ISSN 2004-2965 Energy Proceedings, Vol. 18, 2021

International Conference on Applied Energy 2021
Nov 29 – Dec 02, 2021, Bangkok, Thailand
Paper ID: # 745

Data-driven prognostics for proton exchange membrane fuel cell degradation by deep learning method

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ABSTRACT

The durability of Proton exchange membrane fuel cell (PEMFC) is one of the technical challenges restricting its commercial application. In order to enhance the reliability and durability of PEMFC, a feature extraction method based on bi-direction long short-term memory (Bi-LSTM) and bi-direction gated recurrent unit (Bi-GRU) is proposed in this paper, which can effectively extract deeper degradation features. Feature extraction model linked with echo state network (ESN), which form a fusion prognostic framework to realize short-term degradation prediction and remaining useful life (RUL) estimation. For short-term prediction, only the first 200 hours of voltage degradation data were used for training can achieve an acceptable and accurate prediction, which the root mean square error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2) are 0.0235, 0.0195 and 0.9822, respectively. Comparing with traditional machine learning methods, proposed fusion prognostic framework shows the best predictive performance. Besides, a 100-step sliding windows method based on the fusion prognostic framework is used to implement RUL estimation. The results show that the percentage error (E_r) is only 1.22% with the first 200 hours training data. The proposed method has great significance for guiding online testing and health management of PEMFC.

Keywords: PEMFC, Prognostic, Remaining useful life, Bi-LSTM-GRU, Deep learning

NONMENCLATURE

Abbreviations	
Bi-LSTM	bi-direction long short-term memory
Bi-GRU	bi-direction gated recurrent unit
ESN	echo state network
PSO	particle swarm optimization
RUL	remaining useful life
Symbols	
A	Current
V	Voltage
t	Time Step

1. INTRODUCTION

PEMFC is considered to be one of the most promising alternative power supply for automotive power sources, which has the characteristics of high energy conversion efficiency, high power density, low operating temperature, less operating noise, clean and pollution-free, etc [1-4]. However, short lifespan blocks the large-scale commercialization of PEMFC [1,5-8]. Therefore, Prognostic and Health Management (PHM) technology is needed to predict the health status of PEMFC throughout the whole life cycle to extend the lifespan and enhance the performance of PEMFC.

2. PAPER STRUCTURE

2.1 Introduction

In general, there are two approaches for PEMFC prognostic: model-based methods and data-driven methods [9]. Model-based method rely on physical modeling of PEMFC degradation behavior, whereas are highly complex and require a depth understanding of the internal reaction mechanism of PEMFC. And the model varies with different types of fuel cells, which make these prognostic methods hard to be transferred to other types of fuel cells. In contrast, the data-driven approach simply uses historical data to predict performance degradation trends of PEMFC, which can avoid complex physical models and having much more flexibility and applicability comparing to the model-based method.

In this paper, a comprehensive prognosis method based on Bi-LSTM-GRU and ESN is proposed innovatively, which can perform short-term degradation prediction and estimate RUL. The short-term prediction and RUL estimation process are shown in Fig 1 The use of Bi-LSTM can effectively avoid the problem of gradient explosion and disappearance, and be more suitable for capturing the information of adjacent time nodes [10-12]. The Bi-GRU tends to grasp overall time series information [13]. ESN replaces the traditional flatten layer as the final output layer. In addition, ESN introduces a large number of sparse neurons to further reduce the risk of overfitting, which is a simple linear fitting without considering the excessive training time.

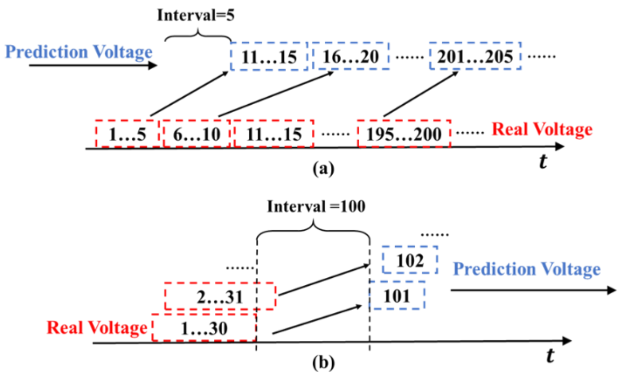

Fig 1 (a) Short-term degradation prediction; (b)RUL estimation

This paper is organized as follows: *Section 2.2* describe two experimental PEMFC stacks. The fusion prognostic framework is introduced in *Section 2.3* The experimental results and discussion are shown in *Section 2.4* The conclusion of this paper is given in *Section 2.5*

