Advanced Prognostic Method of Proton Exchange Membrane Fuel Cells Based on Particle Swarm Optimization-Bidirectional Long Short-Term Memory Neural Network and Transformer

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Abstract: Proton exchange membrane fuel cell (PEMFC) system is a complex, nonlinear, multi-scale, and multidisciplinary system. It is difficult to develop a single method to collect all characteristic parameters and predict the PEMFC degradation trend. In this work, an advanced prognostic method, named Particle Swarm Optimization (PSO)-Bidirectional Long Short-Term Memory (BiLSTM) and Transformer hybrid method, is proposed. Meanwhile, a Bayesian model is used as an evaluation model to conduct uncertainty analysis for the future prediction dataset. As for the performance indices, the determination coefficient R^2, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used to conduct accuracy analysis for both the training dataset and test dataset, and a comprehensive performance evaluation metric is established for the PEMFC system in this work. Comparing the proposed hybrid method with the traditional BiLSTM method, it is found that the hybrid one performs better according to the comprehensive evaluation metric.

Keywords—PEMFC, degradation prognostics, PSO-BiLSTM-Transformer, Bayesian neural network

I. INTRODUCTION

As global energy issues become increasingly serious, it is important to develop new energy technologies to reduce pollution and the demand for fossil fuels. Proton exchange membrane fuel cell (PEMFC) is an energy conversion device converting hydrogen chemical energy to electricity and heat, with the advantages of high efficiency, high energy density, and zero pollution. PEMFC is widely used in many fields, such as transportation and power generation equipment. Under these circumstances, it is of great importance to conduct aging trend prediction in PEMFC systems for enabling fault tolerant control, predictive maintenance, and extending the system operating lifetime.

Prognostic methods for PEMFCs can be generally categorized as model-based, data-driven, and hybrid methods that combine the two. Within the data-driven framework, Li et al. used the echo state network to predict the voltage degradation of the PEMFC system based on the health factor extracted by the variable parameter model [1]. There are some other data-driven prediction methods using the FC stack temperature and current to improve the PEMFC system prediction accuracy [2, 3]. Wang et al. presented the hybrid method and used the prediction results of the semi-empirical model to correct the data-driven results [4]. Hua et al. presented the echo state network to conduct the uncertainty analysis [5]. Zuo et al. presented a deep-learning based prognostic framework to perform the prediction work [6-7]. Yue et al. proposed the convolutional neural network to mitigate error accumulation problem and used dynamic durability test data for model training and validation [8-9]. Yue et al. proposed an online adaptive prognostics-based health management strategy for fuel cell hybrid electric vehicles, which can improve the durability of the fuel cell thanks to online health monitoring [10]. Lv et al. proposed the Empirical Model, Capacity Recovery-Identification Correction and Machine Learning co-driven method to address the inaccurate and unreliable RUL predictions [11]. Wang et al. presented deep learning prognostics for dynamic operating proton exchange membrane fuel cells under dynamic condition [12-15]. Zuo et al. conducted research on the degradation root causes of a PEM fuel cell operating under dynamic loads and a dynamic load-based long-term durability test is designed and performed to collect the durability dataset [16-17]. Liu et al. thoroughly reviewed the prognostics research of PEMFCs and classified the prognostics methods and degradation indexes [18]. Pan R, et al. presented an analytical equivalent circuit model to conduct PEMFCs health degradation assessment and the Kramers-Kronig transformation is used to validate the data effectiveness [19]. Yue et al. proposed a multi-input time-series prediction network based on an echo state network, which takes the future current into consideration. A degradation trend extraction method was proposed and the remaining useful life of the fuel cell was predicted [20].

He et al. proposed an unsupervised learning based autoencoder method to encode the load cycles and extracted the intermediate layer features as degradation indexes for prediction, which better restored the degradation process of fuel cells under dynamic loads [21]. Xie et al. used deep neural network method to predict system parameters, and proposed a method to reconstruct voltage profiles through comprehensive system parameters [22]. Liu et al. classified the automotive operating conditions of fuel cells into four categories based on current density, and trained a multi-input fuel cell performance degradation prediction model based on Bayesian ridge regression and Gaussian process regression using the operating times of the four categories as inputs [23].

