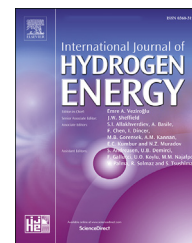Available online at www.sciencedirect.com

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Investigation of PEMFC fault diagnosis with consideration of sensor reliability

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ABSTRACT

Despite the wide range of applications for the polymer electrolyte membrane fuel cell (PEMFC), its reliability and durability are still major barriers for further commercialization. As a possible solution, PEMFC fault diagnosis has received much more attention in the last few decades. Due to the difficulty of developing an accurate PEMFC model incorporating various failure mode effects, data-driven approaches are widely used for diagnosis purposes. These methods depend largely on the quality of sensor measurements from the PEMFC. Therefore, it is necessary to investigate sensor reliability when performing PEMFC fault diagnosis.

In this study, sensor reliability is investigated by proposing an identification technique to detect abnormal sensors during PEMFC operation. The identified abnormal sensors will be removed from the analysis in order to guarantee reliable diagnostic performance. Moreover, the effectiveness of the proposed technique is investigated using test data from a PEMFC system, where fuel cell flooding is observed. During the test, due to accumulation of liquid water inside the PEMFC, the humidity sensors will give misleading readings, and flooding cannot be identified correctly with inclusion of these humidity sensors in the analysis. With the proposed technique, the abnormal humidity measurements can be detected at an early stage. Results demonstrate that by removing the abnormal sensors, flooding can be identified with the remaining sensors, thus reliable health monitoring can be guaranteed during the PEMFC operation.

Introduction

As an environmentally friendly alternative for electrical power generation, polymer electrolyte membrane fuel cells (PEMFCs) have potential for widespread application, including stationary power station, automotive, and consumer devices. However, PEMFC reliability and durability are still two major barriers for further commercialization.

In order to address the above issue, many studies have been devoted in the last few decades to evaluate PEMFC state during operation using fault diagnostic techniques. From the results, PEMFC faults can be detected and the sources for occurrence of faults can also be determined, which can be used for the design of mitigation strategies to recover and extend PEMFC performance. From these studies, the diagnostic techniques can be loosely divided into two groups,

data-driven approaches [1—16,27—33] and model-based methods [17—26].

With model-based techniques, a model should be developed to represent the PEMFC behaviour, by calculating the residuals between model outputs and actual measurements, PEMFC faults can be detected and isolated [26]. From previous studies, different models are developed for fault diagnosis purposes, including white-box models using space differential formulas to express the mass and momentum equilibriums of the PEMFC system [17,25], black-box models deriving PEMFC inputs and outputs relationships by training algorithms [20,24], and grey-box models combining both features from physical white-box models and empirical black-box models [18,19],[21—23]. However, it is noted that due to the complexity of PEMFC systems and its electrochemical properties, it is usually extremely difficult to develop reliable models incorporating all the possible failure mode effects [8,26]. On this basis, data-driven fault diagnostic approaches are more widely applied for PEMFC fault diagnosis.

In data-driven approaches, features are extracted from the PEMFC measurements using signal processing techniques, and the PEMFC state can be determined by applying pattern recognition methods to these features [8,11]. From previous studies, several different methodologies can be applied to extract features from the PEMFC sensor measurements, including principal component analysis (PCA) [16,27], kernel PCA (KPCA) [28], Fisher discriminant analysis (FDA) [29], kernel FDA (KFDA) [30], and signal processing techniques [7,31—33] like fast Fourier transform (FFT), short-time Fourier transform (STFT), wavelet transform (WT). Moreover, several pattern recognition algorithms have been applied to the extracted features to evaluate the PEMFC condition [34—36], such as Gaussian mixture model (GMM), support vector machines (SVM), k-nearest neighbour (KNN), self-organizing map, etc.