2.2 PEMFC system

The BI-LSTM-GRU and ESN fusion prognostic method is verified by IEEE PHM 2014 data challenge [14], where the data includ FC1 under steady-state operation and FC2 under dynamic operating conditions.

The tests were carried out on a test stand developed by the Fuel Cell Laboratory (FR CNRS 3539). The test bench is suitable for PEMFCs up to 1 kW. The test system consists of the fuel cell system, the control system, the electronic load and the LabView interface, where the fuel cell system consists of the fuel cell stack and the auxiliary system. The collected aging parameters are shown in Table 1. The output voltage of PEMFC is used as an indicator of stack degradation in this paper.

Table 1 Ageing parameters gathered during experiments

Parameter	**Physical meaning**
Time	Time Ageing time (h)
U1 to U5 ; Utot	Single cells and stack voltage (V)
I ; J	Current (A) and current density (A/cm^2)
TinH2 ; ToutH2	Inlet and Outlet temperatures of H_2 (℃)
TinAIR ; ToutAIR	Inlet and Outlet temperatures of Air (℃)
TinWAT ; ToutWAT	Inlet and Outlet temp. of cooling Water (℃)
PinH2 ; PoutH2	Inlet and Outlet Pressure of H_2 (mbara)
PinAIR ; PoutAIR	Inlet and Outlet Pressure of Air (mbara)
DinH2 ; DoutH2	Inlet and Outlet flow rate of H_2 (l/mn)
DinAIR ; DoutAIR	Inlet and Outlet flow rate of Air (l/mn)
DWAT	Flow rate of cooling water (l/mn)
HrAIRFC	Inlet Hygrometry (Air) - estimated (%)

2.3 Network framework

In this section, LSTM, Bi-LSTM and ESN network will be introduced respectively. For space constraints, the details of GRU and Bi-GRU architecture can be seen in Ref. [13].

2.3.1 LSTM

As a special Recurrent Neural Network (RNN), LSTM has the ability of long-term memory [15]. A LSTM unit is shown in Fig 2. X_t is the input of the current step. h_t denotes the output of the current step. C_t is the cell state of the current step, which is key to long-term memory. X_{t-1}, h_{t-1} and C_{t-1} stand the input, output and the cell state of the pervious step, respectively. The mathematical mechanism of the three gates of LSTM can be expressed as:

$$f_t = \sigma\left(W_f[X_t, h_{t-1}] + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i[X_t, h_{t-1}] + b_i) \tag{2}$$

$$\tilde{C}_t = tanh(W_c[X_t, h_{t-1}] + b_c) \tag{3}$$

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \tilde{C}_t \tag{5}$$

$$o_t = \sigma(W_o[X_t, h_{t-1}] + b_o) \tag{6}$$

$$h_t = o_t \otimes tanh(C_t) \tag{7}$$

where $W_x\,(x = i, f, c, o)$ are weight matrix, $b_x\,(x = i, f, c, o)$ are deviation vector. f_t, i_t, o_t represent forget gate, input gate and output gate, respectively.

