Evaluation Method for Feature Selection in Proton Exchange Membrane Fuel Cell Fault Diagnosis

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Abstract—Considering the fact that various features can be used in proton exchange membrane fuel cell (PEMFC) fault diagnosis, while the lack of feature evaluation method brings great difficulty in selecting appropriate features at practical PEMFC applications, a generalized feature evaluation and selection method is urgently required in PEMFC fault diagnosis. This article proposes a novel feature evaluation method, where feature discrimination capacity and robustness are evaluated. With the proposed method, features providing accurate and consistent diagnostic performance can be discriminated. In this study, features widely used in existing PEMFC fault diagnosis are utilized, which are extracted from either PEMFC voltage or multisensor signals, and their effectiveness in identifying faults at different PEMFC systems is investigated. Results demonstrate that with the proposed evaluation method, available features from various PEMFC test data can be ranked based on their diagnostic results. From the findings, appropriate features for PEMFC fault diagnosis can be determined. Moreover, early stage PEMFC faults can also be distinguished with high ranking features. This will be beneficial in practical PEMFC systems, where mitigation strategies can be taken to remove the effect due to early stage faults.

Index Terms—Discrimination capacity, fault diagnosis, feature evaluation, proton exchange membrane fuel cell (PEMFC), robustness.

I. INTRODUCTION

Due to scarcity of petroleum energy and corresponding issues like greenhouse effect, alternative energy sources, including hydrogen, wind, photovoltaic, etc., have received much attention in the last few decades. Among these alternative energy sources, hydrogen and fuel cell technology, especially PEMFC, have gained more interest due to characteristics such as zero-pollution and high efficiency [1]–[3]. However, its further commercialization is still restricted by limited reliability and durability of PEMFC systems [4].

To address these issues, a set of fault diagnostic techniques has been proposed and applied to detect and isolate PEMFC faults. These techniques can be divided into three categories, including model-based methodologies, data-driven techniques, and knowledge-based approaches [5], [6]. Based on the diagnostic results, proper mitigation strategies can be taken to remove or reduce the influence of PEMFC faults, such that reliability and durability of PEMFC systems can be improved. As PEMFC is multidomain knowledge combined system, it is difficult to develop an accurate model for simulating effects of different PEMFC faults [6], [7], which constrains the use of model-based methodologies in PEMFC fault diagnosis. Moreover, from previous studies [8], [9], PEMFC decay mechanisms due to various faults have not been fully clarified, thus incomplete or even conflicting expert knowledge may be obtained, leading to the difficulty of using knowledge-based techniques for identifying PEMFC faults. Therefore, in most existing studies regarding PEMFC fault diagnosis, data-driven techniques are used [10]–[12].

In data-driven fault diagnostic techniques, features representing the PEMFC state should be extracted from various PEMFC test data, i.e., cell voltage, temperature, gas pressure, relative humidity, etc. These features are then classified using pattern recognition methods, from which different PEMFC faults can be discriminated [13]. Therefore, appropriate selection of features is the key for reliable PEMFC fault diagnosis.

Since PEMFC voltage can directly represent the PEMFC performance change, in previous studies, various features extracted from PEMFC voltage have been used to identify different
PEMFC faults. These features include time-domain features like principal component analysis (PCA) [14]–[16], Fisher discriminant analysis (FDA) [7],[17], and autocorrelation standard deviation (ACSD) [18]; frequency-domain features such as root mean square frequency (RMSF) and frequency power spectrum [19]; time-frequency domain features from wavelet transform (WT) [20]–[28] and wavelet packet transform (WPT) [29]–[32].

Hua et al. [14] investigated the effectiveness of detecting PEMFC sensor network failure using PCA method. Kim et al. [18] extracted ACSD from PEMFC voltage for diagnosing insufficient reactant gas issue. In [25], high air stoichiometry ratio was identified by extracting features from PEMFC voltage with WT analysis. Steiner et al. [29] extracted features from PEMFC voltage using WPT to identify PEMFC flooding fault. Furthermore, features were extracted using WPT analysis from PEMFC voltage, where PEMFC flooding fault and the transition from normal to flooding could be discriminated [30].

