Fault Diagnosis of PEMFC Systems In The Model Space Using Reservoir Computing

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***Abstract*—Artificial neuron network provides a promising solution for fault diagnosis of fuel cell systems. A recently proposed novel framework of recurrent neuron network named Reservoir Computing is focused with only its output weights to be trained, which is rather advantageous for online adaption in real-time applications. In a previous work, its simplicity and efficiency has been demonstrated. This paper focus on a novel attempt of performing fault diagnosis directly in the reservoir computing based model space (current-voltage model) instead of the original data space (voltage signal). No additional feature extraction procedure is needed and abnormal health states could be detected directly in the model space (in the form of evolution of output weights).**

Keywords—PEMFC system; fault diagnosis; reservoir computing; model space; dynamical conditions

I. Introduction

Fault diagnosis plays a critical role in reinforcing the durability and reliability of polymer electrolyte membrane fuel cell (PEMFC) systems, which are regarded as two main bottlenecks for the commercialization phase. According to whether an analytical PEMFC model exists, existed fault diagnosis methods can be categorized into two general kinds: model-based and data-driven methods [1], [2]. Among the data-driven methods, artificial neural network (ANN), especially the recurrent neural network (RNN) type, provides a promising solution as it demonstrates a strong capability in the modeling or pattern recognition tasks of nonlinear dynamical systems, while no deep knowledge about the underlying physical processes is required [3]–[5]. Theoretically, it can approximate arbitrary dynamical systems with arbitrary precision, also called "the universal approximation property", under mild and general assumptions.

Concerning the practical applications especially for real-time fault diagnosis of PEMFC systems, the online adaption capability of the method is highly desirable [6]. Traditional RNN methods generally suffer from a high computational complexity, a slow convergence rate and the existence of bifurcations (resulting in local optima or even non-converging of the training process). To overcome their limitations, a fundamentally novel framework for RNN design and training was proposed independently by Prof. Jaeger in 2001 under the name of Echo State Network (ESN) [7] and by Prof. Maass under the name of Liquide State Machine (LSM) [8]. Together with the later appearing Back-Propagation De-Correlation (BPDC) learning rule, they are collectively referred to as Reservoir Computing (RC).

RC differs from traditional RNN in that a large number of neurons are used (tens to thousands vs. tens of neurons in traditional RNN) and in that only the output weights need to be trained (usually in a linear way, while all the connection weights are trained in the traditional RNN) [9]. Therefore, it can greatly facilitate the training phase and further the online adaptation process in the real-time applications. Excellent performances of RC are reported in the literature in various practical applications, including the speed recognition task (word error rate 0% vs. 0.6% of previous methods) [10], the non-linear wireless channel equalization task (improved by two orders of magnitude) [11], the prediction of the chaotic dynamics (improved by three orders of magnitude) [12].

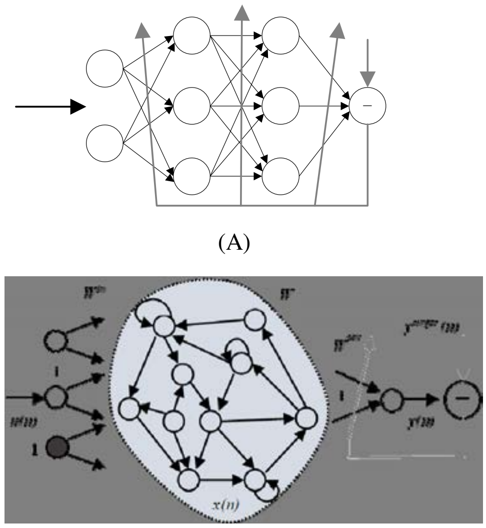
Despite its simplicity and efficiency, it is still a novel concept in the fuel cell (FC) fault diagnosis domain. An initial attempt of applying RC for PEMFC system diagnosis was made in [13]. Four fault types were targeted, including CO poisoning, low air flow rate, defective cooling and natural degradation. An excellent classification rate of the 99.9% in the training phase and 93.4% in the testing phase was obtained respectively. Meanwhile, the influence of a set if RC key parameters was studied. Nevertheless, only the static operating conditions were studied. This work was further developed in [14], [15] under PEMFC dynamic profiles and with an automatic optimization procedure separately. These previous works considered the stack voltage as a reliable health indicator of the FC system and took it as the only RC input and performed pattern recognition in a supervised way (each fault corresponds to a certain voltage pattern).