However, it should be mentioned that as the data-based diagnostic approaches depend largely on the measurements from PEMFC, the quality and quantity of the measurements can greatly affect the diagnostic performance. Moreover, as a set of sensors are usually installed in the PEMFC to collect enough information from the system, the effect of sensor reliability on PEMFC fault diagnosis should be better understood for reliable diagnosis. Although sensor selection algorithms have been applied in PEMFC to determine the optimal sensors for health monitoring [37], which can reduce the complexity of reliability of multiple sensors, only very limited studies have been devoted to the sensor reliability, especially in the field of PEMFC fault diagnosis. Therefore, it is necessary to investigate the effect of sensor reliability in the diagnostic procedure, and propose corresponding mitigation in order to provide reliable diagnostic performance during the system operation.

In this study, the effect of sensor reliability on fault diagnosis is investigated using test data from a PEMFC system, and results demonstrate that the unreliable sensors can affect the PEMFC diagnostic performance significantly. On this basis, an approach is proposed to identify the abnormal sensors during the PEMFC operation, by monitoring features extracted from each sensor. The identified abnormal sensor is then removed from the analysis, and the diagnostic performance using the remaining sensors will be studied. In order to keep the consistency, the same data-driven approaches are applied to the datasets with and without abnormal sensors. Results demonstrate that with abnormal sensors being identified and removed from the analysis, reliable diagnostic performance can be guaranteed and PEMFC state can be determined with good quality.

Data-based approaches and its performance in PEMFC fault diagnosis

Description of data-based diagnostic approaches

In this study, several data-based approaches are used in PEMFC diagnostic analysis, including Kernel principal component analysis (KPCA), wavelet packet transform, and singular value decomposition (SVD) technique. It should be noted that these techniques will only be described briefly herein, and more details can be found in Refs. [8,11].

As mentioned in section Introduction, as multiple sensors are commonly used to monitor PEMFC performance, this can lead to a high-dimension dataset. In order to reduce the computational time and complexity, KPCA is utilized to reduce the dimension of the original dataset while keeping the useful information in the original dataset. Wavelet packet transform is then applied to extract features from the reduced dimensional dataset. Compared to wavelet transform, wavelet packet transform can provide more coefficients as both detail and approximation are filtered, which can better represent the original dataset [11]. As a set of features can be extracted using wavelet packet transform, SVD is applied to select the features containing the most information, which can be used to determine the PEMFC state. Fig. 1 illustrates the flowchart of data-driven approaches in PEMFC fault diagnosis.

Description of PEMFC test

The test rig with capability of 80 W is used to provide the PEMFC test data in this study, which contains a fuel cell stack,
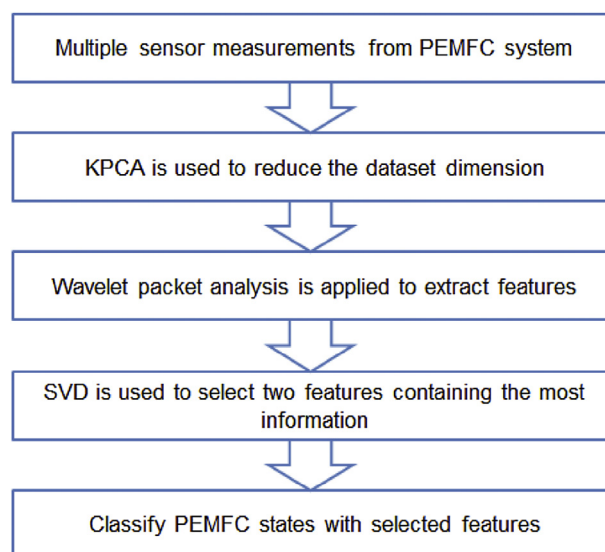

Fig. 1 — Flowchart of data-driven approaches in PEMFC fault diagnosis.

air and hydrogen supply systems, cooling system, and TDI power load bank to 'waste' the energy produced from the stack, which is depicted in Fig. 2.

Single-cell stack is used in the test with each cell having an active area of 100 cm^2, as manufactured by Pragma Industries, which uses the same materials and technologies as commercial PEM fuel cells, hence it can simulate the operation of the commercial fuel cells in practical applications.

