A review on non-model based diagnosis methodologies for PEM fuel cell stacks and systems

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Abstract:

A review of non-model based methodologies applied to diagnosis of Proton Exchange Membrane Fuel Cell (PEMFC) system is presented. Three types of non-model based methods including artificial intelligence, statistical method and signal processing method are discussed and compared. The artificial intelligence one, divided into Neural Network (NN), Fuzzy Logic (FL) and neural-fuzzy method, is applied as a fault classifier which is quite different from its role in model-based method. Linear feature reduction methods including Principle Component Analysis (PCA) and Fisher Discriminant Analysis (FDA), and nonlinear ones such as Kernel PCA (KPCA) and Kernel FDA (KFDA) are demonstrated as part of statistical methods. Additionally, a statistical theory based classifier- Bayesian Network (BN) is also introduced in this part. As for signal processing method, both Fast Fourier Transform (FFT) for stationary signals and short-time Fourier Transform (STFT), as well as Wavelet Transform (WT) for non-stationary signals are introduced. Since each method has its advantages and limitations, a comparison is made finally and hybrid approaches resulting from integration of different methods are believed to be promising.

Keywords: PEMFC; non-model based diagnosis; artificial intelligence; statistical method; signal processing

1. Introduction

Proton Exchange Membrane Fuel Cell (PEMFC) is one of the most promising energy technologies nowadays. It has the advantage of low-operating temperature, high current density, fast start-up ability and also suitability for discontinuous operation [1,2]. All of these characteristics make it attract more and more attentions. However, reliability and durability remain the most challenging problems for its commercialization. A PEMFC system is a complex integration of chemical, electrical, mechanical and thermal managements. In general, degradation or failure of the system may be induced by bad water management [3], Membrane Electrode Assembly (MEA) contamination, and reactant starvation [4]. Some common fault sources of a system such as sensors and actuators malfunction [5], improper operation and control, are also possible causes. In terms of occurring time, three degradation classes could be distinguished: long-term degradation, degradation due to transients and also incident-induced degradation [4]. Generally, monitoring of PEMFC system should be capable to deal with nonlinear, multi-fault source and different time-scale problems.

In recent years, various diagnosis methodologies have been developed and each has its advantages and limitations. According to whether a model is necessary, diagnosis methods can be classified into two general types: model-based one and non-model based one. For the former one, an analytical model based on a deeper understanding of the internal process of the fuel cell system or a black-box model should be built first. Since fault diagnosis in this case is usually based on the residuals generated between the experimental results and the model outputs, this kind of method is also called residual-based method [6]. Non-model based method could be either knowledge-based or signal-based. The objective of this kind of method is to obtain fault information based on heuristic knowledge or signal processing or a combination of both. Compared with model-based method, non-model based one is a relatively new trend in diagnosis of PEMFC system, but its application in other fields has already been widely and extensively studied.

Although there are some existing reviews about PEMFC system, few of them have focused on respective diagnosis methods. Yuan et al. 2007 [7] presented AC impedance technique applied in PEMFC field. Hissel et al.2008 [8] summarized various modeling techniques used for PEMFCs and also the systems including the ancillaries. Different electrochemical diagnostic tools such as Electrochemical Impedance Spectroscopy (EIS) and Cyclic Voltammetry (CV) in PEM research were reviewed in [9]. Yousfi Steiner et al. 2008 [10] proposed a review focused on PEMFC voltage degradation associated with water management. Further, Yousfi Steiner et al. 2009 [4] published another review mainly dealing with PEM catalyst degradation and starvation issues. However, emphases of these two papers are mainly on causes and consequences of respective faults instead of fault diagnosis. Venkatasubramanian et al. 2003 [5,11,12] classified various diagnosis methods into qualitative, quantitative and process history based methods, based on which three reviews are achieved respectively. These three reviews are very comprehensive and detailed, but they don't address any special applications.

With the development of various methods dedicated to PEMFC system diagnosis, there seems to be necessary to summarize them and indicate a possible trend for PEMFC diagnosis. In this paper, fault diagnosis methods, mainly non-model based ones applied in PEMFCs field are emphasized on.

According to their principles of operation, non-model based methods in this paper are classified into artificial intelligence (AI) ones, statistical ones and signal processing ones. AI approach including Neural Network (NN), Fuzzy Logic (FL) and neural-fuzzy method plays an important role in fault diagnosis domain. Usually, they can be applied to constitute a pattern classifier for discriminating different types of faults. Statistical method including variable dimension-reduction methods- Principle Component Analysis (PCA) and Fisher Discriminant Analysis (FDA), and also a statistical classifier-Bayesian Network (BN) are addressed. Stationary signal processing methods like Fourier transform (FT) and non-stationary signal processing methods such as short-time Fourier Transform (STFT) and Wavelet Transform (WT) are efficient tools in extracting valuable features that can reflect the occurrence of certain types of faults. The various non-model based methods can be summarized in figure 1.

Figure 1. Classification of non-model based method

In the following sections, three kinds of non-model based approaches are introduced successively. Evolutions and improvements of the applied approaches are also suggested on the basis of the results obtained in other domains. It is worth noting that no single method can satisfy all the requirements of system-monitoring. Hybrid methods integrating characteristics of different methods could be very interesting for overcoming the limitations of each one, and it could be also a new trend. Finally, comparison of each method is made and hybrid methods are discussed.

2. AI methods for PEM fault diagnosis

In the field of fault diagnosis, AI has attracted a lot of attention. It is very effective in recognition of fault patterns or its sources without system structure knowledge. The idea is to find relevant features that describe specific patterns in the feature hyperspace, depending on the state of the system (in normal or faulty operation). There is thus a need to classify the data points and determine at which class they belong to. This part focuses on applications of three kinds of AI methods: NN, FL and neural-fuzzy method. Due to its inherent pattern recognition capabilities and its ability to handle noisy data, NN is one of the most popular methods for fault diagnosis [13]. FL is mainly devoted to handle the impreciseness or uncertainty in the system in a way that mimics human reasoning [14]. A neural-fuzzy method combines the adaptive capability of NN and also the qualitative reasoning ability of FL. It has been proved to have superior recognition accuracy and better generalization capability compared with a single NN [15,16].