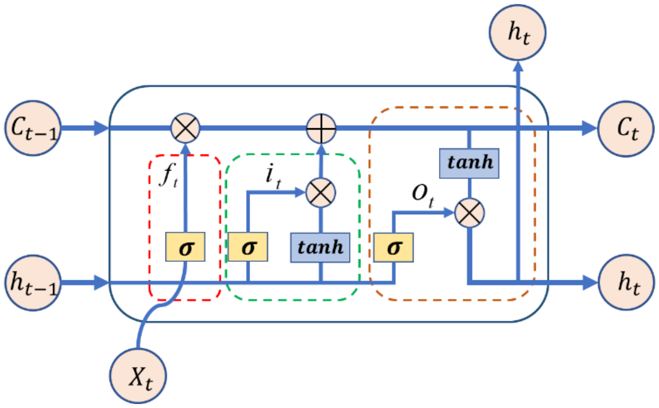

Fig 2 LSTM architecture flowchart

2.3.2 Bi-LSTM

The propagation of the Bi-LSTM is to divide the neurons into two directions, one for forward and another for backward direction [11]. This bidirectional propagation mechanism correlates states on both sides of time series information simultaneously, thus improving the long-term dependence of learning and increasing the accuracy of the model. As shown in Fig 3, the forward hidden state h and backward hidden state h' are concatenated to get the final output.

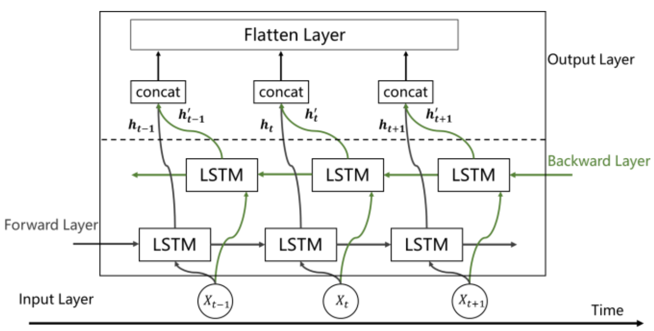

Fig 3 Bi-LSTM architecture flowchart

2.3.3 ESN

As shown in Fig 4, the ESN replaces the hidden layer of the RNN with a large dynamic reservoir that can be excited by suitable inputs [16]. Interestingly, the input weight matrix W_{in} and recurrent weight matrix W_{res} of the network are initialized (do not change). Therefore, only the output weight matrix W_{out} needs to be optimized by linear regression methods, which greatly improves the computational efficiency of the ESN. At the same time, it avoids the occurrence of local optimization in optimization algorithms such as gradient descent, that is, over-fitting.

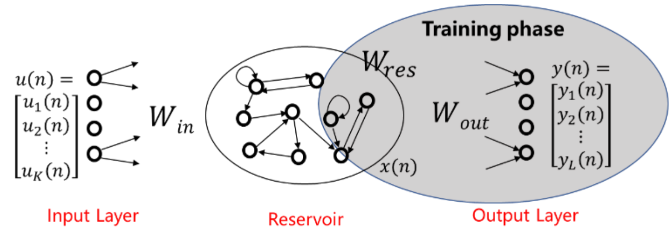

Fig 4 ESN architecture flowchart

2.3.4 *Prognostic implementation based on the fusion approach*

In this paper, a two-layer Bi-LSTM-GRU model is constructed as a hidden feature extraction tool, with hyperparameters determined based on particle swarm optimization (PSO) algorithm. While the role of the ESN model is to establish a mapping between hidden features and predicted values, which the values of key parameters is taken according to Ref [16].

The works of this paper are executed on an Intel Core processor i5-10400CPU 2.9GHz and NVIDIA GeForce GTX 1660s GPU with 6GB memory. The Bi-LSTM-GRU is based on Pytorch, while ESN framework is conducted based on NumPy.

2.4 *Results and Discussion*

In this section, the Bi-LSTM-GRU and ESN fusion prognostic framework are validated by IEEE challenge data. The prediction performance of this framework in short-term prediction and RUL estimation is discussed respectively, which are compared with the traditional SVR, LSTM, GRU.

