Fault Detection Methods Suitable for Automotive Applications in Proton Exchange Fuel Cells

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Received: 15 August 2022 | Revised: 5 September 2022 | Accepted: 20 September 2022

Abstract-The fault conditions degrade the performance of proton exchange fuel cells and reduce their useful life. The prolonged existence of a fault condition can permanently damage the fuel cell. This paper proposes four methods for fault detection and fault type isolation. These methods were based on the coefficient of variance, ratios of change in output power to change in voltage and change in output voltage to the change in current, fuzzy membership values and Euclidian distance, and wavelet transform. These methods are non-invasive to the fuel cell and involve non-destructive testing. These methods were experimentally validated.

Keywords-PEM fuel cell; fuel cell faults; coefficient of variance; fuzzy membership values; wavelet

I. INTRODUCTION

A Proton Exchange Membrane Fuel Cell (PEMFC) is the most suitable fuel cell for automotive applications [1]. PEMFC performance is optimum when the operating conditions are appropriate. The fuel cell performance degrades due to poor thermal and water management [2], while prolonged water flooding can cause mechanical damage. An experiment using the Energy Intensity of reconstructed Vibrating voltage (EIV) based on the wavelet transform was proposed in [3]. The factors affecting the performance of fuel cells in automobiles are described with the help of faults [4], using cause-and-effect chain analysis. Several studies investigated fuel cell degradation [5], fault detection [6], and lifetime prediction in automobiles [7]. The degradation of the fuel cell output under various fault conditions and aging was studied in [8]. Output voltage and power degradation for the expected output are modeled as ratios that can detect the fault, and their thresholds help to isolate the defect type [9].

In [10], a diagnostic survey of fuel cell stacks was compiled to summarize faults in fuel cells, their causes, and existing methods to detect them. Statistically, water flooding is the largest (33%) contributing fault in fuel cell systems. Model-based and non-model-based methods were analyzed in [11] for fault diagnosis. A data-driven singular value decomposition method was applied in [12] to fuel cell parameters to detect faults. Data-driven diagnostics measure parameters and estimate the potential issue in a fuel cell. An aging data test was simulated for short-term prognosis in [13]. Several issues and solutions in fuel cell diagnostics were described in [14]. Electrochemical Impedance Spectroscopy (EIS) is a widely used technique in fuel cell fault diagnosis [15]. EIS has proven to be an effective tool in detecting fuel cell flooding and degradation and is also able to differentiate flood and drying faults in fuel cells [16]. EIS can be used to detect and isolate faults in fuel cells [17]. EIS experimental data were recorded for 35 days in [18] and were analyzed using Artificial Neural Networks (ANN). EIS has been used to determine the state of health of the fuel cells in electric vehicles [6] and detect catalyst degradation in fuel cells [19]. EIS is an offline technique for fault diagnosis. The estimation of online parameters for EIS was recently studied in [20]. The impedance obtained from EIS was further analyzed as wavelet energy using wavelet and wavelet packet decomposition [21]. The data obtained using EIS was converted to the frequency domain using the Morlet wavelet [22]. In [18], current interruption and injection of current pulses were used to overcome issues with the EIS method. Other methods to detect faults in fuel cells are Principle Component Analysis (PCA) [23], fuzzy inductive reasoning [24], fuzzy logic, delta V analysis using the COMSOL model [25], Kalman filter-based approach [26], external magnetic field-based tomography

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methods [27], Takagi-Sugeno interval observer approach [28], and ANN-based approaches [29].

