Remaining Useful Life Prediction for a Multi-stack Solid Oxide Fuel Cell System with Degradation Interactions

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***Abstract*—Due to the constraints of manufacturing and materials, high-power plants cannot rely on only one solid oxide fuel cell stack. A multi-stack system is a solution for a high-power system, which consists of multiple fuel cell stacks. A short lifetime is one of the main challenges for the fuel cell before large-scale commercial applications, and prognostic is an important method to improve the reliability of fuel cells. Different from the traditional prognostic approaches applied to single-stack fuel cell systems, the key problem in multi-stack prediction is how to solve the correlation of multi-stack degradation, which can directly affect the accuracy of prediction. In response to this difficulty, a standard Brownian motion is added to the traditional Wiener process to model the degradation of each stack, and then the probability density function of the remaining useful life (RUL) of each stack is calculated. Furthermore, a Copula function is adopted to reflect the dependence between life distributions, so as to obtain the remaining useful life for the whole multi-stack system. The simulation results show that compared with the traditional prediction model, the proposed approach has a higher prediction accuracy for multi-stack fuel cell systems.**

***Index Terms*—Degradation interaction, multi-stack, remaining useful life (RUL), solid oxide fuel cell (SOFC).**

I. Introduction

DUE to the scarcity of fossil fuel resources and environmental concerns, new energy sources are being sought. A Solid Oxide Fuel Cell (SOFC) is a high-temperature fuel cell that operates between 500°C and 1000°C, which can directly convert chemical energy into electrical energy. Because of its high temperature, the SOFC can use diversity of fuel sources, such as biogas and ethanol [1].

In recent years, a large number of industrial applications require high-power supply stacks, such as space exploration vehicles, transportation industry, etc. [2]. Due to the constraints of manufacturing and materials, high-power plants cannot rely on only one SOFC stack, but multi-stack SOFC systems are needed to support a high-power output, in which multiple single stack units are connected in series or parallel architectures. The modular design of the multi-stack system makes it easier to implement in practical applications.

In actual operations, the SOFC performance may inevitably degrade [3]. Previous studies have mentioned that proper prognostic methods can help reduce SOFC failures and downtime, thereby extending their lifetime and reducing costs [4]. A large number of prognostic methods have been developed for SOFCs. Based on the principle of performance degradation mechanisms, several physical degradation models were established to describe the SOFC degradation process [5], [6]. The data-driven SOFC degradation model is primarily divided as follows: 1) The SOFC system degradation process is expressed in a certain functional form, and then the parameters in the models are identified by techniques, such as the Kalman filter [7]–[9]; 2) Using the semi-Markov model [10], [11], neural network [12] and other artificial intelligence algorithms, the time evolution law from historical data to future data is mined based on the historically measured voltage data of the stack, and then the future voltage of the target stack is predicted.

Despite the great progress in prognostic strategies, the current research is primarily designed for the single-stack SOFC system, while is not suitable for the multi-stack system. For the multi-stack system, there exists correlations among the degradation of the stack. Neglecting the interdependency between stack degradation will result in an inefficient prediction [13]. Therefore, a prognostic approach is proposed to calculate the multi-stack system's RUL in this study.

II. Methodology

The proposed prognostic approach for the multi-stack SOFC system is given in Fig. 1. Considering the correlation between multiple stack degradation, a nonlinear Wiener process with a standard Brownian motion is taken to describe the degradation

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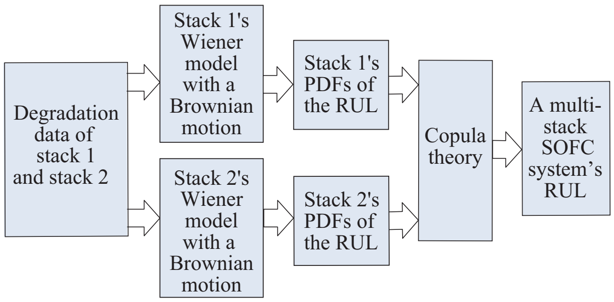


Fig. 1. The proposed prognostics strategy for the multi-stack SOFC system.

of the multi-stack SOFC system. Then using the first hitting time (FHT) theory, the probability density function (PDF) of RUL for each stack is calculated. Finally, a Copula function is used to analyze the correlation among RUL distributions, and the PDF of RUL for the whole multi-stack SOFC system is obtained.

A. A Multi-stack Degradation Model

The multi-stack SOFC system is composed of several stacks, and these stacks work in the same environment, therefore the

degradation of these stacks will be affected by common factors. The Wiener process is one type of special Markov process that conforms to normal random characteristics. Therefore, a traditional Wiener model combined with a standard Brownian motion is built to describe the multi-stack degradation process:

$$\Delta V^{(i)}(t) = V^{(i)}(0) - V^{(i)}(t) = \alpha^{(i)} t^{b^{(i)}} + \beta^{(i)} B(t) \quad (1)$$

where $\Delta V^{(i)}(t)$ and $V^{(i)}(t)$ are the voltage degradation value and real value of the ith stack at time t respectively. In this study, the multi-stack SOFC system consists of two stacks, i.e$i = 1, 2$. $V^{(i)}(0)$ is the initial value of $V^{(i)}(t)$. $\alpha^{(i)}$ is a random parameter, which follows a normal distribution. $\alpha^{(i)} t^{b^{(i)}}$ is the corresponding drift coefficient of $\Delta V^{(i)}(t)$. $b^{(i)}$ is a fixed parameter. $\beta^{(i)}$ is the diffusion coefficient of the ith stack. $B(t)$ is the standard Brownian motion.

In practical applications, the measurement voltage signals often have certain errors due to measurement tools and environmental influences. Therefore, the measured voltage of the ith stack $Y^{(i)}(t)$, is written as follows:

$$Y^{(i)}(t) = V^{(i)}(0) - \Delta V^{(i)}(t) + \chi^{(i)}(t) \quad (2)$$

where $\chi^{(i)}(t)$ is identically normal distributed with mean zero and variance $(\varepsilon^{(i)})^2$.

