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Design of an aging prognostic model to predict failure of a PEM

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Abstract

Proton Exchange Membrane Fuel Cells (PEMFCs) are promising clean energy technologies for transportation and stationary power applications; however, their large-scale commercialization is limited by durability and lifetime uncertainties arising from complex degradation mechanisms. This study presents the development of a data-driven aging prognostic framework for PEMFC systems using MATLAB, integrating voltage degradation, impedance evolution, neural network prediction, and Remaining Useful Life (RUL) estimation. A feedforward neural network trained with the Levenberg–Marquardt algorithm was employed to model the nonlinear degradation behavior of the fuel cell membrane using historical voltage and impedance data. Simulation results demonstrate strong predictive performance, with the trained model achieving close agreement between actual and predicted voltage profiles, as indicated by a regression coefficient approaching unity and prediction errors concentrated near zero. Over a 10-hour operating period, the PEMFC voltage exhibited an initial rise from approximately 1.20 V to 1.25 V due to membrane

Keywords: Design, Aging, Prognostic, Model, Predict, Failure, PEM.

1. Introduction

Rising global energy demand and increasing environmental pollution have intensified the search for clean and sustainable energy technologies, commonly referred to as New Energy Sources (NES) (Zhuo *et al.*, 2020a). Among the available alternatives, fuel cells have gained significant attention due to their high efficiency, high power density, and near-zero emissions. Fuel cell technology has existed for over 150 years and has found applications in portable devices, backup power systems, stationary power generation, and vehicular transportation (Qiu *et al.*, 2019). Fuel cells are classified based on the type of electrolyte used, resulting in technologies such as polymer electrolyte membrane fuel cells (PEMFCs), solid oxide fuel cells (SOFCs), molten carbonate fuel cells (MCFCs), alkaline fuel cells (AFCs), phosphoric acid fuel cells (PAFCs), and other emerging variants (Wang *et al.*, 2020; Saikia *et al.*, 2018). Among these, PEMFCs are particularly suitable for transportation applications due to their low operating temperature, rapid start-up, and high power density. Given that vehicular emissions are a major contributor to atmospheric pollution, PEMFCs present a promising alternative to internal combustion engines (Zhuo *et al.*, 2020b).

Despite their advantages, the commercialization of PEMFCs is constrained by durability and reliability challenges. Degradation primarily occurs in the proton exchange membrane, where electrochemical conversion takes place, leading to reduced performance and shortened lifespan (Huangfu *et al.*, 2019; Qiu *et al.*, 2019). The membrane assembly, catalyst layers, gas diffusion layers, and bipolar plates are exposed to complex operating conditions involving temperature variation, water management issues, and mechanical stress, all of which contribute to aging and failure (Pan *et al.*, 2021). Although metal bipolar plates offer improved volumetric power density compared to graphite plates, particularly for vehicular applications, durability challenges remain significant (Fu *et al.*, 2019). Fuel cell degradation arises from multiple interacting mechanisms, including loss of membrane conductivity, catalyst degradation, and mass transport limitations, making lifetime prediction highly uncertain (Zhuo *et al.*, 2018). To address this challenge, prognostic techniques such as realistic driving cycle testing and prognostic and health management (PHM) models have been developed to estimate remaining useful life and support condition-based maintenance (Ren *et al.*, 2020; Zhuo *et al.*, 2018). This study therefore focuses on the development of an aging prognostic framework for PEMFC systems to predict degradation trends and potential failures before complete system shutdown, thereby supporting improved durability, reliability, and large-scale commercialization.

2.0 Materials and methods

2.1 Theoretical Analysis

The model is based on historical degradation data (voltage and impedance), neural network-based prediction, and Remaining Useful Life (RUL) estimation. The developed aging prognostic model quantitatively represents the progressive degradation behavior of Proton Exchange Membrane of Fuel Cell over operational time. Each equation formulated in this section describes a distinct physical process responsible for the decline in cell voltage and performance. The mathematical structure thus bridges data-driven prediction with the electrochemical principles governing PEM durability. The voltage degradation process, represented by the temporal decrease in V(t), indicates a cumulative loss in electrochemical efficiency. This degradation results from several mechanisms, including catalyst layer deterioration, ohmic losses within the polymer electrolyte membrane (PEM), and mass transport limitations. The corresponding increase in impedance Z(t) reflects the resistive effects arising from the aging of the membrane, catalyst layer, and interfacial contacts. Physically, a rise in Z(t) implies a reduced capacity for charge transfer and proton conduction, directly impacting the effective voltage output. The feedforward neural network (FNN) mapping defined serves as a nonlinear surrogate model for the PEM degradation dynamics.