2.1 Neural network (NN)

Inspired by biological NNs, artificial neural network (ANN) was proven to be a powerful tool for learning and constructing a nonlinear mapping when a given set of input and output data is available. In recent years, numerous papers about PEMFC diagnosis using ANN have been published. However, most of them are model-based [17–21]. In this paper our focus is on its application in non-model based fault diagnosis as a fault classifier.

Hamming neural network (HNN) is a competitive NN which is specially designed for binary pattern recognition issues. Given an input pattern, its objective is to decide a representative pattern closest to it. HNN usually consists of two layers: a feed-forward layer and a recurrent layer, as shown in figure 2. The former one calculates correlations or inner products between each representative pattern and input pattern while the latter one determines a winner that can finally represent the input pattern.

Figure 2. Hamming neural network [22]. P: prototype input vector, W^1: weight matrix of feedforward layer, b^1: bias vector, S: the number of neurons, W^2: weight matrix of the recurrent layer.

In [22], a HNN is used for pattern recognition in order to monitor the state of health (SOH) of PEMFC. Representative FC output voltage (FOCV) patterns are collected by performing a designed pulse current profile on 20 single PEMFCs. Four statistical features including average, standard deviation (both with and without fixation at the initial operating points) and minimum of the FCOV are extracted from each pattern and are further used for HNN training. In the next step, the HNN is applied to identify the FCOV pattern that is the closest to the pattern of the arbitrary cell to be measured.

The representative loss ΔR_{d}, defined as the sum of activation and concentration losses, is applied as a SOH indicator. ΔR_{d} of 20 representative patterns are calculated, based on which SOH of each pattern is given, e.g. SOH=1 corresponds to a fully fresh cell, while SOH=0 corresponds to a fully aged cell. Thus, given an arbitrary cell, its FCOV pattern can be recognized through HNN and then based on the selected pattern, its SOH can be calculated easily without the need of repeated parameter measurement of the cell. However, SOH diagnosis in this paper is only performed on a single FC. Furthermore, only SOH is given without knowledge of fault type.

Besides HNN, Multi-layer Perception Neural Network (MLPNN), Probabilistic Neural Network (PNN), Radial Basis Function (RBF) network and Learning Vector Quantization (LVQ) are also commonly used methods for pattern recognition. Comparative studies of those NN's performances in various applications like disease diagnosis and vehicles gear estimation are given by [23–25].

Compared with the traditional analytical methods, a NN approach has the advantage of excellent nonlinear approximation ability [20]. Furthermore, it has a low sensitivity to noise and can be built based on incomplete database [18]. However, several limitations exist when applying NN for fault diagnosis. Firstly, the mentioned NN classifiers are always supervised techniques, which means that data set under normal and different faulty operating conditions should be obtained and trained for fault classification. This could be time-consuming when performing experiments on FC system and may cause irreversible damage to the system under faulty operating conditions. In fact, this is a common problem existing in non-model based methods. Another concern of employing NN is related to its training. As measured variables and fault patterns increase, a bigger and more complex network has to be designed to diagnose the faults properly. This could lead to a difficult learning of all fault patterns within an acceptable performance goal [26].

2.2 Fuzzy Logic (FL)

Like NN, FL can either be used as a residual generator or as a pattern recognition method. One of the interesting tools for fault diagnosis is the fuzzy clustering: the idea behind is the allocation of data points into a number of clusters. Data points with the most similarity will be allocated in the same cluster, while dissimilarities between each cluster will be as large as possible. When used for fault diagnosis, each cluster could represent a certain type of fault in the system. Each data point to be diagnosed can be represented by a vector consisting of certain number of features which are relevant to the faults relevant fault information. Figure 3 shows a schematic diagram, in which three clusters (c_1, c_2 and c_3) are obtained on a two-dimensional feature space (f_1 and f_2). Fuzzy clustering has been already widely applied in fields such as image processing [27,28], rotating machinery [29], human activity [27], etc.

Figure 3. Fuzzy clustering diagram

The application of fuzzy clustering for PEMFC system diagnosis was proposed in [2]. Authors have proposed a PEMFC durability diagnosis methodology based on fuzzy k-means clustering. Two types of experiments, steady-state operation and real transportation load cycle respectively, are performed on 100 W FC stacks during 1000 hours. The first step is to extract features that can mostly represent the stack aging. Two features namely the difference between polarization resistance and internal resistance, and maximal absolute phase value of the Nyquist plot are considered according to prior knowledge. Fuzzy clustering algorithm is then performed on the 2-D feature space to produce three clusters; each of them corresponds to a specific behavior of the FC stack, named “young”, “middle aged” and “old”.

The proposed methodology has the advantage of easy implementation and capability to explain the cause of degradation. As it is not time-consuming, it can be applied as an efficient tool for real-time monitoring and diagnosis. However, some further work can be done to complete diagnosis task. Since this work mainly focus on aging test, features used may not be suitable when coming to diagnosis of other kinds of faults in PEMFC system. Furthermore, it only deals with one type of fault/degradation. In the case of two or more than two faults, dimension of feature space may need to be extended.

In order to diagnose multi-faults existing in a system, Liu et al.2005 [29] provided an encouraging solution. They combined fuzzy c-means clustering and fuzzy integral techniques to form a two-step diagnosis strategy. First, multi-classifiers were constructed based on different feature groups. Recognition rates of each classifier for existing faults were then obtained, which reflect the importance of the classifier in recognizing each fault. In the next step, both membership degrees and recognition rates were applied as inputs of the procedure of fuzzy integral fusion. The membership degrees reflect the initial judgments of the classifiers for the current faults, and recognition rates contain historical information. A final decision was then made. The proposed method is evaluated by data collected from rolling element bearings. Three kinds of faults were classified with an excellent accuracy which was superior to that of a single classifier. However, feature selection has to be improved, which means that the most relevant or effective features corresponding to a specific fault should be identified first. This procedure is highly expected to be applied for PEMFCs' diagnosis of multi-faults given relevant features (e.g. drying, flooding and gas leakages inside the stack which are the most investigated ones).

