved, the obtained equivalent output error injection is computed online to reconstruct the possible faults in the system. The fault indicator considered in this work is the oxygen excess ratio. It is estimated as a function of the cathode pressure, supply manifold pressure, and stack voltage. Similarly, the work is purely validated using simulated data; experimental validation could be of great importance.

Recent papers such as [33–35] tend to incorporate some simulated fault scenarios into the design of the LPV observer models. The approaches make use of the unknown input observers (UIO) concept for designing the augmented LPVs model.

3.1.3. Parity-Space Method

This is another analytical redundancy method that is specifically intended for linear systems. A linearized model of the PEMFC, which is considered a member of a nonlinear model set, is adapted to generate residuals via the parity space algorithm. The parity space algorithm is summarized in [36]. The algorithm is used to generate two residuals as a function of input/output variables that are sensitive to the three considered fault scenarios. While the faults considered include flooding, drying, and over-voltage of the compressor, the isolation step is based on fault signature. The input variables include the load current and input voltage to the compressor, while the output variables are the stack voltage, pressure at the supply manifold, and compressor output flow rate. The work is extended to incorporate nonlinear parity-space in [37] for nonlinear residual generation, where four residuals are generated to identify four faults, which are the input voltage drop of the compressor motor, over-current of the fuel cell stack, pressure drop in the supply manifold, and pressure increase in the return manifold. However, fault diagnosis based on the linear system will depend on the linearization point and thus lacks robustness to other operating conditions and aging.

Due to the complexity of while-box models of a PEMFC system for model development, a “minimal behavioral model” of the system could be sufficient. For this reason, black-box approaches are considered alternatives.

3.2. Black-Box Methods

Black-box models, also referred to as data-driven models, are derived from historical data obtained through suitable experiments on the real system rather than relying on physical equations. These methods have been utilized in research to develop a model of the PEMFC for estimating various fault indicators. Artificial neural networks and support vector machines are the commonly used black-box techniques for generating residuals.

3.2.1. Neural Network Method

Artificial neural networks (ANNs) have emerged as a powerful tool for modeling non-linear systems when input and output data are available. ANNs are inspired by biological neural networks and are capable of capturing complex relationships. A common type of ANN is the feed-forward neural network (FNNs). In FNNs, the input signals flow in one direction, from input to output. This type of network is limited to static mappings between input and output spaces. In contrast, recurrent neural networks (RNNs) allow signals to flow in both forward and backward directions, enabling outputs at a given moment to depend not only on the current input but also on previous inputs and outputs [38].

In [39], an FNN trained with backpropagation was employed for modeling a PEMFC. The PEMFC model was constructed using a stack consisting of 20 cells with an active surface area of 100 cm^2 and a power output of 500 W. Data for training and testing the model was generated in a MATLAB/Simulink environment. The input variables considered were stack current, stack temperature, hydrogen flow rate, and oxygen rate, while the output of the model was the stack voltage. The model's performance was validated through experimental tests, and the comparison between the trained model and the real system response was evaluated using metrics such as the mean squared error (TMS) and the predictive mean squared error (PMSE). The computational time for the model's predictions was less than 1 s.

However, it is worth noting that the generated training data only accounted for nominal conditions, and therefore the static model developed may not be sufficiently effective for fault diagnosis under varying operating conditions. To address this limitation, the authors improved their work in a subsequent study [40] by developing a dynamic model of the PEMFC using a recurrent neural network topology. In this enhanced model, stack voltage prediction was based on inputs including air humidity level, stack temperature, hydrogen flow rate, and oxygen flow rate. Nevertheless, it should be mentioned that although this dynamic model provides improves adaptability, it still does not consider aging effects, and predicting stack voltage alone may not be adequate for comprehensive fault detection.

