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Prognosis of fuel cell degradation under different applications using wavelet analysis and nonlinear autoregressive exogenous neural network

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Abstract

This paper presents the degradation prognosis of Proton Exchange Membrane Fuel Cell (PEMFC) operated under several conditions based on the combination of two types of data: data from postal fuel cell hybrid electric vehicles equipped with PEMFC and carrying out their postal delivery missions and PEMFC degradation data from laboratory. The prognosis is based on wavelet analysis and Nonlinear Autoregressive Exogenous Neural Network (NARX). The influences of historical state, operating conditions (load current, relative humidity, temperature, and hydrogen pressure), global degradation trend, and recovery phenomena on the degradation prognosis of PEMFC are considered. Firstly, the raw voltage degraded waveform of PEMFC is decomposed into multiple sub-waveforms by the wavelet analysis. Then, the degradation prognosis of each sub-waveform is made by NARX. Finally, the overall degradation prognosis of PEMFC is gotten by combining the degradation prognosis of each sub-waveform. Experimental results have shown that the novel prognosis method which exploits the two types of data results in a reliable model that covers PEMFC degradation over a wide range of operating conditions. The proposed prognosis method not only can make an accurate degradation prognosis of PEMFC with less learning data but also can use directly the raw experimental data with large fluctuation.

Keywords: PEM fuel cell; degradation prognosis; wavelet analysis; nonlinear autoregressive exogenous neural network; fuel cell hybrid electric vehicle.

1. Introduction

With environmental protection and increasing energy demand, sustainable green energy is regarded as the main direction of future energy development [1]. The fuel cell directly converts the chemical energy of the fuel into electricity without being restricted by the Carnot cycle [2]. The fuel cell has the advantages of high specific energy, high energy conversion efficiency, no pollution, low noise, many types of fuel, etc [3]. The fuel cell is widely used in cogeneration, power plants, fuel cell electric vehicles, portable power systems, distributed generation, and other fields [4]. Due to the fact that its distinguishing features include low operating temperature, lower pressure ranges, small size, and no chemical hazards to the human body, Proton Exchange Membrane Fuel Cell (PEMFC) has received high attention from the government, industry, and academia [5]. Currently, PEMFC is regarded as the most likely candidate for transportation and other mobile applications [6]. PEMFC can avoid some battery problems, such as the use of pollutant materials and long charging time [7]. However, durability and cost seriously affect the large-scale commercial application of PEMFC [8]. The degradation of carbon support and Platinum (Pt) nanoparticles will cause the reduction in the performance of PEMFC [9]. The maximum service life of PEMFC under transportation conditions is around 3000 h, while the expected life of PEMFC is at least 5000 h for commercial transportation applications [10]. Prognostics and health management can predict the degradation of PEMFC and provide an appropriate maintenance plan to reduce the cost and improve the durability of PEMFC [11]. Therefore, the degradation prognosis is very important for the operation and maintenance of PEMFC [12].

The degradation of PEMFC is caused by the degradation of its main components [13]. The main components of PEMFC are bipolar plates, Gas Diffusion Layers (GDL), electrodes, catalysts, and proton exchange membranes. In the long-term operation of PEMFC, these components will experience different degradations [14]. The bipolar plates undergo corrosion, fractures, and deformation. The GDL undergoes structural changes, porosity loss, and hydrophobicity loss. The electrodes and catalysts undergo Pt dissolution, Pt agglomeration, Pt oxidation, and carbon corrosion. The proton exchange membranes undergo decomposition, creep, fatigue, and hot-dot. The degradation of PEMFC usually causes the output voltage to drop, the output power to decrease, the internal resistance to increase, etc [15]. Therefore, the output voltage, output power, and internal resistance are often selected to

represent the degradation state of PEMFC [16]. In this paper, the output voltage is selected as a degradation indicator of PEMFC because it has been measured to monitor the PEMFC performance.