When applying fuzzy clustering for fault diagnosis of PEMFCs, several critical points should be taken into account: feature selection, determination of optimal number of clusters, objective function construction. Optimal number of clusters can be given either by prior knowledge [2] or considering some criteria such as partition coefficient (PC), classification entropy (CE) , separation index (SC) and Xie-Beni index [30–32].

About objective functions, besides those of the well known fuzzy k-means or c-means clustering, other improved versions, such as kernel based fuzzy clustering [32] and fuzzy clustering with multi-medoids (FMMdd) [33]seem to be very interesting. As for feature selection, it is a common concern for the classifiers mentioned in this paper. It can be done either by human expertise or by automatic feature extraction methods such as wavelet transform (WT), PCA. Certain parts of section 3 and section 4 are contributed to introduce various feature selection methods.

2.3 Neural-fuzzy method

A new trend in applying AI for fault diagnosis is the combination of FL and NN, of which one most popular form is adaptive Neuro-Fuzzy System (ANFIS). It integrates ANNs' adaptive capability and fuzzy logic qualitative approach [34]. By adopting ANN to construct the fuzzy system, which means designing and adjusting the parameters of a fuzzy inference system by utilizing the learning method of ANN, a reliable fuzzy inference system can be realized according to input and output samples even without human expertise [35]. A typical ANFIS has been shown in figure 4. It consists of five layers, including input membership function layer, rule layer, normalization layer, output membership function layer and output layer. A cycle represents a fixed node and a square corresponds to an adaptive node.

Figure 4. A typical ANFIS architecture [15]

Several papers can be found about applications of ANFIS in PEMFC diagnosis, but most of them are model-based [35–37]. However, in other fields such as rotating machinery and medicine, numerous applications of ANFIS as a fault classifier can be found. In [15], authors applied ANFIS for classification of four types of faults occurring in bearings. Four most superior features are selected through an improved distance evaluation technique as inputs of ANFIS. The outputs are seven numbers corresponding to seven kinds of faults. Through comparison with a MLPNN classifier, it can be found that ANFIS has better classification success rate and generalization performance. Khezri et Jahed 2007 [38] introduced ANFIS in electromyography domain for recognizing six patterns. The study indicated that ANFIS real-time based learning method is viable and has high degree of correctness. In [39], ANFIS was constructed for heart valve disease diagnosis based on features extracted by discrete wavelet transform (DWT) and reduced by PCA. A Linear Discriminant Analysis (LDA) –ANFIS based intelligent diagnosis system was presented in [40] for diabetes. LDA was applied for feature extraction which supply feature vectors including most of the useful information from original vectors to inputs of ANFIS classifier. A classification accuracy of 84.61 % was obtained.

Through these papers, the feasibility of ANFIS in recognizing fault patterns can be proven and these could also be instructive for its further application in PEMFC system.

Unlike its application for modeling, when used for pattern classification, ANFIS takes superior features that contain rich faulty information as its inputs instead of those who can mostly represent the system. As its reliability and robustness in real-time fault classification, it is very suitable for nonlinear systems such as FC system which may have noisy data measurements, multi-faults and incomplete human expertise. When appropriate features corresponding to objective faults have been found, ANFIS can also be trained and validated for FC diagnosis. It can be believed that ANFIS could be an alternative promising technique for future fault diagnosis of PEMFC system.

3. Statistical methods for PEM fault diagnosis

Methods based on multivariate statistical analysis offer an alternative for diagnosis of PEMFC system. Usually, a huge amount of data from the system can be obtained during different processes, while most of them are highly correlated. In order to extract the most discriminating features from the original data, dimension-reduction methods are highly expected. According to the literature, the most frequently used variable dimension-reduction methods are Principle Component Analysis (PCA) and Fisher Discriminant Analysis (FDA). Since they are linear methods which assume there is a linear correlation among the variables, they are not suitable for extracting variables' nonlinear features. Thus nonlinear methods, like KPCA and KFDA are also introduced. In addition, a probability theory based classifier-BN is also included in this part.

3.1 Principle Component Analysis (PCA)

PCA is one of the most popular dimension-reduction methods, which can reduce effectively the dimensionality of process variables while retaining the most valuable information contained in the variables. Through PCA, correlated variables are converted into uncorrelated principle components which could represent the largest variance among the variables. A geometric interpretation of PCA is shown in figure 5, in which x_1 and x_2 are original variables. The first principle component (y_1 axial vector) represents the largest variance existing in the variables; the second principle component (y_2 axial vector) represents the second largest variance in x_1 and x_2. As for higher dimensional spaces, more principle components could be obtained to represent the high dimensional original variables [41].

Figure 5. A geometric interpretation of PCA [41]

In [42], PCA was employed to explore the most contributing variables to the system outputs (stack voltage and stack current). The authors performed polarization curves on a PEMFC stack and acquired more than 100 variables, including inputs, outputs and others. PCA was applied to visualize and analyze correlations of all the variables in two hyperspaces. The first hyperspace displayed the evaluation of the principle components with sample time, which can reflect the FC stack state, stable or transient. A second hyperspace demonstrated the participation of each original variable within the value of the principle components. The analysis results of PCA were finally verified by a multi-linear regression based empirical model. PCA is shown to be a useful tool to explore correlations among variables and could be helpful for understanding the physical process in the FCs.

According to the literature, PCA can be applied for fault diagnosis in two ways. The first way is related to a principle component model. According to the theory of statistics, all the process variables under normal operating conditions are random variables which have near normal distributions [41,43]. Thus, the principle component model built under normal operating conditions can be used as a fault detection reference. When the divergence of the components from the model exceeds a certain value, a fault can be alarmed. Usually, some statistics such as T^2, square prediction error (SPE) or Q statistic, exponentially weighted moving average (EWMA) will be applied as FC health indicators [44,45]. The second way is implemented combining PCA (dedicated to feature reduction) with fault classifiers such as NN, Bayesian network. In multivariate systems such as PEMFC system, usually a large amount of variables can be obtained simultaneously. If these variables are directly used as inputs of pattern classifiers, a heavy burden both on the computations and accuracies of the classifiers will be produced. Thus a feature reduction step is extremely necessary.

