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Remaining useful life prediction of PEMFC based on long short-term memory recurrent neural networks

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ABSTRACT

To solve the prediction problem of proton exchange membrane fuel cell (PEMFC) remaining useful life (RUL), a novel RUL prediction approach of PEMFC based on long short-term memory (LSTM) recurrent neural networks (RNN) has been developed. The method uses regular interval sampling and locally weighted scatterplot smoothing (LOESS) to realize data reconstruction and data smoothing. Not only the primary trend of the original data can be preserved, but noise and spikes can be effectively removed. The LSTM RNN is adopted to estimate the remaining life of test data. 1154-hour experimental aging analysis of PEMFC shows that the prediction accuracy of the novel method is 99.23%, the root mean square error (RMSE) and mean absolute error (MAE) is 0.003 and 0.0026 respectively. The comparison analysis shows that the prediction accuracy of the novel method is 28.46% higher than that of back propagation neural network (BPNN). Root mean square error, relative error (RE) and mean absolute error are all much smaller than that of BPNN. Therefore, the novel method can quickly and accurately forecast the residual service life of the fuel cell.

Introduction

AMONG the current fuel cell techniques, proton exchange membrane fuel cell (PEMFC) is considered to be the most common new-generation power generation devices for the distributed power generation, backup power supplies, and trams [1–4]. However, because of its shorter service life and higher development cost, the large-scale industrial application of PEMFC is affected [5–11]. Therefore, Prognostics and health management (PHM) technologies are needed to ensure long-term service for fuel cells [12–15]. More precisely, remaining useful life (RUL) predictions of PEMFC are the central concern area. The purpose is to identify the degradation trend of the PEMFC at an early phase and estimate its residual service life to achieve health management of full lifecycle.

At present, research with the residual service life prediction of PEMFC has just started. Prediction methods of PEMFC remaining life are classified into three types:

Model-driven method

The model-driven method relies on fuel cell load conditions, material properties, degradation mechanism and failure mechanism to achieve the prediction of residual life.

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Marine Jouin et al. [16] have proposed a PEMFC prediction method based on particle filter (PF) framework. Three empirical voltage degradation models have been tested: a linear model, an exponential model, and a logarithmic linear model. In the learning stage, particle filter can recursively estimate the probability density function (PDF) of the model state. The experimental results indicate that the logarithmic linear model can predict the RUL of the fuel cell with 95% accuracy after 500 h of operation. Based on the estimation of the cell voltage degradation rate, Xinfeng Zhang et al. [17] have presented an empirical life prediction model for automotive PEMFC. The load curve term and the aging term are brought into the concentration loss, ohmic loss and activation loss, respectively. Load current and load voltage are used to define characteristic values. The voltage aging rate is developed as a linear function of the proper amount of the load curve. Laboratory data are adapted to match the factors and verify the model. Xian Zhang et al. [18,19] have presented a PEMFC damage tracking and residual life prediction method based upon the unscented Kalman filter (UKF). In order to establish the relationship between the operating conditions and the degradation rate of the electrochemical surface area (ECSA), the damage degree of the fuel cell is also characterized and the predictive-oriented catalyst degradation model is developed. The size of the ESCA is used as an indicator of aging and the RUL is predicted by associating the ESCA with the output voltage. The results show that the method can successfully track the damage variables and predict RUL throughout the degradation process. Mathieu Bressel et al. [20–22] have proposed a PEMFC residual life prediction approach based upon an extended Kalman filter. The method uses an extended Kalman filter to evaluate time-varying parameters and their derivatives. It provides predictive results under dynamic operating conditions to better reflect the operational characteristics of the actual fuel cell stack. Huicui Chen et al. [23] have proposed a fast prediction method for PEMFC residual life. The assessment method realizes on-line prediction of remaining life by renovating the surrounding impact factors and voltage drop rate induced by operating conditions.

Data-driven method

The data-driven method uses monitored historical data to predict the remaining life of PEMFC. Without the expertise of fuel cell models or systems, the underlying algorithm is fast and efficient.

S. Morando et al. [24–26] have proposed a PEMFC aging prediction algorithm based on echo state network (ESN). The short-time Fourier transform is preprocessed, and the voltage data of the stack is fed into the net. Neuron pool is adapted to replace the neural network of the original hidden layer. The existing PEMFC voltage degradation data are used to train network parameters. To estimate the remaining service life of PEMFC, an iterative structure is used to predict the fuel cell voltage. Kamran Javed et al. [27–30] have developed a data-driven approach based on the constraint summation wavelet-extreme learning machine (SW-ELM) to predict the PEMFC stack. This integration strategy has also been extended to two fast learning association networks, namely the leaky-echo state network (Leaky-ESN) and the extreme learning machine (ELM) [31]. Based on the 1150-h and 1750-h monitoring data of two groups of PEMFC, the robustness and practicability of each integrated method are compared. Compared with the experimental results of Leaky-ESN and ELM under conditions of constant operation requirements and limited training data, the overall prediction performance of SW-ELM is better. The PEMFC prediction ought to rely on a forecast of voltage aging tendency instead of practical signals. Li Zhu et al. [32] have proposed a PEMFC residual service life prediction method based on Gaussian process state space (GPSS) model. The learning phase duration is 400 h, and the failure threshold of PEMFC is defined as 96% of the initiative voltage (3.212 V). When $T = 889$ h, the actual value of output voltage is below the failure threshold. To assess the precision rate of the forecasting results, negative log-predictive likelihood (NLL), mean squared error (MSE) and mean absolute error (MAE) are described as evaluation indicators. Among them, MAE and MSE are adopted to work out the deviation between the actual value and the average value of the estimated value, respectively. NLL is selected to evaluate the indeterminacy of the assessed value. Between [350 h, 850 h], the GPSS model is refreshed every 50 h with the new datum. The 95% confidence interval is used to represent the uncertainty of the predicted results. The comparison with the back-propagation neural network (BPNN) shows that GPSS can provide predictive confidence level with prediction variance and the result is closer to the actual voltage. Yiming Wu et al. [33–35] have proposed a performance degradation prediction method for PEMFC based on adaptive relevance vector machine (RVM). In order to obtain the behavioral characteristics of the PEMFC aging data during training, the design matrix is extended by adding non-nuclear columns. Experimental voltage aging data of two diverse PEMFC stacks (8 kW PM 200 PEMFC and 1.2 kW Ballard PEMFC) are used to train and test adaptive RVM. The results show that the prediction results of adaptive RVM are in good agreement with the experimental results under five different operating conditions. R.E. Silva et al. [36] have proposed a PEMFC degenerate prediction method based on adaptive neuro-fuzzy inference system (ANFIS). The output voltage is used to predict the aging of the fuel cell system. The voltage signal is divided into two parts: normal operation and external disturbance. Its purpose is to reduce the prediction error caused by external disturbance. In the long run test, this method is evaluated by predicting the output voltage change of fuel cell stack under constant operating conditions. The results show that ANFIS is very suitable for predicting time series, especially the performance loss caused by fuel cell system degradation.

