



Data-driven proton exchange membrane fuel cell degradation predication through deep learning method

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HIGHLIGHTS

- Deep learning method is used to predict fuel cell degradation.
- G-LSTM cell based RNN is deployed for the prognostic.
- Aging experimental tests with different fuel cells are conducted.
- The G-LSTM can make predictions within the same framework.
- The proposed prognostic model can be applied to online diagnosis.

ARTICLE INFO

Keywords:

Fuel cell
Prognostics
Degradation model
Long short-term memory
Deep machine learning

ABSTRACT

Proton exchange membrane fuel cells (PEMFCs) is one of the principal candidates to take part of the worldwide future clean and renewable energy solution. However, fuel cells are vulnerable to the impurities of hydrogen and operating conditions, which could cause the degradation of output performance over time during operation. Thus, the prediction of the performance degradation draws attention lately and is critical for the reliability of the fuel cell system. In this work, we propose an innovative fuel cell degradation prediction method using Grid Long Short-Term Memory (G-LSTM) recurrent neural network (RNN). Long short-term memory cell can effectively avoid the gradient exploding and vanishing problem compared with conventional neural network architecture, which makes it suitable for the prediction problem for long period. By paralleling and combining the cells, Grid long short-term memory cell architecture can further optimize the prediction accuracy of the fuel cell performance degradation. The proposed prediction model is experimentally validated by three different types of PEMFC: 1.2 kW Ballard Nexa fuel cells, 1 kW Proton Motor fuel cells and 25 kW Proton Motor fuel cells. The results indicate that the proposed Grid long short-term memory network can predict the fuel cell degradation in a precise way. The proposed deep learning approach can be efficiently applied to predict the lifetime of fuel cell in transportation applications.

1. Introduction

Fuel cell technology is considered one of the most attractive power sources for future transportation system due to the concerns for environment preservation and fossil fuels depletion [1]. Among different fuel cells types, proton exchange membrane fuel cell (PEMFC) is considered the most suitable one for automotive applications due to its low operating temperature, higher power density and short start time.

Thanks to the advancement in material engineering, the PEMFC can now satisfy the power demand and operating requirements of vehicular applications. However, the fuel cell lifetime should still be increased in order to meet the requirements of transportation applications.

The degradation performance of PEMFCs is strongly influenced by the operating conditions [2]. Durability is a main concern to successful deploy the fuel cell system on the market [3]. Thus, in order to control efficiently the fuel cell system and maximize the fuel cell lifetime, the

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degradation phenomena should be understood in a clear way and be able to be predicted by a precisely degradation model.

The fuel cell degradation model can usually be classified into two categories: model based and data based. Most of the researches in literature conduct the degradation prediction through building semi-empirical models [4–11]. The fuel cell degradation in both electrical and mechanical domains are analyzed to predict the voltage drop as the operating time increased. The electrodes and electrolyte degradations are also discussed in order to develop the prediction models. One of the advantages of the model-based methods is that they do not require a large amount of experimental data. However, all these proposed semi-empirical models still depend on experimental measurements and must be previously adapted for different types of fuel cells to be able to predict the performance degradation.

In order to improve the adaptability and the accuracy of the degradation model, data-driven degradation predictions and diagnostic methods are adopted to fuel cell related applications recently. In [12] the authors proposed a hybrid data-driven method combined with conventional model-based approach for PEMFC prognostics. Procedures for data selection and processing are proposed, whereas the proposed method still suffers from computational issues, which is not suitable for online diagnostic problem. Another work dedicating PEMFC prognostics has been proposed by Javed et al. in [13]. The presented model used a constraint based summation wavelet extreme learning machine (SW-ELM) to improve the robustness and the applicability of long-term prognostics of PEMFC for online applications. The developed algorithm is able to predict PEMFC lifetime under dynamic load conditions as well. Similar works have been proposed by Ibrahim et al. in [14]. The authors deployed a wavelet-based approach for online fuel cell remaining useful lifetime prediction. A prognostics method based on adaptive neuro-fuzzy inference systems is proposed to make long-term prognostics for PEMFCs by using the filtered data in [15]. However, these works are all focused on the long-term prognostic of the fuel cell. It is well known that, the short-term prognostics is also very important for the fuel cell lifetime and energy management systems. By applying the Kalman Filter into industrial applications, particle filter has been successfully deployed for the prognostics of the fuel cell in [16–18]. Mathieu et al. [16] proposed a prognostic method for the fuel cell by an observer based on an Extended Kalman Filter. The state of health and the dynamic of the degradations is estimated. Although the proposed methods are effective for the prognostics, analytical degradation models still need to be built in prior. A holistic solution towards prognostics of industrial PEMFC is proposed in [17]. Although it involves an efficient multi-energetic model suited for diagnostics and prognostics, the prediction by using this model has not yet been fully developed. Similar work in [18] used particle filtering framework. However, the model cannot make degradation predication. Wu et al. [19,20] proposed a fuel cell prognostic method by using the relevance vector machine (RVM). The authors have modified and improved the basic RVM algorithm and achieved higher prediction accuracy for both short and long-term prediction. However, the prediction RVM model needs to be re-trained from scratch once the fuel cell operating conditions change. Research work in [21] used cyclic voltammetry and linear sweep voltammetry to estimate the internal state of the fuel cell stack. Although it is a commonly used diagnostic approach, the prediction of the degradation cannot be done online in practical applications. Li et al. [22,23] proposed an effective long-term prognostics algorithm based on mode space learning. The prognosis-oriented features are firstly fitted by a series signal segments, and then extracted from the model parameters. The remaining useful life estimation of PEMFCs under certain current profiles can be obtained, whereas the short-term performance is not discussed. Onanena et al. contributed to the prognostic on fuel cell in [24]. Both the static and dynamic information extracted from the stack, which include polarization curve records and electrochemical impedance spectroscopy (EIS) measurement, can be used for the proposed pattern-recognition-based diagnosis approach to