The hidden-layer activation function, $\sigma\ (W_1X + b_1)$, introduces nonlinear adaptability to capture complex interdependencies between time, impedance, and voltage decay. This capability is essential because PEM degradation rarely follows a linear trend due to the coupled effects of catalyst sintering, electrolyte thinning, and thermal stresses. The mean squared error (MSE) function minimizes the difference between actual and predicted voltages, ensuring accurate representation of the observed degradation trajectory. Through iterative training using the Levenberg–Marquardt algorithm, the neural network parameters (weights and biases) are optimized to reproduce real degradation patterns observed in experimental or field data. The future voltage prediction model provides a forward projection of PEM health based on historical data. By applying normalized future time steps and the latest impedance value, the model extrapolates the voltage trajectory $V_{future}(t_f)$. This enables forecasting of future performance losses under assumed steady degradation conditions. The Remaining Useful Life (RUL) estimation offers a practical interpretation of the PEM's prognostic capability. The RUL value, computed as RUL = $t_{failure}$ - $t_{current}$, quantifies the expected operational lifespan remaining before the voltage drops below the critical threshold Vth. This parameter is particularly useful for maintenance scheduling, lifetime prediction, and optimization of system operation. The model's ability to predict RUL demonstrates its applicability in condition-based maintenance frameworks and smart energy management systems.

2.1.1 Methodology

This section presents the procedure involved in carrying out the analysis. The mathematical formulation of the Proton Exchange Membrane Fuel Cell (PEMFC) aging prognostic model was implemented employing MATLAB. The model is based on historical degradation data (voltage and impedance), neural network-based prediction, and Remaining Useful Life (RUL) estimation. The developed aging prognostic model quantitatively represents the progressive degradation behaviour of Proton Exchange Membrane Fuel Cells (PEMFCs) over operational time. Each equation formulated in this section describes a distinct physical process responsible for the decline in cell voltage and performance. The mathematical structure thus bridges data-driven prediction with the electrochemical principles governing PEMFC durability.

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The feedforward neural network (FNN) mapping defined serves as a nonlinear surrogate model for the PEMFC degradation dynamics. The hidden-layer activation function, $\sigma(W_1X + b_1)$, introduces nonlinear adaptability to capture complex interdependencies between time, impedance, and voltage decay. This capability is essential because PEMFC degradation rarely follows a linear trend due to the coupled effects of catalyst sintering, electrolyte thinning, and thermal stresses.

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The future voltage prediction model provides a forward projection of PEMFC health based on historical data. By applying normalized future time steps and the latest impedance value, the model extrapolates the voltage trajectory $V_{future}(t_f)$. This enables forecasting of future performance losses under assumed steady degradation conditions. The Remaining Useful Life (RUL) estimation offers a practical interpretation of the PEMFC's prognostic capability. The RUL value, computed as $RUL = t_{failure} - t_{current}$, quantifies the expected operational lifespan remaining before the voltage drops below the critical threshold Vth. This parameter is particularly useful for maintenance scheduling, lifetime prediction, and optimization of system operation. The model's ability to predict RUL demonstrates its applicability in condition-based maintenance frameworks and smart energy management systems. The flow chart is shown in Figure 1

