International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 0655

SOH ESTIMATION AND RUL PREDICTION FOR SOFC BASED ON THE FRAMEWORK OF DATA-DRIVEN AND DEGRADATION MODEL

Yuanwu Xu[1], Xiaolong Wu[1], Xiaobo Zhong[1], Dongqi Zhao[1], Jianhua Jiang[1], Zhonghua Deng[1], Xiaowei Fu[2], Xi Li [1*]

1 School of Artificial Intelligence and Automation, Key Laboratory of Image Processing and Intelligent Control of Education Ministry, Huazhong University of Science and Technology, 430074 Wuhan, Hubei, China (Corresponding Author)

2 College of Computer Science and Technology, Hubei Province Key Laboratory of Intelligent Information Processing and Real-time Industrial System, Wuhan University of Science and Technology, 430081 Wuhan, Hubei, China

ABSTRACT

Due to the inherent degradation of materials and the influence of various operating conditions such as load, temperature, and fuel supply, the health state of the solid oxide fuel cell (SOFC) will be inevitably degraded, resulting in system fault or even failure. The state of health (SOH) estimation and remaining useful life (RUL) predicition are beneficial to the maintenance of the SOFC systems, such as preventing unplanned shutdown, which is of great significance for ensuring the safety, reliability, and economy. Therefore, based on the framework of the data-driven and degradation model, this paper develops a method for SOH estimation and RUL prediction for SOFC. Finally, the framework was validated using long-term experimental data from a 1-cell stack.

Keywords: SOFC, data-driven, degraded model, SOH estimation, RUL prediction

NONMENCLATURE

Abbreviations	
SOFC	Solid Oxide Fuel Cell
PHM	Prognostic and Health Management
SOH	State of Health
EOL	End of Life
RUL	Remaining Useful Life
PF	Particle Filtering
KF	Kalman Filtering
UKF	Unscented Kalman Filter
Symbols	
n	Discrete time index
$f(.)$	State function
$g(.)$	Degradation function
$h(.)$	Output function
x	State vector
y	Output vector
u	Input vector
w	Noise vector
θ	System parameters vector
α	Degradation parameters vector

1. INTRODUCTION

The SOFC has emerged as a promising power generation device which has the advantages of high efficiency, fuel flexibility, environmental friendliness and the ability of cogeneration [1]. It is considered as a promising alternative source for portable devices, transportation vehicles, and distributed power generation [2]. However, the health state of SOFC will be inevitably degraded due to inherent degradation of materials and the influence of various operating conditions such as load, operating temperature, and fuel supply, etc., leading to system faults or even failure. The bottlenecks of short service life, rapid performance degradation, and high maintenance cost seriously restrict the large-scale deployment and commercial promotion of SOFC [3]. Many studies [4] have shown that prognostic and health management (PHM) can greatly improve the service life of SOFC, and indirectly reduce its maintenance cost by estimating failure time in advance.

The performance of SOFC is affected by a number of internal and external factors, such as fuel cell design and assembly, material aging, or inappropriate operating conditions [5], etc. Although the degradation mechanism of SOFC has not been fully studied, from the perspective of SOFC stack, the existing literature shows that the degradation of SOFC, especially caused by intrinsic factors, can be observed from the components of the stack:

- Glass-ceramic sealant/Steel interconnect: Changes in the properties of the steel interconnect, such as oxidation; deformation or even cracking caused by thermal gradient and mismatch of coefficient of thermal expansion between adjacent components [6];
- Cathode: Densification of cathode in real life environment; Manganese segregation [7];
- Anode: Sintering of metallic phase in anode in real life environment [8];
- Electrolyte: Phase change in electrolyte; Manganese diffusion into YSZ electrolyte [9];

The degradation of SOFC can generally be equivalent to the increase of internal resistance, which leads to the decrease of power generation, the increase of heat generation and the decrease of output voltage under the same input conditions [10]. Therefore, in our research, the performance degradation of SOFC is equivalent by modeling the internal resistance of SOFC.

The PHM is a new approach for system health management [11]. PHM can provide SOH estimation and RUL prediction to improve the service life of SOFC, increase system reliability, and indirectly reduce its maintenance cost [12]. Therefore, the purpose of this paper is to develop a method for SOH estimation and RUL prediction for SOFC. The method is based on the framework of the data-driven and degradation model. Thanks to the hypothesis of the degradation model and the data-driven approach [13], we can estimate the SOH of SOFC, and predict its future behavior through the degradation model, and then calculate its RUL.