Despite the advancements in data-driven prognostic methods, a significant gap remains in effectively modelling the multi-scale dynamics and long-term dependencies of PEMFC degradation. Existing methods, such as individual LSTM or transformer models, often struggle with hyperparameter sensitivity and the inability to capture both local and global features. To bridge this gap, this study proposes a hybrid PSO-BiLSTM-Transformer model. Meanwhile, existing performance metrics are largely confined to accuracy-oriented measures, which are inadequate for comprehensively assessing prognostic performances. This work aims to establish a more comprehensive performance evaluation metric that jointly considers prediction accuracy and prediction uncertainty.

This study aims to propose an advanced prognostic method capable of addressing the difficulties linked to both the multi-timescale dynamics and uncertainty characteristics of PEMFC systems. The remainder of this article is organized as follows. Section II introduces the prognostic methodology, including data preprocessing, hybrid method, and performance indexes. Section III presents the initial experimental validation results, including a preliminary assessment based on an open-source dataset. Section IV concludes the paper.

II. SYSTEM MODELING

A. Data preprocessing

Data preprocessing can improve model performance and improve data quality. There are three steps in the data processing part, including data downsampling, Kalman filtering, and data normalization.

Data downsampling is performed to reduce the amount of data by lowering the sampling rate, improving processing efficiency, and at the same time assisting in filtering out noise and performing multi-scale analysis. Kalman filter provides an optimal estimate of the state of a dynamic system from a series of noisy measurements. Data normalization is the process of scaling numerical data into a specific range, typically [0, 1]. This makes different features comparable and helps machine learning algorithms perform better and converge faster.

B. PSO-BiLSTM and Transformer hybrid method

The prognostic methodology based on PSO-BiLSTM-Transformer method is shown in Fig. 1. The traditional LSTM method introduced the mechanisms of the input gate i_t, forget gate f_t, and output gate o_t to solve the issues of gradient vanishing and exploding that existed in traditional RNNs [24]. In the formula, parameter t is time step and parameter b is bias term. x_t denotes the feature vector input into the network at time step t. The method possesses improved capabilities for modeling long-term dependencies. The input gate $i_t$determines which unit information needs updating, the forget gate f_t is responsible for deciding which information should be discarded, and the output gate o_t determines the output value based on the unit state. The operational mechanism can be described as follows [25].

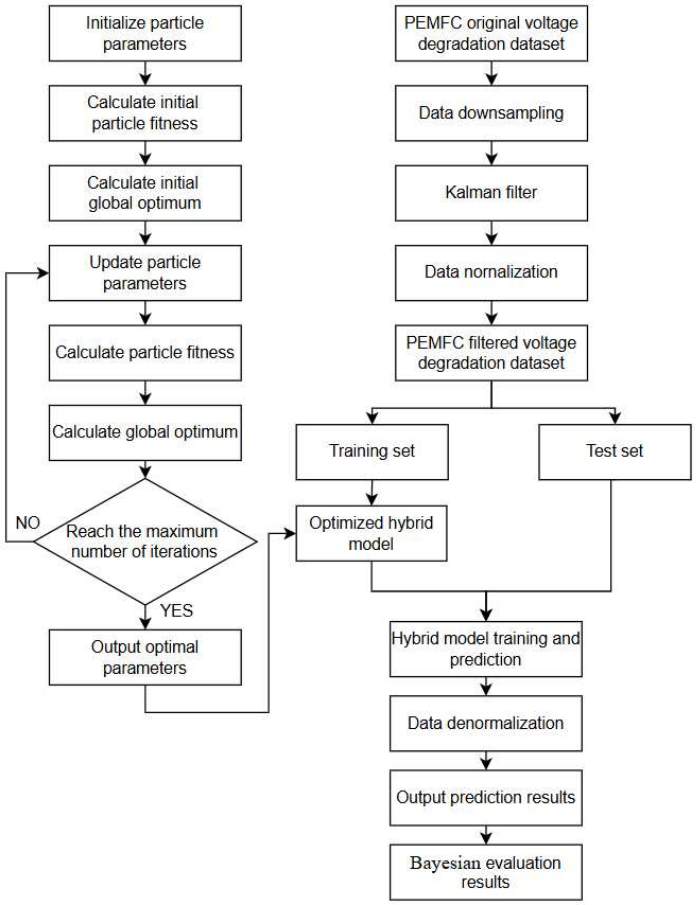


Fig. 1. Prognostic methodology based on the PSO-BiLSTM - Transformer method.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