The prognosis methods of PEMFC are usually divided into 3 categories: model-driven methods, data-driven methods, and hybrid methods [17]. The model-driven methods make the degradation prognosis of PEMFC based on the empirical or semi-empirical degradation model of PEMFC [18]. The degradation trends are simulated through the empirical or semi-empirical degradation model of PEMFC. Three empirical degradation models combined with particle filter are proposed to forecast the degradation and Remaining Useful Life (RUL) of PEMFC [19]. The semi-empirical degradation model combined with the extended Kalman filter is presented to make the degradation prognosis of PEMFC [20]. The Gaussian degradation model combined with an unscented particle filter is developed to make the state of health estimation and RUL prognosis for PEMFC [21].

The PEMFC is a complex, multivariable, and strongly coupled dynamic nonlinear system. The degradation of PEMFC involves the multi-scale (nanometer scale, cell scale, and system scale) and multi-material (carbon fibers, metal, Pt, and Nafion membrane). It is difficult to build the accurate mathematical degradation model of PEMFC because its degradation mechanism is not fully known [22].

The data-driven methods make the degradation prognosis of PEMFC by learning the degradation trend from recorded aging data based on artificial neural network and fuzzy system [23]. The echo state network is proposed to estimate the performance degradation and RUL for PEMFC [24]. The long short-term memory recurrent neural network is applied to predict the degradation and remaining life of PEMFC [25]. The self-adaptive relevance vector machine method is developed to predict the performance degradation of PEMFC [26]. The adaptive neuro-fuzzy inference system method is proposed to forecast degradation in PEMFC [27].

The hybrid methods integrate the advantages of model-driven methods and data-driven methods to make the degradation prognosis of PEMFC [28]. The hybrid method based on three empirical degradation models and the least square support vector machine method is presented to make the degradation and RUL prognosis for PEMFC [29]. The autoregressive and moving average model integrated the time delay neural network is developed to predict the performance degradation of PEMFC [30]. A semi-empirical degradation model integrated the automatic machine learning algorithm is proposed

105 to estimate the degradation trend and forecast the RUL for PEMFC [31].
106 Compared with model-driven methods and data-driven methods, the hybrid
107 methods require the most computation.

108 The degradation prognosis of PEMFC in most literature studies consider
109 the influence of the historical state, and rarely consider the impact of operat-
110 ing conditions on degradation prognosis. However, the operating conditions
111 have a great influence on the performance of PEMFC [32]. Water flooding
112 in the bipolar plates and membrane electrode assembly can cause gas starva-
113 tion and may accelerate the corrosion of bipolar plates, electrodes, catalysts,
114 GDL, and membrane [33]. Dehydration of membrane causes high membrane
115 resistance, tearing, and cracking [34]. When gas starvation occurs at the
116 cathode, it will cause the coalescence of the catalyst [35]. When gas starva-
117 tion occurs at the anode, it will cause carbon support corrosion [35]. Gas
118 starvation may cause the change of electrode thickness, uneven current and
119 voltage distribution, porous structure collapse, and reverse polarity [36]. The
120 temperature has a certain effect on water saturation pressure and membrane
121 hydration [37]. The temperature will affect the water distribution, gas dis-
122 tribution, and chemical reactions, which cause hot spots in the membrane
123 and accelerate the decay of the catalyst [38]. Frequently changing load brings
124 the challenges for water management, thermal management, and gas manage-
125 ment, which may cause gas starvation, water flooding, dehydration, hot spot,
126 etc [39]. The start-stop process causes the increase of resistance, high-load
127 operating conditions may accelerate the dissolution of Pt, and rated operat-
128 ing condition leads to a decrease in the electrochemically active area [40]. The
129 historical state and operating conditions including the load current, relative
130 humidity, temperature, and hydrogen pressure are considered by Nonlinear
131 Autoregressive Exogenous Neural Network (NARX) in this paper. NARX
132 is a recurrent dynamic neural network, which has good dynamic character-
133 istics and anti-interference ability in the nonlinear problems of time series
134 prediction.

