Fault diagnosis of practical proton exchange membrane fuel cell system using signal-based techniques

This item was submitted to Loughborough University's Institutional Repository by the/an author.


Additional Information:

- This is a conference paper.

Metadata Record: https://dspace.lboro.ac.uk/2134/17251

Version: Accepted for publication

Publisher: Institut National Polytechnique de Toulouse (University of Toulouse)

Rights: This work is made available according to the conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0) licence. Full details of this licence are available at: https://creativecommons.org/licenses/by-nc-nd/4.0/

Please cite the published version.
Fault diagnosis of practical proton exchange membrane fuel cell system using signal-based techniques

Lei Mao¹, Lisa Jackson¹, Sarah Dunnett¹
¹Department of Aeronautical and Automotive Engineering, Loughborough University, Leicestershire, LE11 3TU
l.mao@lboro.ac.uk

Abstract

In the past few decades, hydrogen fuel cells have been suggested as an alternative energy source and engineered for a range of applications including automotive, stationary power, and consumer electronics. However, the durability and reliability of hydrogen fuel cells still remain major hurdles for its wider application.

Several researchers have investigated the diagnosis of faults in fuel cell systems, various techniques have been performed to detect and isolate fuel cell faults using different measurements, including current, fuel cell voltage, polarization curve, electrochemical impedance spectroscopy, etc. However, in practical fuel cell systems, a series of sensors will be used to capture the system performance, thus the information contained in these sensors should be fully utilized for reliable diagnostic results.

In this paper, a diagnosis procedure will be applied to practical fuel cell systems under the combined load condition. After collecting a series of measurements from the system, two techniques, principle component analysis (PCA) and Fisher linear discriminant analysis (LDA), are used to reduce the dimension of the original dataset, then coefficients are extracted from the reduced dataset using wavelet packet (WP) transform to form features for diagnosis. Results demonstrate that with the proposed procedure, different states of fuel cell system can be distinguished with good quality.

Keywords: Fuel Cells, Load Current, Fault Diagnosis, Signal-based Techniques

1. Introduction

The demand for less polluting energy generation technologies has been increased in the last few years. Among these technologies, the proton exchange membrane fuel cell (PEMFC) receives much attention, as it can convert the energy into electricity directly and produce only water and heat. In the past few decades, PEMFC has been applied in many applications including automotive, stationary power, and consumer electronics. However, for further commercialization, durability and reliability of fuel cells are still the critical issues.

In order to guarantee the safety of fuel cells during their operation, the number of fault diagnostic studies of fuel cells has grown rapidly. A series of signal-based technologies have been proposed in the last few decades to detect and isolate faults of fuel cells [1-14]. According to these studies, different information and processing techniques should be used for various fuel cell system loading conditions. For fuel cells under steady state condition, signal processing techniques can be applied to sensor measurements to extract features for fault diagnosis [1-9]. On the other hand, when subjected to dynamic load, varying load current effect should be considered in the fault diagnostic analysis. Based on previous results [10-14], information including load current and fuel cell system performance, such as polarization curve, and electrochemical impedance spectroscopy (EIS), are usually measured to indicate and isolate faults of fuel cell systems.
From previous studies, however, only several sensor measurements are selected for fault diagnosis, while in practical fuel cell systems, a series of sensors will be installed to record the performance of the fuel cells. This will add to the complexity of the signal processing procedure, as increased sensors will add more information about the fuel cell performance. Thus a signal processing procedure should be proposed to accommodate useful information from these sensors.

In this paper, a general signal-based diagnostic procedure is applied to a practical fuel cell system for fault diagnosis. The practical fuel cell system and recorded measurements in steady state tests will be presented in section 2. Section 3 will describe the signal-based diagnostic procedure, several signal processing techniques are used, including PCA and LDA for dataset dimension reduction, wavelet packet (WP) transform for extracting features. In section 4, results from the signal-based procedure will be demonstrated. Finally, conclusions will be given and suggestions are proposed for further work.

2. Description of practical fuel cell system

In the study, a practical fuel cell system used in a real application is selected for analysis. Evaporatively cooled (EC) fuel cell system is designed for high volume, low cost manufacturing applications, it utilizes the benefit of heat from vaporization instead of circulating coolant through the cells, thus reducing complexity, mass and cost. Figure 1 depicts the block diagram of the EC fuel cell system.

![Figure 1 Block diagram of EC fuel cell system](image)

It can be observed from the figure above that during the EC fuel cell operation, hydrogen and air are injected into the anode and cathode electrodes of the stack, respectively. Water is also injected into the stack and partly evaporated within the stack, which will remove heat. Moreover, as a liquid/vapor mix will be formed to carry thermal energy, stack exhaust is condensed in the heat exchanger to recover and return sufficient water to the water tank in order to maintain water balance in the system.

