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Data-driven flooding fault diagnosis method for proton-exchange membrane fuel cells using deep learning technologies

Bin Zuo [a,b], Zehui Zhang [c,*], Junsheng Cheng [a,b,*], Weiwei Huo [d], Zhixian Zhong [e], Mingrui Wang [f]

[a] College of Mechanical and Vehicle Engineering, Hunan University, Changsha, China
[b] State Key Laboratory of Advanced Design and Manufacturing for Vehicle Body, Hunan University, Changsha, China
[c] College of Software, Nankai University, Tianjin, China
[d] School of Mechanical and Electrical, Beijing Information Science and Technology University, Beijing, China
[e] College of Mechanical and Control Engineering, Guilin University of Technology, Guilin, China
[f] Dongfeng Motor Corporation Technology Center, Wuhan, China

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ABSTRACT

Effective and accurate diagnostic methods are necessary to ensure the stable and efficient operation of proton exchange membrane fuel cells (PEMFC). In practice, the voltage drop is commonly used as the detection indicator of the flooding fault. However, the output power changes also affect the voltage of the PEMFC. To better diagnose the flooding fault under load-varying conditions, a data-driven method for PEMFC using deep learning technologies is proposed, which can automatically extract fault features for the raw data to diagnose the flooding fault. First, the indicators for the fault diagnosis model are selected to meet the actual situation according to the water transport mechanism and auxiliary systems of the general fuel cell stack. And the collected data are transformed into a 2-D graph to visually represent the characteristics of the time-series data. Then, the convolutional neural network is adopted to develop the fault diagnosis model. In addition, the batch normalization method is used to alleviate feature distribution differences and enhance the model generalization. Finally, the trained model is applied to detect the flooding fault. A real PEMFC experiment dataset is adopted to verify the diagnostic performance of the method. Experiment results show that the proposed model can effectively identify the flooding fault of the fuel cell accurately under load-varying conditions, and achieves over 99% accuracy.

1. Introduction

In recent years, the research on clean power sources has become an important research direction to alleviate the issues related to global warming and environmental pollution[1-4]. Among different technical routes, the proton-exchange membrane fuel cell (PEMFC) can convert hydrogen into electricity, and its by-products only have water and heat [5]. Owing to its excellent advantages such as zero pollution, low noise and high efficiency, PEMFC is becoming a credible candidate to provide green energy [6]. During the last decade, PEMFC applications such as electric ferries, electric vehicles and green buildings, have increased in number as relevant researches [7]. However, during the fuel cell system operation, operational faults may be experienced, such as flooding [8], air starvation [9], and membrane drying [10], which usually result in performance degradation and lifetime reduction. The limited reliability and durability of the PEMFC restrict its widespread commercialization application [11-13]. Therefore, in addition to research materials, effective fault diagnosis methods are also important for improving durability and saving maintenance costs.

In a PEMFC, an electrolyte membrane allows protons to pass but elections cannot pass it [10,11]. At the anode catalyst, the hydrogen atoms are split into protons and electrons. The protons and the electrons go through the membrane and external circuits respectively, which produces electric energy for external electrical loads. In addition, the water and heat are generated at the cathode catalyst layer. These electrical reactions are expressed as follows:

$$\text{Anode: } H_2 \rightarrow 2H^+ + 2e^- \quad (1)$$

$$\text{Cathode: } 2H^+ + 1/2O_2 + 2e^- \rightarrow H_2O \quad (2)$$

* Corresponding authors.
E-mail addresses: zhangtianxia918@163.com (Z. Zhang), chengjunsheng@hnu.edu.cn (J. Cheng).

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For high-power fuel cell applications, such as automobiles, ships and trains, it generally generates excess water as listed in Eq.(2), which may lead to the blockage of the flow channel, i.e. the water flooding fault [11–14]. Water accumulation would hinder the transmission of reactants, reduce the active area of the catalyst, and result in gas starvation[15]. It is worth noting that the gas starvation will lead to irrecoverable damage of the fuel cell [16]. Therefore, the flooding fault diagnosis method is very important to prolong the lifetime of the FC stacks.

Researchers have made a lot of efforts to investigate the water transport in the PEMFC, where the transparent fuel cell, X-ray radiography, and neutron imaging were utilized [17-19]. Though these methods are not applicable for real FC systems, they help to understand the mechanism of the flooding fault and explore the variation rules of monitor parameters, which can guide the development of corresponding fault detection models. For instance, the fuel cell voltage is confirmed as the most basic monitor indicator for fault detection. Based on this, Damour et al.[20] used the empirical mode decomposition method to extract fault features from the voltage to detect water faults.

To realize online fault detection, researchers proposed plenty of fault diagnosis methods, which involve electrochemical impedance spectroscopy (EIS)-based methods, physical model-based methods, data-driven methods. EIS-based methods[21] utilize the impedance spectrum to detect the faults of the fuel cell, since the impedance spectrum involves rich status information of the fuel cell. The EIS experiment results are usually analyzed with an equivalent circuit model to investigate the variation of element parameters for fault detection. Ren et al. [15]proposed an impedance-based measuring method for zero-phase ohmic resistance, and utilized a semi-empirical equivalent circuit model to study the change of mass transfer in the water flooding process. Zheng et al. [22] developed a double-fuzzy fault detection method based on EIS and fuzzy clustering and fuzzy logic, which can automatically learn diagnosis rules from experiment data. Due to the non-invasiveness and accurate fault detection, EIS-based methods are widely researched. However, the EIS-based methods need a long collecting data time[21], which results in the methods being unsuitable for online applications. In addition, the EIS equipment is too expensive.

