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A Data Driven Fuel Cell Life-Prediction Model for a Fuel Cell Electric City Bus

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Abstract

Life prediction is a major focus for a commercial fuel cell stack, especially applied in fuel cell electric vehicles (FCEV). This paper proposes a data driven fuel cell lifetime prediction model using particle swarm optimized back-propagation neural network (PSO-BPNN). For the prediction model PSO-BP, PSO algorithm is used to determine the optimal hyper parameters of BP neural network. In this paper, total voltage of fuel cell stack is employed to represent the health index of fuel cell. Then the proposed prediction model is validated by the aging data from PEMFC stack in FCEV at the actual road condition. The experimental results indicate that PSO-BP model can predict the voltage degradation of PEMFC stack at actual road condition precisely and has a higher prediction accuracy than BP model.

Introduction

In recent years, with the outstanding of global environmental pollution and energy problems, fuel cells are drawing increasing attention due to their high energy density, low emissions, and environmental friendliness [1]. Among all types of fuel cells, Proton Exchange Membrane Fuel Cell (PEMFC) is regarded as the best alternative to traditional internal combustion engines in vehicles due to their low operating temperature, high power density and zero emissions. However, due to the high maintenance cost and short service life of fuel cells, large-scale commercial applications of proton exchange membrane fuel cells (PEMFCs) in vehicles have been limited [2]. Therefore, improving the fuel cell life is very important for the application of fuel cells in mobile vehicles. In this case, the life prediction of fuel cells is greatly needed. Accurately predicting the evolution of fuel cell performance with a short experimental aging data of fuel cells can help to optimize the management strategies of fuel cell system and also improve the system efficiency, which leads to the increase of the useful lifetime of fuel cells [3].

At present, fuel cell life prediction methods are mainly divided into two types: model-driven methods and data-driven methods. The model-driven method predicts the performance degradation of fuel cell mainly by studying the chemical and physical mechanisms inside fuel cells. And performance degradation of fuel cell can be detected and predicted by the model-driven method [4]. In most literatures about model-driven method, the life of fuel cell is predicted through building fuel cell semiempirical models [5, 6, 7, 8, 9, 10, 11]. However, model-driven method is limited by specific experimental conditions and may not be suitable for all types of fuel cells.

The data-driven method mainly uses experimental aging data to predict fuel cell life time without deep understanding the internal mechanism of fuel cell. Compared with model-driven method, data-driven method is more adaptive and has higher prediction accuracy. There are many kinds of data-driven methods, such as artificial neural network (ANN), support vector machine (SVM), Relevance Vector Machine (RVM), Gaussian process state space (GPSS), etc. Yiming Wu et al. [12] developed a fuel cell performance prediction model using Relevance Vector Machine (RVM) and enhance the prediction performance of the model by improving the training algorithm of the relevance vector machine. The prediction results of the improved RVM model are compared with the classic SVM model and the comparison show that the prediction performance of improved RVM model is better. Hou Y et al. used genetic algorithm-BP neural network model to predict voltage of fuel cell stack under dynamic cycle [13]. Li Zhu et al. proposed a prediction method based on Gaussian process state space to predict voltage degradation of fuel cell stack and compared it with the BP neural network model [14]. Kamran Javed et al. applied Summation Wavelet- Extreme Learning Machine (SW-ELM) algorithm to predict voltage degradation of fuel cell and used aging data from two different PEMFC stacks to verify robustness and applicability of this method for an online application [15]. Yamini et al. proposed a BP neural network prediction method that uses fuel cell temperature, humidification temperature, gas flow rate, and current density as inputs and

TABLE 2 Degradation prediction results of two models with training data at 65%

	MAPE	RMSE	R^2
PSO-BP	0.0019	0.6094	0.9964
BP	0.0117	4.1724	0.8073

TABLE 3 Degradation prediction results of two models with training data at 70%

	MAPE	RMSE	R^2
PSO-BP	0.0011	0.2496	0.9994
BP	0.0068	2.7594	0.9100

TABLE 4 Degradation prediction results of two models with training data at 75%

	MAPE	RMSE	R^2
PSO-BP	0.0015	0.3802	0.9986
BP	0.0052	2.2101	0.9573

The MAPE, RMSE and R^2 of the two models with different training phase at 65%, 70% and 75% are concluded in Table 2, 3 and 4, respectively. As shown in Table 2, 3 and 4, the RMSE and MAPE of PSO-BP model is much smaller than those of BP model and R2 of PSO-BP is closer to 1, which indicates the higher prediction accuracy of PSO-BP model over BP model. According to the prediction results of the two models with different training data, it can be concluded that the PSO-BP model make more accurate prediction of PEMFC performance degradation than BP model.

Conclusions

In this paper, the PSO-BP model is used to predict the life of PEMFC stack at actual road. By applying PSO algorithm in the BP network, the prediction accuracy of the model can improve a lot. The PSO-BP model is validated by the aging data obtained from the PEMFC stack operated at actual road. To reduce the prediction error, data smoothing and data normalization techniques are employed to preprocess the experimental data of PEMFC. Based on the preprocessed data, the prediction model is trained and formed by the input-output data from aging data of PEMFC. The current and operation time are set as input parameters while voltage is set as the output parameter of the model. The results show that PSO-BP can effectively predict the PEMFC life at actual road and the prediction accuracy of PSO-BP is much better than the BP model. In future work, PEMFC prediction model with more operation parameters will be considered.

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Definitions/Abbreviations

PSO - Particle swarm optimization algorithm

BP - Back propagation neural network

PSO-BP - Particle swarm optimized back-propagation neural network

FCEV - Fuel cell electrical vehicle

RUL - Remaining useful life

PEMFC - Proton exchange membrane fuel cell