In the test protocol, the stack temperature is decreased to trigger the PEMFC flooding at cathode side, then the temperature is increased to remove the flooding effect and recover the PEMFC performance, after operating at normal operation for a certain duration, the PEMFC flooding is triggered again with reduced stack temperature, this procedure is depicted in Fig. 3. It should be mentioned that the linear voltage drop at about 3000s, 4800s, and 6000s is due to the varying current densities, where corresponding PEMFC voltage is collected to generate the polarization curve. With this test protocol, the test data can be divided into four phases, including normal to flooding, flooding to normal, normal, and normal to flooding. Table 1 lists the sensors used in the test for monitoring PEMFC performance. It should be mentioned that during this procedure, constant current density is used.

Performance of data-driven approaches in PEMFC fault diagnosis

With the collected sensor measurements listed in Table 1, the data-based approaches described in section Description of data-based diagnostic approaches can be applied to determine the PEMFC state.

Only the first two phases (normal to flooding, and flooding to normal shown in Fig. 3) in test are used to illustrate the performance of data-based diagnostic approaches, since misleading measurements from sensors are observed in the last two phases, which will be further described in the following section.

As described in section Description of data-based diagnostic approaches, a high dimension dataset can be reduced using KPCA, in this study the original dataset is projected to the first four principal directions, as sufficient information (over 90%) of the original dataset can be included in the first four principal directions [11], and diagnostic results at these
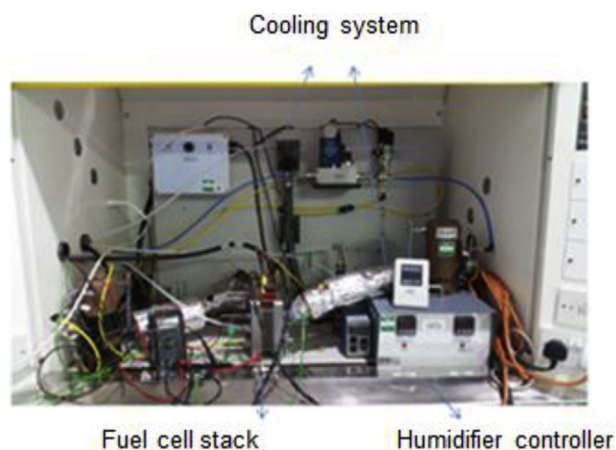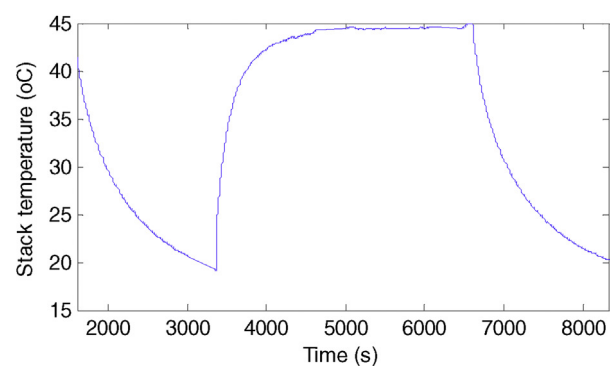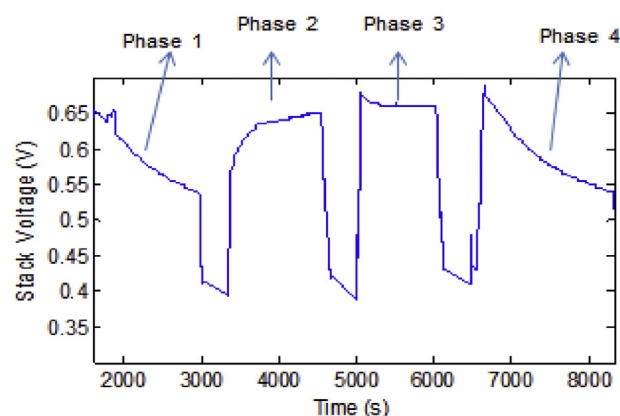

(a) Stack temperature

(b) Stack voltage

Fig. 3 – Sensor measurements during the test.