In Sisworahardjo's study [41], they present an ANN-based model of a 100 W portable PEMFC, constructed using experimental data. The model utilizes a multi-layer feedforward ANN with four fully connected layers, including two hidden layers, and employs a back-propagation training algorithm. The stack temperature and load current are considered as input variables, while the stack voltage, output power, and hydrogen flow are the output variables. To assess the model's performance, the output of the trained ANN is compared to experimental data. Evaluation is performed using three statistical indices: absolute mean error (AME), standard deviation error (SDE), and root mean square error (RMSE). These indices measure variations, unbiasedness, and accuracy of voltage, power, and hydrogen flow. However, although these indicators are effective for detecting certain faults, additional indicators are necessary to adequately detect other fault categories. Furthermore, the developed model has not undergone robustness testing for aging effects and dynamic operating conditions.

Moreover, in [42], a genetic algorithm neural network (GANN) and Taguchi method are combined for estimating PEMFC stack voltage. The input variables considered are stack temperature, load current, oxygen flow rate, hydrogen flow rate, and oxygen/hydrogen pressure. The approach is compared with GANN and BPNN, both without utilizing the Taguchi method. Laboratory experiments are conducted to compare the estimation values of

PEMFC output voltage using the proposed approach, GANN without Taguchi, and BPNN models. Results show that the proposed method has significantly smaller errors, indicating better performance in estimating PEMFC output voltage. The learning performance of the approach is evaluated using root mean square error (RMSE). However, stack voltage estimation alone is insufficient for fault detection, and the model lacks robustness testing for aging and dynamic operating conditions.

Likewise, in [43], a high-power fuel cell simulator based on a recurrent neural network (RNN) is proposed. The simulator models a 5 kW commercial PEMFC stack (NUVERA) using a limited amount of experimental data. The data include seven input variables (stack electronic load, air mass flow, hydrogen mass flow, nitrogen mass flow, cathode water injection, anode temperature, and stack temperature) and two output variables (stack voltage and cathode temperature). The simulation performance is evaluated by calculating the mean square error (MSE) for comparing the simulated values to the real values in the validation set. While voltage and temperature prediction can be useful for diagnosing water management faults, additional variables are necessary to detect other fault scenarios effectively.

In [38], an Elman neural network (ENN) is utilized for detecting water management faults in PEMFCs. The ENN is a type of RNN with inputs, hidden layers, and output layers. Residuals are generated from four sets of input variables (stack temperature, dew-point temperature, load current, and air inlet flow rate) using the trained neural network's output, which includes stack voltage and pressure drop. By comparing these residuals to a predetermined threshold, fault detection between flooding and non-flooding states in the fuel cell's health can be achieved. The data used for modeling the ENN was obtained from a 20-cell, 1 kW PEMFC test bench. Subsequently, in [44], the diagnostic tool is enhanced to detect both flooding and drying faults using the same input and output variables. However, these approaches are limited to water management faults and have not been tested with aged fuel cells or dynamic operating conditions.

In Kamal's works [45,46], fault diagnostic tools for PEMFCs under closed-loop control are developed. A combination of feed-forward and feedback controllers is designed to regulate the oxygen excess ratio during variations in stack current. The study proposes using a radial basis function (RBF) network as the system model for residual generation, which is sensitive to faults. Simulations are conducted to test the approach's performance with simulated faults in components such as actuators and sensors. The network's output variables include stack voltage, net power, and oxygen excess ratio, while the input variables are cell voltages and stack current. However, it should be noted that the proposed approach can only detect one fault condition at a time, highlighting the need for an extension to handle multiple faults and considerations of robustness in aging and dynamic operating conditions.

The artificial neural network (ANN) method offers advantages over white-box methods. ANNs can learn complex nonlinear models from input/output datasets, providing fast and reliable results with a short computation time. Additionally, ANNs' inherent properties, such as low sensitivity to noise and incomplete information, make them suitable for modeling multi-physics and multi-scale PEMFC systems. However, when utilizing an ANN for fault detection and diagnosis, several challenges arise. Data acquisition for training the network can be time consuming and costly, particularly when considering robustness to aging and dynamic operating conditions. Furthermore, applying faulty operating conditions may lead to irreversible damage to system components. As the fault diagnosis paradigm incorporates more faults, additional variables are required, increasing the complexity of the network and the time needed for data generation on a test bench. Other interesting ANN-based approaches can be found in [41,47–50].