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

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

$$c_t = f_t \cdot c_{t-1} + i_t \tilde{c}_t \quad (4)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \cdot \tanh(c_t) \quad (6)$$

BiLSTM consists of two LSTM networks with opposing directions. It aggregates the output from the forward LSTM and the output from the backward LSTM to form the BiLSTM output, denoted as y, the formula is as follows [26]:

$$\vec{h}_t = f(\vec{W} \cdot [\vec{h}_{t-1}, x_t] + \vec{b}) \quad (7)$$

$$\overleftarrow{h}_t = f(\overleftarrow{W} \cdot [\overleftarrow{h}_{t-1}, x_t] + \overleftarrow{b}) \quad (8)$$

$$y_t = g(W \cdot [\vec{h}_t, \overleftarrow{h}_t] + b) \quad (9)$$

The Transformer model was proposed by Vaswani et al. [27]. Different from the traditional recurrent neural network (RNN) model, the basic operation unit of the Transformer model is a multi-head self-attention mechanism, and the structure adopts the form of encoder-decoder. The operation process of the multi-head self-attention mechanism is as follows:

$$MultiHead(Q,K,V) = Concat(head_1, \cdots, head_h)W^0 \quad (10)$$

$$Head_i = Attention(Q_i, K_i, V_i) \quad (11)$$

$$Attention(Q,K,V) = Softmax(\frac{QK^T}{\sqrt{d_k}})V \quad (12)$$

The PSO is an intelligent biological optimization algorithm proposed by Kennedy et al. [28], which originated from the simulation and research on the regularity of bird flock foraging behavior. It assigns initial positions and velocities to particles in space, and the particles randomly iterate and search for the objective function value in the solution space at a certain speed. The quality of the particle position is evaluated by the fitness value of the objective function. The PSO method is commonly used for BiLSTM hyperparameter optimization.

In this work, BiLSTM is configured with two hidden layers, each containing 64 hidden units. The Transformer model is configured with four attention heads and an embedding dimension of 128. The PSO algorithm uses a population size of 30. Besides, the models are trained using the Adam optimizer with a maximum of 200 epochs. The initial learning rate is set to 0.01, with a learning rate drop factor of 0.1, and a learning rate drop period of 300 epochs. The training dataset ratio is set as 0.8 after preliminary experiments with different training-testing split ratios.

C. Comprehenseive performance metric

A comprehensive performance metric is established to jointly evaluate prediction accuracy and prediction uncertainty.

The accuracy dimension of the proposed evaluation metric is quantified using three performance indexes evaluated on the test dataset, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the coefficient of determination (R^2).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \in [0, +\infty) \quad (13)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \in [0, +\infty) \quad (14)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \in [0,1] \quad (15)$$

The uncertainty dimension is evaluated using three performance indexes for the prediction dataset: Confidence Interval (CI) Coverage, Error Distribution and Kullback–Leibler (KL) Divergence. These indexes are used to assess the uncertainty of long-term predictions.

III. Experimental Verification

A. PEMFC system experimental platform

An initial experimental validation is performed based on an open dataset from the IEEE PHM Data Challenge 2014 [29]. There are two parts of the dataset. The first part is a 1 kW PEMFC stack on which long-term tests (1000 h) have been carried out under quasi-stationary conditions. The second part deals with a fresh 1kW PEMFC stack. On this second FC stack, long-term tests (1000 h) with current ripples were performed.

FC stack 1 (without ripple) testing protocol [29] includes：

1. Electrochemical Impedance Spectra (EIS) performed before polarization at nominal current density (0.7 A/cm²).
2. Polarization curve from 0 to 1A/cm² of 1000 s.
3. EIS performed after polarization (0.7; 0.45; 0.20 A/cm²).

The PEMFC system experimental platform is shown in Fig.2 [29, 30]. The PEMFC system experimental platform includes 1 kW PEMFC stack, air supply, cooling System, electronic load, sensors reference conditioning, data acquisition system, LabVIEW Interface and control system. The control system is integrated into the test bench and sends control signals to auxiliary systems to ensure the normal operation of the system. In the aging experiments, the PEMFC system operated for more than 1000 h at the nominal current density.