The physical model-based methods usually include two steps: calculation and evaluation of the deviation. The deviation is calculated by the difference between the monitor values and the physical model output values. When the deviation exceeds a threshold value, the method presumes a fault emergence. Polverinoet et al. [23] proposed a lumped parameter model and used causal computation analysis to calculate a deviation. Hernandez et al.[24] developed the equivalent circuit model for the PEMFC, and its resistance variation of specific resistance is taken as the representation of the water flooding fault. Hu et al. [25] proposed a model-based method to estimate the liquid saturation and current density difference which can demonstrate the oxygen starvation level of the fuel cell and developed a fuel cell cathode model to incorporate the effect of the water flooding. Due to the hardware resource limitation of the embedded controller, the complex gas–liquid two-phase flow models do not apply to diagnose the fuel cell faults. Furthermore, as the model contains multi-domain knowledge, the design of a reliable physical model is extremely difficult.

Causes for the performance changes of the fuel cell under different operating conditions, have not been elucidated yet. Therefore, data-driven methods have been extensively used in existing PEMFC fault diagnosis researches. Many data-driven fault diagnosis methods were proposed based on pattern recognition algorithms, such as Decision Trees, Gaussian Naive Bayes (GaussianNB), Support Vector Machine (SVM), and k-nearest neighbors algorithm (KNN) [26,27]. For instance, Kamal et al. [28] used the radial basis function neural network to detect the different faults of the FC. In [29], an SVM-based fault diagnosis model and diagnosis rules were proposed to achieve fault detection.

Recently, with the progress of artificial intelligence technologies, neural networks such as deep neural networks (DNN) and convolutional neural networks (CNN) have been introduced to the fault diagnosis field [30,31]. Hossein et al. [32] used a deep neural network model to develop a water coverage ratio estimation method. Gu et al. [8] utilized long short term memory (LSTM) model to detect the flooding fault, which avoids using too many sensors in the FC. Due to the excellent feature extraction ability of the CNN, it is very suitable and has been widely used in classification tasks, especially in the fault diagnosis field. Manno et al.[33] proposed a CNN-based method for automatic fault diagnosis in photovoltaic systems using thermographic images. Praveen et al.[34] proposed a CNN model to detect the faults for the distributed power system integrated with distributed generators. Liu et al. [35] developed a CNN-based fault diagnosis method where Fisher discriminant analysis (FDA) is used to extract feature maps from monitor voltage signals. However, the diagnosis performance of the method may be affected by load-varying situations.

For on-board PEMFC systems, the monitor signals of the auxiliary systems can represent the fuel cell operation state. Although the voltage drop is commonly used as the indicator of flooding fault detection, the load-varying can also affect the output voltage of the fuel cell, which may reduce the diagnostic accuracy. To solve the issue, inspired by prior diagnostic studies, a data-driven fault diagnosis method is proposed to identify the flooding fault of the fuel cell. The contributions of this article are summarized as follows:

(1) In order to make the best of the existing sensors, the input features of the proposed fault diagnosis model are selected according to the water transport mechanism and auxiliary systems of the FC stack. Therefore, our proposed method does not need to install new sensors (such as humidification sensors) to the FC stack.
(2) To be close to real industrial scenarios, the load-varying condition is considered in this study. In addition, multiple signals are transformed to 2D data via the data processing techniques, and the batch normalization method is used to alleviate feature distribution difference, which can improve the generalization ability and convergence rate.
(3) A real fault dataset of the FC is adopted to evaluate the diagnostic performance of the proposed method. Experiment results demonstrate that the diagnostic model can effectively detect the flooding fault of the FC under load-varying conditions, and achieves over 99% accuracy.

The remainder of the paper is organized as follows. Section 2 presents the background knowledge of the method, consisting of the PEMFC system, diagnostic indicator selection and convolution neural network. Then, the proposed method is presented in Section 3, and the performance evaluation is depicted in Section 4. Finally, we discuss and conclude this study in Section 5 and Section 6, respectively.

2. Basic knowledge

2.1. Fuel cell power system

To provide useful power for industrial/ individual equipment, the PEMFC must cooperate with several auxiliary systems, such as the hydrogen supply, air supply, and temperature control systems [8,36]. As shown in Fig. 1, the electrical system controls the output voltage of the FC via the DC-DC converter. The hydrogen supply and air supply subsystems control the supplement gas flows for the fuel cell stack by utilizing back-pressure valves. The relative humidity of the input air is regulated by a humidifier. The temperature control system adjusts the heat dissipation of the FC by controlling the speed of the cooling pump and the opening ratio of the electronic thermostat, which ensures that the FC operates at an appropriate temperature. The developed fault diagnosis model utilizes the data collected from the above auxiliary devices, which does not need to install more extra-sensors.