135 The degradation of PEMFC includes global degradation trend (irreversible
136 degradation phenomena) and recovery phenomena [41]. The global degra-
137 dation trend refers to the irreversible loss of PEMFC performance as the
138 PEMFC runs for a long time [42]. The global degradation trend is caused by
139 the degradation of bipolar plates, electrodes, catalysts, gas diffusion layers,
140 and membranes. Recovery phenomena refer to a certain degree recovery per-
141 formance of PEMFC, when the PEMFC undergoes stop/start, characteristic
142 test, or large changes in operating conditions [43]. For example, when the

143 gas supply is sufficient, the PEMFC performance recovers after gas starva-
144 tion is improved [44]. Recovery phenomena are the transient process during
145 the degradation of PEMFC. Most of the previous prognosis methods only fo-
146 cused on the global degradation trend, while both global degradation trend
147 and recovery phenomena are considered by wavelet analysis in this paper.

148 Wavelet analysis is an effective time-frequency analysis method. It has
149 the ability to characterize signal local information in time-frequency domain,
150 and is widely used in image compression, signal processing, and information
151 extraction.

152 The existing prognosis methods rarely use directly raw experimental data
153 to predict the degradation of PEMFC. Because the raw experimental data
154 of PEMFC includes complex fluctuations and recovery phenomena. The raw
155 experimental data of PEMFC in different applications is directly used to
156 predict the degradation in this paper.

157 Considering the historical state, operating conditions, and different degra-
158 dation phenomena, this paper presents the degradation prognosis method
159 based on wavelet analysis and NARX for PEMFC operated under different
160 applications. The main contributions are summarized as follows:

- 161 1. The proposed prognosis method makes degradation prediction of PEMFC
162 based on the raw experimental data.
- 163 2. The NARX, which considers the historical state and exogenous inputs
164 (load current, relative humidity, temperature, and hydrogen pressure), is
165 applied to the degradation prognosis of PEMFC operated under different
166 applications.
- 167 3. The global degradation trend and recovery phenomena of PEMFC are
168 analyzed by wavelet analysis, which can effectively improve the accuracy
169 of the degradation prognosis of PEMFC.
- 170 4. Experimental results show that this presented method is robust and can be
171 applied to the degradation prognosis of PEMFC in different applications.

172 In Section 2, the durability tests of PEMFC operated under different
173 applications are presented. Section 3 proposes the degradation prognosis of
174 PEMFC based on NARX and W-NARX. Section 4 presents the validation
175 of the method on the basis of experimental results. Moreover, these results
176 are compared with NARX and different learning data. Section 5 provides
177 Conclusions.

2. Durability tests of PEMFC operated under different applications

2.1. Durability test of PEMFC in FCHEV operated under real conditions

The durability test of PEMFC is made in Fuel Cell Hybrid Electric Vehicle (FCHEV) operated under real conditions. The MOBYPOST project has developed ten FCHEVs (Fig. 1) to complete commercial mail delivery tasks on the real road [45]. PEMFC and lithium batteries provide power for FCHEV. Integrating lithium batteries into FCHEV can prevent PEMFC from frequently starting and shutting down, which reduces the PEMFC degradation and increases its lifetime [46]. The main parameter of PEMFC in FCHEV operated under real conditions is shown in Table 1. In order to control and monitor the PEMFC in FCHEV, the operating conditions including load current, voltage, relative humidity, temperature, hydrogen pressure, and state of charge of the hydrogen tank and battery are measured by FCHEV electronic control unit every second. PEMFC adopts the open cathode type with natural humidification. In order to avoid flooding, regular purge is conducted in the hydrogen circuit. The stop/start of PEMFC that greatly changes the distribution of water, gas, and heat in the PEMFC stack causes the recovery phenomena.