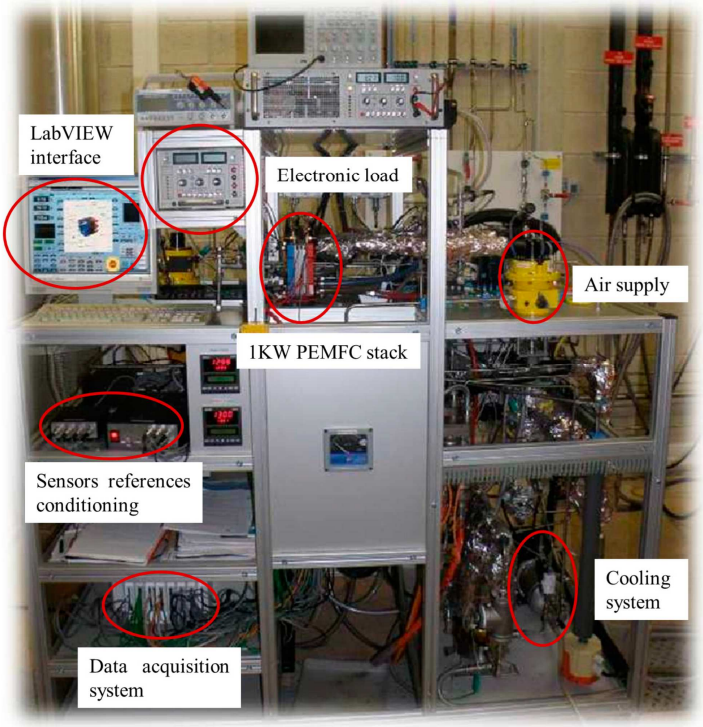


Fig. 2. PEMFC system experimental platform from French FEMTO-ST Institute/FCLAB [29].

B. Experimental Verification

1) Verification of training and test datasets

The operating time of the PEMFC system is 420 h. There are 5,000 filtered voltage samples. The dataset was selected because it covers the most significant, high-quality degradation period under stable conditions, providing a robust baseline for validating long-term prognostic stability. The MAE, RMSE and R^2 are used as Performance indexes to verify the training dataset and test dataset in the PEMFC system. The verification of the training dataset and test dataset are shown in Tab. 1.

Tab.1. Accuracy evaluation of the training and test datasets

Performance indexes	training set	test set
MAE	0.00044112	0.00043041
RMSE	0.00061389	0.00059731
R^2	0.96401	0.96388

2) Verification of future prediction dataset

The Bayesian evaluation model is used to conduct uncertainty analysis for future prediction dataset. Based on the historical dataset, the model can be used to predict future voltage trend. There is one predicted voltage curve. The future data prediction is shown in Fig. 3. There are ten predicted voltage curves and one mean voltage curve. The historical data, future predicted data and future predicted mean data are shown in Fig. 4. Confidence interval is set up to comprehensively evaluate the prediction results. Mean prediction results with 95% confidence intervals are shown in Fig. 5.

KL Divergence is a mathematical measure of how one probability distribution differs from a second, reference probability distribution. The index is used to assess the uncertainty of long-term predictions. Based on KL Divergence, there is a comparison of voltage data probability distribution for original data and generated data. A comparison of voltage data probability distribution is shown in Fig. 6. The probability distribution of original data and generated data is shown in Fig. 7. The blue part is the probability distribution of the original data. The orange part is the probability distribution of the generated data. The comprehensive evaluation matrix is shown in Tab. 2. The uncertainty-related evaluation results are as follows:

(1) The proportion of PSO-BiLSTM-Transformer prediction values that fall within the 95% confidence interval by Gaussian Process Regression (GPR): 100.00%.

(2) PSO-BiLSTM Prediction Error: mean = 0.0008, standard deviation = 0.0002.

(3) The KL Divergence result is 0.1955 (<0.5). The result can effectively verify the results of Bayesian neural network for uncertainty analysis.