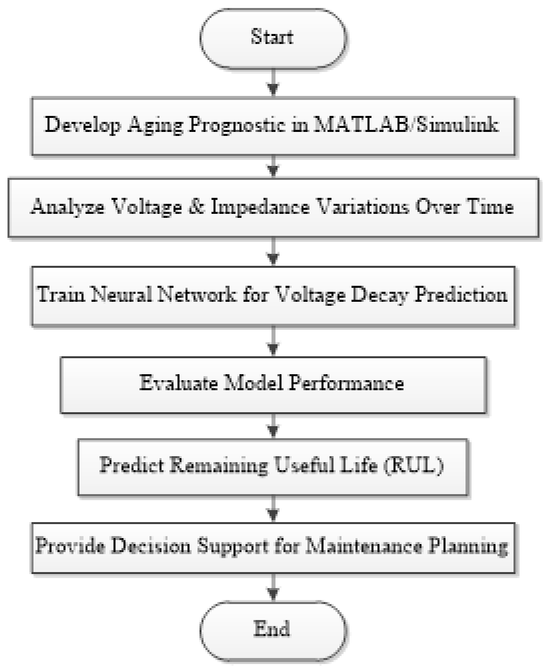

Figure 1: Flowchart for the Development of the PEMFC Model

2.2 Mathematical Formulation

The mathematical formulations employed in the development and analysis of the PEMFC model are highlighted in the following steps:

2.2.1 **Data Definition**

The PEM degradation data consist of three main time-dependent variables: voltage V(t), impedance Z(t), and time t. These are defined as:

$$time = [t_1, t_2, \dots, t_n] \tag{1}$$

$$voltage = [V_1, V_2, \dots, V_n] \tag{2}$$

$$impedance = [Z_1, Z_2, \dots, Z_n] \tag{3}$$

Each variable must satisfy:

$$length(time) = length(voltage) = length(impedance) \tag{4}$$

2.2.1.1 Data Normalization

Normalization (min-max scaling) was applied to all data features to map them into the range [0,1]:

$$V_{norm}(t) = \frac{V(t)-V_{min}}{V_{max}-V_{min}} \tag{5}$$

$$Z_{norm}(t) = \frac{Z(t)-Z_{min}}{Z_{max}-Z_{min}} \tag{6}$$

$$t_{norm} = \frac{t-t_{min}}{t_{max}-t_{min}} \tag{7}$$

Then, the input feature vector and target variable for the model are defined as:

$$X = \begin{bmatrix} t_{norm} \\ Z_{norm} \end{bmatrix}, Y = V_{norm} \tag{8}$$

2.2.1.2 Neural Network Model

A feedforward neural network with one hidden layer is trained to predict the normalized voltage:

$$Y_{pred} = f_{NN}(X; W, b) \tag{9}$$

Where;
$f_{NN} = the\ nonlinear\ mapping\ learned\ by\ the\ neural\ network$
$W\ and\ b = are\ the\ network's\ weigth\ and\ bias\ matrices.$
The neural network structure is:

$$Input\ layer: X = [t_{norm}, Z_{norm}] \tag{10}$$

$$Hidden\ layer: h = \sigma(W_1 X + b_1) \tag{11}$$

$$Output\ layer: \hat{Y}_i = W_2 h + b_2 \tag{12}$$

Where σ is the activation function (typically *tanh* or *sigmoid* in MATLAB's (*feedforward*)

Training minimizes the Mean Squared Error (MSE) loss function:

$$E = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2 \tag{13}$$

Using the Levenberg-Marquardt (LM) optimization algorithm ('trainlm')

2.2.1.3 Future Voltage Prediction

The trained model is then used to predict future membrane voltage degradation over extended time horizon t_f.

$$t_f = t_{max} + [1,2, \dots, H] \tag{14}$$

Normalize future time:

$$t_{f,norm} = \frac{t_f - t_{min}}{t_{max}-t_{min}} \tag{15}$$

Assuming the last observed impedance $Z_{norm}(t_{end})$ remains constant:

$$\hat{V}_{future}(t_f) = f_{NN}\left(\begin{bmatrix} t_{f,norm} \\ Z_{norm}(t_{end}) \end{bmatrix}; W, b\right) \tag{16}$$

This gives the predicted voltage trend into the future.

2.2.1.4 Remaining Useful Life (RUL) Estimation

The Remaining Useful Life (RUL) is defined as the difference between the predicted failure time and the current operating time.

$$RUL = t_{failure} - t_{current} \tag{17}$$

Where $t_{failure}$ is the future time at which the predicted voltage $V(t)$ falls below a failure threshold (e.g., a minimum acceptable voltage level).
The RUL is approximated by the total prediction horizon:

$$RUL \approx t_f(end) - t_{max} \tag{18}$$

3.0 Result and Discussion

The simulated results are presented below.