To identify the hidden parameters, convert. (1-2) into the following discrete time equations [14]:

$$\begin{aligned} \Delta V^{(i)}(t_k) =& \Delta V^{(i)}(t_{k-1}) + \alpha^{(i)}(t_{k-1})(t_k^{b^{(i)}} - t_{k-1}^{b^{(i)}}) \\ &+ \beta^{(i)}(B(t_k) - B(t_{k-1})) \quad (3) \\ \alpha^{(i)}(t_k) =& \alpha^{(i)}(t_{k-1}) + \lambda^{(i)} \quad (4) \\ Y^{(i)}(t_k) =& V^{(i)}(0) - \Delta V^{(i)}(t_k) + \chi^{(i)}(t_k) \quad (5) \end{aligned}$$

where t_k is the discrete time point, $k = 1, 2, \cdots, K$, K is sampling points. $\lambda^{(i)}$ is an additive Gaussian process noise of the random parameter $\alpha^{(i)}$, $\lambda^{(i)} \sim N(0, (\sigma^{(i)})^2)$. Using the Expectation Maximization (EM) algorithm, the parameters $b^{(i)}$, $\beta^{(i)}$, $\sigma^{(i)}$ and $\varepsilon^{(i)}$ are estimated, and their estimated values are expressed as $\hat{b}^{(i)}$, $\hat{\beta}^{(i)}$, $\hat{\sigma}^{(i)}$ and $\hat{\varepsilon}^{(i)}$. Furthermore, based on the Kalman filter, the degradation of voltage $\Delta V^{(i)}(t_k)$ and the random parameter $\alpha^{(i)}(t_k)$ are updated, and the updated values are expressed as $\Delta\hat{V}^{(i)}(t_k)$ and $\hat{\alpha}^{(i)}(t_k)$.

B. Remaining Useful Life of Each Stack

If the voltage value exceeds a certain threshold, it is considered that the single stack has failed. Therefore, at time t_k, the remaining useful life of the ith stack, $L_k^{(i)}$, is defined as follows:

$$\begin{aligned} \mathrm{RUL}_k^{(i)} : L_k^{(i)} =& \{l_k^{(i)} : V^{(i)}(t_k + l_k^{(i)}) \le V_{\text{threshold}}^{(i)} \\ & | V^{(i)}(t_k) > V_{\text{threshold}}^{(i)}, t_k > 0\} \quad (6) \end{aligned}$$

where $V_{\text{threshold}}^{(i)}$ is the corresponding failure threshold.

Applying the FHT theory [15], the PDF of the remaining useful life for the ith stack is given by:

$$\begin{aligned} f_{\mathrm{RUL}}^{(i)}(l_k^{(i)} | Y_{1:k}^{(i)}) =& \sqrt{\frac{(C_k^{(i)})^{-2}}{2\pi \left| k_{\alpha,k}^{(i)} (B_k^{(i)})^2 + C_k^{(i)} \right|}} \\ & \cdot \left(w_k^{(i)} (\hat{\beta}^{(i)})^2 - \frac{w_k^{(i)} E_k^{(i)} k_{\alpha,k}^{(i)} B_k^{(i)} + C_k^{(i)} E_k^{(i)} \hat{\alpha}^{(i)}(t_k)}{C_k^{(i)} + k_{\alpha,k}^{(i)} (B_k^{(i)})^2} \right) \\ & \cdot \exp\left(-\frac{\begin{array}{c}(V^{(i)}(0) - V_{\text{threshold}}^{(i)} - \Delta\hat{V}^{(i)}(t_k) - \\ ((l_k + t_k)^{\hat{b}^{(i)}} - t_k^{\hat{b}^{(i)}})\hat{\alpha}^{(i)}(t_k))^2\end{array}}{2(C_k^{(i)} + k_{\alpha,k}^{(i)} (B_k^{(i)})^2)} \right) \quad (7) \end{aligned}$$

where

$$\begin{aligned} C_k^{(i)} &= k_{v,k}^{(i)} - (k_{c,k}^{(i)})^2 (k_{\alpha,k}^{(i)})^{-1} + (\hat{\beta}^{(i)})^2 l_k^{(i)} \\ B_k^{(i)} &= (l_k + t_k)^{\hat{b}^{(i)}} - t_k^{\hat{b}^{(i)}} + k_{c,k}^{(i)} (k_{\alpha,k}^{(i)})^{-1} \\ w_k^{(i)} &= V^{(i)}(0) - V_{\text{threshold}}^{(i)} - \Delta\hat{V}^{(i)}(t_k) \\ &\quad + k_{c,k}^{(i)} \hat{\alpha}^{(i)}(t_k) (k_{\alpha,k}^{(i)})^{-1} \\ E_k^{(i)} &= ((l_k + t_k)^{\hat{b}^{(i)}} - t_k^{\hat{b}^{(i)}})(\hat{\beta}^{(i)})^2 + k_{c,k}^{(i)} (\hat{\beta}^{(i)})^2 (k_{\alpha,k}^{(i)})^{-1} \\ &\quad - \hat{b}^{(i)} (l_k^{(i)} (\hat{\beta}^{(i)})^2 + k_{v,k}^{(i)} \\ &\quad - (k_{c,k}^{(i)})^2 k_{\alpha,k}^{(i)}) (l_k^{(i)} + t_k)^{\hat{b}^{(i)} - 1} \quad (8) \end{aligned}$$

where $Y_{1:k}^{(i)}$ represents the data set of the output voltage measurement values from t_1 to t_k. $k_{\alpha,k}^{(i)}$ and $k_{v,k}^{(i)}$ are the variances of the posterior distribution of $\alpha^{(i)}(t_k)$ and $\Delta V^{(i)}(t_k)$, $k_{c,k}^{(i)}$ is the covariance between $\alpha^{(i)}(t_k)$ and $\Delta V^{(i)}(t_k)$.