Tab.2. Uncertainty evaluation of the prediction dataset

Evaluation indicator	PSO-BiLSTM	PSO-BiLSTM-Transformer
95% confidence interval	100%	100.00%
Mean error	0.0016	0.0008
KL Divergence	0.3275	0.1955

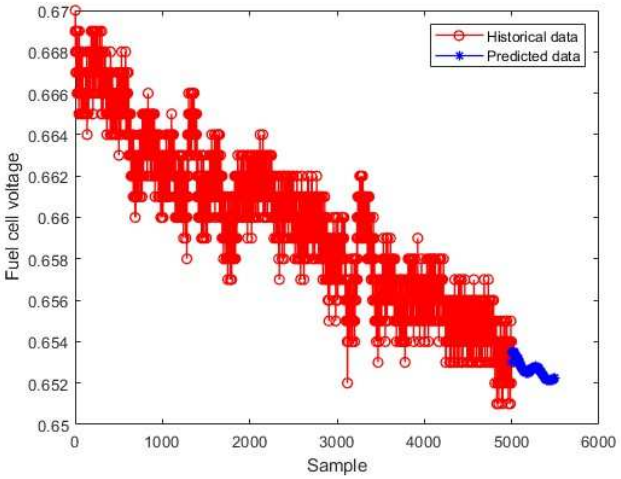


Fig. 3. Future data prediction.

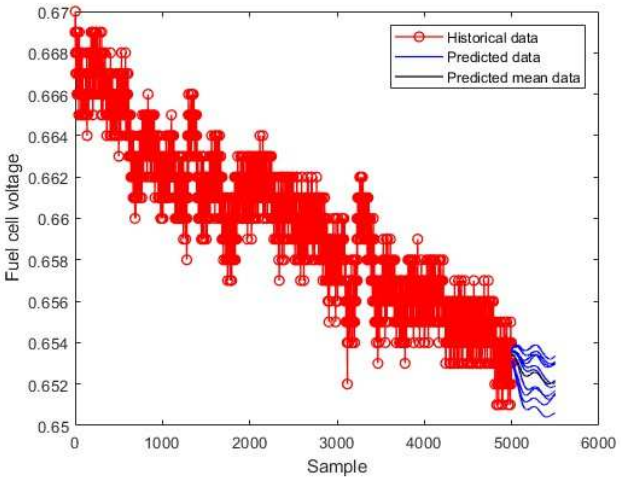


Fig. 4. Historical data and future predicted data.

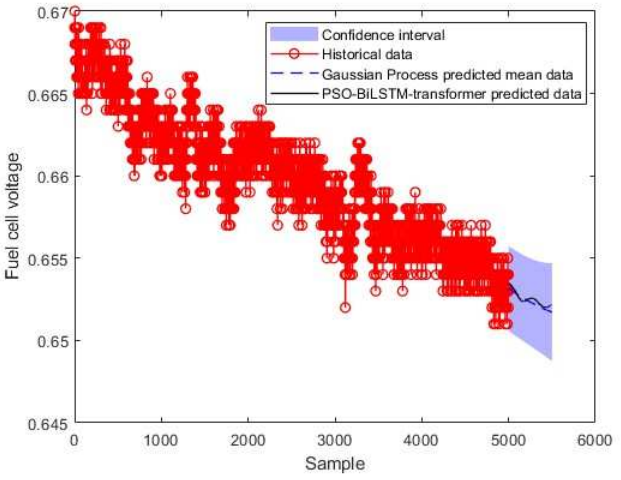


Fig. 5. Mean prediction results with 95% confidence interval.

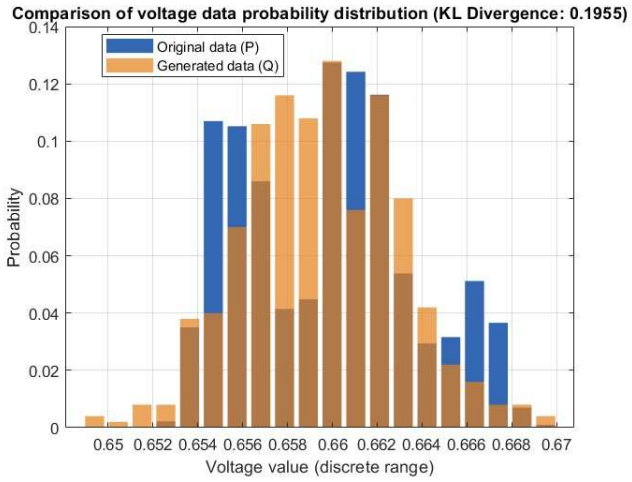


Fig. 6. Comparison of voltage data probability distribution.