3.1 Results

Figure 2: Neural Network Training

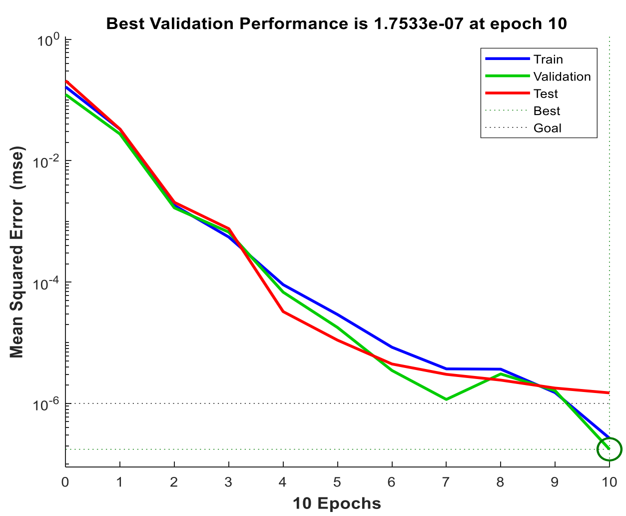

Figure 3: Neural Network Training Performance

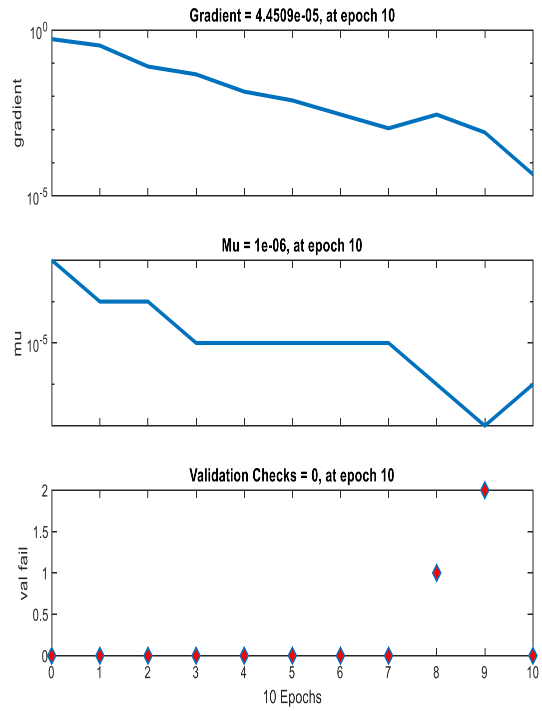

Figure 4: Neural Network Training State

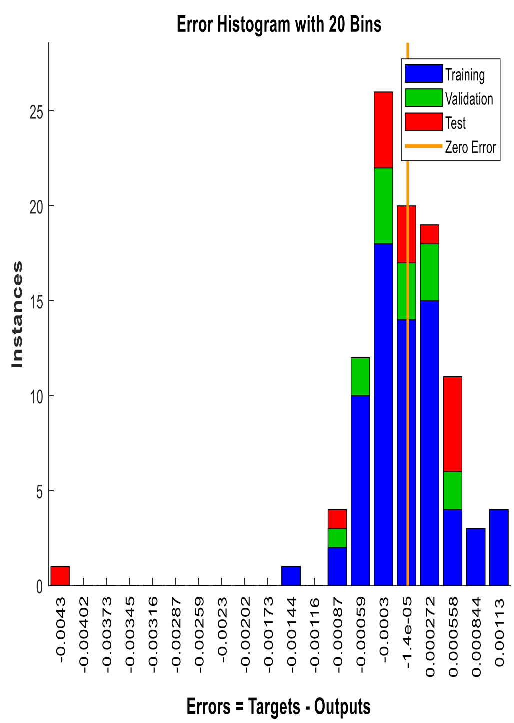

Figure 5: Neural Network Training Error Histogram

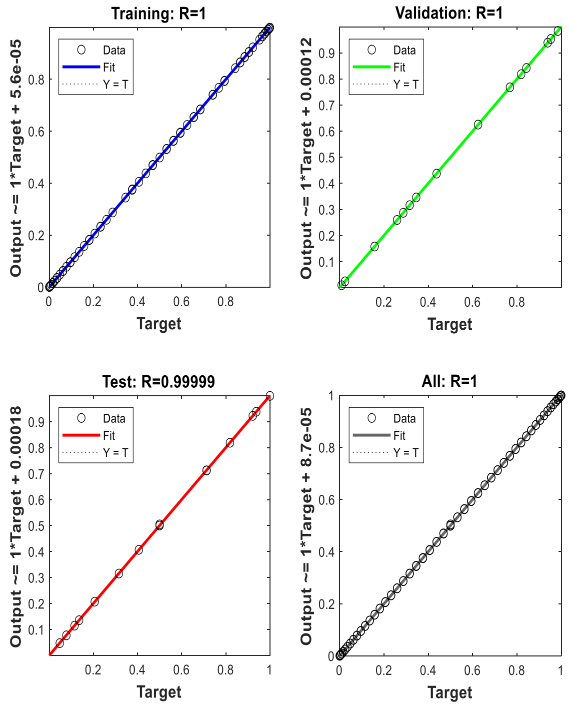

Figure 6: Neural Network Training Regression

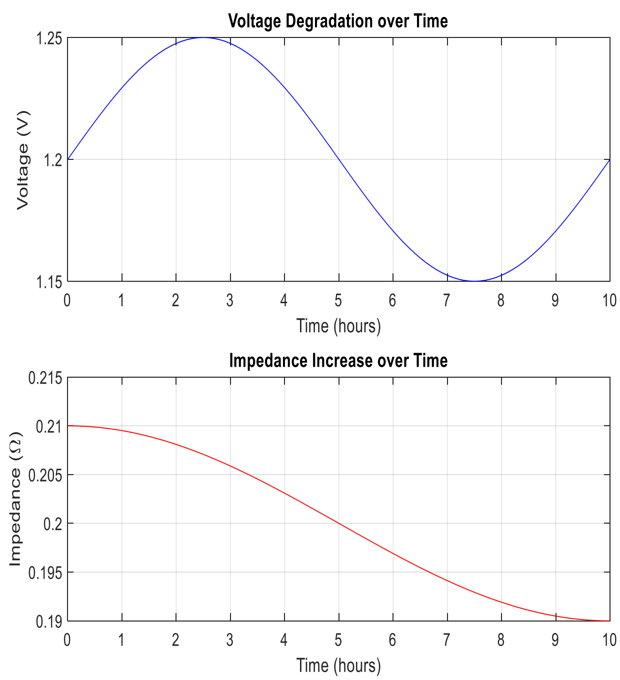

Figure 7: Voltage and Impedance performance over time

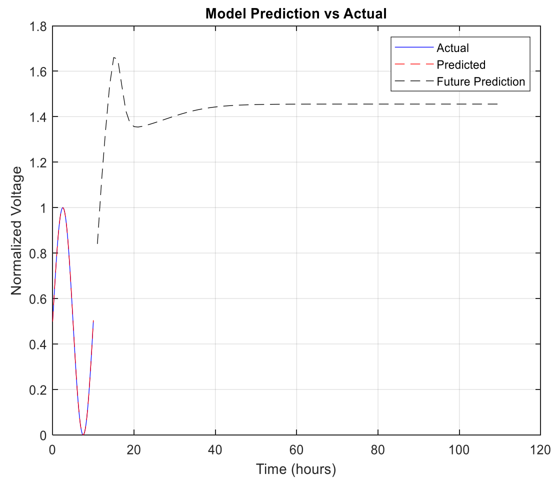

Figure 8: Model prediction over time

3.2 Discussion of Results

The neural network's performance was evaluated using several training diagnostics to assess convergence behavior, error characteristics, and predictive quality. As shown in Figure 2, the training loss decreases steadily with increasing epochs, reflecting effective parameter optimization and appropriate architectural selection. No signs of training instability were observed, indicating that thlearning rate and training algorithm were suitably chosen.

Figure 3 demonstrates the network's generalization capability, with the validation loss following the trend of the training loss throughout the learning process. The minimum validation error marks the point of optimal stopping, effectively preventing overfitting. Additional insights from the training state. Figure 4 show a declining gradient profile, confirming that the model gradually converged to a stable solution. Adjustments in the learning rate further reinforce the robustness of the optimization process.