Hybrid method

The hybrid method is a hybrid model combining or integrating multiple strategies. It can make up for the shortcomings of a single approach and give rein to the behalf of different models for obtaining the best performance.

Yujie Cheng et al. [37,38] have proposed the residual life prediction method of fuel cell based on the least square support vector machine (LSSVM) and regularized particle filter (RPF). First, PEMFC premier prediction is implemented by LSSVM. Then, the forecasted voltage of LSSVM is taken as the observation value of the new system by the RPF. The uncertainty characteristics of the prediction result are output in the form of RUL probability distribution. Compared with RPF and PF, the novel method has the best predictive performance. Jiayu Chen et al. [39] have proposed a PEMFC residual life prediction method based on unscented particle filter (UPF) and second-order Gaussian mixture model. The initial forecast time is set at five hundred hours, and the fault threshold is set at 805 h (96% of the initial voltage). The experiment result indicates that the prediction precision rate of the novel method is 99.51%. Hao Liu et al. [40] have proposed a short-term prediction method for fuel cells based on the wavelet analysis (WA) and the group method of data handling (GMDH). The performance of the prediction method is described by the root mean square error (RMSE), mean absolute percentage error (MAPE) and coefficient of determination (R2). Two sets of PEMFC aging test data sets are used to prove the effectiveness of the scheme under different current load conditions. Compared with the traditional GMDH simulation results, this method cannot only provide more accurate short-term prediction results but also can directly use the original experimental data with large disturbance. However, the computational cost of the above work is high and time-consuming, which is not suitable for predicting the residual service life of PEMFC online. The RUL prediction problem of the PEMFC system is very complicated. There are many challenges such as high noise, large peaks and enormous data volume, which will cause significant fluctuations in the prediction results and affect the final decision-making. In order to predict the service life of fuel cells for city buses, Zunyan Hu et al. [41] have proposed a reconstructed PEMFC RUL prediction model. Considering the sensor error and temperature fluctuation, the voltage model is divided into 3 parts (logarithmic voltage part, the linear part, and constant part) to simplify the fitting process. The model is in good agreement with the primary data, and there are only 2 changeable parameters U_{eq} and R. Based on the resistance and degradation mechanism of ECSA, the degradation model with 2 parameters is added to the voltage model and a 4-step life prediction method is presented to evaluate the voltage drop. The verification results show that the fourteen-day training dataset can ensure that the differences in the prediction voltage are less than 1%, indicating that the proposed model is reliable and robust. Daming Zhou et al. [42] have proposed a PEMFC performance aging prediction algorithm based on the degenerate empirical model and nonlinear autoregressive neural network (NARNN), which can precisely acquire the long-term PEMFC voltage drop tendency and nonlinear voltage variation characteristics. 3 diverse types of PEMFC stack experimental aging datasets (Ballard NEXA 1.2 kW PEMFC stack of 400 h aging test; PM 200 8.0 kW PEMFC stack of 10000 h aging test; 600 W PEMFC stack of 1200 h aging test) are used to verify the accuracy and robustness of the novel algorithm.

In the past decade years, with the development of deep learning techniques, deep learning models are gradually applied into the study of the time series prediction. The deep learning model is a type of depth neural network model with numerous nonlinear mapping levels. Deep learning can extract features from the input signals layer by layer. It can also excavate more profound potential laws. In many deep learning models, recurrent neural network (RNN) introduces the concept of time series into network structure design, which makes it more adaptable in time series data analysis. Among many RNN variants, the long short-term memory (LSTM) model compensates for the problems of gradient disappearance, gradient explosion and long-term memory deficiency of RNN. It makes the recurrent neural network be able to use long-distance sequence information effectively. The LSTM has numerous successful adhibitions in the study of time series data in different fields, such as image title modeling, speech recognition, language-dependent language modeling, machine translation, multimedia-related audio, video data analysis, road transportation, relevant traffic flow rate predictions, as well as medically relevant protein secondary structure sequence predictions. At present, there is no literature on the application of LSTM RNN to the field of PEMFC RUL prediction.

