## PHM ORIENTED BEHAVIOR MODELING FOR PEM FUEL CELL SYSTEMS VIA DELAYED FEEDBACK RESERVOIR COMPUTING MODEL

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#### ABSTRACT

In this paper, a framework named *model space* based PHM design is proposed for PEM fuel cell systems. The objective is to address the PHM problem in consideration of the various operating conditions and system dynamics. In this frame, modeling of fuel cell systems is realized via a type of black box model named Delayed Feedback Reservoir Computing Model (DFRCM). The modeling and the PHM performance is validated using experimental data.

### I. INTRODUCTION

Knowing that reliability and durability are two key criteria for commercialization of Polymer Electrolyte Membrane Fuel Cell (PEMFC) technologies, efforts have been taken not only to improve the fuel cell (FC) design and assembly, but also to optimize system operations. This necessitates the availability of automatic detection and isolation of the faults and reconfiguration of the control system accordingly. Recently, topics on Prognostics and Health Management (PHM) of PEMFC systems have attracted increasing attention of both academic and industrial communities.

Fault diagnosis and prognosis are two main elements in the PHM cycle. Fault diagnosis is deserved to detecting and isolating the faults that occur at different parts of the system. While the main goal of prognosis is to estimate Remaining Useful Life (RUL) and associate a confidence interval [1]. A main branch of theories on diagnosis and prognosis methods are built with the assumption that the system process model is available. The fault diagnosis can be realized by comparing the measured physical variables with the ones that calculated with the model and a part of measured data. While, prognosis can be realized by evaluating the variation of some crucial parameters of the system model.

PEMFC systems are undoubtedly complex and nonlinear ones which involve the phenomenons of electro-chemistry, fluid mechanics, thermodynamics. Modeling an arbitrary PEMFC system with first principle is always considered as a tough task. As well, various parameters, structures and control laws exist for different FC designs and applications. Some well-established models, such as the one proposed in [2], may not be well fitted for other systems with different system parameters, constructions and control laws. The adaptation of a model form for an alternative FC system is not a trivial task.

Meeting the above mentioned difficulties on first principle modeling, the researchers have been trying to analyze some crucial variables by adopting advanced signal processing and machine learning techniques to solve the PHM problems, meanwhile avoid the modeling process. For instance, concerning fault diagnosis aspect, Zheng et al. [3] propose to realize the fault diagnosis via analyzing Electrochemical Impedance Spectroscopy (EIS) with some machine learning tools. Benouioua et al. [4] achieve fault diagnosis by analyzing voltage signal via wavelet transformation combined with multifractal formalism. Concerning prognosis aspect, method named Echo State Network is used to simulate and predict the trajectory of FC voltage degradation [5].

The common points of the above work is that the FC stack is assumed to operate at a constant or quasi constant operating conditions. In such conditions, the factors which affect the variation of the FC behaviors are limited to the faults and ageing effect. However, the assumption seems to be hard to arrive in practical cases. First, the FC systems are usually operated in a varied operating condition with dynamic and transitional processes. The variation of FC behaviors can be affected by changing operating condition other than faults or ageing effect. Second, it has been found that the degradation mechanism is highly dependent on operating conditions. The operations such as dynamic load cycling, startup/shutdown significantly accelerate the degradation rate of FCs. Hence, PHM strategy should be designed in consideration of the different operating conditions and dynamic processes.

To conquer the above mentioned problem, a framework of PHM is proposed in this paper. In the framework, fault diagnosis and prognosis are not investigated in the data space but in the model space. The inherent idea is that, the data sampled in normal state with dynamic process in wide operating range can be described by a behavior model. The parameters of the model is constant if there are no faults and ageing effect. On contrary, some faults or degradations related to ageing effect are detected if the parameters of the model are changed to some degree.

Considering that a process model can probably well describe the dynamic process in a wide operating range, and a sufficiently accuracy, generalized, but not sophistical first-principle model is hard or even impossible to obtain for PEMFC systems, the model selected to describe the FC stack is a recently proposed model. The model, inherently belongs to black-box model class, is named Delayed Feedback Reservoir Computing Model (DFRCM) in this study. The main advantages of this modeling technique are that the model fitting process can be efficiently performed. Meanwhile, the high modeling precision can be maintained.

In the rest of the paper, the frame work of *model space* based PHM strategy is introduced firstly in Section II. Then, the main effort is taken to presenting the technique DFRCM in Section III and its application for PHM oriented PEMFC system modeling in Section IV. Finally, the study is concluded in Section V.

