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Fault detection and isolation of PEMFC systems: a classification approach

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ABSTRACT:
This paper proposes a data-driven diagnostic approach for Polymer Electrolyte Membrane Fuel Cell (PEMFC) systems. Fault detection and isolation (FDI) is realized by analyzing individual cell voltages. A feature extraction method *Fisher Discriminant Analysis* (FDA) and a multi-class classification method *Directed Acyclic Graph Support Vector Machine* (DAGSVM) are utilized successively to extract the useful features from raw data and classify the extracted features into various classes related to health states. Experimental data of two different stacks are used to validate the proposed approach. The results show that five concerned faults can be detected and isolated with a high accuracy.

KEYWORDS: PEMFC systems, Fault detection and isolation, Classification, Cell voltages.

1 Introduction

Polymer electrolyte membrane fuel cell (PEMFC) has been considered to be one of the most promising fuel cells, especially for mobile applications. Fault diagnosis of PEMFC, as a crucial factor of system operations, has to be overcome for its commercial viability.

Modeling a PEMFC system usually needs to identify a number of fundamental parameters, which could be a difficulty or even impossible task. The conventional model-based diagnosis methods are therefore not adapted in practice with such constraints. Recently, some data-driven methods, such as the artificial intelligent and signal processing ones, have been employed to figure out PEMFC diagnosis problems [1] [2]. With the data mining capabilities of these methods, the diagnosis oriented information can be extracted from data without sophisticated modeling. Hence, this is a promising direction of PEMFC diagnosis. However, most of the available papers focus on the detection of some special faults, fault isolation is somehow neglected. Moreover, the accuracy and the implementation cost are not evaluated with enough emphasis.

The paper proposes a data-driven approach for PEMFC diagnosis, which has the capabilities of both fault detection and isolation (FDI). In addition, the performance of the approach, in aspects of the accuracy of the FDI and the cost of implementation, is high sufficiently. In the frame of the approach, FDI problem is treated as a classification problem, and FDI is realized by classifying the data to varied classes that represent the normal state and the concerned faulty states. Specifically, individual cell voltages are chosen as the original variables for diagnosis, which economize the cost of measurement. Two stages are performed to process the data and achieve the diagnosis procedure. In the first stage, Fisher discriminant analysis (FDA), as a feature extraction method, is used to extract the diagnosis oriented features as well as reduce the data dimension. In the second stage, a classification tool DAGSVM (Directed Acyclic Graph Support Vector Machine) is carried out in the feature space to realize FDI.

To verify the effectiveness and universality of the proposed approach, the experiments of a 40-cell stack and an 8-cell stack were carried out respectively in our lab. The data of normal state and various faulty states were recorded to train and test the algorithms. The diagnosis results of the two stacks show that different faults can be detected and isolated with high accuracy. Additionally, the proposed methods can be implemented by an embedded chips for online diagnosis.

2 Cell voltages: variables for diagnosis

The output stack voltage is usually considered as a signal for fault diagnosis. However, only stack voltage is not always sufficient to fulfill the fault isolation task. Moreover, it is found that the cell voltages which compose the stack voltage are usually not homogenous even in normal case. Without doubt, the individual cell voltages can supply more information than mere stack voltage. Essentially, different faults can lead to different spatial distributions of temperature, humidity, and gas fluids inside a stack, and thus result in the different spatial distributions of individual cell voltages. Hence, the individual cell voltages were chosen as the original variables for FDI in this study.

3 Diagnosis methodologies

3.1 Framework of the diagnosis approach

The proposed diagnosis approach combines the FDA and the DAGSVM methods. Fig. 1 outlines the framework of the diagnosis approach. As the figure shows, it contains the off-line training stage and on-line performing stage.