Examples of applications of PCA can be found in [41]. A principle component model is built for diagnosis of PEMFC systems used in shuttle buses. Four principle components are obtained by applying PCA based on analysis of 17 different significant parameters of the system. For fault detecting, an improved statistic namely exponentially weighted average of SPE is applied for the system monitoring. Advantages of this method are its easiness and low requirements in computing capability. Thus it can be realized in real time control. However, when a significant number of faults in the system occur, a single PCA model seems difficult to deal with. In this case, a possible solution is constructing multi-PCA models which are separately trained with variables under each fault condition [43,46].

The second way by taking the outputs of PCA for fault classification can be found in [47]. PCA was performed based on data obtained from Acoustic Emission (AE) technique. Two-dimensional projections in axis spaces were employed for visualization of three AE events occurring in a single PEMFC. A good agreement was reached compared with the experimental conditions. However, the clustering was performed manually and no classifier was applied for automatic classification. In fact, combination of PCA method and fault classifier is very common in other fields, which could provide a promising choice for multi-fault diagnosis in PEMFC system [48–51]. For example, in [48], PCA has been applied in conjunction with an ANFIS classifier for disease diagnosis. Four kinds of states are finally classified with a highest accuracy of nearly 90% compared with other classifiers without applying PCA. A combination of PCA and NN classifier is proposed in [49]. A 60 dimensional input space is reduced to a 20 dimensional one by using PCA. The classification performance is significantly improved compared to an “alone-NN” classifier. In this sense, PCA can be employed to help designing classifiers, which is attractive for online operations.

Despite its ability in handling high-dimensional, noisy and high correlated data, PCA still has the limitation of poor performance in nonlinear chemical processes [52]. That is due to its assumption that the process variables are linear-correlated. One of the nonlinear forms of PCA is Kernel PCA (KPCA) which is developed in recent years for tackling the nonlinear problems. Relevant applications can be found in [45,52–56].

3.2 Fisher Discriminant Analysis (FDA)

FDA is another kind of dimensionality reduction technique that shows excellent performance for fault diagnosis. In practical processes, data collected from different operating conditions are recorded and categorized into different classes. The main idea of FDA is to determine a set of discriminant vectors by maximizing the scatter among the classes while minimizing the scatter within each class [57]. According to this characteristic, FDA can be used to isolate different fault classes and thus help to analyze the fault sources [58]. As FDA’s objective is consistent with that of fault identification, FDA usually has better performance than PCA in fault diagnosis [43,59].

A graphic interpretation with two variables is shown in figure 6. The two dimensional space is composed of x_1 and x_2 axial components, in which triangle and circular points represent points in two different classes, and y_1 is the projection axis. Unlike PCA which seeks a direction for the largest variance, FDA seeks a direction that is efficient for discrimination.

Figure 6. A geometric interpretation of FDA

FDA's application in PEMFC system diagnosis is still a new field. But its excellent performances in other nonlinear chemical processes provide a promising perspective. An application of FDA for diagnosis of Tennessee Eastman (TE) process was presented in [43]. In this paper, FDA was performed to diagnosis 21 faults occurring in the plant and its misclassification rate is much lower compared to that of PCA.

Though FDA has better performance than PCA in classification problems, it is still a linear method, which means for nonlinear systems its performance may degrade. In order to have a better monitoring of the nonlinear systems, some improved versions such as KFDA is proposed and has been more and more used in recent years [59–61]. The basic idea of KFDA is to map the original variable space into high-dimensional feature space via a nonlinear kernel function and then to perform linear FDA in the nonlinear mapped feature space to find the discriminant vectors for classification [61]. In [59], a KFDA based pattern recognition method was developed for diagnosing a TE process. For comparison, PCA, KPCA, FDA, KFDA based feature extraction methods are also performed. Detection and isolation rates of four fault patterns applying each method are listed and KFDA shows better performance.

A simple comparison of methods described in part 3.1 and part 3.2 is summarized as follows. For diagnosis of nonlinear system, it is better to choose kernel function based (K-) methods. Although they are nonlinear methods, they do not involve nonlinear optimization procedure. Linear PCA/FDA calculation procedures can be directly applied on the feature spaces (mapped from original space via kernel functions). However, these nonlinear methods have drawback of increasing computation time compared with linear ones. In addition, data patterns in the feature space are rather hard to interpret in the input data space [59]. From the aspect of fault classification, FDA and KFDA generally have better performance than PCA and KPCA. As in the calculation procedure, their objective is to have optimal discriminant vectors, while for PCA methods, during the extraction of maximal variances, some important information for classification may be lost comparing with FDA.

Table 1. A comparison of the introduced dimension-reduction methods

3.3 Bayesian Network (BN)

Bayesian network (BN) is one kind of statistical classifiers. It can be expressed under the form of probabilistic graphical models in which the nodes represent random variables, and the arcs represent conditional independence [62]. Construction of a BN consists of two parts: finding the network structure and calculating the conditional probabilities from the measured data [63]. A representative structure of BN is shown in figure 7: nodes are arranged into three layers- sensors, patterns and fault causes. The relationship among the nodes in each layer is cause-effect one which can be quantified by conditional probabilities.

For fault diagnosis, a large database composed of various fault records is essential for the construction of a BN. The cause-effect structure is then generated based on the database by applying probabilistic methods or a combination with human knowledge [62]. According to the literature, BN provides a natural tool for dealing with three diagnosis problems: reasoning, decision and uncertainty [63,64].