2.1.1 *Evaluation index of prediction accuracy*

In this paper, for short-term prediction, three statistical criteria standards of RMSE, MAE and R^2 are selected to evaluate the performance of the prediction. The smaller RMSE and MAE are, the higher accuracy of the model. The larger value of R^2 indicates the better prediction accuracy. When the prediction result is completely consistent with the real label, the calculation formula of R^2 = 1. The formulas for calculating these standards are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_1^N \left(Y(t) - \hat{Y}(t)\right)^2} \tag{8}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_1^N \left|Y(t) - \hat{Y}(t)\right| \tag{9}$$

$$R^2 = 1 - \frac{\sum_1^N \left(Y(t)-\hat{Y}(t)\right)^2}{\sum_1^N \left(Y(t)-\bar{Y}(t)\right)^2} \tag{10}$$

where $Y(t)$ is the actual measured voltage, $\hat{Y}(t)$ is the predicted voltage value, $\bar{Y}(t)$ indicates the mean value of the measured voltage, and N is the number of measured voltages.

As for RUL estimation, the E_r between the actual RUL (RUL_{Act}) and the predicted RUL (RUL_{Prdt}) is usually used to determine the accuracy of the RUL estimation [23].

$$E_r = \frac{|RUL_{Act} - RUL_{Prdt}|}{RUL_{Act}} \tag{11}$$

2.1.2 Short-term prediction

The aging data of FC1 are first used to train the Bi-LSTM-GRU and ESN fusion prognostic framework and to validate the prediction results. The prediction results are compared with the degradation prediction results of SVR, LSTM and GRU models, as shown in Fig 5. A total of 200 epochs are trained, and the fusion model begin to converge in the 10th epoch. The LSTM model has the best prediction results in the training phase, but performs poorly in the validation phase with RMSE, MAE and R^2 of 0.0408, 0.0331, 0.9665 respectively, which we consider may be due to overfitting. On the other hand, the GRU model shows more accurate predictions in the validation phase, although it fluctuated more in the training phase. We speculate that this may be due to the fact that GRU has fewer internal covariates and removes the cell state C_t, thus capturing the long-term decay trend better than LSTM. The SVR has the largest RMSE, MAE of 0.989, 0.1063, and R^2 is 0.7946. In comparison, the fusion method has the lowest RMSE and MAE in the verification stage, which are 0.0235 and 0.0195 and the R^2 is highest at 0.9822. It should be noted that it is a prediction that we only use the voltage of the first 200 hours.

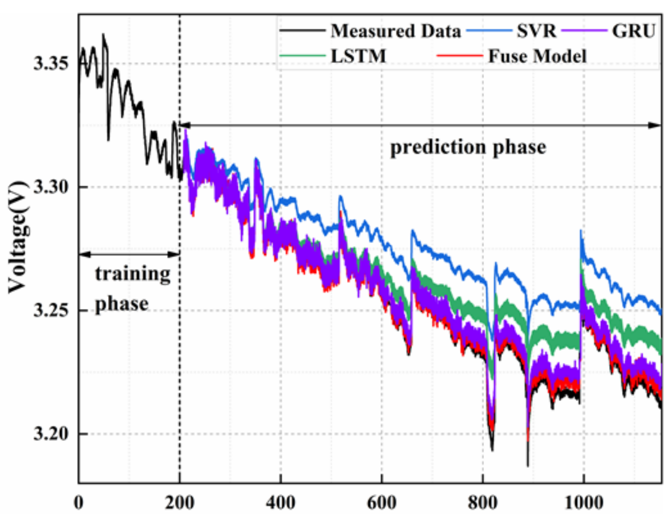

Fig 5 Short-term degradation prediction results of the four methods with 200h data training (FC1)

To further verify the universality of the fusion model, the degradation voltage data of FC2 under dynamic operation is used for verification. The prediction results of the Bi-LSTM-GRU and ESN fusion model is shown in Fig 6. It can be seen that the results of the fusion method can fit the measured data well with 200h training data. The RMSE, MAE and R^2 of fusion model are 0.0197, 0.0155, 0.9818, respectively, which seems to show a better result than FC1. The results can be explained by the obvious degradation trend of the variable load data in the early stage, where the fusion model can accurately extract these unexplainable characteristics.