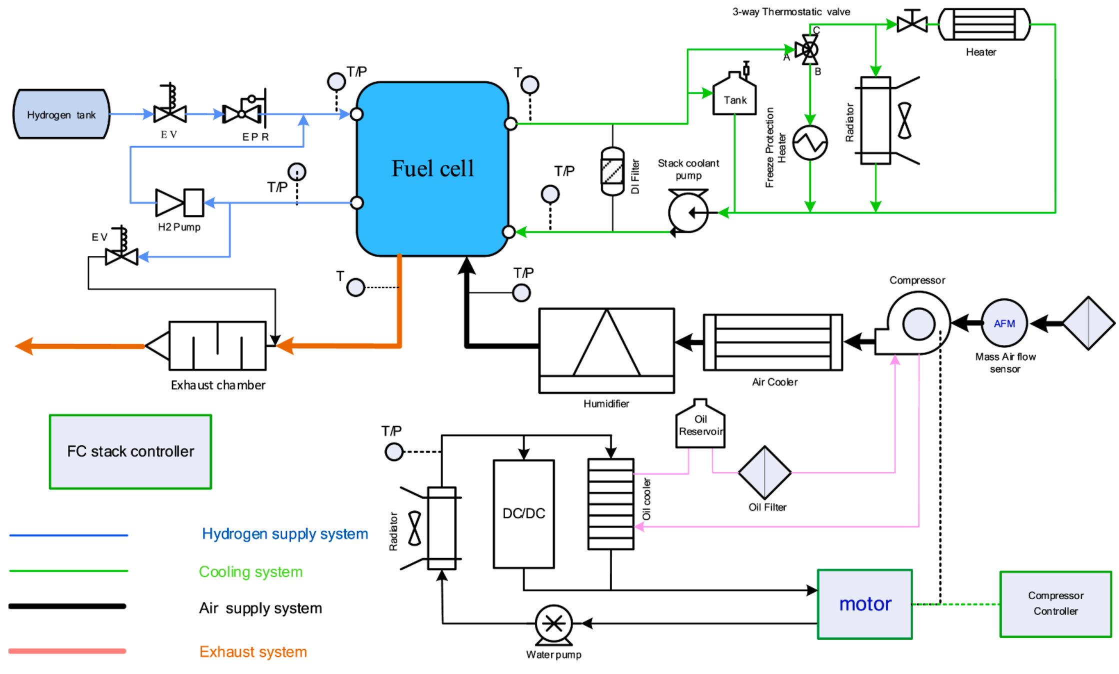


Fig. 1. Diagram of the PEMFC system.

2.2. Diagnostic indicator selection

For data-driven methods, the diagnostic indicator selection is crucial to the model performance. In this subsection, the diagnostic indicator selection is investigated by analyzing the water transport mechanism and considering auxiliary systems of the FC stack. To ensure the fuel cell proper operation, the membrane should contain certain water to make the protons pass through it. In FC stacks, the water transports include electro-osmotic drag (EOD), back diffusion (BD), hydraulic permeation (HP), water convection and diffusion, and convective mass transfer in the gas channel[37-39], as presented in Fig. 2. Water is produced in the cathode and expelled by the flow of the unreacted gas or purged. The water content in the fuel cell is affected by several transportation channels. The process that water being dragged by the protons passes the membrane is called electro-osmotic drag[40]. Back diffusion (BD) refers that the excess water generated at the cathode diffuses back to the anode [41]. During the operation of the fuel cell stack, water molecules are generated on the cathode with the oxygen reduction reaction. The water molecules diffuse to the membrane and the gas diffusion layer [37]. The amount of generated water is proportional to the current density of the stack. Therefore, this study selects the current density of the FC as the indicator.

EOD and BD are dominated for water transport in the fuel cell, which significantly affects the humidity of the membrane. The papers[8,42] demonstrated that the EOD coefficient is closely related to temperature. Wei et al.[37] found that the amount of water transport is related to the water content gradient, pressure difference and temperature. Therefore, the air inlet pressure, air inlet temperature, hydrogen inlet temperature, stack temperature and stack output voltage are also selected as the indicators. The air inlet temperature has a great relationship with the water saturation pressure of air gasses.

In summary, this study selects the indicators of the system accessories as the inputs of the proposed fault diagnosis model according to their relationship with the water status of the FC. All the indicators can

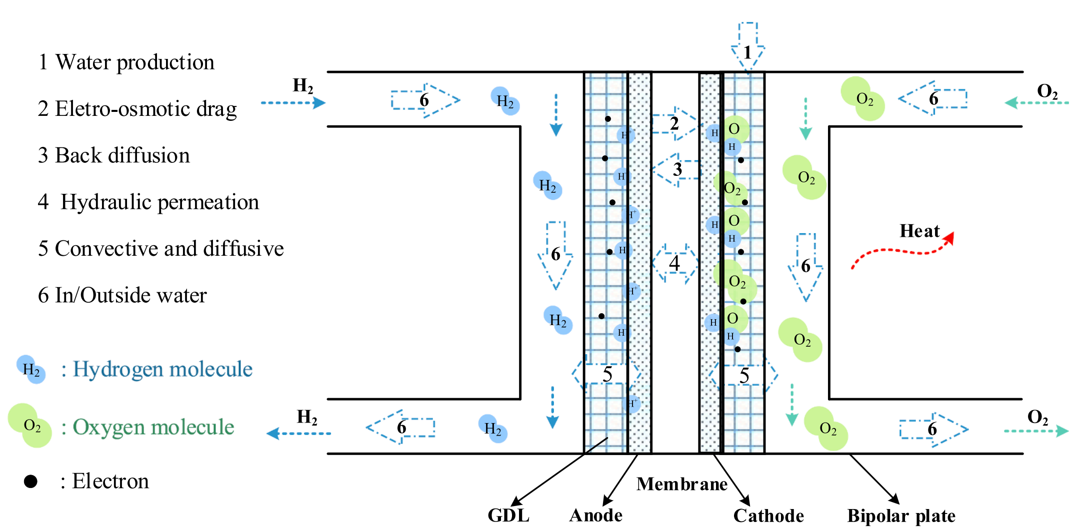


Fig. 2. The water transports in the PEMFC.

be monitored by the common monitor system for the fuel cell, which avoids installing expensive sensors such as humidity sensors and reduces the total system cost.

