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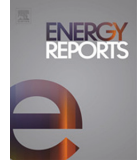
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Data-driven fuel cell performance prediction by transfer learning and dynamic time warping

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Abstract

The increase of world energy demand contributes to the development of renewable energy sources. Fuel cells, which use hydrogen to deliver energy, have seen a promising future. Fuel cells have been investigated since the last 50 years but they are still relatively absent for the commercial use due to the large exploitation cost and poor durability. One of the reasons is that the health state of a running fuel cell is hard to evaluate due to the system complexity and insufficient data. To tackle this problem, this paper proposes a data-driven fuel cell performance prediction method based on transfer learning and dynamic time warping. Historical data is trained in the source domain to build a model that can be transferred to the target domain and can be fine-tuned with only a small volume of online measurement. To improve the model recognition, dynamic time warping technology is applied to quantify the similarity between two different time series so that similar instances can be selected to build the neural network prediction model. Results show that, compared to traditional prediction method, the proposed prediction method has improved the prediction accuracy by almost 50%.

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Keywords: Dynamic time warping; Proton exchange membrane fuel cell; Performance prediction; Transfer learning

1. Introduction

Hydrogen, as an energy carrier, has emerged as a promising solution to the increasingly serious fossil fuel depletion and environmental problems [1]. In transportation sector, proton exchange membrane fuel cells (PEMFCs) are playing an important role in automotive traction systems owing to their advantages of quick start-up, low operation temperature, high energy density, etc. Moreover, PEMFCs regenerate electricity from hydrogen and air, and do not emit carbon dioxide or fine particles as conventional fuels do. However, the performance and durability

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of PEMFCs are the main obstacles to their massive industrial production and global adoption [2]. Researches on materials and component design have been conducted in recent years to enhance the durability of PEMFCs from the component level and the cell level, however, durability-oriented control and management strategies are rarely discussed on the stack level and the system level [3]. This is due to the reason that the PEMFC systems are multi-physics and multi-time scale, and it is difficult to detect the health state of a running PEMFC stack. Today, several models are developed, either based on physical equations or on experimental data. However, and especially if the model is to be used for control and management, limitations of physical models become obvious. For instance, some internal parameters are hard to access due to the limitations of sensor technology, or measuring these parameters is too costly [4]. It is, therefore, necessary to find ways of predicting fuel cell health status using in-situ data-driven approach, in which on-board measurement techniques are used to feed the data-driven methods for health state determination of the stack.

Data-driven methods investigate the internal connections inside the data and can be deployed to estimate and predict the health state of an on-board PEMFC. As no model is required in data-driven methods, the performance of data-driven method highly depends on the topology of neural networks and the selected input parameters. Liu et al. (2020) have performed a dedicated literature survey on data-driven PEMFC prognostics methods and classified the methods into neural network based methods and other methods, like ageing pattern recognition, autoregressive methods, etc. [4]. In the literature, researchers have made continuous efforts to improve the design of neural network based methods in order to improve the prediction performance. For example, Wang et al. (2022) have developed a navigation sequence driven long short-term memory (LSTM) network to predict the degradation of a fuel cell stack [5]. The novel topology with a navigation sequence can deal with the model recognition uncertainties and enhance long-term prediction performance. Similarly, Benagoune et al. (2022) have proposed to predict the dynamic ageing performance of PEMFCs with the help of a non-dynamic autoregressive prediction sequence and combine it with a convolutional neural network to predict the future performance with predictable dynamics [6]. Vichard et al. (2020) have developed a multi-input neural network based on the echo state network for PEMFC degradation prediction, and found out that the operation condition, such as the stack temperature, has an influence on the fuel cell stack degradation. The degradation prediction result has been improve by considering the temperature as an input of the echo state network [7]. Moreover, Zhang et al. (2021) have developed a multi-step input and multi-step output neural network based on LSTM, which turns out to achieve better performance in short-term prognostics of PEMFCs [8]. For long-term prognostics, Zhang et al. (2021) have proposed to use a variable-step prediction structure, which adapts the prognostics steps based on the prediction horizon and eliminates the indeterminacy of long-term prediction to a large extent [8].