Figure 7. Bayesian network structure for fault diagnosis in a PEMFC [65]

An application of BN for diagnosis of a PEMFC system was presented in [62]. Four types of faults in this system were diagnosed: faults in the air fan; faults in the refrigeration system; growth of the fuel crossover; and faults in the hydrogen pressure. In the first step, fault records are collected based on a mathematical model of the FC system. Then probabilistic methods including Bayesian-score (K2) and Markov Chain Monte Carlo (MCMC) algorithms are applied on the databases to qualify and quantify the dependency relationship among the variables. To improve the network structure, some constrain-based conditions and knowledge are applied. For the diagnostic process, the evidence was based on observations of variables that can be easily monitored by sensors like voltmeters, ammeters, thermocouples, etc. This allows an easy implementation of fault diagnostic processes in FC systems. The final diagnostic results show agreement with the original fault causes. However, this work is validated only by simulation results. Furthermore, the fault supervisor always indicates the fault cause as the one showing the biggest probability. This could reduce the diagnosis accuracy in some extent.

More recent work [63] focused on the diagnosis investigation on large PEMFC stacks composed of a number of elementary cells, unlike the former ones mainly on a single cell. In order to facilitate the characterization and diagnostic of the FC stack, a new high voltage impedance spectrometer is designed. A naïve Bayesian classifier, based on the so-called Bayesian theorem has been chosen as Bayesian structure. It is particularly suitable when the dimensionality of inputs is high. To differentiate between 6 operating modes, twelve variables are chosen as inputs. This paper has mainly focused on researching the influence of Learning Database (LD) size. It was found that when LD size was chosen as 25%-75% of the global database, a maximum rate of good classification (91%) can be reached.

A discrete BN was designed in [66] to estimate the input variables of FC system given a set of output measurements. The BN structure was determined by combination of expert knowledge and K2 algorithm. Data discretization is stressed in this paper, during which variables are represented by multi-distinct values instead of Booleans ones like in (Riascos et al. 2007). In order to prove the generality of the network structure, two different SOFC stacks with 6 cells are applied and reasonable accuracies are obtained.

Although encouraging diagnosis results for PEMFC system can be reached, this method is still not so popular in FC domain until now. A related problem may concern the large data set which is needed for construction and calculation of a BN. A recent paper by Liu et Jin [64] provides a possible solution. The authors aimed to explore an improved BN method to detect and diagnose the faults based on an incomplete and small data set. The proposed method is applied in the assembly process. BN approach shows strong diagnostic robustness under the condition of incomplete evidence and measurement noises. However, it still has a way to go for real process monitoring.

4. Signal processing methods for PEM fault diagnosis

Many signals obtained from the PEMFC system processes show oscillations that are due either to harmonic or to stochastic nature, or both. If changes of these signals are related to faults in the process, signal processing approaches can be applied for fault diagnosis [67]. When performing a signal processing based diagnosis method, there are two things needed to be considered: determining which signals to be applied for monitoring, and choosing an efficient signal analysis approach for interpreting [68].

In this part, two kinds of signal processing techniques, including Fast Fourier Transform (FFT) and Wavelet Transform (WT) will be introduced. These two techniques provide a view of signals in frequency domain, which may explore some significant information that cannot be conceived in time domain otherwise. Main principles are simply introduced and their applications in PEMFC system diagnosis are focused. Additionally, some interesting signals related to certain types of faults in the system are summarized according to the literature (Table 2).

4.1 FFT and STFT

The main idea of FFT is converting a signal from time domain into frequency domain by applying some transform functions. The signal is then represented by magnitude and phase components at each frequency. Customarily, the original signal is converted into power spectrum, which is magnitude of each frequency component squared [69]. Then significant components can be obtained by analyzing the spectrum.

Chen et al. (2008) [69] used FFT to correlate the stack voltage evolution with the pressure drop signal across the electrodes. Both the steady-state and dynamic behavior of a commercial 10-cell PEMFC stack were investigated. To indicate the water behavior in cathode/anode, dominant frequency of pressure drop signal was obtained. And the stack voltage change can also be predicted. The idea of this approach is utilizing frequency analysis of pressure drop signal as a diagnostic tool for PEMFC stack dynamic behaviors. However, even if the FFT-based methods lead to fine frequency resolution, they are not adapted to non-stationary signals which are typically extracted from the FC during operation.

According to the principle of FFT, satisfactory analysis can be acquired only limited to stationary or periodic signals, whose frequencies remain constant. In contrast, when analyzing transitory signals, FFT has poor performance due to its constant time and frequency resolution [70,71]. Thus, it is not a suitable method for diagnosis of PEMFC system, whose operation always contains a lot of transient processes, i.e. start-up process, load changes. Therefore, other approaches are required for investigating non-stationary signals which may contain important information about the occurring fault.

STFT is a modified version of the traditional FFT. Having a similar principle to the FFT’s, it is easy to understand and apply. The basic difference with FFT, however, is its moving window process, through which the original signal in time domain is broken up into a set of small segments. Each segment can be assumed to be stationary and then is processed by the traditional FFT [72]. Additionally, it has a two-dimensional (time-frequency) representation that shows directly how the frequency of the signal changes with time.

Usually, STFT has good performance for signals that have uniform energy distribution within an analyzing window [73]. However, an apparent drawback of STFT that prevents its wider application is its invariant window size, which will lead to a dilemma between time and frequency resolutions for non-uniform distributed signals. In this case, a good location in both time and frequency for a signal cannot be achieved simultaneously [71,74].

To overcome this shortcoming, other algorithms such as Windowed Fourier Ridges, Wigner-Viller Distributions [75], Choi–Williams Distribution (CWD), Born–Jordan distribution and the Zhao–Atlas–Marks distribution [76] are applied. These transformations have the following general form [77]:

$$D(t,\omega) = \iiint e^{j(\xi\mu - \tau\omega - \xi t)} \varphi(\xi,\tau) * f(\mu + \frac{\tau}{2}) f^*(\mu - \frac{\tau}{2}) d\mu d\tau d\xi \quad (1)$$

where t is the instantaneous time, ω the instantaneous frequency; τ, ξ and μ the integration variables; and $\varphi(\xi, \tau)$ a kernel function. The selection of an relevant kernel function is a critical issue.

Prieto et al. (2011) [71] presented a diagnosis method based on CWD for detecting permanent-magnet synchronous motors (PMSM). CWD is applied here as an alternative of STFT for feature extraction. Feature coefficients are calculated based on an effective feature-extraction parameter- fractal dimension (FD). Healthy and faulty conditions of the motor can be clearly differentiated by applying the proposed method. Applications on FC stack are also promising since there is some similarity between FC stack and PMSM since both of them operate under non-stationary conditions.