In this paper, the PEMFC residual service life prediction method based on LSTM RNN is proposed for the first time, which can significantly reduce the computational complexity while ensuring the prediction accuracy. The technique uses regular interval sampling and locally weighted scatterplot smoothing (LOESS) to reconstruct and smooth the original aging samples. The samples are filtered by normalization. LSTM RNN is used to forecast the remaining service life of the test set. At [0 h, 1154 h], a total of 143862 sets of steady-state experimental data of 1 kW PEMFC system are presented to prove the effectiveness of the novel method. The prediction results of the BPNN algorithm are compared to demonstrate the efficacy of the unique technique further.

PEMFC system

The test bench (Fig. 1) is suitable for 1 kW fuel cell stack. To control the running conditions of fuel cells precisely, a lot of physical parameters contained in the PEMFC system can be regulated and measured (Table 1).

- Hydrogen and air hygrometry rates, gas flow rates, stack temperature;
- Inlet and outlet flow rates (of cooling water, air and hydrogen), inlet and outlet pressures (of hydrogen and air), inlet and output temperatures (of cooling water, air, and hydrogen), voltages of monocell and the whole stack, current can be controlled by an upper computer.

The gas humidification subsystem is accomplished by two independent boilers placed upon the stack. Hydrogen and air intercross respective evaporators before attaining the PEMFC stack. Whereas, the air boiler is only heated to acquire the requested relative humidity. In the meanwhile, the hydrogen boiler remains at the ambient temperature with dry anode gas. The temperature of the PEMFC stack is dominated by a cooling water subsystem. The current provided by the PEMFC system is restrained by an electronic load. The schematic diagram of PEMFC testing is shown in Fig. 2.

The PEMFC stack is integrated at FCLAB, which have five single cells. The active area of each cell is 100 cm^2. The PEMFC is implemented with machined flow distribution plates,

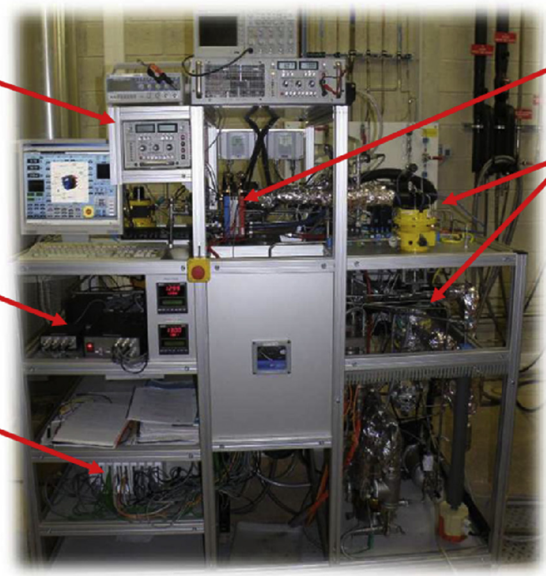

Fig. 1 – PEMFC stack test bench.

diffusion layers, and commercial membranes. The maximal and the nominal current density of PEMFC are 1 A/cm^2 and 0.70 A/cm^2 respectively.

Related Theory

In this paper, the prediction model is constructed based on the long short-term memory recurrent neural network and the locally weighted scatterplot smoothing method. The establishment process of long short-term memory recurrent neural network and locally weighted scatterplot smoothing method is described as follows:

Deep learning

Deep learning is a distributed feature learning method [43–45]. The main idea is to extract the essential characteristics of data by multiple progressive training layers. Overcome the deficiency that shallow training structure cannot effectively reflect the complex characteristics of data. In the structure of deep learning algorithm, each training layer is deepening of the previous layer. Gradually dig out the characteristics of the input data for classification or regression analysis as shown in Fig. 3. Deep learning algorithm adopts a multi-layer structure. The original chaotic information can be trained many times. Gradually extract information and ultimately get the essential characteristics of data.

Table 1 – The range of physical parameters controlled.

Parameters	Control ranges
The flow rate of cooling water	0–101 L/min
The temperature of the control range	20 °C–80 °C
PEMFC current	0–300 A
The flow rate of air	0–100 L/min
The flow rate of H_2	0–30 L/min
The temperature of the reaction gas	20 °C–80 °C
The pressure of the reaction gas	0–2 bars
The humidification of the reaction gas	0–100% RH

Recurrent neural network

The recurrent neural network is a kind of neural network especially dealing with sequential data [46–48]. Unlike conventional neural networks, recurrent neural networks preserve, learn, and record historical information in sequence data through the periodic connection of the hidden layer nodes. The structure of RNN includes input layer, hidden layer, and the output layer, as shown in Fig. 4. The layer is connected with the layer by the weight.

As shown in Fig. 4, U, V, and W are the weights of the input layer to the hidden layer, the hidden layer to the hidden layer, and the hidden layer to the output layer, respectively. Different from the traditional neural network, RNN has the idea of parameter sharing. There are the same parameters U, V and W between layers. This dramatically reduces the parameters needed to learn in the network and shortens the training time of the model. However, RNN has great difficulty in dealing with distant nodes in the time series. Because the calculation of the relationship between nodes with faraway distances involves multiple multiplications of the Jacobian matrix. This can result in the gradient disappearance (which occurs frequently) or gradient expansion (which happens less often). Long short-term memory network can solve this problem well.