Moreover, in order to improve the diagnostic performance, multiple signals can be collected from the PEMFC system, thus features can be extracted from multisensor signals and used in PEMFC fault diagnosis. Li et al. [7] compared the performance of various feature extraction techniques for multidimensional dataset, including PCA, FDA, kernel PCA (KPCA), and kernel FDA (KFDA). Mao et al. [9] used KPCA for reducing dimension of multidimensional dataset, and extracted features using WPT for PEMFC fault diagnosis. Zhao et al. [15] applied PCA to multisensor signals, where features were deduced to identify different PEMFC faults.

It can be concluded from above studies that with appropriate features extracted from PEMFC test data, different PEMFC faults can be identified accurately. Several studies have been devoted to the selection of features, such as features from EIS [33] and features from EIS and polarization curve [34]–[35]. However, these selection methods are proposed for specific PEMFC signals, such as EIS, while generalized selection method for features extracted from different PEMFC signals still requires further investigation. This will be beneficial in practical PEMFC systems, where various test data and associated extracted features can be obtained. Moreover, in previous feature selection studies, the performance of selected features at different PEMFC systems has not been investigated, which hinders the clarification of their robustness.

In this article, a novel method for evaluating feature effectiveness in PEMFC fault diagnosis is proposed. With the proposed method, appropriate features can be selected to provide accurate and consistent diagnostic performance at different PEMFC systems. In the analysis, effectiveness of feature evaluation method in identifying the features that better diagnose PEMFC flooding and dehydration at two different PEMFC systems is investigated. The reason of using flooding and dehydration is that they are usually experienced during PEMFC operation, and their effects can be removed efficiently with accurate identification and proper mitigation strategies. The novel contributions of this work lies in the following two aspects. Firstly, multiple signals from PEMFC system are used in the study, thus the proposed method can be utilized to determine proper features from different PEMFC signals. This will be beneficial in practical PEMFC applications where multiple signals and associated features are available. Secondly, two PEMFCs with different dimensions and technical parameters are used in this study, thus the robustness of the proposed method at different PEMFC systems can be clarified. Therefore, the proposed work can bridge the gap between various features proposed in literatures for PEMFC fault diagnosis and determination of appropriate features for reliable fault diagnosis in practical PEMFC applications. Moreover, although features are selected to identify PEMFC flooding and dehydration in this study, the proposed method can be easily expanded to other states of health.

This article is organized as follows. In Section II, various features extracted from PEMFC test data are described, and the proposed method for evaluating feature discrimination capacity and robustness is presented. Section III presents two tested PEMFCs and corresponding test data at different states of health. In Section IV, the proposed method is applied to evaluate features, and the rank for feature suitability is obtained. In Section V, the effectiveness of proposed feature evaluation method is studied using PEMFC test data, i.e., various features are ranked with the proposed evaluation method, and this rank is validated using actual diagnostic results. Moreover, performance of two high ranking features in identifying early stage change in PEMFC state of health is further investigated. Finally, Section VI concludes this article.

II. DESCRIPTION OF FEATURES AND PROPOSED EVALUATION METHOD

In this section, several features used in the previous studies for PEMFC fault diagnosis, including those from PEMFC voltage and multisensor signals, will be described. Moreover, an evaluation method is proposed to investigate feature effectiveness in distinguishing PEMFC states at different PEMFC systems.