## II. FRAMEWORK OF MODEL SPACE BASED PHM STRATEGY

Traditionally, PHM is realized in the data space. In this paper, the framework in which the PHM is realized in the model space instead of data space is proposed. As shown in Fig. 1, the model space based PHM strategy is divided into learning phase and implementing phase. In the learning phace, the historical data including input and output ones are firstly segmented into a series of data segments. Then, using these data segments, a series of models with the same form can be fitted. Therefore, the model parameters corresponding to the data segments can be obtained. In the implementing phase, fault diagnosis and prognosis can be implemented based on the obtained system parameters. For instance, the fault detection problem can be considered as a outlier detection problem [6]. While prognosis can be considered as a curve fitting or regression problem.



Fig. 1. Schematic of model space based PHM

The benefits of this framework can be summarized as follows:

• In a real FC system, a variety of dynamic processes exist at the moments of starting up, shutting down, increasing and decreasing the load. The data sampled in dynamic processes are not time-independent. Dynamic processes are considered in this framework though fitting the models with time series. • The models are fitted using both input and output data. Therefore, the impacts of input variables other than faults and ageing effect are taken into account.

# III. DELAYED FEEDBACK RESERVOIR COMPUTING MODEL

Recurrent neural network (RNN) has been considered as a powerful tool to model a nonlinear and dynamic system, as it can exhibit a nonlinear dynamical temporal behavior. At the early of the last decade, a new paradigm, called Reservoir Computing (RC) emerges which solves the training problems of RNN effectively from a new perspective [7].

More recently, a simple structure consisting a single non linear node and a delay line, i.e. DFRCM in this paper, is proposed to implement RC experimentally via optoelectronic tools [8]. The results proposed in [8] show that the very simple structure has high-level information-processing capabilities in both dynamic system modeling and pattern classification aspects. Taking into account the characteristics of simple structure and high performance in modeling dynamical systems, DFRCM is selected to project the data into model space.

#### A. Principle of DFRCM

The general scheme of DFRCM is shown in Fig. 2. In the structure, a nonlinear node with delayed feedback is used. A reservoir is obtained by dividing the delay loop into N intervals and using time multiplexing. The input states are sampled and held for a duration  $\tau_D$ , where  $\tau_D$  is the delay in the feedback loop. For any time, the input state is multiplied with a mask, resulting in a temporal input stream J(t) that is added to the delayed state of the reservoir  $x(t - \tau_D)$  and then feed into the nonlinear node. The output is calculated as the weighted sum of the state variables [8].



Fig. 2. Illustration of basic RC structure [8]

## B. Steps to realize a general DFRCM

#### Step 1: Time multiplexing

The input stream u(k) undergoes a sample-and-hold operation, resulting in a stream I(t) that is constant in time delay  $\tau_D$ , as

$$I(t) = u(k) \in \mathcal{R}^{M \times 1} \quad \text{for } \tau_D k \le t < \tau_D(k+1) \quad (1)$$

Within one delay of  $\tau_D$ ,  $N_{node}$  virtual nodes are defined.  $\tau_D$  is separated into  $N_{node}$  sub time interval, denoted as  $\delta \tau_D = \tau_D / N_{node}$ .

Defining periodic mask function, as:

$$M(t) = W_{I,i} \in \mathcal{R}^{1 \times M}, \ i = 1, \dots, N_{node}$$
(2)

for  $(i-1)\delta\tau_D \leq t < i\delta\tau_D$  and  $M(t+\tau_D) = M(t)$ . Generally, the values of  $W_{I,i}$  are chosen randomly from some probability distribution.

Then, the value to be injected into the reservoir is given by

$$J(t) = M(t) \cdot I(t) \tag{3}$$

#### **Step 2: States calculation**

In the reservoir, the nonlinear evolution equation is implemented. In this paper, referring the proposal of [9], the nonlinear equation of the following form is considered:

$$\tau \frac{dx(t)}{dt} + x(t) = \beta \sin^2[\alpha x(t - \tau_D) + \gamma J(t) + \Phi]$$
 (4)

where  $\tau$  is the internal characteristic time scale of the nonlinear dynamic; x(t) is the state variable of the reservoir;  $\beta$ ,  $\alpha$ ,  $\gamma$ ,  $\Phi$  are parameters to be initialized.

The equation can be realized using the ronge-kutta method (RK4). The integration time step, denoted as h, is a fraction of response time  $\tau$ .