In this paper, an innovative framework of performing PEMFC fault diagnosis utilizing RC is developed, inspired by the idea of "learning in the model space" proposed in [16]. It differs from the previous works in that it performed fault diagnosis directly in the RC based model space instead of the original data space. A brief introduction of RC basics is made in the following section. The experimental work performed by the authors is introduced in section 3. Section 4 provides more details on the RC based fault diagnosis methodology. The conclusion and perspectives is given in the final section.

II. RESERVOIR COMPUTING BASICS

A. *Principal of Rerservoir Computing (RC)*

RC differs from the traditional RNN training methods in two basic aspects. First, the internal connections are assumed to be fixed and are not updated during training. Second, only the output weights need to be determined in the training process and they can easily be calculated by linearly regression techniques [17]. The training process is thus strongly simplified, and for online adapting algorithm, this is rather advantageous. A schematic illustration is shown in Fig. 1.



(A)

(B)

Fig. 1. Traditionnal RNN and RC paradigm: (A) Traditional gradient-descent based RNN training methods adapt all connection weights, including input-to-RNN, RNN-internal, and RNN-to-output weights. (B) In RC, only the RNN-to-output weights (bold arrows) are adapted ([13]).

Generally, RC consists of three distinct parts: an input layer, a reservoir and an output layer. The input layer is connected to the reservoir via a randomly generated input weight matrix (W^{in}), which remains unchanged during training. The reservoir contains many randomly interconnected nodes (via W) which are also left untrained [17]. When excited by the input signals, the reservoir exhibits complex transient dynamics, which are further read out by the output layer via an output weight matrix (W^{out}). As shown in Fig.1 (B), the update equations of a typical structure are

$$\tilde{x}(n) = \tanh(W^{in}[1;\, u(n)]+Wx(n\text{-}1))$$
$$x(n) = (1\text{-}\alpha)x(n\text{-}1)+\alpha\tilde{x}(n) \qquad (1)$$

Where $u(n)$ is the input vector, $x(n)$ is a vector of reservoir neuron activations and $\tilde{x}\,(n)$ is its update at time step n. and W^{in} and W are respectively the input matrix and recurrent matrix, α is the leakage rate.

The linear readout layer is defined as

$$y(n) = W^{out}\,[1;u(n);x(n)] \qquad (2)$$

Where $y(n)$ is the output vector, W^{out} is the output weight matrix and it can be calculated by minimizing the Mean Square Error (MSE) between $y(n)$ and $y^{target}\,(n)$. The most universal and stable solution to calculate W^{out} is the ridge regression, also known as regression with Tikhonov regularization [18]:

$$W^{out} = \mathrm{Y}^{target}\mathrm{X}^{T}(\mathrm{XX}^{T} + \beta\mathbf{I})^{-1} \qquad (3)$$

Where β is the regularization coefficient and $\mathbf{I}$ is the identity matrix.

B. *RC model based fault diagnosis*

The fundamental idea of applying RC for fuel cell fault diagnosis is to represent directly the original data (e.g. stack voltage) by sliding RC models and to perform fault diagnosis directly in the obtained model space. Abnormal behaviors occurring in the PEMFC system will be reflected in the deviation of the output weight matrix. No additional feature extraction based on the data space is thus needed. A more robust representation of the fuel cell health behavior could be obtained. A framework of the proposed fault diagnosis methodology is illustrated in Fig. 2. In the initial stage of this work, stack current (I_{stk}) and stack voltage (V_{stk}) are applied as RC input and output separately. The corresponding W^{out} is generated by a linear combination of different internal states (plotted in blue lines in the reservoir). Under different operating conditions, the evolution of W^{out} could be analyzed for fault diagnosis. More details are given in section IV.