A. Features From PEMFC Voltage

In this section, various features extracted from PEMFC voltage and widely used in PEMFC fault diagnosis are presented, which are listed below. More details about these features can be found in corresponding references.

\[
\text{ACSD} \quad [18] \quad \text{ACSD} = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (R_{xx}(k) - \mu)^2} \tag{1}
\]

where \( R_{xx}(t) = \sum_{k=0}^{N-1} x(k) \cdot x(t + k) \) is the autocorrelation function of signal \( x(t) \) (PEMFC voltage herein), \( N \) serves as the bound of sampling scope width, \( \mu \) stands for autocorrelation function arithmetic average.

\[
\text{RMS} \quad [38] \quad \text{RMS} = \sqrt{\frac{1}{N} \sum_{t=1}^{N} x(t)^2} \tag{2}
\]

\[
\text{Kurtosis} \quad [37] \quad \text{RMS} = \sqrt{\frac{1}{N} \sum_{t=1}^{N} x(t)^2} \tag{3}
\]
where \( x_i \) stand for PEMFC voltage signal, \( \bar{Y} \) is the average value of the signal, \( s \) served as the deviation, and \( N \) is data length.

\[
\text{RMSF} = \left( \frac{1}{n} \sum_{k=1}^{n} Y(k)^2 \right)^{1/2},
\]

\( Y(k) = \sum_{n=0}^{N-1} x(n)w(n) e^{-j \frac{2\pi nk}{N}}, \)

where \( w(n)W_{N,k}^P \) is the frequency ingredients value, \( w(n) = (1 - \beta - \beta \cos(\frac{2\pi n}{N-1})) \) is the window function.

Normalized Energy \cite{20, 30}:

\[
E_P = \frac{1}{N_p} \sum_{j,k} |W_{j,k}^P|^2
\]

where \( E_P \) is the normalized energy for specific wavelet (or wavelet packet) \( P \), \( N_p \) is the number of wavelet coefficients; \( W_{j,k}^P = a^{-1/2} \int x(t)\psi^* (\frac{t-b}{a})dt \) is the wavelet (or wavelet packet) coefficient; \( x(t) \) is the PEMFC voltage signal; \( \psi \) is a basic wavelet, \( a, b \) are the scale and shift parameters corresponding to frequency and time, respectively.

It should be noted that as both WT and WPT have been applied for feature extraction in PEMFC fault diagnosis \cite{6, 9, 29}, they are selected in this study. The difference between them is that WT can be seen as a kind of filters letting signal \( x(t) \) to pass through and get low-pass results (approximations) while both low-pass approximations and high-pass details can be extracted using WPT. Therefore, WPT can be used to address the issues of relatively low resolution at high-frequency region.

### B. Features From Multisensor Signals

In this section, features extracted from PEMFC multisensor signals are presented. Based on the previous studies \cite{7, 9, 11}, KPCA shows superior performance over other dimension reduction methods such as PCA, FDA, and KFDA. As the focus of this study is proposing an evaluation method for features extracted from different PEMFC signals, for simplification purpose, only KPCA is used herein for feature extraction from PEMFC multisensor signals due to its several advantages. Firstly, KPCA can extract higher-order correlations between the original inputs. More number of principal components can also be extracted in KPCA, eventually resulting in the best generalization performance. Second, since PEMFC is a highly nonlinear system, and KPCA is a nonlinear PCA by generalizing the kernel method into linear PCA. Thus, KPCA can maximally eliminate the correlation between parameters in PEMFC. Thirdly, KPCA algorithm is computationally less expensive, which can be used for effective online fault diagnosis. Last but not least, low-dimensional data extracted by KPCA can be regarded as the estimated value of original data while maintaining its physical significance, which is helpful to analyze comparative results of different features in this article.

KPCA is a two-step process; firstly the nonlinear correlated original data is mapped to a higher dimensional space using kernel functions, where the linear relationship can be obtained. PCA is then applied in the new space. The procedure of using KPCA for dimension reduction is as follows, and more details about this technique can be found in \cite{39–41}.

#### 3) Use Jacobi iterative algorithm to calculate the eigenvalues of \( KL(\lambda_1, \ldots, \lambda_n) \), and corresponding eigenvectors \( (\psi_1, \ldots, \psi_n) \).

#### 4) The eigenvalues are sorted in descending order \( (\lambda_1 > \ldots > \lambda_n) \), and the eigenvectors are adjusted accordingly \( (\nu_1 > \ldots > \nu_n) \).