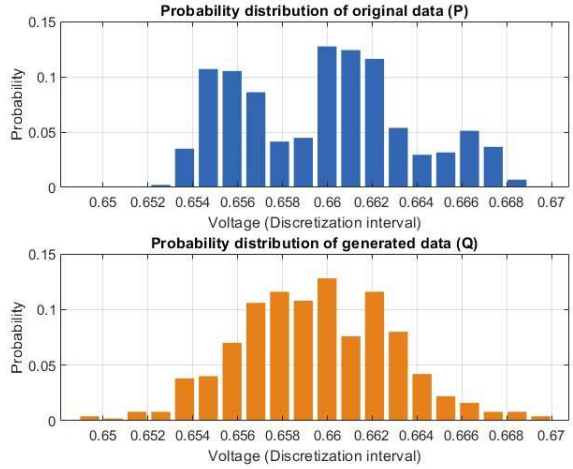


Fig. 7. Probability distribution of original data and generated data.

IV. Conclusion

FC aging prediction is of great significance for extending its operating lifetime and breaking through the bottleneck of large-scale commercial applications. Since the PEMFC system is a complex nonlinear system with strong coupling and multiple time scales, and has both linear and nonlinear characteristics, it is difficult to fit its data well using a single traditional time series model. Therefore, this work proposes an advanced hybrid prognostic method combining PSO-BiLSTM and Transformer to predict the performance degradation trend of FCs, with the major results as follows:

1. A comprehensive performance evaluation metric that jointly considers prediction accuracy and prediction uncertainty is established in the work. The MAE, RMSE and R^2 are used as performance indexes to conduct accuracy analysis for both training and testing datasets. The Bayesian model is used as an evaluation model to conduct uncertainty analysis for future prediction dataset.

2. The hybrid method performs better under the established comprehensive evaluation metric. An initial comparison between PSO-BiLSTM and PSO-BiLSTM-Transformer is made to demonstrate its superior performance. A more comprehensive comparison with existing benchmark methods will be added to the full version. The hybrid model can be used widely in historical data and future prediction data.

3. The hybrid method enables long-term prediction for future data and the prediction performance is validated using a Bayesian evaluation model.

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References

[1] Li Z, Zheng Z. Outblb R. Adaptive prognostic of fuel cells by implementing ensemble echo state networks in time-varying model space [J]. IEEE Trans on Industrial Electronics, 2020, 67(1): 379-389.

[2] Chen K, Laghrouche S, Djerdir A. Health state prognostic of fuel cell based on wavelet neural network and cuckoo search algorithm [J]. ISA Transactions, 2021, 113: 175-184.

[3] Hua Z, Zheng Z, Péra M.C., et al. Remaining useful life prediction of PEMFC systems based on the multi-input echo state network [J]. Applied Energy, 2020, 265: 114791.

[4] Wang Y, Wu K, Zhao H, et al. Degradation prediction of proton exchange membrane fuel cell stack using semi-empirical and data-driven methods [J]. Energy and Al, 2023, 11: 100205.

[5] Hua Z, Zheng Z, Pera M, et al. Statistical Analysis on Random Matrices of Echo State Network in PEMFC System's Lifetime Prediction [J]. 2022, 12: 3421.

[6] Zuo J, Lv H, Zhou D, et al. Deep learning based prognostic framework towards proton exchange membrane fuel cell for automotive application [J]. Applied Energy 2021, 281: 115937.

[7] Zuo J, Lv H, Zhou D, et al. Long-term dynamic durability test datasets for single proton exchange membrane fuel cell [J]. Data in Brief 2021, 35: 106775.

[8] Yue M, Zhang X, Teng T, et al. Recursive performance prediction of automotive fuel cell based on conditional time series forecasting with convolutional neural network [J]. International Journal of Hydrogen Energy, 2024, 56: 248.

[9] Yue M, Jemei S, Zerhouni N, et al. Health-conscious energy management for fuel cell hybrid electric vehicles based on prognostics-enabled decision- making [J]. IEEE Transactions on Vehicular Technology, 2019, 68: 11483.

[10] Yue M, Masry Z, Jemei S, et al. An online prognostics-based health management strategy for fuel cell hybrid electric vehicles [J]. International Journal of Hydrogen Energy, 2021, 24: 46.