For ith virtual node of the kth discrete reservoir, the state is given by

$$x_i(k) = x \left( k\tau_D - (N-i)\delta\tau_D \right) \tag{5}$$

the states of all the nodes in kth discrete reservoir is collectively expressed as  $\boldsymbol{x}(k) = [x_1(k), \dots, x_{N_{node}}(k)]^T$ .

Step 3: Output calculation

То

$$y(k) = W_O \boldsymbol{x}(k) = \sum_{i=1}^{N_{node}} w_i \cdot x_i(k)$$
(6)

where  $w_i \in \mathcal{R}^{L \times 1}$  is the element of *output weight matrix*  $W_O = [w_1, \ldots, w_{N_{node}}] \in \mathcal{R}^{L \times N_{node}}$ .

So-called *ridge regression* is used to pursue the weight matrix in the training process.  $W_O$  is obtained through

$$W_O = (X_{train}^T X_{train} + \lambda I)^{-1} X_{train}^T Y_{train}$$
(7)

where I is  $N_{node}$  order unit matrix,

$$X_{train} = \begin{bmatrix} \boldsymbol{x}(1)^T \\ \vdots \\ \boldsymbol{x}(N_{train})^T \end{bmatrix}$$
$$Y_{train} = \begin{bmatrix} \boldsymbol{y}(1)^T \\ \vdots \\ \boldsymbol{y}(N_{train})^T \end{bmatrix}$$

DFRCM can be summarized as Algorithm 1.

## Algorithm 1 DFRCM

## **Training:**

- 1: Collect  $N_{train}$  input and output data, i.e.  $\boldsymbol{u}(1), \boldsymbol{u}(2), \ldots, \boldsymbol{u}(N_{train}),$  and  $\boldsymbol{y}(1), \boldsymbol{y}(2), \ldots, \boldsymbol{y}(N_{train}).$
- 2: Initialize parameters  $\beta$ ,  $\alpha$ ,  $\gamma$ ,  $\Phi$ ,  $\tau_D$ ,  $N_{node}$ , h,  $\tau$ ,  $\lambda$ . Among them,  $\tau$  is set as the base value, h and  $\tau_D$  are set with respect to  $\tau$ .
- 3: Define mask function M(t) according to (2).
- 4: Calculate J(t) according to (3).
- 5: Initial  $x(t), 0 \leq t < \tau_D$ .
- 6: Calculate  $X_{train}$  according to (4) by using RK4 method.

7: Calculate  $W_O$  according to (7).

## **Performing:**

- 1: For a new input series  $\boldsymbol{u}(1), \ldots, \boldsymbol{u}(N_p)$ .
- 2: Repeat step 2 to step 6 in training procedure.  $X_{N_p}$  is obtained.
- 3: Calculate  $\boldsymbol{y}(1), \ldots, \boldsymbol{y}(N_p)$  using  $X_{N_p}$  and  $W_O$  according to (6).

## C. Remarks

Algorithm 1 presents the training and performing procedures to achieve a general modeling. In this study, DFRCM is adopted not for a traditional modeling goal but for PHM. To be specific, the parameters of output matrix  $W_O$  obtained in training procedure are considered as the variables for diagnosis and prognosis goals.

## IV. APPLICATION OF DFRCM FOR PEMFC SYSTEM

In this section, the DFRCM is applied for real PEMFC systems in two aspects. In the first aspect, DFRCM is used for modeling the dynamic behaviors of a commercial PEMFC system. In the second aspect, DFRCM is used to extract the PHM oriented features.

## A. Example 1: Modeling dynamic profiles for a commercial PEMFC system

The concerned PEMFC system is a commercial air-cooled 1.2-kW Ballard NEXA system. This stack is supplied by compressed air and hydrogen and is cooled with air fans. The detailed technique parameters can be found in [10]. From the test bench, the stack voltage, stack temperature, load current, reactant air flow rate, cooling air flow rate, and environment temperature can be measured. A DC electronic load is used to simulate an arbitrary current profile with abundant dynamic processes.

In the experiment, a dynamic current cycle during 522 s was produced using the electronic load. The current form is shown in Fig. 1. To construct the DFRCM for this cycle, the environment temperature, current, cooling air flow, and stack temperature are considered as the input variables. While the reactant air flow and stack voltage are seen as the output variables. Actually, the reactant air flow is regulated with respect to the current value. The stack voltage is normally considered as the output variable of the whole system.



Fig. 3. Load current profile

The first 312 samples are used for training, while the rest 211 samples are used to test the trained model. The parameters used for the modeling procedure are summarized in Table I.

