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### A hybrid method for remaining useful life prediction of fuel cells under variable loads\*

Chu Wang, Zhongliang Li, Rachid Outbib, Manfeng Dou

Abstract— Cost and durability are crucial factors limiting the widespread commercialization of proton exchange membrane fuel cells (PEMFC). Prognostics, aiming at health indicator extraction and remaining useful life prediction, is a key issue for durability enhancement. However, PEMFC deploying prognostics for PEMFC under dynamic load still faces challenges in extracting health indicators reliably and predicting the degradation evolution efficiently. This work proposes a data-driven PEMFC prognostics approach, in which Hilbert-Huang transform is used to extract health indicator in dynamic operating conditions and symbolic-based gated recurrent unit model is used to predict the remaining useful life. The proposed method is tested using long-term dynamic load ageing experiments. The results show that the method can provide reliable prognostics horizons and improve real-time performance.

#### I. INTRODUCTION

Proton exchange membrane fuel cells (PEMFCs) are carbon-emission avoiding energy conversion devices, which are considered a promising alternative to fossil fuels [1]. Nevertheless, the cost and the performance still constrain the wider commercialization of PEMFCs. Especially in the transportation field, the durability of PEMFCs emerges as a major bottleneck. For instance, fuel cell electric vehicles (FCEVs) suffer from complex operating conditions, which accelerate the degradation of PEMFCs. The maximum average durability of FCEVs is about 4000 hours, while the performance will degrade by 30% after 5000 service hours [2].

Prognostics and health management (PHM) is a promising durability enhancement solution for PEMFCs. In turn, the remaining useful life (RUL) can be predicted to support condition-based maintenance (CBM) [3]. However, dynamic mission profiles make it difficult to access the health indicator (HI) directly. Several scholars extract the inherent degradation parameters of PEMFC by mechanistic models and utilize filter methods to identify these parameters as HIs [4-6]. Li et al. deploy the linear parameter-varying (LPV) model in a series of sliding data segments and consider the reconstructed virtual steady-state stack voltage as HI [7]. Yue et al. present a polarization function-based model in [8] and segment the measured voltage to extract HI using a nonlinear regression method. However, these methods have shortcomings such as high computational cost, requiring extra characterization tests, and hardly tracking transient dynamics.

C. Wang, Z. Li and R. Outbib are with the LIS Lab (UMR CNRS 7020), Aix-Marseille University, 13397 Marseille, France (e-mail: chu.wang@lis-lab.fr; zhongliang.li@lis-lab.fr; rachid.outbib@lis-lab.fr). The prognostics dedicated RUL prediction needs to extend the prognostics horizon (PH) to the order of hundreds to thousands of hours [3]. Thus, long-term prognostics provide ample time to develop maintenance schedules to avoid fatal failures. In state-of-the-art works, extended Kalman filter (EKF) based methods [4, 5], long short-term memory (LSTM) network based methods [6, 9, 10], and echo state network (ESN) based methods [7, 8, 11] are used to predict the RUL under dynamic mission profiles. Most of these methods often need cautious model configurations and the RUL performance in these proposed works is not fully justified due to limited data and evaluation criteria.

In this work, a data-driven prognostics method based on time-frequency analysis and symbolic recurrent neural networks (RNNs) is proposed. Specifically, the long-term degradation component of the dynamic stack voltage is first extracted as HI using the Hilbert-Huang transform (HHT). The HI is compressed using adaptive Brownian bridge-based aggregation (ABBA) and represented as а reduced-dimensional symbolic sequence [12]. Gated recursive unit (GRU)-based RNN predicts the reduced-dimensional symbol sequence. Further, the predicted sequences are reconstructed to obtain future HI trends, which are eventually used to estimate the RUL. The proposed method is evaluated using dynamic load ageing experimental data of PEMFC. In comparison with other state-of-the-art methods, the proposed method takes the shortest computational time while extracting reliable HI. In the RUL prediction phase, the proposed method provides effective PH up to hundreds of hours scale.