#### 5) The eigenvectors are orthogonalized by the Schmidt orthogonalization method, namely, \( \alpha_1, \ldots, \alpha_n \).

#### 6) Calculate the cumulative contribution rates of the eigenvalues \( (B_1, \ldots, B_n) \), according to the given extraction efficiency \( P \); if \( B_i > P \), extract \( i \) principal components \( (\alpha_1, \ldots, \alpha_i) \).

#### 7) Calculate the projection of the corrected kernel matrix \( KL \) on the eigenvectors, \( Y = KL \times \alpha, \alpha = (\alpha_1, \ldots, \alpha_i) \). Projection \( Y \) is the result of data after KPCA dimensionality reduction.

In this analysis, KPCA is applied to reduce the dimension of multisensor signals, then either WT or WPT is used to extract wavelet/wavelet packet coefficients from the first two principal components. From the results, normalized energy is calculated using (5). This procedure can be depicted in Fig. 1.

From above descriptions, a total of eight features are extracted from PEMFC voltage and multisensor signals, which are listed in Table I. It should be noted that although only features from PEMFC voltage and multisensor signals are used in this study, features extracted from other PEMFC signals, including polarization curve, EIS, etc., can also be evaluated using the proposed method presented in the next section.
C. Proposed Feature Evaluation Method

In order to compare the effectiveness of various features in PEMFC fault diagnosis, an evaluation method is proposed to evaluate feature discrimination capacity and robustness.

As described in Section I, two different PEMFCs are tested in the analysis, and PEMFC test data (either voltage or multisensor signals) at three states of health, including normal, flooding, and dehydration, are collected from each PEMFC. Therefore, with each feature listed in Table I, six values can be calculated. Fig. 2 plots these values, where each point represents feature values at the same state from two PEMFCs.

As illustrated in Fig. 2, the consistency of feature performance at different PEMFCs can be obtained by evaluating distance from each point to the "identical value" line highlighted in Fig. 2.

For example, the feature consistency in identifying normal state at two PEMFC systems can be evaluated by calculating the distance between the point representing normal state and the "identical value" line, which is expressed as $M_n$. Similarly, the feature consistency for evaluating flooding and dehydration states can be obtained by calculating corresponding points in Fig. 2 to the "identical value" line, as expressed with $M_f$ and $M_d$.

\[
M_n = \text{Distance} ([A1, B1], \text{identical value line}) 
\]

\[
M_f = \text{Distance} ([A2, B2], \text{identical value line}) 
\]

\[
M_d = \text{Distance} ([A3, B3], \text{identical value line}). 
\]

It should be mentioned that the distance between the point $(x_1, y_1)$ and the line $(Ax + By + C = 0)$ can be calculated as

\[
\frac{|Ax_1 + By_1 + C|}{\sqrt{A^2 + B^2}}. 
\]

Moreover, the feature performance of discriminating different PEMFC states of health can be evaluated by calculating Euclidean distance between two points representing different states. The following equations express the feature discrimination capacity over different states, where $N_{nf}, N_{nd}$, and $N_{fd}$ represents feature effectiveness in discriminating normal and flooding state, normal and dehydration, and flooding and dehydration, respectively.

\[
N_{nf} = \text{Euclidean distance} \left( (A_1, B_1), (A_2, B_2) \right) 
\]

\[
N_{nd} = \text{Euclidean distance} \left( (A_1, B_1), (A_3, B_3) \right) 
\]

\[
N_{fd} = \text{Euclidean distance} \left( (A_2, B_2), (A_3, B_3) \right). 
\]

Based on Fig. 2, the distance between points representing different states can be used to evaluate feature discrimination capacity. Thus, with vector $[N_{nf} \quad N_{nd} \quad N_{fd}]$, higher mean value and smaller standard deviation indicate all three states have relatively larger distance, thus can be used to express better discrimination capacity.