In [30], an ANN model was downloaded to an FPGA hardware platform to study 3 faults in a fuel cell system. A sliding mode algorithm was used for the observer design and MATLAB/Simulink was used to implement the ANN in [31]. Fuel cell degradation prognosis was performed based on Nonlinear Autoregressive Exogenous Neural Networks (NARX) and wavelet analysis in [32]. Degradation prognosis was also studied in [33] by using a degradation model based on the Wavelet Neural Network (WNN) and Cuckoo search algorithm. Energy management in PEMFC vehicles was studied using a MATLAB/Simulink model in [34]. Wavelet transforms were used in [35] for energy management optimization strategies on FCEVs. Model-based techniques have been described for offline [36] and online [37] fault detection. The online automotive fuel cell degradation was studied by modeling an electrical load in [4]. Fuel cell degradation over a period causes internal changes inside the cell. These internal change behaviors were studied with the help of polarization curves and an adaptive neuro-fuzzy interference system for prognosis [38]. A fuzzy logic model was applied in [39] to common automotive stress conditions to diagnose faults. In [40], mathematical models were used to determine a fuel cell's health and predict its useful life. In [41], the useful life of the fuel cell was determined using a particle filtering framework. Fuel cell State Of Health (SOH), useful remaining life, and robustness were estimated in [42] using an extended Kalman filter. In [43], artificial intelligence was used to estimate useful life and predict the degradation of a fuel cell. The echo state network is an AI tool to estimate the useful life of a fuel cell stack by considering the mean voltage of the cells [44]. A time delay NN was used along with the Auto-Regressive Moving Average (ARMA) model for the prognosis of degradation. The ARMA model was used in [45] to predict the useful life of PEM fuel cells along with a physical aging model and time delay NN. The ARMA results for the lifetime prognosis of PEM fuel cell stacks were found satisfactory when compared with back propagation neural networks and least square fitting [46]. The simulation results of Model Predictive Control (MPC) based on the ARMA model were found to have better control performance than MPC based on a rigorous linear model. Fuel cell degradation prediction based on the ARMA model was found accurate in long-term forecasting [47]. A fault model based on the Coefficient of Variance (CV) was developed and experimentally validated in [48]. The durability of the fuel cell was analyzed by characterizing the voltage consistency [49] and consistency [50] using CV.

Most fault detection methods are offline, and the above-presented studies use fixed loads. However, the load on an automotive PEMFC is dynamic. This paper focuses on online fault detection and isolation methods. Detecting fault conditions by merely measuring and analyzing the output voltage and current makes the models practical in automobile applications, as it enables analysis with minimum sensors and no downtime. This study compared the fault detection and isolation models, CV, and ratios of 4 novel methods developed using fuzzy membership functions and wavelets.

II. EXPERIMENTAL OBSERVATIONS

Experiments were conducted on two 25cm^2 PaxiTech fuel cells using the PEM fuel cell test setup, FCT-50S, and FCT-Lab. One cell was newly constructed and the other one was aged, having run for more than 2000 hours. The aged fuel cell had a 90% degradation in power delivery compared to the new one. Faults were injected into the aged fuel cell, and the changes in polarization curves were observed. A water-flooded cell showed around a 30% decrease in performance in terms of power delivery. The reactant gas starvation fault showed around 55% degradation in the cell performance. A high-operating-temperature fault cell could not be able to deliver power. Figure 1 shows the polarization curves of the experiments.