However, most researches focus on the prediction performance improvement of the constructed neural networks regarding the input sequences and the topology. Few of them have discussed the prediction horizon. Most PEMFC prognostics works in the literature tend to start prediction from the second half of ageing experiment data [9,10]. This is because that the prediction accuracy of data-driven methods is based on a certain training data volume. If the data volume for training is small, the neural network cannot be effectively trained and recognized. On the contrary, as long as the amount of the training data is large enough, the neural network is fully trained and can well express the internal mapping relations of the data. Meanwhile, it can reduce the outliers in the data and obtain reliable prediction result. For example, Li et al. (2020) have found that the existing degradation prediction method can meet the reliability requirements only when the prediction range is within 350 h for a 1500 hours' fuel cell ageing dataset [11]. However, an effective performance prediction method must be capable of evaluating and predicting the health state of the system throughout its life cycle in order to ensure the implementation of the subsequent real-time control and management strategies. Therefore, a performance prediction method for PEMFCs under full lifetime cycle, especially in the early stage, is demanding.

This paper proposes a transfer learning based PEMFC performance prediction method, in which historical datasets are trained offline to establish a knowledge base so that only a small volume of data is required for the online prediction. Dynamic time warping method is used to select the most relevant degradation behaviour to train the neural network model based on the online measurement. The proposed method aims to achieve accurate performance prediction, especially at the early stage of the fuel cell operation. Two ageing experiments have been conducted to validate the effectiveness of the proposed method.

The following sections are arranged as: Section 2 introduces the proposed data-driven PEMFC performance prediction method based on transfer learning and dynamic time warping; Section 3 describes the ageing experiments and the corresponding data structure used for validation, and demonstrates the results and some comparisons; and Section 4 concludes the paper.

2. Performance prediction method

The proposed PEMFC performance prediction method is implemented based on Multi-Layer Perceptron (MLP). A transfer learning scheme with dynamic time warping (DTW) is proposed to enhance the recognition capability of the model so that it can be used to predict the future performance evolution with a small volume of online measurement. The corresponding methodology is presented in this section.

2.1. Neural network topology

An MLP is built to perform the prediction task. MLP is a multi-layer neural network derived from perception learning algorithm, which calculates the output using the following equations:

$$u = \sum_{i=1}^n w_i x_i + b \tag{1}$$

$$y = \text{sign}(u) = \begin{cases} +1, & u > 0 \\ -1, & u \leq 0 \end{cases} \tag{2}$$

MLP is constructed based on the deepening of the perception learning algorithm on the network level, which can deal with nonlinear problems and can simulate any complex function theoretically. MLP has multiple layers including input layer, output layer and the layers in the middle, namely, hidden layers. An MLP structure with one single hidden layer and the corresponding feed-forward process is shown in Fig. 1.

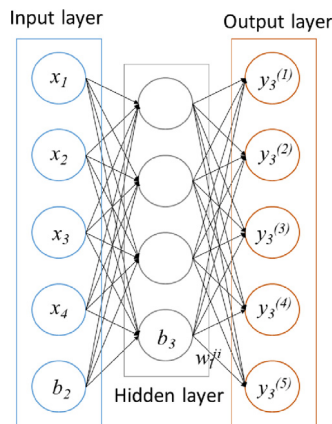


Fig. 1. Feed-forward process of MLP.

Therefore, the output of an MLP is calculated based on (3), where x is the input, u is the hidden state, y is the output, w is the weight and b is the bias. $f(\cdot)$ is activation functions. Suppose that there are L layers, $w_l^{(ji)}$ is the weight from the i th neuron on the $(l-1)$ th layer to the j th neuron on the l th layer, and $b_l^{(j)}$ is the bias of the j th neuron on the l th layer.

$$\begin{cases} y_l^{(j)} = f(u_l^{(j)}) \\ u_l^{(j)} = \sum_{i \in L_{l-1}} w_l^{(ji)} y_{l-1}^{(i)} + b_l^{(j)} \\ y_l = f(u_l) = f(W_l y_{l-1} + b_l) \end{cases} \tag{3}$$

The neurons in the MLP are trained with the backpropagation learning algorithm and the prediction is performed on the output layer by an iterative scheme until reaching the failure threshold.