At time t_k, the mean RUL for the ith stack, $\bar{L}_k^{(i)}$ is defined as follows [16]:

$$\bar{L}_k^{(i)} = \int_0^\infty t \cdot f_{\mathrm{RUL}}^{(i)}(t | Y_{1:k}^{(i)}) \mathrm{d}t \quad (9)$$

C. Remaining Useful Life of the Whole Multi-stack SOFC System

The multi-stack SOFC system is assumed to be failed as long as any stack degradation hits the failure threshold.

Therefore, the RUL of the whole multi-stack is defined as follows:

$$\mathrm{RUL}_k : L_k = \min\{L_k^{(1)}, L_k^{(2)}\} \tag{10}$$

where $L_k^{(i)}$ is the RUL of the ith stack at time t_k, and L_k is the RUL of the two-stack system at time t_k.

According to the Sklar theorem [17], any multivariate joint distribution can be written by univariate marginal distribution functions with a Copula function. Therefore, the cumulative distribution function (CDF) for the whole multi-stack system's RUL is calculated as follows:

$$\begin{aligned} F_{\mathrm{RUL}}(l_k|Y_{1:k}^{(1)}, Y_{1:k}^{(2)}) &= P\{\min(L_k^{(1)}, L_k^{(2)}) \le l_k\} \\ &= \sum_{i=1}^{2} F_{\mathrm{RUL}}^{(i)}(l_k^{(i)}|Y_{1:k}^{(i)}) - \\ &\quad C(F_{\mathrm{RUL}}^{(1)}(l_k^{(1)}|Y_{1:k}^{(1)}), F_{\mathrm{RUL}}^{(2)}(l_k^{(2)}|Y_{1:k}^{(2)}); \theta) \end{aligned} \tag{11}$$

where

$$F_{\mathrm{RUL}}^{(i)}(l_k^{(i)}|Y_{1:k}^{(i)}) = \int_0^{l_k^{(i)}} f_{\mathrm{RUL}}^{(i)}(s|Y_{1:k}^{(i)})\mathrm{d}s \tag{12}$$

where $C(\cdot)$ is a Copula function, which describes the dependence between the stack's RUL [18]. $F_{\mathrm{RUL}}^{(i)}(l_k^{(i)}|Y_{1:k}^{(i)})$ is the CDF of RUL of the ith stack. θ is a correlation coefficient, which is identified by using the maximum likelihood estimation (MLE) method [19].

By taking the derivative of F_{RUL}, the PDF of RUL of the multi-stack SOFC system is deduced as follows:

$$\begin{aligned} f_{\mathrm{RUL}}(l_k|Y_{1:k}^{(1)}, Y_{1:k}^{(2)}) &= f_{\mathrm{RUL}}^{(1)}(l_k^{(1)}|Y_{1:k}^{(1)}) + f_{\mathrm{RUL}}^{(2)}(l_k^{(2)}|Y_{1:k}^{(2)}) \\ &\quad - f_{\mathrm{RUL}}^{\mathrm{union}}(l_k|Y_{1:k}^{(1)}, Y_{1:k}^{(2)}, \theta) \end{aligned} \tag{13}$$

where

$$\begin{aligned} &f_{\mathrm{RUL}}^{\mathrm{union}}(l_k|Y_{1:k}^{(1)}, Y_{1:k}^{(2)}, \theta) = \\ &c(F_{\mathrm{RUL}}^{(1)}(l_k^{(1)}|Y_{1:k}^{(1)}), F_{\mathrm{RUL}}^{(2)}(l_k^{(2)}|Y_{1:k}^{(2)}); \theta) \prod_{i=1}^{2} f_{\mathrm{RUL}}^{(i)}(l_k^{(i)}|Y_{1:k}^{(i)}) \end{aligned} \tag{14}$$

where $f_{\mathrm{RUL}}^{\mathrm{union}}$ is the joint distribution function of the multi-stack SOFC system. $c(\cdot)$ is the PDF of Copula function $C(\cdot)$.

The mean RUL of the multi-stack SOFC system is calculated as follows:

$$\bar{L}_k = \int_0^{\infty} t \cdot f_{\mathrm{RUL}}(t|Y_{1:k}^{(1)}, Y_{1:k}^{(2)})\mathrm{d}t \tag{15}$$

III. Results

In the following sub-section, a multi-stack SOFC model is built to obtain the degradation data, and then the proposed approach is employed to predict the RUL for the multi-stack system.

A. Data Collection

The schematic diagram for the multi-stack SOFC system designed in this study is given in Fig. 2. Each stack is composed of a number of cells connected parallelly, and the structure of each fuel cell is similar. The exhaust of the first stack is sent directly to the second stack.

According to mechanical, chemical and electrochemical principles, the stack and the other components models can be established, which have been introduced in a previously published literature [20]. Furthermore, the multi-stack SOFC system model is built in the Matlab / Simulink environment, which is shown in Fig. 3. The input variables are the inlet fuel flowrate, the inlet air flowrate, load current, the inlet fuel and air mole fractions. As the voltage can reflect the performance changes inside the SOFC, the voltage is used as the degradation indicator.

Here, using nickel coarsening and oxidation as an example, the detailed degradation mechanism and the degradation model can be found in Parhizkar [21]. The normal model in Fig. 3 is combined with the degradation model to form the multi-stack degradation model. The current variation is shown in Fig. 4(a), and the inlet fuel and air flowrates are 0.093 mol/s and 0.56 mol/s, respectively. The inlet hydrogen and oxygen mole fractions are 0.8 and 0.21, respectively. The inlet gas temperature is 298 K, the operating time is 3000 h, and the number of cells in both stacks is 23. The collected voltage degradation data of the two stacks are shown in Fig. 4(b).