Table 1 – Sensors used in the PEMFC test.	
Sensor	**Sensor**
Current density	Stack voltage
Air inlet flow rate	Hydrogen inlet flow rate
Air inlet pressure	Hydrogen inlet pressure
Air inlet humidity	Hydrogen inlet humidity
Air inlet temperature	Hydrogen inlet temperature
Stack temperature	

principal directions can be obtained and used for cross-validation. Fig. 4 depicts the diagnostic results using described data-driven approaches at the first two principal directions, where features 1 and 2 are the normalized energies selected from singular value decomposition (SVD), which contain the most significant information from the original signals. It should be mentioned that the flooding scenario is defined when a 3% stack voltage drop is observed, this is defined to investigate the effectiveness of data-driven approaches in identifying early stage flooding.

It can be found that the normal and flooding states contained in phases I and 2 can be discriminated clearly using data-driven approaches, indicating that with reliable sensor readings, even the early stage flooding can be identified accurately, which allows mitigation strategy to be taken to recover the PEMFC performance.
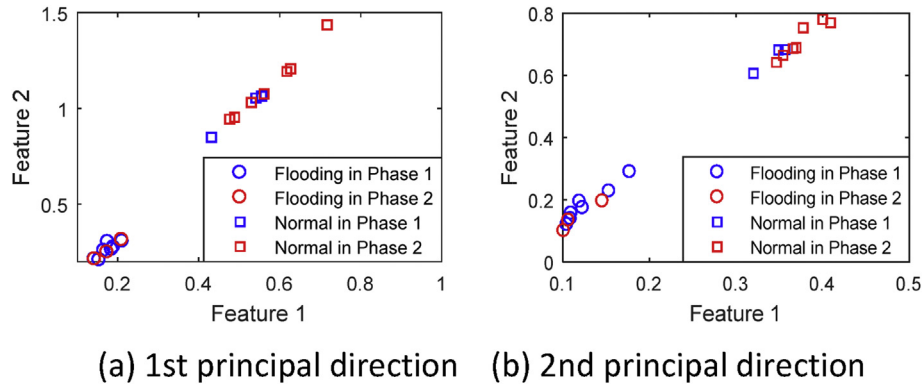

Fig. 2 – Fuel cell test rig.

(a) 1st principal direction   (b) 2nd principal direction

Fig. 4 − Diagnostic results using data-driven approaches.

Effect of sensor reliability in PEMFC fault diagnosis and corresponding mitigation

Effect of sensor reliability in PEMFC diagnosis

From section Data-based approaches and its performance in PEMFC fault diagnosis, it can be seen that with reliable sensor measurements, early stage flooding can be identified with good quality using data-driven approaches.

However, with the PEMFC operation, the sensors may lose their reliability and misleading measurement may be provided.
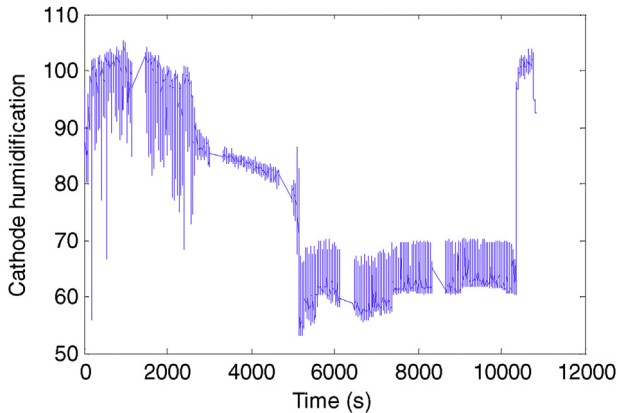

Fig. 5 − Readings from cathode humidifier.

Fig. 5 depicts the readings from the cathode humidifier in the test. It can be seen that the humidifier provides reliable measurements at the first two phases, but from phase three, i.e. PEMFC normal state, the humidification has a sudden drop, which is due to the water drop on the humidifier instead of the actual PEMFC performance change, since all the other sensors are not affected.

The effect of sensor reliability on PEMFC fault diagnosis is studied by including the unreliable sensors (humidifier herein) in the diagnostic analysis, it should be mentioned that the same data-based approaches described in section Description of data-based diagnostic approaches are used. Fig. 6 depicts the diagnostic results of the first three phases.