2.2. Transfer learning

As an important technology in machine learning, transfer learning serves especially for those applications with limited training data because it can transfer the knowledge learned with similar historical datasets to the model

training in real time. Generally, in the source domain, sufficient historical data is available to train the neural network, however, in the target domain, one may be not able to obtain enough data to train the model. In this situation, transfer learning helps to accelerate the training efficiency in the target domain by fine-tuning the trained model in the source domain with a small volume of real-time data [12]. The working process of the proposed prediction method using transfer learning and DTW is shown in Fig. 2, in which DTW is deployed to select the most similar instants from the source domain.

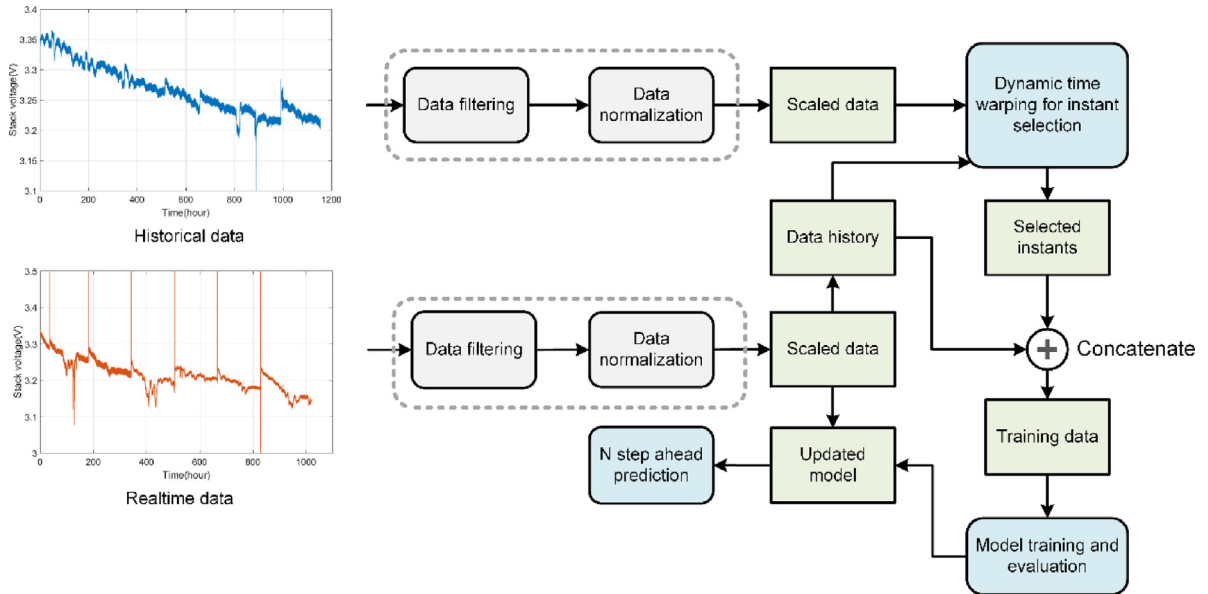


Fig. 2. Working process of the proposed prediction method using transfer learning and DTW.

In the proposed method, the historical data in the source domain and the real-time data in the target domain are firstly filtered and normalized. The selected instances by DTW are used as the training dataset and are used for neural network training and evaluation. Once the network model is trained, the scaled real-time data is used to fine-tune and update the model for better online adaption. The updated model is used to predict the N step ahead.