Figure 1: MOBYPOST fuel cell hybrid electric vehicle

2.2. Durability test of PEMFC operated under quasi-dynamic load current

The durability test of PEMFC operated under a quasi-dynamic load current is made on the power test platform of FCLAB, as shown in Fig. 2. The

Table 1: The operating conditions of PEMFC in FCHEV operated under real conditions

Parameter	Value
PEMFC weight	2.7 kg
Number of cells	40
Active area	100 cm ²
PEMFC maximum power	1 kW
PEMFC rated current	34 A
PEMFC rated voltage	31 V
Relative humidity	35%-78%
Temperature	50 °C
Hydrogen pressure	0.6 bar

quasi-dynamic load current is a constant current of 70 A plus a ripple current of 7 A. The main parameter of PEMFC operated under the quasi-dynamic load current is shown in Table 2, more detailed descriptions of the PEMFC can be found in [47]. In order to control and monitor the PEMFC performance, operating conditions including load current, single cell and stack voltage, relative humidity, temperature, gas flow, air pressure, and hydrogen pressure are measured every half minute. In order to characterize the health status of the PEMFC, the Electrochemical Impedance Spectroscopy (EIS) and polarization curve tests are made approximately weekly (0 h, 35 h, 182 h, 343 h, and 515 h). The characteristic test that greatly changes the distribution of water, gas and heat in the PEMFC stack causes the recovery phenomena.

2.3. Durability test of PEMFC operated under constant load current

The durability test of PEMFC operated under constant load current is made on the test platform of FCLAB (Fig. 2). The constant load current is a constant current of 70A. The main parameter of PEMFC operated under constant load current is shown in Table 3. The operating conditions including load current, single cell and stack voltage, relative humidity, temperature, gas flow, air pressure, and hydrogen pressure are also measured every half minute. the EIS and polarization curve tests are also made approximately weekly (0 h, 48 h, 185 h, 348 h, 515 h, 658 h, and 823 h). After each characteristic test, the recovery phenomena of PEMFC are found.

Figure 2: The durability test of PEMFC in power test platform of FCLAB

Table 2: The main parameter of PEMFC operated under the quasi-dynamic load current

Parameter	Value
Number of cells	5
Membrane thickness	25 μm
GDL thickness	415 μm
Active area	100 cm ²
PEMFC current	70 A with 7 A ripple
Relative humidity	52 %
Temperature	54 °C
Hydrogen pressure	1.3 bar

Table 3: The main parameter of PEMFC operated under constant load current

Parameter	Value
Number of cells	5
Membrane thickness	25 μm
GDL thickness	415 μm
Active area	100 cm ²
PEMFC current	70 A
Relative humidity	50 %
Temperature	54 °C
Hydrogen pressure	1.3 bar

3. PEMFC prognosis method

3.1. Prognosis of PEMFC based on NARX

NARX combines the nonlinear mapping ability of the artificial neural network and the time series concept of the dynamic autoregressive model to solve the problem of time series prognosis [48]. NARX, which takes into account the historical state and exogenous input (operating conditions), is very suitable for the prognosis of PEMFC. The basic structure of NARX is shown in Figure 3.

As shown in Fig. 3, the NARX consists of an input layer, a hidden layer, and an output layer. X represents operating conditions that include load current, relative humidity, temperature, and hydrogen pressure. Y represents the output voltage of the PEMFC. $Y(t)$ is the historical state of PEMFC, $Y(t+1)$ is the prognosis state. d is the maximum delay, w is the weight, b is the threshold. f_1 and f_2 are activation functions of hidden layer and output layer, respectively.

The prognosis of PEMFC based on NARX is defined as the following equation.

$$Y(t+1) = f[Y(t), \dots, Y(t-d+1), X(t), \dots, X(t-d+1)] \quad (1)$$

The hidden layer output is obtained by equation 2.

Figure 3: Basic structure of nonlinear autoregressive exogenous neural network

$$h_i = f_1[\sum_1^d W_{11}X(t) + \sum_1^d W_{12}Y(t) + b_1], i = 1, \dots, L \quad (2)$$

where h_i is the output of the i -th neuron in the hidden layer, and L is the number of neurons in the hidden layer.

The output layer output is obtained by equation 3.

$$o_j = f_2[\sum_1^L W_2h(i) + b_2], j = 1, \dots, m \quad (3)$$

where o_j is the output of the j -th neuron in the output layer, and m is the number of neurons in the output layer.