It can be seen from Fig. 6 that with unreliable cathode humidifier, misleading results are obtained using data-based diagnostic approaches, i.e. the state of phase 3 is identified as a new category instead of the normal state. If prior information is given that only two states exist, i.e. normal and flooding states, some features in phase 3 will be classified as the flooding state as they are more close to the features representing the actual flooding states based on the Euclidean distance. This becomes more serious at the 2nd principal direction (Fig. 6b) where most features of phase 3 are classified as flooding state. Therefore, in order to maintain reliable diagnostic performance, the readings from sensors should be analysed to confirm their reliability during system operation, and unreliable sensors should be identified at a very early stage.
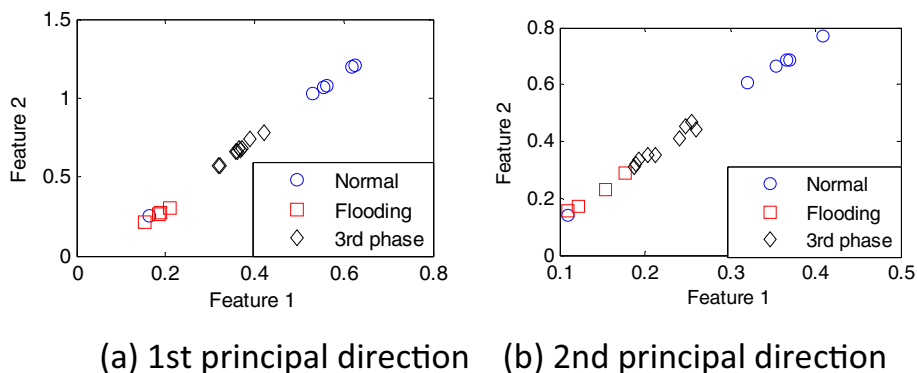

(a) 1st principal direction   (b) 2nd principal direction

Fig. 6 − Diagnostic results using all the sensors.

Proposed approach for identifying unreliable sensors

From previous studies, information from signals can be extracted to represent its variation during operation [38–40], including mean value, standard deviation, and slope, which are also used herein for expressing the sensor reliability. It should be mentioned that only the single sensor abnormality is investigated in this study, as only one abnormal sensor is observed in the PEMFC test, reliability of multiple sensors can be studied in a similar manner.

In this study, the measurements from the sensors are monitored every 5s for the reliability check with the features
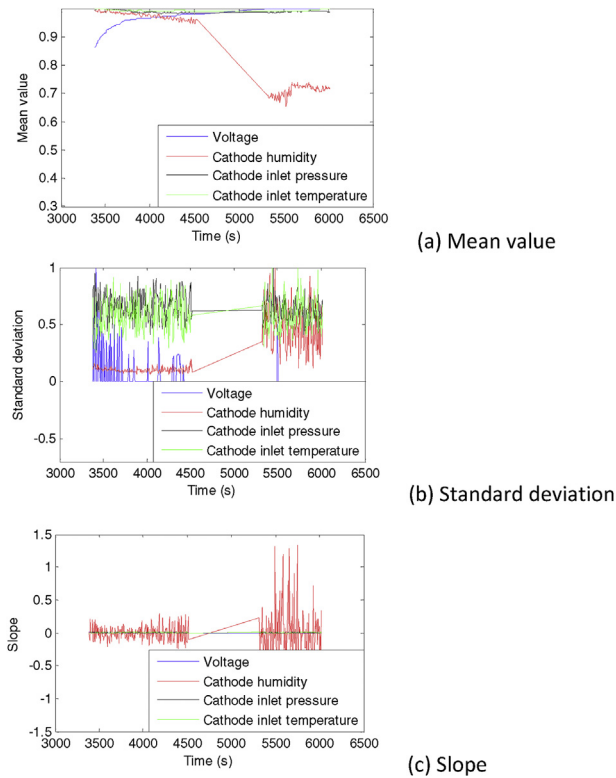
extracted from each sensor. This 5s monitoring interval guarantees that the unreliable sensor can be identified at an early stage. Fig. 7 shows the evolution of these indicators extracted from the sensor measurements. It can be observed that only some sensors are depicted herein to better illustrate the abnormality of the cathode humidifier. It should be mentioned that in the current study, the cathode humidity sensor loses its reliability at phase 3, where PEMFC is under normal operation as PEMFC voltage drop is not observed at this phase from Fig. 3b, thus the sudden variation in the extracted features can indicate the abnormal sensors.