2.3. Dynamic time warping (DTW)

Transfer learning is used to build a model using historical data, while the built model is used for online prediction. The prerequisite of using transfer learning is that the systems in the source domain and in the target domain have similar behaviour. Therefore, it is necessary to quantify the similarity between the historical data and the real-time data so that the most similar instances could be found to train the model and to improve the model recognition. DTW is such a method for similarity calculation. In general, the similarity between two time series is calculated by Euclidean distance:

$$D_{eu}(X, Y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \tag{4}$$

This calculation is based on the hypothesis that the two time series have the same lengths. However, if X and Y have different numbers of elements, $D_{eu}(X, Y)$ turns out to be large even if the two time series might be similar. DTW distance is proposed to overcome this problem. It calculates the shortest warping path, which is built by calculating the best alignment between the two time series using a matrix:

$$D_{DTW}(X, Y) = \arg \min(W = w_1, w_2, \dots, w_k) = \arg \min \sqrt{\sum_{k=1, w_k=(i,j)}^K (x_i - y_j)^2} \tag{5}$$

where X and Y are two time series with different length, while x_i and y_j are the i th and j th element of X and Y . w_k is the warping path of element (i, j) . Therefore, it can determine the similarity between two time series with different lengths by warping them non-linearly in the time dimension [13]. Fig. 3 shows the process of implementing DTW. Only selected instances from the whole source data are used to train the neural network model, as shown in Fig. 2.

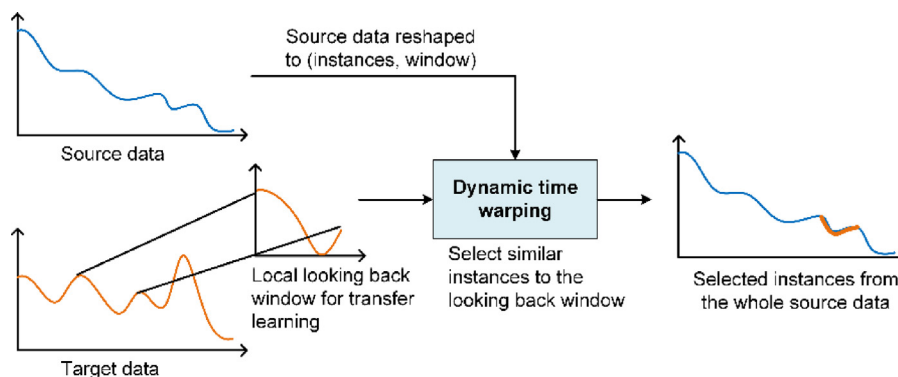


Fig. 3. Working principle of DTW.

3. Experiments and result discussion

3.1. Fuel cell ageing experiments

Two ageing experiments have been executed on a 1 kW test bench located in FCLAB laboratory (FR CNRS 3539),¹ France. The two tested stacks are both of 5 cells with an active area of 100 cm². The two stacks are loaded with different current densities: one with a constant current density of 0.70 A/cm² and the second is loaded with a dynamic current density by adding a ripple current density, denoted as “FC1” and “FC2”, respectively. The details of the experiment setup are described in Table 1.

Table 1. Ageing experiment setup.

Parameter	Value
Active surface	100 cm ²
Number of cells	5
Gas pressure	0–2 bar
Air flow	0–100 l/min
Hydrogen flow	0–30 l/min
Cooling water flow	0–10 l/min
Cooling temperature	20–80 °C
Maximum operation temperature	80 °C
Maximum current (current density)	100 A (1 A/cm ²)
Nominal current density	0.70 A/cm ²
Ripple current	0.14 A/cm ² oscillating with the frequency of 5 kHz

The obtained measurements consist of cell voltages, current density, inlet and outlet gas temperature and pressure, inlet and outlet water temperature, flows rates, inlet air hygrometry, etc. The stack voltage is calculated by adding cell voltages together. 143 863 and 127 370 monitoring samples are obtained for FC1 and FC2, respectively. The stack voltage evolutions of the two stacks are plotted in Fig. 4 and are used as the PEMFC degradation performance indicator.