In order to test the proposed prognostics approach, three test samples are collected with the current time as the 1600th hour, the 1900th hour and the 2200th hour respectively. In the following sub-section, the proposed algorithm and the traditional prognostic method which ignores the correlation of multi-stack degradations are employed to execute prognostics for the multi-stack SOFC system.

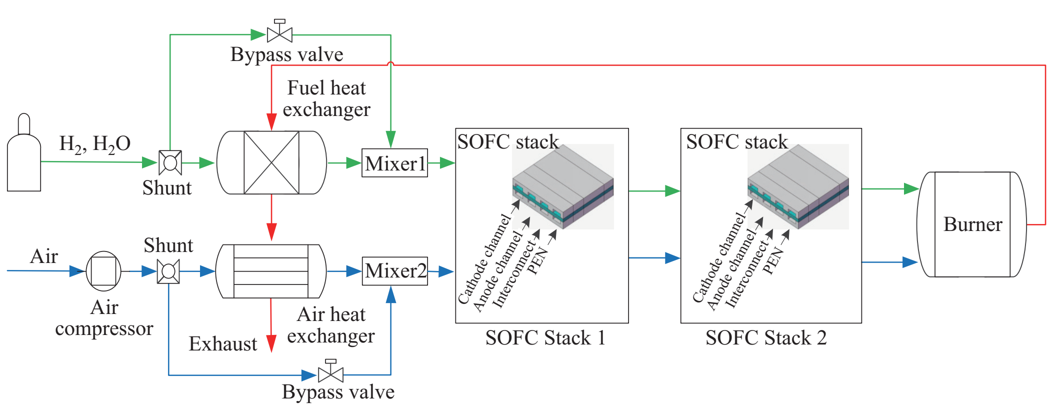


Fig. 2. Structure diagram of a multi-stack SOFC system.

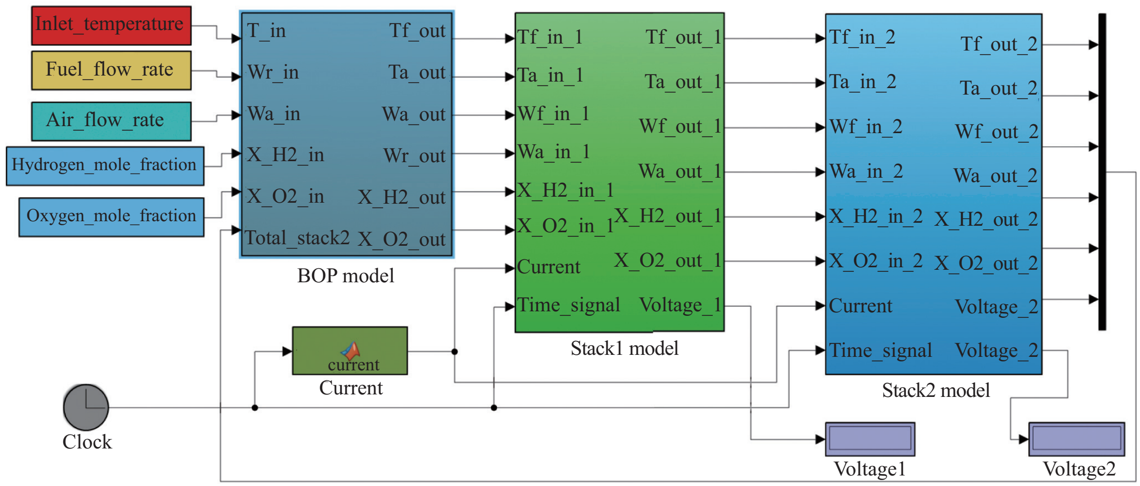
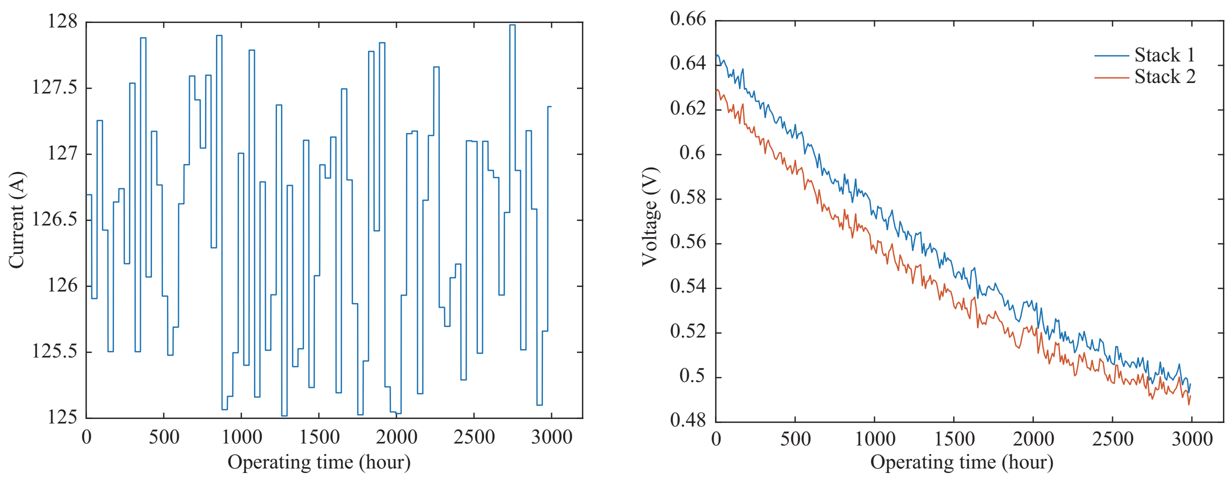


Fig. 3. The multi-stack SOFC system model built in SIMULINK environment.