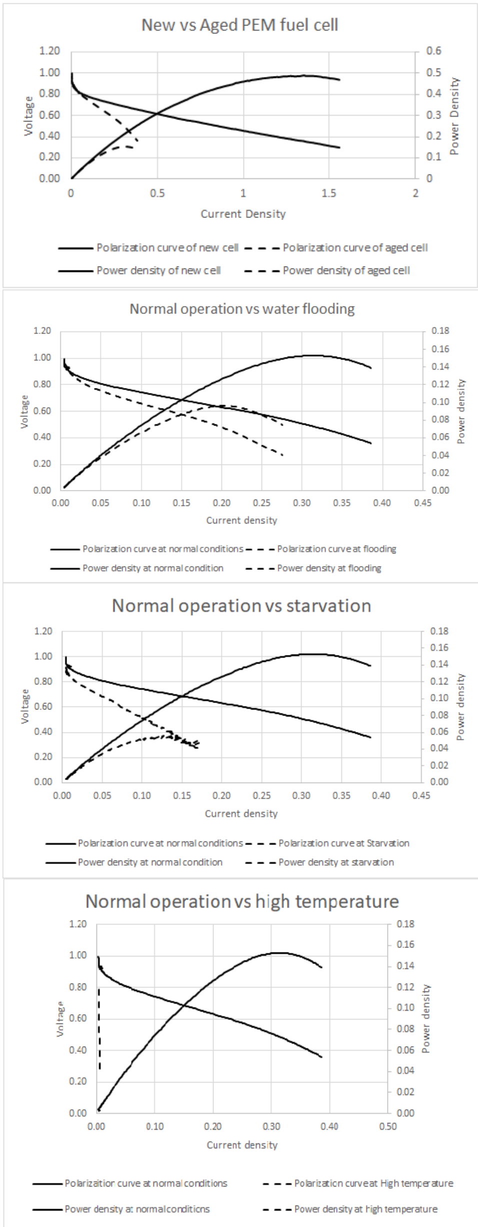

Fig. 1. PEM fuel cell performance in operating conditions [7].

III. DEGRADATION AND FAULT DETECTION METHODS

Four methods were used to examine performance degradation and fault detection of the fuel cell. This section presents the methods and their results.

A. Coefficient of Variance

CV is used to measure the fuel cell output voltage dispersion and degree of asymmetry [51], and analyze its reliability using the stress-strength interference method [52]. The CV is a ratio of the standard deviation σ to the mean μ, as shown in (1). CV measures the relative variability of the parameters and can be used to compare the voltage degradation of a PEMFC for a given current.

$$CV = \frac{\sigma}{\mu} \times 100\% \quad (1)$$

The coefficients of variance for the fuel cell output voltage CV_V, the current density CV_{CD}, and the cell power CV_P were calculated for aged cells and cells operating in fault conditions [48]. The experimental results showed that the CV values could differentiate the degradation performance.

B. Ratio Comparison

Experimental observations showed that fuel cell voltage drops for the current. This method compares the rate of change in the PEMFC output voltage to the change in its output current, using (2). Another ratio was calculated as the change in the PEMFC output power to the change in output voltage, shown in (3).

$$\left(\frac{dV}{di}\right)_{cell} \neq \left(\frac{dV}{di}\right)_{Healthy\ cell} \quad (2)$$

$$\left(\frac{dP}{dV}\right)_{cell} \neq \left(\frac{dP}{dV}\right)_{Healthy\ cell} \quad (3)$$

Ratios were calculated for the fuel cell under test and compared to the ratios of a healthy cell with the same specifications. The cell could have a fault condition if the ratio values do not match. Similarly, the ratios can be compared to the threshold to isolate the fault type, as shown in (4) and (5):

$$\left(\frac{dP}{dV}\right)_{cell} \approx \left(\frac{dP}{dV}\right)_{fault\ threshold} \quad (4)$$

$$\left(\frac{dV}{di}\right)_{cell} \approx \left(\frac{dV}{di}\right)_{fault\ threshold} \quad (5)$$

Figures 2 and 3 show, respectively, the ratios *dP/dV* and *dV/di* for each operating condition. The graphs show the difference in the performance of the fuel cell in a fault condition from a healthy one [9].

C. Fuzzy Membership Values and Euclidian Distance Method

The fuzzy linear membership function of the values was used to compare the output voltage and current values of the fuel cell. The fuzzy linear membership values were obtained for the dataset. These membership values were comparable as they were unit free. The fuzzy Linear Membership function for the *i*-th observation defines a linear membership function as:

$$\mu(x) = \left(\frac{i^{th}\ observation - lowest\ observation}{i^{th}\ observation}\right) \quad (6)$$