3.2.2. Support Vector Machine Method

The support vector machine (SVM) is a powerful black-box modeling tool. It has superior generalization ability, which remains unaffected by the dimensionality of the input data. The fundamental concept behind SVM involves mapping nonlinear and inseparable input data to a high-dimensional feature space where linear separation is possible. This mapping is achieved through a nonlinear technique called kernel dot product, and subsequent linear regression is performed in this feature space. As summarized in [51], the support vector machine offers several significant advantages. Firstly, by incorporating a kernel, SVM overcomes the challenges of using linear functions in high-dimensional feature spaces. This transformation allows the optimization problem to be reformulated as dual convex quadratic problems. Secondly, SVM provides a unique solution since the optimization problem is convex. In contrast, artificial neural networks often encounter multiple solutions associated with local minima, which can make them less robust across different samples. Thirdly, SVM demonstrates good out-of-sample generalization. Through the appropriate selection of parameters, SVM can maintain robustness even when the training sample exhibits bias.

The support vector machine (SVM) differs from artificial neural networks by being based on the statistical learning and structure risk minimization (SRM) principle, rather than the empirical risk minimization (ERM) principle. This distinction allows SVM to maintain its quality and complexity regardless of the dimensionality of the input space.

In another study [52], an SVM model was developed to predict the cell voltage of a proton exchange membrane fuel cell (PEMFC) based on measurements of current and cell temperature. The choice of load current as an input variable was due to its direct relationship with an uncontrollable load, while cell temperature was selected based on its significance in determining terminal voltage and its ease of measurement compared to other operating parameters. The SVM model was constructed in three steps: data preparation, training the model, and predicting new input data. The trained SVM model, with optimized parameters, achieved a prediction time of less than 10 ms and a squared correlation coefficient as high as 99.7%. However, the accuracy of stack voltage prediction might be compromised under certain operating conditions, leading to the improvement of the model in a subsequent work [53]. This improved model proposed a hybrid approach that combined a least-square support vector machine (LS-SVM) with a pressure-incremental model. The LS-SVM model incorporated current and temperature using particle swamp optimization (PSO), while the pressure-incremental model had a single empirical coefficient for anode and cathode pressures. The output of the model was stack voltage, and the inputs included current, temperature, and gas pressure at the anode and cathode. It should be noted, however, that stack voltage alone is insufficient for accurate fault detection.

In the article [54], a least square support vector machine (LS-SVM) model is introduced for modeling a PEMFC. The LS-SVM model, utilizing a radial basis function (RBF) kernel, is employed to construct a nonlinear offline model of the PEMFC. The training samples used for establishing the model consist of temperature response values under various gas and cooling water flow rates of the stack, as well as the output power of the stack. The SVM model is implemented in the MATLAB/Simulink environment to estimate an optimum oxygen ratio during abrupt changes in stack current. The experimental results presented in the study demonstrate the effectiveness of this approach. However, it is noted that predicting the PEMFC stack temperature alone is insufficient for detecting major faults within the system.

Similarly, another SVM model is presented in [55], aimed at mapping the oxygen excess ratio of PEMFC as a function of stack current and compressor voltage. However, just like the previous study, relying solely on the indicator of oxygen excess ratio proves inadequate for accurately detecting major faults in the PEMFC.

In addition, in [56], the dynamic characteristics of a PEMFC stack are described using an SVM-ARX (linear autoregression model with exogenous input) Hammerstein model. The LS-SVM with a radial basis function kernel is utilized to represent the static nonlinear block within the Hammerstein model, while the dynamic linear block is implemented using linear autoregression (ARX). The data for identifying the multiple-input multiple-output (MIMO) Hammerstein model is obtained from a dynamic physical model of a 3 kW PEMFC stack. The linear model parameters and static nonlinearity are simultaneously obtained by solving a set of linear equations followed by singular value decomposition (SVD).