4.2 Wavelet Transform (WT)

For the analysis of transitory signals, wavelet analysis is another option that mitigates the dilemma between time resolution and frequency resolution. The wavelet theory was developed in the late 1980s by Mallat [78], and Daubechies [79]. The basic idea of the WT is to represent any arbitrary function *f* (t) as a superposition of wavelets (quick definition of wavelets). It can be performed based on many types of wavelet basis, called mother wavelets. With them, one can obtain a better approximation of short-time signal changing with sharp transients [67]. Compared with STFT, WT uses a size-adjustable window. When the local area has a high frequency, the window will be shorter; on the contrary, when the local area has a low frequency, the window will be larger [68]. Its main advantage is its ability of providing the best possible tradeoff between time and frequency resolution.

There are two general types of WT: the Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT). The former one is more efficient for the time and frequency resolution of the signal, while DWT has a higher calculation speed [80,81]. Additionally, DWT has a powerful de-noising capability [82]. An important issue when utilizing WT is the selection of mother wavelets [83]. Since our focus is on WT's application for fault diagnosis, this issue will not be addressed here.

Figure 8. Three level signal decomposing diagram [84]

Recent application of WT in PEMFCs is shown in [85]. WT analysis is performed based on stack voltage measurements for discriminating whether the stack is flooded or not. Complete wavelet Packet decomposition is applied, consisting in decomposing the approximation signal and also the detailed signal, resulting in richer information. In the analysis, all the voltage measurements obtained during each experiment (flooding and non-flooding) were transformed into WP domain using Daubechies wavelets at level 3. A preliminary analysis of data used in each class is thus performed in order to check whether the data collected within the same class exhibit a similar behavior. Finally, two features were extracted to build a two-dimensional space for classifying the state of the stack. The experimental results obtained in this study proved the feasibility and reliability of WT method.

This method uses only the stack voltage and can be adapted to a large set of FC configurations and applications. However the work is to be continued and improved in three aspects. The first improvement is to adapt the algorithm to an online, real time diagnosis. On the other hand, features reduction and selection as well as the discrimination must be automated. Finally, the present method gives a global FC SOH but do not localize the flooding.

When applying WT for fault diagnosis, the more common way is combining it with a fault classifier like ANN, BN and Support Vector Machines (SVM), in which WT is used for feature extraction. In [86], a DWT and ANN based algorithm for estimation of fault location is presented. DWT is used for data preprocessing and ANN is applied as pattern classifier, for training and testing. In [74], PNN is performed for detecting 3 fault types based on WT. A high accuracy is achieved in the simulation work for determining the type of the fault in the power system. In [87], ANFIS is trained as the pattern classifier for decision making based on DWT feature vectors. In [88], a new technique combining DWT and SVM is proposed. By comparison with BPNN and the coefficients DWT, the proposed method gives highly satisfactory accuracy. In [84], Bayesian classifier is used for the identification of fault location and its size based on the feature extracted by DWT.

As mentioned above, the determination of signals to be monitored should be the first thing to do when applying signal processing methods. Numerous researches focus on finding out a relationship between certain signals and the occurrence of some specific faults. According to the literature, signals that may reflect the occurrence of a certain type of fault are listed in table 2.

Table 2. Signals related to certain types of faults in PEMFC system

It can be found that stack/cell voltage and pressure drop signals are more commonly used. Since they are quite easy to monitor, it could be believed that a powerful tool combined with these fault relevant signals and WT analysis will be very promising for future real-time diagnosis of PEMFC system monitoring.

5. Integration of various methods

In the above sections, three general types of methods are presented. Each one has its advantages and weaknesses. Table 3 has been given to show some examples of applications of each method. Some methods, such as FDA are not listed in the table since they have not yet been put into practical uses for FEMFC diagnosis according to the current literature.

Table 3. Examples of set-up of each method and their comparison

According to the different characteristic of each method, a general structure of fault diagnosis based on non-model based method can be depicted in figure 9. It consists of four steps-data preprocessing, feature extraction, feature reduction and fault classification.

Figure 9. Role of each kind of method in fault diagnosis

1) Monitoring and pre-processing of original data. Polarization curves, electrochemical impedance spectroscopy (EIS), cyclic voltammetry (CV), linear sweep voltammetry (LSV), etc, can be applied as original data for further fault analysis [9]. Since data from different sensors may have different ranges, e.g. pressure in millibars and voltage in tens of volts, it is necessary to normalize them into range of [-1, +1] (for example). This could facilitate further processing steps. Additionally, original data usually contains some extent of noise. A de-noising procedure may help to decrease the misclassification rate.

2) Feature extraction. Its task is to extract features which are relevant to the target fault from the original data. It is worth noting that the process of extraction also contains a certain degree of reduction. FFT, STFT and WT techniques can be included into this step, since they aim to convert the time-domain data into frequency- domain one, providing a new view of the original data.

3) Feature reduction. In most cases, features extracted from the original data are highly correlated. A feature reduction step means to convert a high-dimensional feature space into a low-dimensional feature space, while retaining as much information as possible. In this sense, (K) PCA, (K) FDA can be involved. What should be noted is that, sometimes feature extraction and reduction can be integrated into one step. Also, roles of methods included into these two parts could be exchanged.

4) Fault classification. Based on the low-dimensional feature space, a proper classifier should be further designed for fault classification. This classifier can either be a qualitative one or be a quantitative one. NN, FL, neural-fuzzy method and BN can be chosen in this step.

As it is well known, no single method can satisfy all the requirements for the monitoring of a complex system like PEMFC system. One method may complement another to obtain better performance. Thus hybrid approaches based on the above mentioned methods are highly expected. In fact, during former discussions about each single method, some combinations such as WT with ANN, ANFIS and BN classifier, also PCA with ANN classifier, have already been demonstrated to be effective for fault diagnosis.