This paper is divided into four main parts. Firstly, section 1 introduces the significance of SOH estimation and RUL prediction of SOFC. Section 2 describes the methods of PHM with an emphasis on the method based on the framework of data-driven and degradation model. This part helps us understand the goals of SOH estimation and RUL prediction and how to perform them. Then, the whole proposition is applied in Section 3 and illustrated by the long-term experimental data from a 1-cell SOFC stack. In section 4, the results of SOH estimation and RUL prediction are evaluated and discussed. Finally, section 5 is the conclusion.

2. THE FRAMEWORK OF DATA-DRIVEN AND DEGRADATION MODEL

When SOFC runs, performance degradation is unavoidable. Degradation causes system parameters to change, such as the increase of internal resistance. The discrete time dynamic model with degradation can be defined as:

$$\begin{aligned} x_{n+1} &= f\left(x_n, u_n, \theta_n, w_x\right) \\ \theta_{n+1} &= g\left(\theta_n, \alpha_n, x_n, w_\theta\right) \\ y_n &= h\left(x_n, u_n, \theta_n, w_y\right) \end{aligned} \tag{1}$$

Among them, $f(.)$, $g(.)$, and $h(.)$ are the state, degradation, and output functions; x_n, y_n, and u_n are the state, output, and input vectors; θ_n and α_n are the system and degradation parameters vectors; w_x, w_y, and w_θ are system, measurement, and degradation noise;

The acceptable range of system performance is determined by the N_C deterministic constraints $C_{EOL} = \{c_i\}_{i=1}^{N_c}$ (where c_i maps the current system performance to the Boolean domain $B = [0,1]$ at each sample time n); Define the system threshold function T_{EOL}. When any constraint in C_{EOL} is violated, T_{EOL} equals 1, otherwise T_{EOL} equals 0, as follows

$$T_{EOL}\left(x_n, u_n, \theta_n\right) = \begin{cases} 1, & if\ 0 \in \{c_i(x_n, u_n, \theta_n)\}_{i=1}^{N_c} \\ 0, & otherwises \end{cases} \tag{2}$$

At the current time n, end of life (EOL) is denoted by E_n, which is defined as the earliest time to reach the failure threshold (i.e., $T_{EOL} = 1$), as follows.

$$E_n \triangleq \inf\{k \in \mathbb{Z} : k \geq n\ and\ T_{EOL}(\mathbf{x}_k, \boldsymbol{\theta}_k, \mathbf{u}_k) = 1\} \tag{3}$$

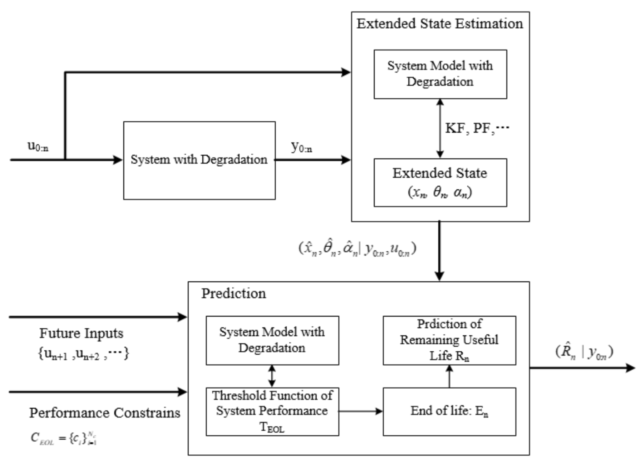

Fig. 1. The framework of data-driven and degradation model for SOH estimation and RUL prediction

At the current time n, the remaining useful life (RUL) is denoted by R_n, is expressed as:

$$R_n = \left(E_n - n\right)\Delta t \tag{4}$$

where Δt is the sampling time.

Therefore, the SOH estimation and RUL prediction based on the framework of the data-driven and degradation model are mainly divided into two parts: i) SOH estimation ii) RUL prediction, as shown in Fig. 1.

3. SOH ESTIMATION AND RUL PREDICTION FOR SOFC

The output voltage of SOFC equals its nernst voltage minus three losses, as follows,

$$V_{sofc} = E_{nernst} - R_{ohm} I - V_{con} - V_{act} \tag{5}$$

Where V_{act}, V_{con}, and R_{ohm} represent activation loss, concentration loss, and ohmic resistance; I represent current; The detailed information on modeling can refer to previous work [14].

As mentioned in section 1, the performance degradation of SOFC is equivalent to the change of internal resistance. The internal resistance of SOFC is modeled by degenerate parameters α_1 and α_2, as follows,

$$R_{ohm}(t) = R_{ohm}(0)(1+\alpha_1(t)) \tag{6}$$

$$\alpha_1(t) = \alpha_2 \times t \tag{7}$$

Among them, α_2 is the derivative of $\alpha_1(t)$.