The biggest difference between the NARX and the general BP neural network is that state delay is added in the NARX. The historical state of PEMFC is considered by the state delay [49]. The parameters of weight and threshold for NARX are trained and adjusted in consideration of operating conditions and the historical state. Therefore, the NARX is considered to apply in the prognosis of PEMFC that greatly affected by operating conditions and the historical state.

252 3.2. Prognosis of PEMFC based on NARX and wavelet analysis

253 Wavelet analysis decomposes time series signals through multi-resolution
 254 analysis. The multi-resolution analysis is the theoretical basis for signal
 255 decomposition and reconstruction under wavelet basis [50]. For any mea-
 256 surement signal, the multi-resolution analysis can decompose it into detail
 257 part and low frequency part, and then further decompose the low frequency
 258 part, which can be repeated to any scale. The decomposition process can be
 259 expressed by equation 4.

$$V = D1 \oplus A1 = D1 \oplus A2 \oplus A1 = \dots = D1 \oplus An \oplus \dots \oplus A1 \quad (4)$$

260 Based on the multi-resolution analysis theory, the Mallat algorithm of
 261 wavelet decomposition is proposed. The decomposition algorithm can be
 262 expressed as the following equation [50].

$$\begin{cases} a_0 = V \\ a_j = \sum_k h(t - 2k)a_{j-1} \\ d_j = \sum_k g(t - 2k)a_{j-1} \end{cases} \quad (5)$$

263 where the low frequency part/approximation part $Aj = [a_1, a_2, \dots, a_j]$ is
 264 called the j-th layer approximation coefficient, and the high frequency part/
 265 detail part $Dj = [d_1, d_2, \dots, d_j]$ is called the j-th layer detail coefficient. $H =$
 266 $\{h_j\}_{j \in \mathbb{Z}}$ and $G = \{g_j\}_{j \in \mathbb{Z}}$ are low-pass filter and high-pass filter respectively.

267 The signal decomposition process is shown in Figure 4. $A1$, $A2$, and $A3$
 268 are low frequency part, and $D1$, $D2$, and $D3$ are high frequency part.

269 The wavelet coefficients of each layer can be restored to the original se-
 270 quence length by single reconstruction [50]. The reconstruction algorithm of
 271 wavelet coefficients is expressed as follows:

$$a_{j-1} = \sum_k h(t - 2k)a_j + \sum_k g(t - 2k)d_j \quad (6)$$

272 Decompose the time series signal into multiple sub-waveforms, and then
 273 the prognosis of multiple sub-waveforms can greatly increase the accuracy of
 274 signal prediction. The raw voltage waveform of PEMFC is decomposed by
 275 wavelet analysis. The low frequency part reflects the overview of the volt-
 276 age degraded waveform (global degradation trend), and the high frequency
 277 part reflects the detail of the voltage degraded waveform (fluctuations and

Figure 4: The voltage signal decomposition process based on wavelet basis

278 recovery phenomena of PEMFC). The prognosis of PEMFC using NARX
 279 and wavelet analysis is presented in Fig. 5.

Figure 5: The degradation prognosis of PEMFC based on NARX and wavelet analysis

280 As shown in Fig. 5, the wavelet analysis is firstly adopted to decompose
 281 the raw voltage degraded waveform of PEMFC into multiple sub-waveforms.
 282 Then, the prognosis of each sub-waveform is made separately by NARX.
 283 Finally, the prognosis of W-NARX is obtained by adding the prognosis of
 284 each sub-waveform.

285 4. Results and validation

286 4.1. Setting of the prognosis method

287 For NARX, the historical status, load current, relative humidity, tem-
288 perature, and hydrogen pressure are selected as the input variables. The
289 output voltage of PEMFC is selected as the output variable. The number of
290 maximum delay is selected as 3. The number of neurons in the hidden layer
291 of NARX is chosen as 10. The activation function in hidden layer is set to
292 sigmoid, and the activation function in output layer is set to linear.

