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Fault diagnosis and prognostic of solid oxide fuel cells

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HIGHLIGHTS

- A scheme that simultaneously performs fault diagnosis and prognostic is proposed.
- A LS-SVM model is built to identify SOFC fault type.
- HSMM method is employed to predict the remaining useful life of SOFC.

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ABSTRACT

One of the major hurdles for solid oxide fuel cell (SOFC) commercialization is poor long-term performance and durability. Accurate fault diagnostic and prognostic technologies are two important tools to improve SOFC durability. In literature, plenty of diagnosis techniques for SOFC systems have been successfully designed. However, no literature studies SOFC fault prognosis approaches. In this paper a unified fault diagnosis and prognosis strategy is presented to identify faults (anode poisoning, cathode humidification or normal) and predict the remaining useful life for SOFC systems. Using a squares support vector machine (LS-SVM) classifier, a diagnosis model is built to identify SOFC different types of faults. After fault detection, two hidden semi-Mark models (HSMMs) are respectively employed to estimate SOFC remaining useful life in the case of anode poisoning and cathode humidification. The simulation results show that the fault recognition rates with the LS-SVM model are at best 97%, and the predicted error of the remaining useful life is within ±20%.

1. Introduction

Due to lower emissions, high efficiency, useful waste heat and fuel flexibility, solid oxide fuel cells (SOFCs) are a vital generating device, which are widely applied in auxiliary power units (APUs) and stationary power generators [1]. However, poor durability and long-term performance are still one of the major hurdles for SOFC commercialization.

Fault diagnosis and prognosis technologies are considered as two important tools to improve system reliability and lifetime. In the last ten years, various diagnosis approaches for SOFC systems have been developed. These works can be sorted in two main categories: 1) model-based fault diagnosis methods. Firstly build a SOFC model, which includes either physical models [2–6] or black models [7]. Then compute the instantaneous remoteness between the real SOFC behavior and the expected healthy behavior. Finally through the residue analysis, faults can be detected. 2) non-model-based fault diagnosis approaches. These methods involve fault-tree algorithms [8,9], principal component analysis methods [10], and artificial neural networks (ANN) [11]. A complete study on SOFC diagnosis methods is done in an overview [12]. These fault diagnosis approaches can efficiently optimize control actions and enhance degradation prevention capabilities for SOFC systems. However, fault diagnosis technology can not predict the future degradation trend of SOFC systems. If the SOFC degradation can be estimated before it completely fails, maintenance persons will have time enough to make maintenance plans and get replaced components. This may decrease repair and maintenance costs, and avoid the SOFC unscheduled downtime.

Thus, prognosis technology is developed, which has the ability to estimate a system future degradation trend before the system completely fails. The International Standard Organization defines prognostics as the remaining useful life estimation [13]. In recent years, prognostics have been successful used in many fields, such as mechanical systems [14,15], electrochemical devices [16,17], and air

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cooling systems [18]. However, as far as we know, no literature studies the prognosis approaches for SOFC systems. In Ref. [19], Dario proposed prognostics for the SOFC system. However, this study did not investigate the SOFC remaining useful life estimation. Using model-based prognostic methods, Refs. [20–22] proposed the remaining useful life prediction for proton exchange membrane fuel cell (PEMFC) systems. However, these model-based prognostic approaches are computationally expensive, and it is a difficult task to construct the models.

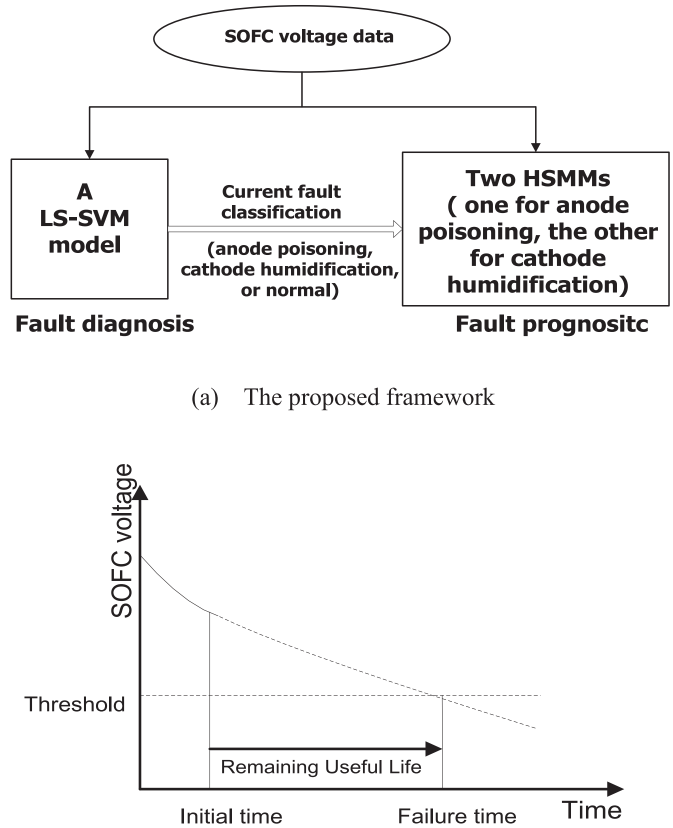
Motivated by the above need, a unique scheme that simultaneously performs fault diagnosis and prognostic is proposed for the SOFC system in this work. Firstly, a least squares support vector machine (LS-SVM) classifier is investigated to identify the SOFC current fault type. Due to the advantages for solving nonlinear and small samples, LS-SVM models are widely applied in various fields for fault diagnosis, such as bearing [23], blast furnace [24], and cooling system [25]. However, practical application of the LS-SVM model to identify the SOFC faults can not be found in prior papers. Secondly, hidden semi-Mark models (HSMMs) are employed to estimate the remaining useful life of the SOFC. SOFC systems usually experience several degraded states to reach failure, which can be represented by various states of an HSMM. Through computing the duration time of each health state, the remaining useful time of the SOFC system can be predicted.