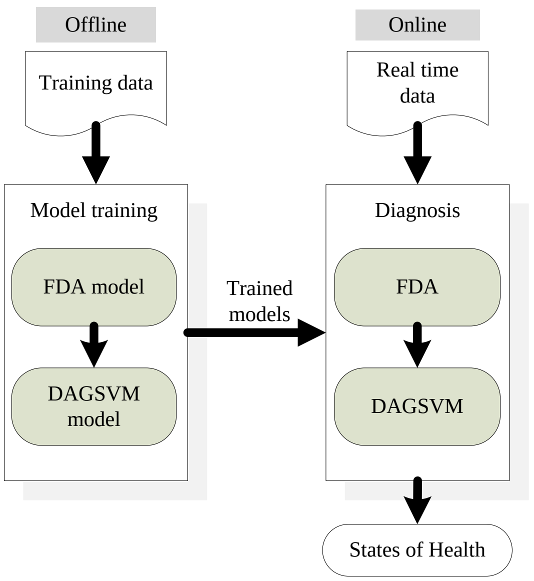


Figure 1: Flowchart of the proposed diagnosis approach

In the off-line training process, the training samples in the training dataset are distributed in various classes that represent health states, including the fault free state and a number of concerned fault states. The labeled samples were firstly used to train the FDA model. Through solving the eigenvalue problem, FDA model can be obtained for performing use. At the meantime, he training samples can be projected to the feature space. Then, the features of training dataset were employed to train DAGSVM. As FDA, the trained model is exported for the performing use.

In the on-line performing process, with the aid of the obtained projecting vectors, FDA is firstly performed by projecting the real time sample into the feature space. DAGSVM is then carried out to classify the projected vector into a certain class and complete the diagnosis procedure.

The diagnostic problem can be mathematically abstracted as follows. Let $H \in \mathbb{N}$. Suppose that we have a training dataset of N H-dimensional samples $\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_N$, which are distributed in C classes denoted by V_1, V_2, $\ldots$, V_C. The sample number in V_i is N_i. FDA and DAGSVM models are trained based on the training dataset. Through the trained models, a real-time sample $\boldsymbol{v}$ can be classified into a defined class $V_i,\ i = 1, \ldots, C$.

In the following, the two methods FDA and DAGSVM are presented. In order to keep the main clue, and avoid the sophisticated theoretical deduction process, the methods are introduced in a simplified manner. Firstly, the objectives and principles of the methods are given. Then. the methods are abstracted as algorithms. The correlated references are given for more details.

3.2 FDA

FDA is a supervised technique developed for extracting useful features from raw data in hope of obtaining a more manageable classification problem. The objective of FDA is to find mapping vectors that make the data in the same class concentrated while the data in varied classes separated [3] [4]. The objective of the training process is to find L ($L < M$) M-dimension unit projecting vectors: $\{\boldsymbol{w}_1, \boldsymbol{w}_2, ..., \boldsymbol{w}_L\}$. With these vectors, a real-time sample $\boldsymbol{v}$ can be projected to a L-dimension feature space, the projected vector $\boldsymbol{z}$ is expressed:

$$\boldsymbol{z} = [\boldsymbol{w}_1^T\boldsymbol{v}, \boldsymbol{w}_2^T\boldsymbol{v}, \ldots, \boldsymbol{w}_L^T\boldsymbol{v}]^T \tag{1}$$

The projected samples in training dataset can be denoted as $\{\boldsymbol{z}_i : i = 1, \ldots, N\}$. FDA can be briefly formulated by Algorithm 1.

Algorithm 1 FDA

Training:

1: Collect labeled samples: $\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_N$.

2: Calculate within-class-scatter matrix $\boldsymbol{S}_w$ and between-class-scatter matrix $\boldsymbol{S}_b$.

$$\boldsymbol{S}_w = \sum_{i=1}^{C} \sum_{\boldsymbol{v}_n \in V_i} (\boldsymbol{v}_n - \bar{\boldsymbol{v}}_i)(\boldsymbol{v}_n - \bar{\boldsymbol{v}}_i)^T$$

$$\boldsymbol{S}_b = \sum_{i=1}^{C} N_i(\bar{\boldsymbol{v}}_i - \bar{\boldsymbol{v}})(\bar{\boldsymbol{v}}_i - \bar{\boldsymbol{v}})^T$$

where $\bar{\boldsymbol{v}} = \sum_{n=1}^{N} \boldsymbol{v}_n/N$, and $\bar{\boldsymbol{v}}_i = \sum_{\boldsymbol{v}_n \in V_i} \boldsymbol{v}_n/N_i$.

3: Set $L = C - 1$, and find the L eigenvectors of $\boldsymbol{S}_w^{-1}\boldsymbol{S}_b$ with non-zero eigenvalues: $\boldsymbol{w}_1, \ldots, \boldsymbol{w}_L$.

Performing:

Calculate the projected vector of a new sample as (1).

3.3 DAGSVM

SVM is considered as a powerful classification method [5]. DAGSVM is a multi-class SVM classification tool based on a set of binary SVMs.

