2022-01-0687 Published 29 Mar 2022

Dynamic Durability Prediction of Fuel Cells Using Long Short-Term Memory Neural Network

Liying Ma, Suhang Peng, Minghui Zhong, Wenqi Li, Changlong Jiang, Xiangmin Pan, and Yongping Hou
Tongji University

Citation: Ma, L., Peng, S., Zhong, M., Li, W. et al., "Dynamic Durability Prediction of Fuel Cells Using Long Short-Term Memory Neural Network," SAE Technical Paper 2022-01-0687, 2022, doi:10.4271/2022-01-0687.

Received: 20 Jan 2022 Revised: 20 Jan 2022 Accepted: 10 Jan 2022

Abstract

Durability performance prediction is a critical issue in fuel cell research. During the demonstration operation of fuel cell commercial vehicles in China, this issue has attracted more attention. In this article, the long short-term memory neural network (LSTMNN), which is an improved recurrent neural network (RNN), and the demonstration operation data are used to establish the prediction model to predict the durability performance of the fuel cell stack. Then, a model based on a back-propagation neural network (BPNN) is established to be a control group. The demonstration operation data is divided into training group and validation group. The former is used to train the prediction model, and the latter is used to verify the validity and accuracy of the prediction model. The outputs of the prediction model, as the durability performance evaluation indexes of the fuel cell, are the polarization curve (current-voltage curve) and the voltage decay curve (time-voltage curve). Moreover, mean absolute percentage error (MAPE) and relative error are adopted to assess the prediction performance of the model. Ultimately, it is proved that LSTMNN performs better in durability performance prediction of fuel cell stack through dynamic data on the actual road by comparing the prediction results of LSTMNN with that of BPNN.

Introduction

Nowadays, environmental pollution and energy crises are becoming increasingly serious due to the increasing number of vehicles. People are seeking a new powerplant that can replace internal combustion engines in vehicles. In this situation, the Proton Exchange Membrane Fuel Cell (PEMFC) stands out from many solutions according to its advantages: zero pollution, high energy density, low noise, and high efficiency. However, the cost and durability of the fuel cell restrict its widespread commercialization. Therefore, how to improve the remaining useful life (RUL) of fuel cells has become a long-term research focus. According to the US Department of Energy (DOE) standard: the RUL of a fuel cell refers to the time it takes for the maximum power of the stack to decrease to 90% of the rated power [1]. Accurate and effective remaining useful life predictions can help improve the durability performance of fuel cells. In this case, the durability of fuel cell prediction has become crucial.

The prediction methods of the remaining useful life can be divided into two types: model-driven methods and data-driven methods. The model-driven methods predict the remaining useful life of fuel cells by learning electrochemistry and physics knowledge, analyzing the operation mechanism and degradation mechanism of fuel cells. Constructing semi-empirical formulas is widely used in this type of method [2-4]. However, the PEMFC system is a complex system containing multiple physical quantities and multiple scales and has the characteristics of nonlinearity, coupling, and irreversibility. In addition, the loading conditions such as temperature, pressure, airflow, and other external influencing factors are prone to change. These reasons make the model very complicated and limit the prediction accuracy and efficiency of the model.

The data-driven methods can directly connect the working condition parameters of the stack and the remaining service life index, just like a black box control. This type of method does not require a priori degradation model and has a good ability to fit nonlinearity. So, it has received widespread attention and become a focus in recent research. The data-driven methods mainly include: artificial neural network (ANN), support vector machine (SVM), Relevance Vector Machine (RVM), echo state network (ESN), extreme learning machine (ELM), adaptive neuro-fuzzy inference system (ANFIS), Gaussian process state-space (GPSS), etc. S. Morando, et al. [5, 6] proposed a PEMFC RUL prediction model based on echo state network. They input the stack voltage data processed by the short-time Fourier transform into the network. Then, they replaced the original hidden layer of the network with a neuron pool and used the existing stack voltage degradation data to train the network. They used an iterative structure

TABLE 5 The R^2 of the voltage prediction model at 115A.

Training percentage	40%	50%	60%
BPNN	0.8935	0.8541	0.9077
LSTMNN	0.9410	0.9938	0.9971

TABLE 6 The MAPE of the voltage prediction model at 190A.

Training percentage	40%	50%	60%
BPNN	1.0544	1.7828	1.4504
LSTMNN	0.7919	0.3864	0.0446

TABLE 7 The R^2 of the voltage prediction model at 190A.

Training percentage	40%	50%	60%
BPNN	0.8136	0.8597	0.9348
LSTMNN	0.9877	0.9932	0.9967

prediction at 190A is similar to that at 115A. The voltage prediction of the LSTMNN model follows the experimental curve more closely than that of the BPNN model. Table 6 and Table 7 present the MAPE and R^2 of the two prediction models. LSTMNN model performs better than BPNN model in durability performance prediction at 190A according to the tables.