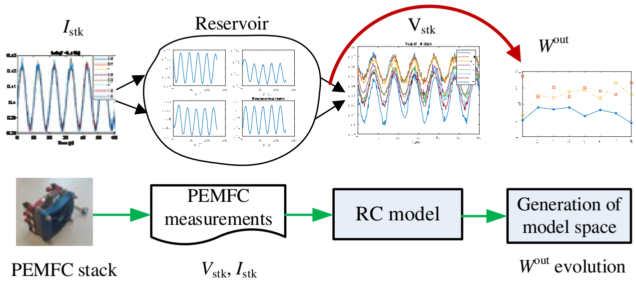


Fig. 2. Framework of the proposed RC based fault diagnosis methodology

III. PEMFC SYSEM DESCRIPTION

A. *1 kW experimental test bench*

A three-month experimental characterization of the ZSW 5-cell fuel cell stack (BZ 100_13) was performed within the French FCLAB laboratory (FR CNRS 3539), with its active surface 96 cm^2, taking into consideration the influence of the operating current I_{stk} and seven operating parameters, including: the air/H_2 stoichiometry (FSC/FSA), the air pressure (P_{air}), the stack temperature (T_{stk}), the anodic/cathodic relative humidity (RH_{H2}/RH_{air}) and the cooling water flow rate (F_{water}).

The influence of I_{stk}, under both the static condition and the dynamic excitations was studied. Three forms of excitations were performed, i.e. sinusoidal, square and sawtooth, each form with 2 magnitudes respectively, i.e. 2A and 5A, and 5 exciting frequencies, i.e. 1000 Hz, 100 Hz, 30 Hz, 10 Hz, 5 Hz, 1 Hz, 0.1 Hz. Sampling frequencies are 50 kHz, 5 kHz, 2 kHz, 500 Hz, 250 Hz, 50 Hz and 5 Hz respectively. Corresponding Labview control surface is shown in Fig.3 left.

Table 1 shows the nominal operating parameters of the studied PEMFC system. In the initial stage of this work, the influence of air stoichiometry (FSC) is firstly studied to verify the efficiency of the proposed methodology.

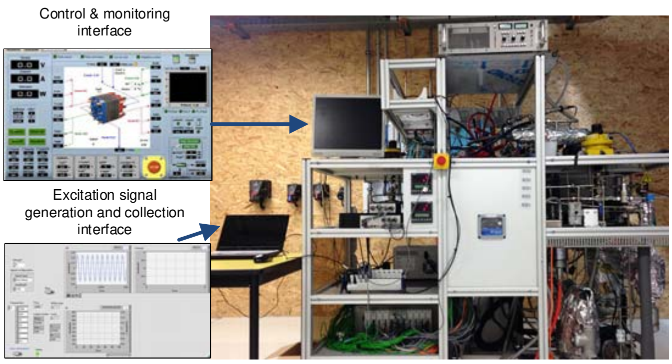


Fig. 3. 1 kW test bench with its control interfaces

TABLE I. PEMFC SYSETEM OPERATING PARAMETERS

System parameters	Operating range	
Current	Max 120A	
Voltage	Max 0.95*5 = 4.75V	
Power	Max 45*5 = 225W	
Stack temperature	10-65°C at stack outlet	
Pressure	Anode	Max 2.0 bar_{abs} (0.1 1.0 bar_g)
	cathode	Max 2.0 bar_{abs} (0.1 1.0 bar_g)
Flow rate and utilization	Hydrogen	Min 0.2 l/min/cell Max 1.4 l/min/cell 60-80 % utilization
	Air	Min 0.7 l/min/cell Max 5 l/min/cell 25 - 50 % gas utilisation
Cathode relative humidity	Humidified air	50-100% Dew point 25 - 55 °C
Anode relative humidity	hydrogen	Dry to dew point 55 °C
CO tolerance	Max.10 ppm	

IV. FAULT DIAGNOSIS METHODOLOGIE USING RC

A. RC model

The fuel cell stack is operated under a constant DC current 40A with an additional and sinusoidal perturbation of low amplitude (typically 5% of the DC component). The voltage response of the stack is measured. Different operating conditions are applied, mimicking a fault in the air supply system (Fig. 4). As a matter of fact, the air stoichiometry factors are varied from high values to low values (from 4 to 1.5, with 2.8 as nominal value).

A one-input and one-output small RC model is trained to model the voltage response of the stack under different FSCs. The RC critical parameters are initially chosen as: number of internal nodes = 20, leakage rate α = 0.3, regularization parameter $\beta = 1\times 10^{-8}$, input matrix W^{in} and internal recurrent matrix W are generated randomly in the range of [-0.5, 0.5]. It should be noted that these parameters can be further optimized to adapt a certain task. And global optimization methods, such as genetic algorithm, and big bang crunch algorithm can be selected to perform automatic optimization [15,18].