On the other side, with the distance between point and "identical value" line, the feature consistency at different systems can be evaluated, with smaller distance indicating better consistency. Therefore, with vector $[M_n \quad M_f \quad M_d]$, smaller mean value and smaller standard deviation indicate all three states have relatively small distance to identical value’ line, thus can represent better consistency at all three PEMFC states of health.

Therefore, two indicators are developed to evaluate the feature discrimination capacity and robustness, which can be written as $f_{\text{dis}}$ and $f_{\text{rob}}$, respectively, as follows:

\[
f_{\text{dis}} = \frac{m ([N_{nf}, N_{nd}, N_{fd}])}{\sigma ([N_{nf}, N_{nd}, N_{fd}])} 
\]

\[
f_{\text{rob}} = m ([M_n, M_f, M_d]) \times \sigma ([M_n, M_f, M_d]) 
\]

where $m$ and $\sigma$ are the mean value and standard deviation of the vector, respectively. Smaller $f_{\text{rob}}$ value indicates the feature is more consistent at different PEMFC systems, thus has better robustness; while larger $f_{\text{dis}}$ value indicates the feature has better capacity to discriminate various PEMFC states.

With two proposed indicators from (12) and (13), the feature suitability in PEMFC fault diagnosis can be calculated with the following equation:

\[
f = \frac{f_{\text{dis}}}{f_{\text{rob}}} 
\]

where $f$ is the feature suitability in PEMFC fault diagnosis. Larger $f$ value indicates the feature is more suitable for PEMFC fault diagnosis.

From (14), various features extracted from different PEMFC signals can be ranked, and high ranking features can be selected to provide accurate and consistent diagnostic performance.

III. TESTED PEMFC SYSTEMS AND TEST DATA AT DIFFERENT STATES OF HEALTH

In this section, two PEMFC testing systems used in the analysis will be described, and the test data collected from PEMFCs at different states of health, including normal, flooding, and dehydration states, will also be presented.
A. Tested PEMFC Systems

The first PEMFC testing bench has rated power of 80W, and includes reactant gas supply systems, coolant systems, and a single PEMFC with open cathode (PEMFC1), which is shown in Fig. 3(a). The single cell used in this test has active area of 100 cm$^2$, and is fabricated by Pragma Industries using commercial PEMFC materials and technologies, including a PEM, silicon-sealing gaskets, and carbon diffusion materials.

In the second test, a PEMFC testing equipment with rated power of 60W is used, which consists of a single PEMFC as shown in Fig. 3(b) and ancillary systems such as reactant gas supply systems. It should be noted that compared to the first testing system, coolant system is not included in the second system. The single cell with open cathode (PEMFC2) used in this test has active area of 25 cm$^2$, and is manufactured with similar materials to those of PEMFC1, including carbon diffusion materials, PEM, etc., but manufactured by HEPHAS energy. The technical parameters of two PEMFCs are listed in Table II.

B. Test Data at Different PEMFC States

In the study, different PEMFC states of health, including normal, flooding, and dehydration, are tested at two PEMFCs. Table III lists the operating parameters used in the tests at different PEMFC states of health.

In the analysis, the PEMFC normal state is obtained by applying constant current density and nominal control parameters listed in Table III. Fig. 4 depicts the PEMFC voltage at normal state. It can be seen that at normal condition, constant PEMFC voltage can be obtained during PEMFC operation, and performance decay is not observed, indicating that the PEMFC voltage drop in the following tests is only due to the change of its state of health (flooding or dehydration in this study).

In the test, flooding and dehydration states are obtained by reducing and increasing the cell temperature, respectively. By reducing the cell temperature below the reactant gas dew point temperature, the liquid water will be condensed from humidified gas. With the accumulation of liquid water, the gas channel will be blocked and reactant gas cannot reach the catalyst layer, causing PEMFC performance decay; this is depicted in Fig. 5. In the test, the gas dew points at anode and cathode are set to different values (which are determined by adjusting inlet gas temperature and relative humidity at anode and cathode sides), such that water is only condensed at cathode side in the test, thus flooding is caused at cathode side.