estimate the remaining useful life of PEMFCs. EIS method is also deployed in [25] for the degradation prognostic of the fuel cell. Since additional efforts of EIS measurement and calculation are required, the proposed method cannot be directly used for online diagnostic control.

As can be seen from the previous mentioned literature, most of the prognostic methods use the fuel cell output voltage value to monitor the performance degradation. Thus, we can simply regard the degradation prediction as a time series problem, and model it using machine-learning methods. Among different kinds of neural networks, recurrent neural network (RNN) is suitable for the series data processing, which can be applied to the fuel cell degradation prediction problem. Liu et al. [26] proposed a combined wavelet analysis and the group method of data handling (W-GMDH). Although the model accuracy can reach the degradation prediction requirement, the proposed method is not capable to forecast the degradation in a future time. Suk et al. [27] proposed an accelerated degradation test (ADT) approach to reduce the fuel cell degradation testing time. Although the degradation trend can be obtained, the ADT may bring errors since the real degradation trend cannot be fully simulated. Morando et al. [28,29] deployed a PEMFC ageing forecasting algorithm based on the echo state network. The network must be trained with filtered data, and many parameters need to be configured for fuel cell voltage ageing forecasting, which makes the proposed method difficult to apply. However, the results obtained with a Mean Average Percentage Error (MAPE) of less than 5% prove the effectiveness of RNN based predicting approach.

The Long Short-Term Memory network (LSTM) is a type of RNN that achieves state-of-the-art results on challenging prediction problems. Deep learning methods like LSTM can be used to predict time series problem for both short and long periods. Compared with traditional RNN, LSTM is capable to avoid gradient exploding and gradient vanishing problem, which can make the short-term memory last for a long period of time [30]. Fuel cell aging under thousands hours operating makes LSTM suitable as a degradation prediction approach. The simple architecture also enables LSTM to be easily applied to online diagnostic control, which can help to design and verify the fuel cell system control methods [31]. In this paper, an innovative deep learning data-driven model for PEMFC degradation prediction is proposed based on LSTM network, which has never been discussed in the literature. Moreover, based on the conventional LSTM network, the paper proposes a Grid LSTM (G-LSTM) architecture to further improve the prediction accuracy. The proposed model is then verified by experimental aging test results of three different types of PEM fuel cells under eight different operating conditions. The main contributions of this paper can be summarized as follows:

1. Fuel cell degradation experiments are conducted with 8 different fuel cells under various operating conditions. The operating time ranges from hundreds of hours to ten thousand hours. All experimental aging data is recorded to evaluate the fuel cell operating performance.
2. Based on the conventional Recurrent Neural Network (RNN), the long short-term memory (LSTM) cell is added in order to avoid gradient vanishing and exploding. Such a deep learning method is then originally applied to the degradation prediction of the fuel cell.
3. Based on the basic LSTM cell, a Grid LSTM architecture is proposed and implemented to predict the fuel cell degradation. The corresponding training algorithm is designed to predict the degradations of different fuel cells under the same framework. The performance of the proposed deep learning G-LSTM RNN is verified by the experimentally measured degradation data.

The paper is organized as follows: Section 2 presents the fuel cell configurations, and their aging experimental test results under varies operating conditions. The deep learning approach by G-LSTM network is developed and analyzed in Section 3. In Section 4, the model prediction results are compared with the previous experimental measured

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