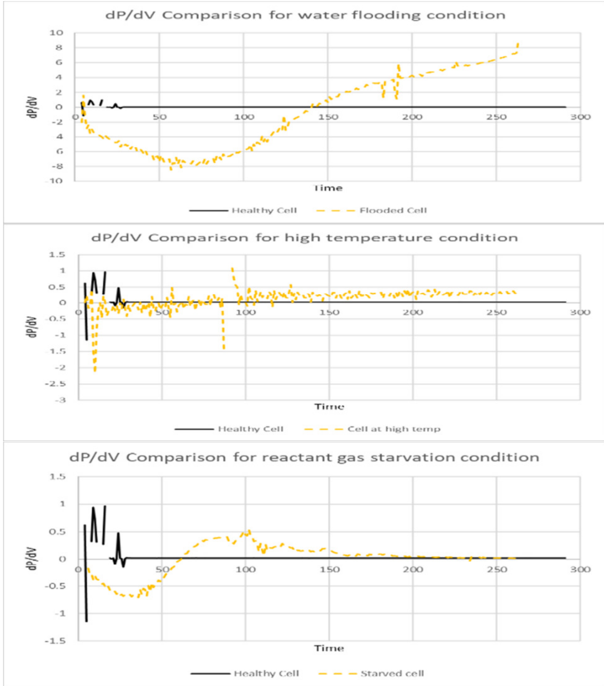

Fig. 2. *dP/dV* curves in different conditions [9].

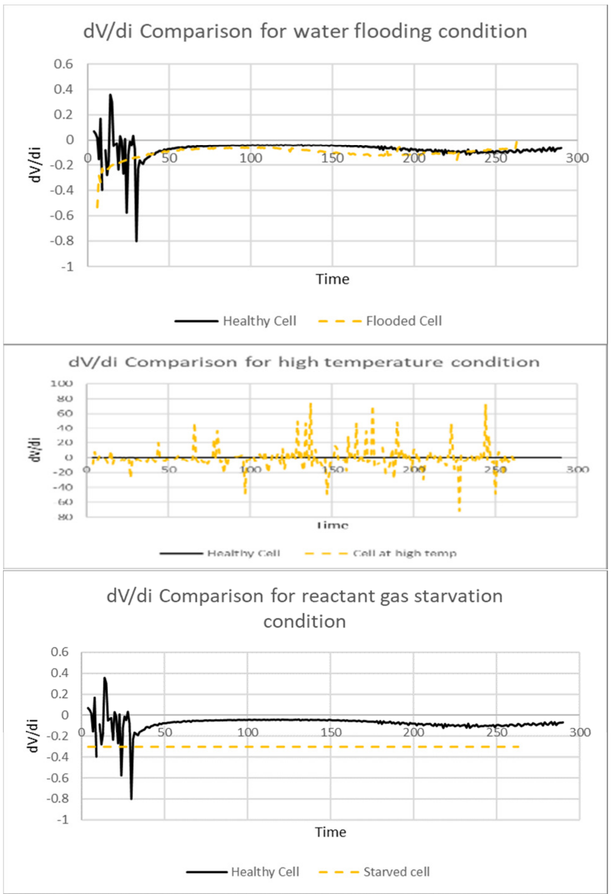

Fig. 3. *dV/di* curve comparison between healthy and faulty operating conditions [9].

The value of the membership function lies between 0 and 1. The smallest observation has a membership value of zero ($m(x)$=0). The membership values for the current and voltage observations can be used to calculate the Euclidean distance between the standard and the observed values.

Let $\mu_i(x)$ denote the membership values for the k-th observed current value and $\mu_v(x)$ denote the membership value for the k-th observed voltage value. The corresponding point in the membership plane for the observed current and voltage values is given by $M(\mu_i(x), \mu_v(x))$. Similarly, the point in the membership plane for benchmark values obtained from healthy cell be $M'(\widetilde{\mu_i}(x), \widetilde{\mu_v}(x))$. The Euclidean distance between MM' can be calculated by:

$$d = \sqrt{\left(\mu_i(x) - \widetilde{\mu_i}(x)\right)^2 + \left(\mu_v(x) - \widetilde{\mu_v}(x)\right)^2} \quad (7)$$

The fuel cell operation is desirable when the distance d is minimum, whereas a larger value of d indicates that the fuel cell is operating in a potential fault condition. Figure 4 shows the fuzzy membership values obtained under various operating conditions. The distance between the fuzzy membership values can be calculated using the Euclidean distance.