2.3. Convolutional neural network

CNN is a common feed-forward neural model, where multiple convolutional filters are used to extract the features from the input data [43,44]. As shown in Fig. 3, a CNN mainly contains convolutional layers, pooling layers, and fully connected layers. As the number of convolutional layers increases, the CNN increases in its complexity and can extract deep features from raw data. In addition, due to sparse connection and weight sharing, the CNN can avoid the occurrence of overfitting compared to the DNN[45].

1) Convolutional layer

In a convolutional layer, the convolutional operation is applied to the input data by using a bank of learnable filters, which can be expressed as

$$y_j^l = f\left(\sum_{i=1}^{k} w_{i,j}^l \otimes x_j^{l-1} + b_j^l\right) \tag{1}$$

where, l represents the layer number, x_j^{l-1} represents the j-th input map, $w_{i,j}^l$ represents the kernel of the i-th filter connected to the j-th input map, b_j^l denotes the bias, f denotes the nonlinear activation function, and $\otimes$ denotes the convolutional operation. In this study, rectified linear unit (ReLU) function is adopted since it can accelerate convergence rate and alleviate gradient vanishing, which can be expressed as:

$$f(x) = \begin{cases} 0 & x \leqslant 0 \\ x & x > 0 \end{cases} \tag{2}$$

2) Pooling layer

To improve the efficiency of the CNN, the pooling layer is applied to reduce redundant feature maps. The pooling layer contains two types: max pooling and average pooling. Referring to the prior studies, the max-pooling layer is used in this article, which can be expressed as

$$y_j^l = max\left(w(s_1, s_2) \cap x_j^{l-1}\right) \tag{3}$$

where $w(s_1,s_2)$ denotes the pooling window.

3) Fully connected layer

Convolutional layers and pooling layers generally are used as feature extraction layers. Following the feature extraction layers, the fully connected layer (FC) is used as the output layer. It is worth noting that the input of the FC layer is a one-dimensional vector. The mathematical expression of the FC layer is shown as follows

$$x_j^l = f\left(\sum_{i=1}^{k} w_{i,j}^l \times x_j^{l-1} + b_j^l\right) \tag{4}$$

3. Method

We use four parts to present our proposed fault diagnosis method for the fuel cell in detail. First, considering the input format of the CNN-based model, the data processing technologies are introduced. Next, the structure of the fault diagnosis model is described. On this basis, the implementation procedures of the fault diagnosis method are given.

3.1. Data processing

The raw data generated by the sensors generally need to be processed for model training. In this study, the processing methods consist of data normalization, data reconstruction and data segmentation.

(1) Data normalization: The range of the raw data points is usually different, which may result in training difficulty and low convergence rate. To alleviate or eliminate the impact, the raw data generally require to be normalized, which is a way to adjust the value of the numeric variable in the sample dataset to a typical scale. This article adopts the relatively simple and effective max normalization method, which can be calculated as

$$x = \frac{x - min(x)}{max(x) - min(x)} \tag{5}$$

(2) Data reconstruction: Data reconstruction method is used to convert the training sample to the input format of the model. For this study, the time sequence monitor data are converted to the matrix format by the sliding window. The reconstruction method is shown in Fig. 4.

(3) Data Segmentation: In deep learning, the data usually are divided into training, validation, and testing datasets. The training dataset is adopted to train the deep learning model. The validation dataset is adopted to adjust the hyper-parameters of the model according to the validation classification results. The testing dataset is adopted to verify the performance of the deep learning model.

3.2. Flooding fault diagnosis model

3.2.1. Structure

In this study, the fault diagnosis model consists of two convolutional layers with batch normalization method, followed by a flatten layer and

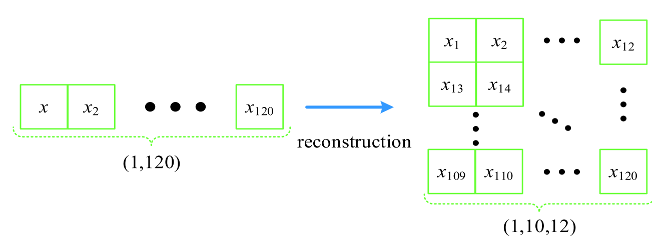


Fig. 4. The Data reconstruction method.

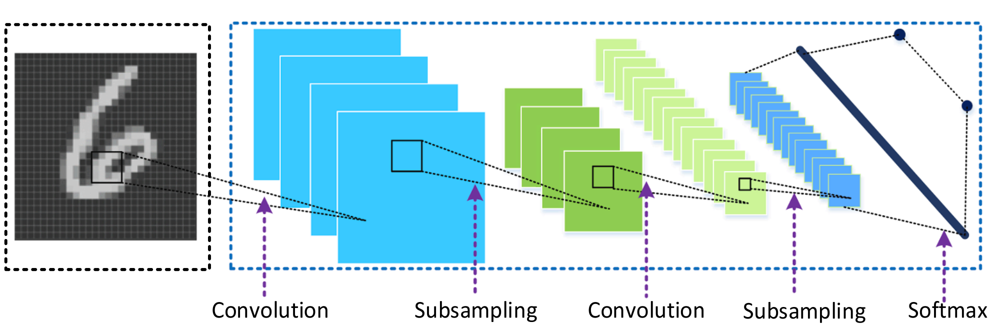


Fig. 3. The structure of the CNN.

two fully connected layers, as shown in Fig. 5. All convolutional layers use 5 × 5 filters with a stride of 1, and Softmax layer is used for the output layer.