It can be seen that by monitoring the features extracted from each sensor, the abnormal sensor can be clearly observed, in this case, the features from the cathode humidifier shows a sudden change when reaching the 3rd phase, whilst the other sensors, especially the voltage sensors, do not show the indication of PEMFC performance variation.

By extracting and monitoring features from each sensor, the abnormal sensors can be identified at the early stage and can then be removed from the sensor dataset used in the diagnosis. Therefore, in this study, the cathode humidity is removed from the fault diagnosis, and diagnostic results using the remaining sensors are depicted in Fig. 8. The same data-based approaches in section Description of data-based diagnostic approaches are used herein for the fault diagnosis. It should be mentioned that with prior knowledge it is known that only two states exist, i.e. normal or flooding, k-means clustering algorithm is applied to cluster the features to determine the state of phase 3.

As can be observed from Fig. 8, by removing the cathode humidity from diagnostic analysis, the state at phase 3 can be successfully classified as the normal state, while the flooding scenario can still be discriminated with good quality.

With the same features extracted from each sensor, measurements at phase 4 (shown in Fig. 3) are investigated, and evolution of these features from phase 2 to phase 4 is depicted in Fig. 9.

From Fig. 9, the voltage at phase 4 shows clear variation, indicating the PEMFC performance change, which is due to the decrease of PEMFC stack temperature. Since inputs to PEMFC are not changed in the test, significant variation should not be observed in the inlet measurements. However, cathode
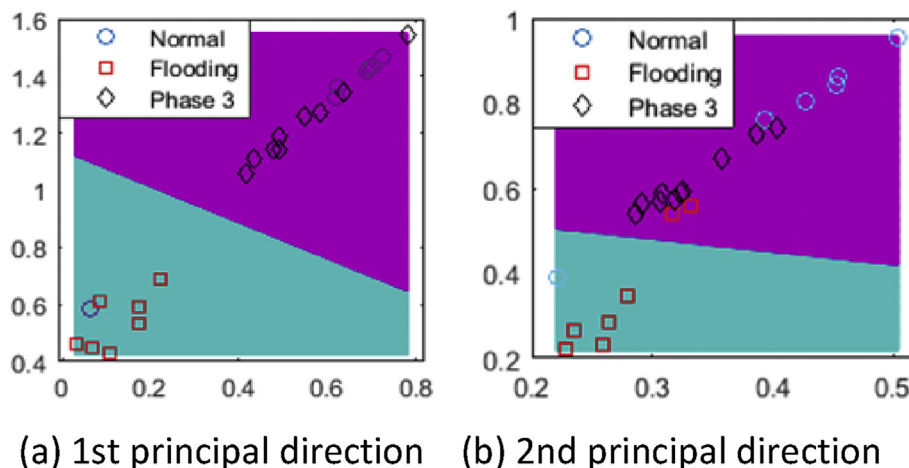

Fig. 7 – Evolution of features between phase 2 and phase 3.

(a) 1st principal direction　　(b) 2nd principal direction

Fig. 8 – Diagnostic results using sensors with cathode humidity.

(a) Mean value

(b) Standard deviation

(c) Slope

Fig. 9 − Evolution of features between phase 2 and phase 4.

It can be seen that by removing the cathode humidity from the analysis, which is identified as abnormal, the early flooding of PEMFC occurred at different phases can be discriminated with good quality using the data-based diagnostic approaches. From the results, mitigation strategies can be taken to remove the flooding effect before catastrophic failure of PEMFC system.

From the above results, it can be concluded that with high reliability of sensors, the proposed data-driven approaches can provide reliable diagnostic performance, i.e. early stage fuel cell flooding can be identified with good quality. However, with the involvement of abnormal sensors, misleading results will be provided and diagnostic results are no longer reliable.