Eq.(4)-(6) is discretized and then reduced to the form of Eq.(1), where y_n = v_{sofc}; $\alpha_n = [\alpha_1, \alpha_2]$; $\theta_n = [E_{nernst}, V_{act}, V_{conc}, R_{ohm}]^{T}$, $u_n = I$; As shown in Fig. 2., the experimental data came from a 1-cell SOFC stack. More detailed information on the experiment can be found in [15]. During the experiment, a temperature controller was used to ensure operating temperature at 750 ℃, so x_n = T = 750 ℃;

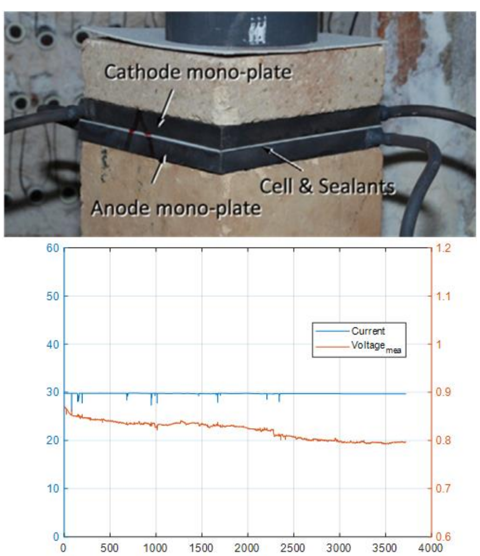

Fig. 2. (a) 1-cell SOFC stack (b) the voltage during its constant discharge current operation

4. TEST RESULTS AND DISCUSSIONS

Under the framework of the data-driven and degradation model, particle filtering (PF) or Kalman filtering (KF) is generally used for SOH estimation and RUL prediction. In this paper, UKF is used to estimate SOH.

4.1 Test results

The long-term degradation estimation results can be obtained by the method based on the framework of the data-driven and degradation model. In Fig.3., it can be found that the estimated long-term degradation trend can track the general degradation trend of SOFC voltage.

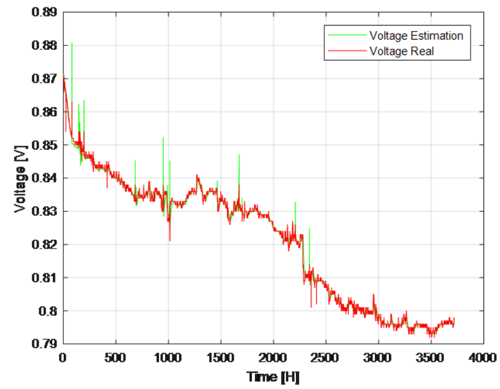

Fig. 3. Long-term degradation trend estimation

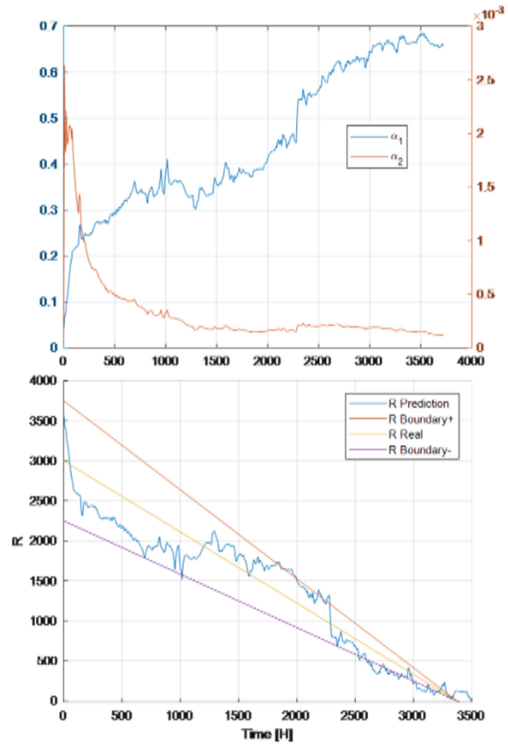

Fig. 4. (a) SOH estimation (b) RUL prediction

The estimation results of SOH can be obtained. As shown in Fig.4.(a), the parameter α_1 represents the SOH of SOFC. The larger the value of α_1, the more serious the aging degree is. The parameter α_2 indicates the aging rate. It can be seen that the aging rate of SOFC tends to be stable after 1500 hours. The RUL can be predicted by combining the SOH estimation results with the degradation model. As shown in Fig.4.(b), most of the RUL predicted results are within the 1 ±0.25 confidence interval.