In this fuel cell system, several sensors can be placed at the inlets and outlets of the stack modules to record stack performance, such as stack voltage, inlet pressure, flow rate, temperature, etc. In order to maximize the information from the fuel cell system, all the recorded measurements are used to identify faults of the fuel cell system.

3. Signal-based diagnostic techniques

With recorded measurements from EC fuel cell systems, signal processing techniques can be applied to extract features for fault diagnosis. However, due to the high dimension of the measurement dataset (22 sensors in this study), techniques reducing dataset dimension should be applied before extracting features. Furthermore, after feature extraction, features containing significant information will be selected using signal processing techniques to
identify system faults. In this section, the signal processing techniques used in the study will be presented.

3.1. Reduction of high dimensional dataset

In this study, the dimension of original dataset will be reduced using PCA and LDA. It should be mentioned that prior knowledge about data classes is required for the analysis when applying LDA.

PCA is a multivariate statistical method using orthogonal transformations to convert more relevant variables into a set of uncorrelated variables called principal component. With the transformation, the high dimension variable space will be reduced based on the lowest missing rule and can be expressed using a few principal components, this is depicted in Figure 2, where the uncorrelated data can be obtained with the first principal component (u axis) and the second principal component (v axis).

![Figure 2 Data transformation with PCA](image)

Principal components can be found by calculating eigenvalues and eigenvectors of the data covariance matrix, the eigenvector with the largest eigenvalue is the direction of greatest variation, the eigenvector with the second largest eigenvalue is the direction of the second highest variation, and so on. By projecting the original data into these directions, principal components can be obtained [9].

Like PCA, LDA seeks to reduce the dimensionality of the original dataset, but will preserve as much of the class discriminatory information as possible. Assuming the test data includes C (?) different classes, (C-1) projections should be determined by the projection matrix, W, as \( y = W^T x \), where \( y \) is the projected dataset, \( x \) is the original data matrix. The procedure of applying LDA can be expressed as follows.

1) Calculate within class scatter

\[
S_W = \sum_{i=1}^{C} S_i
\]

where \( S_i = \sum_{x \in w_i} (x - \mu_i)(x - \mu_i)^T, \mu_i = \frac{1}{N_i} \sum_{x \in w_i} x \)

where \( w_i \) represents the ith class, and \( N_i \) is number of data in the ith class.

2) Calculate between class scatter

\[
S_B = \sum_{i=1}^{C} N_i (\mu_i - \mu)(\mu_i - \mu)^T
\]

where \( \mu = \frac{1}{N} \sum_{x} x = \frac{1}{N} \sum_{i=1}^{C} N_i \mu_i \)
3) Define mean vector and scatter matrices for the projected data

\[ \tilde{\mu}_i = \frac{1}{N_i} \sum_{y \in w_i} y, \quad \tilde{S}_W = \sum_{i=1}^{c} N_i (\tilde{\mu}_i - \tilde{\mu})(\tilde{\mu}_i - \tilde{\mu})^T \]  

(3)

\[ \bar{\mu} = \frac{1}{N} \sum_{y} y, \quad \bar{S}_B = \sum_{i=1}^{c} N_i (\bar{\mu}_i - \bar{\mu})(\bar{\mu}_i - \bar{\mu})^T \]  

(4)

4) Define the ratio of between class to within class scatter

\[ f(W) = \frac{\bar{S}_B}{\bar{S}_W} = \frac{W^T S_B W}{W^T S_W W} \]  

(5)

5) Determine the optimal projection matrix \( W^* \) which maximizes the above ratio, the columns of this matrix should be eigenvectors corresponding to the largest eigenvalues of the following generalized eigenvalue problem

\[ W^* = \arg \max \left| \frac{W^T S_B W}{W^T S_W W} \right| \]  

(6)

3.2. Feature extraction and generation

After reducing the original dataset, features can be extracted for fault diagnosis. Wavelet packet (WP) transform is selected in the study to achieve this purpose. The principal of WP transform is letting the signal pass through filters to get low-pass results (approximation) and high-pass results (detail). Compared to conventional wavelet transform, WP transform can give more coefficients as both approximation and detail will be filtered to get the next level approximation and detail, respectively [15-16], this can be expressed in Fig.3, where WP transform is applied over three levels, and for each transform, both low pass coefficient \( g[n] \) and high-pass coefficient \( h[n] \) are obtained.