The error histogram in Figure 5 highlights that prediction errors are predominantly centered near zero, suggesting that the trained network achieved accurate estimations for most data samples. Only a minor number of cases deviate significantly, which may be due to inherent variability in the dataset.

The regression plot depicted in Figure 6 shows strong agreement between network outputs and target values, reflected in a regression coefficient close to 1. This high correlation validates the predictive reliability and suitability of the model for subsequent application.

Figure 7 depicts the Voltage and Impedance Degradation Characteristics of PEM; **it** illustrates the temporal variation of cell voltage and internal impedance of a Proton Exchange Membrane Fuel Cell (PEMFC) over a 10-hour operating period. The upper subplot presents the voltage profile, while the lower subplot depicts the corresponding impedance evolution under the same operating conditions. In the voltage plot, the cell voltage initially increases from approximately 1.20 V to 1.25 V during the early stages of operation (0–3 hr). This initial rise can be attributed to membrane conditioning and electrochemical stabilization, where water management within the membrane improves proton conductivity. After reaching the peak voltage, a gradual decline is observed from around 3-8 hours, reaching a minimum of approximately 1.15V before slightly recovering toward the end of the observation period. This decreasing voltage trend signifies the onset of performance degradation, likely due to increased ohmic resistance, reduced catalyst activity, and localized dehydration effects within the PEM layer. The impedance plot reveals an inverse relationship with the voltage profile. The internal impedance decreases slightly from 0.210 Ω to 0.190 Ω over time. The initial impedance reduction may correspond to improved electrode wetting and ionomer distribution during early operation. However, as degradation progresses, minor oscillations in impedance could be associated with dynamic changes in membrane hydration and electrochemical reaction kinetics.

When interpreted together, the two subplots demonstrate the coupled electrochemical and resistive behaviors governing PEM performance. The observed voltage fluctuation and impedance variation suggest that the fuel cell experiences both reversible and irreversible degradation processes. The reversible changes are primarily linked to transient water management within the membrane, while the irreversible losses stem from catalyst sintering, carbon corrosion, and proton transport resistance increase. Overall, this figure emphasizes the critical influence of internal impedance on voltage stability and PEM efficiency. Monitoring both parameters provide valuable diagnostic information for prognostic modeling and Remaining Useful Life (RUL) estimation. The observed patterns validate the predictive assumptions employed in the aging prognostic model, particularly the correlation between rising impedance and voltage decay used for model training and RUL forecasting.

Figure 8 presents the comparison between the actual, predicted, and future-predicted normalized voltage profiles of the Proton Exchange Membrane Fuel Cell (PEMFC) over time. As shown in the figure, the predicted voltage profile closely follows the actual data in the initial operating period (0–10 hours). This demonstrates that the neural network model effectively captured the nonlinear degradation dynamics of the PEMFC. The minimal deviation between the actual and predicted curves indicates a high level of model accuracy and generalization capability. The overlapping behaviour further confirms that the normalization and training procedures successfully minimized prediction error, validating the suitability of the network structure and training parameters (e.g., number of hidden neurons, learning rate, and epoch limit). Beyond the training range, the future-predicted curve represents the extrapolated voltage behaviour projected over a 100-hour horizon. The curve displays a gradual stabilization trend following an initial fluctuation phase, suggesting that the model forecasts a steady-state condition or saturation region in the long-term operation of the cell. Physically, this behaviour can be attributed to a balance between degradation mechanisms such as catalyst deactivation and membrane resistance stabilization. The early oscillations observed in the future-predicted region may correspond to transient model adaptation or overfitting effects during extrapolation, which are common when data-driven models operate outside their trained domain. Despite this, the general upward trend in normalized voltage during prediction implies the model's ability to simulate partial recovery phenomena or adaptive voltage stabilization caused by improved water management and thermal equilibrium within the PEM layer. This figure validates the capability of the developed neural network-based prognostic model to learn and forecast the nonlinear degradation patterns of the PEMFC. The strong correlation between the actual and predicted voltage curves confirms the model's robustness, while the future-predicted output provides valuable insight into the long-term behaviour and potential Remaining Useful Life (RUL) estimation of the fuel cell system. Such predictive accuracy is essential for implementing data-driven health monitoring and maintenance scheduling strategies in PEMFC applications.