Here, another good example is shown in [94]. A digital band-pass filter is first designed to reduce the negative effect of noise. Then PCA is applied to reduce the correlations among each sensor measures. Based on the new uncorrelated sensors, WT is performed to extract the wavelet coefficients, the dimension of which is further reduced by PCA. Fault classification is finally done by constructing a binary decision tree. Efficiency of the proposed methodology is validated on a complex chemical plant-TE process.

6. Conclusions

In this paper, three non-model based methodologies are outlined and discussed. Artificial Intelligence methods are very suitable for fault classification when given discriminating features. The second class of methods which is based on statistical analysis, such as PCA, provides an effective tool for variable dimension-reduction. Thus initially high correlated variables are converted into a small number of uncorrelated features. Furthermore, a PCA model under normal conditions is built as a reference for fault detection. Or the acquired features are used as inputs of fault classifiers. It is worth noting that, although PCA is the most widely used method, FDA has better diagnosis performance, as it seeks a relevant direction for discrimination. In order to extract nonlinear features among variables, Kernel PCA and Kernel FDA which apply kernel functions are further introduced. Additionally, Bayesian Network (BN), as one kind of statistical classifiers is also included in the second class. It consists of two parts- a network structure and conditional probabilities among nodes in different layers, and it provides an effective tool for dealing with three diagnosis problems: uncertainty, decision and reasoning. The third class-signal processing method is based on analysis of signals which can reflect the occurrence of certain types of faults. According to former researches, some relevant and commonly used signals, such as stack/cell voltage and pressure drop signals are listed. As the traditional FFT has the limitation of incapability to analyze non-stationary signals, some improved versions, such as STFT, CWD and WT are further discussed. Among them, WT is believed to be the most promising one due to its excellent time and frequency resolutions. In the final part of this paper, hybrid method which integrates different kinds of methods is introduced. This kind of method is believed to be a new trend in fault diagnosis of PEMFC system.

This paper is the second part of two review papers which aim to give an overview on diagnosis methodologies for PEMFCs. Compared with model-based methodology, a potential problem existing in non-model based one relates to the need of datasets that must include the targeted fault condition.

This could be very time-consuming when generating the related fault in the actual system, especially in the case of multi-faults. Furthermore, this may cause irreversible damages to the system.

However, non-model based methodology is still believed to be promising in future study of PEMFC system, due to its characteristics of simplicity, flexibility, capability of dealing with nonlinear problems, no requirement of system structure knowledge.

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8. References

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Table1 A comparison of the introduced dimension-reduction method

Characteristics	Linear	Nonlinear
Representation	PCA	KPCA
Classification	FDA	KFDA

Table2 Signals related to certain types of faults in PEMFC syste

Articles	Signals	Related fault type in PEFCs
Chen et Zhou. (2008) [69]	Cathode pressure drop	Cathode flooding
	Anode pressure drop	Water present at anode
Hernandez et al. (2006) [89]	Individual cell voltage variance; mean voltage	Flooding
Shen et al. (2008) [90]	A temporary voltage fluctuation	Air starvation
Niroumand et al. 2010 [91]	Pressure–cell voltage ratio	Low cathode/ anode flow rates
Barbir et al. (2005) [92]	Cathode pressure drop	Flooding
	Cell resistance	Drying
Tian et al. (2008) [93]	Stack open current voltages	Anode/ cathode crossover
Yousfi Steiner et al. (2011) [85]	Stack voltage	Flooding

Table3 Examples of set-up of each method and their comparison

Non-model based methods	References	Single cell/stack	Type of sensors used for diagnosis	Fault types	On /off-line
Neural network	[22]	20 single cells (25cm2)	40 sensors: voltage-20; current-20	SOH (status of health)	off
Fuzzy logic	[2]	100 W FC stack (3 cells, 100cm2)	EIS spectrometer (voltage, current)	1 types: durability	off
Principle component analysis (PCA)	[42]	2.5 kW FC stack (50 cells, 150cm2)	35 sensors: voltage-2; current-1; temperature-22; pressure-6; flow (water, air H2)-5; humidity-1	SOH	off
	[41]	2 FC stack (80kW in total)	17 sensors: voltage-6;current-2; temperature-6; pressure-3	SOH	on
Bayesian network (BN)	[62]	Fault tolerant fuel cell	5 sensors: voltage-1; current-1; temperature-1; pressure-1; power-1;	4 types: Fault by fuel crossover, H_2 pressure; fault in the air blower, refrigeration system.	on (simulation in MatLab)
	[63]	FC stack (20 cells, 100cm2)	EIS spectrometer (voltage, current)	2 types: flooding; drying	off
Fast Fourier transform (FFT)	[69]	FC stack (10 cells)	3 sensors: cathode/anode pressure; stack voltage	1 type: flooding	off
Wavelet transform (WT)	[85]	FC stack (20 cells, 100cm2)	1 sensor: Stack voltage	1 type: flooding	off