Long short-term memory networks

The structure of LSTM network

In general, LSTM network is a particular model in RNN [49–51]. It also has the recursive property of RNN. In a narrow sense, it is an improved model of RNN. It has a unique memory and forgetting mode, which can flexibly adapt to the timing characteristics of network learning tasks. At the same

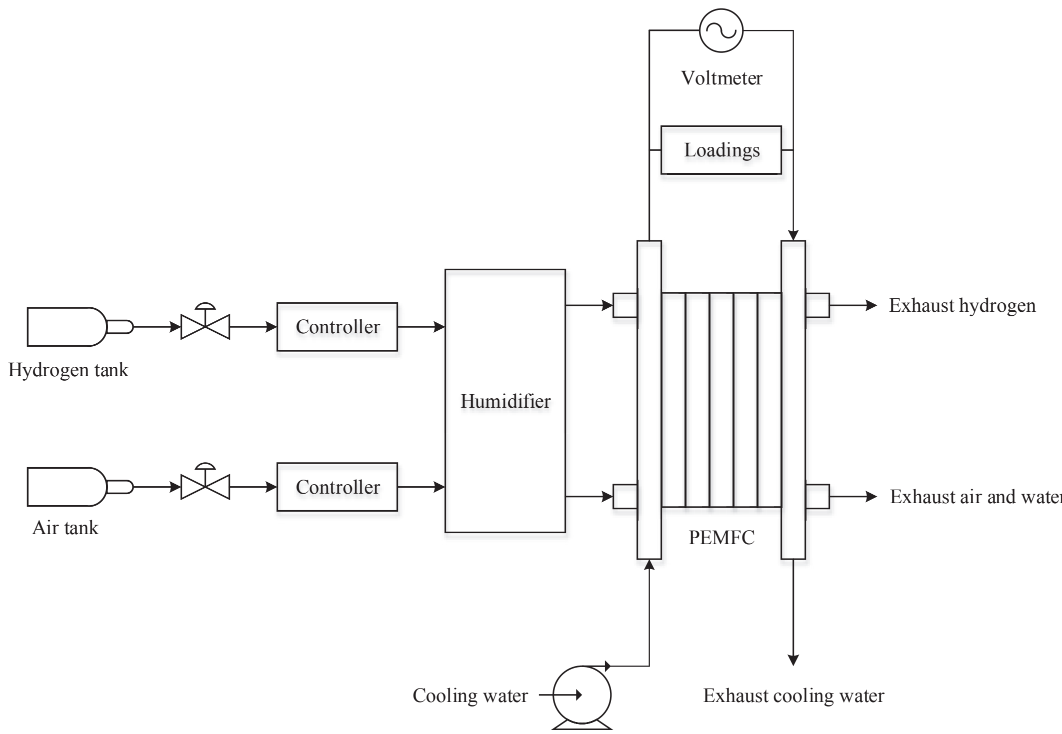

Fig. 2 – The principle scheme of the 1 kW PEMFC system.

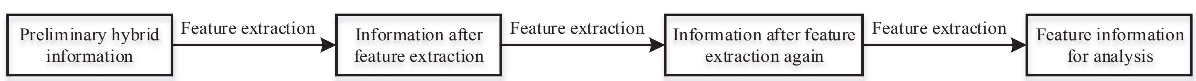

Fig. 3 – The feature extraction process of deep learning.

time, the LSTM network solves the gradient disappearance and gradient explosion problems of recurrent neural networks in the backpropagation through time (BPTT) training process. It can make full use of historical information and the time-dependent relationship of the modeling signal. Recently, the LSTM network has achieved great success in many sequence prediction tasks, such as voice prediction, handwritten word prediction and so on [52–54].

The LSTM network is composed of an input layer, an output layer, and a hidden layer. Compared with traditional RNN, the hidden layer of LSTM is not a common neural unit, but an LSTM unit with unique memory mode. The memory unit structure of LSTM is shown in Fig. 5.

Each LSTM unit has a cell. Its state in the moment t is recorded as c_t. This cell can also be regarded as the memory unit of LSTM. The reading and modification of memory unit in LSTM are realized by controlling the input gate, the forget gate and the output gate. They are generally described by sigmoid or tanh functions. Specifically, the workflow of the LSTM unit is as follows: At each time, the LSTM unit receives input from the current state x_t and the hidden state h_{t-1} of the LSTM at the previous time through three gates. Also, each door also receives an internal information input, which is the state of the

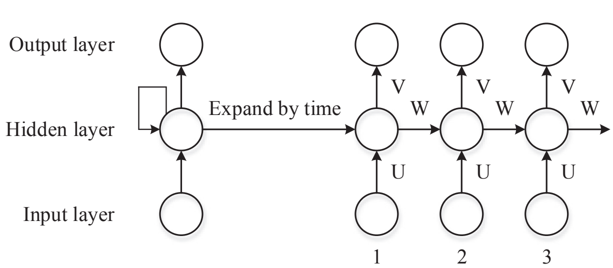

Fig. 4 – The structure of recurrent neural networks.

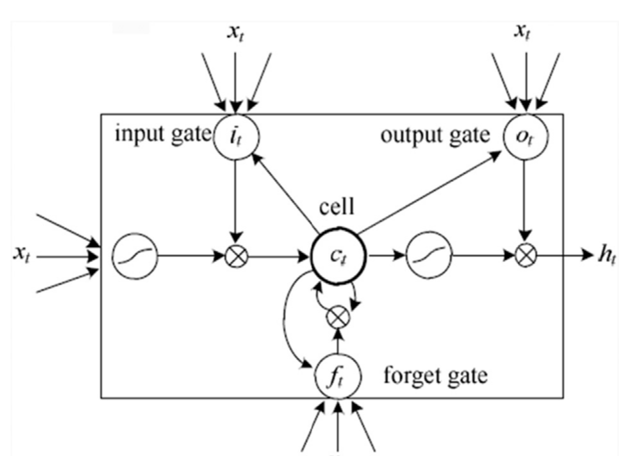

Fig. 5 – LSTM unit.