3.2.2. Batch normalization

Deep learning models usually are delicate to the initial weight parameters and the setting of the optimizer[46,47]. One potential fact behind this issue is the distribution of the inputs to layers somewhere down in the network may change when the model weights are updated. This adjustment in the distribution of inputs to layers is called internal covariate shift, which may reduce convergence speed and generalization ability. To solve the issues, batch normalization as a reparameterization method for neural networks is proposed, which can fundamentally decrease the issue of planning updates across numerous layers [46–48]. The calculation formula of the BN can be expressed as

$$\mu_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \tag{6}$$

$$\sigma_B^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_B) \tag{7}$$

$$\widehat{x}_i \leftarrow \frac{x - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{8}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \tag{9}$$

where μ_B and σ_B^2 denote the mean value and the variance value, respectively; γ and β denote the scale factor and the movement factor, respectively.

3.3. Model training

The diagnosis results are achieved through the softmax layer, and the binary cross-entropy function is selected to compute the empirical loss. The mathematical expression of the loss function is shown as follows

$$J(w,b) = -\frac{1}{m}\sum_{i=1}^{m}[(1-y_i)log(1-h_w(x_i)) + y_i logh_w(x_i)] \tag{10}$$

where, y and $h_w(x)$ denote the label and the predicted probability of the sample, respectively.

The fault diagnosis model needs a lot of iterative calculation on the training data, and uses an optimizer to adjust the model weights for minimizing the empirical loss value. In this study, we use the Adaptive Moment Estimation algorithm (Adam) [49] that can adjust the change degree of the weights. The calculation operation of the Adam can be expressed as follows:

$$m_t = \beta_1 * m_{t-1} + (1-\beta_1) * g_t \tag{11}$$

$$v_t = \beta_2 * v_{t-1} + (1-\beta_2) * g_t^2 \tag{12}$$

where g_t and m_t are the gradient and the momentum term, respectively.

To offset the deviation, the terms are corrected as:

$$\widehat{m}_t = m_t/(1-\beta_1^t) \tag{13}$$

$$\widehat{v}_t = m_t/(1-\beta_2^t) \tag{14}$$

The weights of the model are updated as:

$$w_{t+1} = w_t - \eta \frac{\widehat{m}_t}{\sqrt{\widehat{v}_t} + \varepsilon} \tag{15}$$

where η and w are the learning rate and the weight parameters, respectively.

3.4. Implementation of the proposed model

The raw data collected by the monitor systems are processed, which can be found in Section 3.1. Then, the optimizer uses the training dataset to optimize the weights of the fault diagnosis model. Finally, the effectiveness of the trained model is verified. Based on the above theoretical description, this subsection introduces the implementation of the proposed method which includes four steps: data collection, data processing, model developing and training, and evaluation. The detailed steps for the proposed model are presented as follows (see also Fig. 6):

1. The first step is to obtain the normal and the flooding fault data of the PEMFC using sensor systems.
2. The raw data collected between 0 and 10000 s are processed, which can be found in Section 4.1. The processed data (0 ~ 5000 s) are randomly split into the training and validation datasets, and the remaining data (5000 s ~ 10000 s) are set as the testing dataset.
3. Next step is to decide and implement the basic structure of the CNN model, which can be found in Section 3.3. Design the Adam optimization algorithm and the empirical loss function for the model.
4. The optimizer algorithm optimizes the weights of the model using the training dataset. The crucial hyperparameters of the model are selected based on the experiment results of the training and validation datasets, which include batch size, training epoch, and learning rate.
5. After these steps, the diagnostical performance of the model is verified on the testing dataset. The classification results of the model are compared with the true label of the testing dataset, and the criteria of the classification performance are calculated.

4. Model evaluation

4.1. Dataset collection and processing

The raw data are collected from the 80 W PEMFC system which

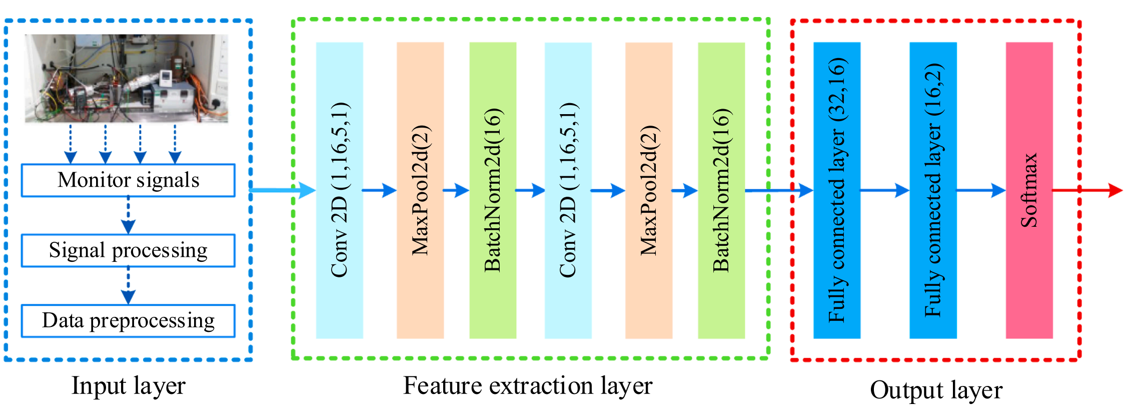


Fig. 5. The architecture of our fault diagnosis model.