TABLE I PARAMETERS USED FOR MODELING NEXA PEMFC SYSTEM

β	$\alpha$	$\gamma$	Φ	$ au_D$	$N_{node}$	h	λ
0.85	1	0.5	0.76	160	400	0.02	$5 \times 10^{-6}$



Fig. 4. Comparison between measured and simulated stack voltages

The real stack voltage response and the model results are illustrated in Fig. 3. The proposed fuel cell stack model demonstrates great accuracy with regard to the experimental measurements. For the entire stack operating range, the maximum relative error in voltage is less than 5%. The voltage dynamic behavior is well reproduced by the model.

#### B. Example 2: model based PHM

1) Experimental setting: The concerned fuel cell stack is designed with the structure of open cathode and dead-end anode. Some crucial parameters are listed in Table II.

 TABLE II

 Paramenters of the investigated fuel cell stack

Fuel cell type	Open cathode/Dead-end anode		
Nominal pressure at hydrogen inlet	0.35 bar		
Number of cells	15		
Nominal output current	8 A		
Nominal output power	84 W		
Maximum temperature	75 °C		
Maximum current	13.45 A		
Lowest permitted stack voltage	7.5 V		

A current profile obtained from the real motive application is simulated thanks to the programmable DC load. A length of current shape is shown in Fig. 5. It can be seen that the current varies between 0 and 8 A.



Fig. 5. Current profile

Stack voltage, individual cell voltages (cell voltages 1 to 15), temperatures (temperatures of the positions cell 1, cell 8, and cell 15), current. Sample frequency is 5 Hz.

The data during the 1500 h test were recorded. The overview of the stack voltage evolution is shown in Fig. 6(a). Some details can be seen in Fig. 6(b). These stops are considered as the environment disturbances in this study.

2) DFRCM model identification: The whole data are divided into 1000 equal segments. Thus, the duration of each segment is 1.5 h. For each data segment, a DFRCM model identification is implemented. The model input is defined as the current values of present sample and last two samples (I(k), I(k - 1) and I(k - 2)). After model identification procedure, the output is defined as the current stack voltage (V(k)). The model identification result, i.e. the model output and real measurement, in a segment is shown in Fig. 7. It is seen that the model fits the system behavior well.

3) Prognosis implemented in model space: With the identified model, the prognosis can be implemented in this model space. Here, by setting the input as constant, the corresponding steady state output voltage can be reconstructed. The output in nominal condition can thus be pursued and considered as the prognosis oriented feature. Based on the experimental data,



(a) Stack voltage evolution during the whole test



(b) Details of the stack voltage evolution

Fig. 6. Stack voltage evolution



the calculated nominal stack voltage versus time is shown as the blue line in Fig. 8 and Fig. 9.

With the extracted nominal stack voltage evolution, the prognosis can be implemented by creating a time series model and using the model for prediction. Here, the time series model is a 2nd order state-space system with noise input. The implementation details can be found in [11].

Fig. 8 and Fig. 9 show the mean prognosis results. The prediction horizon in Fig. 8 is 750 h, while the one in Fig. 9 is 300 h. The bounders which correspond to the 99.7 % confidence interval. It can be seen that the prediction values well fit the real signal evaluation in the two cases.



Fig. 8. Model identification result

#### C. Discussion

- In order to obtain a precise model, the data used for model identification should contain sufficient information on the concerned system dynamics. This requires the data segment should be large enough.
- 2) The DFRCM is used to model the concerned fuel cell systems. It should be noted that this specific model



Fig. 9.

Proc. of the Int. Conf. on Integrated Modeling and Analysis in Applied Control and Automation, 2017 ISBN 978-88-97999-88-1; Bruzzone, Dauphin-Tanguy, and Junco Eds.

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can possibly be replace by other models to obtain a comparable performance.

## V. CONCLUSION

In this paper, model space based framework is proposed to design PHM for FC systems. DFRCM, a black-box model, is used as the modeling tool to demonstrate the proposed framework. By exploring the evaluation of the model parameters, PHM in dynamic operating conditions can be realized without knowing the first principle system model in prior. DFRCM is firstly used for modeling the NEXA fuel cell system to validate its modeling capability. Then, this modeling tool is used to solve the prognosis problem for another fuel cell system. The results show that DFRCM is suitable for modeling the dynamics of fuel cell systems. Meanwhile, the model space generated by DFRCM identification can be used for PHM and acquire satisfying performance.

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