![Wavelet packet transform over 3 levels](image)

After obtaining these wavelet coefficients, features can be generated. In the study, normalized energy is generated as a feature, since it can be easily calculated and can give reliable results [6]. Normalized energy can be computed with the following equation.

\[ E^p = \frac{1}{N_p} \sum_{j,k} |C^p_{j,k}|^2 \]  

(7)
where $E^p$ is normalized energy for specific wavelet packet $p$, $N_p$ is number of coefficients in wavelet packet $p$, $C^{P}_{j,k}$ is coefficient in wavelet packet, which are the $h[n]$ and $g[n]$ in Fig. 3.

4. Result and discussion

4.1. Description of sensor measurements

In this section, fault diagnosis of the EC fuel cell system will be performed using the signal-processing techniques outlined above. Fig. 4 depicts some recorded measurements from the system, including load current and stack voltage. It should be noted that ‘Error indicator’ is used to indicate fault of the system when its value jumps to 1, different faults can be identified with various Error indicators.

![Figure 4 Sensor measurements and fault indicators](image)

From the figure above, it can be observed that during system operation in steady state testing, load current might be changed. Based on varying load current and system fault, the measurement signals are divided into three parts shown in Fig. 4.

1) Normal part (with stable load current and without fault);

2) Unknown part (with load current variation but without fault);

3) Fault part (with load current variation and fault);

As can be seen from Fig. 4, normal and fault parts can be distinguished clearly since they have different sensor measurements, however, due to varying load current, the unknown part has similar sensor readings to the fault part, which make it difficult to classify these two categories. Therefore, the purpose of employing signal-based procedure is to classify unknown and fault parts, so that a fault of the EC fuel cell system can be identified.

4.2. Results and discussion

Based on the section, PCA and LDA are used to reduce dimensions of the measurement dataset (22 in the study). According to Eq. (1), the first four principal components are selected, thus the original data will be projected to the first four principal directions. While for LDA, the test data is divided into two parts, half of the data is used for training purposes, while the remaining half is used for testing. It should be mentioned that when performing LDA, only one projected component corresponding to the most discriminatory line is obtained.
Based on previous studies of using wavelet transform for feature extraction [6], WP transform is applied to the data over three levels in the study, which gives 14 normalized energies. From these normalized energies, two features containing the largest normalized energy are selected to classify different cases, as they contain most of the information from the original measurements. With selected features, the processed data can be classified. Figs. 5 and 6 depict classification results using two selected normalized energies from PCA and LDA. As described before, the 1st principal direction from PCA cannot classify unknown and fault cases, while these two categories can be distinguished at other principal directions.

Moreover, the performance of PCA and LDA on fault diagnosis is further studied, their correct classification rates are compared and listed in Table 1. From comparison of the results, it can be seen that compared to PCA, LDA can give more stable classification results, both unknown and fault cases can be distinguished with good quality. While with PCA, some
principal directions may give less percentage rates for identifying fault of the system. It should be noted, however, that prior knowledge about various classes should be obtained to train the LDA algorithm, thus in practical fuel cell systems PCA and LDA should be selected depend on the prior information from the system.

Table 1 Comparison of correct classification rate between PCA and KPCA

<table>
<thead>
<tr>
<th>Direction</th>
<th>PCA</th>
<th>LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Unknown</td>
<td>15%</td>
<td>100%</td>
</tr>
<tr>
<td>Fault</td>
<td>72.7%</td>
<td>90.9%</td>
</tr>
</tbody>
</table>

5. Conclusion

In the paper, a general signal-based diagnostic procedure is applied to the sensor measurements from a practical EC fuel cell system for fault diagnosis. In the process, several signal processing techniques are employed, including PCA and LDA to reduce high-dimensional data, WP transform to extract coefficients from data.

Results demonstrate that by studying mean normalized energy of principal directions and selected features, both PCA and LDA can classify unknown and fault cases with good quality, but LDA can give more stable classification results, which is more useful in practical systems without prior knowledge about faults.

It should be noted that in classification results, misclassification can be made for unknown and fault cases, in the further study, more complicated features will be used to improve the correct percentage of classification. Moreover, the performance of the proposed procedure will be studied using more test data from practical fuel cell systems, and its performance in classifying different faults will be further investigated.

Acknowledgement

This work is supported by grant EP/K02101X/1 for Loughborough University, Department of Aeronautical and Automotive Engineering from the UK Engineering and Physical Sciences Research Council (EPSRC). Authors also acknowledge Intelligent Energy for its close collaboration in providing necessary information for the paper.

Reference