[11] Lv Z, Chen Z, Wang P, et al. Empirical model, capacity recovery-identification correction and machine learning co-driven Li-ion battery remaining useful life prediction [J]. Journal of Energy Storage, 2024, 103: 114274.

[12] Wang C, Li Z, Dou M, et al. Data-driven prognostics based on time-frequency analysis and symbolic recurrent neural network for fuel cells under dynamic load [J]. Reliability Engineering & System Safety, 2023, 233: 109123.

[13] Wang C, Dou M, Li Z, et al. A fusion prognostics strategy for fuel cells operating under dynamic conditions [J]. eTransportation, 2022, 12: 100166.

[14] Wang C, Li Z, Outbib R, et al. A novel long short-term memory networks-based data-driven prognostic strategy for proton exchange membrane fuel cells [J]. International Journal of Hydrogen Energy, 2022, 47: 10395.

[15] Wang C, Li Z, Outbib R, et al. Symbolic deep learning based prognostics for dynamic operating proton exchange membrane fuel cells[J]. Applied Energy, 2022, 305: 117918.

[16] Zuo J, Steiner N, Li Z, et al. Quantifying degradation in hydrogen fuel cells: A holistic approach combining in situ and ex situ characterizations [J]. Renewable Energy, 2026, 263: 125515.

[17] Zuo J, Steiner N, Li Z, et al. Degradation root cause analysis of PEM fuel cells using distribution of relaxation times [J]. Applied Energy, 2025, 378: 124762.

[18] Liu H, Chen J, Hissel D, et al. Prognostics methods and degradation indexes of proton exchange membrane fuel cells: A review [J]. Renewable and Sustainable Energy Reviews, 2020, 123: 109721.

[19] Pan R, Yang D, Wang Y, et al. Health degradation assessment of proton exchange membrane fuel cell based on an analytical equivalent circuit model [J]. Energy, 2020, 207: 118185.

[20] Yue M, Zhang X, Teng T, et al. Trend-focused dynamic degradation prediction based on echo state networks in automotive fuel cells [J]. Energy Science & Engineering 2024, 12: 1462.

[21] He K, Mao L, Yu J, Huang W, He Q, Jackson L. Long-term performance prediction of PEMFC based on LASSO-ESN. IEEE Transactions on Instrumentation and Measurement. 2021, 70:1.

[22] Xie R, Li C, Ma R, Xu L, Zhou X. An explainable data-driven framework for fuel cell aging prediction under dynamic condition. IEEE Transactions on Industrial Electronics. 2022, 70: 5960.

[23] Liu M, Wu D, Yin C, Gao Y, Li K, Tang H. Prediction of voltage degradation trend for a proton exchange membrane fuel cell city bus on roads. Journal of Power Sources. 2021, 512: 230435.

[24] Zhang M, Han Y, Wang C, et al. Ultra-short-term photovoltaic power prediction based on similar day clustering and temporal convolutional network with bidirectional long short-term memory model: A case study using DKASC data [J]. Applied Energy 2024, 375: 124085.

[25] Houranouran M, Bukhari S, Zafarafar M, et al. COA-CNN-LSTM: coati optimization algorithm-based hybrid deep learning model for PV/wind power forecasting in smart grid applications [J]. Applied Energy 2023, 349: 121638.

[26] Xiao H, Fu L, Shang C, et al. Ship energy scheduling with DQN-CE algorithm combining bi-directional LSTM and attention mechanism [J]. Applied Energy 2023, 347:121378.

[27] Kennedy J, Eberhart R. Particle swarm optimization [C]. Proceedings of ICNN'95-international conference on neural networks. IEEE, 1995, 4: 1942-1948.

[28] Vaswani A, Shazeer N, Parmar N, et al. Attention is all you need[J]. Advances in neural information processing systems, 2017, 30: 5998-6008.

[29] Harel F, Hissel D, Turpin C, Rozière J, IEEE PHM Data Challenge 2014. Fuel Cell Lab (UAR 2200). Available online: https://dataosu.obs-besancon.fr/FR-18008901306731-2021-07-19_IEEE-PHM-Data-Challenge-2014.html.

[30] Wang T, Zhou H, Zhu C. A Short-Term and Long-Term Prognostic Method for PEM Fuel Cells Based on Gaussian Process Regression [J]. Energies, 2022, 15(13), 4844.