As presented in [6], to solve a C-class classification problem, it is necessary to construct all possible binary classifiers from a training set of classes, each classifier being trained on only two out of C classes. There would thus be $C(C-1)/2$ classifiers. In the performing phase, a rooted binary directed acyclic graph (DAG), which has C layers, $C(C-1)/2$ internal nodes and C leaves, is used. As Fig. 2 shows, each node is a binary SVM of ith and jth classes. Given a test sample, starting at the root node, the binary classification function at a node is evaluated. Then it moves to the node in the next layer from either left or right path (depending on the binary classification result). Then, the binary classification function of the next node is evaluated. Therefore, a path is taken before reaching a leaf node which indicates the predicted class. The path is known as the evaluation path which goes through $C-1$ nodes. Carrying out $C-1$ times of binary classifications is needed to derive the final class determination.

3.3.1 Binary SVM

Binary SVM is firstly developed by V. Vapnik [7] and has been widely applied in various domains over the last two decades. A binary SVM looks for an optimal decision hyperplane, which separates the two classes, while at the same time, maximizes the margin between itself and the

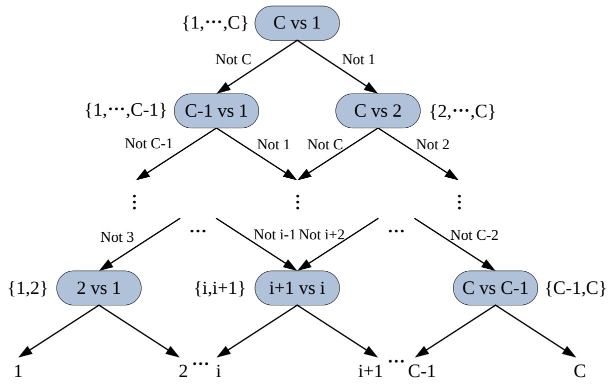


Figure 2: DAGSVM structure

nearest training examples of each class. Take the samples from the first two training classes V_1 and V_2, the binary SVM could be described by Algorithm 2.

Algorithm 2 Binary SVM

Training:

1: Collect $(N_1 + N_2)$ labeled sample $\boldsymbol{z}_1, \boldsymbol{z}_2, \ldots, \boldsymbol{z}_{N_1+N_2}$ from classes Z_1 and Z_2. $g_n \in \{-1, 1\}$, is the class label of sample $\boldsymbol{z}_n$ (-1 for class 1, 1 for class 2). Initial D.

2: Solve the quadratic problem:

$$\begin{aligned} minJ(\boldsymbol{a}) &= \frac{1}{2}\sum_{n=1}^{N_1+N_2}\sum_{m=1}^{N_1+N_2} a_n a_m g_n g_m k(\boldsymbol{z}_n, \boldsymbol{z}_m) - \sum_{n=1}^{N_1+N_2} a_n \\ \text{s.t.} &\sum_{n=1}^{N} a_n g_n = 0, \quad 0 \le a_n \le D, \quad \text{for} \quad n = 1, 2, \ldots, N \end{aligned} \tag{2}$$

where $\boldsymbol{a} = [a_1, a_2, ..., a_{N_1+N_2}]^T$, $k(\boldsymbol{z}_n, \boldsymbol{z}_m)$ is a kernel function.

3: Save support vectors: $\boldsymbol{z}_1^s, \boldsymbol{z}_2^s, \ldots, \boldsymbol{z}_S^s$ and corresponding g_n and a_n, which are denoted by $\{g_n^s\}$ and $\{a_n^s\}$. Support vectors are those samples whose corresponding $a_n > 0$.

Performing:

For a new sample $\boldsymbol{z}$, its class label is determined:

$$g = sign\left\{\sum_{n=1}^{S} a_n^s g_n^s k(\boldsymbol{z}_n^s, \boldsymbol{z}) + b\right\} \tag{3}$$

where

$$b = \frac{1}{S}\sum_{j=1}^{S}\left(g_j^s - \sum_{n=1}^{S} a_n^s g_n^s k(\boldsymbol{z}_n^s, \boldsymbol{z}_j^s)\right)$$

4 Experiments descriptions

4.1 Two PEMFC Stacks

An 8-cell stack and a 40-cell stack were used to carry out various experimental tests, including the ones under fault conditions[1]. Both stacks have the same technology parameters except the number of cells. The nominal operating conditions of the two stacks are summarized in Table 1.

4.2 Experiments

A 1 kW and a 10 kW test benches, which had been developed in-lab, were employed respectively to fulfill the experimental requirements of two PEMFC stacks. Details about the two test benches

[1]The two stacks were fabricated by the French research organization CEA (Alternative Energies and Atomic Energy Commission) in the framework of the French ANR DIAPASON project.