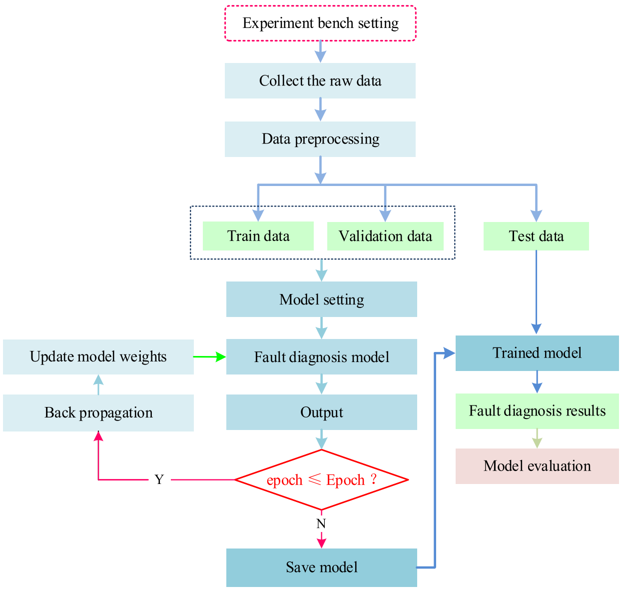


Fig. 6. The implementation process of the proposed model.

includes a single-cell stack, TDI electrical load, cooling systems, and ancillary devices providing air and hydrogen. The PEMFC system is cooled by using deionized water, and the gases are humidified. Fig. 7 (a) shows the PEMFC experiment bench, and Table 1 presents the sensors of the PEMFC. As mentioned in Section 2.2, the monitoring parameters for the PEMFC systems consist of voltage, current, humidity, pressure, etc.

(1) Data collection: To obtain the flooding fault data, the experiment bench lowers the temperature of the FC, which facilitates the condensation and accumulation of liquid water. Some sensor measurement curves of the PEMFC experiment bench are presented in Fig. 7 (b). It should be noticed that the reduction of the output voltage is not necessarily caused by the flooding fault. There are several voltage change periods (1000 ~ 1500 s, 3000 ~ 3400 s, 4500 ~ 5000 s, and 6000 ~ 6500 s) due to that the polarization curve data are collected. Since the polarization curve data involve load-varying operations of the fuel cell, the data are also used in this study.

(2) Data processing: First, the raw data firstly are normalized by the Max-Min normalized method. Then, we reconstruct the normalized data to training samples, and label these samples where '0' and '1' denote the normal and flooding fault states respectively. It is worth noting that, referring to the papers[50], the voltage drops less than 5% are defined as flooding. Finally, the samples (0 ~ 5500 s) are randomly divided into the training dataset (80%) and the validation dataset (20%), and the samples (5500 s ~ 10000 s) are used as the testing dataset.

Table 1
Monitoring parameters of the PEMFC experiment bench.

No. Parameter	6 Anode outlet pressure
1 PEMFC Voltage	7 Stack temperature
2 PEMFC Current	8 Cathode outlet temperature
3 Cathode outlet humidification	9 Anode outlet temperature
4 Anode outlet humidification	10 Cathode outlet flow
5 Cathode outlet pressure	11 Anode outlet flow

4.2. *Experiment settings*

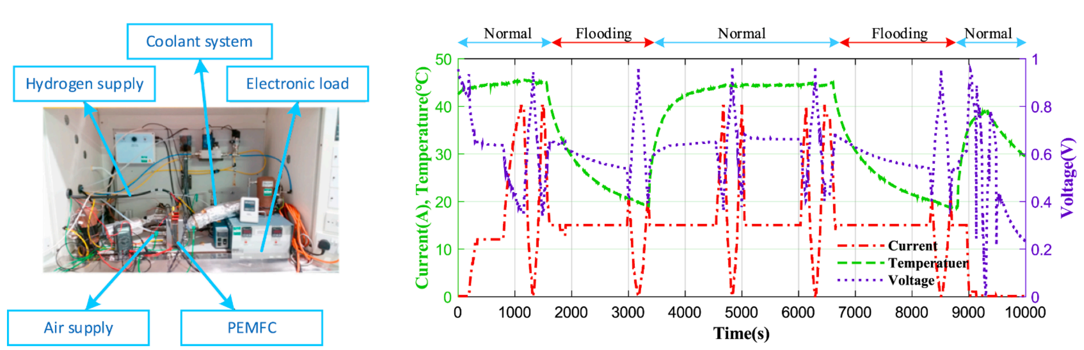
In this study, the experiments are executed on a server with Intel® Core™ i7-6700 and NVIDIA 1080Ti, and the fault diagnosis methods are developed in the Python language using Pytorch and scikit-learn frameworks and run on a server. We set the learning rate η to 0.001, mini-batch size to 64 and epoch to 70. Three common metrics are selected to quantify the model diagnostic performance: accuracy, precision and recall.

4.3. *Case 1 (Ablation experiment)*

To illustrate the different components to the performance of our proposed fault diagnosis model, we conduct ablation experiments. Batch normalization layer and Adam optimizer are investigated to prove the contribution of the components in the fault diagnosis model. For the sake of convenience, the abbreviation of the proposed model trained by the SGD algorithm is recorded as NorCNN-SGD. The experiment curves of the ablation experiments are shown in Fig. 8. The diagnosis results of the ablation experiments are present in Table 2 and Fig. 9, respectively. Among the ablation experiments, our proposed model has the best diagnosis performance. The CNN-BN trained by the SGD with the same learning rate ($\eta = 0.001$) has the lowest convergence rate, because the SGD optimizer only uses first-order gradient descent and does not consider the preceding iterations to gradient update. And the basic CNN model classification accuracy is lower than our proposed model. It indicates that batch normalization and Adam contribute to the high accuracy of the proposed model.