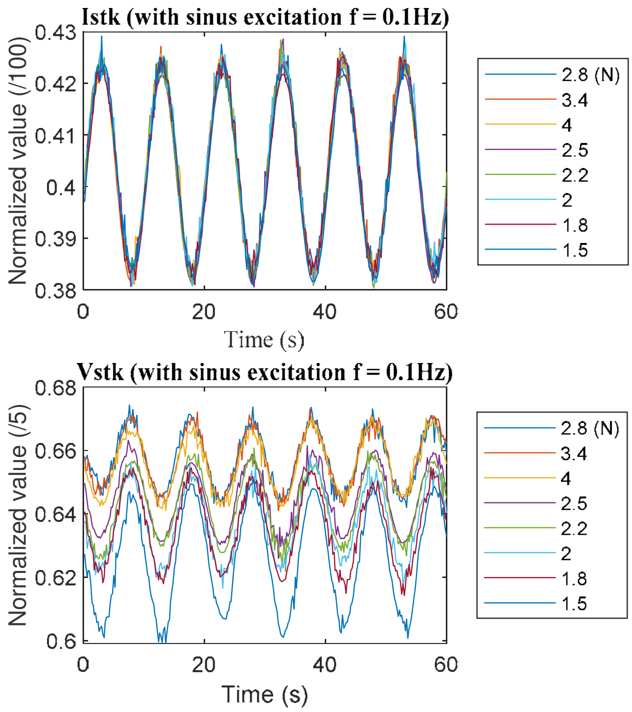


Fig. 4. Stack current (normalized by divising 100) and voltage (normalized by divising 5) under different air stoichiometries (nominal condition FSC=2.8) with sinusoidal excitation 0.1 Hz

Fig. 5 shows the trained RC output and V_{stk} under the nominal condition FSC = 2.8. It could be found that the RC output matches well the real stack voltage, and a Mean Square Error (MSE) is obtained less than 0.003%. Meanwhile, the corresponding output weight matrix W^{out} is calculated and plotted with its 22 elements (i.e. 1+1+20 as indicated in Eq (2)) in Fig. 6. Essentially, W^{out} could be regarded as a group of internal FC system parameters which reflect the nonlinear relationship between the I_{stk} and V_{stk} under the dynamic excitations. This input-output relationship could certainly be established in other simpler nonlinear functions such as polynomial functions. RC model is selected herein considering its demonstrated capacity in dealing with temporal signals in dynamic systems. And this characteristic will be further explored in the following work for dealing with more complex multi-fault diagnosis under dynamic operating conditions.

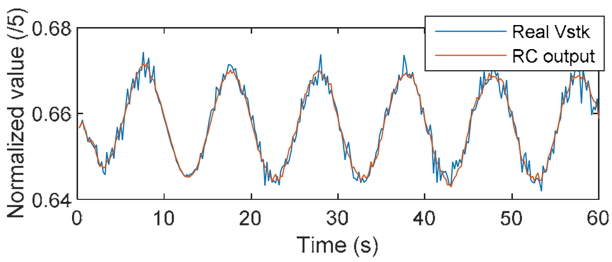


Fig. 5. Stack voltage (FSC = 2.8) under sinusoidal excitation and RC output

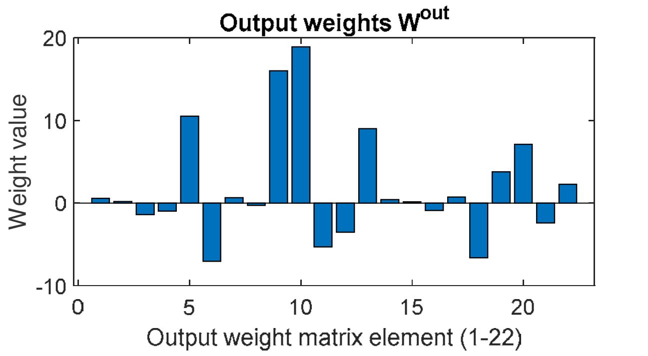


Fig. 6. Output weight matrix elements under nominal operating condition

B. RC model-space based fault diangosis

The basic principal of RC model-space based fault diagnosis is to represent the original signals (i.e. I_{stk} and V_{stk} in this initial work) by dynamic models (reservoirs with linear readouts) and perform diagnosis in the model space of the readouts (i.e. output weight elements). Alternatively, RC model can be regarded as a robust representation of FC system voltage-current behavior. Abnormal health states can result in the deviation of stack voltage from the normal behavior, and this deviation could be reflected in a more robust form of output weight matrix.