Table 1: Nominal conditions of the stacks

Parameter	Value
Stoichiometry H_2	1.5
Stoichiometry Air	2
Pressure at H_2 inlet	150 kPa
Pressure at Air inlet	150 kPa
Differential of anode pressure and cathode pressure	30 kPa
Temperature (exit of cooling circuit)	80 $^{\circ}\mathrm{C}$
Anode relative humidity	50%
Cathode relative humidity	50%
Current	110 A
Voltage per cell	0.7 V
Electrical power of 8-cell stack	616 W
Electrical power of 40-cell stack	3080 W

can be found respectively in [8] and [9].

Five faulty states other than fault free operating state were concerned. As Table 2 shows, the faults, caused by the abnormal operations of the electric circuit, temperature subsystem, air supply subsystem and hydrogen supply subsystem, were taken into consideration. In fact, the failures of the auxiliary subsystems usually result in the abnormal or non-optimal operations suffered by the stack. The faults studied are usually considered as "reversible" or "recoverable", which can be corrected through appropriate operations. In order to obtain the datasets for both training and test aims, experiments were carried out several times in each condition.

Table 2: Various concerned states

Health state description	Location of state	Notation
Nominal operating state	Whole system	Nl
High current pulse or short circuit	Electric circuit	F_1
Stop cooling water	Temperature subsystem	F_2
High air stoichiometry	Air supply subsystem	F_3
Low air stoichiometry	Air supply subsystem	F_4
CO poisoning	H_2 supply subsystem	F_5

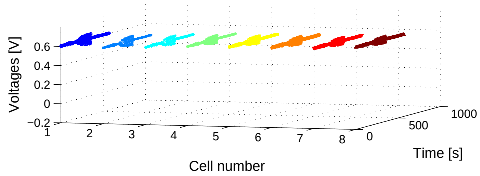
Fig. 3 shows the evolution of the cell voltages in the aforementioned processes. It could be found that the individual cell voltages are distributed more evenly in certain states (Nl, F_3, F_4) than that in others (F_1, F_2, F_5). Moreover, the spacial distribution of individual cell voltages varies with the type of fault.

5 Results and discussion

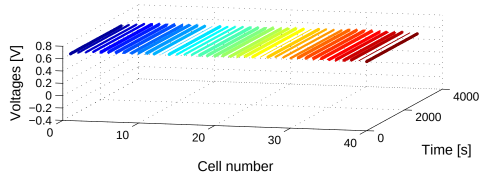
The *confusion matrices* of test data sets for the 8-cell stack and the 40-cell stack are summarized in Table 3 and 4, in which each row represents the diagnosed distribution of the data in an actual class. From the two tables, it can be observed and analyzed that:

- For both stacks, the mis-classifications happen mostly on the data of class F_4. The mis-classified points are located mostly in the class of Nl (some are classified to the F_3 class). This means F_4 is a fault type that is the most difficult to detect. For instance, in Table 4, 4.62% points in the Nl class are mis-classified to the F_4 class, and 14.8% samples in the F_4 class appear in the Nl class. It can be inferred that the faults of stoichiometry variation to a certain extent are light faults compared with other types of faults.

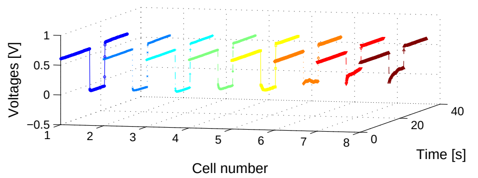
- Some mis-classified samples also appear in class F_1, F_2, and F_5. Actually, from our observations, the mis-classification mostly happens at the initial stage of these faults. It could be



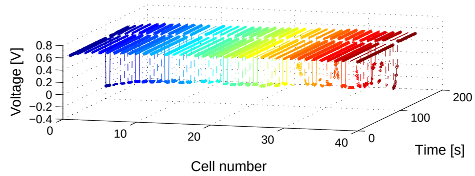
(a) Nl state (8-cell stack)



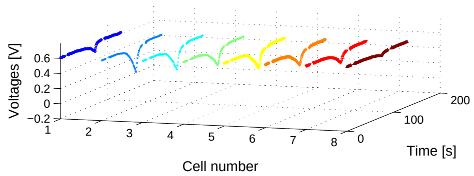
(b) Nl state (40-cell stack)