293 For wavelet analysis, the wavelet function type and decomposition scale
294 have a great influence on the prognosis of PEMFC. The order 6 Daubechies
295 wavelet is selected as the wavelet function. The decomposition scale is deter-
296 mined to ensure that the extracted voltage degradation signal is smooth [51].
297 Considering the accuracy and calculation amount, the number of decompo-
298 sition scale is selected as 3 for the prognosis of PEMFC in this paper.

299 In order to evaluate the calculation complexity of different methods, the
300 calculation time is adopted. The commercial computer with an i5-6300 Intel
301 CPU (2.3 GHz clock and 12GB RAM) is used to execute proposed methods.
302 In order to evaluate the accuracy of different methods, Absolute Error (AE),
303 Relative Error (RE), and Mean Square Error (MSE) are used in this paper.
304 Smaller values of AE, RE, and MSE means higher accuracy for the prognosis
305 of PEMFC.

306 4.2. The prognosis of PEMFC based on the W-NARX and different methods

307 In order to analyze the impact of wavelet analysis on degradation prog-
308 nosis, the prognosis of PEMFC in FCHEV operated under real conditions is
309 made by W-NARX and NARX. 70% of datasets for PEMFC in FCHEV are
310 applied to learn the degradation trend of PEMFC, and remained datasets
311 are applied to verify the prognosis of PEMFC in FCHEV. The sub-waveform
312 prognosis of PEMFC in FCHEV based on the W-NARX is shown in Fig.
313 6. The comparison of the prognosis of PEMFC based on the W-NARX and
314 NARX is shown in Fig. 7. The AE of the two methods is shown in Fig. 8.

315 As shown in Fig. 6, the degradation trend of each wavelet can be accu-
316 rately learned and forecasted by W-NARX for PEMFC in FCHEV. As shown
317 in Fig. 7, the prognosis of PEMFC based on the W-NARX is better than
318 that of NARX. It shows that W-NARX can accurately learn and forecast
319 PEMFC fluctuations and recovery phenomena. As shown in Fig. 8, the AE
320 of NARX is greater than the AE of W-NARX. The MSE of prognosis of

Figure 6: The sub-waveform prognosis of PEMFC in FCHEV under real conditions based on W-NARX

Figure 7: The degradation prognosis of PEMFC in FCHEV under real conditions based on W-NARX and NARX

Figure 8: The AE for degradation prognosis of PEMFC in FCHEV under real conditions based on W-NARX and NARX

321 PEMFC based on the W-NARX is about 0.0059, and the MSE of prognosis
 322 of PEMFC based on the NARX is about 0.0923. The mean RE of prognosis
 323 of PEMFC based on the W-NARX is about 0.1359%, and the mean RE of
 324 prognosis of PEMFC based on the NARX is about 0.3277%. Compared with
 325 the W-NARX, the mean RE of NARX increases by 2.4 times. The reason
 326 why the error of W-NARX is lower than the error of NARX is that the fluc-
 327 tuations and recovery phenomena are decomposed into multiple wavelets by
 328 wavelet analysis to learn and forecast the degradation of PEMFC. The cal-
 329 culation time of W-NARX is about 918s, and that of NARX is about 232s.
 330 Wavelet analysis causes an increase in calculation time. However, compared
 331 with the degraded time of the PEMFC, the calculation time of W-NARX is
 332 very small. Therefore, W-NARX can be regarded as an appropriate prognosis
 333 method to deal with fluctuation and recovery phenomena for PEMFC.

334 In order to verify the advantages of the proposed method, the prognosis of
 335 PEMFC in FCHEV is also made by W-NARX, k-Nearest Neighbors (KNN)
 336 algorithm, Decision Tree (DT), and Support Vector Machine (SVM). The
 337 comparison of the prognosis of PEMFC based on different methods is shown
 338 in Fig. 9. The AE of the prognosis of PEMFC based on the different methods
 339 is shown in Fig. 10. The comparison of the accuracy and calculation time of
 340 the different methods is shown in Table 4.