It should be noted that different techniques have been used to reduce PEMFC temperature at different systems. At PEMFC1, coolants are injected with cooling system to reduce the cell temperature. At PEMFC2, the temperature is reduced by other means.
temperature; while at PEMFC2, since cooling system is not included, the reduction of cell temperature is achieved by decreasing the temperature of anode and cathode humidification tank, thus the temperature difference between the injected gas and PEMFC is increased. Therefore, the low-temperature gas entering the high-temperature PEMFC will cause the PEMFC temperature to drop.

It can be observed that although two testing systems and tested PEMFCs have significant variation, two PEMFCs show similar behavior at flooding state. With the reduction of cell temperature, PEMFC voltage drops, but its decay rate decreases with further cell temperature reduction. This is consistent with previous studies that with existence of flooding, reactant gas channel or GDL will be blocked by accumulated liquid water, causing fast and significant PEMFC performance decay [36]. It should be mentioned that the cell voltage drop cannot be observed at the beginning, but its performance decay rate starts increasing with further development of dehydration.

On the other side, with the increased cell temperature, water inside the PEMFC will be evaporated, which leads to membrane dehydration, and PEMFC performance degradation due to higher membrane resistance and less conductive capacity of dried membrane can be observed. In the test, the cell temperature is increased, and unhumidified gases are injected to achieve dehydration at two PEMFCs.

The cell temperature rise and corresponding PEMFC voltage drop due to dehydration at two PEMFC systems are shown in Fig. 6. It can be seen that compared with flooding, with the increase of cell temperature, significant PEMFC voltage drop cannot be observed at the beginning, but its performance decay rate starts increasing with further development of dehydration. Similarly, since PEMFC voltage drop is not started immediately with cell temperature increase, results in Fig. 6 start when PEMFC voltage drop is observed.

Moreover, it should be mentioned that the same test protocol is used at two PEMFCs for flooding and dehydration (reducing PEMFC temperature for flooding, increasing PEMFC temperature, and feeding unhumidified reactants for dehydration), but due to different technical parameters of two PEMFCs (as listed in Table II), different control parameters for the same state are used. With such procedure, the robustness of selected features in fault diagnosis at different PEMFCs can be further clarified.

In the test, the test data is collected with sampling frequency of 5 Hz. This is determined with the previous study [18] that the frequency spectrum of PEMFC signals is always concentrated at low frequency range of about 2 Hz. It should be mentioned that the time window in Figs. 4–6 is different. For each PEMFC fault in the real world, it is difficult to unify the duration of the faults. Thus, in the study, through resampling the fault data, the dimension of the data is kept same which is beneficial for the followup data processing. Furthermore, in order to remove the influences resulted from different operating conditions and different fuel cells, data preprocessing is carried out to perform the data normalization of the PEMFC test signals listed in Table IV.

Moreover, besides cell voltage, several other signals are collected from PEMFC at different states, such that features from multisensor signals can be extracted, which are listed in Table IV. In this article, all sensor signals (ten signals in Table IV are processed using KPCA. In the analysis, 10D data set is processed by KPCA algorithm, and the eigenvalues $\lambda_1 > \lambda_2 > \lambda_3 > \ldots > \lambda_{10}$ and eigenvectors $\nu_1, \nu_2, \nu_3, \ldots, \nu_{10}$ are obtained. The larger the eigenvalues are, the more effective information they carry. In this study, the largest two eigenvalues and corresponding eigenvectors are selected to represent the original information in multiple signals.

It should be noted that constant signals (like current signal) will not affect the dimension reduction results, and only varying signals can influence results from KPCA. These signal variations are caused by change of PEMFC state of health (flooding or dehydration herein).

### IV. Evaluation of Features With Proposed Method

In this section, the proposed feature evaluation method will be applied to the PEMFC test data. Feature suitability can be calculated with (14) and features can be ranked based on suitability value.