#### II. HEALTH INDICATOR EXTRACTION MODEL

The HHT, proposed by Huang et al. [13], consists of two steps: First, the input signal is decomposed into a series of intrinsic mode functions (IMFs) and a residual using empirical mode decomposition (EMD). Second, the Hilbert spectrum of each IMF is obtained by deploying the Hilbert transform (HT). The combination of EMD and Hilbert Spectral Analysis (HSA) provides a time-frequency-energy analysis method [14].

Generally, EMD sifting is iteratively implemented and stopped under the condition that a monotonic residual is obtained. The residual reflects the trend characteristics in the original signal [15]. The residual contributes to revealing the physical characteristics of the signal as it is the low frequency or null component [14]. In this work, the dynamic voltage of the PEMFC is used as the input signal of EMD sifting. The proper residual from the input signal is identified by iteratively implementing EMD and designated as HI. Considering the instantaneous frequency (IF) is one of the key features for analyzing the signal based on natural conditions [14]. In this paper, an HI extraction process based on IF analysis is proposed as shown in Fig. 1. Instead of pursuing a completely

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monotonic residual as the stop condition of the EMD sifting process, the method analyzes whether the IF of the residual is below a set threshold. IMF should satisfy the following criteria [13]: (1) The number of poles and zeros should not differ by more than one; (2) The mean of the upper and lower envelope curves should be zero.



Figure 1. HHT-based health indicator extraction process

#### III. HYBRID RUL PREDICTION

Thanks to the convincing time series processing capability, several LSTM framework-based prognostics methods are developed for PEMFC [6, 9, 10]. Compared to LSTM, GRU effectively simplifies the hidden unit structure and reduces the number of parameters [16, 17]. This facilitates the training/prediction efficiency of GRU and promises to improve the real-time prognostics performance. As mentioned in our previous works [9, 10, 18], the performance of raw LSTM is not satisfactory in multi-step-ahead prediction in the application of fuel cell prognostics. Similarly, GRU suffers from this issue.

This work proposes an ABBA-based GRU (ABBA-GRU) model to tackle multi-step-ahead prediction involved in prognostics. The historical HI is used as input, while the output is the predicted trend. The core of the ABBA-GRU model includes three components: conversion, prediction, and reconstruction. To improve prediction efficiency and accuracy, HI is normalized and re-scaled to between zero and one before being fed to ABBA-GRU.

The remaining useful life prediction process is shown in Fig. 2. The details about conversion phase and reconstruction phase of ABBA can be found in our previous work [9]. The five-layer GRU model is used in the prediction phase. The previous hidden state  $(h_{t-1})$  together with the current symbol  $(a_t)$  constitute the input. After proper processing by the reset gate  $(r_t)$  and update gate  $(z_t)$ , the current hidden state  $(h_t, i.e., predicted symbol <math>\hat{a}_t)$  is output. In a GRU layer, the hidden units are linked sequentially to form a chain. The functional equations of the GRU are as follows.

$$\begin{cases} r_t = \sigma(W_r a_t + U_r h_{t-1} + b_r) \\ z_t = \sigma(W_z a_t + U_z h_{t-1} + b_z) \\ \tilde{h}_t = \tanh[W_h a_t + U_h (r_t \odot h_{t-1}) + b_h] \\ h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \end{cases}$$
(1)

where  $\sigma$  and tanh represent the activation functions, which are sigmoid and hyperbolic tangent, respectively.  $W_x$ ,  $U_x$ , and  $b_x$  are the input weight matrix, the unit internal weight matrix, and the bias vector, respectively. Among them, the subscript x corresponds to r (reset gate), z (update gate), and h (implicit state). The  $\tilde{h}_t$  is unit internal hidden state (a. k. a., candidate activation) vector. The operator " $\odot$ " denotes Hadamard product.