By monitoring the sensor measurements and extracted features such as mean value, standard deviation, and slope, the abnormal sensors can be identified at an early stage. Results demonstrate that by removing the abnormal sensors from the diagnostic analysis, reliable diagnostic performance can be obtained, and fuel cell faults can be determined with good quality.

In practical systems, the sensor measurements will be collected continuously, thus the features like mean value, standard deviation and slope can be calculated and their evolution can also be monitored. On this basis, the combination of fuel cell voltage (indicating PEMFC condition) and the evolution of index from other sensors can be employed to determine the sensor reliability, i.e. without PEMFC voltage drop, the clear variation in sensor measurement index can

a) 1st principal direction

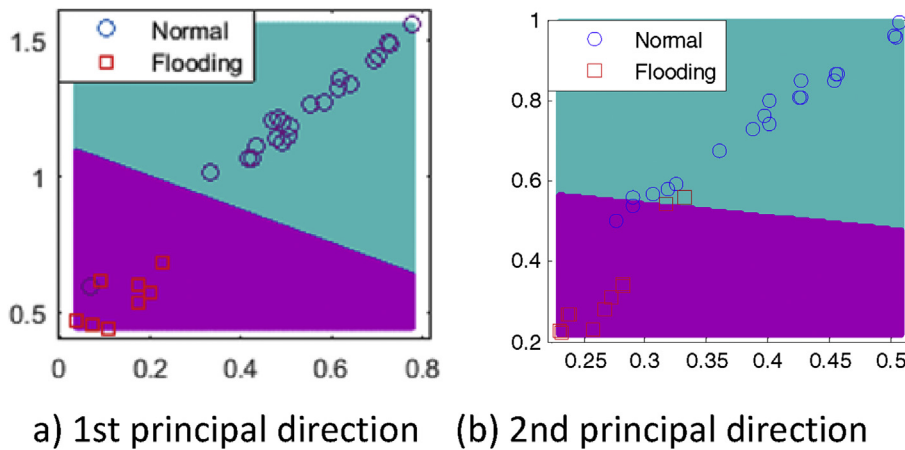

(b) 2nd principal direction

Fig. 10 − Diagnostic results using sensors with cathode humidity.

humidity shows clear variation, indicating the loss of reliability in the cathode humidifier.

With the same data-based diagnostic approaches, the PEMFC state at phase 4 is studied using all the sensors except the cathode humidity. It should be mentioned that similar to the diagnosis in section Performance of data-driven approaches in PEMFC fault diagnosis, the flooding scenario is defined with more than 3% voltage drop, while voltage drop less than 3% is defined as the normal state. Fig. 10 depicts the diagnostic results. Similarly, k-means clustering algorithm is applied to cluster the features to better illustrate the effect of removing abnormal sensors in diagnostic performance.

indicate sensor abnormality. However, it should be mentioned that in the current study, the definition of a threshold for the sensor measurement index to indicate abnormal sensor is not fully investigated, and this will be studied in the future research. Moreover, in the future study, the identification of multiple abnormal sensors will be studied.

Conclusions

In this study, the sensor sensitivity is investigated in PEMFC fault diagnosis, using the test data from a PEMFC system. The

performance of data-based approaches is studied using all the reliable sensor measurements, from which PEMFC normal state and early stage flooding can be discriminated with good quality. The effect of sensor reliability is then investigated, and results show that with inclusion of the abnormal sensor measurements in the analysis, misleading diagnostic performance might be obtained. On this basis, an approach is proposed to identify the abnormal sensors during PEMFC operation, by monitoring the features extracted from each sensor. With the test data from the PEMFC system, the abnormal cathode humidifier can be identified with the proposed approach, and by removing that abnormal sensor from the analysis, the PEMFC normal operation and flooding can be discriminated with good quality using the reaming sensors. Therefore, with consideration of sensor reliability, the reliable diagnostic performance during PEMFC operation can be guaranteed, the faulty state can be identified correctly and the corresponding mitigation strategies can be taken to extend the PEMFC performance. From the current results, further research is suggested, including defining the feature threshold to better evaluate the sensor reliability, and investigating the performance of the proposed methodology in cases containing multiple sensor abnormality.

Acknowledgements

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