Figure1 Classification of non-model based method

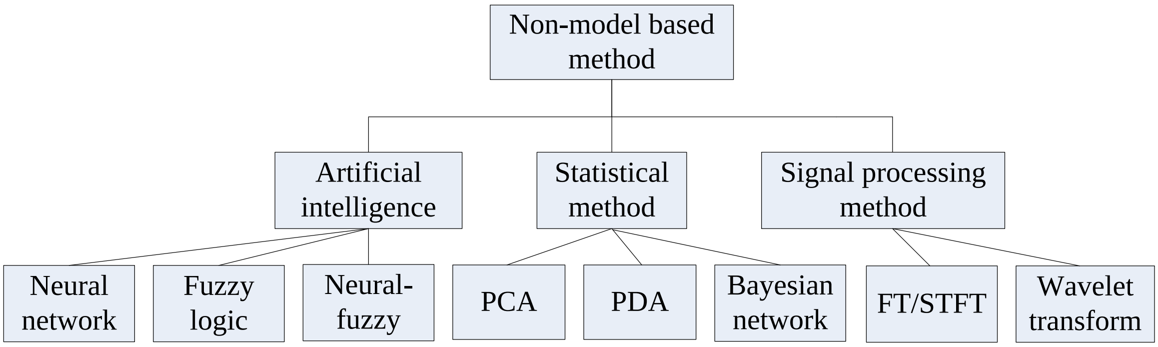

Figure2 Hamming neural network

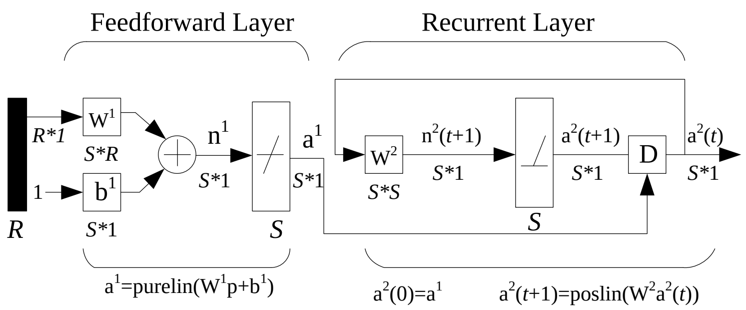

Figure3 Fuzzy clustering diagram

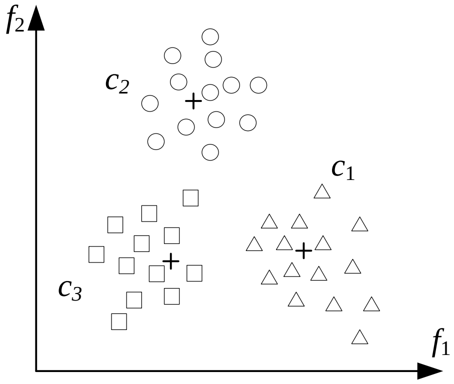

Figure4 A typical ANFIS architecture

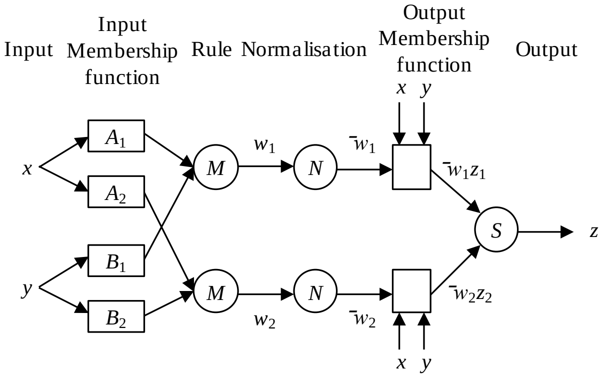

Figure5 A geometric interpretation of PCA

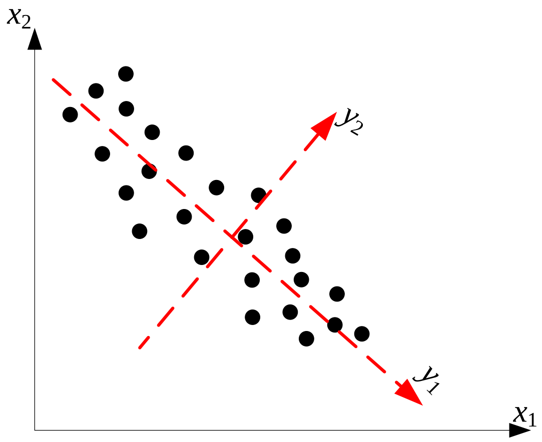

Figure6 A geometric interpretation of FDA

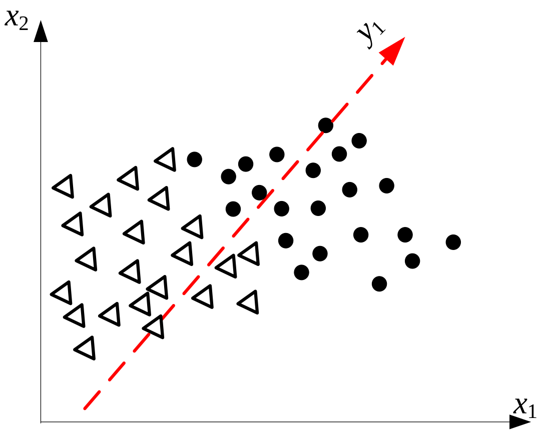

Figure7 Bayesian network structure for fault diagnosis in PEMFC

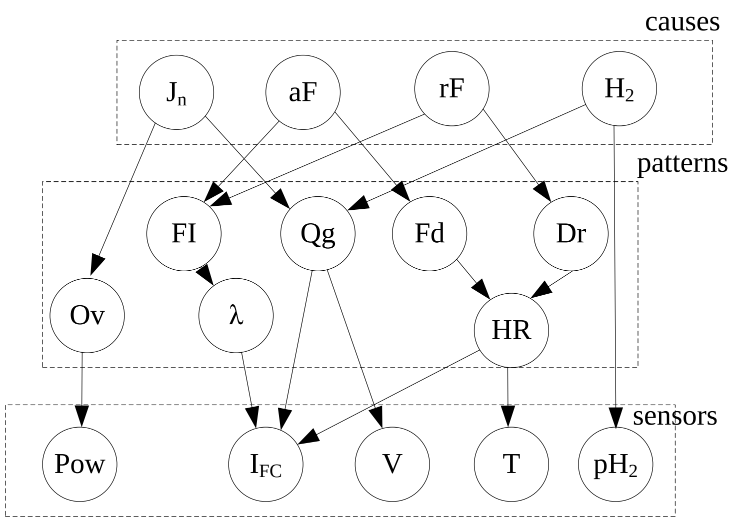

Figure8 Three level signal decomposing diagram

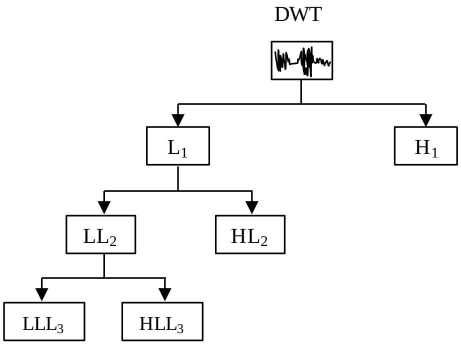

Figure9 Role of each kind of method in fault diagnosis