To validate the proposed PEMFC performance prediction method, the two datasets are used as “historical dataset” and “real-time dataset” alternatively. “Historical dataset” is used to performing the MLP prediction model training, and a certain length of “real-time dataset” is used to in the test phase, which fine-tunes the trained model for online performance prediction.

¹ <http://www.fclab.fr/>.

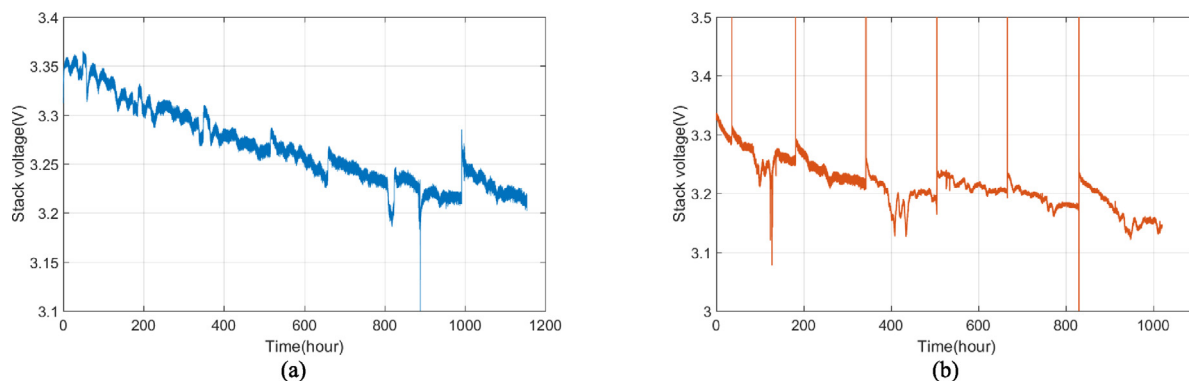


Fig. 4. Ageing experiment data on a 1 kW test bench: (a) FC1 stack voltage evolution under constant current; (b) FC2 stack voltage evolution under ripple current.

3.2. Result discussion

The cross validation is performed with FC1 and FC2. First, FC2 is used as historical dataset and an MLP is trained with the entire FC2 stack voltage data. Then, the trained model is transferred for the online FC1 prediction task. Only 200 hours' data from FC1 is injected to the trained MLP to update the model. 100 tests are repeated to indicate the uncertainty of the results, i.e. the orange shadow shown in Fig. 5, and the median values are calculated as the prediction results, i.e. the orange solid line shown in Fig. 5. The validation is then alternated by exchanging the historical data and the real-time data. Results with the proposed transfer learning and DTW method and those without transfer learning and DTW are compared in Fig. 5. Table 2 compares the root mean square error (RMSE) and the mean average error (MAE) of the results. It could be seen from the results that the proposed PEMFC performance prediction method based on transfer learning and DTW is able to accurately predict the PEMFC performance degradation even with only 200 hours' data. The predicted time series dynamically follow the originally degradation trend. Compared to the method without transfer learning and DTW, the prediction accuracy has been improved by almost 50%.

Table 2. Result comparison.

Historical data:	FC2		FC1		
Real-time data:	FC1		FC2		
		RMSE	MAE	RMSE	MAE
With transfer learning and DTW		0.0098	0.2625	0.0115	0.3040
Without transfer learning and DTW		0.0192	0.4666	0.0205	0.5872

4. Conclusion

Existing data-driven PEMFC performance prediction methods have been developed based on certain training data volume and operation time. However, it is difficult to evaluate and predict the PEMFC state in its early running stage. This paper has proposed a transfer learning based prediction method to deal with the early stage performance prediction problem of the PEMFC. The model trained by the historical data was transferred for online prediction so that it could fasten the online model training and only a small volume of online data was needed to fine-tune the model. The similarity between the historical data and the real-time data was calculated by dynamic time warping method in order to improve the model recognition by training similar instances. A comparison has been conducted between the proposed method and the prediction model without transfer learning and dynamic time warping, which showed that the proposed method could continuously predict the PEMFC performance and the accuracy was improved by almost 50%.