(a) Current variations

(b) Two degradation trajectories

Fig. 4. Voltage degradation data for two stacks.

B. RUL Distribution of Each Stack

After collecting the voltage data, the proposed prognostic method presented in Section II is employed, and the prognostic flowchart is given in Fig. 5. The degradation parameters are estimated jointly using the EM, and the estimated results are given in Fig. 6(a) and (b). Furthermore, using the Kalman filter method, the voltage degradation trajectory is updated and plotted in Fig. 6(c) and (d). The real voltage degradation trajectory is described by the black lines in Fig. 6, which is the same with Fig. 4. For clarity, the relative error (RE) of the estimated voltage is calculated, which is given as follows:

$$RE = \frac{abs\left(V^{(i)}(t_k) - \hat{V}^{(i)}(t_k)\right)}{V^{(i)}(t_k)} \tag{16}$$

Using the nonlinear model, the maximum REs of the estimated voltage are only 4.06% and 1.17% for the two stacks, respectively, which means that the nonlinear multi-degradation model with the standard Brownian motion can effectively describe the voltage degradation for the two stacks.

In this paper, it is defined that the stack fails when the voltage declines by 20%. Therefore, from Fig. 4, the voltage thresholds for the two stacks are 0.5145 V and 0.5021 V at 2392 hours and 2500 hours, respectively. When the current time is set as 1600 hours, 1900 hours and 2200 hours, respectively, the real failure time is 792 hours, 492 hours and 192 hours for the first stack, while it is 900, 600 and 300 hours for the second stack, which are plotted by the red dots in Fig. 7.

Based on (7), the probability density functions of the remaining useful life for each stack are calculated, which are plotted by the blue lines in Fig. 7. Furthermore, the mean RULs for the two stacks are calculated using (9), which are plotted by the blue Asterisks in Fig. 7. For the three test samples, the estimated mean RULs for the first stack are 887 hours, 481 hours and 187 hours, respectively, and the estimated RULs for the second stack are 996 hours, 622 hours and 291 hours, respectively. The related errors of the remaining useful life estimation are given in Table I. For the first stack, the RE of the estimated remaining useful life does not exceed 11.99%, while the RE of the second stack's RUL does not

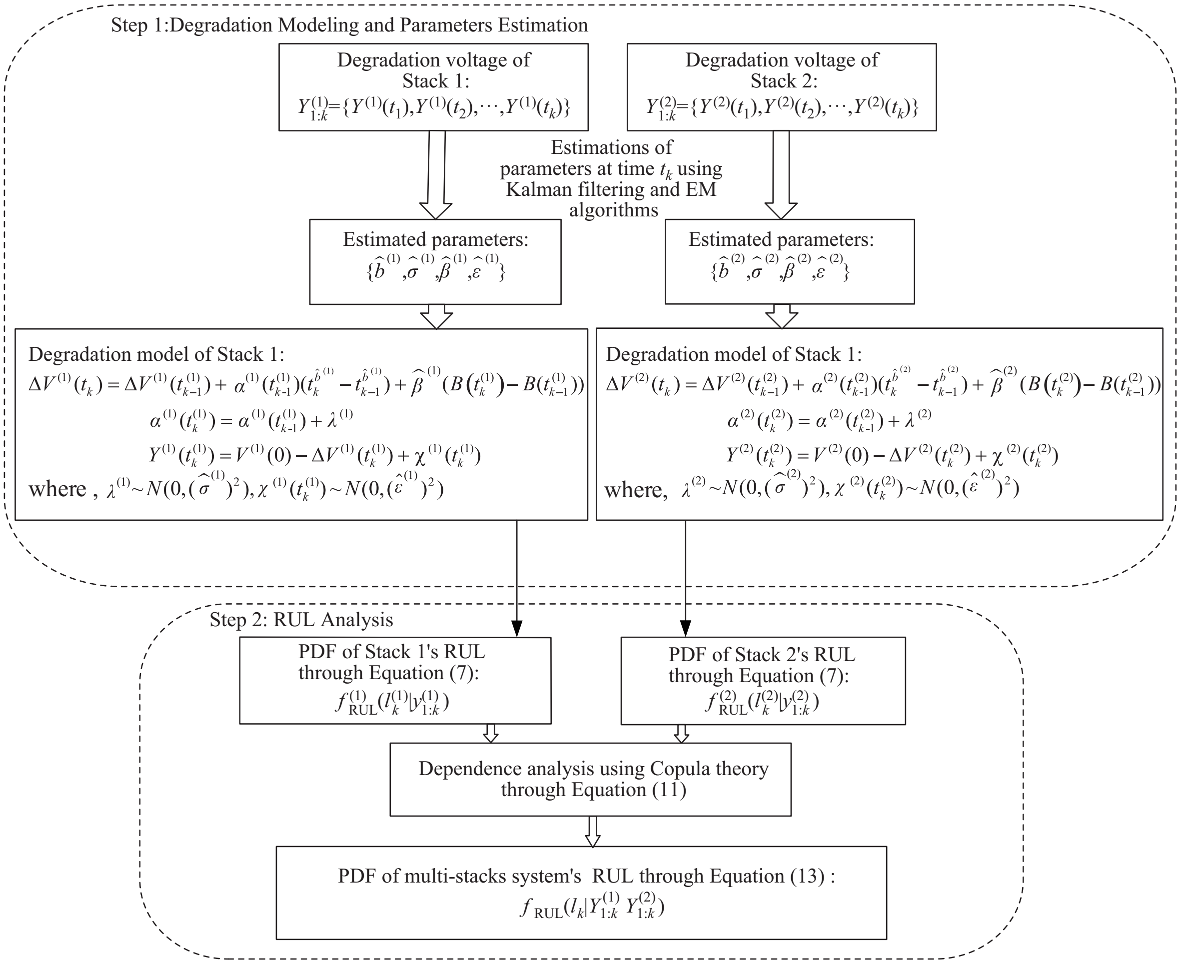


Fig. 5. Prognostics flowchart of the multi-stack SOFC system.