In this study, the PEMFC stack is modeled with three inputs, namely current, stoichiometry at the cathode, and cooling liquid flow rate. The two outputs considered are stack temperature and oxygen partial pressure. However, the analysis reveals that these two indicators alone, without considering stack voltage and pressure drop, are unable to effectively detect water management faults within the system.

3.3. Grey-Box Methods

These methods exploit the merits of both white-box and black-box methods.

3.3.1. Fuzzy-Logic Method

A fuzzy inference system (FIS) is a transparent model that represents system knowledge through the use of explainable rules. Fuzzy logic can deal with system uncertainties, ambiguities, nonlinearities, and also problem complexity reduction [57]. In the field of fault detection, fuzzy logic can be used to generate residuals [58]. Due to its advantages, such as easy implementation, capability to explain the causes of degradation, and less computation time, it can be applied as an efficient tool for real-time monitoring and diagnosis [59]. Most of the works in the literature that employ fuzzy logic for fault diagnosis of PEMFCs focus on fault classification via pattern recognition [58,60–62], while few works employ fuzzy logic as a residual generator.

A method for the adaptive prediction of stack voltage under dynamic operating conditions is presented in [63]. The paper presents the development of a fuel cell stack model. A mutual-information-based technique is employed to select the relevant input variables for approximating the output variables in each auxiliary component. Despite the positive attributes of fuzzy logic, it is not expert by itself, thus it requires human expertise to make it expert and provide the best performance. If the expert assigns the wrong rules, then the FIS produces very bad results. In many cases, there is limited knowledge available regarding the behavior of the system. Therefore, while implementing FIS, we are not sure if the rules are correct. This is why most of the time, we use the hit and trial method to assign the rules and try to obtain the best performance.

3.3.2. Adaptive Neuro-Fuzzy Inference System (ANFIS) Method

The adaptive neuro-fuzzy inference system (ANFIS) is a hybrid system that combines the learning capabilities of artificial neural networks (ANN) with the strong knowledge representation and inference abilities of fuzzy logic. By using an ANN to construct the fuzzy rules, it is possible to design and adjust the parameters of a fuzzy inference system without relying on human expertise. This approach allows for the creation of a reliable fuzzy inference system based on input and output samples, utilizing the learning capabilities of the ANN [64]. In other words, ANFIS can be utilized to identify a nonlinear system model by leveraging the learning mechanism of neural networks to address the limitations of fuzzy inference systems. the neural network identifies and adjusts the parameters of the membership functions and fuzzy rules in the fuzzy system based on the data obtained from the target fuel cell. This is in contrast to traditional fuzzy systems, where the model's rules are generated using expert knowledge. ANFIS combines the advantages of neural networks and fuzzy logic to automatically learn and adapt the parameters of the fuzzy system from the available data. Understanding the characteristics of the training and testing datasets is essential. They should accurately represent the specified domain to ensure reliable and meaningful results in the ANFIS. Although it has not been popular for modeling PEMFCs, it is considered an interesting alternative for residual generation.

The first ANFIS model of a PEMFC was developed in a study by Tao et al. in [64]. The proposed work introduced an ANFIS model that utilizes the fuel flow rate and air flow rate as input variables to predict the stack temperature as the output variable. The simulated results demonstrate consistency between the test data and the model. However, stack temperature alone cannot accurately indicate major faults in PEMFCs.

In addition, in [65], the performance (polarization curve) prediction of the PEMFC is performed using an ANFIS for different operational conditions. The ANFIS model undergoes initial training using a set of input and output data, followed by testing with independent experimental data. The results indicate a high level of agreement between the model predictions and the experimental data across all operating conditions examined in the study. However, despite the potentialities of ANFIS, it suffers from two drawbacks. It can only work for Sugeno-type systems and can be used for one output only. Unfortunately, the prediction of stack voltage alone is not enough to predict many faults.