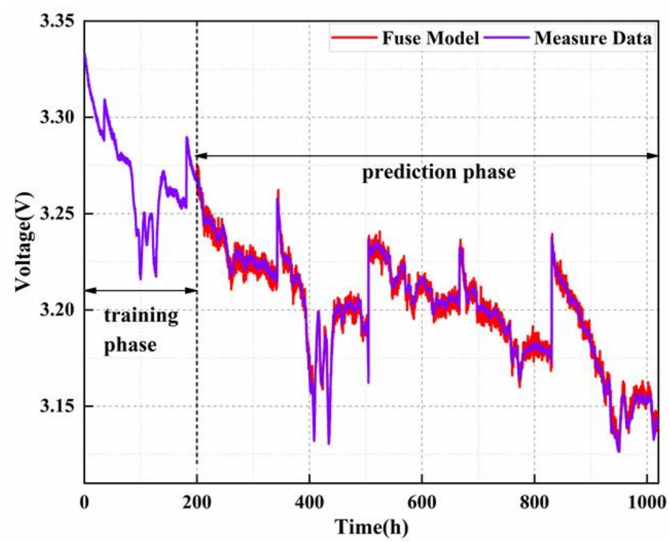

Fig 6 Short-term degradation prediction results of the four methods with 200h data training (FC2)

2.2.3 RUL estimation

In this part, we will present RUL estimation of fusion model with FC1. When the total voltage of the stack drops to 96.5% of the initial voltage, PEMFC is defined as failure [12]. Therefore, for FC1, When T=809h, the total voltage of the stack (U_{tot}) is 3.203V, which is defined as the end of life (EOL) of the stack.

The prediction results are given in Fig 7. Although there are large forecast fluctuations, the fusion model can track long-term nonlinear trend in voltage. In generally, it is not possible to achieve high accuracy for tracking the short-term trend change of the voltage, but a relatively accurate RUL estimation can also be performed. With 200h data for training, the RUL predicted by the fusion model occurs at 616.43h, when the predicted voltage is 3.198V, which is below the threshold. It only differs from the true RUL value of 609h by approximately 7h, with the E_r of 1.22%. In summary, we seem to demonstrate that the proposed comprehensive prognostic framework has excellent short-term prediction and RUL estimation capabilities, with only 200 h of data for training.

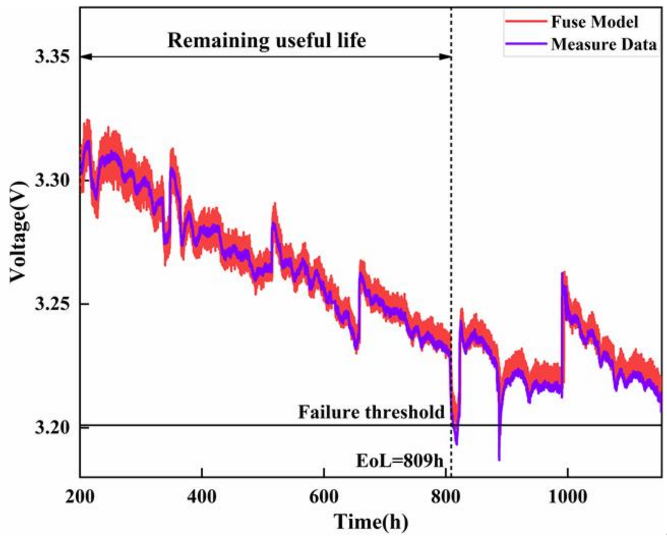

Fig 7 RUL estimation of fusion prognostic method

3. CONCLUSIONS

A fusion prognostic framework has been proposed in this paper in order to predict the voltage degradation of PEMFC stack. The framework prediction results are validated with two different PEMFC stack. Meanwhile, Different machine learning methods are compared with the proposed Bi-LSTM-GRU and ESN framework. The conclusions can be made as follows:

1. The proposed framework can achieve short-term prediction with only the first 200h data for training, which short-term trends in stack decay can be tracked accurately. The RMSE, MAE, R^2 are $0.0235, 0.0195, 0.9822$, respectively.
2. RUL estimation is implemented with proposed fusion framework, which only 200h data for training. The framework can capture long-term change of voltage degradation accurately, with E_r is 1.22%.

The framework can be used to PEMFC lifespan, which also help for online monitor of healthy. In the future, more practical conditions should be considered, such as fuel cell operational status monitoring in vehicle applications.

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