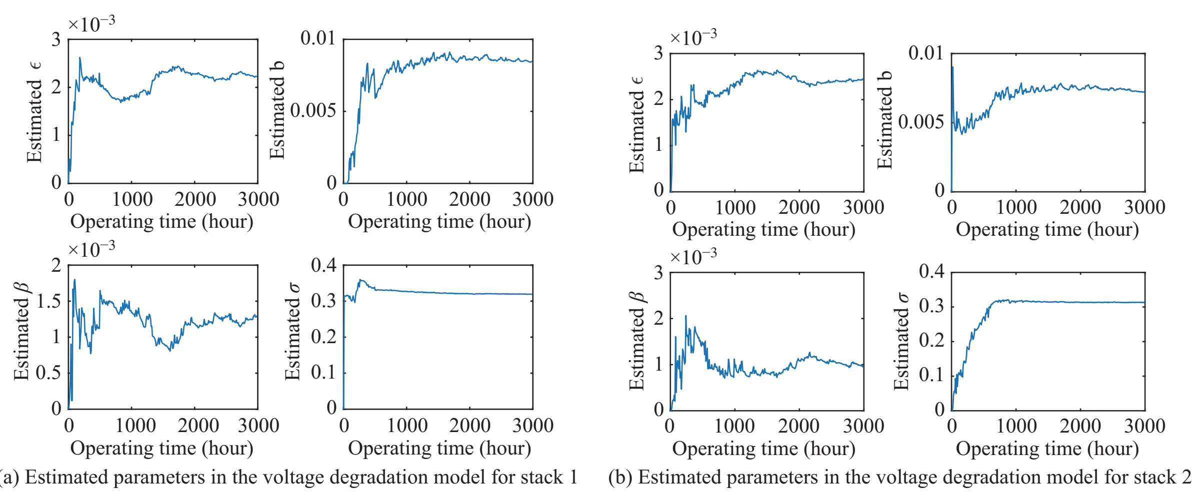


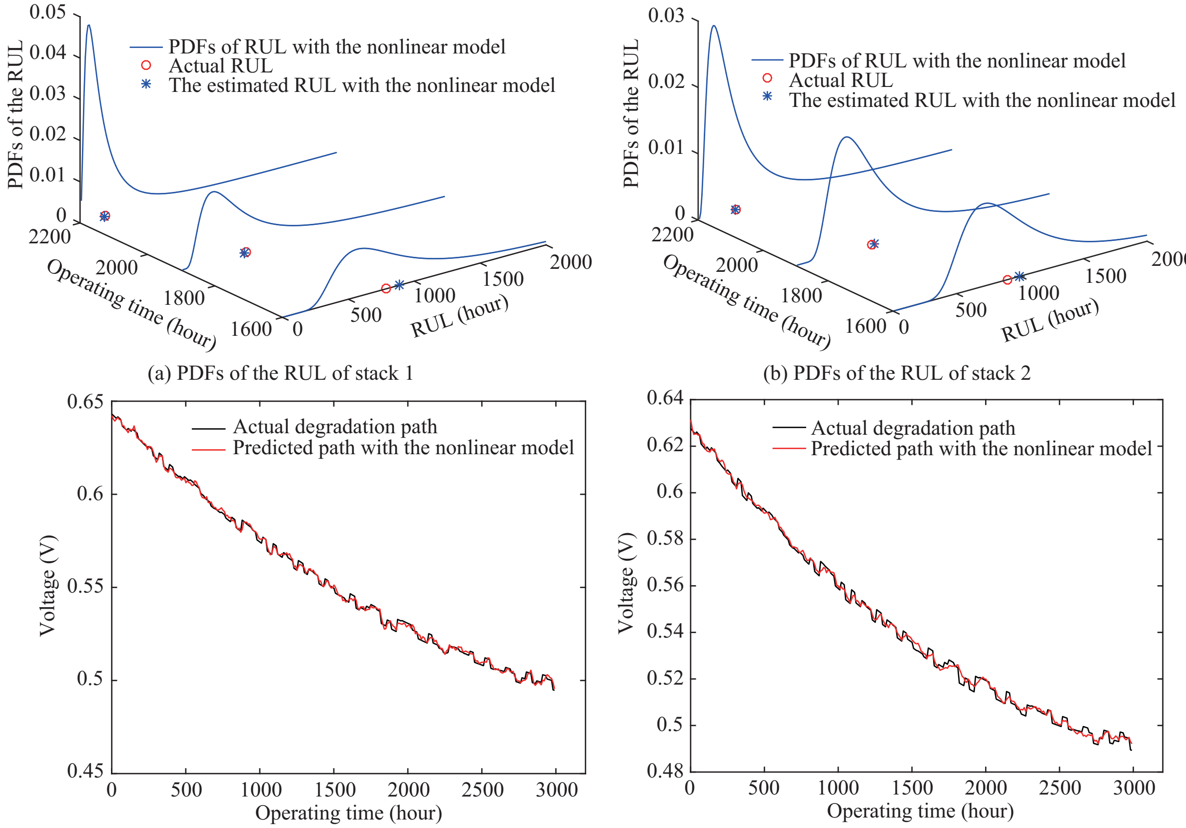
Fig. 6. The predicted voltage degradation paths for two stacks.

exceed 10.67%.

From Fig. 7, at each monitoring moment, the actual remaining life falls within the range of the remaining life probability density curve, and the actual remaining life is located near the remaining life corresponding to the mean value of the PDF. Moreover, with the accumulation of the voltage performance degradation data, the PDF of RUL becomes more and more sharper, indicating that the model parameters are becoming more and more accurate, and the uncertainty of the remaining life prediction continues to decrease.