2. Fault diagnosis and prognosis strategy for SOFC systems

Plenty of experiments show that the SOFC degradation has an influence on the output voltage [19]. Therefore, the SOFC voltage is chosen as the degradation signal in this study. A complete voltage database under the different degradation mechanisms is difficult to obtain. In this paper, the following two degradation mechanisms are taken into account, for the voltage degradation data in these two cases can be collected from the open literature [26,27]:

1) Anode poisoning: Various types of fuels can be applied with the SOFC because of its fuel flexibility. However various impurities contained in the fuel may lower the SOFC performance [28]. Here anode poisoning by Cl_2 is discussed.
2) Cathode humidification: High water vapor concentration in the cathode may lead to a severe degradation of the SOFC performance [29]. Thus this work analyzes the cathode humidification fault (too high humidification).

The objective in this paper is to diagnose the SOFC fault type (anode poisoning, cathode humidification, or normal), and estimate the SOFC remaining useful life before it completely fails. Therefore, the proposed fault diagnosis and prognosis scheme for the SOFC is illustrated in Fig. 1(a). Firstly, using the SOFC individual fault state data sets, a LS-SVM model is built to classify the SOFC fault type. Secondly, two HSMMs are respectively established for fault prognostics in the case of anode poisoning and cathode humidification. Fault prognostics aim at the remaining useful life estimation, and the remaining useful life of the SOFC is defined as the duration between the predicting starting time and the failure time, which is illustrated in Fig. 1(b). When the voltage drops below a critical threshold value, the SOFC is considered to have failed. The threshold value is used to determine the SOFC end, and the selection of the threshold value typically depends on the required precision of the specific application. In the case of anode poisoning fault, reference [26] provides the voltage degradation trend that the SOFC runs for 150 h. Therefore, the threshold is selected as the 150 h value of the SOFC voltage curve. However, in the case of the cathode humidification fault, the threshold value is set at the 1000 h voltage value because reference [27] supplies the 1000-h running history of the SOFC.



(a) The proposed framework

(b) Illustration of the remaining useful life

Fig. 1. Fault diagnosis and prognosis strategy of the SOFC.

3. SOFC fault diagnosis based on a LS-SVM model

Assume training samples $\{(x_k, y_k^{(l)}) | k = 1, 2, \cdots, I; l = 1, 2, \cdots, M\}$. Where, x_k is the input pattern for the k-th training sample of the SOFC, and $y_k^{(l)} \in \{-1, 0, 1\}$ is the output of the l-th output unit for pattern $k.I$ is the training data points and M is the output unit number. Based on the one-versus-one (1 vs 1) output coding algorithm, the M outputs can encode X different fault classes, where, $M = X(X-1)/2$ [30]. In this study, the corresponding target class is three (SOFC normal, anode poisoning, and cathode humidification), i.e., $X = 3$. Thus using the 1 vs 1 output coding, there are three output units in this paper, i.e., $M = 3$.

The LS-SVM classifier for the SOFC is constructed based on the below formulation [31]:

$$\min J(w_l, e_{k,l}) = \frac{1}{2}\sum_{l=1}^{3} w_l^T w_l + \frac{\gamma}{2}\sum_{k=1}^{I}\sum_{l=1}^{3} e_{k,l}^2 \tag{1}$$

$$s.t.\begin{cases} y_k^{(1)}\left[w_1^T\varphi_1(x_k) + b_1\right] = 1 - e_{k,1} \\ y_k^{(2)}\left[w_2^T\varphi_2(x_k) + b_2\right] = 1 - e_{k,2} \\ y_k^{(3)}\left[w_3^T\varphi_3(x_k) + b_3\right] = 1 - e_{k,3} \end{cases}$$

Where, w_l is the weight vector of the l-th output unit, and $e_{k,l}$ is the difference between the expected value and actual value of the l-th output unit for the k-th training sample. γ is a user-defined control