memory unit c_{t-1}. After receiving the input information, each gate will operate on data from different sources and its logic function determines whether it is active. After the input of the input gate is transformed by the nonlinear function, it is superimposed on the state of the memory cell processed by the forgetting gate to form a new memory cell state c_t. Finally, the memory cell state c_t forms the output h_t of the LSTM unit by the operation of the non-linear function and the dynamic control of the output gate. The calculation formula among the variables is as follows:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \tag{2}$$

$$c_t = f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \tag{3}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \tag{4}$$

$$h_t = o_t \tanh(c_t) \tag{5}$$

where, W_{xc},W_{xi},W_{xf} and W_{xo} are the weight matrix connecting the input signal x_t; W_{hc},W_{ih},W_{hf} and W_{ho} are the weight matrix combining hidden layer output signal h_t; W_{ci},W_{cf} and W_{co} are diagonal matrix combining the output vectors c_t and gate functions of neuron activation functions; b_i,b_c,b_f and b_o are offset vector; σ is activation function, usually tanh or sigmoid function.

A training algorithm for LSTM network

At present, for the recurrent neural network model such as LSTM, there are two mainstream training methods, such as the BPTT algorithm and the real-time recurrent learning (RTRL) algorithm. The BPTT algorithm is explicit in concept and efficient in the calculation. It is more advantageous in calculation time than RTRL. The BPTT algorithm is adopted to train LSTM.

The basic idea of BPTT algorithm is as follows: First, the LSTM network is expanded into a deep system in time order.

Then, the classical backpropagation algorithm is used to train the expanded network. Its schematic diagram is as shown in Fig. 6. Like the standard BPNN algorithm, BPTT also needs to apply the chain rule repeatedly. It should be noted that for LSTM networks, the loss function is not only related to the output layer but also related to the hidden layer around the time point.

Locally weighted scatterplot smoothing method

Locally weighted scatterplot smoothing is a novel type of data smoothing algorithm. The local regression model is usually composed of weighted linear least squares and a second-order polynomial model. By setting the window width of the filter, the original signal with noise and a large number of spikes can be effectively filtered (smoothed). The noise and spikes are better filtered by reflecting the overall law of the original data.

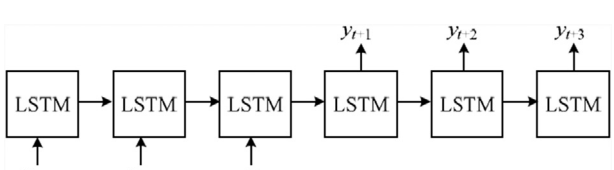

Fig. 6 – LSTM training by BPTT.

To enhance the quality of data and facilitate subsequent processing, the locally weighted scatterplot smoothing is used to smooth reconstructed data. Iterated weighted least squares are used to fit a cluster of data points through LOESS, where the outliers cannot be removed tyrannically. Assuming that data to be smoothed is identified by x and y, smoothing value of (x, y) can be acquired by specifying a weighted regression of the data range adjacent to x. The regression coefficient is defined as follows:

$$w_i = \begin{cases} \left(1 - \left|\frac{x - x_i}{d(x)}\right|^3\right)^3, \left|\frac{x - x_i}{d(x)}\right| \le 1 \\ 0, \left|\frac{x - x_i}{d(x)}\right| \ge 1 \end{cases} \tag{6}$$

In the suiting smoothing fitting formula $\hat{y} = ax + b$, the gradient a and the constants b are determined as:

$$a = \frac{\sum w_i^2 (x - \overline{x})(y - \overline{y})}{\sum w_i^2 (x - \overline{x})^2} \tag{7}$$

$$b = \overline{y} - a\overline{x} \tag{8}$$

where, $\overline{x}$ and $\overline{y}$ are the aggravated averages of x and y, respectively.

Methodology

Prognostic framework based on LSTM RNN

Considering the data characteristics of finite sample points in multivariate time series and the transparent design principle of recurrent neural network simplification, the overall framework of the LSTM RNN prediction model is shown in Fig. 7. There are five functional modules including a hidden layer, an input layer, an output layer, network prediction, and network training. The input layer is adapted to the initial processing of the original time series to meet network input requirements. The hidden layer uses the LSTM memory unit to build a single-layer recurrent neural network. The output layer provides the prediction results. Adam optimization algorithm is adopted in network training. An iterative method is used to predict point-to-point by network prediction.

The specific process of the residual service life prediction of PEMFC based on LSTM RNN is as follows:

1) The actual original aging dataset is obtained through the PEMFC system;
2) One group of data points are extracted at intervals of 1 h to reconstruct data;
3) The locally weighted scatterplot smoothing method is used to smooth the voltage data points;
4) The normalization is used to filter sample data;
5) The sample of [0 h, 550 h] is selected as a training set, and the example of [551 h, 1154 h] is extracted as the test set;