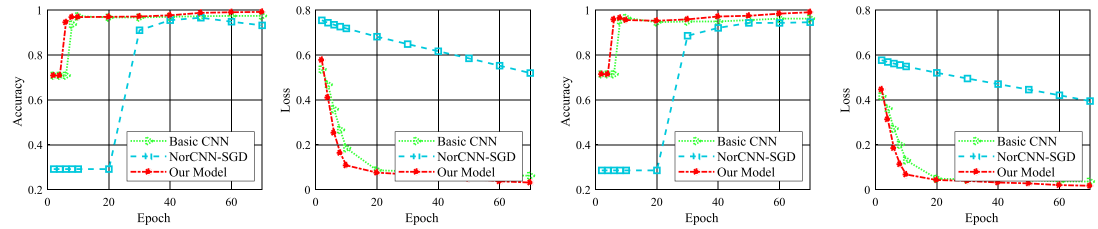
4.4. *Case 2 (Comparison experiments with traditional machine learning models)*

To demonstrate the superiority of our proposed model, some traditional machine learning models are selected for comparison, which include Decision Trees, Gaussian Naive Bayes (GaussianNB), Support Vector Machine (SVM) and k-nearest neighbors algorithm (KNN). These main parameters are present as:



(a) PEMFC experiment bench (b) current, temperature and voltage for the PEMFC

Fig. 7. PEMFC experiment bench and some sensor measurement curves.

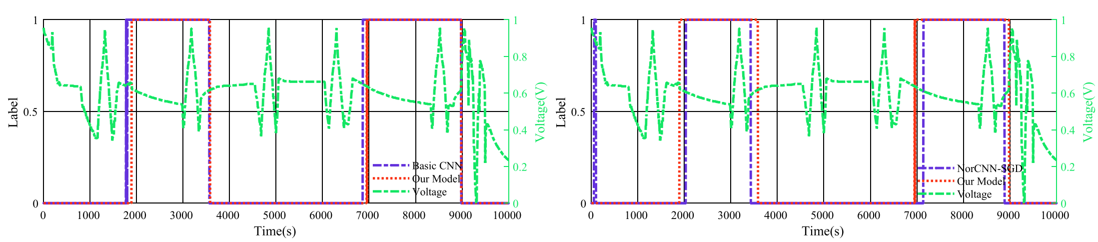


(a) Accuracy on training dataset (b) Loss on training dataset (c) Accuracy on validation dataset (d) Loss on validation dataset

Fig. 8. Training curves of the ablation experiments.

Table 2
Classification results of the ablation experiments.

Dataset	Training			Validation			Testing		
Model\Metric	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall
Basic CNN	97.68%	97.70%	97.68%	97.14%	97.14%	97.14%	98.14%	98.18%	98.18%
NorCNN-SGD	97.14	97.37%	97.14%	97.41%	97.62%	97.41%	91.19%	92.51%	91.19%
Our Model	99.18	99.19%	99.18%	99.05%	99.06%	99.05%	99.29%	99.29%	99.29%



(a) Decision-tree VS our model (b) GaussianNB VS our model

Fig. 9. Classification curves of the ablation experiments.

- Decision Tree: It is a non-parametric model, which can learn decision rules inferred from the training samples. The maximum depth of the model is set to 5.
- GaussianNB: GaussianNB implements the classification by assuming the likelihood of the features to be Gaussian, which can be expressed as $P(x_i|y) = exp(-(x_i-\mu_y)/2\pi\sigma_y^2)/\sqrt{2\pi\sigma_y^2}$.
- KNN: The Euclidean distance is adopted in the KNN, and the considered neighbor number is set to 10.
- SVM: We use the radial basis kernel function as the core function, and set the penalty coefficient and the gamma values to 100 and 0.005, respectively.

Classification results of the traditional machine learning models and our model are presented in Table 3 and Fig. 10. Although these models have excellent diagnosis performance on the training dataset, their results on the testing dataset are not good. We can see that our proposed model achieves outstanding fault diagnosis performance on the testing dataset, of which the accuracy reaches 99.29%, close to 100%, and the precision and recall are more than 99%. From Fig. 10, traditional machine learning models have fluctuations in fault diagnosis, especially in the decision tree model. Compared to these models, our model has excellent robustness ability.