In the analysis, features listed in Table I are calculated with PEMFC test data, which is collected from two PEMFCs at different states of health. It should be noted that only one set of test data at each PEMFC state is required in the evaluation analysis.

Table V lists evaluation results of various features using proposed evaluation method. It should be mentioned that in this study, Gaussian kernel function is used in KPCA analysis for data dimension reduction due to its anti-interference ability to the noise. Moreover, $F_i$ ($i = 1–8$) in Table V is defined to represent corresponding feature listed in Table I.
Several findings can be found from the table. Firstly, features extracted from multidimensional dataset using WT/WPT (F7 and F8) have better diagnostic performance than those from single voltage signal (F5 and F6), especially at discrimination capability. This is consistent with previous studies [6], [10] that multisensor data can provide better diagnostic results. Moreover, among features extracted from PEMFC voltage, frequency-domain (F4) and time-frequency domain (F5, F6) features have better robustness than those from time-domain (F1, F2, and F3). This is also reasonable as the frequency characteristics depend on the signal shape (which is caused by different PEMFC states), while the time characteristics may be affected by signal amplitude (which is caused by different PEMFC properties and operating parameters). Last but not least, it is observed that features from WT and WPT (either from single voltage or multisensor data) have similar robustness and discrimination capacity. The reason for the difference in WT and WPT is that WT also extracts coefficients from details (higher frequency range), but since the frequency power spectrum concentrates on low frequency range at PEMFC system [18], the inclusion of normalized energy from higher frequency range is less sensitive to the PEMFC performance change.

V. PERFORMANCE VALIDATION OF FEATURE SUITABILITY IN PEMFC FAULT DIAGNOSIS

In this section, the feature rank based on its suitability value \( f \) in Table V is validated using actual diagnostic results, which is performed by classifying three PEMFC states at two different PEMFCs using each feature (F1–F8 listed in Table V). Moreover, the effectiveness of high ranking features in identifying early stage PEMFC change in the state of health is also investigated.

With the proposed evaluation method and evaluation results (\( f \) in Table V), eight features extracted from different PEMFC signals can be ranked. Using 1D classifier, that is, only one feature is used to classify three states of health (nominal, flooding, and dehydration in this study) with support vector machine (SVM), the diagnostic results of each feature to three PEMFC states at two PEMFCs can be obtained. Fig. 7 depicts the misclassification rate of each feature.

It can be seen from Fig. 7 that feature discrimination results are consistent with feature suitability from the proposed evaluation method, i.e., features with high \( f \) values have more accurate diagnostic performance. This indicates that the feature effectiveness in PEMFC fault diagnosis can be efficiently evaluated with the proposed method, and this method can be used in practical PEMFC applications as an efficient technique for selecting appropriate features in fault diagnosis.

Moreover, similar to results in Table V, different classification results can be provided using various features. Time-domain features (F1–F3 in Table V) can cause higher misclassification rate, since time characteristics of signals would be easily affected by PEMFC with different technical parameters. On the other side, frequency-domain and time-frequency domain features (F4–F6) can provide better classification compared to that using time-domain features, indicating that even at different PEMFCs, signal from the same state would have similar frequency characteristics. Furthermore, compared to PEMFC voltage, features extracted from multisensor signals can provide better classification results, indicating that multiple signals should be combined to provide better diagnostic performance. This further confirms the necessity of proposing a sensor selection algorithm for different PEMFC signals.

It should be noted that at practical applications, combination of multiple features can be used to further improve the diagnostic performance, where the proposed method can still be used to determine the optimal feature set for PEMFC fault diagnosis.

Moreover, discrimination results of two highest ranking features in Table V (i.e., F4 and F7. Since F7 and F8 have similar suitability and physical meaning, F8 is not included herein) are
Fig. 8. Process of obtaining classification results.