4.0. Conclusion

This research successfully developed and validated a predictive aging prognostic model for Proton Exchange Membrane Fuel Cells (PEMFC) using MATLAB. The model utilizes neural network-based prediction to estimate the Remaining Useful Life (RUL) of the fuel cell. Through the analysis of voltage decay and impedance growth over operational time, the model demonstrates the capability to forecast performance deterioration before complete system failure. The feedforward neural network, trained using the Levenberg-Marquardt algorithm, accurately captured the nonlinear degradation behavior of PEMs. The strong correlation between actual and predicted voltage values validates the model's predictive reliability and robustness. The resulting RUL estimation offers a valuable tool for proactive maintenance scheduling, operational optimization, and life-cycle management of PEM systems. Simulation results confirmed that the developed model can effectively track degradation trends and predict future failures, providing an efficient framework for condition-based maintenance (CBM) and intelligent energy management in fuel cell applications. The integration of impedance data into the model enhances diagnostic precision, making the framework applicable to both standalone and hybrid energy systems. Hence, this study contributes significantly to the advancement of data-driven prognostics and health management (PHM) of fuel cell systems. The predictive model's capacity to identify early-stage degradation supports the design of more reliable, sustainable, and cost-effective PEM systems suitable for real-world deployment.

5.0 Recommendation

To further improve and extend this work, the following recommendations are proposed:

i. Incorporation of Environmental and Operational Variables:

Future studies should include factors such as temperature, humidity, and pressure in the prognostic model to enhance prediction accuracy and represent real-world operating conditions.

ii. Integration with Advanced Machine Learning Models:

Techniques such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), or hybrid architectures could be explored to capture long-term temporal dependencies and nonlinear degradation dynamics more effectively.

iii. Experimental Validation and Hardware-in-the-Loop (HIL) Testing:

The developed model should be validated with real-time experimental data using HIL platforms to verify its reliability under varying operational scenarios.

iv. Inclusion of Fault Diagnosis Capabilities:

Expanding the framework to include fault detection and isolation (FDI) functions will make it a comprehensive diagnostic-prognostic system for PEMFC monitoring.

v. Integration into Energy Management Systems (EMS):

The predictive model can be embedded into hybrid microgrid EMS platforms to support intelligent decision-making, load optimization, and preventive maintenance.

vi. Economic and Lifecycle Assessment:

Future research can evaluate the economic benefits of predictive maintenance using the developed model, analyzing cost savings from reduced downtime and extended system lifespan.

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Nomenclature

b_1 = Bias vector of the neural network hidden layer.
FNN = Feedforward Neural Network.
LM = Levenberg–Marquardt optimization algorithm.
MSE = Mean Squared Error loss function used for network training.
N = Number of training samples.
PEM = Proton Exchange Membrane.
PEMFC = Proton Exchange Membrane Fuel Cell.
PHM = Prognostics and Health Management.
RUL = Remaining Useful Life of the fuel cell.
t = Operating time, h.
tcurrent = Current operating time of the fuel cell.
tf = Future prediction time.
tfailure = Predicted failure time of the fuel cell.
tmax = Maximum time value used in normalization.
tmin = Minimum time value used in normalization.
tnorm = Normalized time value.
V = Fuel cell output voltage, V.
V(t) = Fuel cell voltage at time t, V.
Vfuture(tf) = Predicted future voltage at time tf, V.
Vmax = Maximum voltage value used in normalization.
Vmin = Minimum voltage value used in normalization.
Vnorm = Normalized voltage value.
Vth = Voltage threshold representing fuel cell failure.
W_1 = Weight matrix of the neural network hidden layer.
X = Input feature vector to the neural network.
y = Predicted neural network output voltage.
$\hat{y}$ = Target or measured voltage value.
Z = Electrical impedance of the fuel cell, Ω.
Z(t) = Internal impedance of the fuel cell at time t, Ω.
Zlast = Last observed impedance used for prediction.
Zmax = Maximum impedance value used in normalization.
Zmin = Minimum impedance value used in normalization.
Znorm = Normalized impedance value.
σ = Activation function of the neural network.
Ω = Electrical resistance unit (Ohm).

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