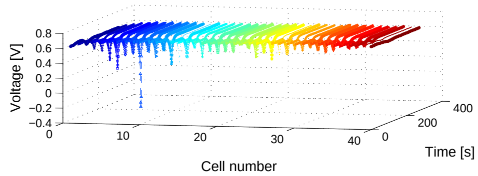
(c) F_1 state (8-cell stack)



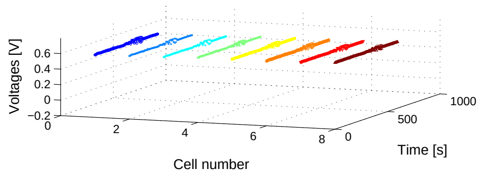
(d) F_1 state (40-cell stack)



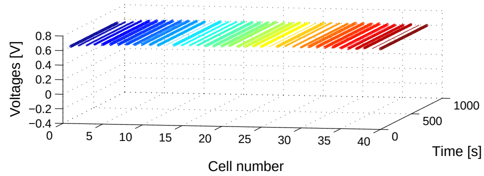
(e) F_2 state (8-cell stack)



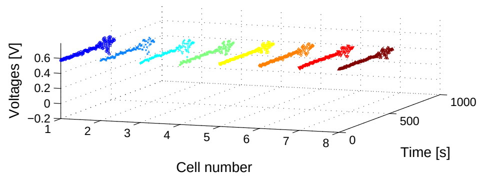
(f) F_2 state (40-cell stack)



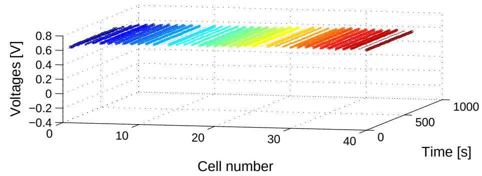
(g) F_3 state (8-cell stack)



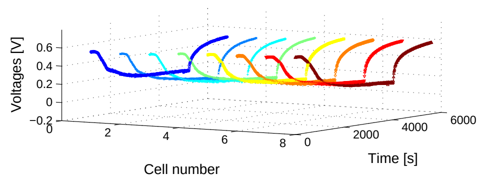
(h) F_3 state (40-cell stack)



(i) F_4 state (8-cell stack)



(j) F_4 state (40-cell stack)



(k) F_5 state (8-cell stack)

Figure 3: The evolution of cell voltages in different processes

thought that these samples are located in the transition zone between the normal state and fault state.

- The test data in classes NI, F_3, and F_4 is from the experiments with EIS tests, which added some current disturbances to the system. With such disturbances, the high classification rates can still be maintained.

For both stacks, when the approach is performed in PC (MATLAB environment), the needed memory is less than 5 kb to save the FDA and SVM models. The performing time is less than 0.5 ms. Hence, the approach is promising for online implementation.

The approach is efficient for detecting and isolating the faults whose data are available to train the diagnosis models. Nevertheless, a sample from an unseen failure mode would be misclassified to one of the known fault classes. Hence, an abundant training dataset, which contains the data from a substantial number of fault classes, is usually necessary for this approach. This is considered as the drawback of the proposed approach.

Table 3: Confusion matrix of the test data after classification for 8-cell stack

		Diagnosed class					
		NI	F_1	F_2	F_3	F_4	F_5
Actual class	NI	1.0000	0	0	0	0	0
	F_1	0	0.9163	0	0	0.0628	0.0209
	F_2	0.0399	0	0.9502	0.0100	0	0
	F_3	0	0	0	1	0	0
	F_4	0.0611	0.0056	0	0.0389	0.8944	0
	F_5	0	0	0	0	0.0092	0.9908

Table 4: Distribution of the test data after classification for 40-cell stack

		Diagnosed class				
		NI	F_1	F_2	F_3	F_4
Actual class	NI	0.9479	0	0	0.0059	0.0462
	F_1	0.0323	0.9355	0	0	0.0323
	F_2	0	0	1.0000	0	0
	F_3	0	0	0	0.9956	0.0044
	F_4	0.1486	0	0	0	0.8514

6 Conclusion

This article proposes a novel data-driven fault diagnosis approach for PEMFC systems. Individual cell voltages serve as the original variables for diagnosis. Two methodologies, FDA and DAGSVM, are employed successively to process the raw data and achieve FDI. The approach was verified by analyzing the experimental data of two stacks. The results show that five concerned faults could be detected and isolated with high accuracy. Moreover, the light computation cost (needed memory and computing time) makes the approach a promising online diagnosis tool.

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