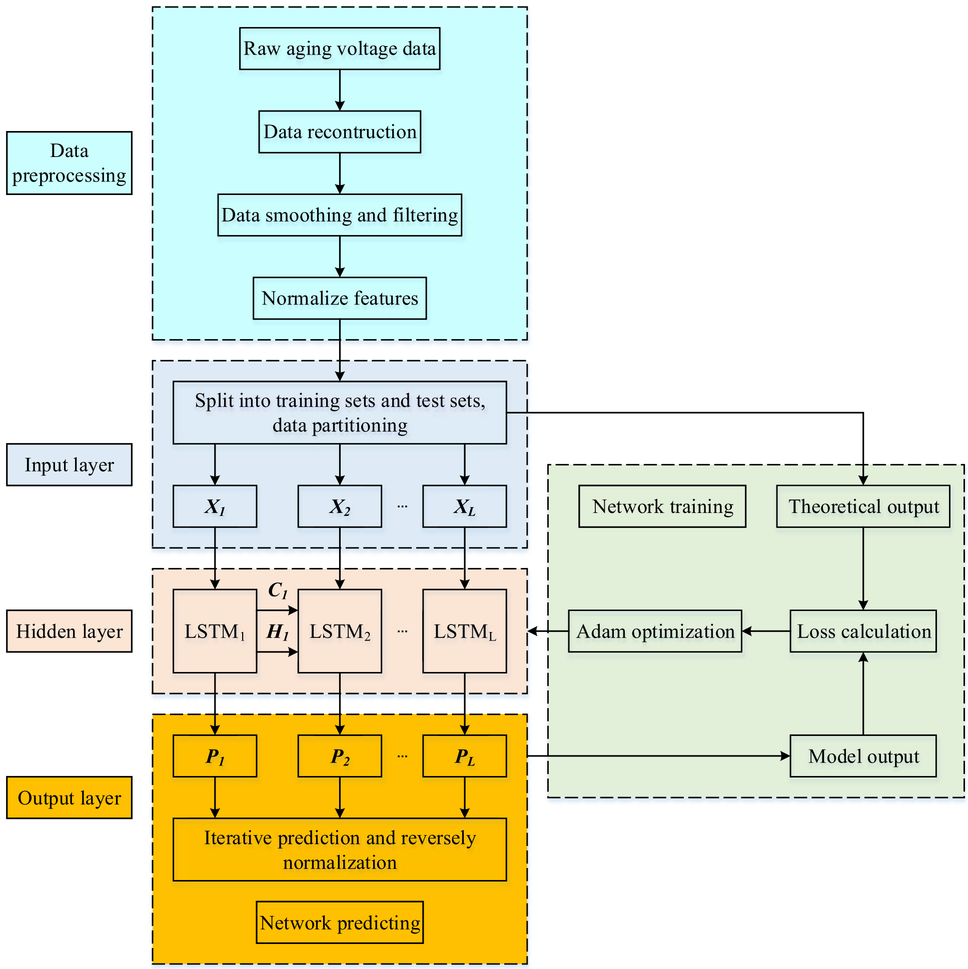

Fig. 7 – RUL prognostic framework for PEMFC based on LSTM RNN.

6) In order to adapt to the input characteristics of the hidden layer, the data set is processed by data partitioning. The length of the partition window is set as L;
7) Build the LSTM RNN model. The number of neurons in the hidden layer, the number of neurons in the output layer, the loss function and the optimizer are set;
8) The training set and test set are sent into the LSTM RNN model. The epoch size and batch size are set;
9) The predicted data set is combined with the test data set, and the scaling is inverted. The error score and RMSE of the model are calculated by predicted and actual values.

Data preprocessing

The 1 kW fuel cell stack runs in 1154 h under 70 A constant current. As time goes on, the voltage of the stack decreases or fluctuates significantly. However, there is no significant change in other parameters. Therefore, the stack voltage is used as a health indicator of PEMFC in this study. The 143862 set of raw data contains a lot of noise and spikes. It can lead to much time spent on computing. Therefore, it is necessary to preprocess the original voltage data.

The original datum is reconstructed to shorten the quantity of datum and abstract typical data. By sampling at [0 h, 1154 h] at a consistent time interval of 1 h, 1155 sets of information datum are chosen to stand for raw data. The reconstructed data are smoothed method to improve the quality of the data by LOESS. The window width of the filter is 20. As can be seen from Fig. 8, the smoothed data not only retains the primary trend of the original information but also effectively removes noise and spikes.

Smoothed data has a total of 24-dimensional properties (Table 2). The dimensionality difference among the parameters is quite significant, which is easy to cause the data distortion. It is difficult to reflect the actual relationship between the relevant variables. To reduce the influence of substantial variable differences on model performance, it is necessary to normalize the smoothed data and map the smoothed data to [0, 1].

When multivariable time series are used to predict the residual service life of PEMFC, the dimension and numerical value of different variables are different. Considering the input and output range of the nonlinear activation function in the model, to avoid the saturation of neurons and to weigh equally the effect of each variable on the output voltage of

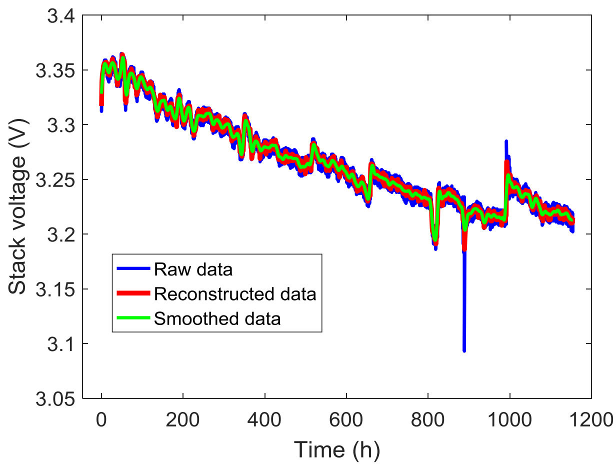

Fig. 8 – Degradation data of stack voltage.

PEMFC, it is essential to a normalized variable and the output voltage time series of PEMFC. The substance is subsumed within the interval [0, 1]:

$$x' = \frac{x - (x_{\max} + x_{\min})/2}{(x_{\max} - x_{\min})/2} \tag{9}$$

where, x_{max} and x_{min} are the maximum and minimum values of the variable, respectively.