Fig. 9. Effectiveness of two high ranked features in identifying early stage change in PEMFC state of health.

also illustrated to further highlight the benefit of the proposed evaluation method. Fig. 8 shows the process for obtaining the classification results, and the results are depicted in Fig. 9. It should be noted that the numbers in parentheses in Fig. 8 are the numbers of PEMFC test data used in the analysis, (correspond to the data points in Fig. 9).

It should be mentioned that in the analysis, the PEMFC test data at each state are decomposed to several segments, and only the first segment is utilized in the diagnosis. With such process, the feature effectiveness in discriminating early stage change in PEMFC state of health can be illustrated.

It can be seen from Fig. 9 that early stage flooding and dehydration can be discriminated with good quality using the two high ranking features. Moreover, same PEMFC state at different PEMFC systems can still be classified as one cluster using the two high ranking features, confirming that the proposed method can determine appropriate features in terms of both discrimination capacity and robustness. The results further indicates the benefit of proposed feature evaluation method in practical PEMFC applications, as with accurate identification of early stage change in PEMFC state of health, PEMFC performance can be efficiently recovered using corresponding mitigation strategies. From Fig. 9, F7 (energy of signal at different frequency bins) at PEMFC normal state has significant smaller value compared to that at flooding or dehydration. This indicates that PEMFC signal energy is uniformly distributed at normal state, while its change of state can make PEMFC signal more concentrated.

It should be noted that as the proposed evaluation method has no specific requirements to the PEMFC state of health, they can be easily expanded to diagnose other PEMFC states. With test data collected at other PEMFC states of health, similar analysis can be performed to evaluate feature discrimination capacity and robustness. Therefore, the proposed method can still be used for the feature selection at other PEMFC states of health. However, at different PEMFC states of health, different features might be determined from the proposed method. This indicates that different features should be selected for identifying different PEMFC states of health.

Furthermore, in the analysis of identifying PEMFC early stage change in PEMFC state of health, fault diagnosis can be performed with the interval of about 2 min. As the diagnosis can be made within few seconds, it is potential to perform online diagnosis in practical PEMFC applications.

VI. CONCLUSION

In the study, a novel feature evaluation method was proposed to investigate discrimination capacity and robustness of features extracted from different PEMFC test data. Based on the results, appropriate features can be determined to provide accurate and consistent performance in PEMFC fault diagnosis.

Three different PEMFC states, including normal, flooding, and dehydration, were used to evaluate feature effectiveness with the proposed method. Furthermore, test data from two different PEMFCs were obtained, with which the feature diagnostic performance at different systems can also be investigated.

From the evaluation results, different classification performance can be obtained with various features. Frequency-domain and time-frequency domain features show better robustness than those from time-domain features, and features extracted from multisensor data can provide better diagnostic performance. This further confirmed the necessity of selecting appropriate features for reliable PEMFC fault diagnosis.

Moreover, the feature suitability determined with the proposed method showed high consistency with actual diagnostic results, indicating that the proposed evaluation method can determine the features providing accurate and consistent diagnostic performance. Compared to previous studies regarding feature selection methods, the proposed method can determine appropriate features among multiple features extracted from various PEMFC signals; this can be better applied in practical applications since multiple PEMFC signals are usually available for the selection.

Furthermore, with selected features from the proposed method, accurate discrimination results can be obtained at two PEMFCs with different technical parameters, indicating that the proposed method can determine appropriate features for
reliable fault diagnosis at practical PEMFC applications. Moreover, PEMFC early stage change in state of health can also be identified and isolated with good quality using selected features with the proposed method. This will be beneficial in practical PEMFC applications for taking proper mitigations to extend PEMFC lifetime.

Since the proposed feature evaluation method has no specific requirements to the PEMFC states of health and extracted features, the proposed work can be easily extended to scenarios with features from more PEMFC test data at other states of health. It should be mentioned that since different PEMFC phenomena will influence the feature performance, when the proposed method is applied to other PEMFC states of health, different features would be selected. Therefore, in practical PEMFC applications, with determined results (appropriate features at different PEMFC states of health), optimal features can be selected for PEMFC state of health monitoring.

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