Fig.7 shows the states of the neurons inside the reservoir and it gives an insight into the dynamic behavior of each neuron evolving with time (200 time steps are plotted). It can be observed that during the initial 50 time steps, the reservoir neurons demonstrate initial transient behavior, and this is called "washout layer". They should be discarded in the training phase.

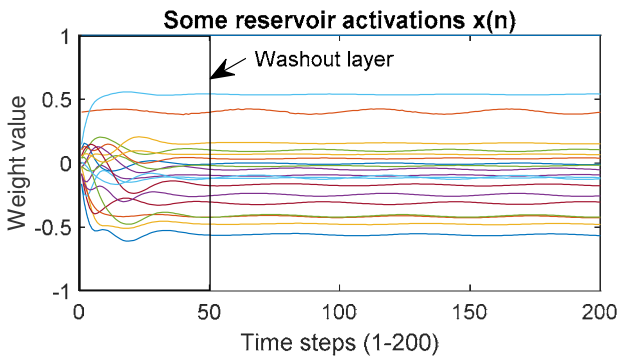


Fig. 7. Iinternal neuron states inside the reservoir

The output weight matrix is obtained during the training phase and the distribution of its elements is given in Fig. 8. This distribution can be related to the air stoichiometry factors and used for diagnostic. To demonstrate more clearly the influence of the air stoichiometry factor, the 6th, 9th, and 20th elements of the output matrix are selected for further observation, as shown in Fig. 9.

In Fig. 9, it can be observed that the lowest and highest air stoichiometries (i.e. 1.5 and 4, corresponding to number 1 and 8 in the horizontal axis) deviate the most from the nominal condition (corresponding to number 6). The feasibility of utilizing the evolution of output weight matrix elements in the model-space is thus demonstrated. This is rather advantageous for real-time applications where the online adaption capability is highly required, as only linear readouts are needed to be recalculated in the proposed method.

In the following work, supervised algorithms such as fuzzy logic, support vector machine can be further applied for fault classification [19].

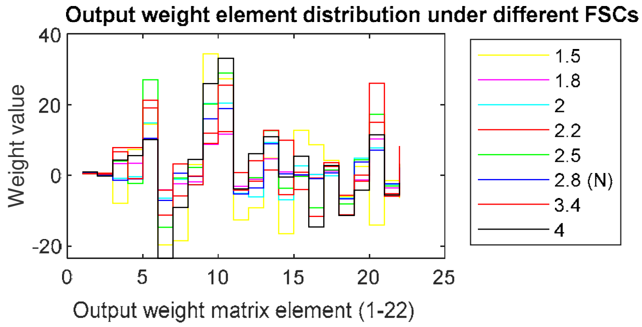


Fig. 8. W_{out} distribution under different FSC configurations

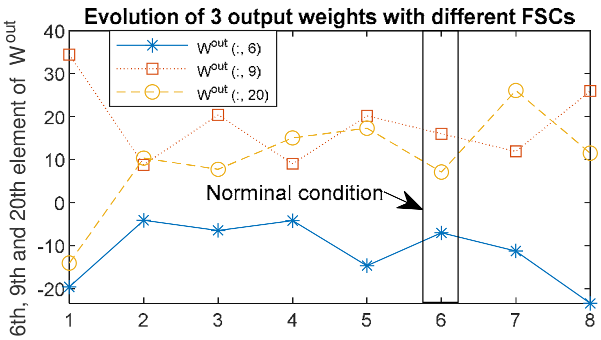


Fig. 9. Variation of the 6th, 9th and 20th element of W_{out} under 8 FSCs

V. Conclusion

In this paper, an initial attempt is made to perform PEMFC system fault diagnosis in the RC based model space. The RC model establishes a relationship between stack current and stack voltage under various dynamic excitations (sinusoidal type). An excellent performance for the modeling task is obtained (less than 0.003%). In the next step, abnormal health behavior could be detected in the distribution of the output weight distribution. This initial work demonstrates the feasibility of the idea of learning in the model space based on RC method.

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