C. RUL Distribution of the Whole Multi-stack SOFC System

If the voltage of any stack reaches the threshold, it causes the failure of the whole multi-stack system. Therefore, for the



(a) PDFs of the RUL of stack 1

(b) PDFs of the RUL of stack 2

(c) Voltage degradation path for stack 1

(d) Voltage degradation path for stack 2

Fig. 7. PDFs of the RUL of two stacks.

TABLE I
RUL PREDICTION ERRORS FOR THE TWO STACKS

Operating time	RUL's RE of stack 1	RUL's RE of stack 2
1600 h	11.99%	10.67%
1900 h	2.24%	3.67%
2200 h	2.60%	3.00%

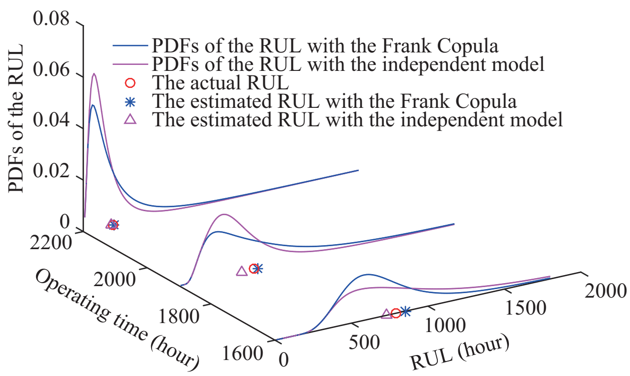


Fig. 8. PDFs of the RUL for the multi-stack SOFC system.

three test samples, the real failure time for the multi-stack is 792 hours, 492 hours and 192 hours, respectively, which are plotted by the red circles in Fig. 8.

Assuming that stack 1 and stack 2 are independent with each other, the CDF of the multi-stack SOFC system's RUL in (11) is transformed into (17):

$$\begin{aligned}
&F_{\mathrm{RUL}}(l_k|Y_{1:k}^{(1)},Y_{1:k}^{(2)})\\
&=P\{\min(L_k^{(1)},L_k^{(2)})\le l_k\}\\
&=1-P\{L_k^{(1)}>l_k\}\cdot P\{L_k^{(2)}>l_k\}\\
&=1-(1-F^{(1)}(l_k^{(1)}|Y_{1:k}^{(1)}))\cdot(1-F^{(2)}(l_k^{(2)}|Y_{1:k}^{(2)}))\\
&=\sum_{i=1}^{2}F^{(i)}(l_k^{(i)}|Y_{1:k}^{(i)})-F^{(1)}(l_k^{(1)}|Y_{1:k}^{(1)})\cdot F^{(2)}(l_k^{(2)}|Y_{1:k}^{(2)})
\end{aligned}\tag{17}$$

By taking the derivative of F_{RUL}, the PDF of RUL for the multi-stack SOFC system without dependence is calculated as follows:

$$\begin{aligned}
f_{\mathrm{RUL}}(l_k|Y_{1:k}^{(1)},Y_{1:k}^{(2)})=&f_{\mathrm{RUL}}^{(1)}(l_k^{(1)}|Y_{1:k}^{(1)})(1-F^{(2)}(l_k^{(2)}|Y_{1:k}^{(2)}))\\
&+f_{\mathrm{RUL}}^{(2)}(l_k^{(2)}|Y_{1:k}^{(2)})(1-F^{(1)}(l_k^{(1)}|Y_{1:k}^{(1)}))
\end{aligned}\tag{18}$$

For the three test samples, using (18), the PDFs of RUL for the multi-stack system are plotted by the red lines in Fig. 8, while using (13), the PDFs of the RUL are marked with blue lines. Using the independent model, the mean RULs of the whole multi-stack SOFC system are calculated, which are plotted by the red triangles. For the three test samples, the mean RULs are 853 hours, 512 hours and 199 hours, respectively. Using the dependent model, the mean RULs of the whole multi-stack SOFC system are given by the blue asterisks. For the three test samples, the mean RULs are 729 hours, 409 hours and 181 hours, respectively. Table II

TABLE II
COMPARISON RESULTS OF RUL PREDICTION FOR THE MULTI-STACK SOFC SYSTEM

Operating time	RUL's RE with the dependent model	RUL's RE with the independent model
1600 h	7.70%	7.95%
1900 h	4.07%	16.87%
2200 h	3.65%	5.73%

shows that the relative errors of RUL predictions for the multi-stack SOFC system. The relative error with the dependent model is smaller than that with the independent one, which means that the independent model ignores the correlation and underestimates the reliability for the multi-stack SOFC system.

IV. Conclusion

With the current material and manufacturing limitations, high-power plants cannot rely on only one SOFC stack. The multi-stack SOFC system is a solution for the high-power system. To improve the reliability of the multi-stack SOFC system, a novel prognostic method has been developed to predict the RULs for the multi-stack SOFC system. The main conclusions are summarized as follows:

To solve the correlations between stack degradation, the nonlinear multi-stack degradation model with the standard Brownian motion has been formulated to describe the voltage degradation for the two stacks, and then the RUL of each stack can be derived. The results show that online prediction for the remaining life of each stack has been perfectly realized. Furthermore, the RUL of the whole multi-stack SOFC system has been calculated. The maximum relative error of RUL prediction for the whole multi-stack SOFC system is 7.7%, which demonstrates that the proposed algorithm can perform effectively for the multi-stack prediction. In the comparative study, the simulation results indicate that the independent model underestimates the reliability of the multi-stack SOFC system, and the proposed prognostic method which considers the correlations among stack degradation can achieve better prognostic results.

The proposed prognostic strategy can help to test the fuel cell performance before its mass implementation in industrial applications and arrange the appropriate health management actions to improve the safety and reliability of the multi-stack system.