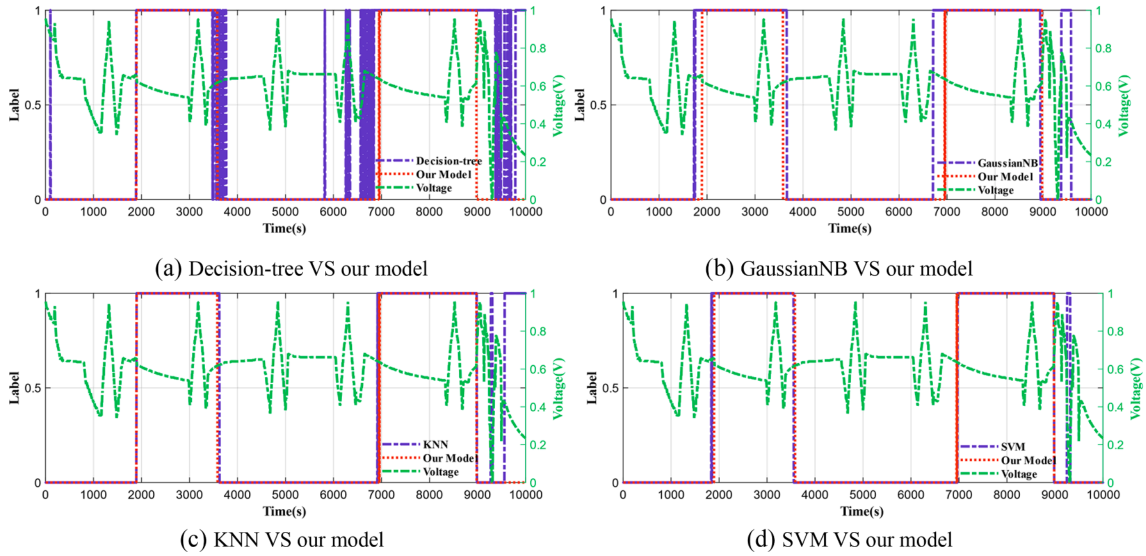
5. Discussion

5.1. Comparison to similar studies

Several current similar works use artificial intelligence technologies to detect the water flooding fault of the fuel cell. Mao et al. [50] proposed a data-driven method to identify fuel cell faults, which uses Kernel principal component analysis and wavelet packet transform to process the monitored data to generate features and adopts singular value decomposition to detect the fault with the features. Similar to traditional machine learning-based methods, the method cannot realize end-to-end fault diagnosis. In addition, it is difficult to choose or design feature extraction methods in practice. To realize end-to-end fault detection, deep learning models are also used to develop fault diagnosis methods. Liu et al. [35] used a normal CNN model to detect fault from feature maps extracted by Fisher discriminant analysis (FDA), however, they only use the voltage monitor data. Gu et al. [8] utilized LSTM to detect

Table 3
Classification results of the traditional machine learning models and our model.

Dataset	Training			Validation			Testing		
Model\Metric	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall
Decision-tree	98.91%	98.91%	98.91%	97.78%	97.77%	97.78%	76.43%	83.91%	76.43%
GaussianNB	97.14%	97.39%	97.14%	96.83%	97.14%	96.83%	88.57%	90.25%	88.57%
KNN	99.86%	99.86%	99.86%	99.68%	99.68%	99.68%	87.43%	89.93%	87.43%
SVM	97.96%	97.95%	97.69%	97.78%	97.80%	97.78%	97.29%	97.32%	97.29%
Our Model	99.18%	99.19%	99.18%	99.05%	99.06%	99.05%	99.29%	99.29%	99.29%



(a) Decision-tree VS our model (b) GaussianNB VS our model

(c) KNN VS our model (d) SVM VS our model

Fig. 10. Classification curves of the traditional machine learning models and our model.

the flooding fault of the FC. In particular, these prior studies do not consider load-varying scenarios. To improve fault diagnosis accuracy and reliability, we utilize a CNN model to fuse multiple sensor signals. Considering the load-varying scenarios, batch normalization technology is used to improve model generalization. Our proposed model is demonstrated to be an effective diagnostic method through a real experiment dataset in Section 4. The advantages of the fault diagnosis method are summarized as follows.

First, a CNN-based diagnostical model is proposed for the PEMFC. The structure of the model is inspired by Pytorch tutorials. The input features of the model are achieved through analyzing the fuel cell monitor system and data reconstruction methods. In addition, the data with varying loads are used to train our proposed fault model. Therefore, the model can identify the flooding fault of the fuel cell accurately under varying working conditions.

Second, the proposed model utilizes batch normalization technologies to accelerate the convergence rate and improve generalization capabilities, that is, the trained model has applicable fault diagnosis performance on the testing data.

However, the fault diagnosis model does not consider the difference between fuel cell stacks. Therefore, we will further explore and solve the problem that the trained model can be applied to diagnose different fuel cell stacks.

5.2. Time of training and testing

The fault diagnosis model needs not only excellent diagnosis performance but also the speed of diagnosis. DL-based fault diagnosis models need pre-training with a lot of labeled samples and then using the trained model to online diagnosis. In this study, the training time and testing time of the different models are listed in Table 4. Compared to other models, our model took a longer training time, since the model training process needs computing gradients and adjusting weights over and over again to obtain the purpose of the model convergence. However, the training time does not to be too concerned, because the processes are executed during the pre-training process. Our main concern is the time required for diagnosing the testing dataset. Table 4 presents the testing time of different fault diagnosis models. From the table, we can see that the GaussianNB has the fastest diagnosing speed. The testing time of our proposed model is approximately 0.0045 s, which is acceptable in the online fault diagnosis task. This is due to the that the fault diagnosis processing of our model does not compute the gradients, which is complicated and cumbersome.

Table 4
Operation time of different models.

Model	Training (s)	Testing (s)
Decision-tree	0.0119	0.0009
GaussianNB	0.0020	0.0010
KNN	0.0009	0.0309
SVM	0.0068	0.0059
Our CNN	1.8494	0.0045

6. Conclusion

In this study, a data-driven method is proposed to diagnose the flooding fault of the fuel cell, which utilizes the batch normalization technology to improve the convergence speed and the generalization ability. The diagnostic indicators for the proposed model are selected through analyzing the water transport mechanism and the auxiliary systems of the fuel cell stack, which does not need to install more extra-sensors. Multiple monitor signals are transformed to 2D data via the data processing techniques, and the convolutional layers of the model can effectively extract fault features from the processed data. Experiment results show that the proposed method has excellent diagnosis performance. Compared to other traditional machine learning models, our proposed model has excellent generalization ability and can diagnosis flooding fault under varying load scenarios and achieves over 99% accuracy.

The future improvement mainly includes further improving model generalization capabilities to apply different fuel cell stacks and complex operating conditions via federated learning technologies.

CRediT authorship contribution statement

Bin Zuo: Methodology, Software, Writing – original draft, Project administration. **Zehui Zhang:** Methodology, Software, Writing – original draft. **Junsheng Cheng:** Conceptualization, Investigation, Methodology, Project administration. **Weiwei Huo:** Formal analysis, Validation. **Zhixian Zhong:** Validation. **Mingrui Wang:** Validation.

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.

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