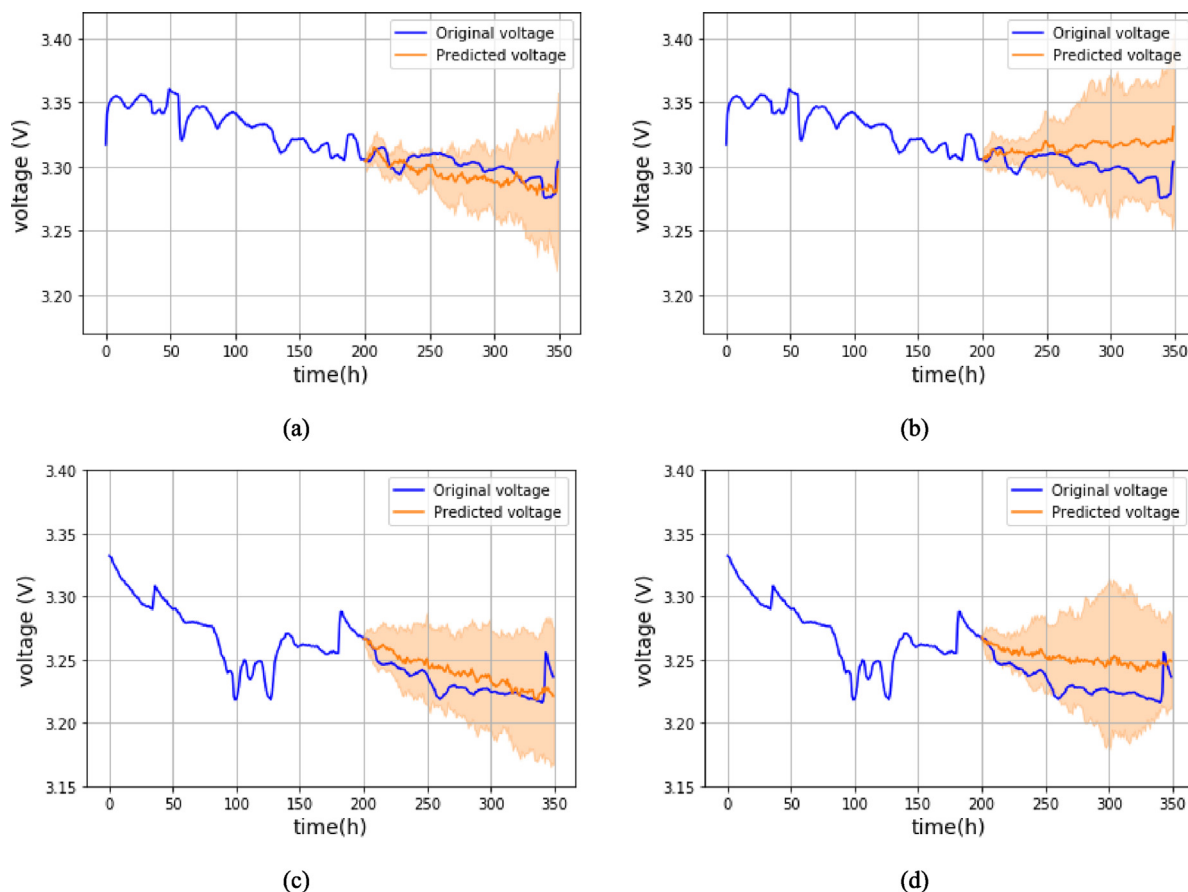


Fig. 5. Prediction result: (a) FC1 prediction starting at 200 h with transfer learning and DTW; (b) FC1 prediction starting at 300 h without transfer learning and DTW; (c) FC2 prediction starting at 200 h with transfer learning and DTW; (d) FC2 prediction starting at 200 h without transfer learning and DTW. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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