Figure 2. Schematic diagram of the remaining useful life prediction process



IV. FUEL CELL AGEING EXPERIMENT

The long-term durability test is from an open cathode/dead-end anode PEMFC under dynamic load. The operating conditions are shown in Table I.

TABLE I. TABLE TYPE STYLES

Parameter	Value
Active surface (cm <sup>2</sup> )	33.63
Pressure at hydrogen inlet (bar)	1.35
Pressure at air inlet (bar)	1.013 (i.e., 1 atm)
Nominal output power (W)	73.5
Operating temperature (°C)	29.6 to 51.7
	(Corresponding to current)
Number of cells	15
Temperature regulate mode	24-V dc air fan
Humidity regulate mode	Non-humidifier
	(self-humidified)

Figure 3. Voltage profiles of dynamic load cyclic from fuel cell ageing experiment



The FC is compactly designed for hybrid electric bicycles. The stack contains 15 cells with an integrated 24V DC fan for air supply and temperature regulation. The operating temperature is related to the load current. In addition, the FC is self-humidifying and performs a purge lasting 0.5 s per 30 s [7]. The mean cell voltage profile from the dynamic load cycle of FC is shown in Fig. 3. In each dynamic cycle, the start-up/standby operating conditions in the hybrid system are simulated [9]. More details about FC and durability testing can be found in our previous works [7, 9].

#### V. PERFORMANCE EVALUATION

The programs used in this paper are developed in Python 3.7.11, Keras version 2.4.3, and Tensorflow version 1.15.0 backend software environments. They are deployed on a desktop computer containing an Intel Xeon E3-1230-v3 processor @ 3.3 GHz and 16 GB memory.

Figure 4. (a) IMFs and residual obtained by EMD, (b) Time-frequency-energy spectrum of the residual



The dynamic voltage is decomposed into eleven IMFs and one residual. Fig. 4 (a) show the partial (1st, 5th, 9th) IMFs and the final residual of FC. Besides, Fig. 4 (b) shows the time-frequency-energy spectrum of the residual. The HHT-based HI extraction method square effectively separates the high-frequency features (IMFs) and the low-frequency feature (residual) of the dynamic voltage signal. The residual retains a relatively high level of instantaneous energy, as in Fig. 4 (b). The instantaneous energy distribution of the residual shows a natural decreasing trend along the ageing time. This allows the residual to indicate the intrinsic degradation process of stack voltage.

Figure 5. (a) Comparison of HI extracted by three methods, (b) Predicted RULs



In addition, the rationality of the proposed method is evaluated by comparing it with two other HI extraction methods. The first method (Curve-fitting) uses the degradation model proposed in [8]. The second method (LPV-ARX) utilizes the linear parameter-varying (LPV) model structure, as in [7], called autoregressive model with exogenous input (ARX). The HIs extracted by all three methods are normalized and rescaled into the range of zero to one. As in Fig. 5 (a), all three methods match well, besides a few outlier points. The computational costs of the three methods are compared, as in Table II.

TABLE II. COMPUTATIONAL COST COMPARISON OF THE THREE METHODS

Method	Execution time (s)
Curve-fitting	55.61
LPV-ARX	1167.77
HHT	21.73

The ABBA-GRU model is deployed at each prognostics point and the RUL is predicted. The RUL prediction results are shown in Fig. 5 (b), all PHs reach 1032.5 hours.

#### VI. CONCLUSION

In this paper, a data-driven prognostics approach is

proposed for fuel cells under dynamic operating conditions. A Hilbert-Huang transform-based method is utilized to extract the health indicator from the dynamic voltage of fuel cells. The historical health indicator data is used to train the ABBA-GRU model, which in turn predicts the degradation trends and the remaining useful life of the stack. The prognostics approach is evaluated with the ageing data. The proposed approach enhances real-time performance while providing a credible prognostics horizon and appropriate prediction accuracy. It facilitates the online deployment of the prognostics method. In future work, efforts will be made to explore prognostics-based operational control strategies to extend fuel cell lifetime.

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