4. Summary and Evaluation

The performance of PEMFCs in terms of reliability and durability is affected by faulty operating conditions and the aging process. While this slows down extensive commercialization of the technology, it also motivates investments in the development of solution strategies. A robust and implementable fault detection and isolation tool is thought to be an excellent candidate for tackling the reliability and durability issues of PEMFCs. Dividing fault detection into pattern recognition and analytical redundancy techniques, the latter is said to have outperformed the former. The comparison of different analytical redundancy methods for fault detection in PEMFCs is presented in Table 1. The criteria for the comparison are based on their benefits, drawbacks, applicability to online fault detection, robustness to dynamic operating condition, and aging consideration. Fault detection techniques in PEMFCs can be classified into three categories: white-box, black-box, and grey-box methods, based on analytical redundancy approaches.

Table 1. Classification and comparison of different model-based diagnosis approaches.

Classes	Sub-Classes	Benefits/Advantages	Limitations/Drawbacks
White-box	Parametric identification	(1) High accuracy and genericity (2) High robustness to aging (3) Robust to dynamic operating conditions	(1) High processing time (2) High structural complexity (3) Difficult for online implementation
	Observer-based	(1) High robustness to model uncertainties (2) Robust to dynamic operating conditions (3) Implementable online	(1) Low genericity (2) Poor robustness to aging
	Parity space	(1) Low processing time (2) Implementable online	(1) Low genericity (2) Poor robustness to aging (3) Poor robustness to dynamic operating conditions
Black-box	Neural network	(1) Short processing time (2) Implementable online (3) Low sensitivity to noise	(1) Low genericity (2) Poor robustness to aging (3) Poor robustness to dynamic operating conditions
	Support vector machine	(1) Short processing time (2) Implementable online (3) Good genericity	(1) Poor robustness to aging (2) Poor robustness to dynamic operating conditions
Grey-box	Fuzzy logic	(1) Short processing time (2) Implementable online (3) Good accuracy	(1) Poor robustness to aging (2) Poor robustness to dynamic operating conditions (3) Dependence on expert rules
	ANFIS	(1) Short processing time (2) Implementable online (3) Good genericity	(1) Poor robustness to aging (2) Poor robustness to dynamic operating conditions (3) Only applicable to SISO systems.

The white-box method employs physical equations that describe the internal phenomena of fuel cells to generate models for residual generation. It can be further divided into the parametric identification method, observer-based method, and parity space method. These approaches aim to provide accurate representations of the system. Despite the excellent performance of these approaches in terms of accuracy, genericity, nonlinear response, adaptability to aging, and robustness to dynamic operating conditions, they suffer from high structural complexity and high computation time, which make them unsuitable for online fault detection and diagnosis.

In contrast, black-box methods such as artificial neural networks and support vector regression are used to develop models for residual generation using experimental data. They have good accuracy, good nonlinear response, and low processing time, which make them suitable for online fault detection and diagnosis. However, they generally depend on the quality and size of the dataset. Moreover, the process of data acquisition through experiments can be time consuming, costly, and sometimes cause irreversible damage to the system. Therefore, it is imperative to note that neither of the two methods can single-handedly satisfy all the requirements for system monitoring. In addition, aging consideration and robustness to dynamic operating conditions are difficult to integrate with these methods.

A good compromise between the white-box and black-box methods are the grey-box methods, which produce a transparent model from knowledge and data. They combine the attributes of both methods but have their drawbacks. It is pertinent to mention that load current is regarded as the unique input variable, while variables such as relative humidity, partial pressure, stack temperature, flow rate, and stoichiometry are regarded as operating conditions. In addition, stack voltage is regarded as the major fault indicator as it is affected by all faults, as can be seen in Table 2. However, residuals generated from estimated and measured stack voltage alone cannot provide a good fault detection tool; they need to be coupled with other fault indicators. Figure 2 presents the histogram of several fault indicators employed for fault detection using analytical redundancy approaches. They include stack voltage, pressure drops, membrane resistance, flow rate, stack temperature, oxygen excess ratio, and others such as compressor speed, mass of hydrogen, or mass of oxygen.