Output voltage prediction data of the PEMFC stack obtained from the prediction model are then reversely normalized to make it of physical significance. The formula of inverse normalization is as follows:

$$x = 0.5\left[x'(x_{\max} - x_{\min}) + (x_{\max} + x_{\min})\right] \tag{10}$$

Evaluation index of prediction accuracy

In order to evaluate the accuracy of prediction results, a series of evaluation indicators should be put forward. In this paper, three symbols of RMSE, MAE and relative error (RE) are selected to test the reliability and effectiveness of the LSTM RNN method. Where MAE and RMSE are presented to work out the cumulative error between the approximated voltage value and real voltage value over the entire range; the RE is used to detect the RE between the predicted RUL and the actual RUL. The relevant formula is as shown in equations (11)–(13).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2} \tag{11}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - y_i\right| \tag{12}$$

where $\hat{y}_i$ is the model output; y_i is the measured value of the aging voltage.

$$RE = \frac{\left(T_{EoL\_prognostic} - T_{Eol\_true}\right)}{T_{EoL\_true}} \times 100\% \tag{13}$$

where $T_{EoL\_prognostic}$ is predicted RUL; T_{Eol_true} is actual RUL.

Table 2 – The aging parameters gathered during experiments.

Parameters	Physical meanings
U_s; U_1~U_5	The voltages of the stack and five single cells (V)
J_i; I	The current density (A/cm^2) and current (A)
Tout_H_2; Tin_H_2	The temperatures of H_2 at outlet and inlet (°C)
Tout_air; Tin_air	The temperatures of air at outlet and inlet (°C)
Tout_wat; Tin_wat	The temperatures of cooling water at the outlet and inlet (°C)
Pout_H_2; Pin_H_2	The pressures of H_2 at the outlet and inlet (mbara)
Pout_air; Pin_air	The pressures of air at the outlet and inlet (l/mn)
Fout_H_2; Fin_H_2	The flow rates of H_2 at outlet and inlet (l/mn)
Fout_air; Fin_air	The flow rates of air at the outlet and inlet (l/mn)
Air_hyg	Air hygrometry at the inlet (%)
F_wat	The flow rate of cooling water (l/mn)

Experimental results and discussion

The prediction model is based on the Python language, and the operating environment is as follows. The central processing unit (CPU): AMD® A8-4500 M™ CPU®1.90 GHz; memory: 8.00 GB; operating system (OS): Ubuntu 16.04.

According to IEEE PHM 2014 Data Challenge [55], 551 sets of data between [0 h, 550 h] are set as a learning set, and 604 sets of data between [551 h, 1154 h] are configured as a testing dataset. The illustration of training and testing datasets is shown in Fig. 9.

The 551 sets of training data are fed into the LSTM RNN model, where the output layer is the stack voltage. 604 sets of test data are sent into the LSTM RNN model for test verification, and the predicted stack voltage is output. The built LSTM RNN model is configured as follows: the number of neurons in the hidden layer is 50; the number of neurons in the output layer is 1; the loss function is the MAE; the optimizer is Adam; the epoch size is 50, and the batch size is 72. The predicted result is shown in Fig. 10.

When the total voltage of the stack is reduced to 96.5% of the initial voltage, the PEMFC failure is defined [55]. The initial voltage of the PEMFC stack is 3.3282 V, and the failure voltage is 3.2117 V. When T = 811 h, the total voltage of the stack is

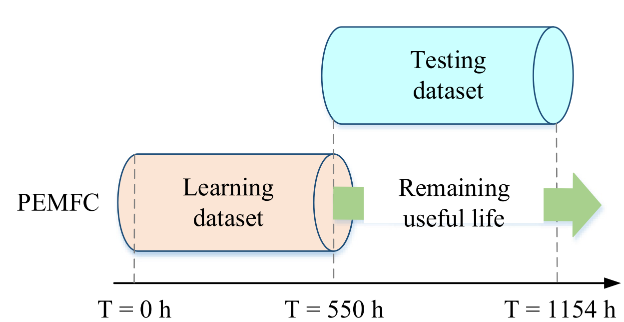

Fig. 9 – Illustration of training and testing datasets.

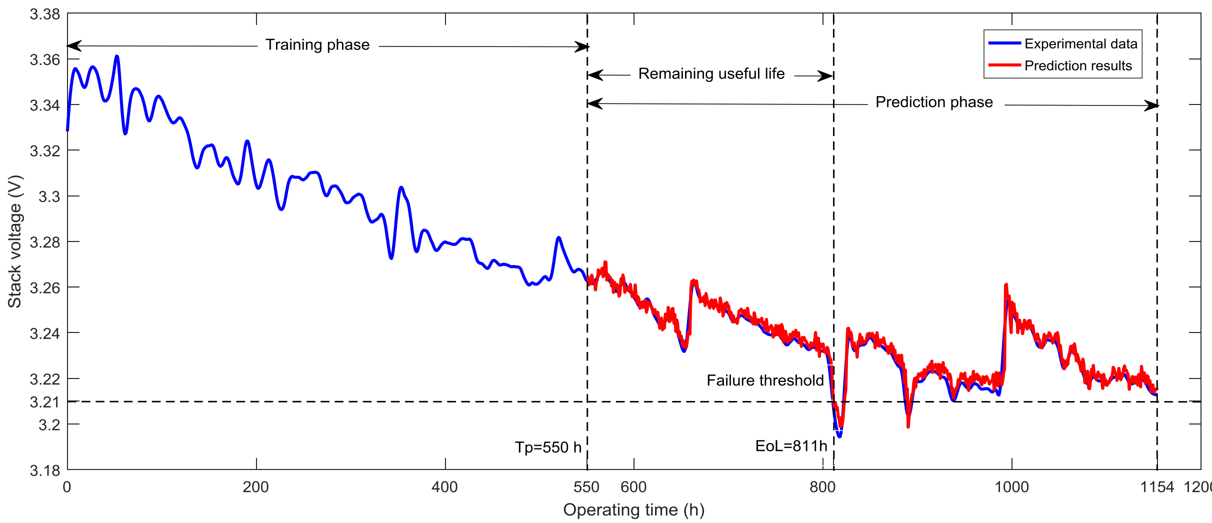

Fig. 10 – Prognostic results of LSTM RNN at $T_p = 550$ h.