Figure 9: The degradation prognosis of PEMFC in FCHEV under real conditions using different methods

Figure 10: The AE for degradation prognosis of PEMFC in FCHEV under real conditions using different methods

Table 4: The comparison of the accuracy and calculation time of the different methods

Method	MSE	mean RE (%)	Time (s)
KNN	1.0749	1.3161	9
DT	0.1553	0.6587	39
SVM	0.1337	0.5049	1338
W-NARX	0.0059	0.1359	918

As shown in Fig. 9, compared with other methods, the prognosis of the proposed W-NARX is closest to the measured data of the PEMFC in FCHEV. As shown in Fig. 10, the AE of the prognosis of PEMFC based on the proposed W-NARX is the smallest. As shown in Table 4, the MSE and mean RE of the proposed W-NARX are the smallest compared with other methods. The proposed W-NARX has higher accuracy than KNN, DT, and SVM.

4.3. The effect of maximum delay on the prognosis of PEMFC

The maximum delay has a great influence on the prognosis of PEMFC. For example, the greater the maximum delay, the more historical information of PEMFC the NARX can remember, but it may also cause overfitting. In order to analyze the effect of maximum delay on the accuracy, the prognosis of PEMFC operated under a quasi-dynamic load current is made by W-NARX with different maximum delays. The maximum delay is set to 1, 2, 3, 4, 5, 7, 10, and 15. In order to reduce measurement errors and calculations, the recorded data is resampled every hour. 70% of datasets for PEMFC operated under quasi-dynamic load current are applied to learn the degradation trend of PEMFC, and remained datasets are applied to verify the prognosis of PEMFC. The prognosis of PEMFC operated under a quasi-dynamic load current based on the W-NARX with different maximum delays are shown in Fig. 11. The AE of the W-NARX with different maximum delays are shown in Fig. 12. The MSE, mean RE, and calculation time of the W-NARX with different maximum delays are shown in Fig. 13, Fig. 14 and Fig. 15, respectively.

As shown in Fig. 11, the degradation trend of PEMFC operated under a quasi-dynamic load current can be accurately learned and forecasted by W-NARX with different maximum delays. As shown in Fig. 12, the maximum

Figure 11: Degradation prognosis of PEMFC under quasi-dynamic load current based on W-NARX with different maximum delays

Figure 12: The AE for degradation prognosis of PEMFC under quasi-dynamic load current based on W-NARX with different maximum delays

Figure 13: The MSE for degradation prognosis of PEMFC under quasi-dynamic load current based on W-NARX with different maximum delays

Figure 14: The mean RE for degradation prognosis of PEMFC under quasi-dynamic load current based on W-NARX with different maximum delays

Figure 15: The calculation time for degradation prognosis of PEMFC under quasi-dynamic load current based on W-NARX with different maximum delays

368 AE of W-NARX with different maximum delays for the prognosis of PEMFC
 369 is less than 0.03V. As shown in Fig. 13 and Fig. 14, when the number
 370 of maximum delay is less than 3, the MSE and mean RE are large. Less
 371 maximum delay contains less degradation information of PEMFC, which
 372 causes an increase in the MSE and mean RE. When the number of maximum
 373 delay is more than 3, the MSE and mean RE are also large. Excessive
 374 maximum delay may lead to overfitting for the prognosis of PEMFC, which
 375 leads to an increase in the MSE and mean RE. As shown in Fig. 15, the
 376 calculation time increases as the number of maximum delay increases. This
 377 indicates that increasing the maximum delay will increase the amount of
 378 calculation. Considering the accuracy and amount of calculation, the number
 379 of the maximum delay is chosen as 3 for the prognosis of PEMFC in this
 380 paper.