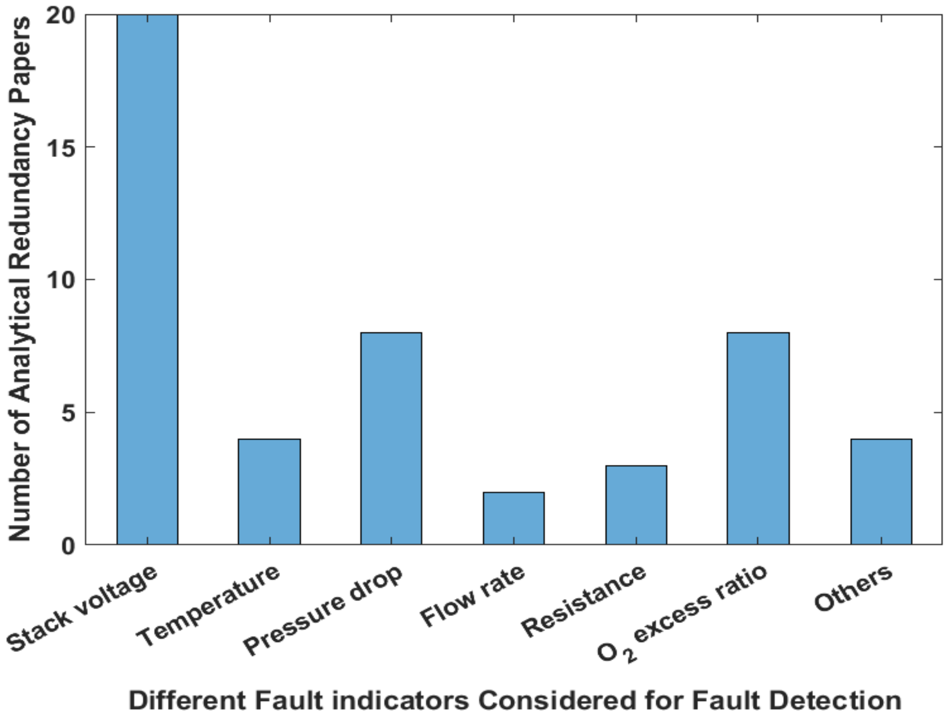

Figure 2. Histogram of fault indicators.

Table 2. Summary of fault indicators predicted in each method.

Methods/Indicators	Stack Voltage	Temperature	Pressure Drop	Flow Rate	Resistance	O_2 Excess Ratio	Others
Parametric identification	[18,19,22,23,26,66]		[22]	[22]	[14,24,25]		
Observer-based	[28–30]	[29]	[28,29,31]			[28–30,32]	[30,31]
Parity space			[37]				[37]
Neural networks	[38–44]	[43]	[38,44]	[41]		[45,46]	[41]
Support vector machine	[52,53]	[56]	[56]			[54,55]	
Fuzzy logic	[63]						
ANFIS	[65]	[64]					

5. Conclusions

This paper critically presented a recent review of analytical-redundancy-based fault detection for PEMFC for transport applications. Being regarded as an excellent candidate for the diagnosis of PEMFCs to improve their reliability and durability, analytical redundancy methods are broadly classified into white-box, black-box, and grey-box methods. In each method, a model of the PEMFC is developed to predict some outputs that are compared with the sensor measurement from the actual system to generate residuals. Depending on the types and values of the residuals, several faults can be classified based on types and severity. The estimated outputs are regarded as fault indicators whose accurate estimation, sensitivity to faults, implementability, robustness to aging, and dynamic operating conditions are used to evaluate the performance of the method. We presented an analysis of each method in terms of these performance criteria. It has been observed that there is a trade-off between implementability and consideration of aging. A similar trade-off also exists between implementability and robustness to dynamic operating conditions. Despite the presence of several analytical redundancy methods for fault detection in PEMFCs, a single implementable approach capable of detecting major faults in the PEMFC that is robust to aging and dynamic operating conditions has not yet been found in the literature. As for future work, a hybrid analytical-redundancy-based approach that combines the robustness of the white-box methods and the implementability of the black-box methods should be proposed. Moreover, a literature review of pattern-recognition-based approaches for fault detection in PEMFCs could be proposed.

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