References

[1] X. L. Wu, Y. W. Xu, T. Xue, D. Q. Zhao, J. H. Jiang, Z. H. Deng, X. W. Fu, and X. Li, "Health state prediction and analysis of SOFC system based on the data-driven entire stage experiment," *Applied Energy*, vol. 248, pp. 126–140, Aug. 2019.

[2] N. Marx, L. Boulon, F. Gustin, D. Hissel, and K. Agbossou. "A review of multi-stack and modular fuel cell systems: Interests, application areas and on-going research activities," *International Journal of Hydrogen Energy*, vol. 39, no. 23, pp. 12101–12111, Aug. 2014.

[3] J. H. Koh, Y. S. Yoo, J. W. Park, and H. C. Lim, "Carbon deposition and cell performance of Ni-YSZ anode support SOFC with methane fuel," *Solid State Ionics*, vol. 149, no. 3–4, pp. 157–166, Aug. 2002.

[4] H. Liu, J. Chen, D. Hissel, J. G. Lu, M. Hou, and Z. G. Shao, "Prognostics methods and degradation indexes of proton exchange membrane fuel cells: A review," *Renewable and Sustainable Energy Reviews*, vol. 123, pp. 109721, May 2020.

[5] V. Zaccaria, D. Tucker, and A. Traverso, "A distributed real-time model of degradation in a solid oxide fuel cell, part I: Model characterization," *Journal of Power Sources*, vol. 311, pp. 175–181, Apr. 2016.

[6] A. V. Virkar, "A model for solid oxide fuel cell (SOFC) stack degradation," *Journal of Power Sources*, vol. 172, no. 2, pp. 713–724, Oct. 2007.

[7] A. Cuneo, V. Zaccaria, D. Tucker, and A. Traverso, "Probabilistic analysis of a fuel cell degradation model for solid oxide fuel cell and gas turbine hybrid systems," *Energy*, vol. 141, pp. 2277–2287, Dec. 2017.

[8] M. Z. Khan, M. T. Mehran, R. H. Song, J. W. Lee, S. B. Lee, and T. H. Lim, "A simplified approach to predict performance degradation of a solid oxide fuel cell anode," *Journal of Power Sources*, vol. 391, pp. 94–105, Jul. 2018.

[9] B. Dolenc, P. Boškoski, M. Stepančič, A. Pohjoranta, and Đ. Juričić, "State of health estimation and remaining useful life prediction of solid oxide fuel cell stack," *Energy Conversion and Management*, vol. 148, pp. 993–1002, Sep. 2017.

[10] X. J. Wu and Q. W. Ye, "Fault diagnosis and prognostic of solid oxide fuel cells," *Journal of Power Sources*, vol. 321, pp. 47–56, Jul. 2016.

[11] X. J. Wu, Q. W. Ye, and J. H. Wang, "A hybrid prognostic model applied to SOFC prognostics," *International Journal of Hydrogen Energy*, vol. 42, no. 39, pp. 25008–25020, Sep. 2017.

[12] D. Marra, M. Sorrentino, C. Pianese, and B. Iwanschitz, "A neural network estimator of solid oxide fuel cell performance for on-field diagnostics and prognostics applications," *Journal of Power Sources*, vol. 241, pp. 320–329, Nov. 2013.

[13] T. Chen, S. L. Zheng, and J. Z. Feng. "Statistical dependency analysis of multiple competing failure causes of fuel cell engines," *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, vol. 231, no. 2, pp. 83–90, Jan. 2017.

[14] S. J. Tang, C. Q. Yu, X. Wang, X. S. Guo, and X. S. Si, "Remaining useful life prediction of lithium-ion batteries based on the wiener process with measurement error," *Energies*, vol. 7, no. 2, pp. 520–547, Jan. 2014.

[15] J. F Zheng, X. S. Si, C. H. Hu, Z. X. Zhang, and W. Jiang, "A nonlinear prognostic model for degrading systems with three-source variability," *IEEE Transactions on Reliability*, vol. 65, no. 2, pp. 736–750, Jun. 2016.

[16] L. Feng, H. L. Wang, X. S. Si, and H. X. Zou, "A state-space-based prognostic model for hidden and age-dependent nonlinear degradation process," *IEEE Transactions on Automation Science and Engineering*, vol. 10, no. 4, pp. 1072–1086, Oct. 2013.

[17] J. Bian, H. Wang, L. M. Wang, G. Q. Li, and Z. H. Wang, "Probabilistic optimal power flow considering the dependence of multiple wind farms using pair diffusive kernel copula," *CSEE Journal of Power and Energy Systems*, doi: 10.17775/CSEEJPES.2020.07010.

[18] Z. Q. Pan, N. Balakrishnan, Q. Sun, and J. L. Zhou, "Bivariate degradation analysis of products based on Wiener processes and copulas," *Journal of Statistical Computation and Simulation*, vol. 83, no. 7, pp. 1316–1329, Feb. 2012.

[19] Y. T. Lin, T. Y. Ji, Y. Z. Jiang, and Q. H. Wu, "Stochastic economic dispatch considering the dependence of multiple wind farms using multivariate Gaussian kernel copula," *CSEE Journal of Power and Energy Systems*, doi: 10.17775/CSEEJPES.2020.03610.

[20] X. J. Wu, L. F. Xu, J. H. Wang, D. N. Yang, F. S. Li, and X. Li, "A prognostic-based dynamic optimization strategy for a degraded solid oxide fuel cell," *Sustainable Energy Technologies and Assessments*, vol. 39, pp. 100682, Jun. 2020.

[21] T. Parhizkar and S. Hafeznezami, "Degradation based operational optimization model to improve the productivity of energy systems, case study: Solid oxide fuel cell stacks," *Energy Conversion and Management*, vol. 158, pp. 81–91, Feb. 2018.

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