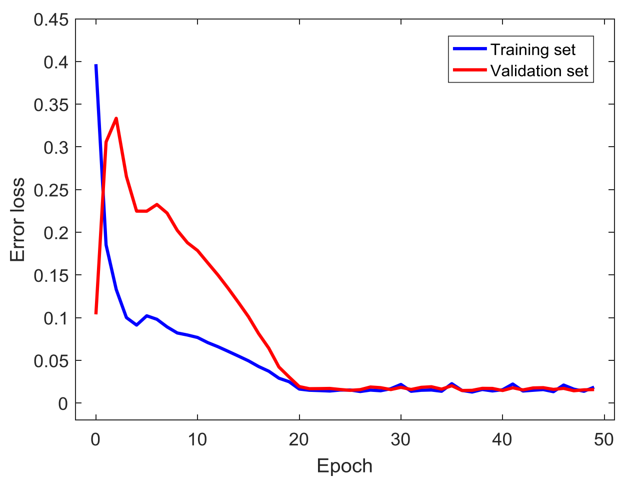

Fig. 11 – System training loss and test loss.

3.2107 V, which is closest to the actual failure voltage. Then, at 811 h, the PEMFC fails. Since the PEMFC is in the learning phase of [0 h, 550 h], the remaining service life is 261 h.

When T = 810 h, the predicted value of the stack voltage is 3.2160 V, which is closest to the actual value of 3.2117 V. When the learning phase is set to 550 h, the predicted RUL and the actual RUL are 260 h and 261 h, respectively. The expected value of RUL is less than the real value of RUL, which is beneficial to improve system performance in practical applications. The LSTM RNN method has better fitting accuracy and smaller RE. The LSTM RNN model can accurately reflect the declining trend of PEMFC. It is suitable for the long-term aging prediction of fuel cells.

The training loss and test loss of the system are shown in Fig. 11, where the definition of error loss is shown in the equation (12). As can be seen from the Fig. 11, LSTM RNN has a faster convergence rate, and it has begun to converge in the 20th epoch. Overall, the test loss is greater than or equal to the training loss, indicating that there is no overfitting problem. The above results show that LSTM RNN has a fast convergence rate and better generalization ability, which have considerable practical value in reality.

In this paper, the BPNN algorithm is used to predict the remaining service life, and the prediction results are compared with LSTM RNN. The PEMFC system has a 24-dimensional property, in which the total stack voltage is the health index for predicting the residual service life of PEMFC. Therefore, the designed BPNN structure is 23-47-1. There are 23 nodes in the input layer, 47 nodes in the hidden layer and one node in the output layer. The training error is 1×10^{-5}. The activation function of the hidden layer is "tansig". The activation function of the output layer is "pureling". Network creation and training functions are "newff" and "train" respectively. The prediction comparison results based on LSTM RNN and BPNN are shown in Table 3. When T = 886 h, the predicted value of stack voltage based on BPNN is 3.2134 V, which is the closest to the actual value of 3.2117 V. The anticipated RUL based on BPNN is 336 h and the expected value of RUL is far higher than the real value of RUL. It has a lag in the actual system and is not conducive to timely and early detection of system faults.

Different from the traditional BPNN, the directional circulation is introduced by LSTM RNN. This allows information to be passed from one step of the neural network to the next. The LSTM RNN can be thought of as a series of BPNN with equal

Table 3 – Prediction results of LSTM RNN and BPNN.

Algorithm	MAE	RMSE	Predicted RUL (h)	RE (%)	Accuracy (%)
LSTM RNN	0.0026	0.003	260	0.7663	99.23
BPNN	0.0234	0.0203	336	29.23	70.77

weights and each neural network will pass information to the next. The state of cells at each time is related to the current input and the previous cell state, while the output at each time is only related to the current cell state. The characteristics of the LSTM RNN information flow enable it to process relevant information before and after, which makes LSTM RNN able to deal with problems of time series prediction well.

As can be seen from Table 3, the MAE, RMSE, and RE of BPNN are much higher than that of LSTM RNN. The comparative analysis shows that LSTM RNN has better prediction results and is more suitable for on-line residual life prediction of PEMFC system.

Conclusions

In this paper, the remaining service life prediction of PEMFC system is studied under steady-state conditions. The residual life prediction method of PEMFC based on LSTM RNN is proposed to realize long-term aging prediction of PEMFC. Equal interval sampling and locally weighted regression scatter smoothing are used to reconstruct data and smooth data. The calculation cost of the data is significantly reduced while the aging tendency of the premier data is reflected. The LSTM RNN is adopted to predict the RUL of the test data. 1154-hour experimental aging analysis of PEMFC shows that the prediction accuracy of the novel method is 99.23%, the MAE and RMSE are 0.0026 and 0.003 respectively. The comparison analysis shows that the prediction accuracy of the novel method is 28.46% higher than that of BPNN. The RE, MAE, and RMSE are all much less than that of BPNN. Therefore, the novel method can quickly and accurately predict the remaining service life of PEMFC. It is more suitable for PEMFC online residual life prediction.

At present, the verification of PEMFC RUL prediction in the situation of the constant operating has been finished and achieved, the implement of forecast during the dynamic load operations is being carried out. The robustness and generalization performance will be further strengthened and improved.

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