4.2 discussions

The method described in this paper can obtain relatively satisfactory SOH estimation and RUL prediction results under constant operating conditions. However, it is difficult to ensure that the operating conditions are constant in actual system operation. Therefore, the method in this paper needs to be further improved, especially for unstable operating conditions.

5. CONCLUSION

In this paper, the methods of SOH estimation and RUL prediction based on the framework of data-driven and degradation model for SOFC are presented. the SOH estimation of SOFC is realized by using UKF algorithm. Combining the SOH estimation results with the degradation model, the future behavior of SOFC is predicted, and then the RUL can be calculated. The results show that this method can realize SOH estimation and RUL prediction.

ACKNOWLEDGEMENT

The authors would like to thank the support of the National Natural Science Foundation of China (61873323, 61773174, 61573162), the Wuhan Science and Technology Plan Project (2018010401011292), the Hubei Province Natural and Science Foundation (2017CFB4165, 2016CFA037), the Open Fund Project of Hubei Province Key Laboratory of Intelligent Information Processing and Real-time Industrial System (No. znxx2018ZD02) and Basic Research Project of Shenzhen (JCYJ20170307160923202, JCYJ20170818163921328).

REFERENCE

[1] Lu Y, Cai Y, Souamy L, et al. Solid oxide fuel cell technology for sustainable development in China: An over-view[J]. International Journal of Hydrogen Energy, 2018, 43(28): 12870-12891.

[2] OFFICE of ENERGY EFFICIENCY & RENEWABLE ENERGY. Comparison of Fuel Cell Technologies. United States; 2016. Available from:
https://www.energy.gov/sites/prod/files/2016/06/f32/fcto_fuel_cells_comparison_chart_apr2016.pdf.

[3] Yokokawa H, Tu H, Iwanschitz B, et al. Fundamental mechanisms limiting solid oxide fuel cell durability[J]. Journal of Power Sources, 2008, 182(2): 400-412.

[4] Wu X, Ye Q, Wang J. A hybrid prognostic model applied to SOFC prognostics[J]. International Journal of Hydrogen Energy, 2017, 42(39): 25008-25020.

[5] Mukerjee S, Leah R, Selby M, et al. Life and Reliability of Solid Oxide Fuel Cell-Based Products: A Review[M] // Solid Oxide Fuel Cell Lifetime and Reliability. Academic Press, 2017: 173-191.

[6] Lin C K, Chen K Y, Wu S H, et al. Mechanical durability of solid oxide fuel cell glass-ceramic sealant/steel interconnect joint under thermo-mechanical cycling[J]. Renewable Energy, 2019, 138: 1205-1213.

[7] Lee I.S., Babcock A., L.G. Fuel Cell Systems program and technology update. 17th annual solid solid state energy conversion alliance worskhop; 2016. Available from:
http://www.netl.doe.gov/File%20Library/Events/2016/sofc/Lee-Babcock.pdf.

[8] Kim S J, Choi M B, Park M, et al. Acceleration tests: degradation of anode-supported planar solid oxide fuel cells at elevated operating temperatures[J]. Journal of Power Sources, 2017, 360: 284-293.

[9] Kawasaki T, Matsuda J, Tachikawa Y, et al. Oxidation-induced degradation and performance fluctuation of solid oxide fuel cell Ni anodes under simulated high fuel utilization conditions[J]. International Journal of Hydrogen Energy, 2019.

[10] Menzler N H, Sebold D, Guillon O. Post-test characterization of a solid oxide fuel cell stack operated for more than 30,000 hours: The cell[J]. Journal of Power Sources, 2018, 374: 69-76.

[11] Liao L, Köttig F. Review of hybrid prognostics approaches for remaining useful life prediction of engineered systems, and an application to battery life prediction[J]. IEEE Transactions on Reliability, 2014, 63(1): 191-207.

[12] Dolenc B, Boškoski P, Stepančič M, et al. State of health estimation and remaining useful life prediction of solid oxide fuel cell stack[J]. Energy Conversion and Management, 2017, 148: 993-1002.

[13] Khorasgani H, Biswas G, Sankararaman S. Methodologies for system-level remaining useful life prediction[J]. Reliability Engineering & System Safety, 2016, 154: 8-18.

[14] Cheng H, Jing S, Xu Y, et al. Control-oriented modeling analysis and optimization of planar solid oxide fuel cell system[J]. International Journal of Hydrogen Energy, 2016, 41(47): 22285-22304.

[15] Yan D, Zhang C, Liang L, et al. Degradation analysis and durability improvement for SOFC 1-cell stack[J]. Applied energy, 2016, 175: 414-420.