Conclusions

In this article, the LSTMNN model is used for durability performance prediction of the fuel cell at actual road conditions. A model based on BPNN is established to be a control group. The raw voltage data is smoothed by Matlab before prediction, and the data is divided into 40%, 50%, and 60% training groups for comparison. The input of the model is current and time, and the output is voltage. Each training group is put into the prediction model to predict the voltage degradation data 32 times, and the data are averaged for analysis. The conclusions are as follows:

1. In terms of prediction accuracy, the prediction error of LSTMNN is much smaller than that of BPNN. The maximum RPE of LSTMNN is less than half of that of BPNN (1.6% vs 4.2%). And, the MAPE of LSTMNN is always smaller than that of BPNN.
2. In terms of prediction effectiveness, LSTMNN can learn the voltage training data well, and the prediction trend is similar to the real data. The R^2 of LSTMNN is closer to 1 than that of BPNN.
3. As the training ratio increases, the accuracy and effectiveness of the LSTMNN prediction model are higher.

In a word, the LSTMNN model performs better than BPNN in the durability performance prediction of the fuel cell. In the future, we will consider modifying the internal parameters of the LSTMNN model to achieve better predictions.

References

1. Huicui, C. and Pucheng, P. "A Study on the Economic Life of the Proton Exchange Membrane Fuel Cells for Vehicles," *Automotive Engineering* 37, no. 9 (2015): 998-1004, (in Chinese).
2. Zhu, D., Pritchard, E.G.D., and Silverberg, L.M., "A New System Development Framework Driven by a Model-Based Testing Approach Bridged by Information Flow," *IEEE Systems Journal* 12, no. 3 (2016): 2917-2924, doi:10.1109/JSYST.2016.2631142.
3. Chen, H., Pei, P., and Song, M., "Lifetime Prediction and the Economic Lifetime of Proton Exchange Membrane Fuel Cells," *Applied Energy* 142, no. 15 (2015): 154-163, doi:10.1016/j. apenergy.2014.12.062.
4. Hou, Y., Yang, Z., and Wan, G., "An Improved Dynamic Voltage Model of PEM Fuel Cell Stack," *International Journal of Hydrogen Energy* 35, no. 20 (2010): 11154-11160, doi:10.1016/j. ijhydene.2010.07.036.
5. Morando, S., Jemei, S., Hissel, D. et al., "Proton Exchange Membrane Fuel Cell Ageing Forecasting Algorithm Based on Echo State Network," *International Journal of Hydrogen Energy* 42, no. 2 (2017): 1472-1480.
6. Morando, S., Jemei, S., Gouriveau, R., et al., Fuel Cells Remaining Useful Lifetime Forecasting Using Echo State Network," in *Proceedings of 2014 IEEE Vehicle Power and Propulsion Conference (VPPC)*, IEEE, Coimbra, Portugal, 2014.
7. Javed, K. et al., "Prognostics of Proton Exchange Membrane Fuel Cells Stack Using an Ensemble of Constraints Based Connectionist Networks," *Journal of Power Sources* 324 (2016): 745-757.
8. Javed, K., Gouriveau, R., Zerhouni, N. et al., "Improving Accuracy of Long-Term Prognostics of PEMFC Stack to Estimate Remaining Useful Life," in *Proceedings of 2015 IEEE International Conference on Industrial Technology (ICIT)*, IEEE, Seville, Spain, 2015.
9. Zheng, L., Hou, Y., Li, W., and Hao, D., "A Data Driven Fuel Cell Life-Prediction Model for a Fuel Cell Electric City Bus," SAE Technical Paper 2021-01-0739 (2021), doi:10.4271/2021-01-0739.
10. Yiming, W., Breaz, E., Fei, G. et al., "Nonlinear Performance Degradation Prediction of Proton Exchange Membrane fuel cells using Relevance Vector Machine," *IEEE Transactions on Energy Conversion* 31, no. 4 (2016): 1570-1582.
11. Yiming, W., Breaz, E., Fei, G. et al., "A Modified Relevance Vector Machine for PEM Fuel-Cell Stack Aging Prediction," *IEEE Transactions on Industry Applications* 52, no. 3 (2016): 2573-2581.
12. Yiming, W., Breaz, E., Fei, G. et al. "Prediction of PEMFC Stack Aging Based on Relevance Vector Machine," in *Proceedings of 2015 IEEE Transportation Electrification Conference and Expo*, IEEE, Dearborn, MI, 2015.
13. Li, Zhu, Chen J. Prognostics of PEM Fuel Cells Based on Gaussian Process State Space Models. *Energy*, 2018, 149: 63-73.
14. https://colah.github.io/posts/2015-08-Understanding-LSTMs/.