381 4.4. The effect of learning data on the prognosis of PEMFC

382 The prognosis of PEMFC operated under constant load current is ana-
 383 lyzed by W-NARX with different learning data. In order to reduce measure-
 384 ment errors and calculations, the recorded data is resampled every hour. The
 385 learning data is respectively chosen as 40%, 50%, 60%, 70%, 80%, and 90%
 386 of datasets for PEMFC operated under constant load current, and remained
 387 datasets are applied to verify the prognosis of PEMFC. The prognosis of
 388 PEMFC operated under constant load current based on the W-NARX with

389 40% of datasets is shown in Fig. 16. The AE of the W-NARX with 40% of
 390 datasets is shown in Fig. 17. The MSE, mean RE, and calculation time of
 391 the W-NARX with different learning data are shown in Fig. 18, Fig. 19 and
 392 Fig. 20, respectively.

Figure 16: Degradation prognosis of PEMFC under constant load current based on W-NARX with 40% of datasets

393 As shown in Fig. 16, the degradation trend of PEMFC operated under
 394 constant load current can be accurately learned and forecasted by W-NARX
 395 with 40% of datasets. As shown in Fig. 17, the maximum AE of W-NARX
 396 with 40% of datasets for the prognosis of PEMFC is less than 0.01V. The
 397 MSE and mean RE of W-NARX with 40% of datasets for the prognosis of
 398 PEMFC are 0.000006 and 0.055%, respectively. It shows that W-NARX can
 399 accurately make the prognosis of PEMFC under the condition of less learning
 400 data. As shown in Fig. 18 and Fig. 19, the MSE and mean RE decreases
 401 as the learning data increases. As more recorded datasets are used to learn
 402 degradation trends of PEMFC, the prognosis of PEMFC based on W-NARX
 403 is more accurate, the MSE and mean RE are reduced. This indicates that
 404 more learning data can improve the accuracy of the degradation prognosis
 405 of PEMFC operated under constant load current. As shown in Fig. 20, the
 406 calculation time increases as the learning data increases. The reason for the
 407 increased calculation time is that more degradation trends of PEMFC need
 408 to be learned in more learning data.

Figure 17: The AE for degradation prognosis of PEMFC under constant load current based on W-NARX with 40% of datasets

Figure 18: The MSE for degradation prognosis of PEMFC under constant load current based on W-NARX with different learning data

Figure 19: The mean RE for degradation prognosis of PEMFC under constant load current based on W-NARX with different learning data

Figure 20: The calculation time for degradation prognosis of PEMFC under constant load current based on W-NARX with different learning data

409 5. Conclusions

410 As a kind of renewable and environmentally friendly energy, PEMFC is
411 regarded as a promising technology to solve the energy crisis and environ-
412 mental crisis. However, the durability caused by degradation seriously limits
413 its commercial application. Degradation prognosis, as the core of prognos-
414 tics and health management, is regarded as an important tool to improve
415 the durability of PEMFC. This paper presents the degradation prognosis of
416 PEMFC operated under different applications based on wavelet analysis and
417 NARX. The accuracy of the degradation prognosis of PEMFC is validated
418 by three durability tests of PEMFC operated under different applications.
419 The main conclusions of this paper are as follows:

- 420 1. Compared with the NARX, the accuracy of W-NARX increases by 2.4
421 times. The wavelet analysis greatly increases the accuracy of the degra-
422 dation prognosis of PEMFC based on NARX.
- 423 2. Compared with KNN, DT, and SVM, the proposed W-NARX has higher
424 accuracy for the degradation prognosis of PEMFC.
- 425 3. The MSE and mean RE are minimal when the maximum delay is 3. Con-
426 sidering the accuracy and amount of calculation, the number of the max-
427 imum delay is 3, which is best for the degradation prognosis of PEMFC.
- 428 4. The mean RE of W-NARX with 40% of datasets for the prognosis of
429 PEMFC is less than 0.06%. The W-NARX has a high accuracy of the
430 prognosis of PEMFC under the condition of less learning data. What is
431 more, more learning data helps to improve the accuracy of the degradation
432 prognosis of PEMFC.

433 The degradation of PEMFC has a great impact on the output perfor-
434 mance of PEMFC. The future research work will consider the presented
435 degradation prognosis method combining with energy management theory
436 to improve the output performance and economy for PEMFC in different
437 applications.

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