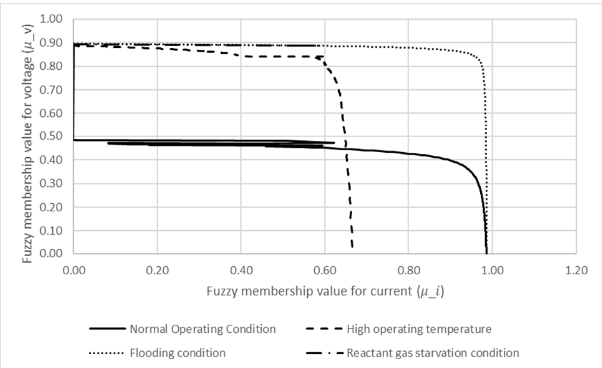

Fig. 4. Comparison of fuzzy membership values.

D. Wavelet Transform

The wavelet transform can be used for non-destructive testing and monitoring the health of a system [54]. The time and frequency domains of a signal provide significant information. Wavelet and its transform are useful to analyze the time and frequency domains of a signal [53]. Equation (8) shows a "mother" wavelet or a wavelet basis function:

$$\Psi_{u,s}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-u}{s}\right) \quad (8)$$

where s is a scaling parameter that allows the dilation of the signal and u is a translational parameter that allows the translation of a signal in time. Hence, it allows time-frequency spectrum generation. However, the resolution of both time and frequency is not high. The following equations calculate a continuous wavelet transform of a time-based signal:

$$W_\Psi[f](u,s) = f, \Psi_{u,s} \quad (9)$$

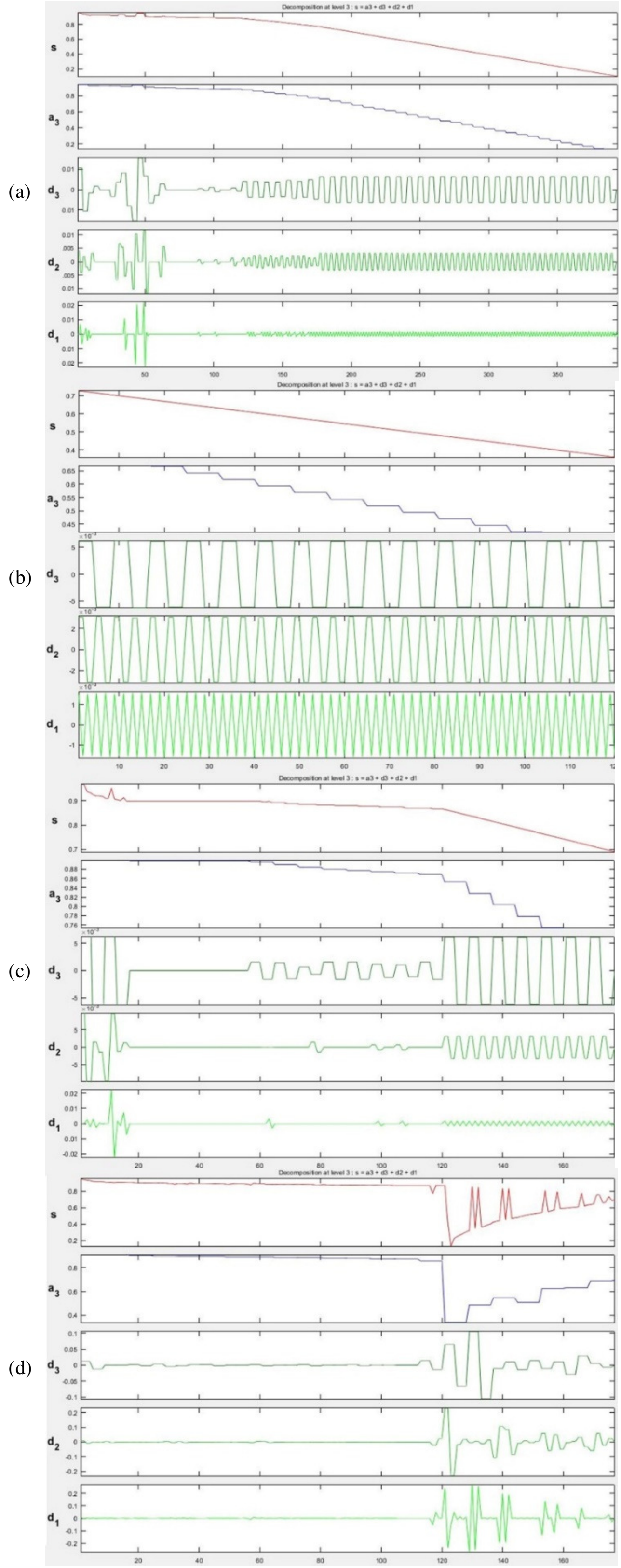

Fig. 5. Haar 3 analysis of PEMFC experimental data under different operating conditions: (a) good cell, (b) old cell, (c) water flooded cell, and (d) starvation.

$$f, \Psi_{u,s} = \int_{-\infty}^{\infty} f(t)\Psi_{u,s}(t)dt \quad (10)$$

Let the time-based signal be $f(t)$. The time-frequency spectrum is obtained by repeating the process over the time and frequency range. However, the discrete wavelet transform can provide a sparser representation [55], as it has an advantage in analyzing signals with sudden transitions. One of the applications can be monitoring a machine failure. Moreover, the computational speed is faster than the continuous transform.

The Haar wavelet transform was used in the analysis, as it is a discrete and the simplest wavelet. The mother wavelet function for the Haar wavelet is described by:

$$\Psi(t) = \begin{cases} 1 & 0 \leq t < 1/2, \\ -1 & 1/2 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases} \quad (11)$$

The mother wavelet is decomposed to approximate components A_j and detailed components D_j. Approximate components are used to analyze information at low frequencies and detailed components are used to analyze information at higher frequencies. The energy of the signal was computed using the following:

$$E_j^d = \sum_k \left|C_j^d(k)\right|^2 \quad (12)$$

where C is the coefficient of the detailed component at level j of the k number of samples.

Haar 3 level decomposition was used to analyze the fuel cell experimental data. Data were analyzed using the wavelet toolbox from MATLAB 2019b. Figure 5 shows the analysis in a graphical form. The pattern of detailed decomposition levels is distinctly different from the healthy PEMFC data. The oscillations in d_1, d_2, and d_3 were observed in a healthy fuel cell when the voltage dropped as the current increased. However, the coefficients had oscillations since the beginning, and the s waveform showed a linear drop.

Oscillations were observed in water-flooded conditions at higher currents. High magnitude oscillations were observed at higher currents in the case of reactant gas starvation conditions. Hence, the pattern in coefficients can differentiate the fuel cell performance during degradation due to the fault condition or aging.

IV. RESULTS AND DISCUSSION

The PEMFC performance was observed experimentally to degrade when the cell was aged or operated in a fault condition. The output performance of the PEMFC was analyzed using methods like CV, comparing ratios, fuzzy membership values, and wavelet transform. All methods used the PEMFC output voltage and current data for fault detection. CV is the simplest method to detect a fault condition. The ratios *dP/dV* and *dV/di* were found to be useful for fault detection and fault type identification. The results obtained from the fuzzy membership values of the PEMFC output voltage and current proved to be an effective method to detect faults. However, the Euclidian distance method should be used to isolate the fault type. On the other hand, the wavelet transform proved to be a better method for fault detection and fault type isolation. The simple discrete form of the Haar wavelet transform was found to be effective. All these methods can be used for online and non-destructive fault detection.

V. CONCLUSION

Fault conditions degrading the performance of a PEMFC were experimentally investigated. As the fault detection methods proposed in this paper were online, non-invasive, and non-destructive, they can be useful in automobile applications. Methods, CV, ratios, and wavelet transform are useful for fault detection and fault type isolation. However, the fuzzy membership method requires further analysis of the Euclidian distance to isolate the fault type. The CV and fuzzy membership value methods are more suitable for online fault detection in an automotive application. However, the wavelet transform method can be used as a self-diagnosis of the fuel cell during startup.

ACKNOWLEDGMENT

This work was supported by the Department of Automobile Engineering, PSG College of Technology, Coimbatore, India. The authors would like to sincerely thank Dr. P. Karthikeyan and his research group for their guidance.

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